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THE ECONOMIC IMPACT OF AUTONOMOUS TECHNOLOGIES AND A MODEL FOR THE CIRCULAR ECONOMY

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INTERNATIONAL UNIVERSITY OF ANDALUSIA - UNIVERSITY OF HUELVA

DOCTORAL THESIS

The economic impact of autonomous technologies and a model for the circular economy

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A thesis submitted in fulfillment of the requirements for the degree of Doctor of Philosophy

in the

Doctoral Programme: Economics, Business, Finance and Computing Science

Declaration of Authorship

I, Pablo CASAS ALJAMA, declare that this thesis titled, “The economic impact of autonomous technologies and a model for the circular economy” and the work presented in it are my own. I confirm that:

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"The ultimate goal of the economic system is not to have a lot of money,
but to have a lot of time and freedom."

Yuval Noah Harari

"It is never too late to be what you might have been."

George Eliot

INTERNATIONAL UNIVERSITY OF ANDALUSIA - UNIVERSITY OF HUELVA

Abstract

Doctoral Programme: Economics, Business, Finance and Computing Science

Doctor of Philosophy

The economic impact of autonomous technologies and a model for the circular economy

by Pablo CASAS ALJAMA

This dissertation offers a comprehensive analysis of the wide-ranging economic implications and labour market consequences of autonomous technologies, while also considering the role of the circular economy in sustaining economic growth. Spanning three thematic areas across nine self-contained essays, the research provides a combination of macroeconomic modelling and microeconomic evidence. The thesis is divided into three main parts, leaving aside the introduction and the concluding remarks. The first part focuses on macroeconomic theoretical modelling of a dual traditional-autonomous economy, employing dynamic general equilibrium models to evaluate the impact of autonomous technologies on the economy. The second part provides microeconomic evidence regarding the influence of autonomous technologies on labour markets. Finally, the third part presents a novel perspective on the integration of circular economy concepts into a neoclassical dynamic general equilibrium model. The thesis initiates its exploration through the lens of a dual traditional-autonomous economy model to study the economic implications of automation, discovering that the effects are largely determined by the adoption rate of autonomous capital and its elasticity of substitution with traditional technology. A significant finding suggests the existence of an adoption rate threshold, beyond which the process of automation can lead to a complete shift from traditional capital and labour. Furthermore, the study uncovers the necessity for a profound reform of current tax systems by observing a reduction in the government's size due to the substitution of traditional tax-bearing inputs with autonomous technology. Further exploration into the optimal tax policy for maintaining the social security contributions to GDP ratio by taxing autonomous capital suggests that a robots' social security tax paid by employers of autonomous capital is the most efficient long-term strategy. The dissertation then pivots to provide microeconomic evidence, examining the impact of digitalization on labour markets, using data from the US and European countries. The research provides a view of the effects of digitalization on the US employment landscape, presenting mappings that classify occupations based on their relationship with automation and AI. The study also investigates the implications of the automation process and AI on early retirement decisions across 26 European countries, revealing a significant role of technological change in these decisions. Moreover, this part analyses the role of computerization, AI, machine learning, and occupational reorganization capacity in unemployment probabilities among older workers, indicating the heterogeneity in the impact of new technologies on the labour market. Finally, this section explores the implications of digitalization for worker mobility, illustrating a significant influence on the relocation of displaced workers. Finally, the thesis presents a novel mathematical description of a circular economy by incorporating the concept into a neoclassical dynamic general equilibrium linear economy model. The study reveals a positive S-shaped relationship between the optimal recycling rate and economic development, concluding that increasing the circularity of the economy is a necessary condition for enhancing social welfare in a growing economy. Overall, the dissertation presents a comprehensive examination of the broad economic impacts of autonomous technologies, while introducing the concept of the circular economy into macroeconomic modelling. The findings have important implications for policy-making, contributing to a better understanding of the technology-driven economic changes.

Abstract in Spanish

Esta tesis ofrece un análisis exhaustivo de las amplias implicaciones económicas y las consecuencias en el mercado laboral de las tecnologías autónomas, considerando también el papel de la economía circular en el sostenimiento del crecimiento económico. Abarcando tres áreas temáticas a lo largo de nueve ensayos independientes, la investigación proporciona una combinación de modelado macroeconómico y evidencia microeconómica. La tesis se divide en tres partes principales, dejando a un lado la introducción y las conclusiones finales. La primera parte se centra en el modelado teórico macroeconómico de una economía dual tradicional-autónoma, utilizando modelos de equilibrio general dinámico para evaluar el impacto de las tecnologías autónomas en la economía. La segunda parte proporciona evidencia microeconómica sobre la influencia de las tecnologías autónomas en los mercados laborales. Finalmente, la tercera parte presenta una nueva perspectiva sobre la integración de los conceptos de economía circular en un modelo neoclásico de equilibrio general dinámico. La tesis inicia su exploración a través del lente de un modelo de economía dual tradicional-autónoma para estudiar las implicaciones económicas de la automatización, descubriendo que los efectos están determinados en gran medida por la tasa de adopción del capital autónomo y su elasticidad de sustitución con la tecnología tradicional. Un hallazgo significativo sugiere la existencia de un umbral de tasa de adopción, más allá del cual el proceso de automatización puede llevar a un cambio total desde el capital y el trabajo tradicionales. Además, el estudio revela la necesidad de una profunda reforma de los sistemas fiscales actuales al observar una reducción en el tamaño del gobierno debido a la sustitución de los insumos tradicionales sujetos a impuestos con tecnología autónoma. Una exploración más profunda en la política fiscal óptima para mantener la proporción de contribuciones a la seguridad social respecto al PIB mediante la imposición de impuestos al capital autónomo sugiere que un impuesto a la seguridad social de los robots pagado por los empleadores de capital autónomo es la estrategia a largo plazo más eficiente. La tesis luego se enfoca en proporcionar evidencia microeconómica, examinando el impacto de la digitalización en los mercados laborales, utilizando datos de los EE. UU. y países europeos. La investigación proporciona una visión de los efectos de la digitalización en el panorama laboral de los EE. UU., presentando mapeos que clasifican las ocupaciones según su relación con la automatización y la IA. El estudio también investiga las implicaciones del proceso de automatización y la IA en las decisiones de jubilación anticipada en 26 países europeos, revelando un papel significativo del cambio tecnológico en estas decisiones. Además, esta parte analiza el papel de la informatización, la IA, el aprendizaje automático y la capacidad de reorganización ocupacional en las probabilidades de desempleo entre los trabajadores mayores, indicando la heterogeneidad en el impacto de las nuevas tecnologías en el mercado laboral. Finalmente, esta sección explora las implicaciones de la digitalización para la movilidad de los trabajadores, ilustrando una influencia significativa en la reubicación de los trabajadores desplazados. Finalmente, la tesis presenta una nueva descripción matemática de una economía circular al incorporar el concepto en un modelo lineal de economía de equilibrio general dinámico neoclásico. El estudio revela una relación en forma de S positiva entre la tasa óptima de reciclaje y el desarrollo económico, concluyendo que aumentar la circularidad de la economía es una condición necesaria para mejorar el bienestar social en una economía en crecimiento. En general, la tesis presenta un examen exhaustivo de los amplios impactos económicos de las tecnologías autónomas, introduciendo el concepto de economía circular en el modelado macroeconómico. Los hallazgos tienen importantes implicaciones para la formulación de políticas, contribuyendo a una mejor comprensión de los cambios económicos impulsados por la tecnología.

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To start, I am profoundly indebted to my supervisors, Conchi and José Luis. Their guidance and support have been an anchor throughout this challenging but rewarding journey. Their steadfast belief in my potential, coupled with their critical insights, have been instrumental in shaping this thesis. Conchi, your comprehensive expertise and meticulousness in research have continuously sparked my intellectual curiosity. Conversely, José Luis, your unique perspective and deep understanding of macroeconomics have pushed me to think beyond the norm and venture into new solutions to the research challenges I encountered. Together, you were not just mentors but also sources of inspiration and motivation. This thesis would not have been what it is without your invaluable contribution.

On that note, I wish to extend my gratitude to other researchers who have worked with me on this thesis, investing in my ideas, and sharing their unique and valuable approaches. I am particularly thankful to Rui Baptista for his warm welcome during my stay at the Instituto Superior Técnico of the University of Lisboa. Equally, I owe a debt of gratitude to Hugo Castro-Silva, not just a great friend, but also an ever-present ally, always willing to clear doubts and assist me in achieving my research goals. I also must acknowledge Jolanda Hessels for her invaluable contribution to this thesis and Anelí Bongers for her guidance during the development of the circular economy model.

In line with this, I would like to extend my thanks to the doctoral students, researchers, and all participants who helped refine this thesis at various conferences and workshops. My fellow doctoral students, including Rui Agostinho, Odra Quesada, Teresa Forner, Miquel Alquézar-Yus, Elisa Failache, Carla Ronza, Afonso Câmara, Giovanni Righetti, Alessio Mitra, and Juan Arnadillo, deserve special thanks for their insightful contributions.

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My grandparents, Mari, Mariloli, and Pedro, have enriched my life with their continuous love and invaluable wisdom, teaching me the importance of resilience and cherishing each moment. Their experiences and life stories have kept me grounded. The strength to overcome challenges, the confidence to follow my path, the achievements that led to this thesis – they are as much a testament to my family's support as they are to my efforts. A special remembrance is for my late grandfather, Pepe, to whom this thesis is dedicated. Although he is no longer physically present, his inspiring memories and impactful legacy continue to strengthen me. His life was a constant reminder of the resilience required in the face of adversity. Even though he did not see this work completed, I hope it serves as a tribute to his enduring influence and honors his memory.

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To José Casas Campillo

Preface

This thesis investigates the technological change of the Fourth Industrial Revolution and proposes a circular general equilibrium model that breaks away from the linear modelling paradigm of the economy. The first part of the thesis analyses the technological change encompassed by autonomous capital using general equilibrium models to gain a comprehensive view of the potential economic impact of autonomous technology. The second part of the thesis employs microeconometric analysis techniques to examine the specific impact of digitalization on various aspects of the labour market. Finally, the circular economy model is presented and the main conclusions of the thesis are summarised, along with avenues for future research.

The journey culminating in the realisation of this doctoral thesis began years ago when my interest in research naturally emerged while I was still a child. From my childhood, I began to be curious about seemingly trivial matters such as the origins of buildings and cars. At that time, I could not even suspect that I was becoming interested in economic growth and technological progress. In my adolescence, I conducted my first research on econophysics at the high-school out of pure interest, long before I even considered that what I was doing was research.

While pursuing my university studies at the University of Málaga, I was fortunate to meet Prof. José L. Torres in the Advanced Macroeconomics course, who guided and educated me in the art of research. During the academic year 2016/2017, I had the good fortune to participate in a university extension course at the Department of Economic Theory and History, aimed at an advanced group of the university for the extension of knowledge in several branches of economics and the introduction to research.

My participation in this university extension course allowed me to learn more about how the department's professors conducted their research and guaranteed me the opportunity to undertake curricular internships at the department. Undertaking these internships and my Final Degree Project under the supervision of Professor Torres was of great help in learning more about the university. The seed of this thesis was born with my Final Degree Project titled "Qualified and Unqualified Life in the Fourth Industrial Revolution: A Dynamic General Equilibrium Analysis".

Given my interest in academic life, Prof. José L. Torres recommended that I enrol in the Master's programme in Economics, Business, Finance and Computing, jointly offered by the International University of Andalusia and the University of Huelva. My Master's thesis consisted of an expansion and refinement of my Final Degree Project, again under the supervision of Professor Torres. In this master's programme, I was fortunate to meet Prof. Concepción Román in the Microeconomic Analysis course. Since then, Professor Román has been willing to introduce me to microeconometric research, welcoming me to the University of Huelva as the supervisor of my doctoral thesis.

This thesis was carried out while working as a research assistant at the University of Huelva and studying a bachelor's degree in Mathematics at the Spanish Distance University. My work as a research assistant at the University of Huelva was firstly carried out under the grant PEJ2018-003473-A during the first two years of the thesis, and subsequently within the project PID2020-115183RB-C22 and as a Temporary Substitute Professor in the Department of Economics.

I cannot be more grateful to my thesis supervisors for having supported me for years and accompanied me on this journey, mentoring me in the art of research and university life. I have been fortunate that two great individuals, two researchers whom I deeply admire, have been willing to share their time with me and allow me to learn from them. I could not have had better mentors.

Part I

Introduction

Chapter 1

Introduction

The literature on automation has been growing rapidly in recent years, with a wide debate about its economic implications (Hanson, 2008; Brynjolfsson and McAfee, 2014; Nordhaus, 2017). The main focus has been on how technological progress will affect labour and labour income, with authors differing in their views on whether complementarity or substitution effects will dominate. Pessimistic visions argue for a decline in employment and labour income (Frey and Osborne, 2017), while more optimistic views emphasize positive impacts on labour. However, the literature has generally overlooked the change in capital composition, assuming new capital is equivalent to old capital, and focusing mostly on robots as substitutes for workers, rather than considering their impact on traditional capital assets. This changing composition of capital in the face of automation is a significant blind spot in the literature. New technologies are not only replacing human labour, but they are also substituting traditional capital assets, which have historically been complementary to labour. This nuanced understanding of the role of automation in the economy is crucial for framing future research and policy discussions.

With advances in AI and robotics raising concerns about the economic implications of the fourth industrial revolution for human labour and income distribution, a number of studies have discussed the necessity of controlling and regulating disruptive technology to protect workers and ensure economic stability (Acemoglu and Restrepo, 2020; Korinek and Stiglitz, 2021; Fernández-Macías et al., 2021; Autor, 2015; Graetz and Michaels, 2018; Klenert et al., 2022; Acemoglu and Restrepo, 2018). Taxing robots has been proposed as a way to delay or discourage automation, obtain additional public revenues for displaced workers, and sustain the social security system (Woirol, 2018; Jimeno, 2019; Basso and Jimeno, 2019; Hoynes and Rothstein, 2019; Cabrales et al., 2020; Jaimovich et al., 2021). The literature on robot taxation is vast, exploring various aspects such as the optimal robot tax rate (Guerreiro et al., 2022; Vermuelen et al., 2020; Thuemmel, 2022; Zhang, 2019; Gasteiger and Prettner, 2022) and the challenges and consequences of implementing such taxes (Mazur, 2019; Marwala, 2018; Chekina et al., 2018; Costinot and Werning, 2018; Kovacev, 2020; Oberson, 2019). However, literature lacks on studies examining the interactions between tax systems and the rise of AI and robotics.

The literature emphasizes that demographic changes and technological shifts interact in complex ways. Lower population growth and population ageing may increase automation, leading to detrimental effects on economic growth in the medium run (Basso and Jimeno, 2021). Pay-as-you-go social security systems face challenges due to demographic shifts and technological innovations driven by automation (Kitao, 2014; Acemoglu and Restrepo, 2022; Basso and Jimeno, 2021). The literature has highlighted the unsustainability of current social security systems, necessitating the restoration of balance through reducing benefits or raising taxes (Kitao, 2014). Moreover, the current tax system has been argued to favor the substitution of labour for capital, incentivizing automation by providing preferential tax treatment for robot workers (Abbott and Bogenschneider, 2018; Huettinger and Boyd, 2020; Soled and Thomas, 2018; Mazur, 2019; Acemoglu and Restrepo, 2019; Acemoglu et al., 2020). There is a pressing need for rigorous research and comprehensive theoretical analyses of the potential taxation of new technologies. Empirical work by Zhang (2019), Thuemmel (2022), and Gasteiger and Prettner (2022) has begun to explore the implications of robot taxes, but more research is needed to understand how these policies could influence income inequality, economic growth, and social welfare in the face of the rapid advancements in automation and AI technologies.

The rapid advancements in AI and robotics have begun to outperform even high-skilled human workers in cognitive and creative tasks, which has sparked a debate on the need for regulation to protect economic stability and workers' livelihoods. The Fourth Industrial Revolution, marked by rapid advancements in technologies such as Artificial Intelligence (AI), Machine Learning (ML), and Robotics, has the potential to bring about significant changes in labour markets worldwide. This technological change presents unique challenges for older workers and policymakers, particularly in the context of an aging population in industrialized countries. The significant transformation of labour markets across the world is a direct consequence of the rapid evolution of digital technologies. The profound impact of this digital revolution on various occupations and workforce dynamics has been a prominent area of study in recent years. The two key aspects of digitalization that have been central to these discussions are its destructive and transformative sides, which have disparate impacts on the labour market.

The labour market impact of digital technologies such as AI and ML has been extensively studied, with Tolan et al. (2021) highlighting that jobs previously thought safe from automation might now be at risk due to increased AI exposure. Similarly, Frey and Osborne (2017) suggest that almost half of US jobs are at high risk of computerization, a trend echoed in Portugal's manufacturing sector (Duarte et al., 2019). However, AI's potential is not limited to job displacement. Recent literature has highlighted its labour-friendly side, with studies documenting a surge in AI-related job vacancies and an increased demand for AI skills in the US economy (Acemoglu et al., 2022; Alekseeva et al., 2021). Furthermore, the emergence of AI has not led to any discernible negative impact on employment or wages, suggesting that it could complement rather than replace human work (Tschang and Almirall 2021).

The macroeconomic implications of technological change are subject to considerable uncertainty (Jimeno, 2019). Key questions include the extent to which machines and human labour will complement or substitute each other, the speed at which tasks currently performed by humans could be automated, and the rate of new task creation. Although some authors emphasize the destructive impact of automation on employment (Frey and Osborne, 2017; Acemoglu and Restrepo, 2020a), others highlight its potential to increase productivity (Graetz and Michaels, 2018) and create new jobs (Damioli et al., 2023). The debate between these opposing views is ongoing.

The labour-saving potential of these technologies has led to concerns about job displacement, especially for certain vulnerable groups such as older workers nearing retirement age (Alcover et al., 2021; Autor, 2015). Simultaneously, the increasing life expectancy and financial pressures on public finances have prompted governments to extend statutory retirement ages and implement more restrictive early retirement policies (European Commission, 2021). This creates a potential contradiction as governments strive to extend working lives while technological changes threaten to displace older workers.

Older workers have been found to experience greater difficulty adapting to technological progress, and this competitive disadvantage has led to a relative deterioration of their job prospects (Schmidpeter and Winter-Ebmer, 2021). The term "digital ageism" has emerged to describe the challenges faced by older people navigating the digital sphere and using online services (Manor and Herscovici, 2021). Moreover, high-skill occupations, which are more likely to be held by older workers, are most exposed to AI, indicating that this age group is at particular risk of displacement (Webb, 2020). In light of these complex and interrelated challenges, this thesis also aims to provide a comprehensive analysis of the impact of new technologies on older workers, focusing on the implications of automation, AI, and ML for early retirement decisions, unemployment, and labour market outcomes. By examining the current state of knowledge and synthesizing insights from the existing literature, this research seeks to inform policy debates and contribute to a deeper understanding of the effects of technological change on the lives and careers of older workers.

The digital revolution, marked by the rise of AI and digital technologies, is reshaping the labour market, with both destructive and transformative impacts. The extent to which these technologies will displace or create jobs remains a contentious issue, but the potential for transformation and growth is undeniable. Therefore, the study of these trends and impacts is vital for informed decision-making related to workforce development, policy planning, and economic growth. These insights will help us navigate the evolving landscape of the labour market, preparing us for the opportunities and challenges that come with the ongoing digital revolution. It is crucial to further our understanding of the interplay between digital technologies and labour dynamics, to optimize the benefits and mitigate the risks. As we move forward, striking a balance between the destructive and transformative aspects of digitalization will be key to fostering a resilient and inclusive labour market.

At the same time, technological progress and the circular economy are closely intertwined. As we strive to create a more sustainable future, the synergy between technological innovation and circular principles will be a key driving force. However, it is important to note that technology alone is not a silver bullet – transitioning to a circular economy also requires changes in policy, business practices, and consumer behaviour. The relationship between technological progress and the circular economy is one of mutual reinforcement. As we grapple with the challenges of resource depletion, climate change, and environmental degradation, it is becoming increasingly clear that the transition to a circular economy – a model that emphasizes the reduction, reuse, and recycling of materials – is a necessity.

Digital technologies such as the Internet of Things (IoT), blockchain, big data, and artificial intelligence (AI) can greatly enhance resource efficiency, traceability, and transparency in supply chains. For instance, IoT devices can monitor and optimize the use of resources in real-time, while blockchain can ensure the integrity and traceability of recycled materials. Technologies such as 3D printing and modular design can support the principles of the circular economy by enabling localized production, customization, and easy disassembly for repair or recycling. On the flip side, the circular economy also drives technological innovation. The necessity to 'close the loop' and create less wasteful systems presents numerous challenges that require innovative solutions. These range from designing products for longevity, creating new business models such as product-as-a-service, to developing novel materials that are eco-friendly and easily recyclable. The move towards a circular economy also spurs innovation by creating new markets and opportunities. Companies that are able to leverage technology to create circular solutions can gain a competitive edge, while also contributing to environmental sustainability.

In traditional economic thinking, economic growth has often been associated with the linear model of "take-make-dispose," which relies on the continuous extraction and consumption of natural resources. However, the limits of this model are becoming increasingly apparent as we face resource depletion, environmental degradation, and climate change. The circular economy offers a promising alternative that decouples economic growth from resource consumption, promoting sustainability while still supporting economic development. Indeed, the focus of traditional economic thinking has been on the maximization of utility and profit, primarily driven by the consumption and production of goods and services. This linear economic model has served us well in terms of economic growth and development for centuries. However, its environmental implications have increasingly become a cause for concern, with the depletion of natural resources and increasing waste generation threatening the sustainability of our economies and the health of our planet.

Overall, integrating the circular economy into our existing linear economy is a complex task that requires a fundamental shift in our economic thinking and practices. Despite the challenges, it presents a unique opportunity to achieve a sustainable, resilient, and prosperous future. Moreover, the inclusion of the circular economy in macroeconomic analysis can provide valuable insights into the economic benefits and trade-offs associated with the transition to a circular economy. It can also help identify the drivers and barriers to this transition, thereby informing effective policies and strategies for promoting the circular economy.

1.1 Contributions of this thesis

The contributions of this thesis in relation to previous work focus on providing new insights into the impact of autonomous technologies on the economy in general (Part II) and on the labour market in particular (Part III), as well as offering a fresh perspective on the economy considering the growing need to break away from the unsustainable linear economic paradigm towards a sustainable circular economy (Part IV).

Part II offers a macroeconomic perspective of the economic impact of autonomous technology on the economy. Specifically, Chapter 2 contributes to the literature by introducing an unconventional production function where two different and alternative technologies can be used for final output: a traditional technology, where a combination of traditional capital and labor is used, and a new technology where only automatic capital is needed for production. As a logical continuation of Chapter 2, Chapter 3 contributes to the literature by analyzing how public finance evolves with the expansion in the economy of the new disruptive autonomous technology. In particular, we examine how total tax revenues, including social security contributions, evolves with automation in the long-run. Finally, Chapter 4 contributes to the literature by exploring the most efficient alternative to tax autonomous capital in order to sustain the social security contributions to output ratio. Specifically, we consider three alternative schemes -taxing robot income, taxing robot investment, and taxing robots as humans- finding that taxing robots as humans is the alternative causing less disruptions in the economy. In addition, we analyze the implications of autonomous capital taxation for the functional distribution of income. To the best of our knowledge, this is the first rigorous contribution considering the autonomous capital taxation as a cantilever for social security in a general equilibrium analysis framework. Previously, literature has considered, separately and briefly, alternative policies for social security sustainability and alternative implementations of autonomous capital taxation.

Part III of this thesis focuses on the analysis of various aspects of the labour market, taking into account the impact of the conglomerate of autonomous technologies labelled as digitalization. Specifically, Chapter 5 is a descriptive exercise classifying occupations according to the current impact of digitalization and future impact expectations. The classifications presented in this chapter are used to analyse the impact of destructive digitalization on early retirement (Chapter 6), as well as to analyse the impact of transformative digitalization on early retirement (Chapter 7) and to examine the implications of digitalization for labour mobility (Chapter 9). Meanwhile, Chapter 8 analyses the impact of computerisation and AI, as well as their interaction (Machine Learning), on the transitions to unemployment of older workers. Regarding geographical coverage, Chapter 5 considers employment in the United States, while Chapters 6, 7, and 8 use data from Europe, and Chapter 9 focuses on the Portuguese labour market.

Delving a bit deeper into the specification of the contributions of the third part of the thesis, we can begin by stating that Chapter 5 contributes to the literature by presenting seven novel mappings of the US employment landscape in relation to the digitalization process. Our approach combines both backward-looking and forward-looking measures, capturing the current state of digitalization and the potential future effects on occupations. Chapter 6 contributes to the literature by analysing the implications of the automation process for the early retirement transitions in 26 European countries. Chapter 7 contributes to the literature by providing new insights to the collision of technological and demographic change by analyzing the effect of AI on the ER decisions in Europe. In order to develop our analysis, we use microdata from the Survey of Health, Ageing and Retirement in Europe (SHARE), a measure of AI advances (Felten et al., 2018) and a measure of AI exposure (Felten et al., 2021). In addition, considering both AI advances and AI exposure we proportionate a new technological classification of occupations in 4 Intelligence terrains (I-terrains). Chapter 8 contributes to the literature by presenting a threefold novelty: (i) analysing the impact of new technologies in the unemployment among older workers in Europe, (ii) considering the impact of AI in unemployment, and (iii) measuring the concrete effect of ML in unemployment Finally, Chapter 9 contributes to the literature by studying labor mobility between occupations at different digitalization exposure levels, and how worker, firm and industry characteristics intervene in such moves. Specifically, we analyze how workers displaced from a job after firm closure move between occupations differently impacted by computerization and artificial intelligence in the Portuguese economy. While the potential for digitalization to create and destroy jobs by making certain skills obsolete while promoting others has been the object of a variety of studies, worker mobility across the digitalization terrains is relatively unaddressed in the literature.

Finally, Part IV of this thesis focuses on capturing the macroeconomic model of the circular economy. Specifically, Chapter 10 contributes to the literature by developing a standard neoclassical Dynamic

General Equilibrium (DGE) model extended by the incorporation of the CE. We depart from previous analyses in ecological economics or industrial ecology, and we use the tools of traditional mainstream neoclassical economics analysis as a prism to offer a new perspective on the CE. The chapter has a twofold purpose. First, we intend to study the economic and environmental implications of the CE from a macroeconomic point of view. Second, we aim to show that traditional neoclassical linear economic models can be transformed and used to study the CE to achieve a better understanding of this issue.

1.2 Chapter overview

This thesis consists of nine self-contained essays structured as follows. It mainly consists of three parts leaving aside this introduction and the concluding remarks.

Part II collects three essays considering the modeling of a dual traditional-autonomous economy using DSGE models. We refer to automation technologies independently as automatic technology and autonomous technology.

Chapter 2 studies the economic implications of automation, considering that automation is affected by disruptive technologies which entail a structural change consisting in the introduction of a new physical capital input (a combination of artificial intelligence and autonomous robots), additional to 'traditional' capital assets and labor. This new 'automatic' physical capital is assumed to carry out production activities without the need to be combined with labor. A simple production function combining both traditional and new technologies is proposed, showing that the consequences of automation depend on the combination of the automatic capital adoption rate and the elasticity of substitution between traditional and automatic technology. We find out that, if the adoption rate is below a threshold that matches the marginal productivity of automatic capital, little effects are derived from automation, independently of the elasticity of substitution. However, if the automatic capital adoption rate is above the threshold level and the elasticity of substitution is higher enough, the automation process can lead to a robocalypse scenario with a total shift of both traditional capital and labor. We estimate, through the benchmark calibration of the model, that the adoption rate threshold for automatic capital is about 22.5

Chapter 3 explores the consequences of automation for public finance. We find that as the automation rate increases, the government size, measured as the fiscal revenues to output ratio, declines due to the substitution of traditional inputs which bear the burden of taxes by the new automatic technology. These results are explained by the effects of automation on labor, where taxation of labor income (including social security contributions) represents the most important source of fiscal revenues in most advanced economies. The paper performs two additional counterfactual experiments. First, we calculate how individual tax rates should be changed in response to automation in order to keep constant fiscal revenues from the different sources of taxes. However, this experiment reveals that this fiscal policy would have significant harmful effects on output and labor, and that a deep reform of the current tax mix is compulsory to offset the effects of automation on public finance. Second, we calculate the tax rate on capital, without modifying the other tax rates, required to keep constant the size of the government, resulting in a capital income tax rate of around 0.77 for an automation rate of 45%.

Chapter 4 analyzes the optimal tax policy to sustain the social security contributions to GDP ratio constant by taxing autonomous capital. We explore three alternative ways of autonomous capital taxation -an autonomous capital income tax, a VAT on autonomous capital investment and a social security tax supported by employers of autonomous capital- under two technological specifications -a framework in which the autonomous technology replaces the traditional capital and labor and a framework in which the autonomous capital replaces labor while complementing traditional capital. We calculate the optimal tax rates to sustain social security size under the three alternative schemes and both technological specifications, finding that these optimal tax rates do not rely on the substitution degree between autonomous and traditional technologies. Both technological specifications indicate that, in the long-run, the robots' social security tax paid by employers of autonomous capital is the more efficient alternative to implement a specific taxation to autonomous capital. Additionally, we analyze the implications of specific autonomous capital taxation for the functional distribution of income.

Part III includes five self-contained essays providing microeconomic evidence targeting the impact of autonomous technologies in the labour market.

Chapter 5 presents seven mappings of the US employment regarding the digitalization process. In order to develop our mappings, we use two destructive digitalization measures -automation degree and computerization probability- and two transformative digitalization measures -AI advances and AI exposure-. Therefore, we consider both a backward-looking and a forward-looking measure at each digitalization side. First, we construct typological mappings for each digitalization side: the automation terrains classify occupations in 4 groups according to the current automation degree and the future computerization probability (destructive digitalization), while the intelligence terrains divide occupations in four groups according to the AI advances and AI exposure (transformative digitalization). Second, we construct two occupational terrains classifications considering the interactions between destructive and transformative effects of digitalization from two time perspectives: the backward-looking occupational terrains collect the current state of digitalization respect to automation degree and AI advances, and the forward-looking occupational terrains collect the expectations about digitalization affectations by considering computerization probability and AI exposure. Third, we propose three extended occupational terrains considering different time perspectives at each digitalization side.

Chapter 6 measures the implications of the automation process in the labour market for the early retirement decisions in 26 European countries. In order to perform the analysis, we use microdata from the Survey of Health, Ageing and Retirement in Europe, occupation-level data on automation degree and automation risk and a technological classification of occupations in 4 terrains. We find that the current technological change is playing a significant role in the early retirement decisions, although it affects heterogeneously certain groups in the sample (regarding gender, education level and job status). This fact leads to a contradiction between governments trying to delay retirement ages and labour markets trying to expel workers earlier. Therefore, we conclude that, in order to elaborate policies on ageing and retirement, the effect of new labour-saving technologies in older worker's decisions must be taken into account. We propose that the delay in statutory retirement ages should be accompanied by training programs and/or policies promoting self-employment for workers at risk of ending their working lives prematurely. Furthermore, the programs aimed to relocate middle-age workers displaced from their original occupations should focus on finding a new occupation among those which are less affected by automation processes.

Chapter 7 analyzes the impact of Artificial Intelligence (AI) in the early retirement (ER) decisions in Europe. In a first stage of our analysis, we use a measure for AI exposure as the main explanatory variable to conclude that expectations on future AI implementations play a relevant role in the ER transitions in Europe. In the second stage of our analysis, we use as the main explanatory variable a novel technological classification that divides the occupations in 4 Intelligence terrains depending on their relation with AI: Human Intelligence terrain for occupations non highly affected by AI, Future AI applications for occupations only affected by a high expectation of AI development, Narrow AI definition for occupations with high AI advances but low AI projections and Artificial Intelligence terrain for occupations highly affected by both AI advances and exposure. We find that workers in occupations with high level of AI advances and high expectations for the further implementation of this technology in the future reduce significantly their probabilities of transiting to ER. When analyzing separately AI advances and AI exposure, we find a significant reduction in the ER likelihood only for workers with higher education. Finally, we highlight that AI may increase or decrease the ER probability depending on the advances-exposure interaction.

Chapter 8 analyses the impact of computerization, AI, ML and occupational reorganization capacity in the probability of unemployment among older workers in Europe. Using data from the Survey of Health, Ageing and Retirement in Europe (SHARE), our results show that, while computerization, and, separately, ML, significantly increase the probability of unemployment among older workers, AI advances and a higher reorganization capacity can significantly reduce it. This fact highlights the heterogeneity of the impact of new technologies on the labour market, since, while one of the fields of the technological revolution (AI) can be shown labour-friendly, a subfield of this technology (ML), an automation technology, can be proved labour-unfriendly. Furthermore, differentiated effects regarding job status are found: employees are significantly pushed to unemployment by computerization and ML, while being protected from unemployment by AI. Civil servants reduce significantly their unemployment probabilities when experiencing higher AI advances and higher reorganization capacity. Self-employed workers are significantly pushed to unemployment only by ML.

Chapter 9 explores the implications of digitalization for worker mobility. Using a Portuguese linked employer-employee longitudinal dataset and a forward-looking occupational classification considering predicted advances in destructive and transformative digitalization, we show that digitalization and the rise of AI are likely to play a relevant role in the relocation of displaced workers. We find that workers with college education, high skills, and experience working in knowledge-intensive sectors are more likely to be relocated in a rising star occupation. Older workers are less likely to transition across occupation types, while female workers are more likely to be impacted by both destructive and transformative digitalization. Periods of non-employment are likely associated with skill depreciation, making it less likely that a displaced worker will return to the same occupational terrain.

Part IV consists of one self-contained chapter presenting a mathematical description of a circular economy considering a DSGE modeling framework.

Chapter 10 studies the economic implications of the circular economy and recycling activities from a macroeconomic perspective. The paper incorporates the circular economy into an otherwise standard neoclassical dynamic general equilibrium linear economy model, in which the production function depends on capital, labor, and raw materials. Raw materials are a composite of natural resources (the linear economy) and recycled material (the circular economy). Waste is a function of consumption but can be incorporated back into production activities through recycling. We find the existence of a positive S-shaped relationship between the optimal recycling rate and economic development, indicating that increasing the circularity of the economy is a necessary condition to augment social welfare in a growing economy. The optimal recycling rate depends positively on the pollution damage and waste content of final consumption goods. Simulation of the model supports the existence of a steady-state Environmental Kuznets Curve (EKC) relationship between the stock of waste and the output in the presence of a circular economy. Finally, we find that while a permanent improvement in recycling technology has positive effects on output, expanding the circularity of the economy, an increase in the cost of natural material has harmful effects on output, increasing waste accumulation and reducing recycling.

Part V concludes the study with a last chapter containing some concluding remarks, highlighting the limitations and outlining the future agenda.

1.3 Publications

Some chapters of this doctoral dissertation are based on research articles published in academic journals or submitted to academic journals and/or presented at various conferences and workshops.

Chapters 2, 3 and 4 are works jointly developed with José L. Torres. Chapter 2 is published in the journal Economics of Innovation and New Technology. Chapter 3 has been presented at the Sixth International ASTRIL Conference, the 47th Symposium of the Spanish Economic Association, the XV Labour Economics Meeting and the 19th edition of the Augustin Cournot Doctoral Days.

Chapter 5, a work jointly done with Hugo Castro-Silva and Concepción Román, has been presented at the Sixth International ASTRIL Conference, the XV Labour Economics Meeting and the 42nd EBES Conference.

Chapters 6, 7 and 8 are works jointly developed with Concepción Román. Chapter 6 is published in The Journal of the Economics of Ageing. This chapter has been presented at the XIV Conference of the Spanish Association of Labor Economics, the 37th Eurasia Business and Economics Society Conference, 10th PhD-Student Workshop on Industrial and Public Economics, the 8th International Conference on Opportunities and Challenges in Management, Economics, and Accounting, the 36th Annual Conference of the Italian Association of Labor Economists, the 23rd Review of Socio Economic Perspectives Conference, the 5th International Academic Conference in the Masters International Research and Development Center and Global Community of Social Science and the VIII International Conference on Applied Economics and Finance. Chapter 7 has been presented at the XV Labour Economics Meeting, the 24th Applied Economics Meeting and the 39th EBES Conference. Chapter 8 has been presented at the XV Labour Economics Meeting and the 24th Applied Economics Meeting.

Chapter 9, a work jointly done with Hugo Castro-Silva, Rui Baptista, Jolanda Hessels and Concepción Román, has been presented at the Workshop of the SPILEF Research Project on new technologies, ecoinnovation, and productivity.

Finally, Chapter 10, a work jointly done with Anelí Bongers, is published in the journal Ecological Economics.

Part II

A macroeconomic perspective

Chapter 2

Automation, Automatic Capital Returns, and the Functional Income Distribution

2.1 Introduction

To produce commuting services, a cab-car needs a cab-driver nowadays. Therefore, it is natural to specify an aggregate production function in which both physical capital and labor are required. Furthermore, this production function is assumed to express some complementarity between both inputs. However, current technological progress is characterized by the creation of a new type of capital (based on a combination of computers, robotics, and artificial intelligence) that can perform production activities in an autonomous way with minimal human intervention.[1] This new "self-driving taxi" is a new type of capital equipment that can substitute both the traditional manual-driving cab and the human cab-driver, and where commuting services can be produced using this new capital alone.[2] In this chapter, we argue that this implies a structural change (a disruption) to the economy production technology, as a new type of capital input is incorporated into production activities. Following standard definitions in the literature (see, for instance, DeCanio, 2016), traditional capital is named just capital, whereas automatic capital is referred as robots. This technological process will result in each particular sector producing a final good using two different technologies. This action will depend on the potential automatic capital adoption rate. The question here is whether it is possible for the two technologies to coexist simultaneously in the different sectors and the economy as a whole, or, by contrast, whether the new technology will crowding-out the old one, generating the so-called robocalypse.

Literature on automation has been growing rapidly during the last decade. Nowadays, there is a wide debate about the economic implications of the automation process although this is not a new topic. The many different views in the literature about the social-economic implications of the same technological change allow to clarify the difficulty of assessing the impact of this phenomenon and past experiences regarding the introduction of new capital equipment. These considerations are of questionable value given the uncertainties about technological progress and the possibility of the technological singularity (Hanson, 2008; Brynjolfsson and McAfee, 2014; Nordhaus, 2017). The main focus have been placed on how this new technological progress will affect labor and labor income. Authors differ in which effect will dominate: complementarity or substitution. Pessimistic visions, adopting a Luddite point of view, bet for an abruptly decline of employment and labor income (for example, Frey and Osborne, 2017) while other optimistic visions argue positive impacts for labor (for example, Ernst *et al.*, 2018). Nevertheless, the literature has not considered the change that has taken place in the composition of capital as the new capital is considered as equivalent to the old one. Indeed, the vast majority of

[1] Grace *et al.* (2018) report that Artificial Intelligence (AI) researchers predict a 50% of probability of robots outperforming all human task by 2045 and substituting all human labor in 120 years. These predictions suggest that AI will outperform humans in a number of activities in the next few decades, such as translating languages (by 2024), writing high-school essays (by 2026), driving a truck (2027), working in retail (2031), writing a bestselling book (by 2049), and working as a surgeon (by 2053).

[2] See Jiang *et al.* (2015) for a discussion of the implications of the particular new disruptive capital asset (self-driving cars). We take self-driving cars just as an example of the characteristics of the new automatic capital, but it can be extended to a number of other production activities.

works on automation consider robots as substitutes for workers, forgetting that they will also replace traditional capital assets which are complement of labor.[3]

Many authors have remarked the current elimination potential of labor-intensive tasks and cognitive demanding tasks (Brynjolfsson and McAfee, 2014; Ford, 2015). Within this stream of thought, Frey and Osborne (2017) argued that 47% of US employment would have been automated by 2033. However, nowadays, even these authors do not support those results (Frey, 2019). Using the same methodology, Bowles (2014) calculated that 54% of European jobs are in high risk of computerization. Other voices claimed that an increase in the robots to workers ratio reduces the employment to population ratio and the wages (Acemoglu and Restrepo, 2019). Chiacchio, Petropoulos and Pichler (2018) use the same methodology to examine the effect of industrial robots in six European countries. Autor and Salomons (2018) also follow this approach to analyze automation in 18 developed countries of the European Union, Australia, Japan, South Korea, and the United States. These authors support Acemoglu and Restrepo (2020a) results. Schlog and Sumner (2018) focus on the effect of automation for workers in developing countries and their battle against what they call the "Robot Reserve Army".[4]

Nevertheless, other scholars highlight that many voices have been raised to highlight the creation of new tasks with technological progress and deny the results obtained by other authors. In this sense, Arntz *et al.* (2016, 2017) repeated the analysis of Frey and Osborne (2017) focusing on tasks instead of occupations to conclude that only 9% of US occupations are potentially automatable. Dauth *et al.* (2017) replicate the empirical work of Acemoglu and Restrepo (2020a) for the case of Germany, not finding a negative effect of robots because other sectors have absorbed the employment lost in the manufacturing industry. Bessen (2017) finds that computer technology is associated with job creation, and Graetz and Michaels (2018) affirm that robots are contributing to labor productivity growth since decades ago. Ernst *et al.* (2018) describe these opportunities regarding the increase in productivity, especially among low-skilled workers due to the tremendously reduced costs of capital. Anwar and Graham (2020) focus on the effects of digital technologies on African workers through the creation of low-skill jobs such as image and video annotation tasks, that require little skills. Furman and Seamans (2018) welcome the potential of AI for increased productivity growth and, at the same time, they propose some alternative policies to mitigate AI-induced labor disruptions (universal basic income, employment subsidies and guaranteed employment). Acemoglu and Restrepo (2018d) emphasize, in a theoretical model, the labor market adjustment against automation: other sectors can reinstate labor that is not needed anymore in certain activities that are now performed by robots.[5]

The literature had adopted alternative approaches to dealing with the emergence of these new capital assets. An earlier attempt is Zeira (1998), which analyses the growth of the technological innovations that reduces labor requirements but raise capital requirements. Sachs and Kotlikoff (2012) present an overlapping generations (OLG) model in which smart machines substitute directly young unskilled

[3] Acemoglu and Restrepo (2018c) collect and review various ways of modeling automation. Among them are the options to interpret this economic process as capital-augmentating or labor-augmentating technological change. Acemoglu and Restrepo (2020) offer a deep thorough vision of automation effects. Jimeno (2019) questions that robotisation and AI have the same economic implications of factor-augmenting technological progress.

[4] Estimated percentage of tasks that can be automated using the current technology in each country have been carried out by Manyika *et al.* (2017). Their estimations suggest that the potential automatic capital adoption rate is above the 45% in every industrialized economy in the world, and that technical automation potential is concentrated in countries with the largest populations and/or high wages.

[5] The World Economic Forum (2018) foresees that automation will eliminate 75 million jobs across the planet by 2025, but will create 133 million newtasks. However, the fact that the capital associated to these employees will be also replaced by new technological devices is a fact that often goes unnoticed, causing us to have a partial vision of the technological change that the economy is experiencing. A computer programming device powered by AI is, of course, more productive than a programmer. The question is whether this device powered by AI is more productive than this programmer and his computer working together. If it turns out that the device powered by AI possesses a larger productivity than the worker and his associated unit of capital, this device will replace both. Thus, where we used to have a worker working with a unit of capital, we will have now a single unit of AI-powered robotic capital .

workers. At the same time, these machines also complement older skilled employees.[6] Sach *et al.* (2015) contrast a robotic firm in which the only input are robots with a traditional firm with machines and labor, in a form similar to our approach. Benzell *et al.* (2017) introduce automation to represent an economy where robots are a combination of code and capital and where the code is produced by high-skilled workers, as well as both high-skilled and low-skilled workers are involved in the production of services. Acemoglu and Restrepo (2018b) develop a model in which tasks previously performed by labor can be automated but where new versions of existing tasks, in which labor has a comparative advantage, can be created. Berg *et al.* (2018) explore different views about how automation may affect the labor market, concretely they present four models reflecting diverse scenarios. In their first model, robots compete against all labor in all tasks, while in the second model, robots compete only for some tasks; the third model states that robots only substitute unskilled labor while complement skilled labor. Finally, the fourth model reduces the robots contribution to production in just one sector. Lin and Weise (2019) propose a similar model to the first one presented by Berg *et al.* (2018), in which robots constitute a labor-replacing capital. They set-up a production function where traditional capital is a complement of human labor and robot capital replaces human labor. Furthermore, they argue that the observed decline in the labor share in the U.S. is a direct consequence of robotization. Nomaler and Verspagen (2020) use a similar production functions for studying the implications of robotization and find that this new technology may lead to the so-called perpetual growth. Here, we depart from the existing literature by adopting a disruptive vision of automation.

This chapter contributes to the literature by introducing an unconventional production function where two different and alternative technologies can be used for final output: a traditional technology, where a combination of traditional capital and labor is used, and a new technology where only automatic capital is needed for production. Traditional capital and labor are complementary and both are substitutes of the new automatic capital. Mathematically, this is represented by a CES nested in another CES function where constant return-to-scale are preserved. The aggregate technology includes two key parameters: the elasticity of substitution of the automatic capital to the combination of traditional capital and labor. It also includes the distribution parameter for both technologies which is assumed to represent the automation adoption rate. We consider that this technological function helps to a more accurate representation of the fundamental characteristics of the incoming automation process, in which traditional capital and labor are being replaced by a new autonomous input productive technology. Our aggregate technology implies that, isolated, traditional technology uses inputs which have decreasing returns. It is worthy to remark that the new technology presents constant returns (similar to an AK-type technology). Indeed, endogenous growth is a particular case of our model, when only the new technology is used for production (see, for instance, Aghion and Howitt, 1998; Acemoglu, 2009). In this simple setting, endogenous growth can arise without the need to consider R&D activities or technological knowledge. Therefore, the model presented here could be considered a simplified version of a more complex model where R&D activities and monopolistic competition issues are considered (for growth models with R&D activities, see Marchese and Privileggi, 2020, and the literature cited therein).

We simulate the model and compute steady states of the main macroeconomic variables for a range of values for the elasticity of substitution between the new and the traditional technologies, as a function of the new automatic capital adoption rate. The automatic capital adoption rate is assumed to be represented by the distribution parameter of the aggregate CES function. The main result of the chapter consists in the finding of the existence of a threshold value for the automatic capital adoption rate. The steady state of the economy for this threshold value does not depend on the elasticity of substitution between new capital and traditional inputs, as the ratio of automatic capital to output is one. Moreover, the threshold value for the adoption rate is equal to the marginal productivity of the new capital, which is just a constant, and depends on the automatic capital depreciation rate and the discount factor. It is also the baseline for the normalization of a family of CES functions when the elasticity of substitution

[6] Another branch of the literature on automation has focused on the relationship of this process with demography to analyze possible consequences originated by the implementation of automation with ageing people. See, for instance, Basso and Jimeno (2019).

varies. For the benchmark calibration of the model, we find that this threshold value is about 22.5%. For an adoption rate of the new technology below that threshold value, the consequences of automation for the economy are mostly negligible, no matter how the elasticity of substitution between both technologies is. However, for an adoption rate above the threshold value, changes in the economy, as a consequence of the incorporation of the new automatic capital, are dramatic and depends on the elasticity of substitution between the two technologies. For a scenario with high elasticity of substitution between traditional production technology and an adoption rate for new capital above the threshold, we find an abrupt increase in the accumulation of the new capital and the output, as well as a sudden reduction in labor. Based of these simulations, we identify two necessary conditions for the robocalypse to occur: a high elasticity of substitution between the traditional and the automatic technology and an automatic capital adoption rate above the threshold.

In addition, we find that the functional distribution of income is not significantly affected when the adoption rate of new capital is below the threshold, although labor share slightly declines as the automatic capital adoption rate increases. However, when the new capital adoption rate is above the threshold and the elasticity of substitution between new capital and traditional technology is higher enough, labor share suddenly declines collapsing into very low values as a consequence of an intense process of labor substitution. When the net income is taken into account (see Karabarbounis and Neiman, 2014b, and Bridgman, 2018) and both traditional and new capital have the same return net of depreciation, the decline in labor share has a lower magnitude. Nevertheless, it is important to remark that it would collapse for a high automatic capital adoption rate and a high elasticity of substitution between traditional and automatic technologies, since these two conditions trigger the accumulation of automatic capital, resulting in a huge amount of output.

For the sake of clarity, the rest of the chapter is organized as follows. Section 2 elaborates a simple model with three inputs: labor, traditional capital and automatic capital, where the production technology is represented by a traditional CES function nested in another CES function. Section 3 presents the calibration of the model economy. Simulations from the model are presented in Section 4, which investigates the implications of the elasticity of substitution between the new capital and the traditional technology and also the automatic capital adoption rate. Section 5 focuses on the consequences for the functional distribution of income. Finally, section 6 derives the conclusions obtained from this research.

2.2 The model

Based on the predictions by AI researchers, the combination of AI and autonomous robots will create new types of capital assets that can perform production activities with minimal human intervention and where this new capital is expected to outperform all human tasks in the near future (Grace *et al.* 2018). This will lead automation to a new stage, where investment in new equipment will introduce a new technology that fully displaces labor in a number of tasks, contrary to more recently proposed models in the literature in which automation results in the displacement of low-skilled workers and routine tasks. Here we consider a model economy with two kinds of capital: K is the traditional capital and D represents the new automatic capital (a combination of AI and robotics). We propose a simple production function where two different technologies can coexist simultaneously: a traditional technology that requires physical capital and labor for production and a new automatic technology that employs only a new capital (hardware and artificial intelligence) for production. In order to get the model closer to economics, we consider a representative household that can freely decide labor time, consumption and investment decisions in both kinds of capital. Whereas traditional technology uses a combination of traditional capital and labor under constant returns to scale (which implies that marginal productivity for both inputs is decreasing), the new technology exhibits constant marginal productivity for automatic capital, which involves endogenous growth. The model is specified in discrete time and it is considered a descentralized economy where households maximize utility in a deterministic intertemporal optimization setting and firms operates in a perfect competition environment. Capital letters represent quantities of aggregate variables.

2.2.1 Technology

The aggregate production technology is a CES function for traditional technology using capital and labor nested into another CES function. In this function, new and traditional technology are substitutes. We define the following aggregate production function to represent these technological combinations:

$$Y_t = \left[\mu X_t^{v} + (1-\mu)\, {D_t}^{v}\right]^{\frac{1}{v}} \tag{2.1}$$

where Y_t is the final output, X_t represents traditional technology, μ is a distribution parameter for the traditional productive factors versus the new technology, D_t is the automatic capital, and v measures the substitution between the traditional production technology and the new technology. The elasticity of substitution between traditional and automatic technologies is defined as $\sigma = 1/(1-v)$.

The traditional technology is represented by another CES function:

$$X_t = \left[\alpha K_t^{\theta} + (1-\alpha)\, L_t^{\theta}\right]^{\frac{1}{\theta}} \tag{2.2}$$

where K_t is the traditional capital, L_t is labor, α is a distribution parameter of inputs and θ measures the substitution between traditional capital and labor. The elasticity of substitution is defined as $\varepsilon = 1/(1-\theta)$. Empirical evidence suggests that $\varepsilon < 1$ (Chirinko, 2008; Eden and Gaggl, 2018), and that $\sigma > 1$ (DeCanio, 2016; Acemoglu and Restrepo, 2019; Lin and Weise, 2019). Therefore, it is assumed that $0 < \varepsilon < 1 < \sigma < \infty$. This implies higher complementarity between traditional capital and labor than between traditional technology and the automatic capital. That is, automatic capital is a substitute for both traditional capital and labor. With that specification, the elasticity of substitution between automatic capital and traditional capital and between automatic capital and labor are both equal to σ (the self-driving taxi substitute in the same proportion to both the taxi-driver and the non-self-driving car). Note that when both elasticities of substitutions are one, the aggregate production function collapse to a standard Cobb-Douglas production function with two capital assets, i.e., $Y_t = K_t^{\alpha\mu} D_t^{1-\mu} L_t^{(1-\alpha)\mu}$.

The key characteristic of that production function is that it embodies two different technologies operating simultaneously, depending on the distribution parameter between traditional and automatic technology. If $\mu = 1$, the production function collapse to the standard CES production function with physical capital and labor, where $Y_t = X_t$. If $\mu = 0$, this represents a technology with no labor and with automatic capital as the only input, with constant returns, $Y_t = D_t$. This specification seems reasonable since we assume that robots and AI do not get tired. If μ is between 0 and 1, we would have a scenario in which, presumably, not all human production activities can be substituted by the new automatic capital and the aggregate technology would be a combination of the traditional CES nested in another CES function with constant return to scale.[7]

[7] We can think about our production function in terms of the Hegelian dialectic. In the Hegelian dialectic there is always a "thesis" and its opposite, an "antithesis", and both thesis and antithesis form a "synthesis". This dialectic was conceived by Hegel as a process that is constantly repeated in life and which is perfect to study history in all its eras. In fact, Marx used his historical materialism (based on the Hegelian dialectic) to study the evolution of productive systems throughout time. There has been always a thesis, when an antithesis appears and confront the preexisting thesis. Thesis and antithesis come together and form a synthesis, which become the thesis of the next stage. In this sense, regarding our production function, the traditional productive system would be a thesis, the new automatic technology the antithesis and our production function the synthesis of these two technologies. If $\mu = 1$, the synthesis between these two technologies would be equal to the previous thesis. On the contrary, if $\mu = 0$, the synthesis would be an automatic economy without labor. For any other values of $\mu \in (0,1)$ we have a synthesis in which traditional and automatic technology coexist.

Firms maximize profits in a competitive environment taken factor prices as given, solving the following static maximization problem at each period:

$$\max \Pi_t = Y_t - W_t L_t - R_{k,t} K_t - R_{d,t} D_t \tag{2.3}$$

From the first order conditions of the firm's profit maximization problem, we obtain the following marginal productivity of each of the three productive factors:

$$R_{k,t} = \alpha \mu Y_t^{1-v} X_t^{v-\theta} {K_t}^{\theta-1} \tag{2.4}$$

$$W_t = (1-\alpha)\, \mu Y_t^{1-v} X_t^{v-\theta} {L_t}^{\theta-1} \tag{2.5}$$

$$R_{d,t} = (1-\mu)\, Y_t^{1-v} {D_t}^{v-1} \tag{2.6}$$

where the Euler Theorem holds, profits are zero and output is distributed among the three productive factors, given the assumptions of a competitive market and constant returns to scale. One of the main concerns about automation is how this process will affect the functional distribution of income. From the above first order conditions, we find out that the functional distribution of gross income for the three factors resulting from our model economy is:

$$S_{l,t} = \frac{W_t L_t}{Y_t} = (1-\alpha)\, \mu Y_t^{-v} X_t^{v-\theta} {L_t}^{\theta} \tag{2.7}$$

$$S_{k,t} = \frac{R_{k,t} K_t}{Y_t} = \alpha \mu Y_t^{-v} X_t^{v-\theta} {K_t}^{\theta} \tag{2.8}$$

$$S_{d,t} = \frac{R_{d,t} D_t}{Y_t} = (1-\mu)\, Y_t^{-v} {D_t}^{v} \tag{2.9}$$

Notice that, at the point in which the stock of automatic capital is equal to output, the automatic capital share is equal to the rate of return to these capital assets and to the automatic capital adoption rate, represented by the distribution parameter $1-\mu$. As we will demonstrate later, this point will be key to assess the effects of automatic capital on the economy. Functional distribution of income at this point is given by:

$$S_{l,t} = (1-\alpha)\mu \frac{L_t^{\theta}}{\alpha K_t^{\theta} + (1-\alpha) L_t^{\theta}} \tag{2.10}$$

$$S_{k,t} = \alpha \mu \frac{K_t^{\theta}}{\alpha K_t^{\theta} + (1-\alpha) L_t^{\theta}} \tag{2.11}$$

$$S_{d,t} = R_{d,t} = (1-\mu) \tag{2.12}$$

2.2.2 Households

To keep the model as simple as possible, we assume that the utility function of our representative household is as follows:

$$U(C_t, L_t) = \gamma log(C_t) + (1-\gamma) log(1-L_t) \tag{2.13}$$

where C_t is total consumption and γ is a parameter reflecting the willingness to sacrifice units of consumption in favor of leisure time. Total available time has been normalized to one, so leisure is defined as $1-L_t$, where $0 \leq L_t < 1$. The representative household satisfies the following budget constraint:

$$C_t + I_{k,t} + I_{d,t} = W_t L_t + R_{k,t} K_t + R_{d,t} D_t \tag{2.14}$$

where I_k is the investment in traditional capital and I_d is the investment in AI and robotics. Notice that in this theoretical framework Euler Theorem holds, and hence, output equals national income, i.e.,

$Y_t = W_t L_t + R_{k,t} K_t + R_{d,t} D_t$. We assume that investment decisions are specific to each capital assets due to the fact they have different characteristics. AI and robotics accumulation process would be presented in the following way:

$$D_{t+1} = (1 - \delta_d) D_t + I_{d,t} \tag{2.15}$$

where $0 < \delta_d < 1$ is the depreciation rate of AI and robotics. Similarly, traditional capital accumulation process is as follows:

$$K_{t+1} = (1 - \delta_k) K_t + I_{k,t} \tag{2.16}$$

where $0 < \delta_k < 1$ is the traditional capital depreciation rate. Following recent literature (Prettner, 2019; Nomaler and Verspagen, 2020), for the sake of simplicity, we assume a linear accumulation of both types of capital, where the technology to produce both types of capital is already available in the economy, without the need of a role for R&D activities, as in Marchese and Privileggi (2020). We assume that depreciation rates are different, and, in particular, that $\delta_d > \delta_k$, which is equivalent to consider that the production cost for automatic capital is higher than the traditional capital's one. This implies that, in equilibrium, the marginal productivity of automatic capital must be higher than the one corresponding to traditional capital.

The maximization problem faced by the infinity-lived representative household with perfect-foresight is given by,

$$\max_{\{C_t, L_t\}} \sum_{t=0}^{\infty} \beta^t \left[\gamma ln C_t + (1-\gamma) \, ln(1 - L_t) \right] \tag{2.17}$$

subject to restrictions (2.14), (2.15), and (2.16), where K_0 and D_0 are given, and where β is the intertemporal discount factor.

Equilibrium conditions, representing Euler equations, from the household's maximization problem are,

$$\frac{1-\gamma}{\gamma} \frac{C_t}{1 - L_t} = W_t \tag{2.18}$$

$$1 = \beta \frac{C_t}{C_{t+1}} \left(1 - \delta_k + R_{k,t+1}\right) \tag{2.19}$$

$$1 = \beta \frac{C_t}{C_{t+1}} \left(1 - \delta_d + R_{d,t+1}\right) \tag{2.20}$$

making reference to optimal labor supply, investment decision on traditional capital and investment decision on automatic capital, respectively. These three equilibrium conditions together with the following transversality conditions for each type of capital, where λ_t denotes the Lagrange's multiplier associated to the household maximization problem (i.e., the shadow price of consumption):

$$\lim_{t \to \infty} \beta^t \lambda_t K_{t+1} = 0 \tag{2.21}$$

$$\lim_{t \to \infty} \beta^t \lambda_t D_{t+1} = 0 \tag{2.22}$$

and initial conditions, fully characterize optimal trajectories for the variables in the long-run. Notice that these equilibrium conditions establish a direct relationship between depreciation rates and returns of both traditional and automatic capital, as net marginal productivities are equal, such as:

$$R_d - \delta_d = R_k - \delta_k \tag{2.23}$$

2.3 Calibration

The model is calibrated to an artificial economy where the two key parameters for studying the consequences of automation by the introduction of the new technology are kept free.[8] These parameters represent the distribution parameter in the final production CES technology, μ, and the elasticity of substitution between the automatic and the traditional technology, $\sigma = 1/(1-v)$. Discount factor parameter, preference parameter, and technological parameters of the traditional technology are calibrated using standard values in the literature. We fix $\beta = 0.975$, $\gamma = 0.4$, $\alpha = 0.35$, $\varepsilon = 1/(1-\theta) = 0.90$ and $\delta_k = 0.06$, using an annual basis. We choose an elasticity of substitution lower than one between traditional capital and labor, consistent with Chirinko (2008), Eden and Gaggl (2018) and Lin and Weise (2019).

The first key parameter of the model is the distribution parameter in the final production CES technology. We argue that this technological parameter can be interpreted as the adoption rate of the new technology in relation to the traditional one, where the distribution parameter for the new technology is $1-\mu$, and where μ is the weight for the traditional technology in the aggregate CES function. This adoption rate can be defined as the percentage of tasks in the production system assumed by automatic technology.[9] We choose a range of values for automatic capital adoption rates between 1% and 45%, so we analyze feasible scenarios according to the estimations of the percentage of tasks that can be automated using current technology, up to the value reported by Manyika *et al.* (2017). This implies that in the simulations of the model, the technological distribution parameter μ is in the range 0.55 - 0.99.

The second key parameter of the model is the elasticity of substitution between traditional technology and the automatic technology, σ. Robots and humans are assumed to have a high elasticity of substitution, although there is a lack of estimations in literature.[10] However, we should bear in mind that our model does not collect implicitly the elasticity of substitution between humans and robots, but an elasticity of substitution between the automatic capital and both labor and the traditional capital of the same magnitude. The elasticity of substitution among automatic and traditional capital is even less documented than the substitution effects between humans and robots. Our model estimates that, if a robot replaces a human, it also substitutes the capital associated to this humans professional occupation. Consequently, the elasticity of substitution between automatic and traditional technology must be related to the elasticity of substitution between humans and robots. For the elasticity of substitution between the new automatic technology and the traditional technology, we explore the interval between 1 and 5, which implies that $v \in (0 : 0.8)$.

The automatic capital depreciation rate is an important additional parameter in our model economy and in assessing the economic implications of automation. Depreciation rates are expected to largely vary between the two types of capital assets in our model, where automatic capital is expected to have a higher depreciation rate. Indeed, new technological devices such as computers, telecommunications equipment and software have a higher depreciation rate than more traditional capital assets. Investment in these types of capital assets has increased the total depreciation rate for total physical capital in the economy. Automatic capital depreciation rate emerges as an important parameter driving the effects of automation. First, it introduces a difference in the returns to both types of capital. Second, the automatic capital depreciation rate is a key parameter for assessing the impact on the new technology on the economy. Graetz and Michaels (2018) consider a robots depreciation rate of ten per cent. Abeliansky

[8] As we use the model to calculate steady states and not transition dynamics, the CES functions are not normalized in the lines suggested by de La Grandville (1989). Nevertheless, the main results in the chapter indicate the basis for such normalization in the case one is interested in computing transition dynamics for a family of CES functions when the elasticity of substitution varies.

[9] According to Manyika *et al.* (2017), the percentage of tasks that can be automated using current technology is higher than 45% for industrialized countries. This "percentage of tasks that can be automated using current technology" would be the empirical counterpart to our definition of automatic capital adoption rate.

[10] Lin and Weise (2019) states an elasticity of substitution of 5. Artuc, Bastos and Rijkers (2018) set it at 10. Acemoglu and Restrepo (2020a) assume an infinite elasticity of substitution between humans and robots. DeCanio (2015) concludes that this elasticity of substitution is for sure above 2.1.

TABLE 2.1: Calibrated parameters

	Parameter	Definition	Value
Preferences	β	Discount factor	0.975
	γ	Consumption-leisure preference parameter	0.40
Technology	α	Capital share in the traditional technology	0.35
	δ_k	Traditional capital depreciation rate	0.06
	δ_d	Automatic capital depreciation rate	0.20
	ε	Traditional capital-labor elasticity	0.90
	σ	Traditional-automatic technologies elasticity	[1-5]
	μ	Technologies distribution parameter	[0.55-0.99]

and Prettner (2017), following Graetz and Michaels (2018), also assume a robotic depreciation rate of 10%. This depreciation rate would be higher than the one established by the International Federation of Robotics (2016), which sets a lifetime horizon of 12 years for robots. Lin and Weise (2019), along with Krusell *et al.* (2000), set out a quarterly depreciation of robots at 0.0515. In our case, automatic capital is assumed to represent the most advanced technology in the economy, and, therefore, we determine $\delta_d = 0.20$, according to the depreciation rate traditionally assumed for R&D capital. This percentage is reflected in the EU KLEMS data and has been documented by numerous authors (see, for example, Hall, 2005). Table 2.1 summarizes the benchmark calibration of the parameters of the model and the range of values for the two parameters under investigation.

Given the calibrated model, we investigate steady states resulting from combinations of different values for the two key parameters: the elasticity of substitution among traditional and automatic technologies and the automatic capital adoption rate. This is why we solve the following system of 11 equations for eleven unknown quantities, $(Y, C, K, D, X, L, W, I_k, I_d, R_k, R_d)$, where variables without a time index represent steady state values:

$$R_d = \frac{1}{\beta} - 1 + \delta_d \tag{2.24}$$

$$R_k = \frac{1}{\beta} - 1 + \delta_k \tag{2.25}$$

$$I_d = \delta_d D \tag{2.26}$$

$$I_k = \delta_k K \tag{2.27}$$

$$W = \frac{1-\gamma}{\gamma} \frac{C}{1-L} \tag{2.28}$$

$$Y = \left[\mu X^{v} + (1-\mu)\ D^{v}\right]^{\frac{1}{v}} \tag{2.29}$$

$$X_t = \left[\alpha K_t^{\theta} + (1-\alpha)\ L_t^{\theta}\right]^{\frac{1}{\theta}} \tag{2.30}$$

$$C = Y - I_d - I_k \tag{2.31}$$

$$L = \left[\frac{Y^{1-v}\,(1-\alpha)\,\mu X^{v-\theta}}{W}\right]^{\frac{1}{1-\theta}} \tag{2.32}$$

$$K = \left[\frac{Y^{1-v} \alpha \mu X^{v-\theta}}{R_k}\right]^{\frac{1}{1-\theta}} \tag{2.33}$$

$$D = Y \left[\frac{(1-\mu)}{R_d} \right]^{\frac{1}{1-v}} \tag{2.34}$$

The model satisfies the Blanchard-Kahn rank condition (Blanchard and Kahn, 1980), indicating that the steady state is unique. Given that log-linearization of the equations of the model around the steady state only ensures local stability, it is assumed that initial conditions (K_0, D_0) are in the neighborhood of the steady state, such as any trajectory determined by the original non-linear Euler equations leads to the steady state as $t \to \infty$.[11]

2.4 Traditional versus automatic technology and the adoption rate

In this section, we explore the parametric space of the model economy and compute steady states depending on the values of the two fundamental parameters of the proposed technology: the elasticity of substitution between the traditional and the automatic technology, and the distribution parameter representing automatic capital adoption rate. We present the results for four values of the elasticity of substitution between traditional and automatic technology: 1, 1.5, 2 and 5.

We find a particular value for the automatic capital adoption rate for which any steady state value depends on the elasticity of substitution between the traditional and the automatic technology. This is equivalent to the baseline point for a family of normalized CES functions. This occurs because, in this particular steady state, the ratio of automatic capital to output is one. This threshold value for the adoption rate of automatic capital is just equal to the marginal productivity of this new type of capital $(1-\mu = R_d)$, which remains a constant and depends on the automatic capital depreciation rate and the discount factor. For the benchmark calibration of the model we find that this threshold value is about 22.5%. This value is essential for assessing the effects of automation on the main variables of the economy. For an adoption rate of the new technology below that threshold value, the consequences of automation are almost insignificant regardless of the elasticity of substitution between both technologies. However, for an adoption rate above the threshold value, changes in the economy provoked by the new capital could be dramatic, depending on the elasticity of substitution between the two technologies. Another property of the threshold is that the stock of automatic capital and the output level are equal at this point, $Y = D$. Therefore, we can clearly identify which parameters influence the threshold, as it is collected in equation (24).

The threshold point is equivalent to the baseline point for the normalization of a family of CES functions for different elasticities of substitution. As shown by de La Grandville (2016), the distribution parameter of a normalized CES function (interpreted here as the adoption rate of the automatic capital) is the geometric mean of the capital share and the interest rate such as $1-\mu = S_d^{(1-v)} R_d^{v}$. In our model, the baseline point for the normalization of the CES functions implies that the distribution parameter is equal to the interest rate, and hence, in the threshold point the automatic capital share is equal to:

$$S_d = 1 - \mu = R_d = \frac{1}{\beta} - 1 + \delta_d \tag{2.35}$$

Figure 2.1 plots the steady state values for output, labor, traditional capital, and automatic capital as a function of the adoption rate of automatic capital and for the four selected values of the elasticities of substitution. We find that, for the low values of the adoption rate of automatic capital, the new technology has little effect on the main macroeconomic variables. As we observe in Figure 2.1, steady state values of labor, output and automatic and traditional capital are almost the same for any elasticity of substitution between the traditional and the automatic technology. At the threshold, steady state

[11] We thank one anonymous referee for notice us about this important stability issue. In solving the model, we used an eigenvalue/eigenvector decomposition method. This solution method requires that, for a nonlinear model, a linear approximation must be obtained, and therefore, the stability conditions are approximate. As a consequence, steady state of the economy could never be reached, given that the computed equilibrium only guarantees local stability.

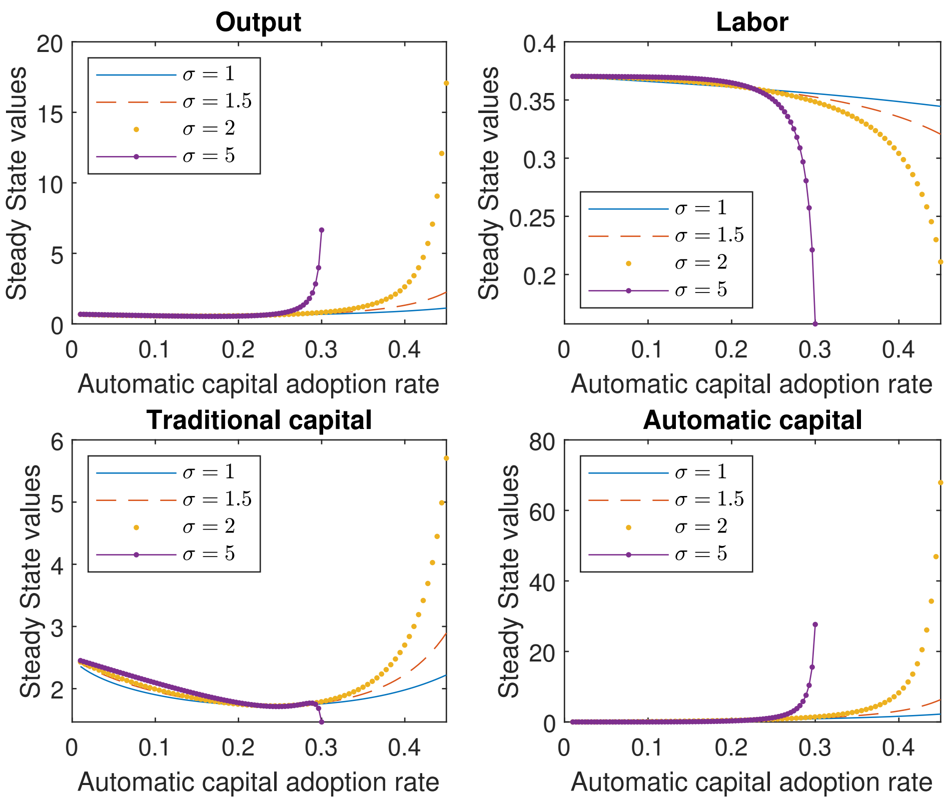


FIGURE 2.1: Steady state values for output, traditional capital, labor, and automatic capital as function of the automatic capital adoption rate and the elasticity of substitution between traditional technology and automatic technology.

values are the same for any elasticity of substitution since the family of CES functions for any value of the elasticity of substitution intersect at this point. For values above the threshold, the elasticity of substitution is crucial. For a scenario with high elasticity of substitution between traditional production technology and an adoption rate for new capital far above the threshold, we find an abruptly increase in the accumulation of the new capital and output, and a sudden reduction in labor. Based on these simulations, we find two necessary conditions for the so-called robocalypse to occur: a high elasticity of substitution between the traditional and the automatic technology and an automatic capital adoption rate above the threshold.

In a scenario where the automatic capital adoption rate is very high (say more than 0.5), no matter how the elasticity of substitution between both technologies is, the automatic capital will dominate, increasing output to spectacular values and reducing traditional inputs to minimum quantities. For a high elasticity of substitution between the new and the traditional technology (i.e., $\sigma = 5$), it is observed a dramatic and sudden fall in labor while automatic capital and output increase exponentially when the automatic capital adoption rate is above the threshold. We find that the lower the elasticity of substitution, the lower the effect provoked by the introduction of the automatic technology is, once the threshold level has been surpassed. In fact, when the elasticity of substitution is, for instance, of a magnitude of 1, it is observed a slight fall in labor time together with a slight increase of automatic capital and output, but it does not take place an abrupt change. However, the effects of the new technology increase for higher values of the elasticity of substitution.

As it can be observed, traditional capital falls softly as the automatic capital adoption rate augments until the threshold. For automatic capital adoption rates above the threshold, we estimate that, initially, the stock of traditional capital increases as the adoption rates increases, as shown in the bottom left of Figure 2.1. This positive effect on traditional capital is provoked by the rise of returns of traditional capital when the distribution parameter of the CES function is above the threshold. However, when the adoption rate of the new technology reach a certain level, it is observed a sudden drop in the stock of traditional capital. Indeed, if the elasticity of substitution is large, say of a magnitude of 5, it is observed that this sudden drop occurs for an adoption rate around 25%. For lower values of the elasticity of substitution, the adoption rate must be large enough (higher than the range shown in the Figures) for this effect to be observed.

A different behavior is found in terms of labor, in spite that the elasticity of substitution between the new technology and traditional capital and between new technology and labor are both the same. First, working time remains almost constant for automatic capital adoption rates below the threshold independently of the elasticity of substitution between traditional and new technology. When automatic capital adoption rate is above the threshold, labor starts to be very sensitive to the introduction of the new capital depending on the elasticity of substitution. We observe a dramatic decline in labor for values of σ larger than 2.

In sum, we find the existence of a relatively large range of plausible values of the automatic capital adoption rate for which the irruption of the automatic capital has little consequences on the economy, independently of the elasticity of substitution between traditional and automatic technology. In addition, it is clear from these results that the elasticity of substitution of AI and robotics concerning the traditional productive factors can vary from sector to sector, task to task, and so on. Therefore, it is relevant to analyze the possible impact of Industry 4.0 technology in an economy depending on the adoption rate of this technology and the elasticity of substitution regarding the rest of productive inputs. One could think about a scenario where the automatic capital adoption rates are higher than 45%, as this is a potential adoption rate for current technology estimated in some studies. Our model considerably illustrates the consequences of this situation. According to the benchmark calibration applied to it, this scenario corresponds to an economy well above the threshold value. Importantly, the threshold value is increasing with the depreciation rate of automatic capital. For the threshold to be around 45%, the depreciation rate should be around 0.425, a value much higher than the depreciation rate for any existing capital assets (although not different from the allowed depreciation rates for computers in taxing schemes). The most eye-catching scenario is one of high substitution effect that represents the exponential growth of the automatic technology. Curiously, the most striking one would be the vision more accepted by literature.[12]

From previous results, it is clear that the identified threshold value is key for assessing the consequences of automation through automatic capital. The value of this threshold is just the marginal productivity of automatic capital. In steady state, it depends only on the discount factor and on the depreciation rate of automatic capital. In practice, the range of variation of values for the discount factor is small, so the depreciation rate of automatic capital would be the most influential parameter determining the threshold.

Figure 2.2 depicts the threshold value as a function of δ_d and β. Given the benchmark depreciation rate, the threshold value varies from 16% to around 20% for a range of values of the discount factor between 0.99 and 0.95. The most influential parameter is the depreciation rate of automatic capital. For a depreciation rate of 0.15, the threshold value is approximately 0.18, whereas for a depreciation rate of 0.25, the threshold increases to 0.28, as the relationship between both variables is linear. In short, given that the threshold depends directly on the robots' depreciation rate, the higher the automatic capital depreciation rate, the lower impact the process of automatic capital adoption will have in the economy.

[12] Lin and Weise (2019), Eden and Gaggl (2018), Acemoglu and Restrepo (2020a), DeCanio (2016), and Artuc, Ethar and Rijkers (2018), who, among others, assume high substitution effect of AI and robotics.

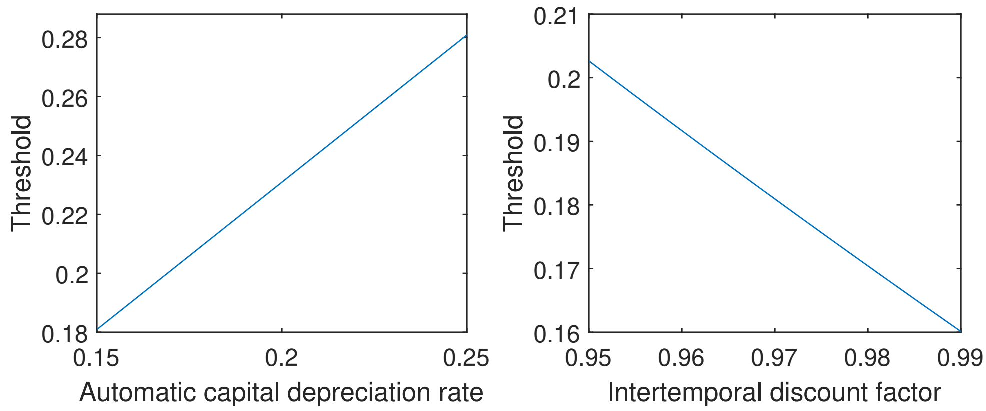


FIGURE 2.2: Automatic capital adoption rate threshold as a function of automatic capital depreciation rate and intertemporal discount factor.

Afterwards, we focus on the effects of automation on labor and wages. Figure 2.3 plots steady state for labor as a function of the elasticity of substitution between new and traditional technology for different values of the automatic capital adoption rate. The case for which labor is a constant for any value of the elasticity of substitution corresponds to an adoption rate equals to the threshold. For automatic capital adoptions rates below the threshold, we find that the response of labor is almost constant for any value of the elasticity of substitution and even positive as the elasticity of substitution increases. However, for values of the adoption rate above the threshold, the response of labor is negative and dramatically depends on the elasticity of substitution. If the elasticity of substitution is low enough, little effects of the new technology on labor are observed. However, as the elasticity of substitution increases, the negative impact on hours is exacerbated. This reduction in labor reflects a reduction in working hours. This remark is important, given that in our theoretical framework a representative household maximizes her utility and chooses the optimal level of labor supply and leisure. In this context, a reduction in labor (working hours) is equivalent to an increase in leisure, which augments utility. Hence, a reduction in labor is not a necessary condition for a "robocalypse" to occur. This will also depend on how wages and total labor income are affected.

Figure 2.4 plots the wage (left graph) and total labor income (right graph) as a function of the adoption rate. We find that wages decrease as automation advance for automatic capital adoption rates below the 22.5% threshold. These finding would match empirical results in literature. For instance, Acemoglu and Restrepo (2020a) study the effects of a robot density increase in the labor market, and they conclude that one more robot per a thousand worker reduces wages by 0.25-0.5 percent and the employment to population ratio by 0.18-0.24. Then, we know for sure that it also reduces labor compensation, and therefore, the labor share. We should bear in mind that the study analyzes data from 1990 to 2007, so it puts the focus on a period with low robotization. In relation to that, we have already observed that its effects on the economy for automatic capital adoption rates lower than 22.5% are not remarkable.

As we can notice, over the threshold, wages increase as automation advance. These findings coincide with those made by Nomaler and Verspagen (2020). This is a consequence of the higher productivity produced by the incorporation of the new technology, which also fosters labor productivity. As a result, we find that total labor income decreases for low values of the adoption rate as automation progresses, but that the effects of increasing automation, once the threshold level is exceeded, are positive for labor income. This positive effect is higher as the elasticity of substitution increases, until the economy reaches

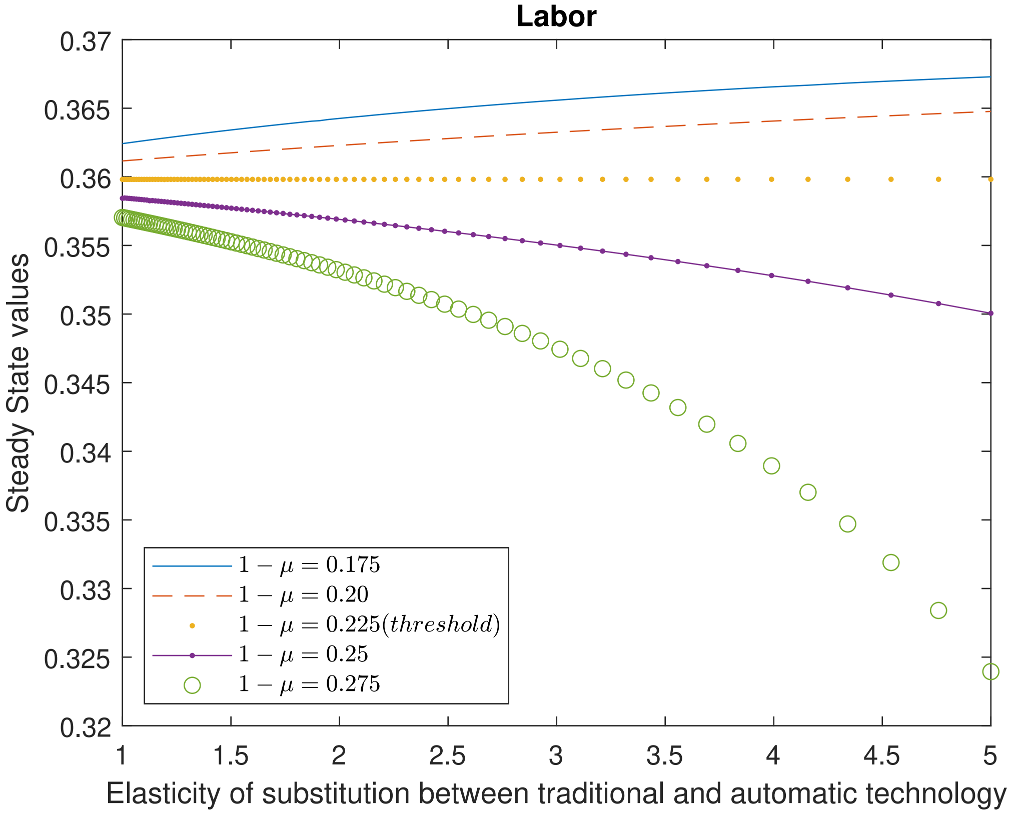


FIGURE 2.3: Evolution of labor time regarding the elasticity of substitution between traditional and automatic technology for automatic capital adoption rates below and above the 22.5% threshold.

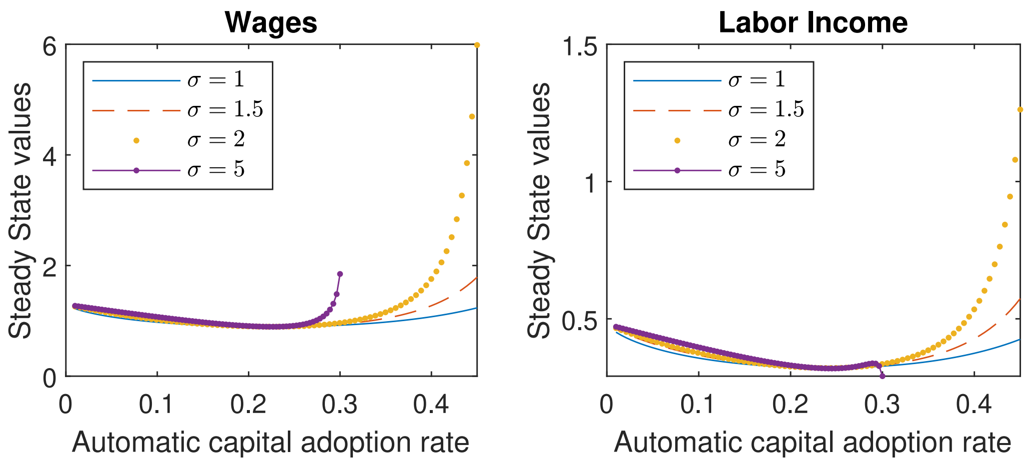


FIGURE 2.4: Steady state values for wages as function of the automatic capital adoption rate and the elasticity of substitution between traditional technology and automatic technology.

a singularity (in the figure only observed for an elasticity of substitution of 5), where the robocalypse scenario occurs. For lower values of the elasticity of substitution, the robocalypse scenario does occur only for values of the automatic capital adoption rate above the range of values considered.

Some important implications can be derived from all previous results. The model indicates the existence of threshold conditions that divide the economy in two different worlds, where the threshold value reflects an economic singularity if the elasticity of substitution between the traditional and the automatic technology is large enough. On the one hand, in a world where the automatic capital adoption rate is below the threshold, the new technology does not provoke significant changes in the main macroeconomic variables, independently of the elasticity of substitution between the traditional and the automatic technology. On the other hand, in a world where the automatic capital adoption rate is above the threshold, this technology represents a structural change and its impact in the economy relies on the elasticity of substitution between the traditional and the automatic technology.

Although the model represents an economy at an aggregate level, we can extract some considerations at a sectoral level. In the economy, it should be expected that sectors would have different adoption rates for automatic capital. Whereas the adoption rate of automatic capital can be large in some sectors, in others, the adoption rate could be lower. Automatic technology would have no effects on employment in those sectors with a low adoption rate of the new technology. We find that, in sectors where the presence of AI and robotics represents less than the estimated value of 22.5%, labor and traditional capital increase with the elasticity of substitution while AI and robotics decrease. In sectors where the presence of AI and robotics represents more than 22.5% of the total productive factors, labor falls when the elasticity of substitution rises while traditional capital, AI and robotics augment. Then, we can conclude that AI and robotics are destined to dominate those sectors in which their capacity for implementation is higher than this threshold. This technology, in the long run, will not settle down in those sectors in which they have no capacity to represent more than 22.5% of the productive factors.

Felten *et al.* (2018) provide a measure of the AI capacity of penetration in different sectors by identifying AI advances at the occupation level, indicating how AI changes occupations' characteristics. Fossen and Sorgner (2019) build on Felten *et al.* (2018) and Frey and Osborne (2017) to bring a vision of the transforming and destructive effects of AI and robotics. They identify the occupations with low destructive effect (those with less than a 70% of computerization probability in Frey and Osborne, 2017) and high transformer effect (more than a 3 in the scale of advances in AI provided by Felten *et al.*, 2018) as the "rising stars". However, occupations in the "human terrain" represent a very low number if we compare them with the other groups and most of them have a probability of computerization higher than 0.5. Therefore, we can argue that almost none occupation is saved from being transformed or eliminated by AI and robotics. Taking into account current and potential productivity and capacity of these technologies to spare human labor, it is clear that the occupations affected by the so-call "transformation" by AI advances will experience a decrease in labor needs. This decrease can lead to a working day reduction or labor demand contraction and it will mainly depend on the regulation imposed from labor market institutions.

Overall, the message of this chapter is rather optimistic regarding the impact of automation on the economy. For automation to have dramatic negative effects, the adoption rate of the new technology must be above a identified threshold value. The depreciation rate of new capital assets is increasing, and therefore, the depreciation rate of automatic capital is expected to be high, augmenting the threshold point, and hence, preventing a disruptive effect by the new technology. Even in the case, the automatic capital adoption rate would be above the threshold, robocalypse also requires a high elasticity of substitution between the new automatic technology and traditional technology. To sum up, we find that the probability of a robocalypse is very unlikely to occur. In addition, the automatic capital singularity only appears under very specific conditions. For plausible values of the key variables, the effects of automation are found to be positive, increasing total output and labor income, while allowing a reduction in working hours.

2.5 Automatic capital and the functional distribution of income

One of the most important concerns regarding automation is how this process affects labor share and labor income. The results presented in the previous section show that automation has a positive effect on output and labor income when the adoption rate is above the threshold, except for extremely high values of the elasticity of substitution and the automatic capital adoption rate. In this section, we use the model to investigate the effects of the new automatic technology on the functional distribution of income. A large and increasing body of the literature has focused on the implications of automation for labor compensation and inequality, suggesting also that automation is one of the factors originating the decline in labor share over the last decades (Graetz and Michaels, 2018; Charalampidis, 2020). Indeed, the searching for an explanation on this issue remains one of the fundamental macroeconomic topics nowadays. Karabarbounis and Neiman (2014a) argue that the decrease in the relative price of investment goods induced firms to replace labor inputs for capital inputs. Farmer and Lafond (2016) analyze the predictability of a technological change stating that many technologies follow a generalized version of Moore's law since their costs tend to drop exponentially. Following this idea, the decline of the labor share could be justified by technological change.

We depart from the existing literature by arguing that the cause of the observed decline in labor share does not only rely on the lower price of investment goods but also on the changing character in the new investment goods and to the productivity increase in technologies such as AI and robotics, that is, new automatic capital deepening. Interestingly, Eden and Gaggl (2018) identify the decline in the labor share with a decline in routine occupations. At the beginning of the nineties, routine occupations exceeded non-routine ones but in the middle of the decade, a shift was produced and non-routine occupations exceeded routine ones. In our model economy, total income not only is distributed between labor and traditional capital, but also another fraction is earned by the new automatic capital. The key difference is that, whereas a complementary relationship between traditional capital and labor exits, these two inputs have a substitution relationship with the automatic capital input. Nomaler and Verspagen (2020) argue that robotization will lead to a rising wage rate but ever-declining labor share. Although we use a different technology reflecting automation, our results are consistent with those of Nomaler and Verspagen(2020).

Capital depreciation rate is not only a key variable for assessing the impact of the new technology on main aggregate variables but also is an important factor determining capital consumption. Given the high values of depreciation for the new capital assets, the effects on inequality should be studied once capital consumption is taken into account. However, most of the analysis of labor share and income inequality ignores the distinction between gross and net income due to capital consumption. Karabarbounis and Neiman (2014b) highlight the importance of the physical capital depreciation rate, often neglected, for the study of income distribution and inequality. Bridgman (2018) shows that depreciation and production taxes are important determinants of the labor share, as they are included in total output, and hence, a fall in labor share may not imply a gaining in capital income. He shows that gross labor share has been falling since 1970s, but this net labor share shows a more stable path. We follow Karabarbounis and Neiman (2014b) and Bridgman (2018) analyses that account for capital depreciation in separating gross and net labor shares.

Figures 2.5 and 2.6 plot the steady state functional distribution of income for gross and net income resulting from simulations of the model. We find that the introduction of automatic technology is associated with labor share decline (capital-deepening effect). This labor share fall is higher as higher the automatic capital adoption rate is, and its deepening depends on the elasticity of substitution between the traditional and the automatic technology. For adoption rates below the threshold, little change in labor share is observed as consequence of the introduction of the new technology. However, above the threshold, changes are dramatic.

The estimated functional distribution of income suggests that the mere introduction of automatic capital as an additional input for production implies a decline of the labor share, as little substitution of traditional capital share by the new automatic capital returns is observed. Additionally, this decline

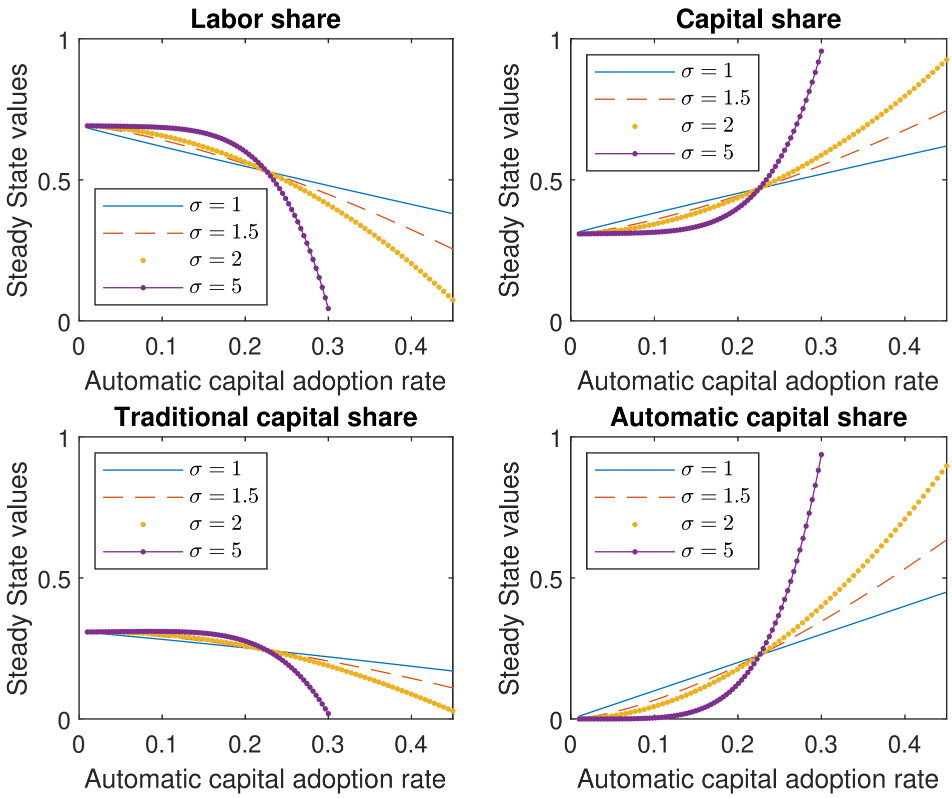


FIGURE 2.5: The functional distribution of income, Automatic capital adoption rate and the elasticity of substitution between traditional and automatic technology. Gross income.

is accentuated by the value of the elasticity of substitution between the new automatic technology and traditional technology. That is, the crowding-out of traditional capital by the new automatic capital is not complete as to offset the effects on labor income. The negative slope curvature of the labor share steady state values, as a function of the automatic capital adoption rate, gets more pronounced as the substitution effect gets higher. Not only labor share declines with the introduction of the automatic capital but also the traditional capital income share. By contrast, the automatic capital income share increases as its adoption rate does. Therefore, automatic capital is not only absorbing the decline in the labor share but also the decline in the traditional capital income share. Again, the overall effects will depend on whether the automatic capital adoption rate is above or below the threshold. Comparing Figure 2.5 and Figure 2.6, we observe how the net income labor share decline is moderate when the automatic capital adoption rate is below the threshold, or in a situation above the threshold when the elasticity of substitution is low enough. That is, with the exception of a robocalypse scenario (high adoption rate and high elasticity of substitution), the new technology has a moderate impact on labor share.

As we can observe in the bottom right plot of Figure 2.5, when the elasticity of substitution among traditional and automatic technology is equal to our lower limit ($\sigma = 1$), the automatic capital share grows in parallel with the adoption rate as in this scenario capital share matches always the adoption rate: $1 - \mu = R_d D / Y$. For a higher elasticity of substitution, automatic capital share increases in a non-proportional way for robot adoption rates below the threshold, but disproportionately for adoption

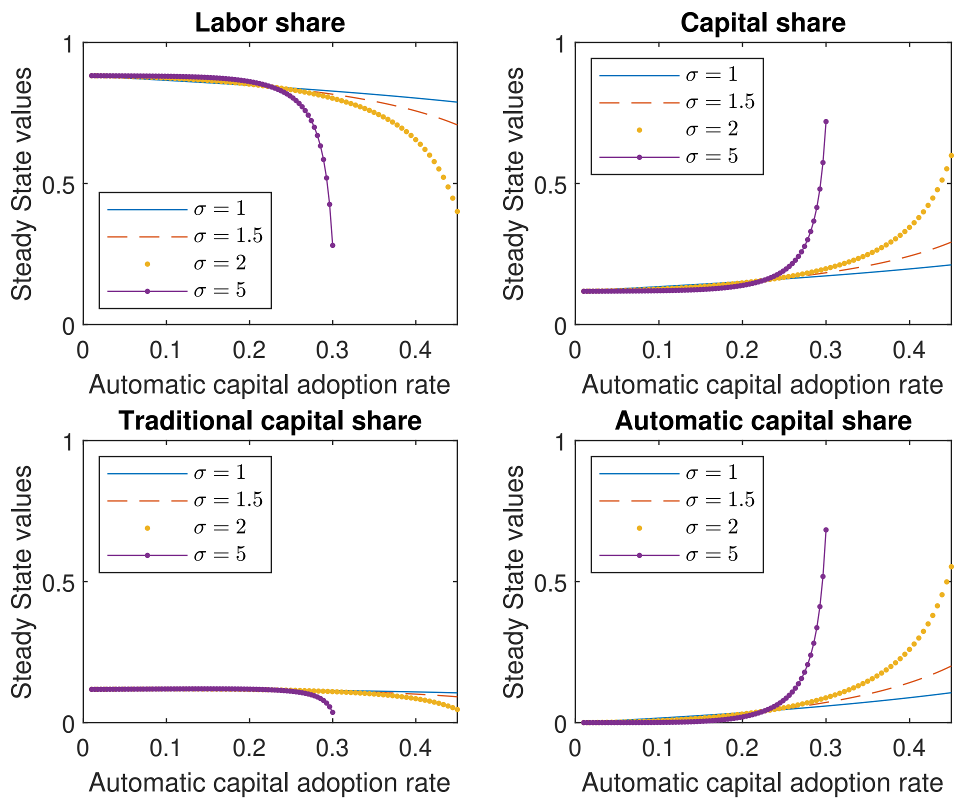


FIGURE 2.6: The functional distribution of income, Automatic Capital adoption rate and the elasticity of substitution between traditional and automatic technology. Net income.

rates above the threshold. Acemoglu and Restrepo (2020) study the effects of a robot density increase in the labor market, and they conclude that one more robot per a thousand worker reduces wages by 0.25-0.5 percent and the employment to population ratio by 0.18-0.24. Then, we know for sure that it also reduces labor compensation, and therefore, the labor share.[13]

Charalampidis (2020) remarks the counter-cyclical character of the U.S. labor share.[14] They justify the causes of its fluctuations with the following elements and proportions: automation (54%), workers' market power (24%) investment efficiency (6%), and the relative price of investment account (4%). For Prettner (2019), automation only explains the 14% of the observed decline of the labor share over the last decades in the United States, while Aum *et al.* (2018) argue that computerization during the 1990s gives a rationale for most of the decline in the labor share between 1980 and 2010 (4 out of 5 percentage points). Guerriero (2019) ascertains the global decline of the labor share, taking into account 151 economies in a panel data analysis and concluding that labor share varies significantly among economies and it has decreased over time especially since 1980. In the case of Europe, Dao *et al.* (2017) analyzes the decrease in the labor income share distinguishing between advanced economies and emerging markets. They discover that half of the overall decline in advanced economy is due to the technological progress and varying exposure to routine occupations.

In the literature, several authors have drawn a very negative picture for future labor share, as well as a horizon of hyper inequality originated by technological progress. For instance, Piketty (2014) argues that capital returns grow more than economic growth itself and this causes inequity. Consequently, under this scenario, it seems clear that the intervention of the government is needed to deal beforehand about what could be a major problem in the forthcoming decades. This is why numerous authors remark the necessity of a robot tax (Guerreiro *et al.*, 2017; Thuemmel, 2018), or an Universal Basic Income (Hoynes and Rothstein, 2019), which could be interpreted as reminiscent of Luddite thought. However, other authors adopt a more optimistic view of predicting a soft transition without dramatic losses in worker earnings. Bongers and Molinari (2020) study trends in average working time from the Industrial Revolution and argue that automation represents a new technological revolution that can have an important impact in the reduction of average working time while increasing compensation to employees level. Our analysis reflects both pessimistic and optimistic views; only under certain very specific conditions (high automatic capital adoption rate and high elasticity of substitution between new capital and traditional technology), working time experiments a great fall. However, for low values of the elasticity of substitution between new and traditional technology and low adoption rate of the new technology, little negative effects on labor share are predicted. As a consequence, only in the scenario where the automatic capital adoption rate is above the threshold, some kind of redistribution policies must be implemented to reduce inequality provoked by automation.

2.6 Conclusions

This chapter develops a simple macroeconomic general equilibrium model to analyze how the introduction of new automatic technology can affect the economy. The main hypothesis is the consideration of a new type of capital (i.e., automatic capital) that can produce final goods in a stand-alone fashion. This new technology directly competes with the traditional one. The example of the combination of a cab-car with a cab-driver in front of a self-driving cab is highly illustrative in order to better understand the implications of this technological change process. The model is simulated and the steady states are computed depending on the new automatic capital adoption rate, which we assume equivalent to the

[13] We should bear in mind that the study analyzes data from 1990 to 2007, so it puts the focus on a period with low robotization and we have already observed that its effects on the economy for automatic capital adoption rates lower than 22.5% are not remarkable. In fact, Charalampidis (2020) highlights that automation shocks are the main cause of the post-2007 cyclical labor share drop.

[14] Leduc and Liu (2019) also find a countercyclical character in it. Their explanation for this fact is that automation improves labor productivity while muting wage increases.

distribution technological parameter of a CES combining both technologies, and on the elasticity of substitution between the traditional and the new technology. From this analysis we draw some important conclusions and key issues that can be worth noting in helping us to consider the potential impact of this new technology.

The most important result of the chapter is the identification of a threshold value for the automatic capital adoption rate which leads to the possibility of two totally different scenarios. The threshold value for new capital adoption rate has a simple interpretation, being equal to the marginal productivity of the new capital in steady state. This allows us to easily identify its determinants: the discount factor and the depreciation rate of the new capital. For the benchmark calibration of the model, where the annual discount factor is 0.975 and automatic depreciation rate is 20%, the threshold value for the new capital adoption rate is around 22.5%. At this threshold, the stock of automatic capital equals the output. For adoption rates below the threshold, where the elasticity of substitution between the traditional and the automatic technology is not a relevant variable, we do not observe significant changes in the main variables of the economy. However, things are completely different when the adoption rate is above the threshold because the elasticity of substitution between both technologies becomes an important variable. In a scenario with an automatic capital adoption rate below the threshold, working time slightly increases as higher is the substitution effect of the new automatic technology. On the contrary, in an scenario with an automatic capital adoption rate above the threshold, we find the opposite process, since labor falls abruptly, although wages and total labor income increase before the singularity appears.

The introduction of the new automatic technology can provoke a radical fall on both working time and labor share, but for this to happen a high substitution effect between the traditional and the automatic technology and a high presence of the new automatic technology are needed. We study the relationship between this new automatic capital and the functional distribution of income with the aim of shedding some light on the decline of the labor share, and we find that the mere introduction of the automatic technology implicitly causes a decline in labor share. The dimensions of this decline depend directly on the elasticity of substitution between technologies and the adoption rate. This decline is almost the same for any elasticity of substitution until the automatic capital adoption rate matches the threshold. Consequently, the elasticity of substitution plays a crucial role in augmenting the decline of the labor share.

From the previous results, we can establish the necessary conditions for the so-called robocalypse to occur. The mere introduction of the automatic capital does not imply a great fall in labor. For an abrupt decline in labor, a high substitution effect between technologies and an automatic capital adoption rate above the threshold are required. These would be the two necessary requirements for the robocalypse to take place: a high adoption rate of automatic technology and a high substitution elasticity between new and traditional technologies. In any other scenario, automatic technology can perfectly coexist with traditional technology having a positive impact on output, wages and labor income as the automatic capital adoption rate increases.

Empirical evidence about robots adoption rates estimates that potential AI and autonomous robot penetration is relatively high (above 45%), a value well above our estimated threshold. Additionally, empirical evidence also affirms that the elasticity of substitution between new and traditional technologies could be also of high magnitude. The combination of that empirical evidence moves the economy to our robocalypse scenario, where labor collapses. The threat of an unprecedented increase in inequality under this scenario can be clearly observed in our analysis of the functional distribution of income. Nevertheless, the high depreciation rate of new equipment (and the increasing depreciation rate over time for computers, telecommunication equipment, software), implies that the threshold adoption rate can be also increasing in the future, reducing the risk of robocalypse, even for the case of high elasticity of substitution between both technologies. Thus, this chapter opens the possibility that the robocalypse scenario could be avoided, as the threshold for the adoption rate will increase at the same proportion than the depreciation rate of new automatic capital assets.

2.7 Technical Appendix

This technical appendix presents the first order conditions of the household maximization problem and the application of the Blanchard-Khan method for proving the existence and uniqueness of the model's solution, using the rank condition approach (Blanchard and Khan, 1980).

2.7.1 The model

Technology

The aggregate production technology is a CES function for traditional technology using capital and labor nested into another CES function. In this function, new and traditional technology are substitute of each other. We define the following aggregate production function to represent these technological combinations:

$$Y_t = \left[\mu X_t^{v} + (1-\mu)\, {D_t}^{v}\right]^{\frac{1}{v}} \tag{A2.1}$$

where Y_t is the final output, X_t represents traditional technology, μ is a distribution parameter for the traditional productive factors versus the new technology, D_t is the automatic capital, and v measures the substitution between the traditional production technology and the new technology. The elasticity of substitution between traditional and automatic technologies is defined as $\sigma = 1/(1-v)$.

The traditional technology is represented by another CES function:

$$X_t = \left[\alpha K_t^{\theta} + (1-\alpha)\, L_t^{\theta}\right]^{\frac{1}{\theta}} \tag{A2.2}$$

where K_t is the traditional capital, L_t is labor, α is a distribution parameter of inputs and θ measures the substitution between traditional capital and labor. The elasticity of substitution is defined as $\varepsilon = 1/(1-\theta)$. Firms maximize profits in a competitive environment taken factor prices as given, solving the following static maximization problem at each period:

$$\max \Pi_t = Y_t - W_t L_t - R_{k,t} K_t - R_{d,t} D_t \tag{A2.3}$$

From the first order conditions of the firm's profit maximization problem, we obtain the following marginal productivity of each of the three productive factors:

$$R_{k,t} = \alpha \mu Y_t^{1-v} X_t^{v-\theta} {K_t}^{\theta-1} \tag{A2.4}$$

$$W_t = (1-\alpha)\, \mu Y_t^{1-v} X_t^{v-\theta} {L_t}^{\theta-1} \tag{A2.5}$$

$$R_{d,t} = (1-\mu)\, Y_t^{1-v} {D_t}^{v-1} \tag{A2.6}$$

where the Euler Theorem holds, profits are zero and output is distributed among the three productive factors, given the assumptions of a competitive market and constant returns to scale.

Households

We assume that the utility function of our representative household is as follows:

$$U(C_t, L_t) = \gamma log(C_t) + (1-\gamma) log(1-L_t) \tag{A2.7}$$

where C_t is total consumption and γ is a parameter reflecting the willingness to sacrifice units of consumption in favor of leisure time. Total available time has been normalized to one, so leisure is defined as $1 - L_t$, where $0 \leq L_t < 1$.

Automatic capital accumulation process is defined as:

$$D_{t+1} = (1-\delta_d)D_t + I_{d,t} \tag{A2.8}$$

where $0 < \delta_d < 1$ is the depreciation rate of automatic capital and I_d is investment in automatic capital. Similarly, traditional capital accumulation is given by:

$$K_{t+1}(1-\delta_k)K_t + I_{k,t} \tag{A2.9}$$

where $0 < \delta_k < 1$ is the traditional capital depreciation rate, and I_k is investment in traditional capital. In order to follow Blanchard and Kahn (1980) procedure to proof the existence and uniqueness of the model's solution, we define the model with an aggregate investment variable. Total investment is defined as:

$$I_t = I_{d,t} + I_{k,t} \tag{A2.10}$$

The representative household satisfies the following budget constraint:

$$C_t + I_t = W_t L_t + R_{k,t}K_t + R_{d,t}D_t \tag{A2.11}$$

Therefore, since $I_t = I_{d,t} + I_{k,t}$, we can write the following capital accumulation process:

$$I_t = K_{t+1} + D_{t+1} - (1-\delta_k)K_t - (1-\delta_d)D_t \tag{A2.12}$$

In the solution of the model, we have to consider the aggregate investment, as the Blanchard and Kahn (1980) method requires the split of the vector of endogenous variables in two vectors: one vector for static variables, and another vector for state and forward-looking variables. Given that in the static system we have only one equation for solving investment (the feasibility condition), we need to aggregate both capitals accumulation processes. The solution of these two capitals is obtained from the system of forward-looking and state variables, given that the model has two equations for the consumption optimal path.

The maximization problem faced by the infinity-lived representative household with perfect-foresight is given by,

$$\max_{\{C_t,L_t\}} \sum_{t=0}^{\infty} \beta^t \left[\gamma lnC_t + (1-\gamma)\, ln(1-L_t)\right] \tag{A2.13}$$

subject to restrictions (A2.11) and (A2.12), where K_0 and D_0 are given, and where β is the intertemporal discount factor. The Lagrange auxiliary function for the household's maximization problem is,

$$\begin{gathered} \underset{(C_t,L_t,K_t,D_t)}{Max} \sum_{t=0}^{\infty} \mathcal{L} = \beta^t[[\gamma log(C_t) + (1-\gamma)log(1-L_t)] \\ -\lambda_t(C_t + K_{t+1} - (1-\delta_k + R_{k,t})\,K_t + D_{t+1} - (1-\delta_d + R_{d,t})\,D_t - W_t L_t)] \end{gathered} \tag{A2.14}$$

where λ_t denotes the Lagrange's multiplier. First order conditions for the consumer maximization problem are:

$$\frac{\partial \mathcal{L}}{\partial C_t} : \frac{\gamma}{C_t} - \lambda_{1,t} = 0 \tag{A2.15}$$

$$\frac{\partial \mathcal{L}}{\partial L_t} : \frac{-(1-\gamma)}{1-L_t} + \lambda_{1,t}W_t = 0 \tag{A2.16}$$

$$\frac{\partial \mathcal{L}}{\partial K_{t+1}} : -\beta^t\lambda_{1,t} + \beta^{t+1}\lambda_{1,t+1}\left[(1-\delta_k) + R_{k,t+1}\right] = 0 \tag{A2.17}$$

$$\frac{\partial \mathcal{L}}{\partial D_{t+1}} : -\beta^t\lambda_{1,t} + \beta^{t+1}\lambda_{1,t+1}\left[(1-\delta_d) + R_{d,t+1}\right] = 0 \tag{A2.18}$$

Equilibrium conditions, representing Euler equations, from the household's maximization problem are:

$$\frac{1-\gamma}{\gamma}\frac{C_t}{1-L_t} = W_t \tag{A2.19}$$

$$1 = \beta\frac{C_t}{C_{t+1}}\left(1-\delta_k+R_{k,t+1}\right) \tag{A2.20}$$

$$1 = \beta\frac{C_t}{C_{t+1}}\left(1-\delta_d+R_{d,t+1}\right) \tag{A2.21}$$

They make reference to optimal labor supply, investment decision on traditional capital and investment decision on automatic capital, respectively. These three equilibrium conditions together with the following standard transversality conditions for each type of capital:

$$\lim_{t\to\infty}\beta^t\lambda_t K_{t+1} = 0 \tag{A2.22}$$

$$\lim_{t\to\infty}\beta^t\lambda_t D_{t+1} = 0 \tag{A2.23}$$

and initial conditions, fully characterize optimal trajectories for the variables in the long-run.

Therefore, the model is composed by the following system of ten equations for ten unknown:

$$Y_t = \left[\mu X_t^v + (1-\mu)\,{D_t}^v\right]^{\frac{1}{v}} \tag{A2.24}$$

$$X_t = \left[\alpha K_t^\theta + (1-\alpha)\,L_t^\theta\right]^{\frac{1}{\theta}} \tag{A2.25}$$

$$R_{k,t} = \alpha\mu Y_t^{1-v}X_t^{v-\theta}{K_t}^{\theta-1} \tag{A2.26}$$

$$W_t = (1-\alpha)\,\mu Y_t^{1-v}X_t^{v-\theta}{L_t}^{\theta-1} \tag{A2.27}$$

$$R_{d,t} = (1-\mu)\,Y_t^{1-v}{D_t}^{v-1} \tag{A2.28}$$

$$I_t = K_{t+1}+D_{t+1}-(1-\delta_k)K_t-(1-\delta_d)D_t \tag{A2.29}$$

$$\frac{1-\gamma}{\gamma}\frac{C_t}{1-L_t} = W_t \tag{A2.30}$$

$$1 = \beta\frac{C_t}{C_{t+1}}\left(1-\delta_k+R_{k,t+1}\right) \tag{A2.31}$$

$$1 = \beta\frac{C_t}{C_{t+1}}\left(1-\delta_d+R_{d,t+1}\right) \tag{A2.32}$$

$$Y = C + I \tag{A2.33}$$

for all $t = 0, 1, 2, ...$

2.7.2 Steady State

The steady state solution of the model is given by the following system of 10 equations for ten unknown quantities, $(Y, C, I, K, D, X, L, W, R_k, R_d)$, where variables without a time index represent steady state values:

$$R_d = \frac{1}{\beta}-1+\delta_d \tag{A2.34}$$

$$R_k = \frac{1}{\beta}-1+\delta_k \tag{A2.35}$$

$$I = \delta_d D + \delta_k K \tag{A2.36}$$

$$W = \frac{1-\gamma}{\gamma}\frac{C}{1-L} \tag{A2.37}$$

$$Y = \left[\mu\, X^{v} + (1-\mu)\; D^{v}\right]^{\frac{1}{v}} \tag{A2.38}$$

$$X_t = \left[\alpha K_t^{\theta} + (1-\alpha)\, L_t^{\theta}\right]^{\frac{1}{\theta}} \tag{A2.39}$$

$$Y = C + I \tag{A2.40}$$

$$L = \left[\frac{Y^{1-v}\,(1-\alpha)\,\mu X^{v-\theta}}{W}\right]^{\frac{1}{1-\theta}} \tag{A2.41}$$

$$K = \left[\frac{Y^{1-v}\alpha\mu X^{v-\theta}}{R_k}\right]^{\frac{1}{1-\theta}} \tag{A2.42}$$

$$D = Y\left[\frac{(1-\mu)}{R_d}\right]^{\frac{1}{1-v}} \tag{A2.43}$$

From these equations, we can obtain steady state expressions where only parameters appear. However, these expressions are too large to be shown in the document. Therefore, we allow variables R_d, R_k, W and X to appear once their steady state expressions have been shown. Note that expressions for interest rates are immediate:

$$R_k = \delta_k + \frac{1}{\beta} - 1 \tag{A2.44}$$

$$R_d = \delta_d + \frac{1}{\beta} - 1 \tag{A2.45}$$

Next, we derive the wage steady state value. In order to do that, we start from equation (A2.5). First, we obtain an expression for Y as a function of model parameters and traditional production D by substituting equation (A2.43) into equation (A2.38):

$$Y = X\left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}}\right)^{\frac{1}{v}} \tag{A2.46}$$

Next, by substituting the previous expression in equation (A2.42), we obtain an identity for K as a function of model parameters and traditional production:

$$K = X\left(\frac{R_k}{\mu\,\alpha\left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu}-\left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}}\right)^{\frac{1-v}{v}}}\right)^{\frac{1}{\theta-1}} \tag{A2.47}$$

We take this expression and introduce it in equation (A2.39) in order to obtain an identity for L as a function of model parameters and traditional production:

$$L = X \left(1 - \alpha \left(\frac{R_k}{\mu\, \alpha \left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}} \right)^{\frac{1-v}{v}}} \right)^{\frac{\theta}{\theta-1}} \right)^{\frac{1}{\theta}} (1-\alpha)^{\frac{(-1)}{\theta}} \tag{A2.48}$$

Now, we take equation (A2.5) and substitute Y and L by the expression we have obtained (A2.46) and (A2.48):

$$W = (1-\alpha)^{\frac{1}{\theta}}\, \mu \left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}} \right)^{\frac{1-v}{v}} \frac{X^{v\theta}}{X^{v\theta}} \left(1 - \alpha \left(\frac{R_k}{\mu\, \alpha \left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}} \right)^{\frac{1-v}{v}}} \right)^{\frac{\theta}{\theta-1}} \right)^{\frac{1}{\theta}} \tag{A2.49}$$

As we can easily observe in the middle of the expression, traditional production goes, so we have an identity for wage depending only on model parameters:

$$W = (1-\alpha)^{\frac{1}{\theta}}\, \mu \left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}} \right)^{\frac{1-v}{v}} \left(1 - \left(\frac{\alpha^{\frac{(-1)}{\theta}} R_k}{\mu \left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}} \right)^{\frac{1-v}{v}}} \right)^{\frac{\theta}{\theta-1}} \right)^{\frac{\theta-1}{\theta}} \tag{A2.50}$$

Now we substitute expression (A2.46) into equation (A2.43) in order to have an identity for automatic capital as a function of model parameters and traditional production:

$$D = X \left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}} \right)^{\frac{1}{v}} \left(\frac{R_d}{1-\mu} \right)^{\frac{1}{v-1}} \tag{A2.51}$$

We introduce this identity and identity (A2.47) in equation (A2.36) and we obtain investment depending on model parameters and traditional production:

$$I = X \left(\begin{array}{l} \left(\frac{R_k}{\mu\, \alpha \left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}} \right)^{\frac{1-v}{v}}} \right)^{\frac{1}{\theta-1}} \delta_k \\ + \left(\frac{R_d}{1-\mu}\right)^{\frac{1}{v-1}} \left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}} \right)^{\frac{1}{v}} \delta_d \end{array} \right) \tag{A2.52}$$

By introducing this expression and expression (A2.46) in equation (A2.40), we obtain the identity for consumption:

TABLE A2.1: Calibrated parameters

	Parameter	Definition	Value
Preferences	β	Discount factor	0.975
	γ	Consumption-leisure preference parameter	0.40
Technology	α	Capital share in the traditional technology	0.35
	δ_k	Traditional capital depreciation rate	0.06
	δ_d	Automatic capital depreciation rate	0.20
	ε	Traditional capital-labor elasticity	0.90
	σ	Traditional-automatic technologies elasticity	2
	μ	Technologies distribution parameter	0.775

$$C = X \left(\begin{array}{c} \left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}} \right)^{\frac{1}{v}} \left(1 - \left(\frac{R_d}{1-\mu}\right)^{\frac{1}{v-1}} \delta_d \right) \\ - \left(\frac{R_k}{\mu\,\alpha \left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}} \right)^{\frac{1-v}{v}}} \right)^{\frac{1}{\theta-1}} \delta_k \end{array} \right) \tag{A2.53}$$

Finally, we substitute our expressions for C and L in equation (A2.37) to obtain traditional production as a function of only model parameters:

$$X = \frac{W}{\frac{1-\gamma}{\gamma} \left(\begin{array}{c} \left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}} \right)^{\frac{1}{v}} \left(1 - \left(\frac{R_d}{1-\mu}\right)^{\frac{1}{v-1}} \delta_d \right) \\ - \left(\frac{R_k}{\mu\,\alpha \left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}} \right)^{\frac{1-v}{v}}} \right)^{\frac{1}{\theta-1}} \delta_k \end{array} \right) + W \frac{\left(1-\alpha \left(\frac{R_k}{\mu\,\alpha \left(\frac{\frac{\mu}{1-\mu}}{\frac{1}{1-\mu} - \left(\frac{R_d}{1-\mu}\right)^{\frac{v}{v-1}}} \right)^{\frac{1-v}{v}}} \right)^{\frac{\theta}{\theta-1}} \right)^{\frac{1}{\theta}}}{(1-\alpha)^{\frac{1}{\theta}}}} \tag{A2.54}$$

The expression for X is too large to fit in the page, so we substitute the wage expression given by equation (A2.54) by the symbol W. As the expression for wage only depends on model parameters, X also depends only on model parameters. By substituting X into the previous expressions we have all variables results as functions of model parameters. We can observe that the solution for the variables in steady state is intractable. Therefore, we solve the steady state of the model numerically. For that, we use a Newton-Raphson type algorithm. Given the calibration of the parameters in Table A2.1, we obtain the steady state values presented in Table A2.2. We repeat this procedure for each value in the range of values for $\mu \in [0.55, 0.95]$ and $\sigma = \{1, 1.5, 2, 5\}$.

TABLE A2.2: Steady state values

Variable	Definition	Value
Y	Output	0.600593778157051
X	Traditional output	0.601584903797054
C	Consumption	0.379346639133977
I	Investment	0.221247139023074
K	Traditional capital stock	1.696831801806420
D	Automatic capital stock	0.597186154573441
L	Labor	0.360325150537142
W	Labor marginal productivity	0.360325150537142
R_d	Automatic capital marginal productivity	0.085641025641026
R_k	Traditional capital marginal productivity	0.225641025641026

2.7.3 Log-linearized model

The Blanchard and Kahn solution method requires the model to be linear. Therefore, we proceed to linearizing the model around its steady state. The model is highly nonlinear, reflecting very complex relationships between different economic variables. This hampers their practical application. To solve this problem, we resort to performing a linear approximation to the equations of the model.

We express the variables of the model as log-linear deviations with respect to their steady state values. The log-linear deviation of a variable u around its steady state, $\overline{u}$, is denoted as $\widehat{u}$, where $\widehat{u}_t = \ln u_t - \ln \overline{u}$. In constructing the log-linear deviations, we follow three basic rules (Uhlig, 1999). First, a variable of the model can be defined as:

$$u_t = \overline{u}^{\widehat{u}_t} \approx \overline{u}(1 + \widehat{u}_t) \tag{A2.55}$$

Second, for the case of the two variables product u_t and z_t, we have:

$$u_t z_t \approx \overline{u}(1 + \widehat{u}_t)\overline{z}(1 + \widehat{z}_t) \approx \overline{uz}(1 + \widehat{u}_t + \widehat{z}_t) \tag{A2.56}$$

that is, we assume that the product of the two deviations, i.e., $\widehat{u}_t \widehat{z}_t$, is approximately equal to zero, as they are small numbers. Third, we assume the following approximation for the power of a variable:

$$u_t^a \approx \overline{u}^a (1 + \widehat{u}_t)^a \approx \overline{u}^a (1 + a\widehat{u}_t) \tag{A2.57}$$

Taking into account the above definitions, the model in log-linearized form is the following:

$$\widehat{y}_t = \mu \widehat{x}_t + (1 - \mu)\widehat{d}_t \tag{A2.58}$$

$$\widehat{x}_t = \alpha \widehat{k}_t + (1 - \alpha)\widehat{l}_t \tag{A2.59}$$

$$\frac{K}{I}\widehat{k}_{t+1} + \frac{D}{I}\widehat{d}_{t+1} = \widehat{i}_t + (1 - \delta_k)\frac{K}{I}\widehat{k}_t + (1 - \delta_d)\frac{D}{I}\widehat{d}_t \tag{A2.60}$$

$$E_t \widehat{c}_{t+1} - \widehat{c}_t = \beta R_k \widehat{r}_{k,t+1} \tag{A2.61}$$

$$E_t \widehat{c}_{t+1} - \widehat{c}_t = \beta R_d \widehat{r}_{d,t+1} \tag{A2.62}$$

$$\widehat{y}_t = \frac{C}{Y}\widehat{c}_t + \frac{I}{Y}\widehat{i}_t \tag{A2.63}$$

$$\widehat{c}_t = \widehat{w}_t - \frac{L}{1 - L}\widehat{l}_t \tag{A2.64}$$

$$\widehat{w}_t = (1-v)\widehat{y}_t + (v-\theta)\widehat{x}_t + (\theta-1)\widehat{l}_t \tag{A2.65}$$

$$\widehat{r}_{k,t+1} = (1-v)\widehat{y}_{t+1} + (v-\theta)\widehat{x}_{t+1} + (\theta-1)\widehat{k}_{t+1} \tag{A2.66}$$

$$\widehat{r}_{d,t+1} = (1-v)\widehat{y}_{t+1} + (v-1)\widehat{d}_{t+1} \tag{A2.67}$$

Given the intractability of steady state expressions, we do not substitute steady state values for the variables in the log-linearized equations. By substituting, we reduce the log-linearized model to a system of six equations for six unknowns (Y, C, I, K, D, L):

$$\widehat{y}_t = \mu\alpha\widehat{k}_t + \mu(1-\alpha)\widehat{l}_t + (1-\mu)\widehat{d}_t \tag{A2.68}$$

$$\frac{K}{I}\widehat{k}_{t+1} + \frac{D}{I}\widehat{d}_{t+1} = \widehat{i}_t + (1-\delta_k)\frac{K}{I}\widehat{k}_t + (1-\delta_d)\frac{D}{I}\widehat{d}_t \tag{A2.69}$$

$$E_t\widehat{c}_{t+1} - \widehat{c}_t = \beta R_d\left[(1-v)\widehat{y}_{t+1} + (v-1)\widehat{d}_{t+1}\right] \tag{A2.70}$$

$$E_t\widehat{c}_{t+1} - \widehat{c}_t = \beta R_k\left[(1-v)\widehat{y}_{t+1} + (v-\theta)(\alpha\widehat{k}_{t+1} + (1-\alpha)\widehat{l}_{t+1}) + (\theta-1)\widehat{k}_{t+1}\right] \tag{A2.71}$$

$$\widehat{y}_t = \frac{C}{Y}\widehat{c}_t + \frac{I}{Y}\widehat{i}_t \tag{A2.72}$$

$$\widehat{c}_t = (1-v)\widehat{y}_t + (v-\theta)(\alpha\widehat{k}_t + (1-\alpha)\widehat{l}_t) + (\theta-1)\widehat{l}_t - \frac{L}{1-L}\widehat{l}_t \tag{A2.73}$$

2.7.4 The log-linearized system in matrix form

Once we have the model in log-linear form, we can proceed with its resolution, although we have to bear in mind that this is an approximation of the original highly nonlinear model. The literature has proposed different alternative methods to solve a DSGE model. The most popular method is the proposed by Blanchard and Kahn (1980). Here, we use this solution method. We start by defining the following two vectors of deviations from the steady state, x_t^0 and s_t^0:

$$x_t^0 = \begin{bmatrix} \widehat{y}_t \\ \widehat{i}_t \\ \widehat{l}_t \end{bmatrix} \tag{A2.74}$$

$$s_t^0 = \begin{bmatrix} \widehat{k}_t \\ \widehat{d}_t \\ \widehat{c}_t \end{bmatrix} \tag{A2.75}$$

where the first vector comprises deviations in production, investment, and employment from their steady state values, that is, static variables;and the second vector is formed by the deviations of the capital stock and consumption, that is, forward looking and state variables.

First, we can write the following system:

$$Ax_t^0 = Bs_t^0 \tag{A2.76}$$

consisting of the following three equations:

$$\widehat{y}_t - \mu(1-\alpha)\widehat{l}_t = \mu\alpha\widehat{k}_t + (1-\mu)\widehat{d}_t \tag{A2.77}$$

$$\widehat{y}_t - \frac{I}{Y}\widehat{i}_t = \frac{C}{Y}\widehat{c}_t \tag{A2.78}$$

$$(1-v)\widehat{y}_t + \left[(v-\theta)(1-\alpha) + (\theta-1) - \frac{L}{1-L}\right]\widehat{l}_t = \widehat{c}_t - (v-\theta)\alpha\widehat{k}_t \tag{A2.79}$$

and where the constant matrices are given by:

$$A = \begin{bmatrix} 1 & 0 & -\mu(1-\alpha) \\ 1 & -\frac{I}{Y} & 0 \\ (1-v) & 0 & \Omega \end{bmatrix}$$

$$B = \begin{bmatrix} \mu\alpha & (1-\mu) & 0 \\ 0 & 0 & \frac{C}{Y} \\ -(v-\theta)\alpha & 0 & 1 \end{bmatrix}$$

and where

$$\Omega = (v-\theta)(1-\alpha) + (\theta-1) - \frac{L}{1-L}$$

We also define the following system in terms of the expected future value of the variables in the model:

$$FE_t s^0_{t+1} + GE_t x^0_{t+1} = Hs^0_t + Jx^0_t \tag{A2.80}$$

where $E_t(\cdot)$ denotes expected value, consisting in the following three equations:

$$\frac{K}{I}\widehat{k}_{t+1} + \frac{D}{I}\widehat{d}_{t+1} = \widehat{i}_t + (1-\delta_k)\frac{K}{I}\widehat{k}_t + (1-\delta_d)\frac{D}{I}\widehat{d}_t \tag{A2.81}$$

$$E_t\widehat{c}_{t+1} - \beta R_d\left[(1-v)\widehat{y}_{t+1} + (v-1)\widehat{d}_{t+1}\right] = \widehat{c}_t \tag{A2.82}$$

$$E_t\widehat{c}_{t+1} - \beta R_k\left[(1-v)\widehat{y}_{t+1} + (v-\theta)(\alpha\widehat{k}_{t+1} + (1-\alpha)\widehat{l}_{t+1}) + (\theta-1)\widehat{k}_{t+1}\right] = \widehat{c}_t \tag{A2.83}$$

where the matrices are given by:

$$F = \begin{bmatrix} \frac{K}{I} & \frac{D}{I} & 0 \\ 0 & -\beta R_d(v-1) & 1 \\ -\beta R_k\left[(v-\theta)\alpha + (\theta-1)\right] & 0 & 1 \end{bmatrix}$$

$$G = \begin{bmatrix} 0 & 0 & 0 \\ -\beta R_d(1-v) & 0 & 0 \\ -\beta R_k(1-v) & 0 & -\beta R_k(v-\theta)(1-\alpha) \end{bmatrix}$$

$$H = \begin{bmatrix} (1-\delta_k)\frac{K}{I} & (1-\delta_d)\frac{D}{I} & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}$$

$$J = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

The system (A2.76) can be written as:

$$x^0_t = A^{-1}Bs^0_t$$

Taking one period ahead, the above system should be:

$$E_t x^0_{t+1} = A^{-1} B E_t s^0_{t+1}$$

Substituting in the system (A2.80) we find that:

$$(F + GA^{-1}B) E_t s^0_{t+1} = (H + JA^{-1}B) s^0_t$$

Solving the matrices, the final system would be:

$$E_t s^0_{t+1} = M s^0_t$$

where:

$$M = (F + GA^{-1}B)^{-1}(H + JA^{-1}B)$$

Operating, we obtain that matrix M is given by:

$$M = \begin{bmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{bmatrix}$$

However, the elements of matrix M are too long to be written, and hence, we have to draw upon numerical analysis. Using the Jordan decomposition, the matrix M can be decomposed such as:

$$M = O^{-1} N O$$

where:

$$N = \begin{bmatrix} N_{11} & 0 & 0 \\ 0 & N_{22} & 0 \\ 0 & 0 & N_{33} \end{bmatrix}$$

and where:

$$O = \begin{bmatrix} O_{11} & O_{12} & O_{13} \\ O_{21} & O_{22} & O_{23} \\ O_{31} & O_{32} & O_{33} \end{bmatrix}$$

Notice that the elements of the diagonal of N are the eigenvalues of the matrix M. In order for the solution to be unique, two eigenvalues must be inside the unit circle, with only one eigenvalue outside the unit circle. This is the so-called Blanchard-Kahn rank condition. If the rank condition does not hold, then the equilibrium is not unique. The columns of O^{-1} are the eigenvectors of the matrix M variables.

However, matrix M is too big for a closed form expression to be obtained. Hence, the only way to obtain a value for eigenvalues is numerically. Using the calibrated values of the parameters and the values of steady state, the matrices results in:

$$A = \begin{bmatrix} 1 & 0 & -0.5038 \\ 1 & -0.3684 & 0 \\ 0.5000 & 0 & -1.2771 \end{bmatrix}$$

$$B = \begin{bmatrix} 0.2712 & 0.2250 & 0 \\ 0 & 0 & 0.6316 \\ -0.2138 & 0 & 1 \end{bmatrix}$$

$$F = \begin{bmatrix} 7.6694 & 2.6992 & 0 \\ 0 & 0.1100 & 1 \\ 0.0749 & 0 & 1 \end{bmatrix}$$

$$G = \begin{bmatrix} 0 & 0 & 0 \\ -0.1100 & 0 & 0 \\ -0.0418 & 0 & -0.0332 \end{bmatrix}$$

$$H = \begin{bmatrix} 7.2092 & 2.1593 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 1 \end{bmatrix}$$

$$J = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

Given that $M = (F + GA^{-1}B)^{-1}(H + JA^{-1}B)$, we obtain that:

$$M = \begin{bmatrix} 0.8127 & 0.2821 & -0.2914 \\ 0.8071 & 0.2802 & -0.3014 \\ -0.0231 & -0.0080 & 0.9579 \end{bmatrix}$$

where

$$N = \begin{bmatrix} -2.2 \times 10^{-17} & 0 & 0 \\ 0 & 1.142 & 0 \\ 0 & 0 & 0.9084 \end{bmatrix}$$

As we can observe, the matrix N has two eigenvalues inside the unit circle and one outside the unit circle. This proves the existence and uniqueness of the solution of the model. We repeat this procedure for each value in the range of values for $\mu \in [0.55, 0.95]$ and $\sigma = \{[1, 1.5, 2, 5\}$, and in all the cases the rank condition holds, that is, two eigenvalues are inside the unit circle and one eigenvalue outside the unit circle.

Chapter 3

Government size and automation

3.1 Introduction

The impressive technological progress in hardware combined with advances in Artificial Intelligence (AI) observed in the last decade has raised a number of concerns about the economic implications of the incoming fourth industrial revolution for human labor and income distribution. In some cases, these concerns resemble a revival of Luddite ideas regarding the incorporation of a new type of capital into production activities as a disruptive technology. These reactionary thoughts find their explanation in the predictions made by AI experts, affirming that there is a 50% chance of AI outperforming humans in all tasks in 45 years and of automating all human jobs in 120 years (Grace et al., 2017). This progressive process of AI gaining competitive advantages against humans promises to have a huge impact in labor markets as has never been seen before. [1] The main characteristic of this new technological revolution is that humans seem to have a minor space to compete with automation and this space is reduced even more as AI and robotics outperform high-skilled human workers even in cognitive and creative tasks, and not just in routine and repetitive tasks as in previous technological revolutions. Faced with this disturbing scenario, it has been common to hear about the necessity of controlling and regulating the new disruptive technology in order to protect workers and economic stability. See, for example, Frey and Osborne (2017), Manyika et al. (2017), Aum et al. (2018), Berg et al. (2018), and Acemoglu and Restrepo (2020a).

The potential impact, particularly on labor, of this combination of AI and robots, is at the frontline of the current economic debate. However, the anticipated effects of "intelligent" or "autonomous" automation do not have a clear answer. Whereas some authors adopt a Luddite view, predicting a scenario with automation displacing human labor (Acemoglu and Restrepo, 2020a; Korinek and Stiglitz, 2021), other authors state that the potential impact of the current generation of robots is limited (Fernández-Macías et al., 2021). In this line, other authors draw attention to the positive effects of automation on productivity and economic growth (Autor, 2015; Graetz and Michaels, 2018), and to increases in aggregate employment (Klenert et al., 2022), and encouraging the creation of new tasks (Acemoglu and Restrepo, 2018d). [2]

This chapter explores a new dimension of automation not previously studied in the literature to the best of our knowledge: its impact on public finance. According to the aforementioned predictions, the current technological revolution also presents a challenging scenario for public finance. Automation will change the relative importance of inputs in the economy and the way in which income is

[1] In particular, it is predicted that AI will outperform humans in translating languages (by 2024), writing high-school essays (by 2026), driving a truck (by 2027) and working in retail (by 2031). Furthermore, in the next decades, the process would make AI outperform humans at writing a bestselling book (by 2049) and working as a surgeon (by 2053).

[2] It is important to note that the concept of what a "robot" varies from one paper to another, leading to different specifications of how robots are incorporated into the aggregate production function. For some authors (i.e., Thuemmel, 2022), a robot is a machine that replaces low-skill workers. In this case, a robot is not different from other traditional capital equipment assets. Other authors (Lin and Weise, 2019) propose a specification for technology in which robots are substitutes for labor, without distinguishing between lowand high-skill workers. In this chapter, we adopt the interpretation of "autonomous" or "intelligent" capital as a combination of robots and AI, and following Casas and Torres (2023), we consider that this autonomous capital is a substitute for both traditional capital equipment and labor.

distributed among production factors. These changes will have a direct impact on public finance given the current tax mix. Recently, the debate has revolved around how to tax the new autonomous capital. Although numerous authors have claimed the necessity of taxing robots, the literature lacks an analysis of the effects of robotization on public finance based on the current tax mix. This chapter contributes to the literature by analyzing how public finance evolves with the expansion in the economy of the new disruptive autonomous technology. In particular, we examine how total tax revenues, including social security contributions, evolve with automation in the long run. In order to carry out this analysis, we use the automation model by Casas and Torres (2023), extended with taxes. Using the steady-state solution of the calibrated model, we carry out three experiments to explore how tax revenues evolve as the new autonomous technology spread through the economy. First, we study how the government size, measured by the fiscal revenues to output ratio, changes as automation increases. We find that as automation increases, the competition between traditional technology and autonomous technology leads to a fall in the size of the government. Automation expands output in the long run but provokes a reallocation of inputs with the subsequent impact on public finance, depending on how the tax mix is designed. Capital income tax revenues remain almost constant, but we find a dramatic reduction in labor income tax revenues and in social security contributions. This is explained by the negative response of labor to automation, where a large fraction of labor is substituted by autonomous capital. These results warn that the standard tax mix adopted by advanced economies, where labor payroll taxes represent a significant fraction of fiscal revenues, is not able to maintain the size of the government as automation increases.

Second, we calculate how tax rates should be adjusted to keep fixed fiscal revenues. As expected, the payroll taxes rates and the consumption tax rate should be increased progressively as automation increases, to compensate for the decline in the tax bases due to the reduction in working hours and the rise in the investment-to-output ratio to compensate for the higher depreciation rate of autonomous capital, respectively. By contrast, we find that the capital tax rate could be reduced slightly as capital income increases because of the accumulation of autonomous capital. However, this type of tax policy would have dramatic harmful effects on economic activity, reducing output and consumption and further depressing labor supply. The results from this experiment arise an important question about how the tax mix scheme should be reformed to accommodate the effects of automation. To answer the above question, the third experiment consists of the calculation of the capital income tax rate necessary to keep fixed total fiscal revenues, without changes in the other tax rates. We find that the capital income tax rate should increase as the rate of automation increases, reaching a value of around 77%, for an automation rate of 45%.

Finally, we carry out a sensitivity analysis to assess the robustness of previous results to different calibrations of the key parameters of the model and alternative specifications of the technology. First, we study how the results from the previous experiments change to alternative values of the elasticity of substitution between the traditional and the new technology. Second, we repeat the simulations using an alternative aggregate production function widely used in the literature, where autonomous technology is a substitute for labor. In both cases, we find that results and insights are robust to alternative calibration and to the alternative specification of the technology.

The structure of the rest of the chapter is as follows. Section 2 discusses the related literature. Section 3 presents a stylized model for automation, where two types of technologies are considered: traditional technology using traditional capital and labor, and autonomous technology using autonomous capital resulting from the combination of robots and AI. The model considers a fully specified tax menu, including a consumption tax, a labor tax, a capital income tax, and a social security tax which payment splits between employees and employers. Section 4 presents the calibration of the model. Section 5 presents the main results from the three experiments. Section 6 presents the sensitivity analyses. Finally, Section 7 collects the main conclusions.

3.2 Related literature

This chapter is related to the literature on taxing robots. The idea of taxing robots is not new and a tax on labor-saving machinery as a policy to help displaced workers already appeared in the US throughout the Great Depression of the 1930s (Woirol, 2018). Several proposals have been done to tax robots with two objectives: first, to delay or discourage automation, and second, to obtain additional public revenues to be transferred to displaced workers and to sustain the social security system. In this venue, the potential negative effects of automation on human labor have also raised concerns about pay-as-you-go social security system sustainability (Jimeno, 2019; Basso and Jimeno, 2019) and voices demanding a universal basic income (Hoynes and Rothstein, 2019; Cabrales et al., 2020; Jaimovich et al., 2021).

Guerreiro et al., (2022) defend that it is optimal to tax robots while there are still routine workers, but once all these workers are retired (automatized), the optimal robot tax should be zero. Vermuelen et al., (2020) propose the distinction across economies with labor surplus and labor scarcity, arguing that only in case of labor surplus it is commendable to tax robots to prevent robotization in order to avoid exacerbating unemployment and wage stagnation. These studies could be linked to the one developed by Thuemmel (2022), who interprets robots as a substitute for routine labor and a complement to non-routine labor to affirm that the optimal robot tax is positive and generates small welfare gains. However, as the price of robots falls, inequality rises and the specific robot tax and its welfare impact become insignificant. When robots get cheap enough to replace all routine labor, the robot tax turns meaningless. Zhang (2019) remarks on the importance of a tax on robots as a useful tool to narrow down the wage gap between unskilled and skilled workers. Moreover, Gasteiger and Prettner (2022) show that a robot tax has the potential to raise per capita output and welfare.

However, specific robot taxes rises a number of difficulties. Mazur (2019) cautions against the use of a robot tax arguing that it is the wrong tool to face the issues driven by automation and warns of the potential consequences of such tax, remarking on the limiting of innovation. Moreover, Marwala (2018) put focuses on the difficulty of distinguishing what a robot is and what a robot is not and concludes that taxing robots is the same as increasing corporate taxes. This difficult task of defining what a robot is and taxing it has led to several approaches and legal analyses about this matter. Chekina et al., (2018) propose applying taxation to new cyber-physical technologies and products of their application, replacing digital transactions and shortfalls in revenues by traditional objects of taxation in the form of tangible assets and people, increasing tax pressure and the degree of progressiveness of taxes and building a new tax space with smart taxes based on real-time principles, smart contracts and Big Data. Costinot and Werning (2018) analyze technology regulation in a second-best world, with rich heterogeneity across households, linear taxes on the subset of firms affected by technological change, and a nonlinear tax on labor income.

With a broader focus, Kovacev (2020) analyze diverse tax systems to conclude that any tax system that relies on human effort to raise revenues is vulnerable to dislocation with the rise of AI and robotics, while Oberson (2019) remarks that tax issues go much beyond the borders of any particular state and argues that they should be analyzed globally taking into account the recent developments in international taxation. [3]

This chapter is also related to the literature exploring the macroeconomic implications of government size. Galí (1994) parameterizes the government size by the income tax rate and the share of government purchases in output, but the focus is studying the effects of government size on output variability. The standard RBC model implies that income taxes are destabilizing whereas government purchases are stabilizing. Fatás and Mihov (2001) find a negative correlation between government size

[3] In general, the debate about the robot tax could be understood as a sub-branch of the economic debate about optimal capital taxation. Recently, Straub and Werning (2020) revisited the Chamley-Judd result (capital should not be taxed in the long run) to overturn it. On the one hand, they affirm that the long-run tax on capital is positive and significant for the main model in Judd (1985) if the intertemporal elasticity of substitution is below one, while it converges to zero at a slow rate (maybe after centuries of high tax rates) for higher elasticities. On the other hand, they provide conditions under which the upper bound on capital taxes in Chamley (1986) binds forever implying positive long-run taxes.

and output volatility both for the OECD countries and across US states. Guo and Harrison (2006) show that the stabilization effects of government fiscal policy are affected by how hours worked are introduced in the households' utility function. They found that the results of previous literature are reversed when preferences are instead convex in hours worked. Here, we adopt a different perspective by accounting for how automation impacts the government size from the tax revenues perspective.

3.3 The model

We consider a model economy with two types of capital: traditional capital and autonomous capital (a combination of AI and robotics). We propose a simple production function where two different technologies can coexist simultaneously: a traditional technology that requires traditional physical capital and labor for production and a new autonomous technology that employs only a new capital (hardware and artificial intelligence) for production. Whereas traditional technology uses a combination of traditional capital and labor under constant returns to scale (which implies that marginal productivity for both inputs is decreasing), the new technology exhibits constant marginal productivity for autonomous capital, which involves endogenous growth. We consider a representative household that can freely decide labor time, consumption, and investment decisions in both kinds of capital. The model includes a government that collects taxes to finance public spending. Five tax rates are considered: a consumption tax, a capital income tax, a labor income tax, and contributions to social security by employers and employees. The model is specified in discrete time and it is considered a decentralized economy where households maximize utility in a deterministic intertemporal optimization setting and firms operates in a perfect competition environment.

3.3.1 The technology

The aggregate production technology is a CES function for traditional technology using capital and labor nested into another CES function. In this aggregate CES function, new and traditional technology are substitutes. We define the following aggregate production function to represent this technological combination:

$$Y_t = \left[\mu X_t^{v} + (1-\mu)\, D_t{}^{v}\right]^{\frac{1}{v}} \tag{3.1}$$

where Y_t is the final output, X_t represents traditional technology, μ is a distribution parameter for the traditional productive factors versus the new technology, D_t is the autonomous capital, and v measures the substitution between the traditional production technology and the new technology. The elasticity of substitution between traditional and autonomous technologies is defined as $\sigma = 1/(1-v)$.

The traditional technology is represented by another CES function:

$$X_t = \left[\alpha K_t^{\theta} + (1-\alpha)\, L_t^{\theta}\right]^{\frac{1}{\theta}} \tag{3.2}$$

where K_t is the traditional capital, L_t is labor, α is a distribution parameter of inputs and θ measures the substitution between traditional capital and labor. The elasticity of substitution is defined as $\varepsilon = 1/(1-\theta)$. Empirical evidence suggests that $\varepsilon < 1$ (Chirinko, 2008; Eden and Gaggl, 2018), and that $\sigma > 1$ (DeCanio, 2016; Acemoglu and Restrepo, 2019; Lin and Weise, 2019). Therefore, it is assumed that $0 < \varepsilon < 1 < \sigma < \infty$. This implies higher complementarity between traditional capital and labor than between traditional technology and autonomous capital. That is, autonomous capital is a substitute for both traditional capital and labor. [4]

[4] For additional information about the characteristics of the production function, see Casas and Torres (2023).

Firms maximize profits in a competitive environment taken factor prices as given, solving the following static maximization problem at each period:

$$\max \Pi_t = Y_t - (1+\tau_t^{sse})W_t L_t - R_{k,t}K_t - R_{d,t}D_t \tag{3.3}$$

where W_t is the wage, τ_t^{sse} are social security contributions paid by the employer, and $R_{k,t}$ and $R_{d,t}$ are the returns to traditional and autonomous capital, respectively. From the first order conditions of the firm's profit maximization problem, we obtain the following marginal productivity of each of the three productive factors:

$$R_{k,t} = \alpha\mu Y_t^{1-\upsilon} X_t^{\upsilon-\theta} K_t^{\theta-1} \tag{3.4}$$

$$(1+\tau_t^{sse})W_t = (1-\alpha)\,\mu Y_t^{1-\upsilon} X_t^{\upsilon-\theta} L_t^{\theta-1} \tag{3.5}$$

$$R_{d,t} = (1-\mu)\,Y_t^{1-\upsilon} D_t^{\upsilon-1} \tag{3.6}$$

where the Euler Theorem holds, profits are zero and output is distributed among the three productive factors, given the assumptions of a competitive market and constant returns to scale.

3.3.2 Households

We assume that the utility function of our representative household is as follows:

$$U(C_t, L_t) = \gamma \log C_t + (1-\gamma)\log(1-L_t) \tag{3.7}$$

where C_t is total consumption and γ is a parameter reflecting the willingness to sacrifice units of consumption in favor of leisure time. Total available time has been normalized to one, so leisure is defined as $1 - L_t$, where $0 < L_t < 1$. The representative household satisfies the following budget constraint:

$$\begin{aligned}(1+\tau_t^c)C_t + I_t \quad = \quad & (1-\tau_t^l - \tau_t^{ssw})W_t L_t + \\ & (1-\tau_t^k)(R_{k,t}K_t + R_{d,t}D_t) + \tau_t^k(\delta_k K_t + \delta_d D_t) + T_t\end{aligned} \tag{3.8}$$

where I is the total investment in capital, τ_t^c is a consumption tax, τ_t^l is labor income tax, τ_t^{ssw} is employees' social security contributions, τ_t^k is the capital income tax, T_t is a lump-sum transfer, and δ_k and δ_d are depreciation rates for traditional and autonomous capital, respectively. As we assume an unique total investment instead of specific investment decisions, we have an unique capital accumulation process presented in the following way:

$$I_t = D_{t+1} - (1-\delta_d)D_t + K_{t+1} - (1-\delta_k)K_t \tag{3.9}$$

The maximization problem faced by the infinity-lived representative household with perfect-foresight is given by,

$$\max_{\{C_t, L_t\}} \sum_{t=0}^{\infty} \beta^t \left[\gamma \log C_t + (1-\gamma)\log(1-L_t)\right] \tag{3.10}$$

subject to restrictions (4.20) and (4.21), where K_0 and D_0 are given, and where β is the intertemporal discount factor.

Equilibrium conditions, representing Euler equations, from the household's maximization problem are,

$$(1+\tau_t^c)C_t = \frac{\gamma}{1-\gamma}(1-L_t)W_t(1-\tau_t^l - \tau_t^{ssw}) \tag{3.11}$$

$$1 = \beta \frac{(1+\tau_t^c)C_t}{(1+\tau_{t+1}^c)C_{t+1}} \Big((1-\tau_{t+1}^k)(R_{k,t+1} - \delta_k) + 1\Big) \tag{3.12}$$

$$1 = \beta \frac{(1+\tau_t^c)C_t}{(1+\tau_{t+1}^c)C_{t+1}} \Big((1-\tau_{t+1}^k)(R_{d,t+1} - \delta_d) + 1\Big) \tag{3.13}$$

representing the optimal labor supply, the investment decision on traditional capital and the investment decision on autonomous capital, respectively. Notice that these equilibrium conditions establish a direct relationship between depreciation rates and returns of both traditional and autonomous capital, as net marginal productivities are equal, such as:

$$R_d - \delta_d = R_k - \delta_k \tag{3.14}$$

3.3.3 Government

The government uses tax revenues to finance lump-sum transfers. We assume that the government balances its budget period-by-period by returning revenues from distortionary taxes to the agents via lump-sum transfers. Total tax collection is specified as follows:

$$T_t = \tau_t^c C_t + (\tau_t^l + \tau_t^{ssw} + \tau_t^{sse}) W_t L_t + \tau_t^k ((R_{k,t} - \delta_k) K_t + (R_{d,t} - \delta_d) D_t) \tag{3.15}$$

where T_t represents fiscal revenues.

3.4 Calibration

The model is calibrated according to an artificial economy using standard values in the literature. Given the specification of the model, the combination of traditional and autonomous technologies is a CES function, where the distribution parameter represents the relative weight of each technology in the economy. We use this distribution parameter of the CES production function as a free parameter representing the penetration of autonomous capital in the economy. The autonomous technology adoption rate, represented by $1 - \mu$, takes values from 0 to 0.45 , where the maximum value is consistent with the estimations about the percentage of tasks in the economy that are potentially automatized by leveraging current technology (Manyika et al., 2017).

As the elasticity of substitution between technologies, $\sigma = 1/(1 - v)$, involves traditional labor and capital on one side and autonomous capital on the other one, it results logically to examine elasticities of substitution lower than the 2.5 estimated by DeCanio (2015). Therefore, we set $\sigma = 2$ and then we provide a sensitivity analysis for the elasticity of substitution in a range from 1 to 5 , which implies a range of values for v between 0 and 0.8. The range of values selected for the sensitivity analysis of this parameter is coherent due to the wide range of values used in the literature. For example, while some authors interpret that robots and labor are perfect substitutes (Acemoglu and Restrepo, 2020a) and other authors establish a high elasticity of substitution equal to five (Lin and Weise, 2019), Decanio (2015) estimates this value at 2.5.

The autonomous capital depreciation rate is another key parameter in our model since it determines the relationship between the (gross) returns of the two types of capital. We fixed it to $\delta_d = 0.20$ annually, according to the depreciation rate traditionally assumed for R&D capital. This percentage is reflected in the EU KLEMS data and has been documented by numerous authors (see, for example, Hall, 2005). This calibration is close to Lin and Weise (2019), which along with Krusell et al., (2000), set out a quarterly depreciation of robots at 0.0515. Graetz and Michaels (2018) set a slightly lower robot depreciation rate of ten percent. Abeliansky and Prettner (2017), following Graetz and Michaels (2018), also assume a robotic depreciation rate of 10%. This depreciation rate would be higher than the one established by the International Federation of Robotics (2016), which sets a lifetime horizon of 12 years for robots.

Tax rates are calibrated according to the OECD average (OECD, 2018; OECD, 2019). Tax rates are fixed to $\tau^c = 0.1832, \tau^l = 0.1646, \tau^{sse} = 0.1589, \tau^{ssw} = 0.0945$ and $\tau^k = 0.2418$ The rest of the parameters are calibrated as standard in the literature. As we focus on the long-run, the time dimensional parameters of the model are calibrated on an annual basis. Therefore, we fix $\beta = 0.975, \gamma = 0.4, \alpha = 0.35, \delta_k = 0.06$, and $\varepsilon = 1/(1 - \theta) = 0.90$, consistent with Chirinko (2008), Eden and Gaggl (2018) and Lin and Weise (2019).

Table 3.1 summarizes the benchmark calibration of the parameters of the model and the range of values for the parameter representing the level of automation of the economy.

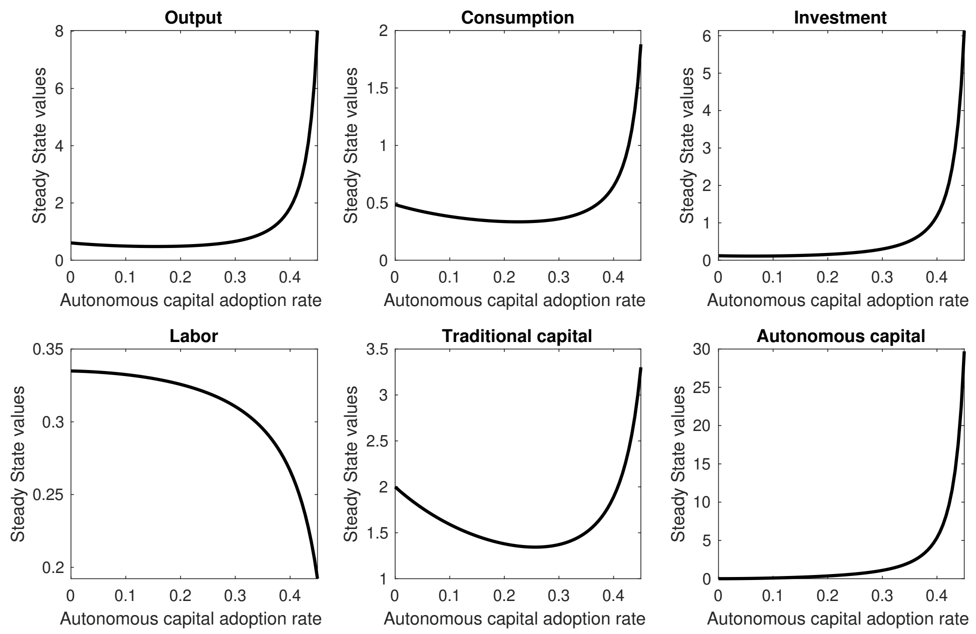
TABLE 3.1: Calibrated parameters

	Parameter	Definition	Value
Preferences	β	Discount factor	0.975
	γ	Consumption-leisure preference parameter	0.40
Technology	α	Capital share in the traditional technology	0.35
	δ_k	Traditional capital depreciation rate	0.06
	δ_d	autonomous capital depreciation rate	0.20
	ε	Traditional capital-labor elasticity	0.90
	σ	Traditional-autonomous technologies elasticity	2.00
	μ	Technologies distribution parameter	[0.55-1.00]
Tax rates	τ^c	Consumption tax rate	0.1832
	τ^l	Labor income tax rate	0.1646
	τ^{sse}	Employer's social security tax rate	0.1589
	τ^{ssw}	Employee's social security tax rate	0.0945
	τ^k	Capital income tax rate	0.2418

3.5 Quantitative results

In this section, we quantitatively measure the implications of automation on the size of the government. We simulate an increase in automation represented by a decline in the aggregate CES distribution parameter μ. A value of $\mu = 1$ indicates an economy with no autonomous capital. We compute a sequence of steady states by reducing the value of this parameter until a value such as labor goes to zero. resulting in a maximum value for the automation rate of 0.45 . Figure 3.1 plots the steady state values of key variables as a function of the automation rate. For relatively low values of automation (automation rates below 0.3), steady-state output remains almost constant and even reduces, although some significant changes are observed in labor and traditional capital. As we can observe, long-run output increases as the automation rate become higher, once the autonomous capital adoption rate is above 0.3. However, the increase in production is not distributed equally between consumption and investment. Automation changes the distribution share of consumption and investment to output, decreasing the consumption-output rate and increasing the investment-output rate, due to the higher depreciation rate of autonomous capital. Indeed, consumption decreases in the first stages of automation, as more income must be allocated to investment spending to finance autonomous capital consumption, given that the depreciation rate of autonomous capital is higher than the depreciation rate of traditional capital. Again, only for a large enough autonomous capital adoption rate, the increase in output can finance both consumption and higher investment in the long run. The changes produced in steady-state output, consumption, and investment are consequences of the substitution among the three production inputs. Autonomous capital stock increases exponentially while traditional capital stock plots a U-shape, decreasing in the first stages of automation and then increasing once the proportion of autonomous capital is large enough.

FIGURE 3.1: Steady state values of key macroeconomic variables as a function of automation



The most dramatic effect of automation is found in the reaction of labor. Automation reduces working hours no matter how the rate of penetration of autonomous capital is. [5] Whereas for low values of automation the negative effects on working hours are relatively small, the substitution effects increase as automation becomes higher. What is clear from the results shown in Figure 3.1, is that automation will change the relative importance of inputs in production and hence, the way how income is generated and distributed in the economy, shifting the tax base from labor to capital. These changes are expected to have a direct impact on public finance depending on the tax mix. We explore three scenarios: (i) how specific tax revenues change with automation given the baseline tax mix; (ii) how taxes rates should be changed to keep fixed tax-specific revenues; and (iii) what should be the capital income tax rate, keeping fixed the other taxes, to keep the size of the government constant.

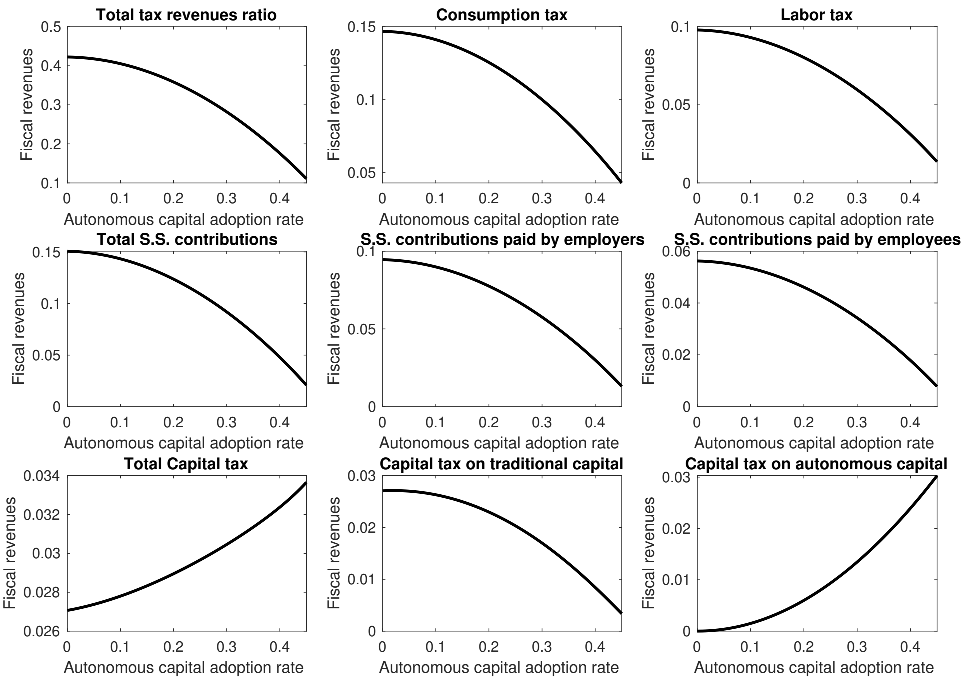
3.5.1 Experiment 1: Automation with fixed tax rates

The first experiment consists of computing fiscal revenues to output ratio (total and tax-specific) as a function of the automation rate keeping fixed the tax rates to the baseline calibration. Results from this experiment are plotted in Figure 3.2. As we can appreciate, the size of the government in the baseline calibration would be 42% in a world without autonomous capital (a production function with only labor and traditional capital). The introduction of autonomous technology pushes down the government size steadily. When the autonomous capital adoption rate reaches the maximum value of 0.45 , the size of the government falls to only 11%. This large fall in the total tax revenues to output ratio finds its explanation in the fall of the revenues to output ratio from all taxes except for the capital income tax. Notice that even revenues from the consumption tax as a fraction of output decline as a consequence of the required higher investment rate as automation increases. That is, automation increases the investment-to-output ratio and decreases the consumption-to-output ratio. In particular, fiscal revenues as a percentage of output levied by the consumption tax goes down from 15% to 5%.

[5] Labor represents working hours in our economy model. The decline in working hours provoked by automation can also be interpreted as a reduction in the workday and not in employment (see Bongers and Molinari, 2020).

A similar loss of fiscal revenues is found for all payroll taxes on labor income (social security contributions and the labor income tax). The observed decline in labor payroll taxes revenues is even more dramatic. Collected revenues from the labor tax to output ratio go from around 10% to 1%, and total social security contributions to output ratio go from around 15% to 2%. Thus, automation would not only reduce tax revenues from labor but also could call into question the sustainability of the pay-as-you-go social security scheme. The only tax that contributes to increases in fiscal revenues is the capital income tax. As we observe in the last row of the figure, the capital income tax revenues to output ratio increases from 2.7% to 3.3%. This is explained by the increase in the autonomous capital income tax collection to output ratio that compensates for and exceeds the drop of the traditional capital income tax collection. However, fiscal revenues from capital income tax represent a small fraction of total fiscal revenues and cannot compensate for the decline in fiscal revenues from other sources.

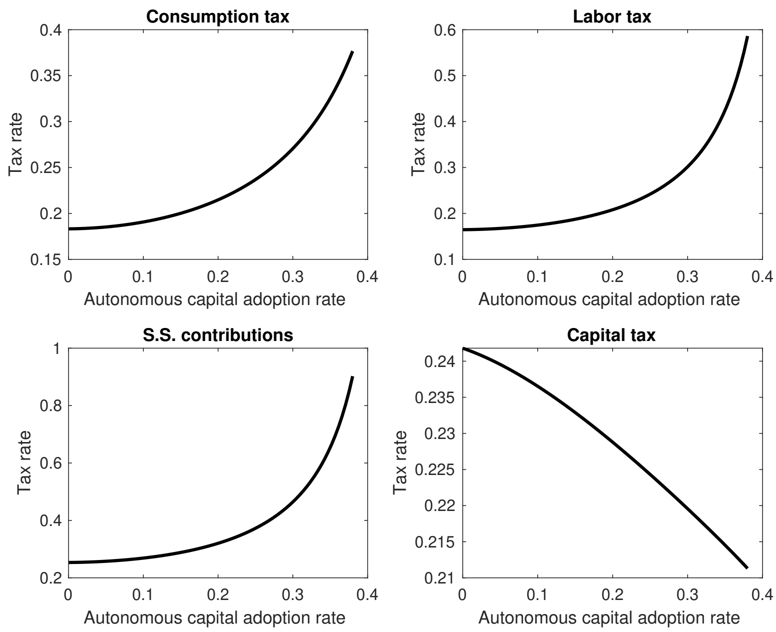
FIGURE 3.2: Steady state values for the ratio of tax revenues to output as function of the autonomous capital adoption rate.



Two key implications can be obtained from previous results. First, while it is logical that in the face of an increase in production, total tax collection will be increased by the expansion of the economy, we find that the automation process causes fiscal revenues to output ratios to collapse. That is, the expansion of the economy exceeds the expansion of public finance. To a large extent, we could say that the penetration of the new autonomous technology causes tax revenues from traditional sources to fall. On the other hand, the expansion of output does not imply equal increases in consumption and investment, but since the expansion of the economy is driven by the new technology with a high depreciation rate, more resources are needed to be allocated to investment, causing the ratio of fiscal revenues from consumption to output to fall as well. Second, the size of the government cannot be maintained with automation and the current tax mix. This is because output expansion far exceeds the expansion of public revenues, which are decreasing in relation to the output as the autonomous capital share increases. This would force the government to increase tax rates parallel to automation.

Furthermore, automation changes the functional distribution of income increasing the capital share, which calls for a reform of the tax mix.

FIGURE 3.3: Tax rates as a function of the autonomous capital adoption rate to keep constant specific-fiscal revenues.



3.5.2 Experiment 2: Automation with fixed tax-specific revenues

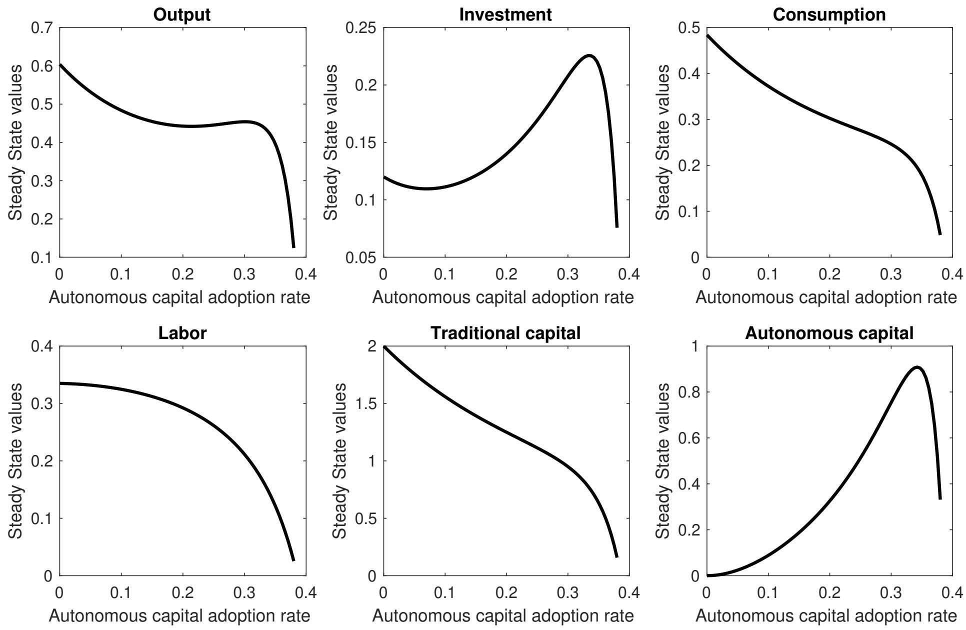
One lesson we learn from experiment 1 is that the current government size is not sustainable with the current tax mix as the automation process progresses. This means that current tax rates should be modified according to the observed changes in the tax bases. Next, we consider a scenario in which specific tax rates are changed to keep fixed the tax burden. This counterfactual experiment would indicate how taxation policy should adapt to the automation process, depending on the changes in the combination of inputs and how income is generated and spent, in order to keep constant the size of the government. Estimated tax rates as a function of the automation rate are shown in Figure 3.3. As we can observe, as automation increases, all tax rates, except the capital income tax rate, should be increased. Specifically, when the adoption rate of autonomous technology reaches the 38 %,[6] the consumption tax rate should be 0.3764 , the labor income tax rate should be 0.5862 , and the total social security contributions tax rate should be 0.9024 in order to keep constant the government size. By contrast, the capital income tax rate should be lower as the accumulation of autonomous capital is fairly enough to keep capital income constant. In this sense, the policy of fixed tax-specific revenues would deepen the income inequality increase caused by automation. [7]

However, such fiscal policy could be impractical and counterproductive. Indeed, the estimated increases in the tax rates to keep constant fiscal revenues are of a large magnitude, increasing distortions

[6]This is the maximum value for $1-\mu$ consistent with the baseline government size with no automation before labor collapses to zero.

[7]See, for instance, Lankisch et al., (2019) and Jaimovich et al., (2021).

FIGURE 3.4: Steady state for key aggregate variables as a function of the autonomous capital adoption rate in a scenario with fixed tax-specific revenues.



in the economy and causing a negative impact on economic activity. Figure 3.4 plots the steady state values of the key macroeconomic variables resulting from the previous tax policy. These figures plot the steady state values for the key variables as a function of the autonomous capital adoption rate and the new taxes rates needed to keep the size of the government constant. As we can observe, this fiscal tax policy causes output to decrease. This fall is accompanied by a decrease in consumption, labor, and traditional capital, while investment and autonomous capital increase before the collapse of labor once the automation rate is above 35%. Therefore, this fiscal policy aimed to keep constant the share of each tax revenue is not a solution in the face of automation. By contrast, this tax policy would accelerate the collapse of the economy (reducing labor to zero) given the higher labor payroll taxes in combination with a higher consumption tax.

The lesson we can extract from this analysis is that the current tax menu cannot be maintained in an environment with high automation and it should be accommodated to the new income generation scenario, where production technology is increasingly dominated by autonomous capital. Likewise, this analysis reveals some insights into how the advance of automation can be directed by fiscal policy.

3.5.3 Experiment 3: Capital income tax to keep total fiscal revenues fixed

Finally, we study a scenario in which only the capital income tax is modified to compensate for all the effects of automation on public finance. In this counterfactual experiment, the consumption and labor income tax rates and the social security contributions rate remain fixed to the baseline calibration values. This experiment is motivated by previous results. First, automation will transform the combination of inputs used in the economy where automatic capital will substitute both traditional capital and labor. In short, automation will increases capital deepening while reducing labor. This changes the functional distribution of income, reducing the labor share and increasing the capital share. Additionally, automation would increase the investment-to-output ratio and thus decrease the consumption-to-output rate. Therefore, capital income would be transformed into the main tax base replacing both labor income and consumption tax bases.

Previous studies have already explored reasons for the optimality of differential capital taxation. In particular, Slavik and Yazici (2014), setting the focus on the marginal tax rates on returns to capital assets, conclude that it is optimal to tax equipment capital at a higher rate than structures. In a quantitative exercise, these authors state that the optimal tax rate on equipment capital is at least 27 percentage points higher than the optimal tax rate on structure capital. Contrary to this idea, we can also find authors defending that capital should not be taxed (Chari et al., 2020). Indeed, one alternative would be to consider two specific taxes for traditional and autonomous capital. However, this would be difficult for practical implementation, as first, we should have a clear definition of what traditional and autonomous capital are, and second, how to distinguish between income produced by each capital. Instead, in this experiment, we maintain the assumption that the capital income tax rate is the same for all types of capital.

Figure 3.5 plots the estimated capital income tax rate as a function of automation that would be required to keep constant the government size. As we can observe, the value of this tax rapidly increases as autonomous technology gains weight in aggregate production. We find an S-shaped relationship between capital tax and automation, resulting in considerably high values for the tax rate. For the maximum automatic capital adoption rate used in the simulation, the tax rate on capital income would be around 80%. At a first sight, this is a substantial value. However, it is also true that capital income becomes the main tax base of the economy as a consequence of automation.

We now turn to study the impact of this capital income tax rate on the rest of the economy. Figure 3.6 plots the key steady-state values of the economy as a function of the new capital income tax that keeps fixed the government size. The consequences of this increasing capital income tax rate are remarkable and different from the previous scenario. In particular, under the implementation of this capital income tax rate policy, output, investment, and consumption describe U shapes as autonomous technology advances and autonomous capital stock increases while traditional capital decrease. This progressive higher capital tax rate reduces capital deepening in the economy. Indeed, the steady-state output is reduced in the initial stages of automation. However, even with an increasing capital income tax rate, autonomous capital is accumulated at a high rate. On the other hand, labor displacement is significantly less intensive under this fiscal scenario compared to the previous one. The increasing capital income tax reduces net income from capital, slowing the substitution of labor for autonomous capital.

It is interesting to contrast the results plotted in Figure 3.6 with Figure 3.4 . In both cases, the size of the government is kept constant for any level of autonomous capital adoption and the only difference is in the tax policy regime. Whereas in Figure 3.6 the size of the government is kept constant by changing only the capital income tax rate, whereas in Figure 3.4 all tax rates are changed by keeping constant fiscal revenues from each source. Differences in both fiscal policy scenarios are significant. In the first case, traditional capital and labor will be substituted by autonomous capital, but as the automation process increases, the effect on output, investment, and consumption turns out to be positive for high values of automation. By contrast, changing all tax rates would lead to a collapse of the economy when the automation capital adoption rate is close to 40%. What these results show is that it turns out to be less distorting increasing the capital income tax to keep fixed the size of the government, an alternative fiscal policy that keeps constant revenues from each tax.

3.6 Sensitivity analysis

In this section, we carry out a sensitivity analysis regarding two key aspects of the automation process. On the one hand, due to the lack of consensus and empirical evidence on the elasticity of substitution between traditional technology and new technology, we repeat the simulations for a range of values of

FIGURE 3.5: Capital income tax rate to keep constant fiscal revenues as function of the autonomous capital adoption rate.

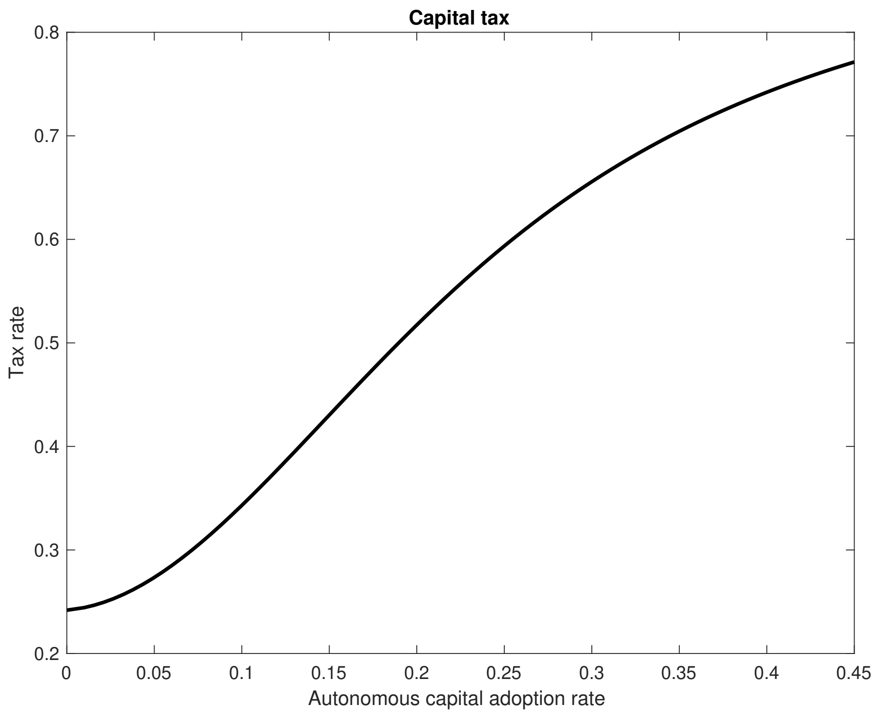
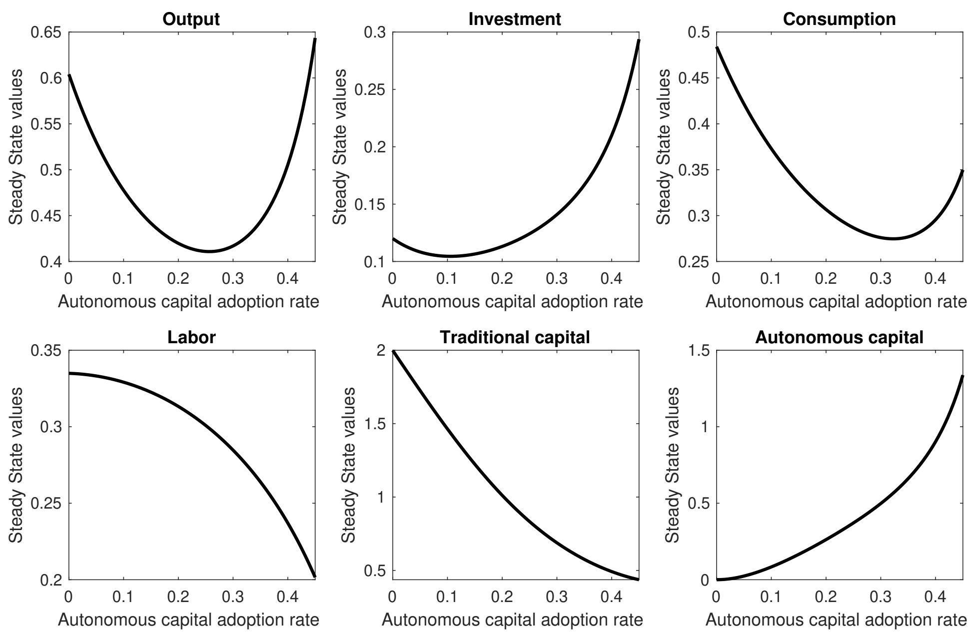


FIGURE 3.6: Steady state values as function of the autonomous capital adoption rate in a scenario with a capital income tax rate to keep fixed the government size.

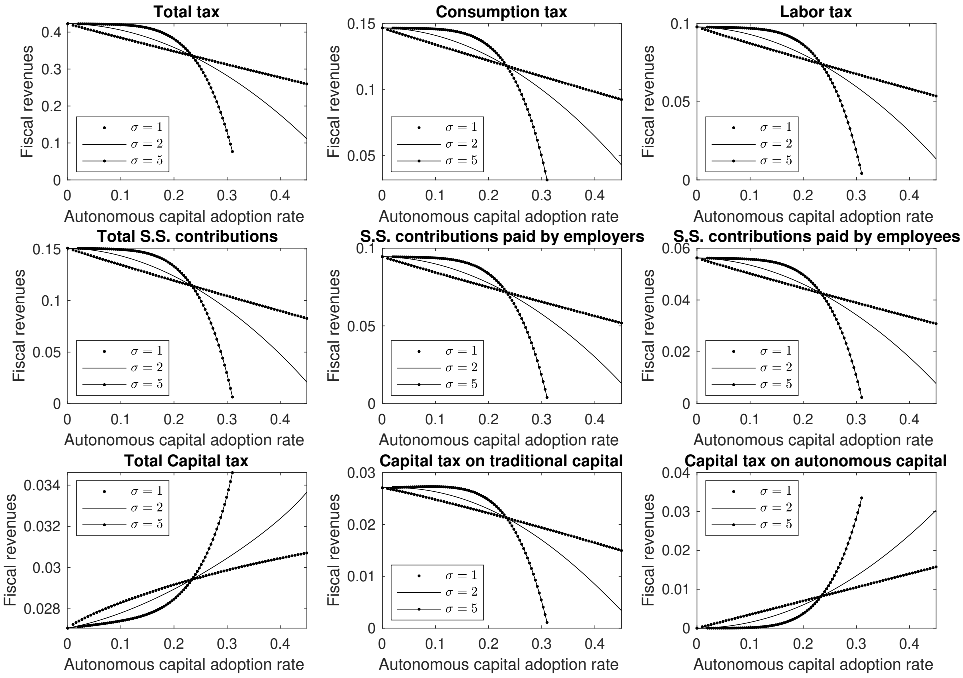


the elasticity of substitution from 1 to 5 . On the other hand, we repeat the simulation using an alternative specification of the production function widely used in the literature. This alternative specification assumes that this new technology replaces human labor, contrary to the model presented in this chapter which assumes that autonomous capital is a substitute for both traditional capital and labor.

3.6.1 Elasticity of substitution between technologies

First, we study the sensitivity of the results to alternative values of the elasticity of substitution between traditional and autonomous technologies. In Figure 3.7, we present all taxes collection as a percentage of output for three alternative values of the elasticity of substitution (1,2, and 5). We can observe that differences are small for low values of the autonomous capital adoption rate. However, for higher values of automation, results are more sensitive to the elasticity of substitution. As the elasticity of substitution increases, automation has a greater impact, accelerating the decline of the government size. For all three elasticities values investigated we find a negative relationship between automation and the government size.

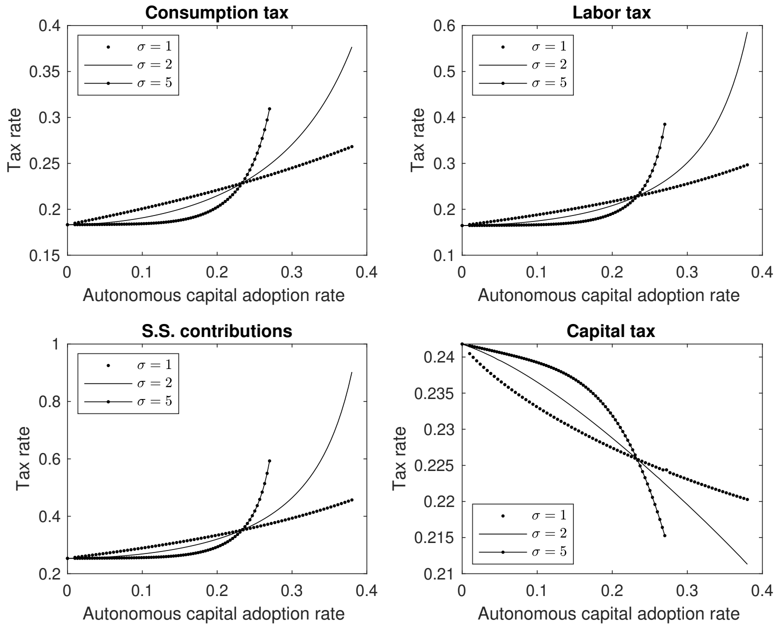
FIGURE 3.7: Fiscal revenues as a percentage of GDP as function of the autonomous capital adoption rate and the elasticity of substitution between traditional technology and autonomous technology.



Next, we carried out a sensitivity analysis on experiment 2 to investigate how sensitive the estimated tax rates required to keep constant fiscal revenues depending on the elasticity of substitution. Results from this sensitivity analysis are plotted in Figure 3.8 . We find that the elasticity of substitution has an impact on the required tax rates, but in all cases, tax rates must be changed in the same direction. The consumption, labor income, and social security contributions tax rates increase with automation, whereas the capital income tax rate reduces with automation.

Estimated tax rates depend on the automation rate. For low values of automation (below an automation adoption rate of 22.5%), tax rates are almost constant for the highest value of elasticity. However, this effect reversed for values of the automation rate above 22.5%. In this case, the greater the elasticity of substitution between technologies is, the greater the negative impact of automation on the government size and thus a larger increase in the tax rates is needed.

FIGURE 3.8: Tax rates to keep constant fiscal revenues as function of the autonomous capital adoption rate and the elasticity of substitution between technology.



Finally, we repeat experiment 3 for the selected values of the elasticity of substitution. Figure 3.9 plots the implicit capital income tax rate required to keep fixed total fiscal revenues as a function of the elasticity of substitution. For the three values of elasticity, we find an increasing trend in the tax rate, with similar values. For an automation rate of 40%, the capital income tax rate should be in a range of 0.65 to 0.80 , for the lower and higher elasticity of substitution, respectively.

3.6.2 Alternative technology

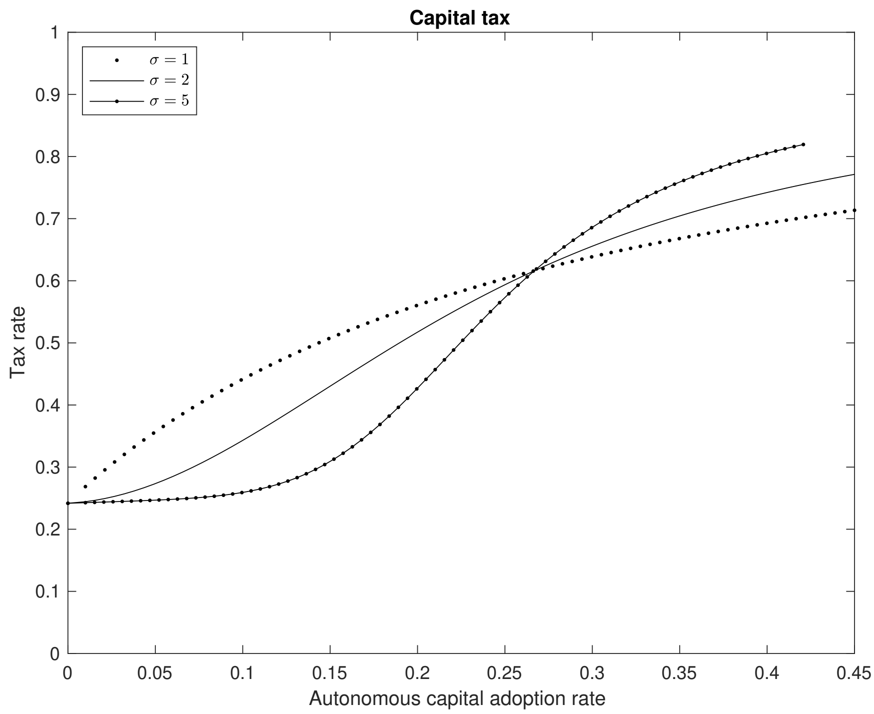
The model used in this chapter assumes that robots and AI are a new type of capital (autonomous capital) that can substitute both traditional capital and labor. This assumption is based on the characteristics of new autonomous capital, a combination of robots and AI that can perform tasks in an autonomous way. In this section, we repeat the previous analysis using the standard production function specification with robots widely used in the literature. This specification consists of assuming that robots replace workers while complementing traditional capital units. This is the technology specification assumed by, for example, Eden and Gaggl (2018), Berg et al. (2018), and Lin and Weise (2019). Under this assumption, the production function would be as follows:

$$Y_t = \left[\mu X_t^{v} + (1-\mu)\, K_t{}^{v}\right]^{\frac{1}{v}} \tag{3.16}$$

where Y_t is the final output, μ is the CES distribution parameter, X_t is a composite of human labor and robots, K_t is the traditional capital, and v measures the substitution between the traditional capital and labor -human or robotic-. The elasticity of substitution between traditional capital and labor -human or robotic- is defined as $\sigma = 1/(1-v)$. X_t represents labor tasks performed by autonomous capital and/or human labor:

$$X_t = \left[\alpha D_t^{\theta} + (1-\alpha)\, L_t^{\theta}\right]^{\frac{1}{\theta}} \tag{3.17}$$

FIGURE 3.9: Capital income tax rate to keep constant fiscal revenues as function of the autonomous capital adoption rate and the elasticity of substitution.



where D_t is the autonomous capital, L_t is labor, α is a distribution parameter of inputs and θ determines the elasticity substitution between robotic and human labor. The elasticity of substitution is defined as $\varepsilon = 1/(1-\theta)$. For simulating this technology, we assume that the parameter σ takes a value of 0.90 while ε takes values between 1 and 5 . Similarly, the parameter μ takes a value of 0.65 while α, the new adoption rate, takes values from 0 to 0.45 , as in the previous simulation. Using this new production function, we repeat the analysis carried out previously to check how sensitive are results to an alternative specification of the technology.

Figure 3.10 plots the relationship between fiscal revenues and the automation rate. It can be observed that the results from the production function specification are almost equal to the ones obtained from the baseline model. That is, the two production functions predict the same relationship between automation and the size of the government; a drop in fiscal revenues as a percentage of output, except for the revenues from the capital income tax. The main difference is found regarding the traditional capital income tax revenues which remain constant with this alternative specification.

Again, the repetition of experiment 2 leads to similar results (Figure 3.11). As a consequence of automation, consumption and payroll tax rates should be increased to keep fixed fiscal revenues from these taxes, whereas the capital income tax would be reduced. Comparing Figure 3.11 with Figure 3.3, we find that required changes in tax rates are slightly less sensitive to automation.

Finally, we repeat experiment 3 using this alternative production function specification. The estimated capital income tax required to keep constant the size of the government as a function of the automation rate is presented in Figure 3.12. We find a similar relationship between the automation rate and the tax rate to the one found in the previous analysis. Estimated values for the tax rate are slightly

FIGURE 3.10: Fiscal revenues as a function of the autonomous capital adoption rate. Alternative production function specification.

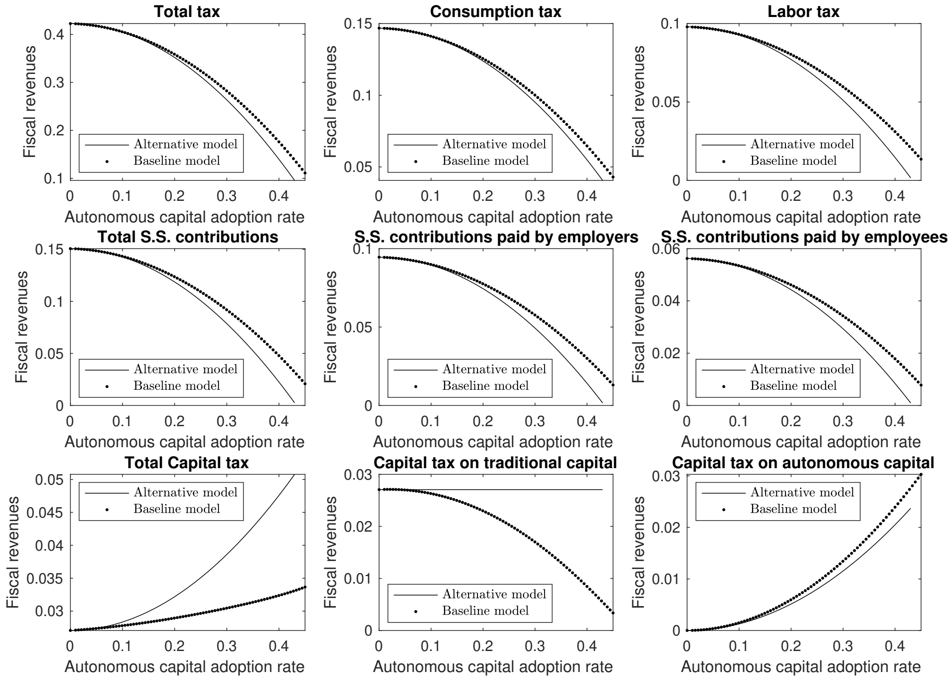
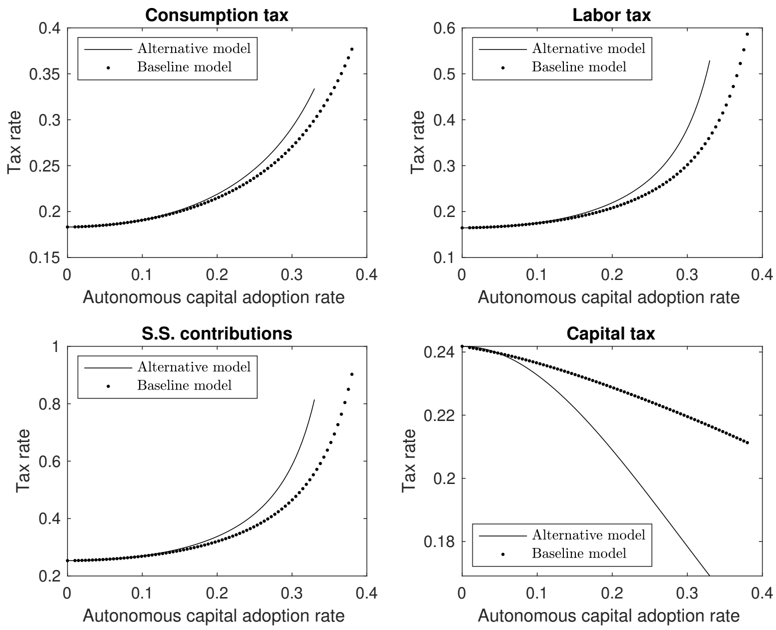
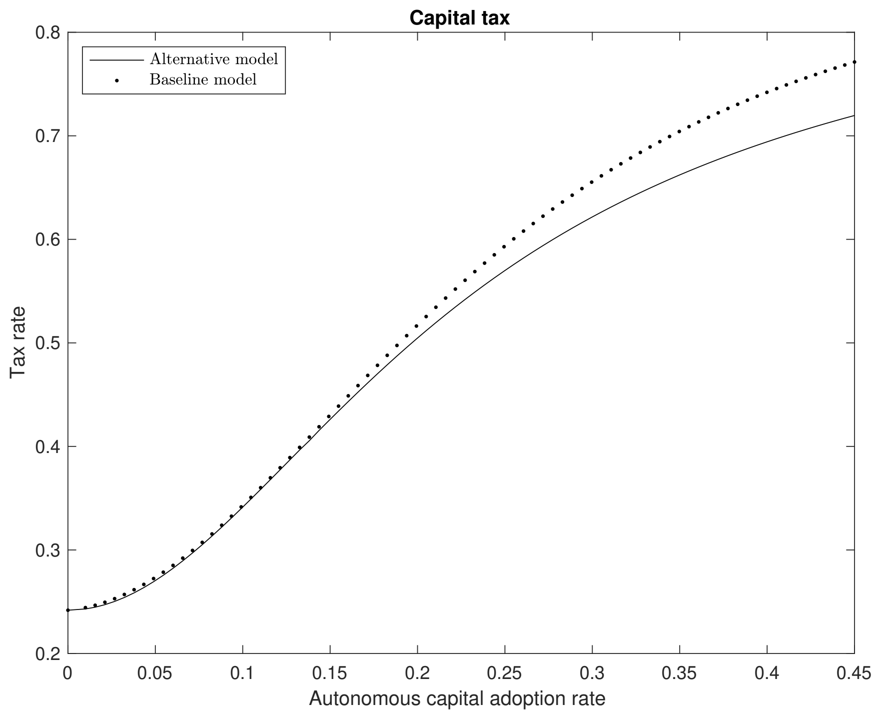


FIGURE 3.11: Tax rates to keep constant fiscal revenues as a function of the autonomous capital adoption rate. Alternative production function specification.



lower than the estimated using the model presented in the chapter but of similar magnitude. For an automation rate of 0.45%, the required capital income tax rate would be around 0.72, compared to a tax rate of 0.77 in the baseline model. Therefore, we conclude that the results of the simulation are robust to the particular specification of the production function.

FIGURE 3.12: Capital income tax rate to keep constant fiscal revenues as a function of the autonomous capital adoption rate. Alternative production function specification.



3.7 Concluding remarks

Recent advances in robotization and AI open a new era for humankind by introducing a disruptive technology with dramatic consequences on the economy. This chapter focuses on the implications of automation for the size of the government, measured as the tax revenues to output ratio. We find that automation significantly affects public finance given its impact on the combination of inputs used for production activities. Automation will have positive effects on the economy but transform production into a more capital-intensive technology. Given that current tax systems are based heavily on taxing labor income, the substitution of labor by the new autonomous capital will have a dramatic impact on fiscal revenues.

Under the current tax mix scenario, automation will expand final output, with a positive impact on all macroeconomic variables, except labor. We find three important results. First, the steady-state ratio of consumption to output decreases with automation. This is because automation implies a higher autonomous capital deepening with a higher depreciation rate compared to traditional capital assets, resulting in a higher steady-state investment ratio. Therefore, more resources are needed to be devoted to replacing depreciated autonomous capital which reduces the ratio of consumption to output. Second, total fiscal revenues increase with automation given the expansion of the economy. Nonetheless, the relative contribution of the different sources of fiscal income changes. The proportion of fiscal revenues from capital increases, whereas the proportion of fiscal revenues from labor income and consumption declines. However, the size of the government, measured as the steady-state ratio of fiscal revenues to output (assumed to be equal to the ratio of government spending to output), declines with automation.

To explore the consequences of automation on the size of the government we proceed as follows. First, we analyze the evolution of fiscal revenues as a fraction of output from each tax as a function of automation, keeping the current tax mix constant. The automation process affects the composition of fiscal revenues, changing the contribution shares of taxes. In particular, the labor tax and the social security contributions progressively diminish their contribution shares in favor of taxing capital. The most important result is that the size of the government decreases with automation. Thus, automation will be an important source of deterioration of public finance stopping the observed trend in the last century of a steady increase in the size of governments in advanced economies.

Given the previous results, we proceed to study how tax rates should be changed to keep constant fiscal revenues. We conduct this experiment tax by tax. We find that all tax rates should be significantly increased, except the capital income tax. However, estimated tax rates turn out to be extremely high, increasing distortions on the economy. Moreover, this new tax policy would eliminate the positive impact of automation on the economy, even accelerating the decline in labor as distortions on the optimal behavior of households would also increase. In sum, the rise in tax rates to compensate for the effects of automation on the fiscal revenues-to-output ratio is not a practical option, and a redesign of the tax system is compulsory.

In light of the aforementioned results, we conduct a third experiment which consists in estimating the capital income tax rate that keeps fixed total fiscal revenues. If capital is the most important input producing income, the tax policy should accommodate automation by increasing capital income taxes. We find that the capital income tax rate would reach a value close to 80% for an automation rate of 45%. This fiscal policy would have less distortionary effects on the economy mitigating the negative effects of automation on labor, although would cancel out the positive effect of automation on final output.

A sensitivity analysis reveals that previous results are robust to different values of the elasticity of substitution between technologies, and to alternative specifications of the production technology.

In summary, two main results are derived from this chapter. First, automation without deep fiscal reform will stop the observed increasing trend in the government size in the economy. Second, automation will put at risk social security sustainability in pay-as-you-go systems. These results contribute new evidence to the debate among scholars about the necessity to carry out profound tax policy reforms to accommodate the impact of automation.

Chapter 4

Social security contributions and autonomous capital taxation

4.1 Introduction

Pay-as-you-go social security systems face a number of challenges. Social security system is viable if the volume of active population increases at a higher rate than the number of pensioners does and if, in addition, active population is employed by the productive system (Kitao, 2014). Nowadays, both prerequisites for social security sustainability are jeopardized. On the one hand, demographic shifts turns the scenario to a volume of active population increasing at a lower rate than the number of pensioners. On the other hand, technological innovations driven by automation biased jeopardizes the fact that the active population is employed by the productive system.

The potential impact of new technologies such as Artificial Inteligence (AI) and robotics is in the frontline of economic debate. The discussion about the implications of new technological change has spread worldwide. Some studies have warned of the new autonomous technology potential to reduce the workforce and cause distortions in labor markets. In addition, this disruptive technological change comes at a time of demographic changes towards an ageing population[1] that threatens the survival of the pay-as-you-go pension system so that governments are extending statutory retirement ages (European Commission, 2021).

In this line, the literature has highlighted that the social security is not sustainable as it is, transmitting the necessity to restore the balance, either by reducing benefits or by raising taxes (Kitao, 2014).[2] Moreover, it has been argued that the actual demographic and technological shifts interact, with aging leading to greater automation levels and to a more intensive use and development of robots (Acemoglu and Restrepo, 2022), indicating that lower population growth and population ageing increase automation and are detrimental to economic growth in the medium run, predicting a fall in output per capita growth, an increase in automation, and a fall in the labour income share and in interest rates (Basso and Jimeno, 2021).

Just as it has been stressed that demographic change drives automation, it has also been highlighted that the current tax system favors the substitution of labor for capital. Then, although the preference for robots over human workers may arise out uniquely of the general preference for capital over labor, workers not only have to compete with rising efficiencies of robots, but also with tax policies incentivizing automation, since most tax systems are designed to tax labor rather than capital encouraging automation by providing employers with preferential tax treatment for robot workers, and in addition, capital taxes have been declining as a share of the tax base (Abbott and Bogenschneider, 2018; Huettinger and Boyd, 2020). The underlying reason for the bias towards labor of tax systems is the consideration

[1] Kitao (2014), following Bell and Miller (2005), highlights that life expectancy has grown dramatically during last decades to 77 years in 2000 and it is projected to reach 85 years by the end of the century, while the dependency ratio is projected to rise rapidly reaching 38% in 2050 and 45% in 2100.

[2] For instance, Blanco-Enmienda and Ruiz-García (2017) analyze the social security sustainability of the Spanish economy to conclude the need for structural reforms of the system so as to make it more sustainable in the long term.

of labor taxes as the more efficient form of taxation, while considering that capital is more mobile than workers involving many jurisdictions and resulting in a sharp downward trend of the capital tax rates.

This idea of capital-enhancing tax systems has been extensively supported by the literature. For instance, it has been remarked that investments in capital are generally taxed more favorably than labor income (Soled and Thomas, 2018), with the tax law currently undertaxing capital income and overtaxing labor income, encouraging the non-optimal use of robots by granting tax preferences to capital income, which creates undesirable economic inefficiencies and deadweight losses (Mazur, 2019), thereby causing the US tax code to aggressively subsidize the use of equipment and taxes the employment of labor leading to potentially excessive automation induced by tax distortions beyond what is socially desirable (Acemoglu and Restrepo, 2019; Acemoglu et al., 2020), by distorting firms' demand for labor versus capital in the form of labor-saving technology to the degree that law effectively taxes the employment of human labor (Estlund, 2018).

The aforementioned interaction points between tax systems, demographic shifts and technological changes have pushed scholars to consider that a full reconsideration of the fiscal and transfer systems may be required once the economic implications of robotics and AI are clearer (Jimeno, 2019), highlighting that the new wave of technological changes may bring a decline in labour shares, at a time in which conventional social policies, which mostly channelled taxes from the young to the old, will require more resources. This necessity for a full reconsideration of the fiscal and transfer systems has reserved an special spot for the idea of the robot tax, defined as any tax measure that specifically increases the tax burden in direct connection with the ownership, use or supply of a robotic system and/or intelligent system (Popovič and Sábo, 2022), or simply as essentially a tax on the capital employed by the business that utilizes the robot (Mazur, 2019).

This chapter explores the most efficient alternative to tax autonomous capital in order to sustain the social security contributions to output ratio. Specifically, we consider three alternative schemes -taxing robot income, taxing robot investment, and taxing robots as humans- finding that taxing robots as humans is the alternative causing less disruptions in the economy. In addition, we analyze the implications of autonomous capital taxation for the functional distribution of income.

To the best of our knowledge, this is the first rigorous contribution considering the autonomous capital taxation as a cantilever for social security in a general equilibrium analysis framework. Previously, literature has considered, separately and briefly, alternative policies for social security sustainability and alternative implementations of autonomous capital taxation. For instance, regarding social security, Kitao (2014) propose four options to make the social security self-financed and sustainable in light of the demographic aging: increase payroll taxes by 6 percentage points, reduce replacement rates by one-third, raise the normal retirement age to 73, or means-test the benefits and reduce them in income. Moreover, while other papers have considered the robot tax as a tool to narrow down wage inequality (Zhang, 2019; Guerreiro et al., 2022) or increase welfare (Gasteiger and Prettner, 2022; Thuemmel, 2022), the optimal way to tax robots in order to sustain social security funds in an scenario of an increasingly aging population with increasing labor market automation remained unexplored.

The rest of the chapter is organized as follows. Section 2 presents a review of the related literature. Section 3 details the model. Section 4 collects the calibration. Section 5 depicts the results, and section 6 summarizes the main conclusions.

4.2 Related literature

This chapter is related to the robot tax literature and, by extension, with all the literature about the autonomous capital technological change. This literature presents a multilevel analysis of the impact of the new generation automation technologies in the workforce. From a macroeconomic perspective, Acemoglu and Restrepo (2020a) conclude in an empirical analysis that one more robot per thousand workers reduces the employment-to-population ratio by 0.2% and wages by 0.42%. At occupation level, Frey and Osborne (2017) brought controversial to the debate by affirming that 47% of american jobs were at high automation risk.[3] At the task level, Manyika et al. (2017) have analyzed the tasks composition of 820 occupations to conclude that, while 60% of all occupations have at least 30% technically automatable activities, less than 5% of occupations consist of activities that are 100% automatable.

As noticeable, researchers in the literature related to the fourth industrial revolution are divided between those who argue that the current industrial revolution is nothing different from previous ones and those who think that this technological revolution is disruptively different from all previous ones. Specifically, between the occupations approach and the tasks approach, there is a relevant difference between assuming that entire occupations (composed of several tasks) are replaceable or only certain tasks can be substituted.

Dengler and Matthes (2018), comparing these two assumptions, find that approximately 47% of German employees experience an automation risk if one assumes that entire occupations are replaceable, while only 15% of German jobs are at risk when assuming that only certain tasks can be substituted. This last estimation downsizing the share of jobs at high computerization risk provided by Frey and Osborne (2017) is closer to the one offered by Arntz et al. (2016 2017) arguing that only 9% of OECD jobs suffer from high automation risk. Abeliansky et al. (2020), offering a range of values for the displacement of employment, estimate that industrial robots will replace 37.9 million workers in 2030 in a high-displacement scenario and 12.2 million workers in a low-displacement scenario, with manufacturing workers being the most vulnerable.

Gomes and Pereira (2020) highlight that the current wave of innovation has implications that escape conventional economic thinking, remarking that the evaluation and prediction of what the new phenomena brings is fundamental to design policies that prevent income inequality to widen and growth to slow down. By building an analytical framework in which they consider three groups of workers -manual, routine and creative- with different substitutability degree with autonomous technologies and an unemployment insurance paid by workers, these authors conclude that there is a winning group in robotization process, the robot owners, and two losing groups: those who eventually become unemployed due to technological progress and those who have to pay taxes to compensate jobless workers.

Why is this technological revolution different and should the bundle of new technologies be fiscally treated differently? A representative fact of the potential impact on society of the new autonomous technologies is that art may no longer be an exclusively human thing. In fact, there is already autonomous technology capable of writing novels, and movie scripts. This potential to perform creative tasks and not just routine tasks with low training requirements makes experts estimate that in about 120 years this technology will surpass humans in all tasks (Grace et al., 2018).

Although some recent contributions point to the labor-friendly side of AI, we must bear in mind that we are considering a practically new born technology. Then, it results logical that at the AI current development state, AI-related job vacancies are rapidly growing (Acemoglu et al., 2022), the demand for AI skills is increasing (Alekseeva et al., 2021) and AI patents have a positive and significant impact in employment (Damioli et al., 2022; Yang, 2022). However, these recent evidences presenting AI as a labor-enhancing transformative technology is compatible with a prediction of labor substitution by AI once this technology fully spreads through the economy reaching its maturity state.

As a concrete example, we can consider the case of "poetry generation" (Linardaki, 2022). While currently AI can be an useful tool to inspire and support students who engage in the poetry writing process (Kangasharju et al., 2022), AI also shows the potential ability to autonomously elaborate poems that can not be distinguished to the ones written by humans (Kobis and Mossink, 2021). Then, we can conclude that AI can be an useful opportunity of complementary capital for writers in the short-run, while being an underlying threat of substitute capital for these same writers in the long term.

Although a lot of ink has been spilled on the possibility of implementing a robot tax, scientifically rigorous works that analyze this issue using mathematical modeling along with precise theoretical analysis for the possible taxation of new technologies and the formation of a new tax code are scarce in the

[3]The approach based on task- and occupation-specific measures of technological impacts has providen measures for Machine Learning suitability (Brynjolfsson et al. 2018), AI advances (Felten et al. 2018), AI progress (Felten et al. 2019), AI impacts (Webb 2020), AI exposure (Felten et al. 2021), and Language Modelers exposure (Felten et al. 2023).

literature. Intimately related with our work, we can consider recent contributions proposing alternative analysis for autonomous capital taxation.

Specifically, Zhang (2019) embeds the use of robots within the specific-factor framework in order to study how automation affects the skilled-unskilled wage gap and discern the need to tax robots in this regard, concluding that a tax on robots unambiguously narrow down the wage gap. Thuemmel (2022) defends that it is optimal to distort robot adoption by arguing that the robot tax (or subsidy) exploits general-equilibrium effects to compress wages, which reduces income-tax distortions of labor supply, thereby raising welfare. Gasteiger and Prettner (2022) analyze the effect of automation in the long-run growth by using the overlapping generations framework, arguing that a robot tax has the potential to raise per capita output and welfare at the steady state. Guerreiro et al. (2022) argue that it is optimal to tax robots in order to reduce income inequality while the current generations of routine workers are active in the workforce. Prettner and Strulik (2020) present a model considering a robot tax as an ad-valorem tax on machine input in production, predicting that growth, education, R&D, welfare, and even net income of high-skilled workers, decline with the robot tax rate.

Amid the speculation, other authors have rejected the idea of a tax on robots, highlighting potential negative effects of it or the difficulty to implement it. Mazur (2019) argues that the robot tax could bring unintended consequences, such as limiting innovation, and advocates rebalancing tax systems so that capital income and labor income are taxed in parity. In this line, Fleming (2019) argues that the discussion should focus on the socioeconomic and organizational dynamics that integrate and guide computational intelligence instead of focusing on the idea of a "robot tax" when proposing solutions that can improve industrial democracy and employee well-being.

As alternative fiscal policies close to the idea of the robot tax, the appearance of the generation of autonomous technologies of the fourth industrial revolution has given momentum to the consideration of an Universal Basic Income in the advanced countries (Hoynes and Rothstein, 2019), along with a revival of the consideration of the negative income tax (Friedman, 1962) and the debate on optimal income taxes (Mirrlees, 1971). Nevertheless, other scholar have suggested that it may be difficult to fight inequality by a universal basic income if growth becomes very much dependent on robot-technology, since the policy would reduce growth substantially (Nomaler and Verspagen, 2020).

4.3 The model

This section presents the model specifying two separated technological frameworks, the households' maximization problem and the government's budget. As technological frameworks, we consider the most widely extended approach in the literature arguing that new autonomous capital exclusively replaces human labor and the approach exposed in Casas and Torres (2023) arguing that new autonomous capital replaces both human labor and traditional capital.

As sources of government financing, the model includes traditional taxes from the current tax menu and three alternatives for autonomous capital taxation. These three alternatives are: an autonomous capital income tax, a VAT over investment in autonomous capital, and a social security tax paid by the employers of autonomous capital. Korinek (2020) remarks that economists' framework for designing tax systems will require some fundamental rethinking in the Age of AI, arguing that there are strong economic efficiency reasons to stop taxing human labor, even before labor is fully redundant. According to Abbott and Bogenschneider (2018), as a matter of taxation, automated workers represent a type of capital investment, and capital income is currently taxed at much lower rates than labor income. Tax incentives to purchase capital assets are likely to result in an overinvestment in automation (Mazur, 2019) in a sense that some scholars advocate for an active and dynamic robot tax in order to dampen the (bursty) rate of unemployment that the automation process may generate (Vermeulen *et al.*, 2020). [4]

[4]See Hemel (2020) for a discussion of the arguments for and against robot taxes.

In order to implement the robot tax, different approaches have been proposed in the literature. For instance, Vishnevsky and Chekina (2018) highlight three main approaches to solving emerging problems of taxation: extended tax coverage of new cyber-physical technologies and products of their use; replacement of digital transactions and shortfalls in revenues by objects of taxation in the form of tangible assets and people; the construction of a new tax space with smart taxes based on realtime principles, smart contracts and Big Data. Oberson (2019) propose three measures: granting a legal personality to robots in order to give them an electronic ability to pay for tax purposes; imputing income to robots in order to charge levied on this "salary"; and the application of VAT on robots' activities. Abbott and Bogenschneider (2018) suggest five options for tax reform: disallow corporate income tax deductions for investments in automation; impose a federal "automation tax"; allow accelerated deductions for future wage expenses; extend the federal self-employment tax to corporations; and increase the corporate tax rate.

4.3.1 Technologies

This section proposes 2 alternative technologies to collect the inclusion of autonomous capital in the economy.

Technology A

As the first technology proposition, we consider the most widely used specification to analyze the impact of new technologies (AI and robots) on the economy. This specification consists of assuming that robots only replace workers while complementing traditional capital units. This is the technology assumed by, for example, Eden and Gaggl (2018), Berg *et al.* (2018), and Lin and Weise (2019). Then, the production function would be as follows:

$$Y_t = \left[\theta X_t^{\frac{\rho-1}{\rho}} + (1-\theta)\, K_t^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}} \tag{4.1}$$

where Y_t is the final output, θ is a distribution parameter, K_t is the tradition capital, and ρ measures the elasticity of substitution between traditional capital and labor -human or robotic. X_t represents collects labor tasks performed by autonomous capital and/or human labor:

$$X_t = \left[\phi D_t^{\frac{v-1}{v}} + (1-\phi)\, L_t^{\frac{v-1}{v}}\right]^{\frac{v}{v-1}} \tag{4.2}$$

where D_t is the autonomous capital, L_t is labor, ϕ is a distribution parameter of inputs and v measures the elasticity of substitution between autonomous capital and human labor. [5]

Firms maximize profits in a competitive environment taken factor prices as given, solving the following static maximization problem at each period:

$$\max \Pi_t = Y_t - (1+\tau_t^{sse}) W_t L_t - R_{k,t} K_t - (1+\tau_t^{ssz}) R_{d,t} D_t \tag{4.3}$$

Where τ_t^{sse} and τ^{ssz} are social security contributions paid by the employer and robots respectively.

From the first order conditions of the firm's profit maximization problem, we obtain the following marginal productivity of each of the three productive factors:

$$(1+\tau_t^{ssz}) R_{d,t} = \phi\theta Y_t^{\frac{1}{\rho}} X_t^{\frac{\rho-1}{\rho} - \frac{v-1}{v}} D_t^{-\frac{1}{v}} \tag{4.4}$$

[5] Note that if the parameter ϕ reach a value of 1 we would say that the autonomous capital can replace humans in all tasks. However if this parameter only reaches a certain percentage of tasks matching the currently automatable tasks it would be an equivalent approach to model robots as substitutes of only routine tasks separated from creative non-automatable tasks (see, for instance, Berg et al., 2018).

$$(1+\tau_t^{sse})W_t = (1-\phi)\,\theta Y_t^{\frac{1}{\rho}} X_t^{\frac{\rho-1}{\rho}-\frac{v-1}{v}} L_t^{-\frac{1}{v}} \tag{4.5}$$

$$R_{k,t} = (1-\theta)\,Y_t^{\frac{1}{\rho}} K_t^{-\frac{1}{\rho}} \tag{4.6}$$

where the Euler Theorem holds, profits are zero and output is distributed among the three productive factors, given the assumptions of a competitive market and constant returns to scale. From the above first order conditions, we find out that the functional distribution of gross income for the three factors resulting under this technological specification is:

$$S_{l,t} = \frac{W_t L_t}{Y_t} = \frac{(1-\phi)\,\theta Y_t^{\frac{1-\rho}{\rho}} X_t^{\frac{\rho-1}{\rho}-\frac{v-1}{v}} L_t^{\frac{v-1}{v}}}{1+\tau_t^{sse}} \tag{4.7}$$

$$S_{k,t} = \frac{R_{k,t} K_t}{Y_t} = (1-\theta)\,Y_t^{\frac{1-\rho}{\rho}} K_t^{\frac{\rho-1}{\rho}} \tag{4.8}$$

$$S_{d,t} = \frac{R_{d,t} D_t}{Y_t} = \frac{\phi\theta Y_t^{\frac{1-\rho}{\rho}} X_t^{\frac{\rho-1}{\rho}-\frac{v-1}{v}} D_t^{\frac{v-1}{v}}}{1+\tau_t^{ssz}} \tag{4.9}$$

Technology B

The aggregate production technology is a CES function for traditional technology using capital and labor nested into another CES function. In this function, new and traditional technology are substitutes. We define the following aggregate production function to represent these technological combinations:

$$Y_t = \left[\mu D_t^{\frac{\sigma-1}{\sigma}} + (1-\mu)\,X_t^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{4.10}$$

where Y_t is the final output, X_t represents traditional technology, μ is a distribution parameter for the traditional productive factors versus the new technology, D_t is the autonomous capital, and σ measures the elasticity of substitution between traditional and autonomous technologies.

The traditional technology is represented by another CES function:

$$X_t = \left[\alpha K_t^{\frac{\varepsilon-1}{\varepsilon}} + (1-\alpha)\,L_t^{\frac{\varepsilon-1}{\varepsilon}}\right]^{\frac{\varepsilon}{\varepsilon-1}} \tag{4.11}$$

where K_t is the traditional capital, L_t is labor, α is a distribution parameter of inputs and ε measures the elasticity of substitution between traditional capital and labor. Empirical evidence suggests that $\varepsilon < 1$ (Chirinko, 2008; Eden and Gaggl, 2018), and that $\sigma > 1$ (DeCanio, 2016; Acemoglu and Restrepo, 2020a; Lin and Weise, 2019). Therefore, it is assumed that $0 < \varepsilon < 1 < \sigma < \infty$. This implies higher complementarity between traditional capital and labor than between traditional technology and the autonomous capital. That is, autonomous capital is a substitute for both traditional capital and labor.[6]

Again, firms maximize profits in a competitive environment taken factor prices as given, solving the following static maximization problem at each period:

$$\max \Pi_t = Y_t - (1+\tau_t^{sse})W_t L_t - R_{k,t}K_t - (1+\tau_t^{ssz})R_{d,t}D_t \tag{4.12}$$

From the first order conditions of the firm's profit maximization problem, we obtain the following marginal productivity of each of the three productive factors:

$$R_{k,t} = \alpha\,(1-\mu)Y_t^{\frac{1}{\sigma}} X_t^{\frac{\sigma-1}{\sigma}-\frac{\varepsilon-1}{\varepsilon}} K_t^{-\frac{1}{\varepsilon}} \tag{4.13}$$

[6]For more information about the characteristics of the production function, see Casas and Torres (2023)

$$(1+\tau_t^{sse})W_t = (1-\alpha)\,(1-\mu)\,Y_t^{\frac{1}{\sigma}}X_t^{\frac{\sigma-1}{\sigma}-\frac{\varepsilon-1}{\varepsilon}}L_t^{-\frac{1}{\varepsilon}} \tag{4.14}$$

$$(1+\tau_t^{ssz})R_{d,t} = \mu Y_t^{\frac{1}{\sigma}}D_t^{-\frac{1}{\sigma}} \tag{4.15}$$

where the Euler Theorem holds, profits are zero and output is distributed among the three productive factors, given the assumptions of a competitive market and constant returns to scale. From the above first order conditions, we find out that the functional distribution of gross income for the three factors resulting under this technological specification is:

$$S_{l,t} = \frac{W_tL_t}{Y_t} = \frac{(1-\alpha)\,(1-\mu)\,Y_t^{\frac{1-\sigma}{\sigma}}X_t^{\frac{\sigma-1}{\sigma}-\frac{\varepsilon-1}{\varepsilon}}L_t^{\frac{\varepsilon-1}{\varepsilon}}}{1+\tau_t^{sse}} \tag{4.16}$$

$$S_{k,t} = \frac{R_{k,t}K_t}{Y_t} = \alpha\,(1-\mu)Y_t^{\frac{1-\sigma}{\sigma}}X_t^{\frac{\sigma-1}{\sigma}-\frac{\varepsilon-1}{\varepsilon}}K_t^{\frac{\varepsilon-1}{\varepsilon}} \tag{4.17}$$

$$S_{d,t} = \frac{R_{d,t}D_t}{Y_t} = \frac{\mu Y_t^{\frac{1-\sigma}{\sigma}}D_t^{\frac{\sigma-1}{\sigma}}}{1+\tau_t^{ssz}} \tag{4.18}$$

4.3.2 Households

The model assumes that the utility function of the representative household is as follows:

$$U(C_t, L_t) = \gamma log(C_t) + (1-\gamma)log(1-L_t) \tag{4.19}$$

where C_t is total consumption and γ is a parameter reflecting the willingness to sacrifice units of consumption in favor of leisure time. Total available time has been normalized to one, so leisure is defined as $1-L_t$, where $0 \leq L_t < 1$. The representative household satisfies the following budget constraint:

$$\begin{gathered}(1+\tau_t^c)C_t + I_{k,t} + (1+\tau_t^{Id})I_{d,t} = \\ (1-\tau_t^l-\tau_t^{ssw})W_tL_t + (1-\tau_t^k)R_{k,t}K_t + (1-\tau_t^k-\tau_t^d)R_{d,t}D_t + \tau_t^k\delta_kK_t + (\tau_t^k+\tau_t^d)\delta_dD_t + T_t\end{gathered} \tag{4.20}$$

where I_k is investment in traditional capital, I_d is investment in autonomous capital, τ^{Id} is a VAT over autonomous capital investment,[7] τ^k is the general tax on capital income and τ^d is the tax on autonomous capital income.[8] As we distinguish between traditional and autonomous capital investments, we have two capital accumulation processes presented in the following way:

$$D_{t+1} = (1-\delta_d)D_t + I_{d,t} \tag{4.21}$$

$$K_{t+1} = (1-\delta_k)K_t + I_{k,t} \tag{4.22}$$

where $0 < \delta_d < 1$ is the depreciation rate of AI and robotics, and $0 < \delta_k < 1$ is the traditional capital depreciation rate. For the sake of simplicity, we assume a linear accumulation capitals. We assume $\delta_d > \delta_k$, therefore, in equilibrium, the marginal productivity of autonomous capital must be higher than the one corresponding to traditional capital.

The maximization problem faced by the infinity-lived representative household with perfect-foresight is given by,

$$\max_{\{C_t,L_t\}} \sum_{t=0}^{\infty} \beta^t \left[\gamma lnC_t + (1-\gamma)\,ln(1-L_t)\right] \tag{4.23}$$

[7] Korinek (2020) states that we should refrain from taxing the robot as a physical vessel but should tax the design of the robot and the programs that are running on it because those are information goods that generate rents.

[8] We specify the tax on autonomous capital income symmetrically respect to the traditional capital tax, so the owners are able to deduct the cost. This is an important aspect since accelerated depreciation for capital investments allows firms to deduct the cost of their robots faster than they could deduct the wage of the payroll of the workers they replace (Porter, 2019).

subject to restrictions (4.20), (4.21) and (4.22), where K_0 and D_0 are given, and where β is the intertemporal discount factor.

Equilibrium conditions, representing Euler equations, from the household's maximization problem are,

$$(1+\tau_t^c)C_t = \frac{\gamma}{1-\gamma}(1-L_t)W_t(1-\tau_t^l-\tau_t^{ssw}) \tag{4.24}$$

$$1 = \beta\frac{(1+\tau_t^c)C_t}{(1+\tau_{t+1}^c)C_{t+1}}\Big((1-\tau_{t+1}^k)(R_{k,t+1}-\delta_k)+1\Big) \tag{4.25}$$

$$1 = \beta\frac{(1+\tau_t^c)C_t}{(1+\tau_{t+1}^c)C_{t+1}}\frac{((1-\tau_{t+1}^k-\tau_{t+1}^d)(R_{d,t+1}-\delta_d)+1+\tau_{t+1}^{Id}(1-\delta_d))}{1+\tau_t^{Id}} \tag{4.26}$$

making reference to optimal labor supply, investment decision on traditional capital and investment decision on autonomous capital, respectively. Optimal trajectories for the variables in the long-run are fully characterize by these three equilibrium conditions together with initial conditions, and the following transversality conditions for each type of capital:

$$\lim_{t\to\infty}\beta^t\lambda_t K_{t+1} = 0 \tag{4.27}$$

$$\lim_{t\to\infty}\beta^t\lambda_t D_{t+1} = 0 \tag{4.28}$$

where λ is the Lagrange's multiplier, shadow price of consumption.

In the model without taxes, considered in Casas and Torres (2023), there is a direct relationship between depreciation rates and returns of both traditional and autonomous capital, as net marginal productivities are equal: $R_d-\delta_d = R_k-\delta_k = \frac{1}{\beta}-1$. If we consider a common capital tax for both traditional and autonomous capital, this connection between net capitals marginal productivities remains. However, the introduction of specific taxation to autonomous techonology breaks the equality between the net marginal productivities of traditional and autonomous capital. In that case, the net marginal productivity of autonomous capital in steady state would be affected by both the VAT on autonomous capital investment and the robot income tax:

$$R_d-\delta_d = \frac{\frac{1}{\beta}-1+\tau^{I_d}(\frac{1}{\beta}-1+\delta_d)}{1-\tau_k-\tau_d} \tag{4.29}$$

As a consequence, we can derive expressions reflecting how the VAT on autonomous capital investment and the robot income tax affect the relation between the net marginal productivities of both capitals, starting from the following identities:

$$\frac{1}{\beta}-1 = (1-\tau^k-\tau^d)(R_d-\delta_d)-\tau^{I_d}(\frac{1}{\beta}-1+\delta_d) = (R_k-\delta_k)(1-\tau^k) \tag{4.30}$$

Thus, when we have $\tau^d = 0$, the VAT on autonomous capital investment affects the relation between net marginal productivities as follows:

$$R_k-\delta_k = R_d-\delta_d-\frac{\tau^{I_d}}{1-\tau^k}(\frac{1}{\beta}-1+\delta_d) \tag{4.31}$$

Aternatively, when we have $\tau^{I_d} = 0$, the robot income tax affect the relation between the net marginal productivities as follows:

$$R_k-\delta_k = (1-\frac{\tau^d}{1-\tau^k})(R_d-\delta_d) \tag{4.32}$$

4.3.3 Government

Government collects taxes from traditional sources (consumption tax, labor tax, capital tax and social security contributions paid by the employers and the employees) and for an specific autonomous capital tax (either the VAT on autonomous capital investment, the robot income tax or the robot's social security tax). In this chapter we do not explore scenarios in which the government taxes autonomous capital in different simultaneous ways, so only one autonomous capital taxation is considered in each simulation. Either $\tau^d > 0; \tau^{I_d} = 0; \tau^{ssz} = 0$, or $\tau^d = 0; \tau^{I_d} > 0; \tau^{ssz} = 0$, or $\tau^d = 0; \tau^{I_d} = 0; \tau^{ssz} > 0$.

$$T_t = \tau_t^c C_t + (\tau_t^l + \tau_t^{ssw} + \tau_t^{sse}) W_t L_t + \tau_t^k (R_{k,t} - \delta_k) K_t + (\tau_t^k + \tau_t^d + \tau_t^{ssz}) R_{d,t} D_t - (\tau_t^k + \tau_t^d) \delta_d D_t + \tau_t^{Id} I_{d,t} \tag{4.33}$$

4.4 Calibration

This section collects the calibration of the model according to an artificial economy following an annual basis, summarized in Table 4.1. The calibration is organized in differentiated parts. First, we calibrate some parameter according to standard well-known values in literature. Second, we calibrate the technological specific parameters of our two technological frameworks so both can be compared with each other sustaining their values in the automation literature. Finally, we calibrate tax rates using OECD data.

As parameters whose values have been consistently argued by previous literature, we set the discount factor, β, equal to 0.975, the consumption-leisure preference parameter, γ, at 0.4, and the traditional capital depreciation rate, δ_k, at 0.06. Within the first technological specification, we set the traditional capital share, θ, as 0.35. For the second technological specification, in order to make the two technological specifications comparable, we set the capital share in traditional technology, α also to 0.35. The elasticity of substitution between traditional capital and labor in *Technology B*, ε, is set as 0.90, lower than one, consistently with Chirinko (2008), Eden and Gaggl (2018) and Lin and Weise (2019). Again, in order to make comparable both technological specification, the elasticity of substitution between traditional capital and effective labor, ρ, is also equal to 0.90.

Automation literature has explored the autonomous capital depreciation rate as an important parameter influencing the economic implications of automation. Graetz and Michaels (2018) consider a robots depreciation rate of ten per cent. Abeliansky and Prettner (2017), following Graetz and Michaels (2018), also assume a robotic depreciation rate of 10%. This depreciation rate would be higher than the one established by the International Federation of Robotics (2016), which sets a lifetime horizon of 12 years for robots. Lin and Weise (2019), along with Krusell *et al.* (2000), set out a quarterly depreciation of robots at 0.0515. In our case, autonomous capital is assumed to represent the most advanced technology in the economy, and, therefore, we determine $\delta_d = 0.20$, according to the depreciation rate traditionally assumed for R&D capital. This percentage is reflected in the EU KLEMS data and has been documented by numerous authors (see, for example, Hall, 2005).

The autonomous capital adoption rate in both technological specifications, ϕ and μ, are explored in the range of values between 0 and 0.45 considering only feasible scenarios, following the results from Manyika *et al.* (2017) stating that the percentage of tasks that can be automated using current technology is higher than 45% for industrialized countries. This "percentage of tasks that can be automated using current technology" would be the empirical counterpart to our definition of autonomous capital adoption rate.

The elasticity of substitution between human labor and autonomous technology has been considered in several studies, although there is a lack of estimations in literature. Lin and Weise (2019) states an elasticity of substitution of 5. Artuc, Bastos and Rijkers (2018) set it at 10. Acemoglu and Restrepo

(2020a) assume an infinite elasticity of substitution between humans and robots. DeCanio (2016) concludes that this elasticity of substitution is for sure above 2.1. In order to consider an elasticity of substitution between traditional and autonomous productive factors prudent enough to allow us to make comparisons between both technological specifications, we set $v = \sigma = 2$, although we calculate optimal autonomous capital tax rates in ranges for v and σ between 1 and 3 in order to show that these elasticities of substitutions do not alter these results.

Tax rates are calibrated according to the OECD average (OECD, 2018; OECD, 2019): $\tau^c = 0.1832$, $\tau^l = 0.1646$,$\tau^{sse} = 0.1589$,$\tau^{ssw} = 0.0945$ and $\tau^k = 0.2418$. The alternative autonomous capital taxation shapes ($\tau^d, \tau^{I_d} and \tau^{ssz}$) are left free exploring optimal values sustaining the social security contributions to output ratio.

TABLE 4.1: Calibrated parameters

	Parameter	Definition	Value
Preferences	β	Discount factor	0.975
	γ	Consumption-leisure preference parameter	0.40
Technologies	δ_k	Traditional capital depreciation rate	0.06
	δ_d	autonomous capital depreciation rate	0.20
Technology A	θ	Traditional capital share	0.35
	ρ	Traditional capital - effective labor elasticity	0.90
	v	Autonomous capital - labor elasticity	2
	ϕ	Autonomous capital adoption rate	[0-0.45]
Technology B	α	Capital share in the traditional technology	0.35
	ε	Traditional capital-labor elasticity	0.90
	σ	Traditional-autonomous technologies elasticity	2
	μ	Autonomous capital adoption rate	[0-0.45]
Traditional taxes	τ^c	Consumption tax rate	0.1832
	τ^l	Labor income tax rate	0.1646
	τ^{sse}	Employer's social security tax rate	0.1589
	τ^{ssw}	Employee's social security tax rate	0.0945
	τ^k	Capital income tax rate	0.2418
Robot taxes	τ^d	Robot income tax	Free
	τ^{Id}	VAT on autonomous capital investment	Free
	τ^{ssz}	Robot's social security tax rate	Free

Given the calibrated model, we solve a system of 10 equations (5 common to each technology and 5 technology-specific) for ten unknown quantities, $(Y, C, K, D, L, X, W, I, R_k, R_d)$, where I denotes total investment as the sum of investments in traditional and autonomous capital: $I = I_k + I_d$.[9] The model satisfies the Blanchard-Khan rank condition (Blanchard and Khan, 1980), indicating that the steady state is unique, transversality conditions holds and that all trajectories are optimal in the long-run.

4.5 Results

This section presents the main results of this research in five phases. First, we show how the social security contributions to output ratio plums under both technological specifications as automation advances. Second, we calculate the autonomous capital tax rates (for the robot income tax, the VAT on autonomous

[9]Steady State expressions considering the two technological propositions can be found in the appendix.

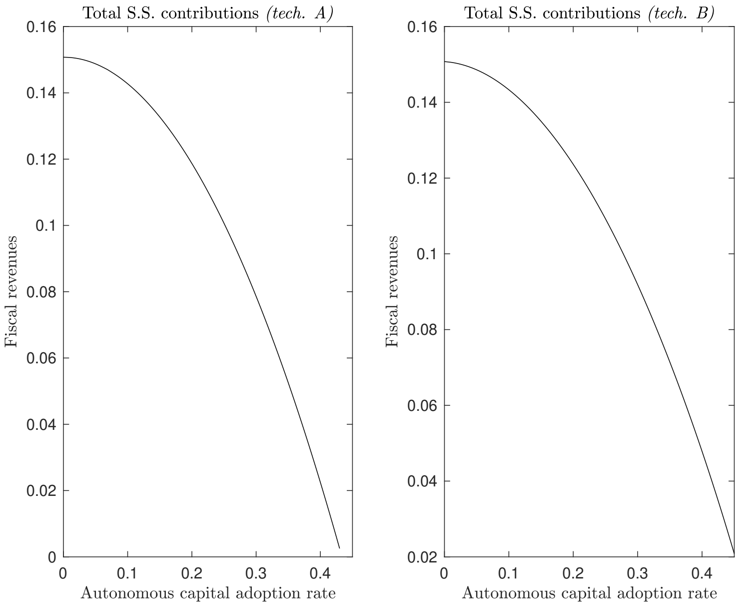


FIGURE 4.1: Steady state values for the ratios of social security contributions to output as a function of automation.

capital investment and the robot's social security) that sustain the social security contributions to output ratio as automation advances under the two technological frameworks. Third, we comment on how the labor and capital shares of social security contributions evolve as automation advances. Fourth, we analyze how the three differentiated fiscal alternative policies taxing autonomous capital affects the evolution of the economy as the autonomous technology adoption rate increase. Finally, we show how the different schemes of autonomous capital taxation affect the functional distribution of income compared to a no autonomous capital taxation scenario.

4.5.1 Automation and social security sustainability

According to the literature, automation significantly reduces the government's tax revenue since most tax revenue comes from labor-related taxes, so worker automation could result in hundreds of billions or even trillions of dollars in tax revenue lost per year at various levels of government (Abbott and Bogenschneider, 2018; Soled and Thomas, 2018; Mazur, 2019; Porter, 2019). In this line, Ahmed (2018) claims the necessity to rethink all assumptions of taxation, arguing that if AI is not correctly taxed, the traditional tax base of workers may shrink to the point that less total taxes are collected, in a sense that governments must carefully develop standards for taxing AI.

This significant automation-induced reduction in the government size is documented in Casas and Torres (2022). As we observe in Figure 1, since social security contributions uniquely rely on human labor, the total social security contributions to output ratio plums as autonomous capital increases its presence in production. This fact matches with the idea that actual tax systems, relying on human effort through income or payroll taxes, are vulnerable to dislocation with the rise of AI and robotics (Kovacev, 2020).

As argued in the literature, new and old forms of progressive taxation should be implemented in the globalized and digitalized world, paying particular attention to understanding both the dynamics of the tax base and the ways in which different types of income have to be taxed (Dosi and Virgillito, 2019). This necessity of rethinking tax systems is also transmitted by Costinot and Werning (2022), who

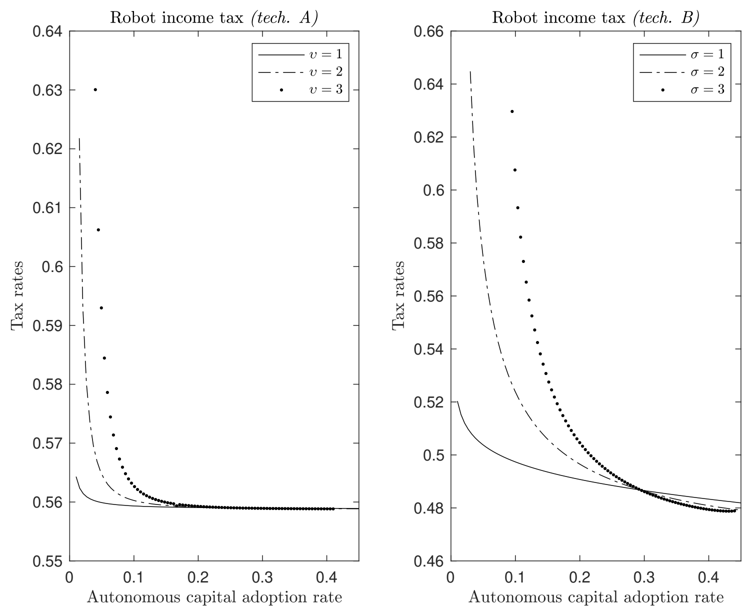


FIGURE 4.2: Robot income tax that sustains the social security contributions to GDP ratio as a function of the autonomous capital adoption rate and the autonomous technology substitutability degree.

explore how government policy should respond to technological change in second best environments —where income taxation is available, but taxes on specific factors are not—, finding that more robots may go hand in hand with more inequality and lower taxes, despite robots being responsible for the rise in inequality, and governments having extreme preferences for redistribution.

4.5.2 The optimal autonomous capital taxation to sustain social security

Figures 2, 3 and 4 plot, respectively, the robot income tax, the VAT on autonomous capital investment and the robots' social security tax that sustain the ratio of social security contributions to output as automation advances. The left-graphs in these figures collects estimations using the first technological specification while the right-graphs collects estimations using the second technological specification. As we observe, the values for these rates tend to be very high to the left of the graphs while they converge to a certain rate for all the elasticities of substitution between traditional and autonomous inputs of production.

We are specifically interested in these rates of convergence for each substitutability degree, since these are the values that we are going to use in the following section to analyze the potential effects that these three alternative fiscal policies of autonomous capital taxation may have in the economy.

Scheme 1: Taxing robot income, τ^d

Figure 2 calculates the robot income tax that sustains the social security contributions to output ratio as automation advances, finding that this tax rate converges to a value of 0.56 under the first technological specification while converging to a slightly lower tax rate around 0.48 under the second technological specification.

As we observe, both technological specifications converge to the same value for every elasticity of substitution considered. The intuition behind these results is that automation makes labor time to

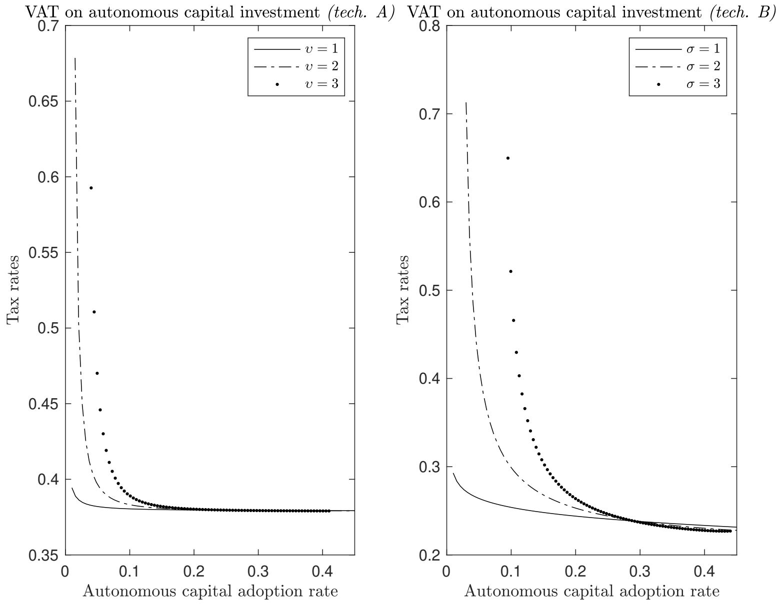


FIGURE 4.3: VAT on autonomous capital investment that sustains the social security contributions to GDP ratio as a function of the autonomous capital adoption rate and the autonomous technology substitutability degree.

decrease and wages to increase. As higher the autonomous capital substitutability is, the decrease (increase) in labor time (wages) is higher, compensating each other and leading to a convergence in the optimal tax rate to sustain social security contributions to output ratio constant. This intuition also highlights that the decline in this ratio is triggered by the exponential increase in output generated by the introduction of the autonomous technology while social security funds collection does not increase at the same rate.

At the first stages of autonomous capital adoption, since the stock of autonomous capital is very reduced and it has to assume the taxation required to compensate the fall in the social security contributions to GDP ratio, the tax rate calculated is high. Finally, every elasticity of substitution converge to the same tax rate for the rest of the autonomous capital adoption process.

This convergence process for different elasticities of substitution is much lower if we assume that autonomous technology does not replace only human labor but also traditional capital. Taken these results to reality, we can conclude that, although in the first stages of automation process there might be not possible to establish a tax policy attaining autonomous capital and social security contributions because of the reduced dimension of this autonomous capital stock, the model show convergence for the optimal tax rates in order to implement the appropriate tax policy once autonomous capital share surpasses a certain threshold around 10 to 20 percent depending on its traditional capital replacement ratio independently of the substitutability degree between new and old technologies. If robots only replace labor, the threshold value would be close to 10% and if robots also replaces traditional capital significantly it would be close to 20%.

Scheme 2: Taxing robot investment, τ^{id}

Figure 3 plots the calculations for the VAT on autonomous capital investment that sustains the social security contributions to GDP ratio as automation advances, finding that this tax rate converges to values of 0.38 under the first technological specification and 0.23 under the second technological specification.

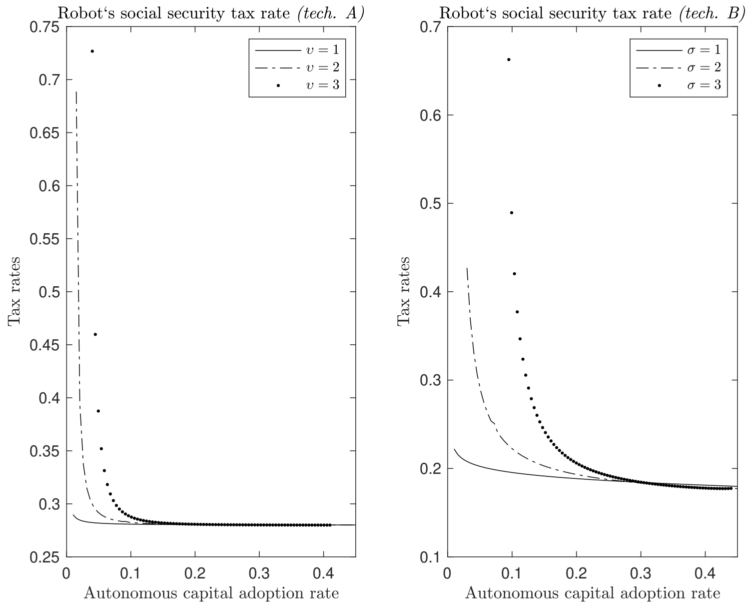


FIGURE 4.4: Robot's social security tax that sustains the social security contributions to GDP ratio as a function of the autonomous capital adoption rate and the autonomous technology substitutability degree.

Scheme 3: Taxing robots as humans, τ^{ssz}

Figure 4 plots the robots' social security tax that sustains the ratio of social security contributions to GDP as the automation of the economy increases. We observe that this tax converges to a value of 0.28 in the case of *Technology A* while it converges to a value of 0.18 for the case of *Technology B*.

As we notice, the calculated tax rates are higher under the first technological specification for the three alternative of autonomous capital taxation and lower for the second technological specification considering the replacement of traditional capital units. The reason behind these differences in the optimal tax rates sustaining social security contributions to output ratio is the fact that the more widely extended technological assumption reflecting the automation process leave aside the fact that autonomous technology also replaces traditional capital. Thus, we can offer a range for the optimal tax rates in which the lower bound is given by the value calculated under *Technology B* and the upper bound is given by the value calculated under *Technology A*.

4.5.3 Labor-Capital shares in social security contributions

Once we have calculated the optimal tax rates for every alternative of autonomous capital taxation, we can calculate how the shares of contributions to social security for both labor and autonomous capital would evolve under each scheme as automation advances. These shares for the three alternative schemes under the two technological specifications can be found in Figure 5. As we observe, capital share in contributions to social security funds increases progressively as automation advances so both labor and capital sustain at a 50% share the social security at a certain autonomous capital adoption rate below 40%.

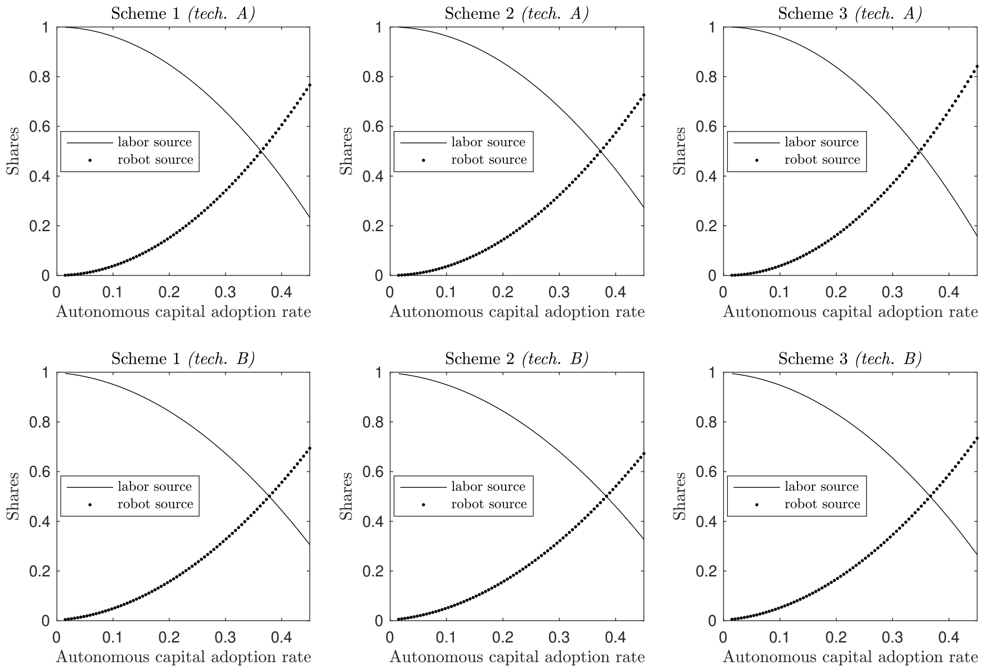


FIGURE 4.5: Share of social security contributions paid by labor and autonomous capital sources as a function of automation.

4.5.4 The economic implications of autonomous capital taxation

Once we have calculated the optimal values for the different alternatives of autonomous capital taxation, we explore the consequences that these alternative fiscal policies may have in the economy as the automation process advances.

Figure 6 and Figure 7 shows the effects of automation in the economy under different fiscal policies regarding autonomous capital taxation according to the technological specifications A and B respectively. As we observe, for both technological specifications the robots' social security tax is the fiscal policy that least affects the benefits of automation in the economy. In the figures we observe 4 alternative scenarios as automation advances: an scenario without specific taxation on autonomous capital and the three alternatives of capital taxation targeted by this study.

Dosi and Virgillito (2019) consider that a robot tax is likely to slow down the adoption of labour displacing technologies although it is still not clear whether it should be on the ownership or the use of robots. As we observe in Figure 5, this effect is observed under the first technological specification only once the autonomous capital adoption rate has surpassed loosely the 30%, while it is not clearly observed in Figure 6 under the second technological specification where labor time is reduced practically at the same rate independently of the autonomous capital taxation scheme implemented.

The reduction of average working time triggered by automation has been extensively documented in the literature. [10] We must bear in mind that our model collects labor time from an aggregated perspective, so we can not specify if the labor time decrease redound in an unemployment increase or just in a reduction of the working day. Regarding this fact, Pi and Fan (2021) analyze the impact of robots on

[10]See, for instance, Bongers and Molinari (2020).

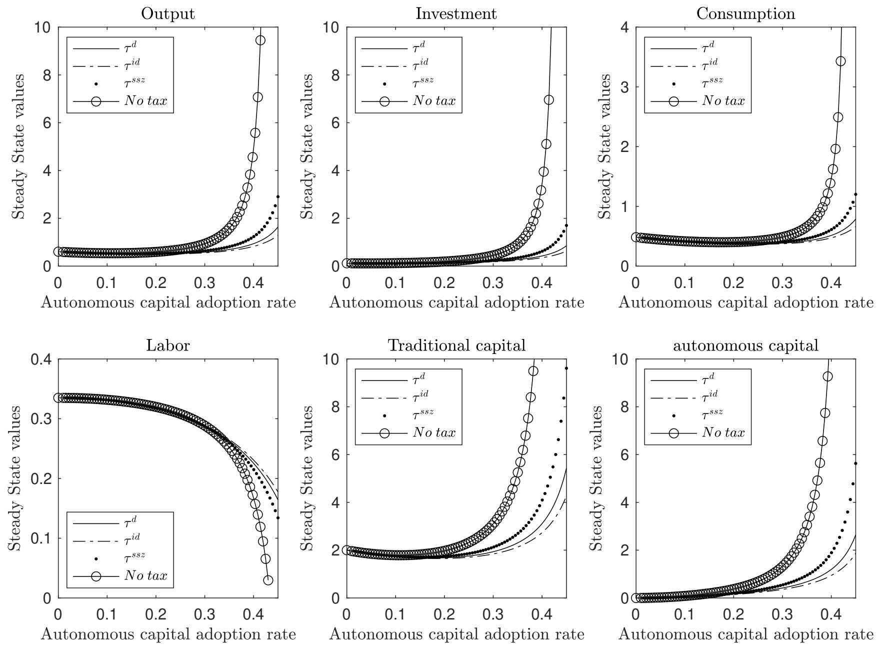


FIGURE 4.6: Steady state values of key macroeconomic variables as a function of automation under different fiscal policies specifically taxing autonomous capital *(Technology A)*.

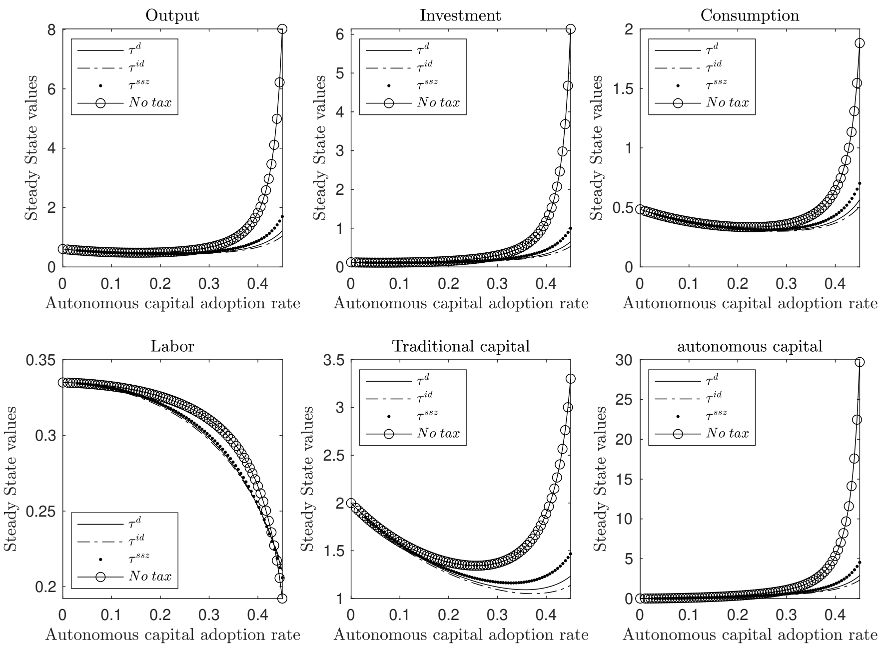


FIGURE 4.7: Steady state values of key macroeconomic variables as a function of automation under different fiscal policies specifically taxing autonomous capital *(Technology B)*.

equilibrium unemployment of unionized workers by building a dynamic game, finding that the effect of robot utilization on equilibrium unemployment is determined by the characteristic of returns to scale in the robot manufacturing sector and that the impact on economy-wide equilibrium unemployment is also determined by the proportion of unskilled labor in the whole economy. On their behalf, Cabrales et al. (2020) deny that a tax on robots do decrease workers' effort although it reduces the probability of worker substitution in an experiment where workers make productive effort decisions and managers can choose between workers and robots to do these tasks.

As we observe, the social security tax rate on robots paid by the employer is the tax policy causing less damage to the economy under both technological specifications. As increasing the share of social security contributions paid by employers has a positive effect on economic activity and welfare (Torres, 2022), we can argue that the reason for the robot's social security tax rate to be the more efficient way to tax the autonomous capital is that this taxation does not directly appear in the households maximization problem.

4.5.5 The functional distribution of income and autonomous capital taxation

One of the main concerns related to the autonomous capital technological change is the effect that new autonomous technologies are triggering in the functional distribution of income. Indeed, literature has suggested automation as one of the factors originating the global decline of labor shares (Graetz and Michaels, 2018; Charalampidis, 2020). For instance, it has been argued that the labor share decline is triggered by technological change (Farmer and Lafond, 2016), the decrease in the relative price of investment goods that induce firms to replace labor inputs for capital inputs (Karabarbounis and Neiman, 2014a), and the decline in routine occupations (Eden and Gaggl, 2018).

According to Prettner (2019), automation explains a 14% of the labor share decline over the las decades in the US. Dao et al. (2017) defend that half of the overall labor share decline in advanced economies is due to technological progress and varying exposure to routine occupations. On their behalf, Aum, Lee and Shin (2018) argue that computerization triggered 4 out of 5 percentage points of labor share decline between 1980 and 2010.

Due to the importance of considering the capital depreciation rate in the analysis of the functional distribution of income (Karabarbounis and Neiman, 2014b; Bridgman, 2018), this section presents both gross and net incomes for both technological specifications. Concretely, Figure 8 and Figure 9 present gross income under *Technology A* and *Technology B*, respectively, while Figure 10 and Figure 11 collect net income under *Technology A* and *Technology B*, respectively.

The gross labor share, as observed in figures 8 and 9, evolves similarly regarding the different fiscal schemes under both technological specifications. We observe that, in gross terms, the three alternative autonomous capital taxation schemes reduce the labor share decline as automation advances, Specifically, the VAT on autonomous capital investment is the scheme that most supports the labor share, followed by the autonomous capital income tax, and finally by the robots' social security tax. These results can be related to Acemoglu et al. (2020), who estimate that moving to optimal taxation of capital and labor would raise employment by 4.02 percent and the labor share by 0.78 percentage point and restore the optimal level of automation. However, results are very different regarding net income, where we take capital depreciation into account.

As we notice in Figure 8, since *Technology A* assumes that autonomous capital only replaces labor, the gross traditional capital share remains constant as automation advances so the gross capital share increase is uniquely driven by the gross autonomous capital share increase. In Figure 9, we observe that gross traditional capital share decrease since autonomous technology also replaces traditional capital under *Technology B*, so autonomous capital is compensating this fall in traditional capital share and explaining the gross capital share increase. Under both technological specifications, the autonomous capital share in total capital is increasing as automation advances. This fact of the share of equipment and machines in capital rising with development, was already highlighted by Zeira (1998), remarking that the ratio of machines and equipment capital to output increased from 0.28 in 1950 to 0.43 in 1995.

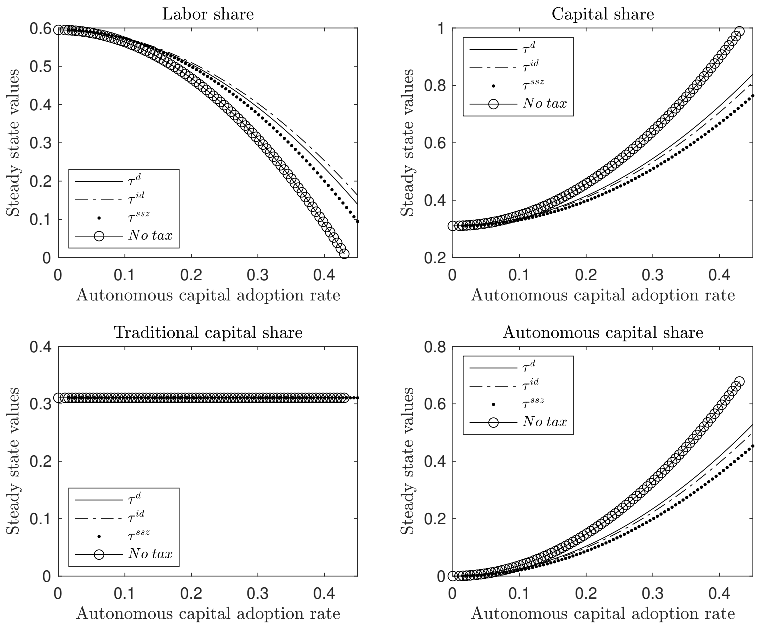


FIGURE 4.8: The functional distribution of income as a function of automation under different fiscal policies specifically taxing autonomous capital *(Technology A)*. Gross income.

As observed in figures 10 and 11 collecting net income, we find different results for both technological specifications. Under *Technology A*, we observe that the three alternative autonomous capital taxation schemes converge to the same value for the labor share when the autonomous capital adoption rate reaches the 45%, indicating that all alternative schemes turn out in a higher net labor share in the long run. However, under *Technology B* the unique alternative scheme for autonomous capital taxation that turns out in a higher net labor share in the long run is the robots' social security tax, while the other two alternative schemes converge to the long-run value without specific autonomous capital taxation.

Overall, we can conclude that a fiscal policy specifically taxing autonomous capital in order to sustain the social security funds in an increasing automation scenario do not rely on significant lower levels of inequality between labor and capital shares. Indeed, autonomous technology should be taxed at a much higher rate in order to have a significant impact in the labor share as automation advances, therein undermining progress to a greater extent and causing greater disruptive effects on the economy. These results provide food for thought to the negative picture draw by several authors for future labor share and inequality. This vision arguing that capital returns grow more than economic growth itself (Piketty, 2014) has led several scholar to claim for the necessity of radical government involvement.

4.6 Conclusions

Automation will put at risk social security sustainability in pay-as-you-go systems (Casas and Torres, 2022), a fortiori with the juncture of demographic shifts towards an increasingly aged population (Acemoglu and Restrepo, 2022; Jimeno, 2019; Basso and Jimeno, 2021). Indeed, new autonomous technologies are arising the necessity of rethinking tax systems worldwide (Ahmed, 2018; Korinek, 2020), since

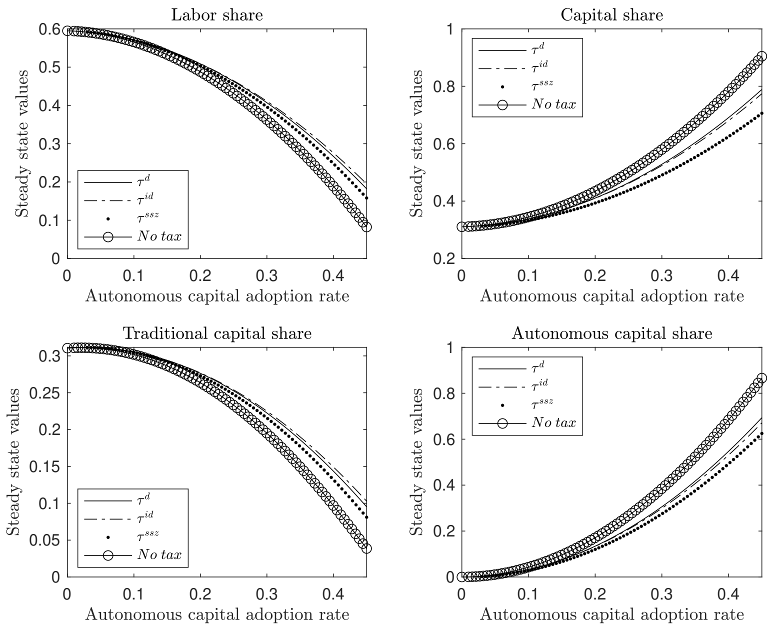


FIGURE 4.9: The functional distribution of income as a function of automation under different fiscal policies specifically taxing autonomous capital *(Technology B)*. Gross income.

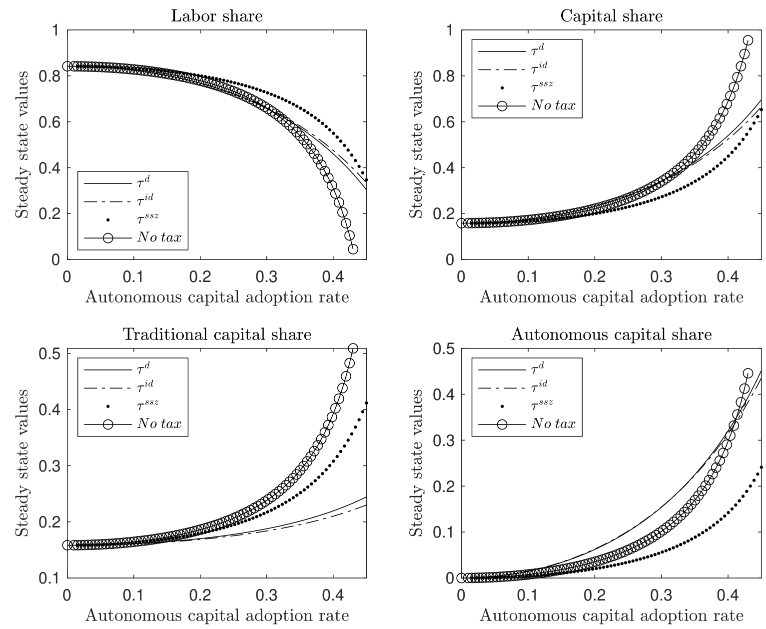


FIGURE 4.10: The functional distribution of income as a function of automation under different fiscal policies specifically taxing autonomous capital *(Technology A)*. Net income.

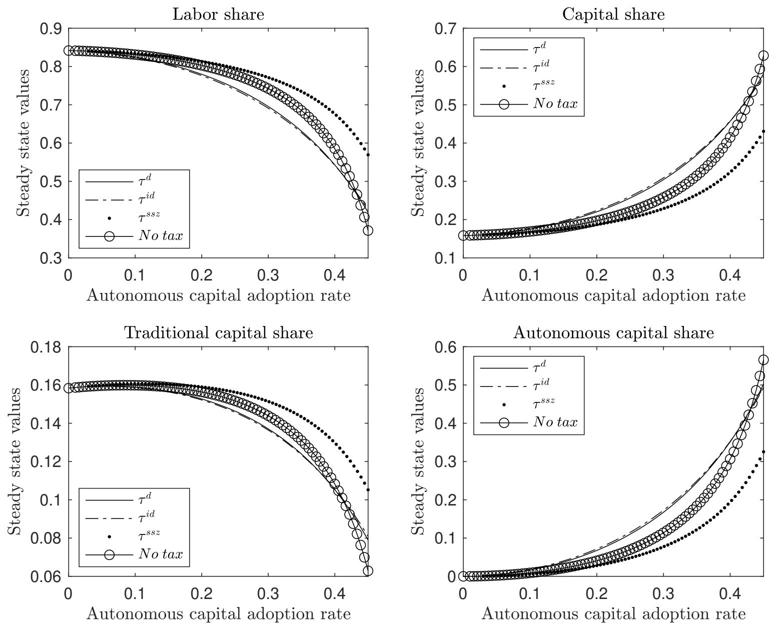


FIGURE 4.11: The functional distribution of income as a function of automation under different fiscal policies specifically taxing autonomous capital *(Technology B)*. Net income.

these labor-biased tax systems (Abbott and Bogenschneider, 2018; Huettinger and Boyd, 2020; Soled and Thomas, 2018) are incentivicing socially undesired automation levels (Acemoglu et al., 2020) while jeopardizing public resources (Kovacev, 2020). These three fundamental elements in current macroeconomic scene -technological change, demographic shift and labor-biased tax systems- interact in a spiral that encourages automation, increasing the need for public resources while restricting them.

This chapter analyze alternative schemes of autonomous capital taxation in order to maintain social security size as automation advances. Specifically, we examine the policies of an autonomous capital income tax, a VAT on the investment in autonomous capital and a social security tax paid by the employers of autonomous technology. Thus, the optimal tax rates at which new autonomous technology should be taxed in order to maintain social security size under each fiscal scheme are calculated under both technological specifications. These tax rates are found to be higher at the three alternative schemes when assuming that autonomous technology only replaces labor while not affecting the traditional capital stock. In addition, the optimal tax rates are found to be independent of the substitutability degree between autonomous and traditional technology. For all the alternative tax schemes for autonomous capital, the policy implies that social security funds are financed at 50% for labor and capital once the rate of adoption of new autonomous technologies passes a threshold of around 35%, from that point on, capital would finance social security to a greater extent than labor.

The effect that the different alternative schemes of specific taxes on autonomous capital would have similar effects on the economy although of different magnitude, with the alternative of treating the new autonomous capital as human labor through the application of social security contribution rates paid by the employer of these technologies being the least distorting alternative. This effect on the economy of taxes on autonomous capital is the expected, limiting the expansion of production generated by the introduction of new technologies, as well as consumption and investment. Consequently, the capital stock grows at a lower rate as the rate of adoption of new technologies increases. However, there is only a visible impact slowing down the decline of labor time in the economy under the technology specification that assumes only replacement of labor by autonomous capital leaving aside the question of replacement of traditional capital units.

When analyzing the implications of autonomous capital taxation for the functional distribution of income, it turns out essential to consider capital depreciation rates, obtaining very different results in gross and net terms. In general, none of the alternative schemes has a significant effect on decreasing the drop in labor share. In gross terms, the VAT to autonomous capital investment is the alternative scheme that sustains the most the labor share while social security contributions paid by autonomous technology employers would be the scheme with the least impact. In net terms we observe the opposite, with this scheme of social security contributions paid by employers of autonomous technology being the policy that shows the most labor share friendly effects.

In summary, this chapter concludes that implementing a social security contribution rate paid by the employers of self-employed capital is the best fiscal scheme alternative when considering the social security sustainability supported by autonomous capital. Specifically, this alternative turns out to be the one causing the least distortions to the economy and having the most favorable implications in mitigating the labor share fall in net terms. These results contribute new evidence to the need to rethink the financing of social security in times of increasing automation. Nevertheless, we should bear in mind that the possible implementation of robot taxes will finally depend on political interests relying on citizens perceptions of such taxes. Regarding this fact, Nam (2019) analyzes citizens attitudes towards four alternative policies preventing job replacement by robotic automation (guaranteed income, robot quotas, extra pay for human interaction, and a national program for displaced workers), relatively less progressive than robot taxes, finding that attitudes differ considerably based on ideology and partisanship.

Appendix: Steady State Expressions

From the households maximization problem

$$R_d = \frac{\frac{(1+\tau^{Id})}{\beta} - 1 - \tau^{Id}(1-\delta_d) + (1-\tau^k-\tau^d)\delta_d}{1-\tau^k-\tau^d}$$

$$R_k = \frac{\frac{1}{\beta} - 1 + (1-\tau^k)\delta_k}{1-\tau^k}$$

$$I = \delta_d D + \delta_k K$$

$$W = \frac{1-\gamma}{\gamma}\frac{(1+\tau^c)C}{(1-L)(1-\tau^l-\tau^{ssw})}$$

$$C = Y - I$$

Under Technology A

$$Y = \left[\theta X^{\frac{\rho-1}{\rho}} + (1-\theta)\, K^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}$$

$$X = \left[\phi D^{\frac{v-1}{v}} + (1-\phi)\, L^{\frac{v-1}{v}}\right]^{\frac{v}{v-1}}$$

$$D = \left[\frac{\phi\theta Y^{\frac{1}{\rho}} X^{\frac{\rho-1}{\rho}-\frac{v-1}{v}}}{(1+\tau^{ssz})R_d}\right]^{v}$$

$$L = \left[\frac{(1-\phi)\,\theta Y^{\frac{1}{\rho}} X^{\frac{\rho-1}{\rho}-\frac{v-1}{v}}}{(1+\tau^{sse})W}\right]^{v}$$

$$K = \left[\frac{(1-\theta)\, Y^{\frac{1}{\rho}}}{R_k} \right]^{\rho}$$

Under Technology B

$$Y = \left[\mu D^{\frac{\sigma-1}{\sigma}} + (1-\mu)\, X^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

$$X = \left[\alpha K^{\frac{\varepsilon-1}{\varepsilon}} + (1-\alpha)\, L^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}}$$

$$K = \left[\frac{\alpha\,(1-\mu) Y^{\frac{1}{\sigma}} X^{\frac{\sigma-1}{\sigma} - \frac{\varepsilon-1}{\varepsilon}}}{R_k} \right]^{\varepsilon}$$

$$L = \left[\frac{(1-\alpha)\,(1-\mu)\, Y^{\frac{1}{\sigma}} X^{\frac{\sigma-1}{\sigma} - \frac{\varepsilon-1}{\varepsilon}}}{(1+\tau^{sse}) W} \right]^{\varepsilon}$$

$$D = \left[\frac{\mu Y^{\frac{1}{\sigma}}}{(1+\tau^{ssz}) R_d} \right]^{\sigma}$$

Part III

A microeconomic perspective

Chapter 5

Revisiting the future of occupations

5.1 Introduction

Digitalization is changing the lives of all economic agents to some extent and in a certain way, transforming the labor market in profound ways, reshaping the nature of work and affecting the future of various occupations. As technology continues to evolve, it is essential to examine the potential impacts of digitalization on employment in order to make informed decisions about workforce development, policy planning, and economic growth.

This chapter contributes to the literature by presenting seven novel mappings of the US employment landscape in relation to the digitalization process. Our approach combines both backward-looking and forward-looking measures, capturing the current state of digitalization and the potential future effects on occupations. By exploring the complex interplay between automation, AI, and the future of occupations, this chapter adds to the growing body of literature on the impact of digitalization on the labor market (Acemoglu & Restrepo, 2018; Autor, 2015; Dauth et al., 2017). In doing so, it seeks to inform the development of policies and strategies that can foster economic growth, social inclusion, and labor market resilience in the face of rapid technological change.

In order to develop our analysis, we revisit Fossen's and Sorgner's (2019) classification by elaborating new typological classifications based on the incorporation of new occupation-level measures on both the destructive and the transformative digitalization sides. Specifically, we consider both a backward-looking and a forward-looking measure for each digitalization side. This consideration allows the elaboration of a concrete typological classification on each digitalization side and occupational terrains from different time-perspectives: backward-looking, forward-looking or complete vision terrains.

We begin by constructing typological mappings for each digitalization side: the automation terrains and the intelligence terrains. The automation terrains classify occupations into four groups based on their current automation degree and future computerization probability, reflecting the destructive side of digitalization (Bessen, 2019). On the other hand, the intelligence terrains divide occupations into four groups according to the AI advances and AI exposure, representing the transformative side of digitalization (Brynjolfsson & McAfee, 2014). Next, we develop two occupational terrains classifications that consider the interactions between the destructive and transformative effects of digitalization from both a backward-looking and a forwardlooking perspective. The backward-looking occupational terrains capture the current state of digitalization with respect to automation degree and AI advances, while the forwardlooking occupational terrains focus on expectations about how digitalization will affect occupations in terms of computerization probability and AI exposure. Finally, we propose three extended occupational terrains that integrate different time perspectives for each digitalization side, offering a more nuanced understanding of the labor market dynamics in the context of digitalization considering both time perspectives (backward-looking and forward-looking) and both digitalization sides (destructive and transformative).

5.2 Literature review

This section presents a literature review targeting the economic impacts of autonomous technologies that started being developed with the computer revolution and have been evolving until the appearance of AI and the spread of digitalization. We may consider that the computer revolution began with the Charles Babbage's idea of the Analytical Engine conceived in 1834 with the article written in 1843 by Augusta Ada Byron, Lady Lovelace, which included descriptive, analytical, contextual, and metaphysical information about the Analytical Engine and also the first 'program' (Toole, 1996). If in every technological change in history we have found winners and losers in the short term (interpreting that society as a whole has always benefited from technological improvements in the long term), in the greatest technological change in history this affectation is even more prominent: from workers who was displaced from their jobs to workers who experienced promotions and/or wage increase due to their skills; and from entrepreneurs who saw their business break up due to new market threats to entrepreneurs who saw their business growth due to new market opportunities. [1]

All these dualities respond to the clearly dual nature of digitalization. That is why, while some workers observe their value plummet in the labor market as they are affected by destructive digitalization, other professionals contemplate their value skyrocket in the labor markets due to the growing demand for their skills, driven by the transformative side of digitalization. [2] This dual fact also explains why some studies, using the same robot data (IFR, 2018), can claim at the same time employment rate and wages reduction (Acemoglu and Restrepo, 2020a) and labor productivity growth (Graetz and Michaels, 2018), highlighting the fact that the process of robotization is industry- and country-sensitive (Gentilli et al., 2020). This duality also matches the answer that Autor (2015) gave to his question: there are still so many jobs because not everything in this technological change is about job destruction, there is also space for transformation - generation and displacement of jobs (automation raises the demand for labor in nonautomated tasks).

5.2.1 Destructive digitalization

When talking about destructive digitalization, it results unavoidable to refer to the famous work of Frey and Osborne (2017) that already created controversy from the publication of the working paper in the year 2013 claiming that 47% of US jobs where at high computerization risk. This Luddite vision have caused that technology entrepreneurs (Elon Musk, Bill Gates, etc) raised their voices in favor of an Universal Basic Income (UBI), although it seems that there is no association between the automation risk and UBI support among citizens (Dermont and Weisstanner, 2020).

Numerous contemporary studies drew conclusions in that direction. For instance, Sorgner (2017) investigated the relationship between the risk of automation of jobs and individuallevel occupational mobility to find that workers in occupations at high automation risk are more likely to experience occupational changes such as losing a job, demotion at the current place of employment, or starting a job in a new field. Other authors have argued that the effects of this destructive digitalization go beyond the professional sphere, generating a situation of stress that can affect the health of workers. For instance, Cheng et al (2021) find that computerization probability may significantly predict workers' health after adjustment for demographic characteristics and psychosocial work conditions, with workers in jobs with a high computerization probability being more likely to have low job control, higher job insecurity, and work-related injury and disease prevalence.

From a theoretical perspective, Acemoglu and Restrepo (2018c) argue that modeling automation as the process of machines replacing tasks previously performed by labor is both descriptively realistic and

[1]See Raj and Seamans (2019) for a review about the economic and organizational consequences of AI, robotics and related technologies.

[2]Digitalization may also deeply transform researchers work: Furman and Teodoris (2020) examine how the introduction of a technology that automates research tasks influences the rate and type of researchers' knowledge production, to find that it increases the production of ideas and induces researchers to pursue ideas more diverse than and distant from their original trajectories.

leads to distinct and empirically plausible predictions, dissuading its modeling as factor-augmenting technological change. However, this alarming speech has been downplayed by other researchers. For instance, by Arntz et al. (2016, 2017), who argue that the actual percentage of jobs at risk of automation in the OECD was 9%. Furthermore, other authors have tinted this alarmist vision by arguing that only certain tasks in an occupation, rather than entire occupations, can be substituted. For instance, Dengler and Matthes (2018) expose that, although assuming that entire occupations are replaceable approximately 47% of German employees experience an automation risk, only 15% of German employees are at risk when assuming that only certain tasks can be substituted.

Following the tasks' approach, Acemoglu and Restrepo (2018d) analyze the automation process in a framework in which tasks previously performed by labor can be automated and new versions of existing tasks, finding two possible scenarios: (i) if the long-run rental rate of capital relative to the wage is sufficiently low, the long-run equilibrium involves automation of all tasks; (ii) otherwise, there exists a stable balanced growth path in which the two types of innovations go hand-in-hand. In other study, these authors propose a task-based model to study the effect of new technologies on labor demand, denying the possibility of all tasks automation, to conclude that, if the origin of productivity growth in the future continues to be automation, the task content of production will decline, highlighting the importance of new tasks generation and other technologies raising the labor intensity of production in order to pursue a continued wage growth commensurate with productivity growth (Acemoglu and Restrepo, 2019).

More recently, Freeman et al. (2020) highlight their skepticism toward projections of massive job upheaval in the foreseeable future by finding that recent changes in job attributes and tasks were driven more by within-occupation changes in work than by the shifts in employment among occupations, being these within-occupation changes generally modest. In addition, Domini et al. (2021), by using employer-employee data for French manufacturing employers over the period 2002-2015 and identifying 'automation spikes' by considering imports of capital goods embedding automation technologies, find that automation spikes are linked to an increase in firms' contemporaneous net employment growth rate, also affirming that automation spikes are not associated with significant changes in the composition of the workforce.

Other authors have approached the automation process from the ICT capital perspective. In this line, Eden and Gaggl (2018) document that the decline in the labor income share since the 1950s has been countered by a rise in the income share of capital goods that embody information and communication technology (ICT) also arguing that there has been substantial reallocation of labor income from occupations relatively substitutable with ICT (routine) to ones relatively complementary (non-routine). These results can be complemented by a skills based explanation: Colombo et al. (2019) explore the relationship between skills and computerization probability, highlighting that both hard skills (advanced ICT skills and skills related to communication and social media) and soft skills (thinking and social interaction skills) tend to be negatively related to the computerization probability.

Also related to this ICT capital perspective, Jerbashian (2019) provides evidence that the fall in prices of information technologies (IT) is associated with a lower share of employment in middle-wage occupations and a higher share of employment in high-wage occupations in industries which depend more on IT relative to industries which depend less. Contrary to this vision, Cortes et al. (2017) argue that the deterioration of employment in middle-wage, routine occupations is primarily driven by changes in the propensity to work in routine jobs for individuals from a small set of demographic groups, which account for a substantial fraction of both the increase in non-employment and employment in low-wage, non-routine manual occupations. Furthermore, they conclude that advances in automation technology on their own are unable to jointly generate changes in occupational shares and employment propensities.

On the other hand, fathoming this evidence of technology automating middle-wage occupations' routine tasks, Downey (2021) argues that technology only partially automates these, simplifying them so that they can be performed by less-skilled workers. Complementary to this study, we can approach tasks automation processes by bringing to the fore the considerations of firms' costs optimization in the tasks automation decisions. In this regard, Feng and Graetz (2020) analyze how job training requirements interact with engineering complexity in shaping firms' automation decisions, to argue that when two tasks are equally complex, firms automate the task that requires more training.

Other authors bear in mind that digitalization interacts with other major economic trends such as globalization. In this line, Foster-McGregor et al (2021) analyze the relation between trade and aggregate automation risk to conclude that automation risk in the highproductivity European countries is higher with trade, which implies that these countries do not, on balance, offshore automation risk, but rather import it. Related to this consideration, Krenz et al. (2021) analyze the offshoring and reshoring decisions of firms in the age of automation, suggesting that increasing productivity in automation leads to a relocation of previously offshored production back to the home economy (concretely, within manufacturing sectors, an increase by one robot per 1000 workers is associated with a 3.5% increase of reshoring activity). In addition, they argue that automationinduced reshoring is associated with an increasing skill premium and increasing inequality, since it leads also to increasing wages for high-skilled workers but without improving low-skilled wages and without creating jobs for low-skilled workers. Related to this consideration, Acemoglu and Restrepo (2018b) present a task-based model analyzing separately the effects of low-skill and high-skill automation.

The interaction between digitalization and the ageing of the population is another nexus of interest in the nowadays economic literature. Indeed, because of an aging population and slower population growth, labor force growth is expected to be slower in 2020-30 than in previous decades (Dubina et al., 2021). Within this strand of literature, Phiromswad et al. (2022) examine and estimate the interaction effects of computerization and population aging on the labor market, to find that computerization and population aging have large and statistically significant effects on employment growth but not earnings growth. These statistically significant effects are also explored by Acemoglu and Restrepo (2022), who describe the ageing of the population as an augmenting-automation process, highlighting that ageing leads to greater industrial automation with a more intensive use and development of robots.

Regarding this fact, Jimeno (2019) argues that it is likely that even though population ageing creates incentives for automation, per capita growth will slow down during the current demographic transition. Related to these studies, Gregoli et al. (2020) examine the impact of automation on aggregate labor force participation rates and individuals' attachment to the workforce in advanced economies, to find significant negative effects of automation on the participation rates of prime-age men and women, confirming that workers previously employed in routinizable occupations are more likely to drop out of the labor force. In addition, they remark that higher spending on active labor market programs and education are associated with smaller negative effects of technological change on participation, highlighting the potential of policy makers to turn the digitalization effects on labor markets from destructive to transformative.

5.2.2 Transformative digitalization

As in the destructive side of digitalization we find the purely common factor of almost every technological change in economic history, accentuated by the new generations of technologies, in the transformative side of digitalization we find, like a flower among the weeds, the Artificial Intelligence (AI). This new technology, understood as the culmination of a process that begins with the glimpse of the first machine, is coming into reality after being widely imagined, fantasized and conceptualized by science fiction.

Numerous authors have highlighted the labor-friendly side of the AI, separating this technology from the traditional conception of work automation technologies. Indeed, Tolan et al. (2021) show that some jobs that were not known to be affected by previous waves of automation may now be subject to higher AI exposure. Acemoglu and Restrepo (2018a) highlight that, although many occupations involve tasks suitable to AI and are likely to experience a displacement effect triggered by this technology, there are still many human skills that we still cannot automate, including complex reasoning, judgment, analogy-based learning, abstract problem-solving, and a mixture of physical activity, empathy, and communication skills. Related to this consideration, Alekseeva et al. (2021) document a high increase in the demand of AI skills between 2010 and 2019 in the US economy across most industries and occupations. From the point of view of AI patents, Damioli et al. (2021) find evidence of a positive and significant impact of AI patent families on employment. However, other authors identify AI as a labor-unfriendly technology. For instance, Bordot (2022) analyzes the influence of robots and AI in the unemployment rate of 33 OECD countries during the $2005 - 2017$ period to find that a 10% increase in the stock of industrial robots implies a 0.42 point increase unemployment rate, while finding a positive correlation between AI and the aggregated unemployment rate.

In this line, Ciarli et al. (2021), by analyzing the emerging trajectories of digital technologies and skills, highlight that digitalization is often more about the displacement and deep transformation of activities and their organization than about a simple one-to- one replacement of jobs. [3] Related to these displacement and transformative effects on labor, Tschang and Almirall (2020) remark the need to articulate the mechanisms by which AI may reduce and augments jobs, and in the process, transform the balance of work available. In addition, they argue that AI is augmenting automation by allowing firms to modularize and control routine work in a way that the remaining work tends to be nonroutine and low skilled (allowing for further replacement in the future), or high skilled. This shift in the skills demand due to digitalization has been also explored in McGuinness et al. (2022), who create a measure of skills-displacing technological change (SDT), defined as technological change that may render workers' skills obsolete, to find that 16 percent of adult workers in the EU are impacted by SDT, with significant variance across countries, ranging from a high of 28 percent in Estonia, to below seven percent in Bulgaria.

This transformative technology harbors a subset of technologies in which a core element is constituted by an assumed labor-destructive sub-technology: the Machine Learning (ML). This sub-branch of AI also accounts for an occupation-level measure of ML suitability developed by Brynjolfsson et al. (2018). The tasks more suitable to ML are those in which the following 8 criteria are fulfilled (Brynjolfsson and Mitchell, 2017): (i) the task implies learning a function that maps well-defined inputs to well-defined outputs, (ii) large (digital) data sets exist or can be created containing input-output pairs, (iii) the task provides clear feedback with clearly definable goals and metrics, (iv) it does not involve long chains of logic or reasoning that depend on diverse background knowledge or common sense, (v) there is no need for detailed explanation of how decisions are made, (vi) there is a tolerance for error and no need for provably correct or optimal solutions, (vii) the phenomenon or function being learned should not change rapidly over time, and, (viii) there is no specialized dexterity, physical skills, or mobility required.

5.2.3 Occupations typologies

To date, few articles have fall on the dual nature of the current technological change. In the intersection between these two technological forces -destructive and transformative-, only time will set the final effect of the 4IR on employment. Exploring the global affectation of 4IR technologies on labor, Benassi et al. (2022) find a positive and significant relationship between firms' stocks of 4IR patents and labor and total factor productivity, specifying that this effect is larger for firms with a long history in 4IR patent filings than for later applicants.

Fossen and Sorgner (2019) develop a pioneering work in identifying the duality of digitalization, identifying automation as the destructive side and AI as the transformative side, and providing a typological classification according to these considerations. As Table 5.1 collects, they propose a mapping of the labor terrain in four differentiated sections according to the digitalization effects upon occupations. Consequently, they identify the human terrain occupations as those lowly affected by either side of digitalization and the machine terrain occupations as those highly affected by both digitalization sides.

[3] See Furman and Seamans (2019) for a review about AI effects on the economy.

Moreover, they name the "Rising stars" occupations to those with low effects from destructive digitalization and high effects from transformative digitalization and the "Collapsing occupations" to those with high effects from destructive digitalization and low effects from transformative digitalization.

TABLE 5.1: Fossen's and Sorgner's (2019) classification

	Destructive digitalization Measured by the computerization probability from Frey and Osborne (2017)	
Transformative digitalization Measured by AI advances from Felten et al. (2018)	Low	High
High	Rising stars	Machine terrain
Low	Human terrain	Collapsing occupations

5.3 Data

Our sample accounts for 674 occupations, those for which we have digitalization measures availability. These 674 occupations cover approximately an 88% of total US employment in 2020. [4] The section is structured as follows: first, we detail the US employment data source; second, we describe the destructive digitalization measures; third, we present the transformative digitalization measures and finally we summarize the interaction between destructive and transformative digitalization and we introduce the occupational terrains.

5.3.1 US employment

We use data from the US Bureau of Labor Statistics. Concretely, we use occupations data at 6-digits level according to the SOC-2010 on total employment in 2020.

5.3.2 Destructive digitalization measures

We consider the current Automation degree from the O* Net database as a backwardlooking measure of destructive digitalization. [5] As a forward-looking measure of destructive digitalization, we consider the Automation probability from Frey and Osborne (2017). We define the complete-vision measure of destructive digitalization, Automation effects, as the mean of current automation degree and the expectations (probability) of automation. Furthermore, we consider a typological classification as a global vision for destructive digitalization effects, the automation terrains (A-terrains) collected in Table 5.2.

As we observe in table 2 we contemplate 4 a-terrains: when we find a low degree of automation as well as a low computerization probability we would be talking about the hands terrain. However when we have a low degree of automation but high computerization probability we would talk about the Rising automation terrain, since although current automation degree is low it is expected to be automated in the following years. Opposite to this terrain, we find a high degree of automation but with a low computerization probability we would speak of the Collapsing automation terrain, since although

[4] On the one hand, we account for different levels of availability for our technological measures: 761 occupations collecting the automation degree, 702 occupation with an associated computerization probability, 773 occupations for which AI advances has been measured and 774 occupations with an AI exposure score. On the other hand, US employment data is available for 820 occupations at 6 digits level SOC-10. Then, in the intersection of these measures we obtain our sample of 674 occupations.

[5] This measure is offered by O* Net in the section of Structural Job Characteristics.

TABLE 5.2: A-terrains classification

	Automation degree	
Automation probability	Low	High
High	Rising automation	Automation terrain
Low	Hands terrain	Collapsing automation

the occupation possess a current high automation degree it is not expected to be fully automated in the near future. Finally, when we have both a high degree of automation and a high computerization probability, the occupation would be in the automation terrain.

5.3.3 Transformative digitalization measures

We consider the current Advances in *AI* from Felten et al. (2018) as a backward-looking measure of transformative digitalization and the Exposure to AI from Felten et al. (2021) as a forward-looking measure of transformative digitalization. We define the completevision measure of transformative digitalization, AI effects, as the mean of current AI advances and the expectations (exposure) of further AI developments. In addition, we consider a typological classification as a global vision for the transformative digitalization effects, the intelligence terrains (I-terrains) collected in Table 5.3.

TABLE 5.3: I-terrains classification

	AI exposure	
AI advances	Low	High
High	Narrow AI definition	AI terrain
Low	HI terrain	Future AI applications

Table 5.3 shows four different I-terrains. When an occupation has a low degree of AI advances and low exposure to AI developments we refer to the Human Intelligence terrain (HI terrain), while if an occupation has both a high degree of AI advances and a high exposure to further AI implementations we would refer to the AI terrain. Moreover, if an occupation accounting for high AI advances but low AI exposure, we would say that this terrain is that of Narrow AI, while, on the opposite side, if an occupation has low AI advances but high exposure to AI progress in the future we would talk about the terrain of the Future AI.

5.3.4 Destructive and transformative digitalization

In this section we put together the destructive and transformative visions of digitalization, introducing the occupational terrains that we are going to use to analyze the US employment both in 2020 and for the projections of the year 2030. In that sense, we begin by briefly describing the continuous measures that we have proposed in the previous sections on destructive and transformative digitalization from the retrospective, prospective and complete view (Table 5.4). Then, we summarize in an unique table (Table 5.5) the terrains proposed on the destructive digitalization side (A-terrains) and on the transformative digitalization side (I-terrains).

Consistently with descriptions in previous sections, we are going to propose three different occupational terrains with three different temporal visions: the retrospective vision, the prospective vision and the complete vision. For the elaboration of these occupational terrains, we take into account both the destructive side and the transformative side of digitalization in each time perspective. Then, we use the retrospective measures of both automation and AI to elaborate the backward-looking occupational terrains, we use the prospective visions of both automation and AI to elaborate the forward-looking occupational terrains and finally we use the complete vision measures of both automation and AI to develop the full vision occupational terrains.

TABLE 5.4: Summary of measures: continuous variables and descriptions

	Time approach	Measure	Brief description
Destructive digitalization	Backward-looking vision	Automation degree	Current automation degree of the occupation.
	Forward-looking vision	Automation probability	Probability that the occupation will be computerized in the time lap between 2023 and 2033.
Transformative digitalization	Backward-looking vision	AI advances	AI progress in the occupation from 2010 to 2015.
	Forward-looking vision	AI exposure	Experts' estimation of AI potential in the forthcoming years

TABLE 5.5: Summary of measures: typologies variables

	Time approach	Measure	Typologies			
Destructive digitalization	Backward-looking vision	Automation degree	Low	High	Low	High
	Forward-looking vision	Automation probability	Low	Low	High	High
	Full vision	A-terrains	Hands terrain	Collapsing automation	Rising automation	Automation terrain
Transformative digitalization	Backward-looking vision	AI advances	Low	High	Low	High
	Forward-looking vision	AI exposure	Low	Low	High	High
	Full vision	I-terrains	HI terrain	Narrow AI	Future AI	AI terrain

Next, we expose the occupational terrains. The elaboration of these occupational terrains in three temporal dimensions of retrospective, prospective and complete vision will allow us to analyze the US employment from this triple temporal perspective, offering an analysis of the degree, exposure and situation of digitalization in the US occupations.

The backward-looking vision

TABLE 5.6: Backward-looking occupational terrains

	Automation degree	
AI advances	Low	High
High	Current stars	Current machine terrain
Low	Current human terrain	Advancing to collapse

As we can observe in Table 5.6, for the backward-looking occupational terrains we take into account the retrospective variables of automation degree (backward-looking destructive digitalization) and advances in AI (backward-looking transformative digitalization). In this sense, if the occupation has a low degree of AI advances and a low automation degree, we would say that it is an occupation of the Current human terrain. If, on the contrary, the occupation has a high degree of automation and a high score of advances in AI, we would situate this occupation in the Current machine terrain. For the case in which the occupation presents a low degree of automation and high progress in AI, we would say that it is a Current star occupation. On the contrary, if the occupation presents low AI advances and a high degree of automation, we would say that the occupation is Advancing to collapse.

The forward-looking vision

TABLE 5.7: Forward-looking occupational terrains

	Automation probability	
AI exposure	Low	High
High	Expected stars	Expected machine terrain
Low	Expected human terrain	Expected to collapse

Table 5.7 presents the forward-looking occupational terrains. These occupational terrains consider the prospective measures of digitalization. Specifically, on the side of destructive digitalization we consider the measure of computerization probability, and on the side of transformative digitalization, we consider the measure of exposure to AI. Therefore, for occupations with a low computerization probability and a low exposure to AI, we would say that they are occupations of the expected human terrain. On the contrary, if we consider occupations with a high computerization probability and high exposure to AI, we talk about the expected machine terrain. For occupations with low computerization probability high exposure to AI, we say that they are the expected stars. On the other hand, we speak of the occupations Expected to collapse when we consider occupations with low exposure to AI and high computerization probability.

5.4 Results

In this section we present the main results obtained in this study. In the first place, we present some descriptions of the employment variables and the digitalization variables. Next, we describe the relationship between digitalization and employment in the US, both on the destructive digitalization side considering the A-terrains and from the transformative digitalization side considering the I-terrains. In the third part of the section, we explore the relationship between the different occupational terrains and US employment (from retrospective, prospective and total perspective views). In the fourth part, we present the extended occupational terrains. For this purpose, we expand the occupational terrains classification of Fossen and Sorgner (2019) both on the destructive side of digitalization (i.e., the automation side) and on the transformative side of digitalization (i.e., the AI side) taking into account retrospective and prospective measures.

5.4.1 Descriptive statistics

Table 5.8 collects the descriptive statistics for the digitalization variables both from the destructive side and from the transformative side and from the retrospective, prospective and global points of view. As we can observe, the degree of automation takes values between 1% and 70%, with an average of 0.286 , while the computerization probability takes values between 0.0028 and 0.99 , with an average of 0.54 . Consequently, the variable that collects the effects of automation, being the mean of both variables, takes values between 0.015 and 0.815 , with its mean value being 0.413 . For the variables of transformative digitalization, we find that advances in AI take values from 1.417 to 6.537 , while the exposure to AI can take negative values ranging from -2.67 to 1.526 .

TABLE 5.8: Descriptive statistics of the main digitalization continuous variables

	Automation degree	Automation probability	AI advances	AI exposure
Mean	0.286	0.54	3.481	-0.098
Median	0.273	0.65	3.457	-0.22
Standard deviation	0.135	0.372	0.726	1.002
Minimum	0.01	0.0028	1.417	-2.67
Maximum	0.7	0.99	6.537	1.526
Number of observations	605	605	605	605

In Figure 5.1 we can observe the histograms of the digitalization variables. On the side of destructive digitalization (upper row) we observe that while the degree of automation is shaped like a bell tilted to the left, the computerization probability is U-shaped. Consequently, the variable that collects the effects of automation presents a histogram with two bells, at left and right, the left one being more pointed and pronounced. On the side of transformative digitalization, we observe that the histogram of the AI advances variable clearly presents a bell shape, while the variable of exposure to AI presents a certain U-shape with a bell on the left, a peak of values at the right end and a smaller number of observations around the 0 value. Consequently, the variable that collects the global effects of AI presents a bell shape flattened at the top.

TABLE 5.9: Correlation coefficients of the digitalization variables

	Automation degree	Automation probability	AI advances	AI exposure
Automation degree	1			
Automation probability	0.2849	1		
AI advances	-0.0885	-0.5210	1	
AI exposure	0.1464	-0.4139	0.2376	1

As we observe in Table 5.9, the destructive digitalization variables correlate positively with each other and negatively with the transformative digitalization variables. The same effect is observed in reverse, with the transformative digitalization variables correlating positively with each other and negatively with the destructive digitalization variables. The only exception to these relationships is the positive correlation between the automation degree and the AI exposure (which also leads the automation degree to correlate positively with AI effects). This fact would mean that occupations with higher automation degree are more exposed to AI further developments.

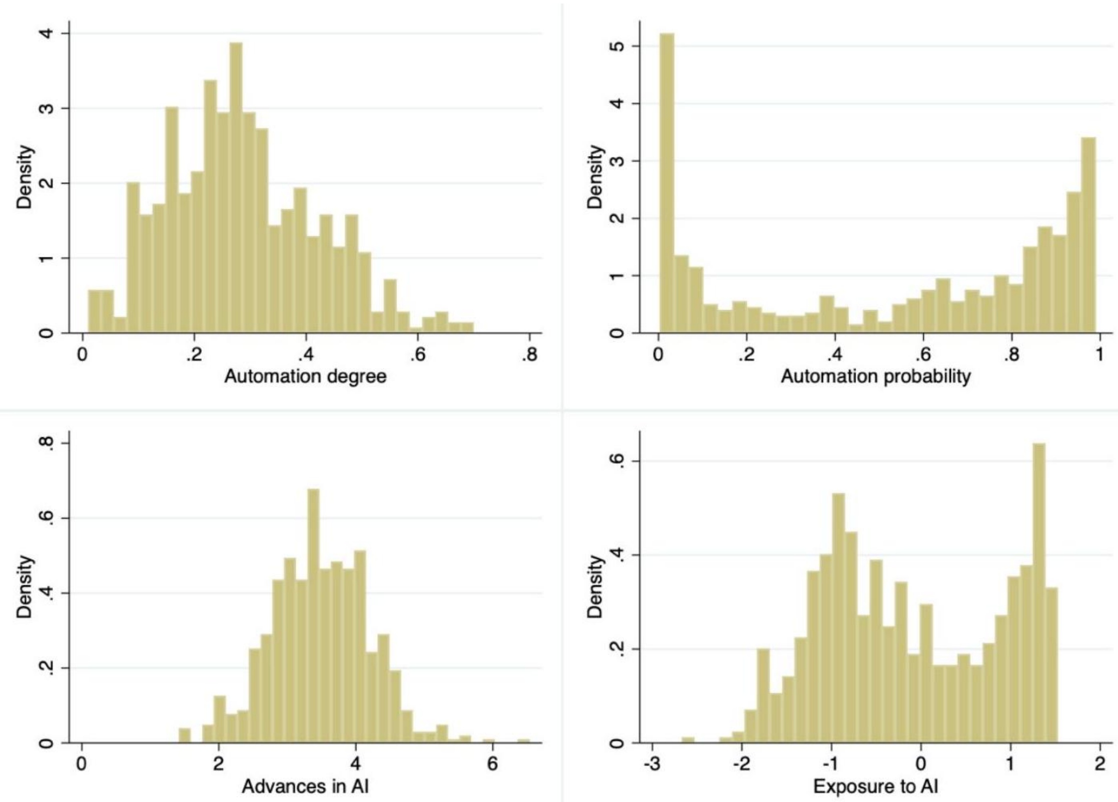


FIGURE 5.1: Histograms of the main variables

5.4.2 Digitalization and US employment

Next, we present a mapping of employment in the US regarding digitalization in the two sides of its duality: the destructive and the transformative. For this purpose, we use both the A-terrains and the I-terrains described previously.

Destructive digitalization and US employment

First, we present the occupations with the highest and lowest degrees of automation, as well as the occupations with the highest and lowest probabilities of automation (Table 5.10), together with the number of jobs covered by each of them. As we can observe, in these occupations with higher and lower degrees and probabilities of automation, there are no occupations massively populated with employment, taking into account that the maximum employment in an occupation for the year 2020 accounts 3,835 thousand jobs, while in Table 5.10 the occupation with the highest number of jobs collects 484.1 thousand jobs.

TABLE 5.10: Destructive digitalization measures and US employment

SOC code	SOC label	Auto. degree	Auto. prob.	2020 US emp.
Occupations with the highest automation degree				
413041	Travel Agents	.7	.099	60.5

Continued on next page

Continued from previous page

SOC code	SOC label	Auto. degree	Auto. prob.	2020 US emp.
435053	Postal Service Mail Sorters, Processors, and Processing Machine Operators	.68	.79	100.4
432021	Telephone Operators	.66	.97	4.8
518091	Chemical Plant and System Operators	.66	.85	29.5
434181	Reservation and Transportation Ticket Agents and Travel Clerks	.65	.61	101.6
Occupations with the lowest automation degree				
499064	Watch Repairers	.01	.99	2.8
499095	Manufactured Building and Mobile Home Installers	.01	.18	3.4
395092	Manicurists and Pedicurists	.02	.95	123
493052	Motorcycle Mechanics	.02	.79	14
395091	Makeup Artists, Theatrical and Performance	.02	.01	3.1
Occupations with the highest computerization probability				
232093	Title Examiners, Abstractors, and Searchers	.51	.99	62.2
419041	Telemarketers	.52	.99	119.7
132082	Tax Preparers	.44	.99	87.4
132053	Insurance Underwriters	.47	.99	119.4
439021	Data Entry Keyers	.46	.99	158.4
519151	Photographic Process Workers and Processing Machine Operators	.56	.99	9.3
254031	Library Technicians	.42	.99	93.1
516051	Sewers, Hand	.19	.99	6.9
434141	New Accounts Clerks	.51	.99	46.1
435011	Cargo and Freight Agents	.34	.99	95.6
499064	Watch Repairers	.01	.99	2.8
Occupations with the lowest computerization probability				
291125	Recreational Therapists	.15	.0028	20.8
491011	First-Line Supervisors of Mechanics, Installers, and Repairers	.12	.003	484.1
119161	Emergency Management Directors	.31	.003	10.5
211023	Mental Health and Substance Abuse Social Workers	.19	.0031	124
291181	Audiologists	.29	.0033	13.7

Figure 5.2 shows the mapping of the US employment with respect to A-terrains, where each bubble represents an occupation and the size of the bubble depends on the number of jobs in the occupation. As we appreciate, there are few occupations that exceed an automation degree of 50%, with practically all occupations below this threshold. As we notice, the computerization probability variable polarizes the occupations between occupations with a high computerization probability and occupations with a low computerization probability with few observations in between these two extremes, as we observed in the regarding histogram shown in Figure 5.1. Therefore, we find a high number of observations in

the terrain of Rising automation as well as a high number of observations in the Hands terrain, with a low number of occupations both in the terrain of Collapsing automation and the Automation terrain.

Complementary to Figure 5.2, Table 5.11 presents the occupations in each terrain that collect a higher level of employment. As logical after observing Figure 5.2, the occupations with the highest employment are in the Hands terrains and the terrain of Rising automation, while the terrain of Collapsing automation and the Automation terrain present less populated occupations.

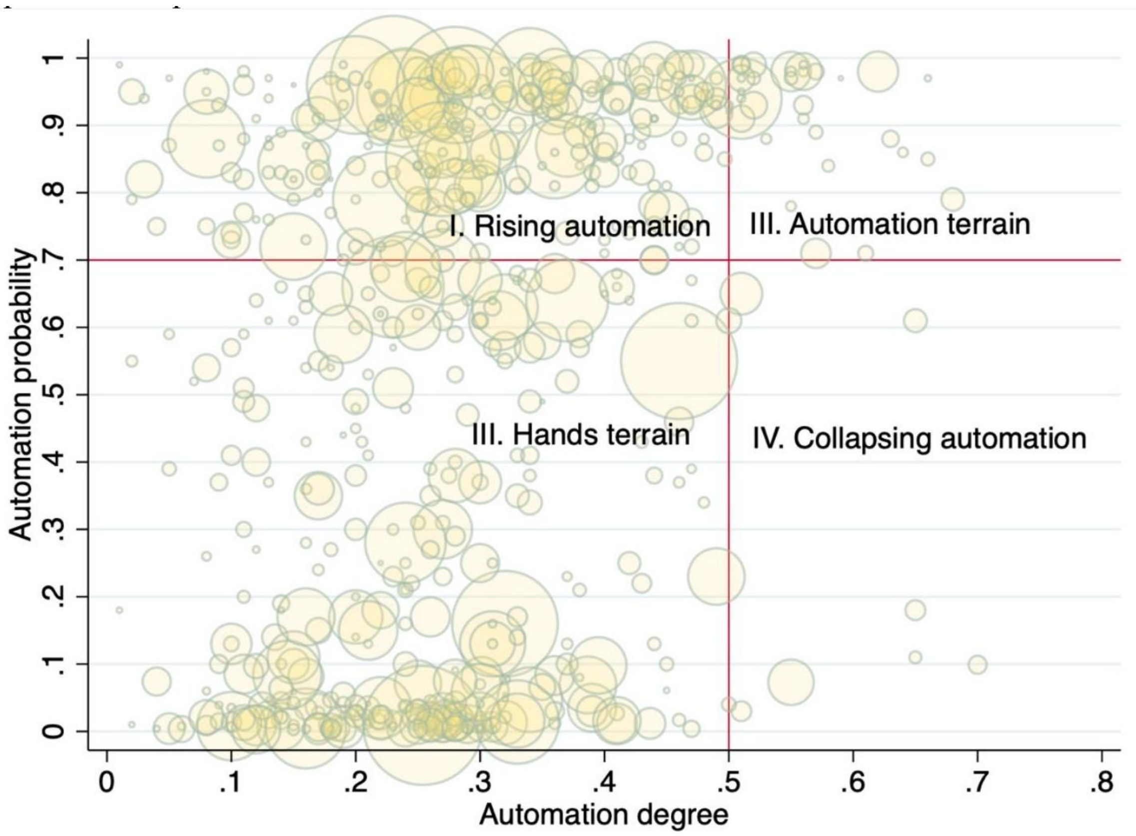


FIGURE 5.2: A-terrains and US employment

TABLE 5.11: A-terrains and US employment

SOC code	SOC label	Auto. degree	Auto. prob.	2020 US emp.
	Occupations with highest US employment in the Hands terrain			
291141	Registered Nurses	.254	.009	3080.1
434051	Customer Service Representatives	.46	.55	2923.4
111021	General and Operations Managers	.32	.16	2411.9
372011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	.23	.66	2217
431011	First-Line Supervisors of Office and Administrative Support Workers	.33	.014	1487.3

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SOC code	SOC label	Auto. degree	Auto. prob.	2020 US emp.
Occupations with highest US employment in the Rising automation terrain				
412031	Retail Salespersons	.29	.92	3835
412011	Cashiers	.23	.97	3379.1
439061	Office Clerks, General	.28	.96	2933.9
537062	Laborers and Freight, Stock, and Material Movers, Hand	.27	.85	2821.7
436014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	.2	.96	2053.5
Occupations with highest US employment in the Collapsing automation terrain				
119111	Medical and Health Services Managers	.55	.073	429.8
514041	Machinists	.51	.65	363
518031	Water and Wastewater Treatment Plant and System Operators	.5	.61	122.1
434181	Reservation and Transportation Ticket Agents and Travel Clerks	.65	.61	101.6
532011	Airline Pilots, Copilots, and Flight Engineers	.65	.18	74.7
Occupations with highest US employment in the Automation terrain				
132011	Accountants and Auditors	.51	.94	1392.2
131031	Claims Adjusters, Examiners, and Investigators	.62	.98	333.8
132072	Loan Officers	.55	.98	322.1
439041	Insurance Claims and Policy Processing Clerks	.56	.98	277.9
516011	Laundry and Dry-Cleaning Workers	.57	.71	175.5

Transformative digitalization and US employment

Once we have observed the mapping of the destructive side of digitalization for the US employment, we move on to observe the mapping of the impact of transformative digitalization on US employment.

Symmetrically to the destructive digitalization mapping section, we first look at the occupations with the highest and lowest scores in AI advances, as well as the occupations with the highest and lowest scores in exposure to AI. We observe that the occupations in these extremes relative to the values of the AI variables are not highly populated with employment. In fact, the occupation in Table 5.12 that encompasses the largest number of jobs (Fitness Trainers and Aerobics Instructors with 309.8 thousand jobs) does not contain even 10% of jobs with respect to the occupation that has the most employment in our sample of 605 occupations.

TABLE 5.12: Transformative digitalization measures and US employment

SOC code	SOC label	AI adv. score	AI exp. score	2020 US emp.
	Occupations with the highest scores in AI advances			
532011	Airline Pilots, Copilots, and Flight Engineers	6.5372877	-.207	74.7
192012	Physicists	5.9072075	1.346	17.4
532012	Commercial Pilots	5.6820021	-.182	39.2
532021	Air Traffic Controllers	5.6803937	1.153	24.5
291021	Dentists, General	5.4143696	-.181	120.3
	Occupations with the lowest scores in AI advances			
419012	Models	1.416977	-1.122	2.7
419041	Telemarketers	1.5099856	1.118	119.7
393093	Locker Room, Coatroom, and Dressing Room Attendants	1.5152327	-.345	12
452041	Graders and Sorters, Agricultural Products	1.5719488	-1.371	32.5
395093	Shampooers	1.8387299	-.905	10.8
	Occupations with the highest scores in AI exposure			
132061	Financial Examiners	4.0538263	1.526	70.8
152011	Actuaries	4.2314577	1.516	27.7
132031	Budget Analysts	3.3814559	1.503	52.5
231023	Judges, Magistrate Judges, and Magistrates	3.9404573	1.496	29.4
433061	Procurement Clerks	2.515487	1.488	63
	Occupations with the lowest scores in AI exposure			
272031	Dancers	3.2159972	-2.67	9
399031	Fitness Trainers and Aerobics Instructors	2.8135116	-2.112	309.8
473014	Helpers–Painters, Paperhangers, Plasterers, and Stucco Masons	2.4188068	-2.045	9.4
472171	Reinforcing Iron and Rebar Workers	3.039923	-1.971	22.1
516021	Pressers, Textile, Garment, and Related Materials	1.9422904	-1.95	30.3

Figure 5.3 shows the mapping of US employment with respect to transformative digitalization, where again each bubble represents an occupation and the size of each bubble reflects the total number of jobs in the occupation. From the outset, we observe a clear difference between the mapping of destructive digitalization and the mapping of transformative digitalization. While in the case of the destructive digitalization mapping we observe a great polarization of the observations due to the U-shape in the histogram of the computerization probability, in the case of the transformative digitalization we observe a mapping with the observations very centralized due to the bell shapes histograms that present both variables of transformative digitalization. In this way, we notice that this mapping looks like a nebula in which the occupations are distributed almost equally in the 4 I-terrains with some fewer occupations in the terrain of Future AI. Complementing the Figure 5.3, Table 5.13 collects the 5 most populated occupations in each I-terrain.

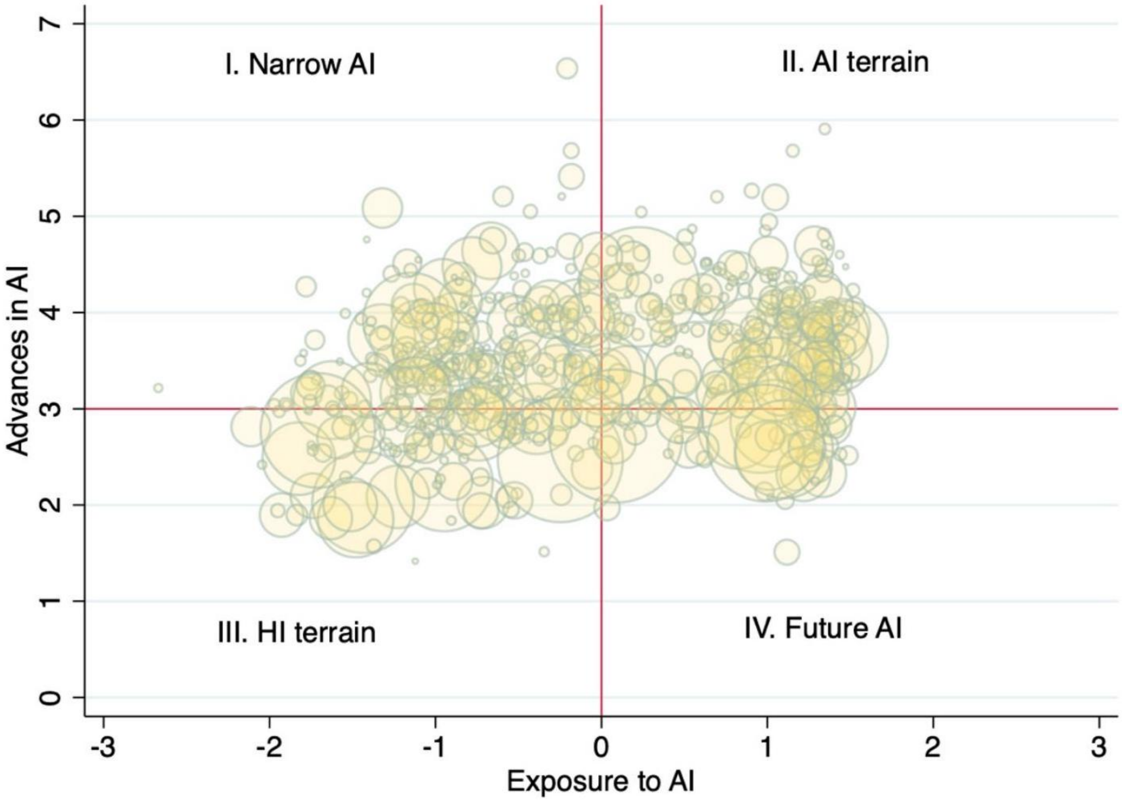

FIGURE 5.3: I-terrains and US employment

TABLE 5.13: I-terrains and US employment

SOC code	SOC label	AI adv. score	AI exp. score	2020 US emp.
Occupations with highest US employment in the HI terrain				
412011	Cashiers	2.4718328	-.248	3379.1
537062	Laborers and Freight, Stock, and Material Movers, Hand	2.7752922	-1.709	2821.7
372011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	2.0306945	-1.436	2217
353031	Waiters and Waitresses	2.2320356	-.948	2023.2
372012	Maids and Housekeeping Cleaners	1.8491679	-1.481	1212.8
Occupations with highest US employment in the Narrow AI terrain				
533032	Heavy and Tractor-Trailer Truck Drivers	3.9176085	-1.149	1951.6
499071	Maintenance and Repair Workers, General	3.6678796	-1.014	1444.1
472061	Construction Laborers	3.0904617	-1.623	1285.2
533033	Light Truck or Delivery Services Drivers	3.1734586	-1.121	1035.8
399011	Childcare Workers	3.4429889	-.383	992.4
Occupations with highest US employment in the Future AI terrain				

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SOC code	SOC label	AI adv. score	AI exp. score	2020 US emp.
412031	Retail Salespersons	2.7165029	.087	3835
439061	Office Clerks, General	2.6438301	.989	2933.9
434051	Customer Service Representatives	2.939477	.956	2923.4
436014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	2.5797276	1.099	2053.5
433031	Bookkeeping, Accounting, and Auditing Clerks	2.8479018	1.04	1620
Occupations with highest US employment in the AI terrain				
291141	Registered Nurses	4.2665367	.229	3080.1
111021	General and Operations Managers	3.3521471	.575	2411.9
431011	First-Line Supervisors of Office and Administrative Support Workers	3.3072996	1.039	1487.3
132011	Accountants and Auditors	3.6984756	1.482	1392.2
411011	First-Line Supervisors of Retail Sales Workers	3.3579433	.019	1390.6

5.4.3 Occupational terrains and US employment

Once we have mapped the US employment from the destructive and transformative sides of digitalization separately to observe how US employment looks on each of the sides of digitalization, we propose mappings for the US employment that collect both sides of digitalization in a coherent way from a triple temporal point of view. In this sense, we collect a triple temporal dimension proposing three mappings: one retrospective, another prospective and another of total vision.

For the retrospective vision, we consider the backward-looking occupational terrains taking into account the automation degree and the AI advances (Table 5.6). For the prospective vision, we consider the forward-looking occupational terrains taking into account the computerization probability and the exposure to AI (Table 5.7). Finally, for the total vision we consider the full vision occupational terrains involving automation effects and AI effects (Table 5.8).

The backward-looking vision

Figure 5.4 shows the mapping of employment in the 605 occupations considered with respect to the retrospective view of transformative and destructive digitalization. Therefore, it shows the current situation of US employment with respect to AI advances and the automation degree of occupations. As we can verify, in general, the occupations do not cross the threshold of 50% automation degree, with few occupations being found in the current machine terrains and the terrain of advancing to collapse occupations. In the upper right corner of the figure, we observe an occupation that stands out for its high score in AI advances and its high automation degree. In particular, this occupation (Airline Pilots, Copilots, and Flight Engineers) accounts for a score of 6.5 in AI advances and a 65% degree of automation, which is consistent with the development of the drones and air navigation industry.

Complementing the vision collected by Figure 5.4, Table 5.14 expose the details in the AI advances score, automation degree and total employment of the highest populated occupation of each backward-looking occupational terrain (the largest bubbles in each terrain of Figure 5.4).

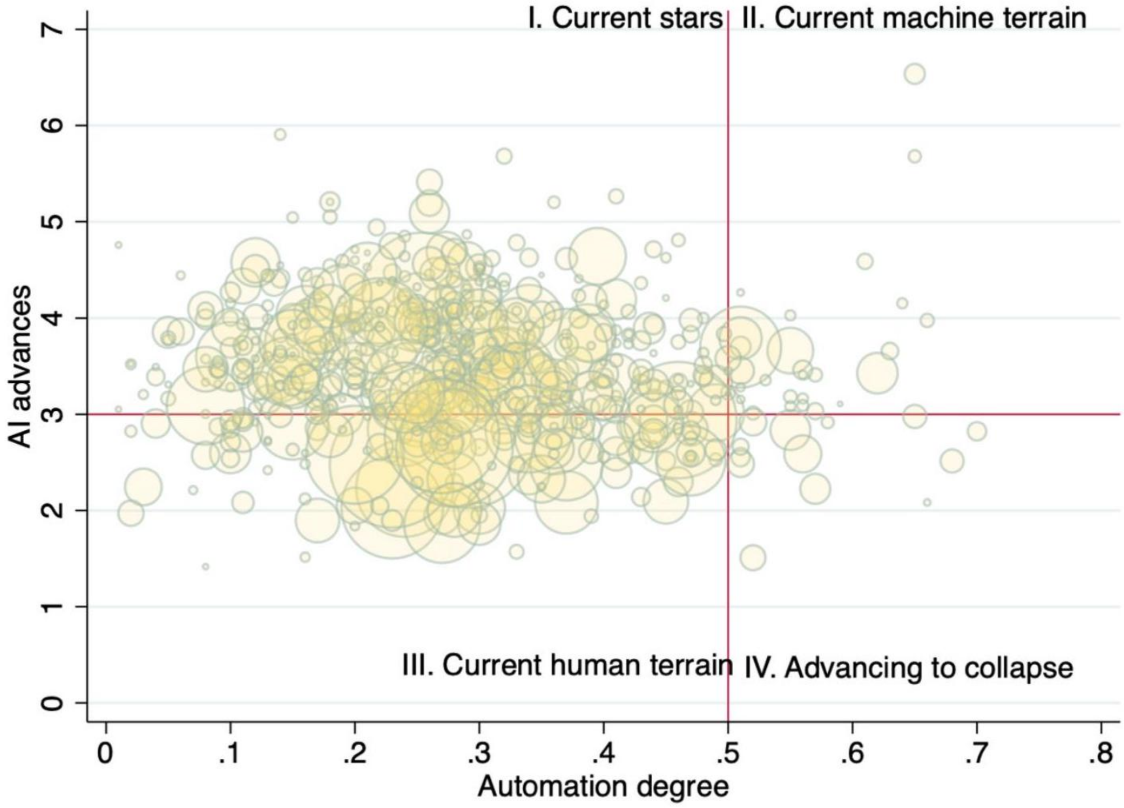

FIGURE 5.4: Backward-looking occupational terrains: US employment

TABLE 5.14: Backward-looking occupational terrains: US employment

SOC code	SOC label	Auto. degree	AI adv. score	2020 US emp.
Occupations with highest US employment in the Actual human terrain				
412031	Retail Salespersons	.29	2.7165029	3835
412011	Cashiers	.23	2.4718328	3379.1
439061	Office Clerks, General	.28	2.6438301	2933.9
434051	Customer Service Representatives	.46	2.939477	2923.4
537062	Laborers and Freight, Stock, and Material Movers, Hand	.27	2.7752922	2821.7
Occupations with highest US employment in the Actual stars terrain				
291141	Registered Nurses	.254	4.2665367	3080.1
111021	General and Operations Managers	.32	3.3521471	2411.9
533032	Heavy and Tractor-Trailer Truck Drivers	.22	3.9176085	1951.6
431011	First-Line Supervisors of Office and Administrative Support Workers	.33	3.3072996	1487.3
499071	Maintenance and Repair Workers, General	.37	3.6678796	1444.1
Occupations with highest US employment in the Advancing to collapse terrain				

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SOC code	SOC label	Auto. degree	AI adv. score	2020 US emp.
132072	Loan Officers	.55	2.8359137	322.1
439041	Insurance Claims and Policy Processing Clerks	.56	2.5882883	277.9
516011	Laundry and Dry-Cleaning Workers	.57	2.2247977	175.5
537081	Refuse and Recyclable Material Collectors	.52	2.9198558	140.5
433051	Payroll and Timekeeping Clerks	.51	2.4858935	137.3
Occupations with highest US employment in the Actual machine terrain				
132011	Accountants and Auditors	.51	3.6984756	1392.2
119111	Medical and Health Services Managers	.55	3.6610198	429.8
514041	Machinists	.51	3.7895303	363
131031	Claims Adjusters, Examiners, and Investigators	.62	3.4276185	333.8
514081	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	.51	3.453315	138.4

The forward-looking vision

Figure 5.5 shows the mapping of US employment with respect to the prospective vision of digitalization, taking into account exposure to AI and the computerization probability. At first glance, clearly differentiated from the retrospective view of the impact of digitalization on employment, we observe that a high number of occupations are in the expected machine terrain and in the terrain of occupations expected to collapse. This figure highlights the fact that, although the technological wave is undoubtedly already having important effects on labor markets, digitalization is currently more about expected potential effects than actual current progresses.

In Table 5.15, we observe that in this case Figure 5.5 includes occupations that account for a large share of employment in the US both in the expected machine terrain and in the terrain of occupations expected to collapse. Therefore, it is to be expected that if the predictions of Frey and Osborne (2017) finally come true, there may indeed be turmoil in the US labor markets such that there will be a large number of job losses and displacements. In this sense, the occupational field of the expected stars also accounts for a wide range of occupations that have a large share of employment in the US, having a high exposure to AI and a low computerization probability. On the other hand, while we see that there is a high number of occupations in the expected human terrain, this fact must be qualified since, as we observe in Table 5.15, among the expected human terrain occupations with the highest number of jobs in the US, 4 of those 5 exceed the 0.6 computerization probability.

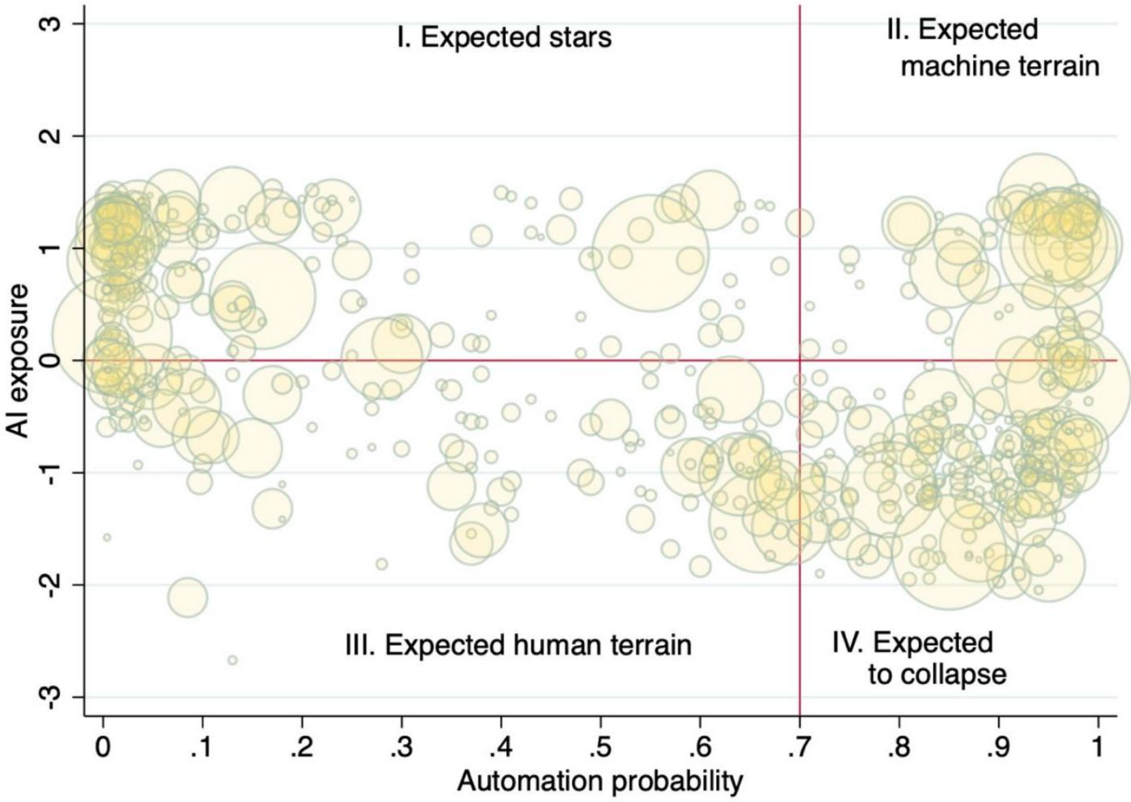

FIGURE 5.5: Forward-looking occupational terrains: US employment

TABLE 5.15: Forward-looking occupational terrains: US employment

SOC code	SOC label	Auto. prob.	AI exp. score	2020 US emp.
Occupations with highest US employment in the Expected human terrain				
372011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	.66	-1.436	2217
499071	Maintenance and Repair Workers, General	.64	-1.014	1444.1
372012	Maids and Housekeeping Cleaners	.69	-1.481	1212.8
533033	Light Truck or Delivery Services Drivers	.69	-1.121	1035.8
399011	Childcare Workers	.084	-.383	992.4
Occupations with highest US employment in the Expected stars terrain				
291141	Registered Nurses	.009	.229	3080.1
434051	Customer Service Representatives	.55	.956	2923.4
111021	General and Operations Managers	.16	.575	2411.5
431011	First-Line Supervisors of Office and Administrative Support Workers	.014	1.039	1487.3
411011	First-Line Supervisors of Retail Sales Workers	.28	.019	1390.6

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SOC code	SOC label	Auto. prob.	AI exp. score	2020 US emp.
Occupations with highest US employment in the Expected to collapse terrain				
412011	Cashiers	.97	-.248	3379.1
537062	Laborers and Freight, Stock, and Material Movers, Hand	.85	-1.709	2821.7
353031	Waiters and Waitresses	.94	-.948	2023.2
533032	Heavy and Tractor-Trailer Truck Drivers	.79	-1.149	1951.6
472061	Construction Laborers	.88	-1.623	1285.2
Occupations with highest US employment in the Expected machine terrain				
412031	Retail Salespersons	.92	.087	3835
439061	Office Clerks, General	.96	.989	2933.9
436014	Secretaries and Administrative Assistants, Except Legal, Medical, and Executive	.96	1.099	2053.5
433031	Bookkeeping, Accounting, and Auditing Clerks	.98	1.04	1620
132011	Accountants and Auditors	.94	1.482	1392.2

5.4.4 Extended occupational terrains

Considering the classification of Fossen and Sorgner (2019) exposed in Table 5.1, we can argue that this classification can be extended taking into account the extra technological measures from the automation side and the intelligence side. More precisely, the Fossen's and Sorgner's (2019) classification considers the computerization probability (prospective vision) as the destructive digitalization measure and the AI advances (retrospective vision) as the transformative digitalization measure. Therefore, adding both a retrospective vision to the automation side and a prospective vision to the AI side harbors space for more detailed extended occupational terrains.

In all the tables in this section, it is represented in green when the extended occupational terrain matches the classification of Fossen and Sorgner (2019), while when a new occupational terrain is proposed as a result of the extension, the imbalance that makes that this new terrain is not framed within those considered by Fossen and Sorgner (2019) is outlined in red.

Extended occupational terrains (A-side)

On the destructive digitalization side, Fossen and Sorgner (2019) measure the effect of automation using the variable proposed by Frey and Osborne (2017). However, on the transformative digitalization side, they use the variable proposed by Felten et al. (2018). This creates a mismatch in the time perspective of both variables since Frey and Osborne (2017) are based on expert predictions about the future while Felten et al. (2018) are based on past developments. Therefore, we add the degree of automation variable as a lagging control variable to the Fossen and Sorgner (2019) classification. As we can observe in Table 5.16, for 348 occupations $(41 + 272 + 11 + 24)$ the binary variables of degree and computerization probability coincide. However, there are other 257 occupations for which there is a mismatch in both binary variables collecting retrospective and prospective destructive digitalization effects. Therefore, we can extend 4 new occupational terrains to the classification proposed by Fossen and Sorgner (2019).

First, we find an occupational terrain in which occupations present low AI advances, low computerization probability but high automation degree. In the Fossen's and Sorgner's (2019) classification this occupation would be labelled as an occupation in the human terrain. We label these occupations as the Automated human terrain and it results logical that there are only two occupations in this new occupational terrain since it is not common for an occupation to have a low automation risk while being highly automated.

Second, we find an occupational terrain in which occupations present high AI advances, low computerization probability but high automation degree. In the Fossen's and Sorgner's (2019) classification this occupation would be labelled as a Rising star occupation. However, we label these occupations as the Automated stars and we find 7 occupations in this new occupational terrain.

Third, we find an occupational terrain in which occupations present low AI advances, high computerization probability but low automation degree. In the Fossen's and Sorgner's (2019) classification this occupation would be labelled as a Collapsing occupation. In consequence, we label them as the Rising collapse occupations and we find 96 occupations in this new occupational terrain. It results logical that almost hundred observations are in this new occupational terrain since it is common that occupations expected to be automated currently present a low automation degree.

Finally, we find an occupational terrain in which occupations present high AI advances and high computerization probability but low automation degree. In the Fossen's and Sorgner's (2019) classification this occupation would be labelled as a Machine terrain occupation. In our case, we label them as the Rising machine terrain occupations and we find 152 occupations in this new occupational terrain. Then, the largest mismatches between the Fossen's and Sorgner's (2019) classification and these extended occupational terrains are derived from the fact of occupations at high automation risk having a current low automation degree, particularly, 248 occupations from the 605 considered.

TABLE 5.16: Extended occupational terrains: automation side

Occupational terrains (Fossen and Sorgner, 2019)	AI advances	Automation probability	Automation degree	A-terrains	Extended occupational terrains (A-side)	Occupations in the terrain
Human terrain	Low	Low	Low	Hands terrain	Human terrain	41
Rising star	High	Low	Low	Hands terrain	Rising star	272
Collapsing occupation	Low	High	High	Automation terrain	Collapsing occupation	11
Machine terrain	High	High	High	Automation terrain	Machine terrain	24
Human terrain	Low	Low	High	Collapsing automation	Automated human terrain	2
Rising star	High	Low	High	Collapsing automation	Automated star	7
Collapsing occupation	Low	High	Low	Rising automation	Rising collapse	96
Machine terrain	High	High	Low	Rising automation	Rising machine terrain	152

Extended occupational terrains (I-side)

The same extension of the classification of Fossen and Sorgner (2019) that we have proposed on the side of destructive digitalization can be carried out on the side of transformative digitalization. In order to do so, besides considering current AI advances, we also consider the AI exposure (Felten et al., 2021). Therefore, when the AI advances matches the AI exposure the Fossen and Sorgner (2019) occupational terrain considered will remain. However, when the AI advances does no match the AI exposure, a new occupational terrain will be considered. In this case, as we observe in Table 5.17, 312 occupations

$(32 + 176 + 66 + 38)$ matches the Fossen and Sorgner (2019) classification while other 293 occupations $(11 + 103 + 41 + 138)$ are situated in new occupational terrains.

The first extension in the occupational terrains arises with the considerations of occupations presenting a low computerization probability and low AI advances but high AI exposure. We classify these occupations as the Future star occupations. Next, occupations with low computerization probability and high AI advances but low AI exposure are classified as Collapsing stars. Accordingly, occupations with high computerization probability and low AI advances but high AI exposure are labelled as Future machine terrain. Finally, occupations with high computerization probability and high AI advances but low AI exposure are labelled as Narrow machine terrain.

TABLE 5.17: Extended occupational terrains: intelligence side

Occupational terrains (Fossen and Sorgner, 2019)	Computerization probability (Frey and Osborne, 2017)	AI advances (Felten et al., 2018)	Exposure to AI (Felten et al., 2021)	I-terrains	Extended occupational terrains (I-side)	Occupation in the terrain
Human terrain	Low	Low	Low	HI terrain	Human terrain	32
Rising star	Low	High	High	AI terrain	Rising star	176
Collapsing occupation	High	Low	Low	HI terrain	Collapsing occupation	66
Machine terrain	High	High	High	AI terrain	Machine terrain	38
Human terrain	Low	Low	High	Future AI	Future star	11
Rising star	Low	High	Low	Narrow AI	Collapsing star	103
Collapsing occupation	High	Low	High	Future AI	Future machine terrain	41
Machine terrain	High	High	Low	Narrow AI	Narrow machine terrain	138

Extended occupational terrains

In the same way that we have developed the previous extended occupational terrains, we can consider an occupational classification that extends the one proposed by Fossen and Sorgner (2019) both from the destructive side and from the transformative side of digitalization. Therefore, it is a classification of extended occupational terrains that includes a double temporal perspective (retrospective and prospective) on each side of digitalization. In this case we find 16 different occupational terrains. In the first place, we have 4 occupational terrains in which both temporal perspectives on each side of digitalization fit, thus fitting with the four occupational terrains proposed by Fossen and Sorgner (2019). Secondly, we find 4 occupational fields whose temporal perspective fits in the destructive side of digitalization but does not fit in the transformative side of digitalization. Thirdly, we find the inverse case in which the temporal perspective fits on the transformative side of digitalization while it does not fit on the destructive side. Finally, we find 4 occupational terrains in which both temporal perspectives do not fit on either side of digitalization.

As we observe in Table 5.18, on this occasion we find that the Automated human terrain contains no occupations, while there are other occupational terrains containing just a few occupations (Collapsing occupations with 4; Machine terrain with 6 occupations; Future stars with 9; Future machine terrain with 7 occupations; Automated stars with 4; From collapsing occupation to rising star with 2; From machine terrain to human terrain with 3). In these extended occupational terrains only 214 from the 605 occupations matches the Fossen and Sorgner (2019) classification.

TABLE 5.18: Extended occupational terrains

Destructive digitalization			Transformative digitalization					
Backward-looking vision	Forward-looking vision	Full-looking vision	Backward-looking vision	Forward-looking vision	Full-looking vision			
Automation degree	Automation probability	A-terrains	AI advances	Exposure to AI	I-terrains	Occupational terrains (Fossen and Sorgner, 2019)	Extended occupational terrains	Occ. in the terrain
Low	Low	Hands terrain	Low	Low	HI terrain	Human terrain	Human terrain	32
Low	Low	Hands terrain	High	High	AI terrain	Rising star	Rising star	172
High	High	Automation terrain	Low	Low	HI terrain	Collapsing occupation	Collapsing occupation	4
High	High	Automation terrain	High	High	AI terrain	Machine terrain	Machine terrain	6
Low	Low	Hands terrain	Low	High	Future AI	Human terrain	Future star	9
Low	Low	Hands terrain	High	Low	Narrow AI	Rising star	Collapsing star	100
High	High	Automation terrain	Low	High	Future AI	Collapsing occupation	Future machine terrain	7
High	High	Automation terrain	High	Low	Narrow AI	Machine terrain	Narrow machine terrain	18
High	Low	Collapsing automation	Low	Low	HI terrain	Human terrain	Automated human terrain	0
High	Low	Collapsing automation	High	High	AI terrain	Rising star	Automated star	4
Low	High	Rising automation	Low	Low	HI terrain	Collapsing occupation	Rising collapse	62
Low	High	Rising automation	High	High	AI terrain	Machine terrain	Rising machine terrain	32
High	Low	Collapsing automation	Low	High	Future AI	Human terrain	From collapsing occupation to rising star	2
High	Low	Collapsing automation	High	Low	Narrow AI	Rising stars	From machine terrain to human terrain	3
Low	High	Rising automation	Low	High	Future AI	Collapsing occupations	From human terrain to machine terrain	34
Low	High	Rising automation	High	Low	Narrow AI	Machine terrain	From rising star to collapsing occupation	120

5.5 Conclusions

Technology has been a driving force in the transformation of labor markets for centuries. In the current era of the fourth industrial revolution, robotics and AI have emerged as the primary factors influencing the future of work. These technologies have the power to displace, transform, create, and destroy jobs, making it essential for economists and policymakers to understand their potential impact.

In this study, we navigate the complex landscape of digitalization to unravel the implications of technological change on the immediate future of work. By analyzing 605 occupations, we assess the current state of automation and AI advances, as well as the expectations for future developments in these areas. Through the construction of various occupational typologies, our research offers a visual representation of the ongoing digitalization process, providing a simplified yet comprehensive understanding of its impact on the labor market.

Our findings suggest that, at least in the short term and given the current level of AI exposure across occupations, there is no need for Luddite alarmism. Both the destructive and transformative forces of digital technological change are expected to reshape labor markets with overall positive outcomes in employment creation. However, these conclusions come with certain caveats. The rapid pace of technological evolution since the late 1960s indicates that even occupations created today, driven by the emergence of new technologies, may eventually become susceptible to automation by future generations of AI.

Indeed, AI technology, while currently displaying a labor-friendly face, holds the potential to replace even itself (He et al., 2021). This underscores the need for continuous monitoring and adaptation of policies and strategies to ensure that labor markets remain resilient and inclusive in the face of ongoing technological advancements. In conclusion, our study provides valuable insights for researchers, policymakers, and businesses as they navigate the ever-evolving landscape of work and strive to create a sustainable, equitable, and prosperous future for all.

Chapter 6

Early retired or automatized? Evidence from the survey of health, ageing and retirement in Europe

6.1 Introduction

New labour-saving technologies such as Machine Learning and Robotics promise to bring profound changes to the labour markets in the coming years (Autor, 2015) and the current technological change is expected to produce a challenge for certain groups of population like older workers close to retirement age (Alcover et al., 2021). Moreover, the ageing of the population in industrialised countries threatens the sustainability of public finances, in such a way that governments are extending the statutory retirement age (European Commission, 2021). These two facts - the automation process and the ageing of the population - lead to a potential contradiction between governments trying to extend statutory retirement ages and labour markets expelling older workers due to current technological changes.

On the one hand, in recent years, experts in Artificial Intelligence (AI) contemplated the capacity of this new technology to assume tasks previously realised by humans. [1] At the same time, it has been analysed the capacity of robotics to affect labour markets by reducing the employment rate (Acemoglu and Restrepo, 2020a) and by increasing the productivity of workers (Graetz and Michaels, 2018). However, although it has been proven that robots adoption reduces the employment rate, the implications of this employment rate reduction for the early retirement transitions have not been broadly studied.

On the other hand, the aged population of industrialised countries makes it impossible to face the current industrial revolution with the same policies used during the previous ones (i.e., the delay of the statutory early retirement age or the provision of generous early retirement schemes). The concept of retirement as an old-age social insurance program appeared for the first time in 1889 designed by Otto von Bismarck, setting the retirement age at 70 years old. The life expectancy of the population in Germany then was around 40 years old, which made this statement realisable. Almost a century later, the early retirement provisions were adopted during the deindustrialization process between the late 1960s and 1970s and immediately after the first severe decrease in industrial employment (Conde-Ruiz and Galasso, 2003). Life expectancy in the countries of the EU then was around 70 years old. Nowadays, with a life expectancy over 80 years old and the deepest technological change ever going on, the idea of incentivizing early retirement transitions for redundant middle-aged workers is out of the debate. In fact, governments are not only delaying statutory retirement ages but also establishing more restrictive qualifying conditions, such as longer minimum contributory periods, stronger disincentives to retire, penalties for early retirement and bonuses for postponing retirement (European Commission, 2021).

[1] Grace et al. (2018) report the researchers' beliefs of AI outperforming humans in many activities in the next ten years, such as translating languages (by 2024), writing high-school essays (by 2026), driving a truck (by 2027), working in retail (by 2031), writing a bestselling book (by 2049), and working as a surgeon (by 2053). Their results from a large survey of machine learning researchers on their beliefs about progress in AI show that experts in AI believe there is a 50% chance of AI outperforming humans in all tasks in 45 years and automating all human jobs in 120 years.

Therefore, what are then the solutions for middle-aged workers seeking to continue their working lives after being displaced by new technologies? In order to elaborate the proper policies on ageing, we measure the impact of new labour-saving technologies in the early retirement decisions. This chapter contributes to the literature by analysing the implications of the automation process for the early retirement transitions in 26 European countries.

In order to perform our analysis, we consider microdata from the Survey on Health, Ageing and Retirement in Europe (SHARE), the automation degree provided by O* NET (2022) and the automation risk provided by Frey and Osborne (2017). Furthermore, we propose a novel occupational classification in 4 terrains depending on the automation impacts experienced by different occupations (A-terrains classification), inspired by the one proposed by Fossen and Sorgner (2019).

The effect of new labour-saving technologies in the early retirement decisions has important implications in the design of public policies on ageing and retirement. Specifically, we find differentiated effects in terms of gender, education and job status, indicating that policies pursuing the enlargement of the working lives of middle-aged workers should be focused on training programs and self-employment benefits and incentives for this group of people. These training programs and self-employment incentives should be designed to guide the labour reintegration of these workers to perform the occupations at the lowest automation risk. In addition, special attention should be provided to the implications of the current technological change regarding the gender gap.

The rest of the chapter is organised as follows. Section 2 presents the literature review and the main hypotheses of this study. Section 3 collects the data used in the analysis. Section 4 details the modelling approach. Section 5 shows results. Section 6 presents some robustness checks. Finally, section 7 summarises the conclusions derived from this research.

6.2 Literature review and hypotheses

This section presents the literature review and the main hypotheses. First, we consider some relevant works on the impact of automation in the labour market. Second, we examine some other noteworthy articles from the extensive literature on the determinants of early retirement. Third, we explore the relation between new technologies and older workers. Finally, we reveal certain works in the intersection of these strands of the literature, where this work fits, and state the main hypotheses to be tested in the empirical analysis.

6.2.1 The impact of automation in the labour market

Recently, many research works have been disseminated in order to clarify current automation processes. One of the main approaches in this analysis of the impact of new technologies in labour markets is that of the potential automation of tasks. In this line, Manyika et al. (2017) analyse more than 2,000 work activities across 800 occupations discovering that about half of all the activities people are paid to do in the world's workforce could potentially be automated by adapting currently demonstrated technologies. They conclude that, while less than 5 percent of all occupations can be automated entirely using demonstrated technologies, about 60 percent of all occupations have at least 30 percent of constituent activities that could be automated.

Following this approach of tasks automation, at the next level of aggregation, we find out the discussion of potential occupations automation. Interpreting the definition of occupation as a set of tasks and calculating the automation potential of each task that makes up an occupation, we obtain data on the automation potential of concrete occupations. By applying this reasoning, Frey and Osborne (2017) assign a specific probability of automation to 702 occupations using the SOC-2010 classification of occupations. In this broadly cited paper, the authors affirm that 47% of all United States (US) employment is at high risk of automation. Later, these results have been revisited by other researchers offering different visions of the automation process and incorporating other probabilities of automation to the discussion. [2] In their study, Frey and Osborne (2017) use the term computerization, as automation by computer means. Since practically all automation processes in the XXI century are computer-based, literature increasingly applies the terms computerization and automation as synonyms, as we do here.

Fossen and Sorgner (2019) investigate the impact of new digital technologies upon occupations arguing that these effects may be both destructive and transformative depending on the destructive repercussions of digitalization (substitution of human labour) and the transformative consequences of digitalization (complementation of human labour). They distinguish between four broad groups of occupations that differ with regard to the impact of digitalization upon them: (i) Rising star occupations, characterised by the low destructive and high transformative effects of digitalization, (ii) Collapsing occupations, with high risk of destructive effects, (iii) Human terrain occupations, with low risks of both destructive and transformative digitalization, and (iv) Machine terrain occupations, affected by both types of effects.

Another approach to analyse the effect of automation on the labour market is the using of data on robot adoption from the part of industries. Acemoglu and Restrepo (2020a) analyse the effect of the increase in industrial robot usage between 1990 and 2007 on US local labour markets, by using a model in which robots compete against human labour in the production of different tasks, to find that one more robot per thousand workers reduces the employment to population ratio by about 0.18-0.34 percentage points and wages by 0.25-0.5 percent. Furthermore, following this approach, Graetz and Michaels (2018) analyse the economic contributions of modern industrial robots by using panel data on robot adoption within industries in 17 countries from 1993-2007 as well as instrumental variables that rely on robots' comparative advantage in specific tasks. They find that increased robot use contributed approximately 0.36 percentage points to annual labour productivity growth, at the same time it raises total factor productivity and reduces output prices. Contrary to the research of Acemoglu and Restrepo (2020a), they argue that robots did not significantly decrease total employment, although they did reduce low-skilled workers' employment share.

To summarise the main today's challenges for this strand of literature, we highlight the three main sources of uncertainty about the macroeconomic implications of the technological change (Jimeno, 2019): the degree to which new machines and human labour will be complements or substitutes in the production of existing tasks embedded in the production of goods and services, the speed to which tasks performed by human labour could be automated, and the rate at which new tasks are created. Then, the new technological changes (robots, artificial intelligence, automation) may increase productivity growth but at the risk of having disruptive effects on employment and wages. [3]

6.2.2 The determinants of the early retirement decision

The early retirement decision is a topic that has been widely covered in the literature. Among the main determinants of the decision, literature have traditionally highlighted personal circumstances such as financial situation and health or macroeconomic situations, as the political regime in which an individual lives or the generosity of the social security system.

About the generosity of early retirement provisions, Conde-Ruiz and Galasso (2003) show, in a descriptive analysis of eleven OECD countries, that early retirement provisions were adopted during the deindustrialization process.

Regarding the implications of political regimes for the early retirement transitions, Bauman and Madero-Cabib (2021) find that early retirement is more frequent in socialdemocratic regimes (Denmark

[2] For example, other authors claim that the same task may have different implications in different occupations. In this line, Arntz et al. (2016, 2017) repeated the analysis of Frey and Osborne (2017) setting the focus on tasks rather than on occupations to conclude that only 9% of the US occupations have high risk of automation.

[3] See Lee and Lee (2021) for a debate about the degree of disruptiveness of the Fourth Industrial Revolution.

and Sweden) than in liberal welfare regimes (Chile and United States). In addition, they find that adverse health conditions are more frequent among early retirees in liberal but not in social-democratic regimes.

Regarding the influence of personal characteristics of an individual into the early retirement decision, Hernoes et al. (2000) indicate that financial incentives, educational background and industry affiliation have an influence on retirement behaviour. By applying a broader approach, Wilson et al. (2020) identify seven early retirement factors: ill health, good health, workplace issues, the work itself, ageism, social norms and having achieved personal financial or pension requirement criteria. Then, they propose six solutions to enable the enlargement of working life: occupational health programs, workplace enhancements, work adjustments, addressing ageism, changing social norms and pension changes.

Furthermore, early retirement literature has analysed in detail the implications for early retirement of concrete policies. In this line, Schils (2008) finds that pursuing a shift from public to private early retirement schemes can lower the incidence of early retirement and, at the same time, the policy can make early retirement more selective, as only the best paid workers are able to afford it. Besides, Hermansen (2015) shows that working in a company that offers reduced working hours to older workers does not have an effect on the relative risk of a 61- or 62-year-old withdrawing a full contractual pension in the next two years of their employment.

The SHARE - used in this study - has been broadly applied to the analysis of early retirement transitions. By using this survey, Siegrist et al. (2007) find a consistent association of a poor psychosocial quality of work with intended early retirement among older employees across all European countries and highlight the necessity of improved investments into better quality of work, in particular increased control and an appropriate balance between efforts spent and rewards received at work. Markova and Tosheva (2020) choose Bulgaria as the setting to analyse the determinants of an early exit from the labour market, finding that the early retirement plans are significantly shaped by gender, finding out that late career Bulgarians with a primary education are more likely to opt for early retirement than to look for low-quality jobs or be unemployed. Angelini et al. (2009) use the SHARE to describe an "early retirement trap" in which the interaction between early retirement and a limited use of financial markets produces financial hardship late in life. Hochman and Lewin-Epstein (2013) find that grandparenthood increases an individual's chances of looking forward to retiring early. This decision would not be forced by the need to care for their grandchildren since the effect observed is stronger in those countries that provide extensive childcare support. [4] Schmidthuber et al. (2021) use the SHARE to investigate how labour market and pension measures associated with active ageing influence retirement behaviour in Austria and Germany. Furthermore, we can find studies establishing a connection of retirement with a healthy diet (Celidoni et al., 2020), social relationships (Comi et al., 2020), or self-employment (Axelrad and Tur-Sinai, 2021).

6.2.3 New technologies and older workers

The technological displacement of older workers and their retraining needs is an ancient topic in economic literature. We find several early statements about older workers suffering greater hardship due to automation (Stern, 1955; Weinberg, 1956; Diebold, 1959; Snyder, 1962), indicating that the extended joblessness suffered by older workers sometimes is not mitigated by the acquisition of a new skill (Weber, 1963).

The interaction between digitalization and the ageing of the population is another nexus of interest in the nowadays economic literature. Within this strand of literature, Phiromswad et al. (2022) examine and estimate the interaction effects of automation and population ageing on the labour market, to find that automation and population ageing have large and statistically significant effects on employment growth but not on earnings growth. These statistically significant effects are also explored by Acemoglu

[4] In this line, Van Bavel and De Winter (2013), using the European Social Survey, find that becoming a grandparent speeds up retirement, especially at the round ages of 55 and 60 years.

and Restrepo (2022), who describe the ageing of the population as an augmenting-automation process, highlighting that ageing leads to greater industrial automation with a more intensive use and development of robots. Regarding this fact, Jimeno (2019) argues that it is likely that even though population ageing creates incentives for automation, per capita growth will slow down during the current demographic transition.

Recently, the term "digital ageism" is gaining prominence, indicating that many older people find it difficult to navigate the digital sphere and to use online services (see, for instance, Manor and Herscovici, 2021). For the particular case of older workers, the competitive disadvantage managing new technologies has been highlighted by several studies, remarking that the relative deterioration of job prospects for older workers implies that this age group increasingly has more difficulties to adapt to technological progress (Schmidpeter and Winter-Ebmer, 2021). For instance, Fezzani et al. (2010) examine whether motor control difficulty has an impact on the acquisition of a computer task and whether such motor difficulty has the same impact for young and older adults, concluding that motor difficulty has a detrimental effect only for older adults.

Borghans and ter Weel (2002) examine the computer use of older workers to conclude that older workers embody less computer skills than younger workers, highlighting that the main distinction lies between the 20-29 year old workers and the others. Regarding this computer use, Birdi et al (1997), prove, in an observational field study, that due to age-related limitations in cognitive capacities, older workers make significantly more intellectual level errors because these levels are more cognitive-resource intensive. In this line, Adler (1988) highlights the perception of greater flexibility of younger workers compared to older workers as a factor for this significant hardship, indicating that older workers are less likely to have the requisite new skills and often presumed to be less able to adapt. Van Dalen et al. (2010) examine stereotypical perceptions of employers and employees regarding the productivity of young and older workers in the Netherlands, finding that both employers and employees rate the productivity of older workers substantially lower than that of younger workers. Regarding these perceptions, McClure (2018) found that technophobes in the US - those who fear automation - tend to be older, female, and have lower education.

This phenomenon regarding the technological hardship of older workers has been studied in several countries. For instance, Ivanov et al. (2020) use data from Bulgaria to conclude that the human life cycle influences how a human looks upon the threat of automation in the workplace, since they find that younger people are more hopeful and flexible while older people are less flexible and less willing to invest time in retooling themselves for the workplace. Heywood et al. (2011), using German establishment data, find that establishments with jobs that require use of computers are less likely to hire older workers. Daveri and Maliranta (2007) study the case of Finland to find that the skills of older workers have been challenged by the unusually fast pace of the IT revolution in that country. Hirsch et al. (2000) examine the hiring opportunities of older US workers, finding reduced opportunities for older workers in occupations with steep wage profiles, pension benefits and computer usage.

Related to the technological hardship, some studies have documented that older workers receive less training than their younger counterparts, while experiencing extra learning difficulties. For instance, Dychtwald et al. (2004) annotate that most human resource practices are often explicitly or implicitly biased against older workers, [5] pointing out that older workers (age 55 plus) receive on average less than half the amount of training that any of their younger cohorts. This training gap of older workers with respect to younger counterparts is more pronounced if we consider that older workers within this age range will typically require up to twice as much time to master a new application or technology if it is weakly related to prior knowledge (Charness, 2006). In addition, lack of confidence in their relevant abilities is another possible source of the difficulties that the elderly may encounter in mastering computer technologies (Marquié et al., 2002).

[5]Slowed performance, decreased ability to learn new skills, increased accidents, rigidity, resistance to supervision, irritability, and poor health are among some of the stereotypical perceptions of the older worker (Stanger, 1985).

These extra learning difficulties for older workers match the statements developed by Bartel and Sicherman (1990) indicating that, according to the theory of human capital, technological change influence the retirement decision of older workers in two ways: (i) workers in industries that are characterised by high rates of technological change will have later retirement ages because these industries require larger amounts of on-the-job training and (ii) an unexpected change in the industry's rate of technological change will induce older workers to retire sooner because the required amount of training will be an unattractive investment.

Wong and Tetrick (2017) highlight that older workers may choose to learn how to navigate new computer systems based on their interest in technology, focusing their attention on achieving a sense of mastery despite common stereotypes. In this sense, automation may be seen for older workers as an opportunity (instead of as a threat) to shift away from physically arduous duties and diversify their job tasks. Indeed, the replacement of physically demanding tasks with the use of home-based communication and information technologies could also allow the older worker to remain employed (Dropkin et al., 2016). In fact, other studies have shown that older workers are as flexible, trainable, and cost-effective as younger employees (McNaught and Barth, 1992; Sterns and Miklos, 1995), while indicating that older workers are not much worse than their younger counterparts in the real-world context in terms of making errors in computerbased work (Birdi et al., 1997). Older workers also show comparable performance on multiple telecommuting tasks to their younger colleagues (Sharit et al., 2004).

6.2.4 Considering automation as a determinant of the early retirement decision

We can find the consideration of automation as a possible cause of early retirement in documents from the 60s. In Barfield and Morgan (1969) we can read "...having experienced a change in the nature of one's job (for example, automation or other technological change) seems associated with having retired or planning to retire early". In this line, Bazzoli (1985) considered that economic variables play a more relevant role than health in retirement decisions.

More recently, Dorn and Sousa-Poza (2005) wonder if early retirement is a free or forced decision to conclude that, although the early retirement decision is usually explained as a supply-side phenomenon, it can also be a demand-side phenomenon arising from the firm's profit maximisation behaviour. These authors give special relevance to the distinction between 'voluntary' and 'involuntary' early retirement, finding the latter particularly widespread in Continental Europe (Dorn and Sousa-Poza, 2010).

Ahituv and Zeira (2011) combine the concepts of early retirement and technical progress to find that technical progress has two opposite correlations with early retirement: while it has a negative effect on labour supply of older workers, it raises wages on average and thus increases the incentive to remain at work.

Finally, an exception for the lack of evidence connecting the process of automation with the early retirement transitions would be the work developed by Yashiro et al. (2022), who measure this connection for the case of Finland by using the automation probability provided by Nedelkoska and Quintini (2018). Another exception is the study developed by Hudomiet and Willis (2021), whose results indicate that many older workers retired earlier than "normal" in the US when automation first penetrated their occupations, suggesting that older workers who are close to the end of their working lives may be forced into early retirement if it is not optimal for them to make human capital investments compensating their skills obsolescence.

6.2.5 Hypotheses

According to Ahituv and Zeira (2011), every technical change involves two effects for older workers: the wage effect - raised aggregate wages - and the erosion effect - the learning efforts dedicated to the new technologies pays off less gains since they have shorter career horizons. In this case, we expect the erosion effect outperforming the wage effect in the automation technical change since capitalised software investment raises worker earnings at a rate that declines after the age of 50 , to about zero beyond 65 (Barth et al., 2022).

Reinforcing this first hypothesis, Georgieff and Milanez (2021) evidence that occupationlevel job tenure has fallen more in occupations at high risk of automation, being this negative effect particularly pronounced among older workers. This fact highlights that the stronger declines in job stability among workers in high-risk occupations have mostly affected older workers. Concretely regarding the impact of automation in the length of working life, Hudomiet and Willis (2021) analyse how automation affected the labour market outcomes of older workers between 1984 and 2017 in the US, finding that there was a temporary knowledge gap between younger and older workers in most occupations that shortened the working lives of older workers and it decreased their wages.

Dychtwald et al. (2004) sketches that because costs and premiums increase with age, employers have a disincentive to retain older workers. This consideration can get accentuated if due to technological advancement and new capital price reduction, it results budget attractive to computerised certain productive processes involving older workers. Another important consideration is that not only direct substitution with new technologies is produced, but also firms may have incentives to substitute older workers for younger workers with higher skills regarding new technologies. In fact, by studying the productivity-wage gaps among age groups, it has been shown that young workers are paid below and older workers above their marginal productivity (Cataldi et al., 2011). Furthermore, it has been proven that technological change influences the retirement decision of older workers (Bartel and Sicherman, 1990). Thus, our first hypothesis states as follows:

H1. *Workers facing a higher impact of automation in their current occupation are more likely to retire early.*

The literature has documented that women have a higher automation risk (Egana-delSol et al., 2022) and value early retirement more than men (Dano et al., 2005). In addition, literature has also collected evidence of age discrimination in hiring against older women, especially those near retirement age (Neumark et al., 2019). Thus, we expect to find that automation influences the early retirement decision differently depending on the gender of the individual and formulate our second hypotheses as follows:

H2a. *Female workers are more likely to retire early than male workers, independently of the automation process.*

H2b. *The early retirement probability of female workers is more affected by automation than the early retirement probability of male workers.*

Macroeconomic models have presented automation as a process in which unskilled workers are displaced by the combination formed by equipment capital and skilled workers. Using this capital-skill complementarity assumption, Krusell et al. (2000) explain the evolution of the skill premium in the US from the 1970's. Under a similar assumption, Sachs and Kotlikoff (2012) present a simple framework in which smart machines substitute directly for young unskilled labour, whereas they are complementary to older skilled workers.

This phenomenon of older skilled workers complementing new capital devices has been also studied at the microeconomic level. For instance, Biagi et al. (2013) find evidence of older employees who use a PC at work having a higher probability of remaining employed in the future. Friedberg (2003) argues that impending retirement, rather than age alone, explains why older workers use computers less than prime-age workers do, highlighting that computer users retire later than non-users. Schleife (2006), using German data, finds a strong and negative relationship between the age of workers and computer use, with a significantly positive correlation of educational level and occupational status on computer use. Then, although older workers are less likely to use computers, educational level is positively correlated with computer use.

Based on the aforementioned evidence, we expect the early retirement probabilities of workers with higher education to remain unaffected by the automation risk, while the early retirement probabilities of the rest of workers are significantly impacted by automation risk. Therefore, we hypothesise the following:

H3a. *Workers with higher education are less likely to retire early than workers without higher education, independently of the automation process.*

H3b. *The early retirement probability of workers with higher education is not significantly affected by automation.*

The retirement behaviour of self-employed workers is different from that of employees or civil servants (Sappleton and Lourenco, 2015). This different behaviour has been covered by the literature, indicating that, in general, self-employed people tend to work longer than individuals employed in organisations (Parker and Rougier, 2007). The fact that the self-employed generally perceive their jobs to be more "autonomous" than employees (Hundley, 2002), being able to self-direct the content of work-related tasks, is one of the characteristics that create the gap in retirement time preferences between selfemployed and employees (Zwier et al., 2020). In addition, transitions to self-employment at old ages have been documented as a bridge to retirement (Nolan and Barret, 2019; Alcover et al., 2021). These transitions to self-employment of the elderly to delay retirement may be exacerbated by automation processes. The risk of job loss due to destructive effects of digitalization may enhance the decision to become self-employed because of a lack of alternative opportunities in dependent employment (Fossen and Sorgner, 2021; Shapiro and Mandelman, 2021). In this context, the appearance of digital technologies may create incentives for both retiring earlier-due to a lack of interest or capacity to adopt the new technology, that may jeopardize the business- as well as for retiring later -to maximize the benefits from the learning efforts to digitalize their businesses to improve customers satisfaction-.

All in all, the above arguments, the procedural utility experienced by self-employed workers (Benz and Frey, 2008) and their autonomy to adapt their jobs to changing environments lead us to hypothesise the following:

H4a. *Self-employed workers are less likely to retire early than employees or civil servants, independently of the automation process.*

H4b. *Automation affects the early retirement probability of the self-employed workers differently compared to employees and civil servants.*

6.3 Data

Our analysis relies upon 3 levels and 5 data sources, as it is detailed below. In the first data level, we use microdata from the Survey on Health, Ageing and Retirement in Europe (SHARE) as a baseline to add the other two levels of data. In the second level, we have data linking occupations with automation measures from two sources: (i) Frey and Osborne (2017) for the automation risk and (ii) O*NET (2022) for the automation degree. The selection of these two automation measures aims to offer a full vision of the automation process collecting both the backward-looking and the forward-looking impacts of automation in occupations. Hence, we can extract conclusions about whether the automation degree or the automation risk are triggering early retirement transitions. Finally, in the third level, we have macroeconomic data to control the economic situation by country (real GDP growth rate, from the World Bank; and harmonised unemployment rate, from Eurostat) and the generosity of social security system (old-aged pensions in PPS per inhabitant, Eurostat). This information about data level and sources is summarised in Table 6.1.

The SHARE is a research infrastructure carried out from 2004 until today, accounting for 480,000 in-depth interviews with 140,000 people aged 50 or older from 28 European countries and Israel. In fact, SHARE is the largest pan-European social science panel study providing internationally comparable longitudinal micro data which allow insights in the fields of public health and socio-economic living conditions of European individuals. From 2004, SHARE has released 8 waves (being the third wave

TABLE 6.1: Data levels and sources

Data level	Data source
Microdata	SHARE (Eurofound)
Early retirement decision, gender, age, cohabiting status, health, financial situation, education, job characteristics	
Measures for technological change by occupation	
Automation risk	Frey and Osborne (2017)
Automation degree	O*NET (2022)
Macroeconomic data by country	
Real GDP growth rate	World Bank
Harmonised unemployment rate and old-aged pensions in PPS per inhabitant	Eurostat

specialised in health and the eighth wave consisting in a COVID-19 survey). In our case, we live aside these special waves 3 and 8 .

In particular, this chapter uses data from the generated Job Episodes Panel. [6] Then, we merge some extra information of respondents from waves 1, 2, 4, 5, 6 and 7. In order to develop our work, it has been particularly important the information provided in the retrospective modules of wave 7 , since they contain information about all working lives of respondents with high degree of detail. Within these modules, we can find the 2008 International Standard Classification of Occupations (ISCO-2008) 4-digits code for all occupations that respondents realised in their working lives. Therefore, these modules result crucial to merge the technological measures of automation degree and risk.

After merging all the information required for our analysis into a single database, we finally stick with 26 European countries, as 3 of the countries in the SHARE (Israel, Ireland and The Netherlands) are lost because of data unavailability (for example, we do not have a disaggregation at 4-digit level for occupations in Ireland). Then, our geographical coverage is the following: Austria, Germany, Sweden, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Czech Republic, Poland, Luxembourg, Hungary, Portugal, Slovenia, Estonia, Croatia, Lithuania, Bulgaria, Cyprus, Finland, Latvia, Malta, Romania, Slovakia.

The job episodes panel and the retrospective information contained in the different waves allow us to follow the individuals for their entire life since birth. However, for assuring representativeness of our results and given that we are trying to measure the impact of the current technological change in the early retirement decisions, we restrict our sample so that (i) time coverage spans 14 years from 2004 to 2017 and (ii) individuals are over 50 , which is the age from which individuals are eligible to be interviewed at SHARE.

Then, the sample is composed by men and women over 50 and younger than their statutory retirement age who are workers (employees, civil servants or self-employed workers) in period t and either (i) become early retirees in period $t+1\,(\mathrm{WO_t} \rightarrow \mathrm{ER_{t+1}})$ or (ii) remain as workers in period $t+1\,(\mathrm{WO_t} \rightarrow \mathrm{WO_{t+1}})$. Finally, our sample is composed of 118,467 observations, corresponding to 17,506 individuals. In this sample, we find 6,340 transitions from work to early retirement.

6.4 Modelling approach

Our dependent variable (early retirement) takes value 1 when a worker decides to retire before his statutory retirement age and 0 when the individual remains working. Thus, given the binary nature of

[6] https://doi.org/10.6103/SHARE.jep.710. See Brugiavini et al. (2019) and Antonova et al. (2014) for methodological details.

our dependent variable, we estimate the probability of early retirement using logit models and report average marginal effects. [7]

As we aforementioned, the main explicative variables are the automation risk (Frey and Osborne, 2017), the automation degree (O*NET, 2022), and the technological classification of occupations -A-terrains classification-constructed using the two aforementioned variables. While the automation risk variable categorises occupations according to their susceptibility to computerisation, based on advances in Machine Learning and Mobile Robotics (forward-looking vision), the automation degree variable indicates the current automation degree of the occupation (backward-looking vision).* [8] *Our destructive digitalization measures rely on the Occupational Information Network, O*NET database, compiled by the US Department of Labor, which is a database of quantitative indicators of occupational requirements, workforce characteristics, and occupation-specific information that constitutes the primary occupational database in the US. The O*NET Data Collection Program provides several hundred descriptive ratings based on O*NET questionnaire responses by sampled workers and occupation experts, providing direct information that is usually difficult to measure. [9]

The first measure considered, the automation risk, is the computerization probability from Frey and Osborne (2017), a measure based on experts predictions regarding potential developments in Machine Learning and robotics. Concretely, the measure captures the risk of the replacement of human workers by machines in the next 10-20 years based on expert judgments and selected characteristics of occupations from the O*NET database. The study by Frey and Osborne (2017) consists of two stages. First, technology experts provide estimates for 71 occupations regarding their automation suitability over the next 20 years. Second, this experts-ranked list of occupations encompasses a training data set for a machine learning algorithm that classifies the remaining occupations in the O*NET database based on job requirements identified as computerization bottlenecks (perception and manipulation, creative intelligence and social intelligence).

The second measure considered is the automation degree from the O ∗ NET database, a measure collecting the current automation degree of occupations. This variable can be found in the database within the consideration of Work Context. More precisely, the variable is framed in the category of Structural Job Characteristics, being part of the subset of variables that measure the relative amounts of routine versus challenging work that the worker will perform as part of a specific occupation. This variable has been previously used for research purposes to investigate the effect of automation levels on US interstate migration (Okamoto, 2019).

We adapt these measures to the 4-digits ISCO08 classification collected by the SHARE database as follows. The automation risk is provided for 702 occupations according to the SOC10 classification, so we establish a direct crosswalk from the 6-digits SOC10 classification to the 4-digits ISCO08 classification. The automation degree is provided for 873 occupations according to O* NET SOC codes, so we establish a crosswalk from O*NET SOC to the SOC18, then a crosswalk from the SOC18 to the SOC10 and finally a crosswalk between the 6-digits SOC10 classifications and the 4-digits ISCO08 classification. Since ISCO08 is a more aggregated classification than SOC10, we account for automation risk and automation degree measures for 407 occupations.

[7] Our results are robust to several specifications of the variance covariance matrix corresponding to the parameter estimates. In addition, we also check if the panel-level variance component is important, but the likelihood-ratio tests performed point for the use of the pooled estimator. Standard errors are clustered at the individual level.

[8] In our analysis, automation risk and automation degree are included as continuous variables, so that we estimate how the probability of early retirement changes when these variables increase in one percentage point. Then, from these continuous variables we construct dummy variables that take value 1 when the automation degree/risk is higher than a predetermined threshold, as it is explained below. These dichotomized versions of the main variables are used in the analysis when looking for differentiated effects of automation for different groups of individuals presented in section 5 below. We have also estimated those models with interactions using the continuous versions of the automation variables. Results are similar to those obtained when using the dichotomised versions of the automation variables.

[9] More information about O* NET database can be found at https://www.onetcenter.org/database.html

TABLE 6.2: Classification of occupations by automation impact: A-terrains classification.

		Automation risk	
		Low	High
Automation degree	High	Collapsing automation (CA)	Automation terrain (AT)
	Low	Hands terrain (HT)	Rising automation (RA)

In order to combine both the forward-looking impact of automation upon occupations, and its backward-looking effect, the proposed classification includes four different types of occupations, as summarised in table 6.2 .[10]

This technological classification is inspired by the one proposed by Fossen and Sorgner (2019). While their classification collects both destructive and transformative digitalization, our classification focuses on destructive digitalization involving both a backward-looking and a forward-looking measure of this technological phenomenon. Specifically, the Fossen's and Sorgner's (2019) classification uses a measure of AI advances (Felten et al., 2018) to collect the effect of transformative digitalization and the Frey and Osborne (2017) measure of automation risk to collect the effect of destructive digitization. It could be argued that the AI advances measure is a backward-looking variable that looks at the current advances that already exist in AI while the Frey's and Osborne's (2017) variable is a forward-looking variable based on experts' opinions about potential developments in Machine Learning and robotics. Consequently, our classification differs from Fossen and Sorgner's (2019) in the sense that we replaced their backward-looking measure for transformative digitalization with a backward-looking measure for destructive digitalization, creating a classification that encompasses only destructive digitalization rather than digitalization in general. To the best of our knowledge, this is the first classification of occupations regarding destructive digitalization considering both its backward-looking and forward-looking dimensions.

Thus, depending on their affectation by the automation degree or the automation risk, occupations can be classified in four different categories. First, occupations with a low degree of automation as well as a low automation risk would be in the Hands terrain. Second, occupations with a low degree of automation but a high automation risk would be in the Rising automation terrain. In this terrain, although the current automation degree is low, it is expected to be automated in the following years. Third, occupations with a high degree of automation but a low automation risk would be in the Collapsing automation terrain. Although occupations in this terrain possess a current high automation degree, they are not expected to be fully automated in the near future. Finally, when we have both a high degree of automation and a high automation risk, the occupation would be in the Automation terrain. Therefore, the variable for the classification of A-terrains takes values from 1 to 4 depending on the classification of the occupation within the four groups considered.

Our control variables include information about demographics, employment and the macroeconomic environment. Thus, we control for gender, age, cohabiting status, physical health -measured in a 1-5 scale from Excellent (1) to Poor (5)-, financial situation -measured as the ability to make ends meet in a 1-4 scale from With great difficulty (1) to Easily (4)-, and having higher education. Regarding employment variables, we consider the job status, which includes three categories (employees -private sector-,

[10] The thresholds for classifying occupations are 70% for the automation risk (this variable takes values from 0.39% to 99% in the sample) and 30% for the automation degree (this variable takes values from 5 to 66 in the sample). While the 70% threshold for the high automation risk was set by Frey and Osborne (2017), we set the threshold for the high automation degree at 30%, close to the median value of the variable (28%). Our results hold when the automation degree threshold is equated to the median value of the variable.

civil servants -public sector-, self-employed workers), the sector of activity (primary sector, manufacturing and construction, and services) and a variable indicating if the individual is working full time or not. In order to control for macroeconomic environment, we use the real GDP growth, the harmonised unemployment rate and the expenditure in old-aged pensions in PPS per inhabitant. [11] We include a variable collecting the effect of the social security system generosity of each country, as it has a strong effect incentivizing the early retirement decision. [12] Last, we use country and wave dummies.

6.5 Results

This section shows the main results of this study, divided in three parts. First, we depict the descriptive statistics and we show the mapping of occupations for the early retirement transitions in our sample. Second, we analyse the association between automation and the probability of early retirement, looking for differentiated effects by gender, education and job status. Finally, we present some additional tests that give confidence to our main results.

6.5.1 Descriptive statistics and the mapping of early retirement transitions in A - terrains

In this subsection, we present a descriptive analysis of our data and offer a vision of the early retirement transitions by occupation in their corresponding A-terrains.

Table A6.1 in the Appendix presents some descriptive statistics of our sample. These descriptive statistics are profiled firstly for the whole sample, then only for the observations regarding the transitions to early retirement and finally for the rest of the observations. As we can observe, there are some conspicuous differences in the value of some variables for observations regarding the switch to early retirement and the rest of observations. First, the mean automation risk is almost 4% higher when the switch to early retirement is produced, while its standard deviation accounts for 1.5% less. We can also find that the mean automation degree is slightly higher for the early retirees, although with the same standard deviation. These differences are also observable in the A-terrains, as, in the switch to early retirement, there are less occupations in the Hands terrain and more in the Automation terrain. About job status, we can find a lower percentage of employees and self-employed while a larger percentage of civil servants in the transitions to early retirement. As logical, the percentage of workers with higher education is lower among early retirees. Furthermore, we can see that the percentage of occupations in the services sector is lower in early retirement transitions and, as indicated by literature, GDP's growth is lower for these observations.

Now that we have described some statistics, we offer a vision of all early retirement transitions in our sample relying on our A-terrains classification. In Figure 6.1 we can find a graph collecting 6,340 early retirement transitions from 387 different occupations. Every bubble matches a concrete occupation, being its centre at the point determined by its automation risk in the x-axis and its automation degree measure in the y-axis. The size of each bubble depends on the number of early retirement transitions that took place in the period 2004-2017 from that precise occupation. The two perpendicular red lines delimit the four A-terrains considered in this research, as presented in Table 6.2 . As we can observe, early retirement transitions are similarly divided among the different terrains, with a lower number of transitions from the Collapsing automation terrain. Specifically, a 26% of the transitions occurred from the Hands terrain, an 11% from the Collapsing automation terrain, a 33% from the Rising automation terrain and a 30% from the Automation terrain.

[11] An equivalent measure would be the Expenditure in social protection -old age function- in PPS per inhabitant, also from Eurostat, as both variables are highly correlated and show very similar results.

[12] OCDE countries have been documented by Blöndal and Scarpetta (1997). If we want to look for specific examples analysing European countries we can find, for example, Blundell et al. (2002) for the case of the UK and Börsch-Supan and Jürges (2009) for the case of Germany.

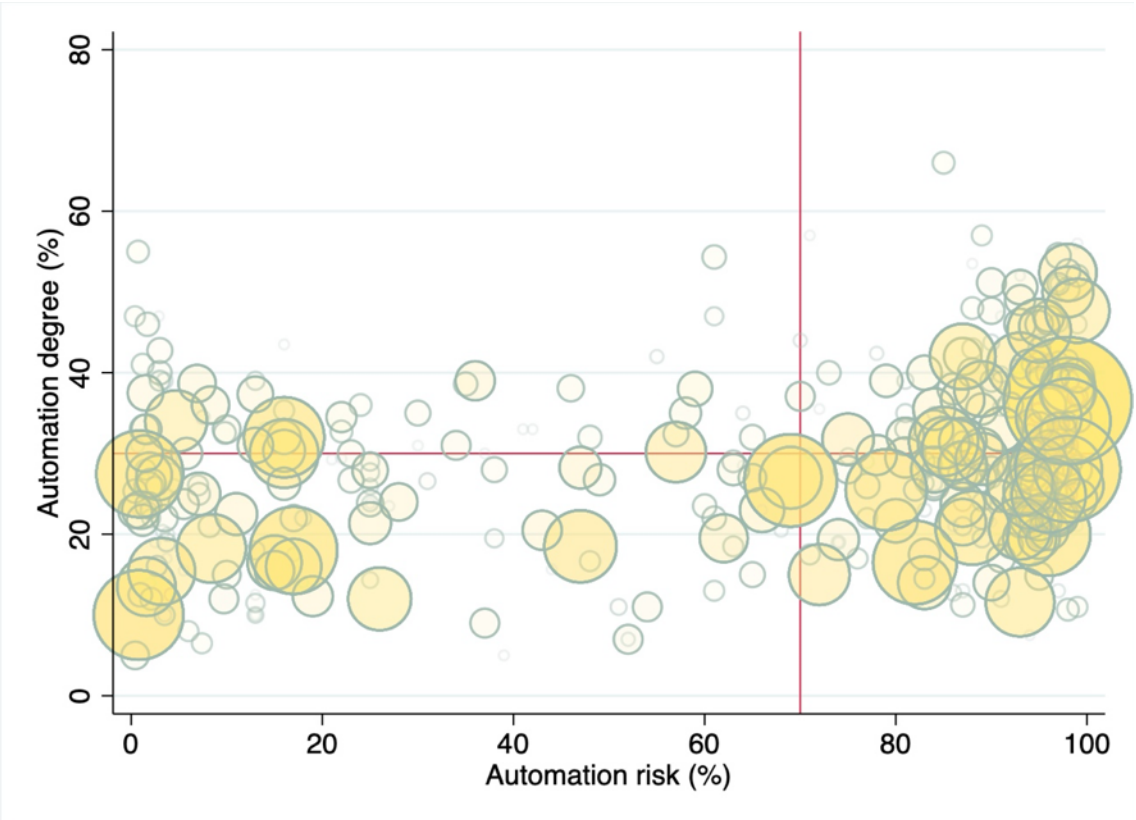

FIGURE 6.1: Early retirement transitions and A-terrains.

Note: Compiled by the authors from the SHARE data and considering the *A*-terrains classification.

In Table 6.3 , we can see the data associated with Figure 6.1 with information of education and job status. In each cell we present the number of early retirement transitions, indicating in parentheses the shares of early retired individuals in each category.

TABLE 6.3: Early retirement transitions and the A-terrains classification

A-terrains	#Early retirement transitions (share in each category)						
	Education		Job Status			Total	
	No HE	HE	EM	CS	SE		
HT	868(0.31)	790(0.29)	620(0.28)	923(0.32)	115(0.26)	1,658(0.30)	26%
CA	472(0.39)	214(0.26)	303(0.31)	266(0.40)	117(0.33)	686(0.34)	11%
RA	1,915(0.38)	168(0.27)	1,202(0.36)	676(0.42)	205(0.31)	2,083(0.37)	33%
AT	1,610(0.37)	303(0.26)	1,073(0.33)	706(0.40)	134(0.28)	1,913(0.35)	30%
Total	4,865(0.37)	1,475(0.28)	3,198(0.33)	2,571(0.37)	571(0.30)	6,340(0.34)	100%
	77%	23%	50%	41%	9%		

Notes: HE: higher education; EM: employee; CS: civil servant; SE: self-employed worker; HT: hands terrain; CA: collapsing automation; RA: rising automation; AT: automation terrain.

As we observe, only 23% of the early retirement transitions come from workers with higher education while the remaining 77% come from workers without higher education. In other words, for every 4 early retirees only 1 has higher education. Also, we observe that only 9% of the early retirement transitions proceed from self-employed workers while the rest come from employees (50%) and civil servants (41%).

Table 6.4 adds a deeper dimension with respect to Table 6.3 , by incorporating the number of early retirees that account for higher education for every combination of job status and terrain. Then, as we can observe, from the 1,913 early retirees that were employees in the Automation terrain, only 303 had higher education. Alike, from the 2,083 early retirees that were employees in the Rising automation terrain, only 168 had higher education.

TABLE 6.4: Early retirement transitions and education level by A-terrains and job status

A-terrains	#Early retirement transitions (share in each category)							
	EM		CS		SE		Total	
	No HE	HE	No HE	HE	No HE	HE	No HE	HE
HT	620(0.28)		923(0.32)		115(0.26)		1,658(0.30)	
	395(0.29)	225(0.27)	404(0.35)	519(0.30)	69(0.30)	46(0.22)	868(0.31)	790(0.29)
CA	303(0.31)		266(0.40)		117(0.33)		686(0.34)	
	202(0.36)	101(0.24)	180(0.46)	86(0.31)	90(0.37)	27(0.24)	472(0.39)	214(0.26)
RA	1,202(0.36)		676(0.42)		205(0.31)		2,083(0.37)	
	1,112(0.37)	90(0.25)	629(0.43)	47(0.30)	174(0.31)	31(0.32)	1,915(0.38)	168(0.27)
AT	1,073(0.33)		706(0.40)		134(0.28)		1,913(0.35)	
	895(0.35)	178(0.27)	605(0.44)	101(0.26)	110(0.29)	24(0.25)	1,610(0.37)	303(0.26)
Total	3,198(0.33)		2,571(0.37)		571(0.30)		16,340(0.34)	
	2,604(0.35)	594(0.26)	1,818(0.41)	753(0.30)	443(0.31)	128(0.25)	4,865(0.37)	1,475(0.28

Notes: HE: higher education; EM: employee; CS: civil servant; SE: self-employed worker; HT: hands terrain; CA: collapsing automation; RA: rising automation; AT: automation terrain.

Table 6.5 also complements Figure 6.1 by presenting the thirty occupations with higher number of early retirement transitions in order to develop a brief qualitative analysis.

It shows the ISCO-08 title of the occupation, the ISCO-08 code, the number of transitions to early retirement from that occupation, the number of workers in each occupation and the ratio between the number of transitions and the number of workers, its associated automation risk, the automation degree and the A-terrain to which the occupation belongs to. The occupations are in descending order by ratio between number of early retirement transitions and total number of workers.

Within these 30 occupations with higher early retirement transitions, we find 2 occupations in the Collapsing automation terrain, 9 in the Automation terrain, 10 Rising automation occupations and 9 occupations from the Hands terrain. We find that 13 of these occupations (almost half) have an associated automation risk higher than 90%. By contrast, we also find 4 occupations with less than 10% of automation risk. In sum, the 30 occupations from Table 6.5 account for 2,545 early retirement transitions, which means that 8% of the 387 occupations account for 40% of the total 6,340 early retirement transitions.

TABLE 6.5: Early retirement transitions and occupation titles.

	ISCO-08 Title	ISCO-08	#ER transitions	Total workers	Ratio: #ER/ total workers	Automation risk	Automation degree	A-terrain
1	Toolmakers and related workers	7222	61	125	.488	93	26.34	RA
2	Bricklayers and related workers	7112	100	211	.474	82	16.5	RA
3	Mail carriers and sorting clerks	4412	57	128	.445	95	45.2	AT
4	Manufacturing labourers not elsewhere classified	9329	62	143	.434	93	40.88	AT
5	Agricultural and industrial machinery mechanics and repairers	7233	77	181	.425	88	20.78	RA
6	Motor vehicle mechanics and repairers	7231	67	162	.414	93	11.6	RA
7	Electrical mechanics and fitters	7412	54	137	.394	93	20.69	RA
8	Secondary education teachers	2330	115	297	.387	.78	10	HT
9	Heavy truck and lorry drivers	8332	94	252	.373	79	25.5	RA
10	Secretaries (general)	4120	99	267	.371	96	20	RA
11	Vocational education teachers	2320	56	151	.371	26	12	HT
12	Accounting and bookkeeping clerks	4311	61	168	.363	96	34.5	AT
13	General office clerks	4110	236	659	.358	98	36.5	AT
14	Shopkeepers	5221	92	260	.354	16	32	CA
15	Freight handlers	9333	68	193	.352	85	31.5	AT
16	Accounting associate professionals	3313	104	310	.336	98	34	AT
17	Primary school teachers	2341	109	324	.336	17	18	HT
18	Cleaners and helpers in offices, hotels and other establishments	9112	123	380	.324	69	26.67	HT
19	Car, taxi and van drivers	8322	66	209	.316	98	28	RA
20	Managing directors and chief executives	1120	67	220	.305	16	30	CA
21	Accountants	2411	58	192	.302	99	47.67	AT
22	Administrative and executive secretaries	3343	55	184	.299	86	30.5	AT
23	Shop sales assistants	5223	159	547	.291	98	28	RA
24	University and higher education teachers	2310	63	218	.289	3.2	15.4	HT
25	Subsistence crop farmers	6310	61	214	.285	87	42	AT
26	Cooks	5120	78	274	.285	96	24.8	RA
27	Nursing professionals	2221	108	391	.276	.9	27.47	HT
28	Domestic cleaners and helpers	9111	54	199	.271	69	27	HT
29	Health care assistants	5321	74	286	.259	47	18.5	HT
30	Child care workers	5311	67	278	.241	8.4	18.25	HT

Note: ER: early retirement.

6.5.2 Early retirement and automation

Here we demonstrate the significance of the automation degree and the automation risk in the early retirement decisions and then show differentiated effects of automation degree, risk and terrains with respect to higher gender, education and job status.

Tables 6.6,7 and 8 collect fifteen estimations of logit models. Concretely, Table 6.6 considers the automation risk as the main regressor, Table 6.7 explores the effect of automation degree and Table 6.8

presents the results for the automation terrains. Each table collects 5 estimations in which the number of control variables increase progressively from the first estimate to the last. The first estimation controls for gender, age, cohabiting status, and includes country and wave dummies. The second estimation also controls health and financial situation. The third estimation also controls for higher education. The fourth estimation adds the job characteristics controls: job status, contract type, and industry. The last estimation also controls for macroeconomic variables: GDP growth, harmonised unemployment rate and old age pensions in PPS per inhabitant.

TABLE 6.6: Determinants of early retirement transitions with special focus on automation risk - Forward-looking vision - Logit estimations

Model	**I**		**II**		**III**		**IV**		**V**	
Predicted probability (y)	0.0535		0.0535		0.0535		0.0535		0.0535	
Independent variables (x)	$\frac{dy}{dx}/y\%$	z-stat	$\frac{dy}{dx}/y\%$	z-stat	$\frac{dy}{dx}/y\%$	z-stat	$\frac{dy}{dx}/y\%$	z-stat	$\frac{dy}{dx}/y\%$	z-stat
Main regressors										
Automation risk (%)	0.27	8.55 ***	0.23	7.17 ***	0.11	3.28 ***	0.11	3.12 ***	0.11	3.13 ***
Controls										
Female[a]	39.03	15.76 ***	38.84	15.67 ***	38.72	15.64 ***	45.78	16.84 ***	46.01	16.9 ***
Age	34.94	72.96 ***	34.79	72.62 ***	34.91	72.86 ***	35.18	73.54 ***	35.25	73.47 ***
With partner[a]	9.54	3.5 ***	9.93	3.64 ***	9.28	3.4 ***	10.40	3.85 ***	10.16	3.75 ***
Health (ref. Excellent)										
Very good			7.96	2.06 **	7.92	2.03 **	8.37	2.15 **	8.41	2.16 **
Good			20.83	5.55 ***	19.28	5.11 ***	19.38	5.15 ***	19.51	5.19 ***
Fair			36.23	8.26 ***	33.53	7.62 ***	33.53	7.65 ***	33.53	7.66 ***
Poor			64.63	8.59 ***	60.59	8.14 ***	61.66	8.24 ***	62.09	8.29 ***
Ability to make ends meet (ref. With great difficulty)										
With some difficulty			8.99	1.94 *	9.41	2.07 **	7.50	1.64	8.07	1.77 *
Fairly easily			1.27	0.28	3.47	0.76	2.10	0.46	2.69	0.59
Easily			2.07	0.43	6.65	1.39	4.57	0.95	4.90	1.02
Education										
Higher education[a]					-26.63	-9.8 ***	-28.04	-10.33 ***	-28.19	-10.39 ***
Job characteristics										
Job status (ref. Employee)										
Civil servant							18.51	6.35 ***	18.17	6.23 ***
Self-employed							-31.48	-9.68 ***	-31.47	-9.66 ***
Full time[a]							27.26	8.55 ***	27.24	8.52 ***
Sector (ref. Primary)										
Manufacturing and Construction							3.97	0.82	3.85	0.79
Services							-14.55	-3.24 ***	-14.89	-3.3 ***
Macroeconomic variables										
GDP growth									-0.58	-1.03
Harmonised unemployment rate									2.48	5.32 ***
Old age pensions pps per capita									0.02	1.57
Country dummies (ref. Spain)	Yes		Yes		Yes		Yes		Yes	
Wave dummies (ref. 2004)	Yes		Yes		Yes		Yes		Yes	
Log likelihood	-18,935.3		-18,855.6		-18,810.8		-18,678.8		-18,660.6	
#obs.	118,467		118,467		118,467		118,467		118,467	

Notes: * 0,1 > p ≥ 0,05; ** 0,05 > p ≥ 0,01; *** p < 0,01. [a] Dummy variable.

The result of the first estimation in Table 6.6 is telling us that an increase of 1% in the automation risk augments, on average, the probability of early retirement by 0.27%. In the estimations III-V an increase of 1% in the automation risk would raise the probability of early retirement by 0.11%. These results mean, in the case of the first estimate, an increase in the probability of early retirement by 27% when traversing the spectrum of the variable. We must also bear in mind that this effect can largely vary between different individuals. In fact, as we observe in figures 6.2, 6.3 and 6.4 and tables 6.9, 6.10 and 6.11, we find differentiated effects for higher gender, education, job status.

Table 6.7 collects the positive significant effect of the automation degree increasing the early retirement probability. As we observe, the significance and the impact of the automation degree is only slightly reduced when we consider the higher education control. Then, we can conclude that automation plays a relevant role in the early retirement decision both from a backward-looking and a forward-looking perspective. Table 6.8 offers the results for the A-terrains as the main regressor, collecting the

TABLE 6.7: Determinants of early retirement transitions with special focus on automation degree - Backward-looking vision - Logit estimations

Model	VI			VII			VIII			IX			X		
Predicted probability (y)	0.0535			0.0535			0.0535			0.0535			0.0535		
Independent variables (x)	$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat	
Main regressors															
Automation degree (%)	0.49	4.13	***	0.48	4.05	***	0.30	2.5	**	0.31	2.53	**	0.31	2.51	**
Controls															
Female[a]	37.93	15.39	***	37.79	15.31	***	38.20	15.46	***	45.27	16.64	***	45.51	16.7	***
Age	34.88	72.84	***	34.74	72.55	***	34.90	72.86	***	35.18	73.54	***	35.24	73.47	***
With partner[a]	9.27	3.4	***	9.96	3.65	***	9.21	3.38	***	10.35	3.83	***	10.10	3.73	***
Health (ref. Excellent)															
Very good				7.85	2.05	**	7.87	2.02	**	8.35	2.15	**	8.40	2.16	**
Good				21.57	5.78	***	19.47	5.17	***	19.56	5.2	***	19.68	5.24	***
Fair				37.93	8.66	***	34.06	7.75	***	34.02	7.77	***	34.01	7.77	***
Poor				66.39	8.8	***	60.99	8.18	***	62.04	8.28	***	62.48	8.34	***
Ability to make ends meet (ref. With great difficulty)															
With some difficulty				8.41	1.8	*	9.24	2.03	**	7.35	1.6		7.91	1.73	*
Fairly easily				-0.27	-0.06		3.07	0.67		1.72	0.38		2.31	0.5	
Easily				-1.24	-0.26		5.73	1.19		3.72	0.77		4.06	0.84	
Education															
Higher education[a]							-28.93	-11.36	***	-30.06	-11.74	***	-30.23	-11.81	***
Job characteristics															
Job status (ref. Employee)															
Civil servant										18.06	6.21	***	17.72	6.1	***
Self-employed										-32.07	-9.93	***	-32.07	-9.91	***
Full time[a]										26.72	8.33	***	26.70	8.3	***
Sector (ref. Primary)															
Manufacturing and Construction										3.98	0.82		3.84	0.79	
Services										-15.08	-3.37	***	-15.44	-3.43	***
Macroeconomic variables															
GDP growth													-0.58	-1.03	
Harmonised unemployment rate													2.48	5.31	***
Old age pensions pps per capita													0.02	1.54	
Country dummies (ref. Spain)	Yes			Yes			Yes			Yes			Yes		
Wave dummies (ref. 2004)	Yes			Yes			Yes			Yes			Yes		
Log likelihood	-18,964.1			-18,873.5			-18,813.0			-18,680.5			-18,662.3		
#obs.	118,467			118,467			118,467			118,467			118,467		

Notes: * 0,1 > p ≥ 0,05; ** 0,05 > p ≥ 0,01; *** p < 0,01. [a] Dummy variable.

complete vision. As we observe, operating in an occupation in terrains more affected by automation implies significantly higher early retirement probabilities.

The results presented in Tables 6.6, 6.7 and 6.8 allow us to confirm the Hypothesis 1 of this study, stating that automation plays an important role increasing the early retirement probability of workers operating in occupation with higher automation degree and/or at a higher automation risk.

As indicated by Brussevich et al. (2019), women perform more routine tasks, on average, than men across all sectors and occupations, and these are the tasks most prone to automation. Therefore, female workers face a higher risk of automation compared to male workers across all occupations. In fact, these authors estimate that 26 million female jobs in 30 countries (28 OECD member countries, Cyprus, and Singapore) are at a high risk of being displaced by technology within the next two decades. Specifically, Brussevich et al. (2018) state that the most disadvantaged group is women with lower secondary education or less, with nearly 50 percent at high risk for automation, relative to less than 40 percent of men with the same education level.

Our work contributes to these contrasted arguments by showing the actual widening of the gender gap regarding the early retirement decision. As our results in Table 6.9 and Figure 6.2 show, facing a greater impact of automation (a higher current automation degree or a higher automation expectancy) implies that women are pushed by new technologies towards the early retirement decision more powerfully than men. In other words, the results show that, being a woman, the fact of being highly affected by automation makes her probability of transitioning to early pre-retirement change significantly. However, being highly exposed to automation does not seem to have a significant impact on the probability

TABLE 6.8: Determinants of early retirement transitions with special focus on A-terrains
Backward & forward-looking vision - Logit estimations

Model	XI			XII			XIII			XIV			XV		
Predicted probability (y)	0.0535			0.0535			0.0535			0.0535			0.0535		
Independent variables (x)	$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat	
Main regressors															
A-terrains (ref. Hands terrain)															
Collapsing automation	10.87	2.73	***	11.14	2.76	***	8.06	1.95	*	13.00	3.08	***	13.09	3.1	***
Rising automation	23.75	7.97	***	20.21	6.74	***	11.15	3.59	***	13.48	4.22	***	13.54	4.24	***
Automation terrain	20.80	7.11	***	19.29	6.53	***	12.01	3.94	***	11.47	3.71	***	11.43	3.7	***
Controls															
Female[a]	40.84	16.23	***	40.40	16.06	***	39.66	15.8	***	46.77	17.09	***	47.01	17.15	***
Age	34.92	72.86	***	34.77	72.54	***	34.90	72.81	***	35.17	73.48	***	35.24	73.4	***
With partner[a]	9.41	3.45	***	9.84	3.6	***	9.23	3.39	***	10.32	3.81	***	10.08	3.72	***
Health (ref. Excellent)															
Very good				8.05	2.09	**	7.96	2.04	**	8.43	2.16	**	8.48	2.18	**
Good				20.81	5.56	***	19.25	5.1	***	19.29	5.13	***	19.41	5.17	***
Fair				36.70	8.37	***	33.75	7.68	***	33.70	7.7	***	33.70	7.7	***
Poor				65.11	8.62	***	60.83	8.15	***	62.02	8.25	***	62.46	8.31	***
Ability to make ends meet (ref. With great difficulty)															
With some difficulty				8.47	1.83	*	9.14	2.01	**	7.13	1.56		7.69	1.68	*
Fairly easily				0.83	0.18		3.25	0.71		1.88	0.41		2.47	0.54	
Easily				1.25	0.26		6.28	1.31		4.12	0.85		4.45	0.92	
Education															
Higher education[a]							-26.41	-9.91	***	-27.61	-10.35	***	-27.76	-10.41	***
Job characteristics															
Job status (ref. Employee)															
Civil servant										19.34	6.6	***	19.00	6.48	***
Self-employed										-32.31	-10.02	***	-32.33	-10.01	***
Full time[a]										26.31	8.17	***	26.29	8.14	***
Sector (ref. Primary)															
Manufacturing and Construction										4.58	0.95		4.46	0.92	
Services										-13.64	-3.04	***	-13.99	-3.1	***
Macroeconomic variables															
GDP growth													-0.60	-1.07	
Harmonised unemployment rate													2.48	5.32	***
Old age pensions pps per capita													0.02	1.56	
Country dummies (ref. Spain)	Yes			Yes			Yes			Yes			Yes		
Wave dummies (ref. 2004)	Yes			Yes			Yes			Yes			Yes		
Log likelihood	-18,934.1			-18,852.6			-18,807.2			-18,672.9			-18,654.7		
#obs.	118,467			118,467			118,467			118,467			118,467		

Notes: * 0,1 > p ≥ 0,05; ** 0,05 > p ≥ 0,01; *** p < 0,01. [a] Dummy variable.

of early retirement for men.

These results can be also observed in the different slopes for males and females in the graphs of Figure 6.2 regarding the relation of their early retirement probabilities and their automation levels (degree and risk). In the case of women, we find a positive slope indicating that a high automation degree and/or risk implies higher early retirement probability while we find a flat slope for males indicating no change in the early retirement probability when switching from a low to a high automation degree and/or risk occupation. Moreover, the significance and concrete values associated with these results can be checked in Table 6.9. Furthermore, as we can observe in the right-graph of Figure 6.2 and Table 6.9 , females account for higher predicted probabilities of early retirement than males at any Automation terrain, being these predicted probabilities higher in the terrains more affected by automation.

The results shown in Table 6.9 and Figure 6.2 allow us to conclude that hypotheses 2a and 2*b* of this study are true, confirming that female workers are more likely to retire early than male workers, independently of the automation process, finding their early retirement probabilities more affected by automation.

In the graphs from Figure 6.3, we can observe the different slopes concerning the probability of early retirement when switching from low to high automation degree/risk for individuals with higher

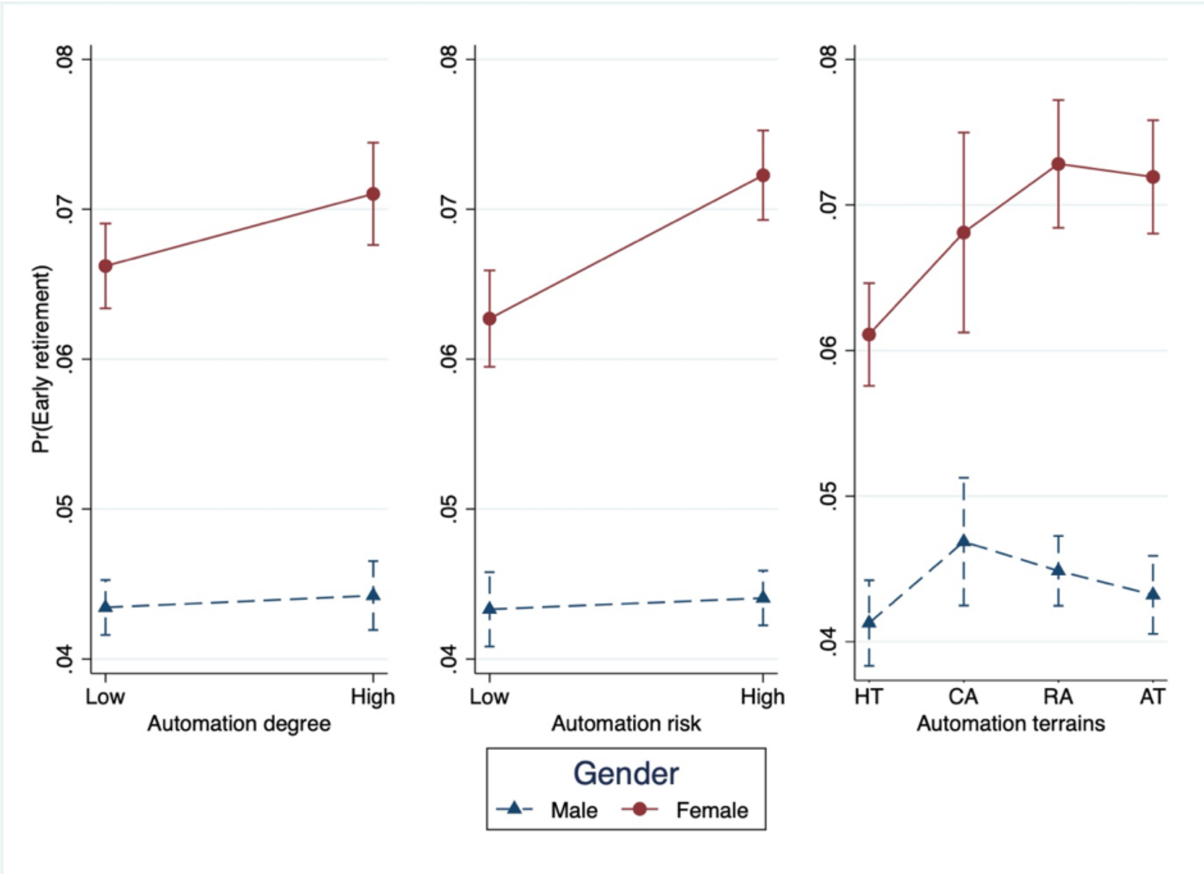

FIGURE 6.2: Early retirement probability, automation and gender.

Notes: Predicted probabilities and marginal effects from table 6.9; HT: hands terrain; CA: collapsing automation; RA: rising automation; AT: automation terrain.

TABLE 6.9: Predicted probabilities of early retirement and marginal effects by gender.

	Predicted probability of early retirement		Marginal effect of automation				Marginal effect of female			
Gender	**Male**	**Female**	**Male**		**Female**		**Male**		**Female**	
			dy/dx	z-stat	dy/dx	z-stat	dy/dx	z-stat	dy/dx	z-stat
Automation risk[a]										
Low	0.0433	0.0627	*Ref.*		*Ref.*		*Ref.*		0.0194	9.33 ***
High	0.0441	0.0723	0.0008	0.47	0.0096	4.44 ***	*Ref.*		0.0282	15.51 ***
Automation degree[b]										
Low	0.0434	0.0662	*Ref.*		*Ref.*		*Ref.*		0.0228	12.68 ***
High	0.0442	0.0710	0.0008	0.54	0.0048	2.23 **	*Ref.*		0.0268	12.54 ***
A-terrains[c]										
Hands terrain	0.0413	0.0611	*Ref.*		Ref.		*Ref.*		0.0198	8.47 ***
Collapsing automation	0.0469	0.0681	0.0056	2.09 **	0.0070	1.82 *	*Ref.*		0.0212	5.10 ***
Rising automation	0.0449	0.0728	0.0036	1.83 *	0.0117	4.17 ***	*Ref.*		0.0280	10.92 ***
Automation terrain	0.0432	0.0719	0.0019	0.95	0.0108	4.16 ***	*Ref.*		0.0287	11.76 ***

Notes: [a] Predicted probabilities and marginal effects are from a model similar to model V in table 6.6 but including interaction term between high automation risk and gender.
[b] Predicted probabilities and marginal effects are from a model similar to model X in table 6.7 but including interaction term between high automation degree and gender.
[c] Predicted probabilities and marginal effects are from a model similar to model XV in table 6.8 but including interaction term between A-terrains and gender.

and no higher education. This slope is more evident for individuals with no higher education while the slope for individuals with higher education is almost non-noticeable. Indeed, if we focus on the confidence intervals, they are perfectly differentiated for individuals with no higher education as the probability of early retirement is significantly larger when the individual carries out a job with high automation degree/risk. For the case of higher educated workers, the probability of early retirement does not increase significantly when switching from low automation affected occupation to a high automation affected occupation, as the confidence intervals to the right and to the left of the x-axis are not in different positions from the perspective of the y-axis. These results are also collected by Table 6.10 . We can find an explanation for this phenomenon by arguing that workers with different levels of training can generate different levels of added value even if they perform the same tasks in the same occupation. This would be another level of heterogeneity to that proposed by Arntz et al. (2016, 2017). If these authors argue that the tasks of the same occupation in different sectors or companies can widely vary, we can go further by affirming that the same tasks from the same occupation, even in the same firm, carried out by workers with different training levels, can derive very different outcomes. In fact, it is a matter of profit maximisation. If a firm accounts for the technology to automatize an occupation and the worker performing this occupation is not very productive and does not add value to the firm, this worker is very likely to go inactive (if he is a middle-age worker, his probability of early retirement will be higher). However, if a firm accounts for the technology to automatize an occupation but the worker who performs this occupation has higher education and is very productive as well as an important value added to the firm, this worker is very likely to remain in his job spot avoiding the automation process. This idea can also be related with the demand of Non-Routine skills [13], by arguing that, as technology augments the productivity of high skill occupations (i.e., with strong interactive and analytical content) while substituting for middle skill occupations (i.e., with higher intensity of routine tasks), it augments the productivity of highly educated workers while substituting for workers without higher education.

To sum up, we find that workers with no higher education and high automation degree/risk are more likely to take the early retirement decision. On the other hand, individuals with higher education

[13] See, for instance, Consoli et al. (2016).

are less likely to retire early independently of the automation impact. Then, we obtain that, while getting higher education drops the early retirement probability for both workers at low and high automation affectation, the transit from a low risk to a high automation impacted occupation only increases the probability of early retirement significantly for individuals with no higher education. As aforementioned, the main message collected by Figure 6.3 and Table 6.10 is that, for middleage workers, obtaining higher education implies getting a shield against early retirement caused by automation.

TABLE 6.10: Predicted probabilities of early retirement and marginal effects by education.

	Predicted probability of early retirement		Marginal effect of automation						Marginal effect of higher education				
Education	**No HE**	**HE**	**No HE**			**HE**			**No HE**		**HE**		
			dy/*dx*	z-stat		*dy*/*dx*	z-stat		*dy*/*dx*	z-stat	*dy*/*dx*	z-stat	
Automation risk[a]													
Low	0.0545	0.0410	*Ref.*			*Ref.*			*Ref.*		-0.0135	-7.38	***
High	0.0602	0.0429	0.0057	3.48	***	0.0018	0.82		*Ref.*		-0.0174	-8.25	***
Automation degree[b]													
Low	0.0570	0.0417	*Ref.*			*Ref.*			*Ref.*		-0.0153	-9.16	***
High	0.0603	0.0420	0.0033	2.12	**	0.0003	0.14		*Ref.*		-0.0183	-8.47	***
A-terrains[c]													
Hands terrain	0.0513	0.0405	*Ref.*			Ref.			*Ref.*		-0.0108	-5.29	***
Collapsing automation	0.0615	0.0430	0.0102	3.38	***	0.0026	0.83		*Ref.*		-0.0185	-4.84	***
Rising automation	0.0604	0.0461	0.0091	4.5	***	0.0057	1.62		*Ref.*		-0.0142	-4.07	***
Automation terrain	0.0601	0.0413	0.0088	4.28	***	0.0008	0.31		*Ref.*		-0.0188	-7.19	***

Notes: [a] Predicted probabilities and marginal effects are from a model similar to model V in table 6.6 but including interaction term between high automation risk and education.
[b] Predicted probabilities and marginal effects are from a model similar to model X in table 6.7 but including interaction term between high automation degree and education
[c] Predicted probabilities and marginal effects are from a model similar to model XV in table 6.8 but including interaction term between A-terrains and education.
HE: higher education.

In the right-graph of Figure 6.3, we see how the probability of early retirement varies for individuals in the different Automation terrains depending on the level of education. As we may observe, both in the graph and in Table 6.10, the lowest predicted probabilities of early retirement are given for individuals with higher education in the Hands terrain and the Automation terrain. This seems like a curious result indicating that, while it is logical that individuals in the Hands terrain with higher education are the less likely to go for early retirement, we must also bear in mind that new technology occupying the Automation terrain are developed, established and controlled by higher educated workers with a crucial role in the technological change (engineers, computer scientists, etc).

Moreover, the right-side graph in Figure 6.3 denotes that the early retirement probability for workers with higher education is always lower than this probability for workers with no higher education in the same automation group. This information can also be found in Table 6.10, where we can see that having a higher education level always reduces the early retirement probability with a significance level of 1% at any automation group. To sum up, Figure 6.3 and Table 6.10 tell us that the safest refuge to hide from early retirement caused by the current technological change is to work in the Hands terrain having higher education, while the highest probabilities of early retirement are found for workers without higher education in the terrains more affected by automation. These results collecting the interaction between automation and education regarding the early retirement probability allows us to confirm hypotheses 3 a and 3 b of this study, stating that workers with higher education are less likely to retire early

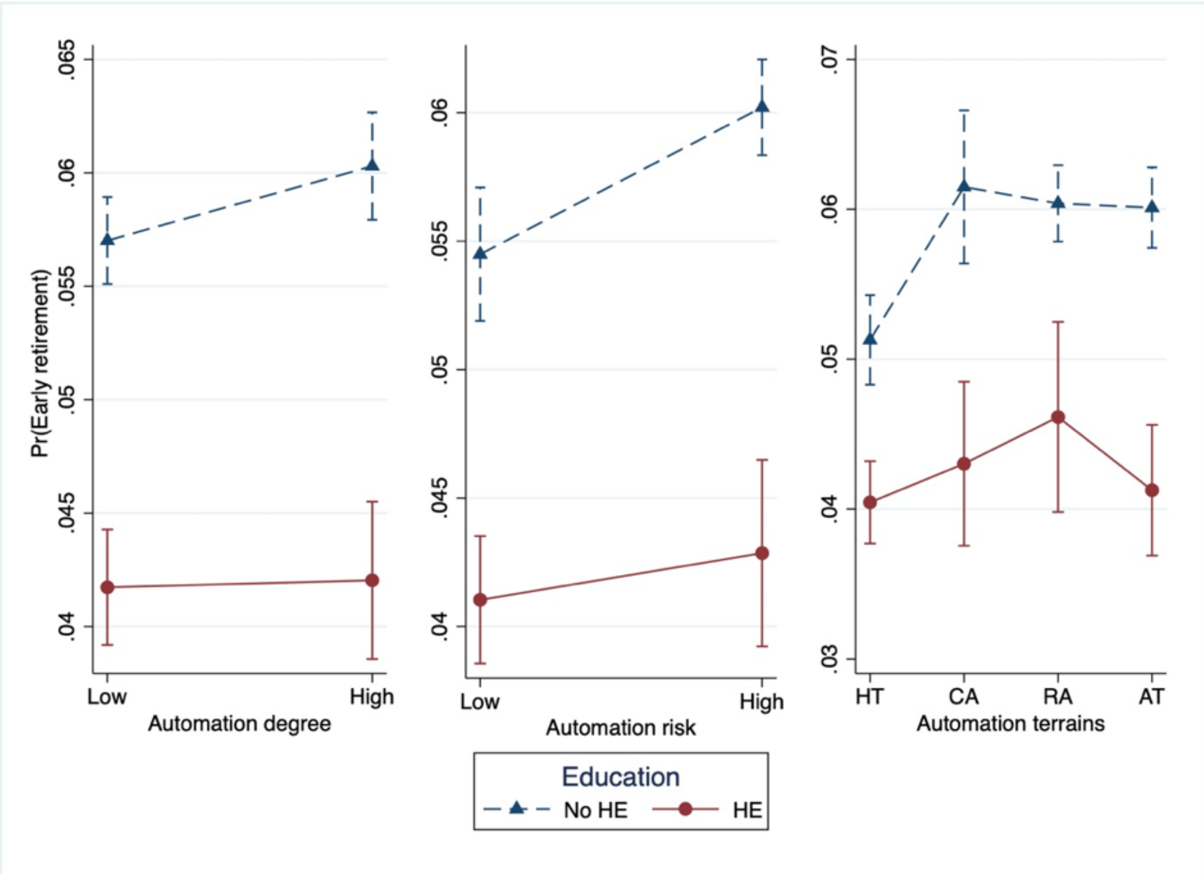

FIGURE 6.3: Early retirement probability, automation and education.

Notes: Predicted probabilities and marginal effects from table 6.10 ; HE : higher education; HT: hands terrain; CA: collapsing automation; RA: rising automation; AT: automation terrain.

than workers without higher education, independently of the automation process and maintaining their early retirement probabilities not significantly affected by automation.

Figure 6.4 and Table 6.11 represent the relation between job status and automation regarding the probability of early retirement. Again, the three graphs in the figure and the table are providing the same information from different perspectives, allowing us to obtain a full vision of the interconnection. In the graphs of Figure 6.4 we can observe how the probability of early retirement changes for workers going from a low to a high automation degree/risk depending on their job status. The red lines and dots collect the effect for civil servants, the blue lines and triangles present the switch for employees and the green dots lines and squares reflect the case of self-employed workers. At first sight, the effect is similar for employees and civil servants while varying largely for self-employed workers (being opposite for the case of automation risk, in fact). On the one hand, for the cases of civil servants and employees, we find positive slopes of the same dimensions at different levels. On the other hand, for the case of self-employed workers, we find a negative slope reflecting that the probability of early retirement decreases when the automation risk increases, but not significantly. Then, while the probability of early retirement for employees and civil servants is increasing with respect to automation degree/risk, the probability of early retirement for self-employed individuals seems to be unaltered by automation degree/risk.

These results seem to be in line with hypotheses 4a and 4 b. It is important to highlight that the non-significance of automation risk or degree on early retirement probability of self-employment workers does not imply that self-employment is not affected by automation. Procedural utility experienced by self-employed workers (Benz and Frey, 2008), their autonomy to adapt their jobs to changing environments (Hundley, 2002) and the use of self-employment as a bridge to retirement (Nolan and Barret, 2019; Alcover et al., 2021) as a result of the automation processes (Fossen and Sorgner, 2021; Shapiro and Mandelman, 2021) give support to the existence of incentives to both retiring earlier as well as for retiring, that can counterbalance each other.

To sum up, the main message collected from Figure 6.4 and Table 6.11 is that self-employed workers have lower predicted probability of early retirement in every Automation terrain and accounting for small variations of the predicted probability when switching terrain, while employees and civil servants account for higher predicted probability in early retirement that can vary broadly when switching terrain. Furthermore, the gap in predicted probability of early retirement between two individuals from different job status can be larger or smaller depending on the Automation terrains they belong to. These results imply that, for middle-aged workers who are unwilling to pursue higher education or start their own business, the best way to enlarge their working lives at least until retirement age is to look for a job in the Hands terrain occupations [14]. Then, the concrete policies designed for these workers should put the focus on relocating them from the terrains affected by automation to the Hands terrain occupations.

In addition, for some workers the idea exposed previously that in order to avoid early retirement caused by automation it would be necessary to obtain higher education or become an entrepreneur may sound utopic, and these results are providing a new perspective: maybe it is not fully necessary to get higher education or become selfemployed but to look for a job in the Hands terrain. In fact, it would be delusional to think that all middle-age workers who have performed the same job (now at high risk of automation) for decades will easily obtain higher education or start a successful business overnight. There is a large heterogeneity of characteristics between individuals in the same risky situation of early retirement from the labour market caused by new technologies. That is why the higher number of possible solutions, the richer baseline information we will have to elaborate fruitful policies.

6.5.3 Robustness checks

This section offers three additional estimations that give confidence to the robustness of our results. Firstly, since self-employed workers retirement behaviour largely vary with respect to the retirement

[14]The Table A6.2 in the appendix collects some occupations of the hands terrain.

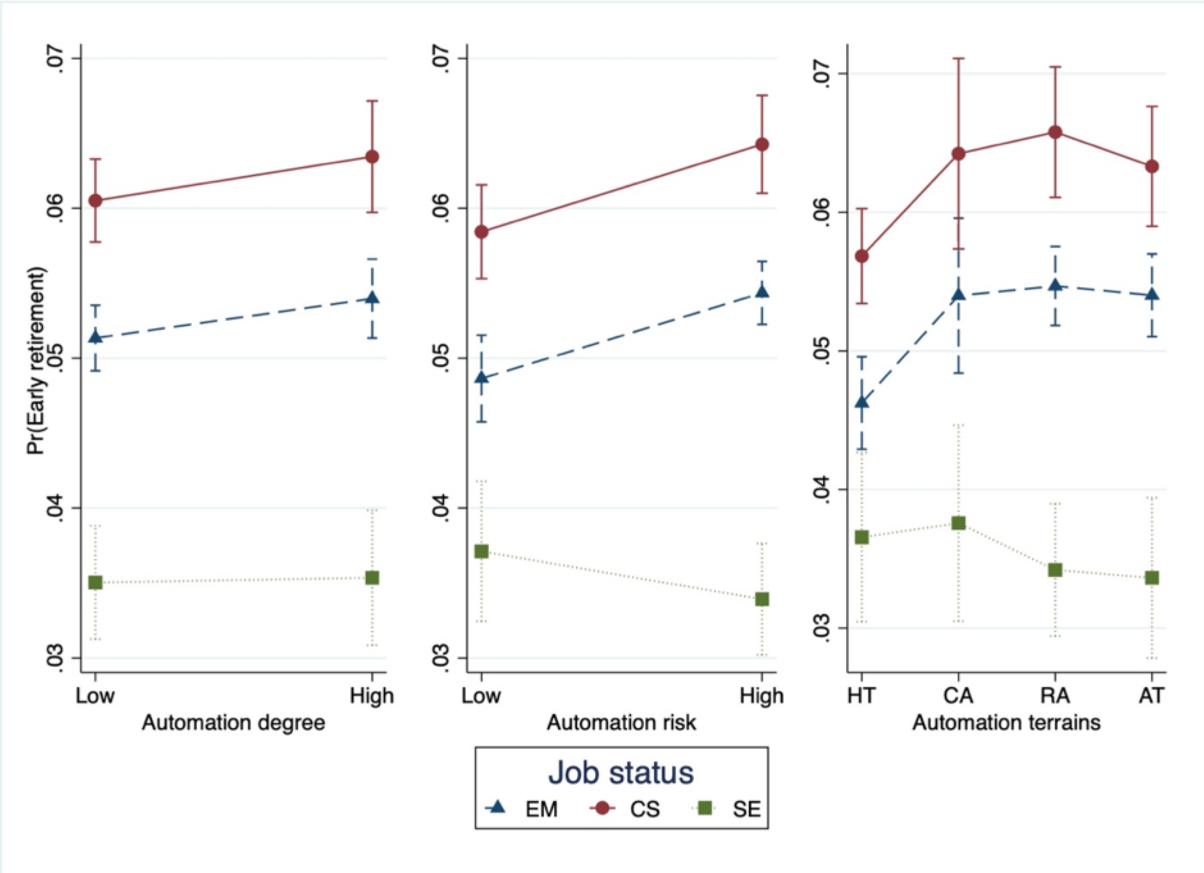

FIGURE 6.4: Early retirement probability, automation and job status.

Notes: Predicted probabilities and marginal effects from table 6.11; EM: employee; CS: civil servant; SE: self-employed worker; HT: hands terrain; CA: collapsing automation; RA: rising automation; AT: automation terrain.

TABLE 6.11: Predicted probabilities of early retirement and marginal effects by job status.

	Predicted probability of early retirement			Marginal effect of automation									Marginal effect of job status						
Job status	**EM**	**CS**	**SE**	**EM**			**CS**			**SE**			**EM**	**CS**			**SE**		
				dy/dx	z-stat		dy/dx	z-stat		dy/dx	z-stat			dy/dx	z-stat		dy/dx	z-stat	
Automation risk[a]																			
Low	0.049	0.058	0.037	*Ref.*			*Ref.*			*Ref.*			*Ref.*	0.010	4.5	***	-0.011	-4.15	***
High	0.054	0.064	0.034	0.006	3.17	***	0.006	2.57	**	-0.003	-1.05		*Ref.*	0.010	4.92	***	-0.020	-9.42	***
Automation degree[b]																			
Low	0.051	0.060	0.035	*Ref.*			*Ref.*			*Ref.*			*Ref.*	0.010	4.91	***	-0.016	-7.35	***
High	0.054	0.063	0.035	0.003	1.54		0.003	1.29		0.0003	0.1		*Ref.*	0.010	4.01	***	-0.019	-6.98	***
A-terrains[c]																			
Hands terrain	0.046	0.057	0.036	*Ref.*			*Ref.*			*Ref.*			*Ref.*	0.011	4.35	***	-0.010	-2.75	***
Collapsing automation	0.054	0.064	0.038	0.008	2.34	**	0.007	1.92	*	0.001	0.21		*Ref.*	0.010	2.27	**	-0.016	-3.57	***
Rising automation	0.055	0.066	0.034	0.008	3.8	***	0.009	3	***	-0.002	-0.6		*Ref.*	0.011	3.95	***	-0.020	-7.3	***
Automation terrain	0.054	0.063	0.034	0.008	3.45	***	0.006	2.34	**	-0.003	-0.69		*Ref.*	0.009	3.43	***	-0.020	-6.13	***

Notes: [a] Predicted probabilities and marginal effects are from a model similar to model V in table 6.6 but including interaction term between high automation risk and job status.
[b] Predicted probabilities and marginal effects are from a model similar to model X in table 6.7 but including interaction term between high automation degree and job status.
[c] Predicted probabilities and marginal effects are from a model similar to model XV in table 6.8 but including interaction term between A-terrains and job status.
EM: employee; CS: civil servant; SE: self-employed worker.

behaviour of employees, with self-employed workers commonly intending to retire later as compared to wage earners (Parker and Rougier, 2007; Kautonen et al., 2012, Hochguertel, 2015), Table A6.3 in the appendix reproduce models V, X and XV but excluding self-employed workers from the sample. As expected given our results, the effect of automation in the early retirement decision is greater with this reduced sample concerning uniquely employees and civil servants. Then, we prove with this robustness check that the particular retirement behaviour of self-employed workers does not alter the results obtained in the estimations of our study.

Secondly, we expose the relation between automation, early retirement and the intention to retire early. The SHARE provides a variable collecting the intention to go for early retirement (question "Looking for early retirement in (main) job"), only available for a reduced number of observations. With this subsample, we estimate the models in Table A6.4, showing that, while logically the intention to retire early increases the early retirement probability, higher automation degree and/or risk increase the probability of intending to retire early. This fact highlights that the variable collecting the intention to retire early is not a measure of the early retirement willingness. Indeed, we do not have a way to clearly distinguish between voluntary and involuntary early retirement decisions since automation has a strong positive effect increasing the probability of looking for early retirement. An alternative way to interpret this phenomenon is that we might consider that intention to early retirement mediates the relationship between automation and early retirement probability. Using the KHB method (Karlson, Holm, and Breen 2012; Breen, Karlson, and Holm 2013), we tested for this possible mediating effect and observed that there exists a significant indirect effect. These results are not reported but are available by request.

Thirdly, we deal with the fact that individuals with the same age residing in countries with different statutory retirement ages may have different behaviours. In this sense, the early retirement decision of individuals with the same age residing in different countries facing distinct statutory retirement ages might differ depending on how long they have to wait until reaching the retirement age. Indeed, they may get penalised (by benefit reductions) differently for their decision to retire early depending on the official retirement age in their country of residence. In consequence, Table A6.5 includes as a regressor the years to statutory retirement age instead of the age control. The variable has a significant negative effect in the early retirement probability indicating that individuals closer to their retirement ages are less likely to retire early. Controlling for the year to statutory retirement ages we observe that our automation variables preserve their significant effect in the early retirement probability.

6.6 Conclusions

Early retirement policies have been around for about 60 years without supposing a big deal for industrialised countries. Nowadays, the ageing of the population combined with a technological change especially aggressive for middle-age workers have made governments rethink and disincentivize these policies. Nevertheless, few alternatives for potential early retirees have been brought into debate.

The reason why no alternative policies to early retirement have been eventually proposed is that, traditionally, early retirement has been assumed to be an individual's decision triggered by preferences. However, this study suggests the possible existence of forced early retirement not only because of health issues, but also due to technological change. [15] Controlling for demographic characteristics, health level, financial situation, previous employment features and country level variables, we find a positive association between the advance of new technologies - i.e. automation - and early retirement decisions in Europe.

As we reveal in the literature review, the consideration of automation as an underlying cause of early retirement has been present in studies since the appearance of these policies although the concrete effect had not been measured until now. Previously, it was better for governments to pay these extra provisions for redundant middle-age workers than slowing down technological change with restrictive labour policies. In fact, the benefits from new technologies for society have been always wider than the cost they bring for some specific groups of population. However, this approach is very poor in assuming that workers who previously performed work absorbed by new technologies can no longer be valuable to the entire human capital of a country. Although the easy way to solve this issue is to pay generous early retirement or unemployment provisions and look aside, if the wealth generated by new technological change allows it, better policies that does not left anyone behind can be elaborated, taking full advantage of both technology and human capital, then maximising the effectiveness of public expenses.

These policies are needed since just delaying retirement ages can simply result in higher unemployment rates, as it has been proved by analysing the increase of retirement ages in the past. For example, Staubli and Zweimüller (2013) consider the effects of a gradual increase in the minimum retirement age from 60 to 62.2 years for men and from 55 to 57.2 for women in Austria between 2000 and 2006, finding that this policy change reduced retirement by 19 percentage points among affected men and by 25 percentage points among affected women (this supposed an increase in employment of 7 percentage points among men and 10 percentage points among women), but at the same time, there was an important spillover effect by increasing the unemployment rate 10 percentage points among men and 11 percentage points among women. [16]

Furthermore, as early retirement is logically detrimental for a society due to human capital losses and a descent in economic growth (Conde-Ruiz and Galasso, 2004), it has also been concluded to be detrimental for individuals acceding to this policy. Within this strand of the literature, Börsch-Supan and Schuth (2014) analyse the implications of early retirement for mental health to conclude that cognition declines with early retirement and the effect on well-being appears to be negative and short-lived rather than long-lasting and positive. [17] Palmore et al. (1984) denote the consequences of retirement, by comparing retired and working men, to find that little, if any, differences in health, social activity, life satisfaction, and happiness were caused by retirement, although they found that early retirement had stronger effects than retirement at normal ages. Then, they conclude that retirement has different effects depending on the type of outcome and timing of retirement.

[15] Perhaps, this fact can be interpreted as one of the underlying reasons for flexible retirement policies failure (Börsch-Supan et al., 2018).

[16] On the contrary, Frimmel (2021) also analyses the case of Austria's reform to conclude that increasing the early retirement age is not only a feasible way to improve the financial sustainability of public pension systems, but it also improves the re-integration of elderly unemployed male workers.

[17] On the contrary, Litwin (2007) finds that early retirement has no effect on life expectancy.

Then, according to these studies, early retirement would be a fruitful policy if it only achieves to helping those individuals who take this decision with total wilfulness, [18] by promoting solutions so the early retirees can have better alternatives avoiding this transition, if it is involuntary. In fact, the reason why opinions are divided regarding the positive (or negative) effects of the decision to go (or not) for early retirement can be explained as a matter of freedom in decision making rather than the decision itself, indicating that the well-being of an individual is greater when he makes the decision he wants and not the one that circumstances force him to make. Then, from the perspective of welfare maximisation, the focus should be on promoting alternative policies that avoid the possibility of forced early retirement rather than eradicating early retirement in general.

We find differentiated effects depending on gender, education level and job status. On the one hand, regarding the education level, we observe that workers with no higher education and high automation degree and/or risk are more likely to make the early retirement decision. In addition, individuals with higher education are less likely to retire early independently of the automation impacts. On the other hand, regarding the job status, we observe that an increase in the automation degree and/or risk from low to high is associated with higher probabilities of early retirement for employees in the private sector and civil servants, but not for self-employed workers. As expected, the probability of early retirement for self-employed individuals is lower for employees and civil servants, irrespective of the automation. Finally, we find higher effects of automation on women's early retirement transitions.

Regarding the A-terrains, we find that self-employed workers, at any terrain, are the individuals with lower early retirement probability while the civil servants are the individuals more likely to go for early retirement. Our findings collect that, while being in distinct terrains does not make a difference in the early retirement probability of selfemployed people, operating in distinct terrains suppose a significant variance in the early retirement probability of employees and civil servants. In addition, getting higher education means a significant descend in the early retirement probability in every terrain. In addition, we find that women account for higher early retirement probabilities at any terrain and these early retirement probabilities of women are more affected by automation than those of men.

In order to take advantage of the accumulated human capital of middle-aged experienced workers, mechanisms should be established to prevent their early exist from the labour market: (i) to increase funding on training programs for these workers [19] instead of establishing generous early retirement schemes (Fouarge and Schils, 2009) and (ii) to promote bridge self-employment policies for older workers to achieve their statutory retirement age (Axelrad and Tur-Sinai, 2021). With a broader scope, we can extend the policy recommendation of increasing spending on education beyond the restrictiveness to older workers and the early retirement decision, since a proper investment in learning and training policy schemes is advisable in the face of any technological change (Vivarelli, 2013).

These advisable policies should provide special gender scopes since we find that the current technological wave affects in a clearly differentiated way to men and women, widening the gender gap regarding the early retirement transitions, although it could be simply a concrete example of the effect of new technologies in deepening the gender gap considering a broader focus. Ultimately, the fact that

[18] Isaksson and Johansson (2000) study compared early retirees and people continuing to work over the years following downsizing with regard to satisfaction, well-being, health, and work centrality, to find that voluntary (as opposed to forced) choice was directly and positively associated with satisfaction, psychological well-being and health for both groups. In this line, Maule et al. (1996) study the early retirement decisions of men working in Britain for a large multinational company in the manufacturing sector to indicate that the decision-making process is complex and cannot be reduced to single-factors like health or financial status, being the most important factor in the quality of life of early retirees was the matching of expectations of further work at the point of decision. Smith (2006) points out another relevant difference between voluntary and involuntary early retirees by observing a significant fall in spending only in the latter's.

[19] A broader vision would say that increasing the general spending in education can downsize early retirement transitions (and/or its negative effects for an individual) whilst increasing life quality. Allel et al. (2021) find that formal education during childhood and adolescence is associated with a long-term protective effect on health and it attenuates negative health consequences of early retirement transitions. Their results indicate that early retirement is associated with worse health outcomes, but education fully compensates for the detrimental association with subjective and physical health. Therefore, this research raises the necessity of adopting a broader vision in the elaboration of policies and programs promoting healthy and active ageing, considering the influence of formal education in shaping older adults' health after the transition into retirement.

new technologies are shortening women's working lives more aggressively than they are affecting men's working lives could be an indication that, in the overall picture, current technological change pushes women out of the labour market more fiercely than men, creating an alert to a possible broadening of the gender gap caused by the impact of new technologies.

Finally, for those cases in which the individual with high early retirement probability shows no interest on getting higher education or becoming self-employed, it is fundamental that the delay in retirement ages is complemented by other instruments like the mapping of the best routes for the avoidance of early retirement in order to help these middle-age workers at high automation risk to continue with their working lives. In fact, the same technological wave displacing middle-aged workers can be very useful to their effective relocation as, for example, big data and machine learning, could be the perfect toolkit to design personalised policies.

Our research is not exempt from limitations. One important limitation relies upon the assumption that the crosswalk between SOC-10 and ISCO-08 is perfect and the job content of an occupation in the US is the same as that of an occupation in any of the 26 European countries of our sample. The automation probabilities have been applied to several analyses targeting European regions. For instance, Crowley et al. (2021) use them to analyse the vulnerability of European regional labour markets to job automation, translating through a crosswalk the 702 occupations at US SOC six-digit level present in Frey and Osborne (2017) to 122 ISCOs at the three-digit level present in the EU Labour Force Survey. As an example of operationalization of this measure using data from a concrete European country, Gardberg et al. (2020) analyse the implications of automation for occupational dynamics in Sweden, adapting these automation probabilities from the American SOC2010 occupational classifications to the Swedish counterpart 3-digit SSYK96 via the European ISCO08 occupational code. Our variable collecting the automation degree presents the same limitations as the automation risk since it belongs to the same data source from which Frey and Osborne (2017) construct their variable, the O*NET database.

6.7 Appendix

TABLE A6.1: Descriptive statistics

	Total sample	Switching to early retirement (S)	Non switching to early retirement (NS)			
#obs. (#ind.)	118,467 (17,506)	6,340 (6,339)	112,127 (11,167)			
Variable	Mean (S.D. overall)	Mean (S.D. overall)	Mean (S.D. overall)	Min	Max	Difference of means NS-S[a]
Main regressors						
Automation risk	62.72% (37.64)	66.28% (36.27)	62.52% (37.71)	0.39	99	-3.76***
Automation degree	27.81% (9.72)	28.11% (9.72)	27.79% (9.72)	5	66	-0.32***
A-terrains	2.56 (1.20)	2.67 (1.16)	2.55 (1.20)	1	4	-0.11***
Hands terrain	31.05%	26.15%	31.32%	0	1	5.17***
Rising automation	10.70%	10.82%	10.69%	0	1	-0.13
Collapsing automation	29.35%	32.85%	29.15%	0	1	-3.70
Automation terrain	28.91%	30.17%	28.83%	0	1	-1.34**
Controls						
Female	51.35%	48.20%	51.52%	0	1	3.32***
Age	55.37 (3.58)	59.21 (3.29)	55.15 (3.47)	50	66	-4.05***
With partner	79.98%	80.66%	79.94%	0	1	-0.72
Health	2.84 (1.01)	3.03 (1.02)	2.83 (1.01)	1	5	-0.21***
Excellent	10.85%	8.00%	11.01%	0	1	3.01***
Very good	23.83%	19.32%	24.08%	0	1	4.76***
Good	40.40%	40.82%	40.38%	0	1	-0.44
Fair	20.55%	25.02%	20.30%	0	1	-4.72***
Poor	4.36%	6.85%	4.22%	0	1	-2.62***
Ability to make ends meet	2.88 (0.97)	2.85 (0.97)	2.89 (0.97)	1	4	0.03***
With great difficulty	8.90%	8.86%	8.90%	0	1	0.04
With some difficulty	26.87%	28.64%	26.77%	0	1	-1.87***
Fairly easily	31.07%	30.91%	31.08%	0	1	0.17
Easily	33.16%	31.58%	33.25%	0	1	1.67***
Education						
Higher education	30.04%	23.26%	30.42%	0	1	7.15***
Job characteristics						
Job status	1.58 (0.68)	1.59 (0.65)	1.58 (0.68)	1	3	0.01
Employee	52.61%	50.44%	52.73%	0	1	2.29***
Civil servant	36.65%	40.55%	36.43%	0	1	-4.12***
Self-employed worker	10.74%	9.01%	10.84%	0	1	1.83***
Full time	86.88%	90.13%	86.69%	0	1	3.43***
Sector	2.59 (0.63)	2.53 (0.65)	2.60 (0.63)			0.07***
Primary	8.14%	9.29%	8.08%	0	1	-1.21***
Manufacturing and Construction	24.26%	28.55%	24.01%	0	1	-4.54***
Services	67.60%	62.16%	67.91%	0	1	5.75***
Macroeconomic variables						
GDP growth	1.96 (3.42	1.70 (3.58	1.97 (3.41	-14.84	11.99	0.27***
Harmonised unemployment rate	8.82 (4.38	8.80 (4.63	8.82 (4.36	2.9	27.5	0.02
Old age pensions PPS per capita	2042.28 (889.24)	2001.57 (851.32)	2044.59 (891.28)	504.68	3,929.77	43.01***

Note: [a] Tests of equality of means between observations not switching to early retirement (NS) and observations switching to early retirement (S); Ho: Mean (NS) – Mean (S) = 0; * 0,1 > p ≥ 0,05; ** 0,05 > p ≥ 0,01; *** p < 0,01.

TABLE A6.2: Some occupations in the hands terrain

ISCO-08 Title	ISCO-08	Automation risk (%)	Automation degree (%)
Dieticians and nutritionists	2265	0.39	18
Education methods specialists	2351	0.42	5
Specialist medical practitioners	2212	0.42	22.85
Generalist medical practitioners	2211	0.42	25.34
Audiologists and speech therapists	2266	0.64	23
Secondary education teachers	2330	0.78	10
Nursing professionals	2221	0.9	27.47
Teaching professionals not elsewhere classified	2359	0.95	12.5
Education managers	1345	1	23
Psychologists	2634	1.2	21.75
Information technology trainers	2356	1.4	27
Child care services managers	1341	1.5	28
Special needs teachers	2352	1.6	13.5
Environmental engineers	2143	1.8	23
Research and development managers	1223	1.8	23.58
Building architects	2161	1.8	26
Civil engineers	2142	1.9	27.33
Traditional and complementary medicine professionals	2230	2	14
Physiotherapists	2264	2.1	12
Photographers	3431	2.1	22
Farming, forestry and fisheries advisers	2132	2.1	26.33
Religious professionals	2636	2.5	19
Telecommunications engineers	2153	2.5	26
Health professionals not elsewhere classified	2269	2.7	16.07
Industrial and production engineers	2141	2.9	27
University and higher education teachers	2310	3.2	15.4
Environmental protection professionals	2133	3.3	20.33
Handicraft workers not elsewhere classified	7319	3.5	10
Handicraft workers in wood, basketry and related materials	7317	3.5	10
Lawyers	2611	3.5	22

TABLE A6.3: Robustness check 1 - Determinants of early retirement transitions excluding self-employed workers

	Model V.R1			Model X.R1			Model XV.R1		
Predicted probability (y)	0.0546			0.0546			0.0546		
Independent variables (x)	$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat	
Main regressors									
Automation risk (%)	0.15	3.99	***						
Automation degree (%)				0.37	2.89	***			
A-terrains (ref. Hands terrain)									
Collapsing automation							13.96	3.1	***
Rising automation							16.52	4.95	***
Automation terrain							13.63	4.25	***
Controls									
Female[a]	44.82	15.85	***	44.19	15.6	***	46.15	16.18	***
Age	35.32	70.32	***	35.31	70.31	***	35.32	70.28	***
With partner[a]	9.66	3.42	***	9.62	3.41	***	9.65	3.42	***
Health (ref. Excellent)									
Very good	8.22	2.01	**	8.27	2.03	**	8.36	2.05	**
Good	19.28	4.87	***	19.44	4.93	***	19.20	4.86	***
Fair	32.62	7.13	***	33.23	7.28	***	32.86	7.2	***
Poor	57.56	7.35	***	57.98	7.39	***	58.04	7.38	***
Ability to make ends meet (ref. With great difficulty)									
With some difficulty	6.94	1.43		6.68	1.38		6.54	1.35	
Fairly easily	0.40	0.08		-0.20	-0.04		0.19	0.04	
Easily	3.44	0.67		2.28	0.44		2.92	0.57	
Education									
Tertiary education[a]	-26.99	-9.4	***	-29.89	-11.08	***	-26.86	-9.55	***
Job characteristics									
Job status (ref. Employee)									
Civil servant	18.80	6.6	***	18.13	6.4	***	19.58	6.85	***
Full time	26.66	7.89	***	25.96	7.63	***	25.69	7.52	***
Sector (ref. Primary)									
Manufacturing and Construction	7.78	1.47		7.41	1.4		8.24	1.57	
Services	-11.15	-2.22	**	-12.22	-2.43	**	-10.24	-2.04	**
Macroeconomic variables									
GDP growth	-0.34	-0.58		-0.35	-0.59		-0.37	-0.63	
Harmonised unemployment rate	2.81	5.62	***	2.81	5.62	***	2.81	5.61	***
Old age pensions pps per capita	0.02	1.97	**	0.02	1.91	*	0.02	1.94	*
Country dummies (ref. Spain)	Yes			Yes			Yes		
Wave dummies (ref. 2004)	Yes			Yes			Yes		
Log likelihood	-16,887.9			-16,891.6			-16,881.8		
# obs.	105,739			105,739			105,739		

Notes: * 0.1 >p ≥ 0.05; ** 0.05 >p ≥ 0.01; *** p< 0.01. [a] Dummy variable.

TABLE A6.4: Robustness check 2 - Determinants of early retirement transitions and intention to retire early

	Model XVI			Model XVII			Model XVIII			Model XIX		
Dependent variable	Early retirement transition			Intention to retire early			Intention to retire early			Intention to retire early		
Predicted probability (y)	0.0219			0.4621			0.4621			0.4621		
Independent variables (x)	$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat	
Main regressors												
Intention to retire early[a]	42.75	8.43	***									
Automation risk (%)				0.10	3.51	***						
Automation degree (%)							0.26	2.51	**			
A-terrains (ref. Hands terrain)												
Collapsing automation										7.04	2.03	**
Rising automation										7.80	2.83	***
Automation terrain										10.53	3.97	***
Controls												
Female[a]	30.90	5.5	***	-0.37	-0.17		-0.69	-0.32		-0.10	-0.04	
Age	44.39	37.76	***	-1.39	-5.58	***	-1.40	-5.6	***	-1.39	-5.57	***
With partner[a]	-0.30	-0.05		7.39	3.11	***	7.27	3.06	***	7.28	3.06	***
Health (ref. Excellent)												
Very good	12.60	1.65	*	13.98	4.38	***	14.04	4.4	***	14.03	4.4	***
Good	21.20	2.89	***	26.69	8.51	***	26.94	8.58	***	26.78	8.54	***
Fair	30.92	3.5	***	45.75	12.37	***	46.21	12.49	***	46.05	12.46	***
Poor	67.86	4.02	***	66.39	10.4	***	66.58	10.43	***	66.65	10.47	***
Ability to make ends meet (ref. With great difficulty)												
With some difficulty	5.29	0.51		0.15	0.04		0.09	0.02		-0.17	-0.04	
Fairly easily	7.86	0.76		-5.90	-1.44		-6.06	-1.48		-6.30	-1.54	
Easily	7.35	0.7		-10.24	-2.4	**	-10.83	-2.54	**	-10.85	-2.55	**
Education												
Tertiary education[a]	-38.40	-7.92	***	-11.82	-4.8	***	-13.92	-5.97	***	-12.36	-5.12	***
Job characteristics												
Job status (ref. Employee)												
Civil servant	14.40	2.41	**	4.38	1.85	*	4.07	1.71	*	4.83	2.03	**
Self-employed	-31.91	-5.13	***	-14.91	-4.72	***	-15.50	-4.92	***	-15.31	-4.85	***
Full time[a]	22.23	3.52	***	6.61	2.18	**	6.06	1.99	**	5.82	1.91	*
Sector (ref. Primary)												
Manufacturing and Construction	3.79	0.37		4.41	1.05		4.16	0.99		4.80	1.14	
Services	-14.80	-1.58		-5.65	-1.44		-6.26	-1.59		-5.08	-1.29	
Macroeconomic variables												
GDP growth	-1.21	-0.89		0.27	1.97	**	0.27	1.94	*	0.27	1.98	**
Harmonised unemployment rate	2.32	1.94	*	0.21	0.99		0.20	0.96		0.20	0.95	
Old age pensions pps per capita	9.7E-2	4.09	***	1.8E-3	0.36		0.00	0.33		0.00	0.36	
Country dummies (ref. Spain)	Yes			Yes			Yes			Yes		
Wave dummies (ref. 2004)	Yes			Yes			Yes			Yes		
Log likelihood	-5,666.2			-46,638.9			-46,660.0			-46,623.8		
#obs.	75,078			75,078			75,078			75,078		

Notes: * 0.1 >p ≥ 0.05; ** 0.05 > p ≥ 0.01; *** p< 0.01. [a] Dummy variable.

TABLE A6.5: Robustness check 3 - Determinants of early retirement transitions – Years to statutory retirement age

	Model III			Model IV			Model V		
Predicted probability (y)	0.0535			0.0535			0.0535		
Independent variables (x)	$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat	
Main regressors									
Years to statutory retirement age	-35.43	-75.38	***	-35.43	-75.38	***	-35.42	-75.31	***
Automation risk (%)	0.10	3.07	***						
Automation degree (%)				0.29	2.42	**			
A-terrains (ref. Hands terrain)									
Collapsing automation							12.84	3.15	***
Rising automation							13.10	4.18	***
Automation terrain							10.46	3.46	***
Controls									
Female[a]	-16.05	-6.3	***	-16.51	-6.46	***	-15.03	-5.87	***
With partner[a]	11.84	4.45	***	11.77	4.43	***	11.77	4.42	***
Health (ref. Excellent)									
Very good	9.44	2.41	**	9.36	2.39	**	9.46	2.42	**
Good	19.10	5.08	***	19.23	5.12	***	18.94	5.04	***
Fair	33.66	7.75	***	34.07	7.85	***	33.75	7.78	***
Poor	69.40	9.44	***	69.77	9.49	***	69.73	9.45	***
Ability to make ends meet (ref. With great difficulty)									
With some difficulty	10.37	2.35	**	10.22	2.31	**	10.09	2.28	**
Fairly easily	4.77	1.08		4.44	1		4.69	1.06	
Easily	6.80	1.45		6.02	1.28		6.49	1.38	
Education									
Tertiary education[a]	-27.76	-10.42	***	-29.75	-11.78	***	-27.46	-10.47	***
Job characteristics									
Job status (ref. Employee)									
Civil servant	19.55	6.79	***	19.08	6.66	***	20.38	7.05	***
Self-employed	-31.43	-10.13	***	-32.05	-10.38	***	-32.24	-10.48	***
Full time[a]	18.60	5.57	***	18.05	5.38	***	17.69	5.25	***
Sector (ref. Primary)									
Manufacturing and Construction	3.51	0.75		3.48	0.74		4.23	0.91	
Services	-12.24	-2.8	***	-12.75	-2.93	***	-11.35	-2.6	***
Macroeconomic variables									
GDP growth	-0.99	-1.77	*	-0.99	-1.77	*	-1.01	-1.81	*
Harmonised unemployment rate	3.01	6.42	***	3.01	6.41	***	3.01	6.42	***
Old age pensions pps per capita	-3.14E-02	-3.08	***	-0.03	-3.1	***	-0.03	-3.08	***
Country dummies (ref. Spain)	Yes			Yes			Yes		
Wave dummies (ref. 2004)	Yes			Yes			Yes		
Log likelihood	-18,717.0			-18,718.6			-18,711.6		
#obs.	118,467			118,467			118,467		

Notes: * 0.1 > p ≥ 0.05; ** 0.05 > p ≥ 0.01; *** p ≤ 0.01. a Dummy variable.

Chapter 7

The impact of Artificial Intelligence in the Early Retirement decision

7.1 Introduction

The potential effect on the employment of the technologies that make up the so-called Fourth Industrial Revolution is one of the main topics in actual economic research. [1] In general, the destructive and displacing effect of these technologies has been the most covered and widespread in the literature (Autor, 2015; Frey and Osborne, 2017; Acemoglu and Restrepo, 2020a). Nevertheless, other authors have highlighted the potential of the current technological change for increasing productivity (Graetz and Michaels, 2018) and create employment (Damioli et al., 2023). In addition, other authors have denied the alarmist Luddite vision of massive job destruction due to automation (Arntz et al., 2016, 2017; Dauth et al., 2017).

The current and potential impact of AI on the labour markets constitutes one of the main aspects of this industrial revolution, since experts estimate that there is a 50% chance of AI outperforming human in all tasks in 120 years (Grace et al., 2018). These estimates raise a debate about whether human work will be replaced by this new technology or, on the contrary, will be complemented by it, raising its productivity in an extraordinary way. In this respect, some authors have already classified the AI as a transformative technology rather than a destructive one due to its complementarity degree with human labour (Fossen and Sorgner, 2019, 2021). Therefore, we would talk about AI complementing Human Intelligence (HI) [2] in a way that human labour productivity can take advantage of both. This fact creates itself a paradigm for human capital, which can now be enhanced by a kind of artificial capital.

Additionally, the ageing of the population is another of the main economic concerns in industrialized countries. In fact, governments not only take measures to mitigate ER but also to delay the statutory retirement ages (European Commission, 2021). The paradigm of an ageing population accompanied by a reduction in the working-age population, presents an important demographic change with numerous consequences in various social, political and economic fields. For instance, the specific political behaviour of the elderly in an ageing population may imply a reduction in education spending and an increase in healthcare spending (Vlandas et al., 2021).

Given these very concrete technological and demographic circumstances in advanced economies, we are in an unique moment in economic history where multiple crucial processes collapse. This encounter of demographic and technological change with the ageing of the population and the rising of new disruptive technologies is originating several economic and political debates. Regarding the economic debate on technological change, Jimeno (2019) remarks that there is uncertainty about the degree to which new machines and human labor will be complements or substitutes in the production of existing tasks embedded in the production of goods and services. On the other hand, Acemoglu and Restrepo (2017) highlight how the current technological change could be burying the negative economic effects

[1] See Raj and Seamans (2019) for a literature review.
[2] See Stadlmann and Zehetner (2021) for an example of comparison between HI and AI competences.

of the ageing of the population assumed by economic literature [3], since the countries undergoing more rapid demographic change are more likely to adopt robots (Acemoglu and Restrepo, 2022).

This chapter provides new insights to this collision of technological and demographic change by analyzing the effect of AI on the ER decisions in Europe. Although ER decisions have been widely studied, and the analysis of the AI characteristics is one of the main topics in recent literature, the nexus between these two concepts stills unexplored. In order to develop our analysis, we use microdata from the Survey of Health, Ageing and Retirement in Europe (SHARE), a measure of AI advances (Felten et al., 2018) and a measure of AI exposure (Felten et al., 2021). In addition, considering both AI advances and AI exposure we proportionate a new technological classification of occupations in 4 Intelligence terrains (I-terrains). For those occupations with a low level of advancement in this matter, we speak of occupations of the HI terrain. For occupations with a high level of current AI advances but low expectations of future development, we speak of the narrow AI terrain. For those occupations with low current advances of AI but great development potential in the future, we speak of the future AI terrain. Finally, for those occupations with a high level of advances and a high expectation of development in the future, we are talking about the AI terrain.

We find that workers more affected by the AI revolution are less likely to transition to ER when the impact of this new technology implies current advances and expectations of future developments. When considering separately AI advances and AI exposure, we observe that AI-impact reducing the ER probability either via current advances or future expectations requires tertiary education to be significant. Indeed, we find a mediating effect of education between AI and ER. These results qualify the conclusions on the influence of the Fourth Industrial Revolution on transitions to ER, pointing out that this technological revolution is made up of a conglomerate of technologies with specific characteristics that can affect various aspects of the labor market in different ways. In this sense, although it has been documented that the automation process pushes old workers to ER (Yashiro et al., 2021; Casas and Román, 2023), the AI revolution affects the ER decision in the opposite direction. To reach a conclusion about the global effect that AI and the automation process can have on ER would require a broader analysis.

Our results are consistent with recent evidence of robots having higher complementarity with older workers (Battisti and Gravina, 2021). Furthermore, connecting our results with the theory of Ahituv and Zeira (2011), we can indicate that, in the AI technical change, the wage effect -raised aggregate wages- outweighs the erosion effect - the learning efforts dedicated to the new technologies pays off less gains to older workers since they have shorter career horizons. Moreover, our results would fix into the concept of "right" AI established by Acemoglu and Restrepo (2020b), with the consideration of a positive economic outcome due to the implementation of AI for older workers in particular and the society from a general perspective. In addition, our analysis can also be related with the literature studying the links between ER and occupational characteristics. In this regard, our contribution would be on the focus of a certain technological characterization of occupations. In this sense, it could be considered that this chapter shares lineage with Hayward (1986), who examines the influence of occupational characteristics on the ER of men, and Schreurs et al. (2011), who investigate workers' ER intention among blueand white-collar workers. Finally, in line with Agarwal and Gort (2002), the fact of AI reducing ER probabilities for workers more affected by this transformative technology may rely on the expansion phase of this technology- intensive industries and this desirable effect of AI in undermining ER transitions may have a near obsolescence date. On the other hand, it can be argued that this desirable effect relies on the transformative laborfriendly characteristics of this disruptive technology.

The rest of the chapter is structured as follows: section 2 presents the literature review and the main hypotheses, section 3 presents the data used, as well as the methodology, the sample and the variables. Section 4 presents the main results and section 5 summarizes the conclusions.

[3] The aging population have been assumed by some economists to have negative effects on economic growth, either because of the lower labor force participation and productivity of older workers (Gordon, 2016) or because aging creates an excess of savings over desired investment, leading to secular stagnation (Hansen, 1938).

7.2 Background and hypotheses

Since this technological change encompasses a conglomerate of diverse technologies and processes, we define a conceptual framework to delimitate the technological target of analysis of this study. Taking as a baseline the simplified vision of the technological change provided by Fossen and Sorgner (2019), we can label the technological change as digitalization and identify both digitalization sides: a destructive side and a transformative side. The destructive digitalization is equated by these authors as computerization, a process that can be briefly defined as computer-based automation and mainly involves robotization, which can be briefly defined as robot-based automation, and Machine Learning. The International Federation of Robots (IFR) defines an industrial robot as an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications", while Brynjolfsson and Mitchell (2017) define Machine Learning as a subfield of AI that studies the question "How can we build computer programs that automatically improve their performance at some task through experience?".

The concept of destructive digitalization emerge as the logical continuation of the process of task automation started with the introduction of the first machines (Hitomi 1994) and its impact on ER has been addressed in Casas and Román (2023). Therefore, the current document focuses on the study of the implications of transformative digitalization for the ER decision. According to Broussard (2018), there are definitions for both "narrow AI" and "general AI". Concretely, the 'narrow' definition of AI refers to computer software that involves highly sophisticated algorithmic techniques to find patterns in data and make predictions about the future, while the 'general' definition of AI refers to computer software that can think and act on its own, which does not yet exist. This chapter address the impact of both AI definitions by considering current advances and future expectations regarding this technology.

This so-called transformative digitalization is going to impact occupations that were previously considered safe in past technological revolutions. In fact, it will affect all occupations to a greater or lesser extent (Acemoglu and Restrepo 2018a; Grace et al. 2018) in a way that some jobs that were not known to be affected by previous waves of automation may now be subject to higher AI exposure (Tolan et al., 2021). Indeed, highskill occupations are most exposed to AI and this fact of AI-exposed jobs being predominantly those involving high levels of education and accumulated experience, yields that older workers who are most exposed to AI (Webb, 2020).

The AI revolution promises to bring multi-level changes to the economy. For instance, Adner et al. (2019) foresee qualitative -and not only quantitative- changes due to three fundamental processes underlying the actual digital transformation-representation, connectivity, and aggregation-, indicating that these processes will continue to push firms in all industries to create and capture value differently, develop new business models and ecosystems, manage new forms of intellectual property, grow scale and scope differently, and create new opportunities and challenges for organization design and management practices. Moreover, the accelerated spread of this technology have been documented from different perspectives. For instance, Acemoglu et al. (2022) document rapid growth in AI related vacancies over 2010-2018, finding that AI-exposed establishments are reducing hiring in non-AI positions even as they expand AI hiring, without finding discernible impact of AI exposure on employment or wages at the occupation or industry level. Related to this rapid spread of AI technologies, Martínez-Plumed et al. (2021) remark the importance to consider the notion of technology "hyper adoption" when analysing the process of AI progress, since this theory states that people adapt to and adopt new technologies much faster than they used to do in the past.

Furthermore, since it has been found that robots have different substitutabilitycomplementarity relation with workers depending on their ages (Battisti and Gravini, 2021), it results logical to expect that AI would also have this different substitutabilitycomplementarity relation with workers depending on their ages. Certainly, literature has stressed out the fact that older workers tend to have more work experience and are therefore, at a similar education level, are more qualified, so the tasks performed by older workers might be more complex than those of younger workers (Bordot, 2022).

According to Felten et al. (2023), AI advances language modelling capabilities can have significant impacts on certain occupations and industries. The authors present a methodology to assess this exposure and find that top exposed occupations include telemarketers and post-secondary teachers, while legal services and securities, commodities, and investments are the top exposed industries. This research highlights the potential economic impacts of AI language modelling and the need for policymakers and stakeholders to consider the implications for affected workers and sectors.

Related to AI language modelling, Floridi and Chiriatti (2020) highlights that readers and consumers of texts will have to get used to not knowing whether the source is artificial or human, "just as today we could not care less about knowing who mowed the lawn or cleaned the dishes". Eloundou et al. (2023) examine the potential impact of Generative Pre-trained Transformer (GPT) models on the U.S. labour market. Their research shows that approximately 80% of the U.S. workforce could have at least 10% of their work tasks affected by the introduction of GPTs, while 19% of workers may see at least 50% of their tasks impacted. This influence spans all wage levels, with higher-income jobs potentially facing greater exposure, indicating that GPTs could have notable economic, social, and policy implications.

Petterson (2019) highlights the extensive promotion of artificial intelligence (AI) as a tool to improve organizational performance and productivity since the 1960s. Today, AI is once again the centre of attention due to its potential role in big business, akin to the rise of big data in the 1990s. However, the author argues that discussions around the potential threat of AI to jobs often overlooks the complex nature of knowledge work, which involves highly complex problem-solving that requires contextual, social, and relational understanding. These elements have no universal rules or solutions, making it challenging to program them into computer systems or replace them with AI. The article draws upon philosopher Herbert Dreyfus' thesis on AI to emphasize the limitations of current AI systems in fully replacing human knowledge work.

Literature has raised a debate about whether AI complements or replaces labour (Tschang and Almirall, 2021). Many studies indicate multiple instances of high complementarity between human labor and AI. Regarding productivity, Yang (2022) estimates the impact of AI technology on the productivity and employee profiles of firms in Taiwan's electronics industry from 2002-2018, using a keyword-matching method to parse the text of Taiwan patent grants. The study finds that AI technology is positively associated with productivity and employment, and that it crucially alters firms' workforce compositions. Regarding employment, Damioli et al. (2023) investigate the job-creation impact of AI technologies on the supply side, where AI development is viewed as product innovations in upstream sectors. The study analyzes a longitudinal sample of over 3,500 frontrunner companies that patented AI-related inventions worldwide between 2000 and 2016, using system GMM estimates of dynamic panel models. The results indicate a positive and significant impact of AI patent families on employment, suggesting that AI product innovation has a labor-friendly nature.

Also studying the implications of AI for employment, Alekseeva et al. (2021) estimate the demand for AI specialists across occupations, sectors, and firms using data on skill requirements in online job postings. They find a significant increase in demand for AI skills across most industries and occupations in the U.S. economy between 2010 and 2019, with the highest demand in IT occupations, followed by architecture and engineering, scientific, and management occupations. The study also shows that firms with larger market capitalization, higher cash holdings, and higher investments in R&D have a higher demand for AI skills, and that job postings requiring AI skills within the same firm or job title have a wage premium of 11% and 5%, respectively. Managerial occupations have the highest wage premium for AI skills, and firms that demand AI skills more intensively also offer higher salaries in non-AI jobs.

All the aforementioned studies highlighting the labour-friendly characteristics of AI lead us to elaborate the first hypothesis of this study considering that AI may reduce the ER likelihood, more so if we consider that AI may relief the workload in many occupations and the replacement of physically demanding tasks with the use of home-based IT technologies allow the older worker to remain employed (Dropkin et al., 2016).

H1. Workers facing a higher impact of AI in their current occupation are less likely to retire early.

Capital-skill complementarity theory argues that unskilled workers are displaced by the combination formed by equipment capital and skilled workers (Griliches, 1969; Krussel et al., 2000). Taking into account the consideration of ageing in the framework of the capital-skill complementarity assumption, Sachs and Kotlikoff (2012) present a simple framework in which smart machines substitute directly for young unskilled labour, whereas they are complementary to older skilled workers. This phenomenon of older skilled workers complementing new capital devices has been also studied at the microeconomic level finding that older employees who use a PC at work having a higher probability of remaining employed in the future (Biagi et al., 2013), so computer users retire later than non-users (Friedberg, 2003) and educational level is positively correlated with computer use (Schleife, 2006).

In this line, Venti and Wise (2015) highlight the importance of education in shaping economic outcomes and the need to consider multiple pathways through which education influences retirement decisions by examining the relationship between education and ER using Social Security Disability Insurance (DI) and early claiming of Social Security retirement benefits data. They find that individuals with less than a high school degree are more likely to participate in DI and claim Social Security benefits early than those with a college degree or more.

Related to this fact, we can consider that workers with higher education are usually the workers performing the high paying jobs so we could also observe this phenomenon by targeting the financial situation instead of the education level. Radl (2012) discusses the impact of ageism in the workplace and how it can prevent the prolongation of working lives, suggesting that social class has a significant impact on retirement age norms, with those in higher social classes having later retirement age norms. Then, this fact of workers in higher social classes (generally, educated workers) having later retirement age norms goes hand-by-hand with the fact of technological progress raising the demand for educated workers (Autor et al. 1998).

The aforementioned literature relating education, skills and technological progress lead us to the proposition of the second hypothesis of this study stating that education plays a relevant role mediating in the relationship between AI and the ER probability. This hypothesis is consistent with the skill-biased technical change theory: unskilled workers are negatively impacted by technological progress while skilled workers benefit from it.

H2. Education plays a mediating role in the relationship between AI and the likelihood of *ER*.

7.3 Data

We construct our dataset upon three data levels. First, we use microdata as a baseline. Second, we merge occupation-level data collecting AI advances and AI exposure (Felten et al., 2018, 2021). Finally, we merge country-level data about GDP growth (World Bank), harmonized unemployment rate (Eurostat) and old-aged pensions in PPS per inhabitant (Eurostat).

Regarding the microeconomic baseline data, we use the SHARE,[4] a research infrastructure developed from 2004 until nowadays. This database, the largest panEuropean social science panel study providing internationally comparable longitudinal micro data which allow insights in the fields of public health and socio-economic living conditions of European individuals, accounts for 480,000 in-depth interviews with 140,000 people aged 50 or older from 28 European countries and Israel. From its beginnings, SHARE has released 8 waves. This survey constitutes a baseline database to study retirement (and particularly ER) from economical and sociological aspects among others.

Our sample covers 118,979 observations (from 17,573 individuals) from 50 to 66 years in the period 2004-2016. The geographical coverage is formed by 24 European countries: Austria, Germany, Sweden,

[4]The SHARE has become a standard database to analyze concrete aspect of retirement in recent years. Concretely, as a few examples of the use of this database to study ER we can mention Siegrist et al. (2007), who study the link between psychosocial quality and ER; Hochman and Lewin-Epstein (2013), who analyze the role of grandparenthood in the ER decision; or Markova and Tosheva (2020), who focus on the exploration of determinants for the phenomenon in Bulgaria.

Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Czech Republic, Poland, Hungary, Portugal, Slovenia, Estonia, Croatia, Lithuania, Bulgaria, Cyprus, Finland, Latvia, Romania and Slovakia.

This sample is constructed taking as a baseline the Job Episodes Panel. [5] Then, we merge extra variables from waves 1, 2, 4, 5, 6 and 7. These added variables include information on physical health, financial status, and education. Finally, we add external information sources: the main explanatory variable at occupation level containing AI exposure and macroeconomic controls at country level (GDP, unemployment rate and old-aged pensions in PPS per inhabitant).

7.3.1 Modelling approach

Our dependent variable (early retirement) takes value 1 when a worker decides to retire before his statutory retirement age and 0 when the individual remains working. Thus, given the binary nature of our dependent variable, we estimate the probability of early retirement using logit models and report average marginal effects.

As the main explanatory variables we consider two occupation-level variables measuring current advances and future expectations of AI impacts (AI advances and AI exposure) and a variable collecting 4 technological terrains regarding the AI current advances and future expected impacts at occupation level. Both main explanatory variables rely on the occupation-level measures provided by Felten et al. (2018, 2021)[6] that are explained below as well as the process of construction of the I-terrains variable.

AI advances (Felten et al., 2018)

This variable collects the AI advances from 2010 to 2015 so it provides a measure for current degree of development of AI for each occupation. This measure fits with the 'narrow' definition of AI, in which AI refers to computer software that involves highly sophisticated algorithmic techniques to find patterns in data and make predictions about the future (Broussard, 2018). This 'narrow' definition of AI could be equated to some extent with Machine Learning. [7]

AI exposure (Felten et al., 2021)

For the development of this measure, the authors go in the opposite direction to that followed in the elaboration of the previous measure, by applying in this occasion a forward-looking approach. Concretely, they base this measure on the meaningful scientific progress in AI applications, covering the fundamental applications in which, according to experts in the field, AI is likely to have implications for the workforce. Then, this measure fits the 'general' definition of AI, referring to computer software that can think and act on its own, which does not yet exist.

As we can observe in Figure 7.1, the variable collecting AI advances presents a bell shape while the variable collecting AI exposure present a flat shape slightly close to a U-shape. Table 7.1 collects a brief description of the AI variables, while Table 7.2 collects the descriptive statistics of these AI variables.

[5]https://doi.org/10.6103/SHARE.jep.710. See Brugiavini et al. (2019) and Antonova et al. (2014) for methodological details.

[6]The AI variables have been obtained through a crosswalk between the Standard Occupational Classification (SOC-2010) and the International Standard Classification of Occupations (ISCO-2008) of the variables provided by Felten et al. (2018, 2021).

[7]See Brynjolfsson and Mitchell (2017) and Brynjolfsson et al. (2018) for a discussion.

TABLE 7.1: Description of the AI variables

Variable	Description
AI advances (Felten et al., 2018)	AI progress in the occupation from 2010 to 2015. Backward-looking vision of AI exposure
AI exposure (Felten et al., 2021)	Experts' estimation of AI potential in the forthcoming years. Forward-looking vision of AI exposure.

TABLE 7.2: Descriptive statistics of the AI variables

	AI advances [Felten et al., 2018]	AI exposure [Felten et al., 2021]
Mean	3.437	-0.005
Median	3.473	-0.019
Standard deviation	0.648	0.945
Minimum	1.417	-2.123
Maximum	5.294	1.446
Number of observations	424	424

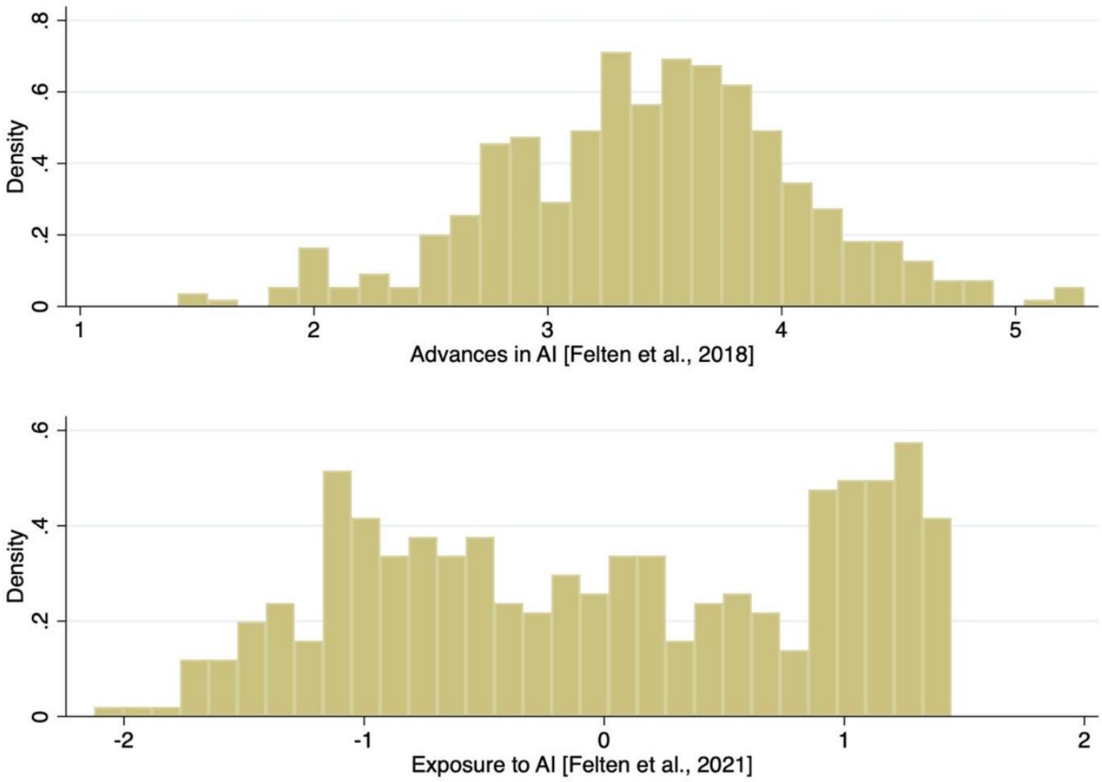

FIGURE 7.1: Histograms of the AI variables

I-terrains

A possibility to collect together both current advances and future developments in AI in one variable is to perform a technological classification of occupations in Intelligence terrains that considers the human-artificial intelligence dichotomy depending on the degree of AI advances in the occupation and its exposure to future AI applications. From now on, we refer to this classification as the I-terrains, collected in Table 7.3. As we can see, this classification comprises 4 clearly differentiated occupational terrains, so we consider a variable that takes values from 1 to 4 :

1. HI terrain: occupations with low effect of AI in actual advances and exposure to future developments.
2. Narrow AI definition: occupations with high AI advances but low exposure to future developments.
3. Future AI applications: occupations with low actual AI advances but high expectation of future developments.
4. AI terrain: occupations with both high advances of AI and exposure to new functionalities.

Our technological classification is inspired by the classification presented by Fossen and Sorgner (2019), which maps occupations considering the transformative and destructive sides of digitalization, equating transformative digitalization to AI and destructive digitalization to computerization. Our classification focuses on the analysis of transformative digitalization from a temporal perspective, considering both the current level of AI advances and the expectation of future developments.

TABLE 7.3: The technological classification of I-terrains.

<table>
<tr><td></td><td></td><td colspan="2">AI advances [Felten et al., 2018]</td></tr>
<tr><td></td><td></td><td>Low</td><td>High</td></tr>
<tr><td rowspan="2">AI exposure
[Felten et al., 2021]</td><td>High</td><td>Future AI applications
(FA)</td><td>AI terrain
(AIT)</td></tr>
<tr><td>Low</td><td>HI terrain
(HIT)</td><td>Narrow AI definition
(ND)</td></tr>
</table>

We consider as control variables the main explicative variables covered by the ER literature. Starting from age, we also consider gender, cohabiting situation, health status, financial situation, tertiary education, job status, contract type, sector, GDP growth, harmonised unemployment rate, the generosity of the social security system. Below, we provide information about the characteristics of each control variable, as well as some references to previous studies in the literature where they have been considered for the analysis of ERs:

Gender (see, for instance, Dahl, Nilsen, and Vaage, 2003): This is a binary variable taking value of 0 if the individual is male, 1 for females. - With partner (see, for instance, Kubicek, et al., 2010): Another binary variables taking value of 1 if the individual is cohabiting, 0 otherwise.
Health (see, for instance, Holtzman et al., 1980; Bazzoli, 1985; Jones et al., 2010): Health status is measured in a range from 1 to 5 : 1 poor, 2 fair, 3 good, 4 very good and 5 excellent.
Financial situation (see, for instance, De Wind et al., 2014): The financial situation is collected as the ability to make ends meet in a 1 to 4 scale: 1 with great difficulty, 2 with some difficulty, 3 fairly easily and 4 easily.
Tertiary education (see, for instance, Allel, León, Staudinger, and Calvo, 2021): Binary variable taking value of 1 if the individual accounts for higher education, 0 otherwise.
Job status (see, for instance, Quinn, 1977): The variable collecting the job status takes value of 1 for employees, 2 for civil servants and 3 for self-employees.
Contract type (see, for instance, Livanos and Nunez, 2017): This variable takes value 1 if the job was always full time, 0 otherwise.

Sector (see, for instance, Kieran, 2001): We use the basic classification in three separated industries: 1 Primary, 2 Manufacturing and Construction and 3 Services.
GDP growth (see, for instance, Kim, 2009): real GDP growth rate from the World Bank.
Harmonised unemployment rate (see, for instance, Bould, 1980; Laczko et al., 1988): in PPS per inhabitant from Eurostat.
The generosity of the social security system (see, for instance, Blöndal and Scarpetta, 1997; Blundell, Meghir, and Smith, 2002): in PPS per inhabitant from Eurostat.

7.4 Results

This section presents the main results obtained in this study. The results are presented in a three-part structure. In the first place,. Descriptive statistics are introduced along with a mapping of ER transitions considering the I-terrains. Second, the impact of AI advances and AI exposure in the ER probability is analysed providing a special focus to education under the consideration of a mediating role. Finally, the AI advances-exposure interaction is explored considering the I-terrains and providing again insights regarding education.

7.4.1 Descriptive statistics and the mapping of ER transitions in I-terrains

The descriptive statistics are presented in Table **??**, showing the differences between the total sample, the observations that concern the transitions to ER and the observations in which the transition does not occur. As we can observe, the mean of the AI exposure variables for the total sample is 0.26 , while the mean of this variable is -0.04 for observations collecting a switch to ER and 0.27 for the rest of observations. Thus, a first descriptive evidence clearly indicates that the AI exposure on the occupations of early retirees are less prominent than these effects on the occupations of individuals who do not end their working life early. This same effect can be observed for the binary variable, collecting whether the AI effect on the occupation performed is high or low. The mean of this variable is 0.510 for observations that do not transition to ER, while it is 0.461 for observations that transition to ER. Therefore, the proportion of 1 s that this variable takes with respect to 0 (high AI effect versus low effect) is higher for observations in which the ER decision is not involved. Regarding the I-terrains, we can observe that the share of observations in the AI terrain switching to ER is lower compared with the share of observations in the AI terrain in the total sample and non-switching to ER. Complementary to this fact, the share of observations switching to ER in the HI terrain and the Narrow AI definition are higher.

In the statistics of the rest of the variables, we can observe the effects widely collected by the ER literature. For instance, in the observations regarding the transition to ER, we observe a higher proportion of individuals with simply fair or poor health, a higher proportion of civil servants, a lower proportion of self-employed workers, a higher percentage of individuals from the primary and secondary sectors, and lower GDP growth.

Figure 7.2 shows 6,358 transitions to ER from 393 different occupations. Each bubble represents an occupation, with its size indicating the number of ERs from that occupation, and its centre located at the point on the map determined by the occupation's degree of AI advances and its score for AI exposure. As we can observe, there are a large number of occupations both in the narrow AI terrain and in the AI terrain more broadly. Specifically, of the 393 occupations with transitions to ER, we find 137 in the narrow AI terrain and 159 in the AI terrain, indicating that 296 of the 393 occupations with transitions to ER present a high degree of progress in AI, while the remaining 97 present a low degree of progress in AI, with 60 of them belonging to the HI terrain. As expected, the terrain with the fewest number of occupations is that of future AI applications, which includes those occupations that currently have a low degree of progress in AI but have a high expectation of future AI development.

Table 7.4 complements the mapping of transitions to ER offered in Figure 7.2, by listing the 30 occupations with the highest number of transitions to ER, ordered from highest to lowest according to the ratio of ERs to total number of workers. As we can see in Table 7.4, among these 30 occupations with the highest number of transitions to ER, we find 6 occupations in the HI terrain, 10 occupations in the narrow AI terrain, 5 in the terrain of future AI applications, and 9 in the AI terrain.

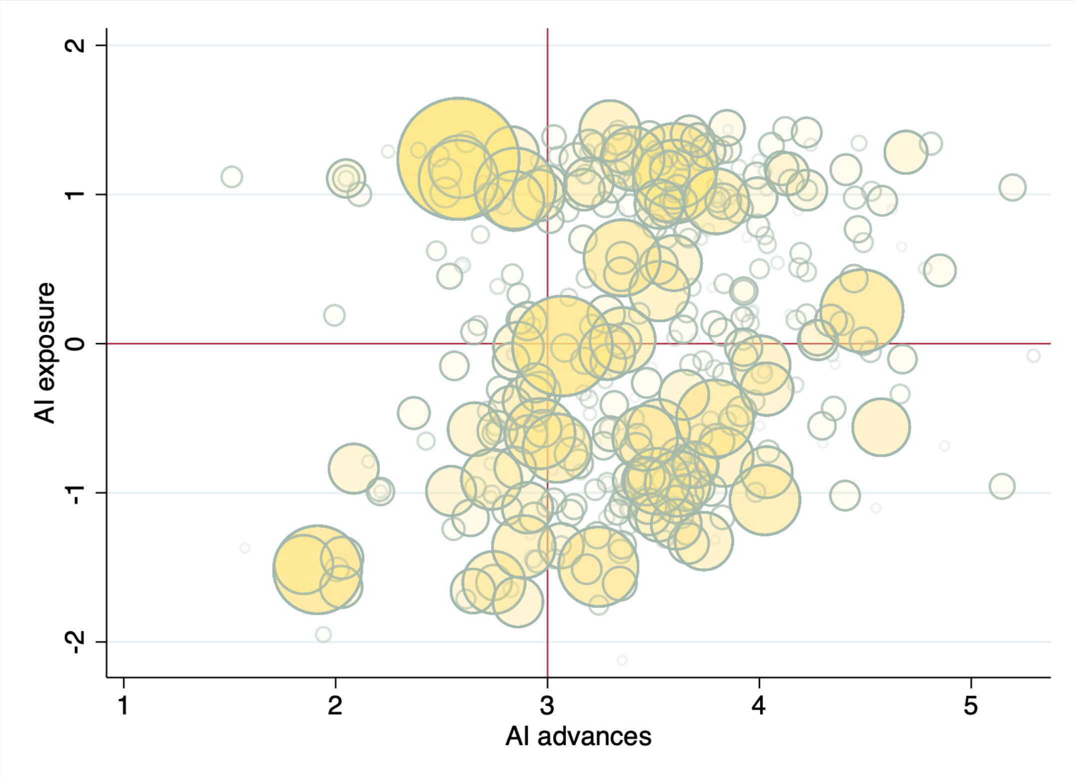

FIGURE 7.2: ER transitions and I-terrains.

Note: Compiled by authors from the SHARE data and considering the I-terrains classification.

7.4.2 ER, AI and education

Table 7.5 shows 5 logistic regression models with progress in AI as the main regressor. Each model progressively adds more control variables, with the first estimation being the most parsimonious, considering only gender, age, cohabitation status, and country and year dummies. The second model adds health and financial situation controls. The third model adds education, while the fourth model adds labor variables (job status, type of contract, and industry), and the fifth model adds country-specific macroeconomic controls (GDP growth rate, unemployment rate, old-aged pensions in PPS per inhabitant). As we can see, the significance of progress in AI fades when we include the education control in the estimations from model 3 onwards. This indicates the possible mediating effect of education on the relationship between the probability of ER and the degree of progress in AI.

Similarly to Table 7.5 , Table 7.6 shows another 5 logistic regression models with increasing number of controls, this time with AI exposure as the main explanatory variable. Although the effect of AI exposure on the probability of ER is significantly negative in all estimations, we observe a decrease in its significance once we introduce the education variable. Again, this suggests a possible mediating effect of education on the relationship between the probability of ER and AI exposure. Consequently, the mediating effect of education on the relationship between AI and the probability of ER would occur both when considering current progress in AI and future development expectations.

TABLE 7.4: ER transitions and occupation titles.

	ISCO-08 Title	ISCO-08	ER transitions	Total workers	Ratio: #ER/total workers	AI exposure	AI advances	I-terrain
1	Toolmakers and related workers	7222	61	125	.488	-.583	3.525	ND
2	Bricklayers and related workers	7112	100	211	.474	-1.495	3.24	ND
3	Mail carriers and sorting clerks	4412	57	128	.445	-.909	2.736	HIT
4	Manufacturing labourers not elsewhere classified	9329	62	143	.434	-1.362	2.888	HIT
5	Agricultural and industrial machinery mechanics and repairers	7233	77	181	.425	-1.047	4.026	ND
6	Motor vehicle mechanics and repairers	7231	67	162	.414	-.939	3.614	ND
7	Electrical mechanics and fitters	7412	54	137	.394	-.761	3.833	ND
8	Secondary education teachers	2330	115	297	.387	1.191	3.601	AIT
9	Heavy truck and lorry drivers	8332	94	252	.373	-.501	3.791	ND
10	Secretaries (general)	4120	99	267	.371	1.099	2.58	FA
11	Vocational education teachers	2320	56	151	.371	.352	3.528	AIT
12	Accounting and bookkeeping clerks	4311	61	168	.363	1.186	2.588	FA
13	General office clerks	4110	236	659	.358	1.238	2.58	FA
14	Shopkeepers	5221	92	260	.354	.575	3.352	AIT
15	Freight handlers	9333	68	193	.352	-.923	3.518	ND
16	Primary school teachers	2341	109	324	.336	1.087	3.6	AIT
17	Accounting associate professionals	3313	104	310	.335	1.04	2.848	FA
18	Cleaners and helpers in offices, hotels and other establishments	9112	123	380	.324	-1.516	1.915	HIT
19	Car, taxi and van drivers	8322	66	209	316	-.633	3.461	ND
20	Managing directors and chief executives	1120	67	220	305	954	3797	AIT
21	Accountants	2411	58	192	302	1426	3295	AIT
22	Administrative and executive secretaries	3343	55	184	299	957	2.843	FA
23	Shop sales assistants	5223	159	547	291	-.016	3.071	ND
24	University and higher education teachers	2310	63	218	.289	1.24	3.401	AIT
25	Cooks	5120	78	274	.285	-603	2.965	HIT
26	Subsistence crop farmers	6310	61	214	.285	-1.601	2.747	HIT
27	Nursing professionals	2221	108	391	.276	.22	4.484	AIT
28	Domestic cleaners and helpers	9111	54	199	.271	-1.481	1.849	HIT
29	Health care assistants	5321	74	286	.259	-.701	3.045	ND
30	Child care workers	5311	67	278	.241	.024	3.355	AIT

In order to further explore the mediating effect of education on the relationship between AI and the probability of ER, Figure 7.3 and Table 7.7 examine the interaction between education and AI variables. By including the interaction between AI advances and education in Model V, and between AI exposure and education in Model X, we observe that the negative effect of AI on the probability of ER is only significant for individuals with higher education. In the case of AI advances, the effect is not significant for individuals without higher education, and in the case of AI exposure, the effect is not significant for individuals without higher education. This non-significant positive effect of the degree of AI advances for individuals without higher education negates the negative significance of ER probability in Model III.

7.4.3 ER, I-terrains and education

Once we have concluded that the effect of AI on the probability of ER is significantly negative for individuals with higher education from both a retrospective view of current advances and a prospective view of potential impact, we move on to study the complete map by analysing the interaction between the degree of AI advances and expectations of future development. In order to do this, we use the technological classification in I-terrains. Given the relevant role that education has been shown to play, we also independently analyse how the degree of AI advances and AI exposure interact for individuals with and without higher education.

TABLE 7.5: Determinants of the ER transitions with special focus on AI advances - Logit estimations

Model	**I**			**II**			**III**			**IV**			**V**		
Predicted probability (y)	0.0534			0.0534			0.0534			0.0534			0.0534		
Independent variables (x)	$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat	
Main regressors															
AI advances	-5.61	-2.92	***	-3.26	-1.69	*	2.36	1.19		-0.06	-0.03		-0.05	-0.03	
Controls															
Female[a]	35.99	14.16	***	36.71	14.42	***	39.18	15.25	***	45.56	16.39	***	45.80	16.44	***
Age	34.87	72.95	***	34.73	72.63	***	34.90	72.98	***	35.19	73.67	***	35.25	73.60	***
With partner[a]	9.37	3.44	***	9.98	3.66	***	9.14	3.36	***	10.36	3.83	***	10.10	3.73	***
Health (ref. Excellent)															
Very good				7.53	1.96	**	7.53	1.94	*	7.99	2.05	**	8.04	2.07	**
Good				21.29	5.71	***	19.18	5.09	***	19.21	5.11	***	19.34	5.15	***
Fair				37.20	8.50	***	33.63	7.65	***	33.42	7.63	***	33.41	7.64	***
Poor				65.67	8.71	***	60.38	8.11	***	61.28	8.19	***	61.73	8.25	***
Ability to make ends meet (ref. With great difficulty)															
With some difficulty				8.48	1.82	*	8.99	1.97	**	7.32	1.60		7.88	1.73	*
Fairly easily				0.18	0.04		2.96	0.65		1.96	0.43		2.55	0.56	
Easily				-0.69	-0.14		5.34	1.11		3.91	0.81		4.24	0.88	
Education															
Tertiary education[a]							-30.62	-11.83	***	-30.85	-11.82	***	-31.02	-11.89	***
Job characteristics															
Job status (ref. Employee)															
Civil servant										17.43	6.02	***	17.08	5.90	***
Self-employed										-32.50	-10.04	***	-32.52	-10.03	***
Full time[a]										27.16	8.51	***	27.14	8.49	***
Sector (ref. Primary)															
Manufacturing and Construction										3.32	0.68		3.15	0.65	
Services										-15.96	-3.56	***	-16.34	-3.63	***
Macroeconomic variables															
GDP growth													-0.60	-1.06	
Harmonised unemployment rate													2.50	5.38	***
Old age pensions pps per capita													0.02	1.58	
Country dummies (ref. Spain)	Yes			Yes			Yes			Yes			Yes		
Wave dummies (ref. 2004)	Yes			Yes			Yes			Yes			Yes		
Log likelihood	-19,026,1			-18,938.9			-18,873.3			-18,740			-18,721.3		
#obs.	118,979			118,979			118,979			118,979			118,979		

Notes: * 0,1 > p ≥ 0,05; ** 0,05 > p ≥ 0,01; *** p < 0,01. [a] Dummy variable.

Table 7.8 presents five models with increasing order of control variables, analogously to Tables 7.5 and 7.6, with the difference that this time the I-terrains are presented as the main explanatory variable. We observe that, taking the terrain of human intelligence as a reference, only workers in the AI terrain have significantly lower probabilities of ER. This indicates that both a high degree of AI advances and high AI exposure are needed for an occupation to experience a decrease in the probability of ER of its workers. In fact, the degree of AI advances affects the probability of ER of each occupation differently depending on the degree of AI exposure of that occupation. Similarly, the degree of AI exposure affects the probability of ER differently depending on the degree of AI advances that each occupation has experienced.

This interaction between the degree of AI advances and AI exposure can be seen in Figure 7.4. The upper graph of Figure 7.4 considers the effect of AI exposure on the probability of ER depending on the degree of AI advances, while the lower graph shows the effect of the degree of AI advances on the probability of ER depending on AI exposure. These graphs have been obtained from an estimation with all control variables considering the interaction between both variables.

As we can observe, AI exposure significantly increases the probability of ER when the degree of AI advances is less than 2.4, while it significantly decreases the probability of ER when the degree of advances is greater than 3.1. On the other hand, we observe that the degree of AI advances significantly increases the probability of ER when the AI exposure variable takes a value less than -0.4 , while it significantly decreases the probability of ER when the AI exposure variable takes values above 0.5 . Therefore, the effect of AI on ER depends on the degree of advances and exposure, requiring a high

TABLE 7.6: Determinants of the ER transitions with special focus on AI exposure - Logit estimations

Model	**VI**		**VII**		**VIII**		**IX**		**X**	
Predicted probability (y)	0.0534		0.0534		0.0534		0.0534		0.0534	
Independent variables (x)	$\frac{dy}{dx}/y\%$	z-stat	$\frac{dy}{dx}/y\%$	z-stat	$\frac{dy}{dx}/y\%$	z-stat	$\frac{dy}{dx}/y\%$	z-stat	$\frac{dy}{dx}/y\%$	z-stat
Main regressors										
AI exposure	-9.89	-8.06 ***	-7.56	-6.03 ***	-2.69	-2.02 **	-2.51	-1.84 *	-2.62	-1.92 *
Controls										
Female[a]	41.05	16.31 ***	40.26	15.99 ***	39.13	15.57 ***	46.19	16.85 ***	46.46	16.91 ***
Age	34.96	73.17 ***	34.80	72.79 ***	34.91	72.97 ***	35.20	73.66 ***	35.26	73.59 ***
With partner[a]	9.66	3.55 ***	9.96	3.65 ***	9.24	3.39 ***	10.45	3.87 ***	10.20	3.77 ***
Health (ref. Excellent)										
Very good			7.55	1.95 *	7.48	1.92 *	7.96	2.04 **	8.01	2.06 **
Good			20.17	5.37 ***	18.83	4.99 ***	18.95	5.03 ***	19.07	5.07 ***
Fair			35.25	8.03 ***	32.95	7.49 ***	32.94	7.52 ***	32.91	7.52 ***
Poor			63.48	8.46 ***	59.80	8.04 ***	60.84	8.14 ***	61.27	8.19 ***
Ability to make ends meet (ref. With great difficulty)										
With some difficulty			9.58	2.08 **	9.55	2.11 **	7.61	1.67 *	8.19	1.80 *
Fairly easily			2.59	0.56	3.98	0.88	2.58	0.56	3.20	0.70
Easily			2.94	0.61	6.87	1.43	4.80	0.99	5.18	1.08
Education										
Tertiary education[a]					-27.96	-10.35 ***	-29.26	-10.83 ***	-29.35	-10.87 ***
Job characteristics										
Job status (ref. Employee)										
Civil servant							17.57	6.11 ***	17.23	5.99 ***
Self-employed							-32.53	-10.10 ***	-32.55	-10.09 ***
Full time[a]							27.53	8.64 ***	27.53	8.62 ***
Sector (ref. Primary)										
Manufacturing and Construction							3.84	0.80	3.71	0.77
Services							-14.50	-3.21 ***	-14.80	-3.26 ***
Macroeconomic variables										
GDP growth									-0.60	-1.05
Harmonised unemployment rate									2.52	5.41 ***
Old age pensions pps per capita									0.02	1.58
Country dummies (ref. Spain)	Yes		Yes		Yes		Yes		Yes	
Wave dummies (ref. 2004)	Yes		Yes		Yes		Yes		Yes	
Log likelihood	-18,996.9		-18,921.7		-18,871.9		-18,738.3		-18,719.5	
#obs.	118,979		118,979		118,979		118,979		118,979	

Notes: * 0,1 > p ≥ 0,05; ** 0,05 > p ≥ 0,01; *** p < 0,01. [a] Dummy variable.

TABLE 7.7: Predicted ER probability, AI and education

Education	Marginal effect of AI			
	No HE		HE	
	dy/dx	Z-stat	dy/dx	Z-stat
AI advances [a]	0.0017	1.29	-0.004	$-2.25**$
AI exposure [b]	-0.0006	-0.76	-0.005	$-3.10***$

impact of both variables for a significant decrease to occur. Additionally, when one variable takes a value below a certain threshold, the other variable has a significant positive effect on the probability of ER.

This interaction reveals a dual effect of AI on the probability of ER when analysed from a comprehensive perspective considering both the degree of current advances and the expectation of future developments in a given occupation. If the degree of advances has a low impact, AI exposure acts to increase the probability of ER. Symmetrically, if AI exposure has a low impact, the degree of AI advances also acts to increase the probability of ER. Similarly, if the degree of advances has a high impact, AI exposure acts to decrease the probability of ER. Similarly, if AI exposure has a high impact, the degree of AI advances also acts to decrease the probability of ER. Figure 7.5 shows the effect that the interaction between the degree of advances and the degree of AI exposure has on the probability of ER. As we

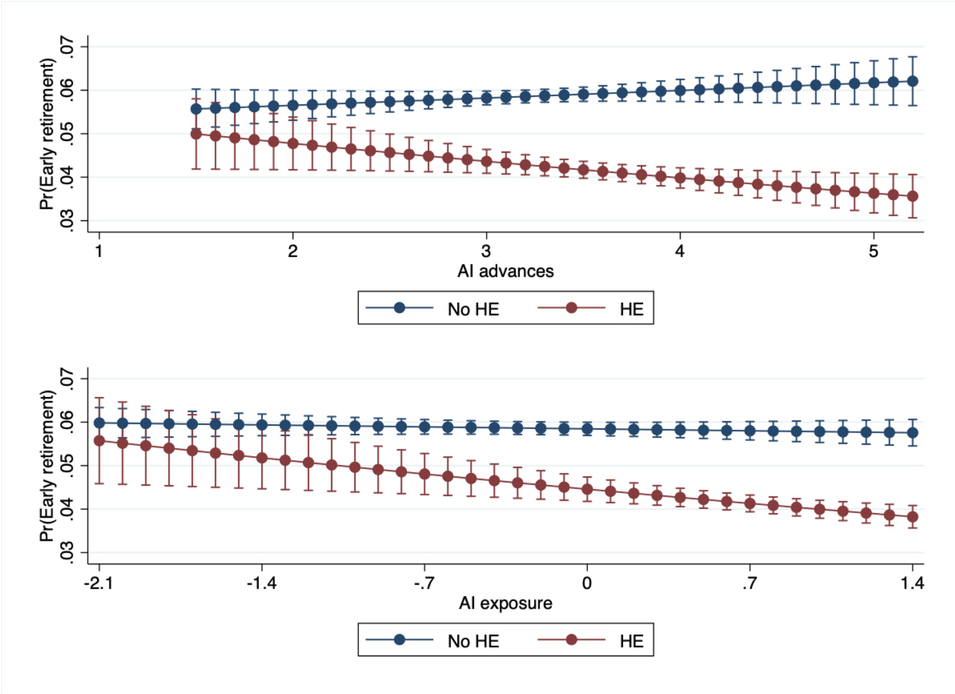

FIGURE 7.3: ER probability, AI and education

can see in the figure, each point in the interaction between the degree of advances and the degree of AI exposure results in a specific probability of ER, thus creating a graph in the form of contour lines in which the probability of ER varies depending on the area observed. As we can see in the graph labels, this interaction between the degree of AI advances and exposure to the interstitial interest is nothing more than our proposal of I-terrains. Therefore, we divide the graph into four sections determined by the threshold values of both variables and name each region according to the corresponding I-terrain.

As we deduced in Figure 7.4, the probability of ER is affected by the interaction between both AI variables at the extremes of the graph presented in Figure 7.5. Specifically, in the lower-left corner and the upper-right corner, we observe lower probabilities of ER. That is, the lowest probabilities of ER occur when both variables coincide at their extremes, that is, either the degree of AI advances and the position are low, or both variables take high values. This decrease in the probability of ER is significantly greater when both variables take high values, as can be seen in Table 7.8 , where we observe that the probability of ER in the AI terrain is significantly lower than the probability of ER in the human intelligence terrain.

On the other hand, we find the highest probabilities of ER in the upper-left corner and the lower-right corner of the graph, where high values of one variable interact with low values of the other. Specifically, the highest probabilities of ER are found in the lower-right corner, indicating that these higher probabilities of ER occur in the scenario in which an occupation is affected by a high degree of AI advances while being associated with low AI exposure. This fact makes future expectations of development in AI crucial when analysing the impact of the current degree of AI advances on a given occupation due to being an emerging technology.

This interaction between the degree of AI advances and AI exposure varies depending on education, as shown in Figure 7.6. For workers with higher education, the degree of AI advances has a significant negative effect on the probability of ER for AI exposure values greater than 0.5 , while AI exposure has a significant negative effect when the degree of AI advances is higher than 3. For workers without higher education, the degree of AI advances has a significant positive effect on the probability of ER for AI exposure values less than -0.4 and a significant negative effect for AI exposure values greater than 1.1. On the other hand, AI exposure has a significant positive effect when the degree of AI advances takes values less than 2.3, while having a significant negative effect when the degree of AI advances takes values greater than 3.2.

Continuing with the findings presented in Figure 7.6, we can see that the interaction between advancements and *AI* exposure has different effects on the likelihood of ER depending on whether individuals have a higher education degree or not. Figure 7.7 reproduces the graph presented in Figure 7.5, disaggregating individuals with and without higher education degrees. As we can observe, the top graph shows how the interaction between the degree of advancement and AI exposure affects the likelihood of ER for individuals with a higher education degree, while the bottom graph shows the effect of the same interaction on the likelihood of ER for individuals without a higher education degree. In both graphs in Figure 7.7, we can see the same effects discussed in Figure 7.5. That is, the lower likelihoods of ER are found in the corners where low and high values of both variables coincide, while the highest values in the likelihood of ER occur in the corners where high and low values of both variables do not coincide. Although this pattern is observed in both graphs, we can clearly see that it has a different impact depending on whether individuals have a higher education degree or not.

Specifically, the likelihood of ER is lower for individuals with a higher education degree when low or high values coincide for both the degree of advancement and exposure to artificial intelligence. On the other hand, the likelihood of ER is higher for individuals without a higher education degree when low or high values do not coincide for both the degree of advancement and exposure to artificial intelligence. That is, for individuals with a higher education degree, the likelihood of ER is lower in the bottom-left and top-right corners of the graph, while for individuals without a higher education degree, the likelihoods of ER are higher in the top-left and bottom-right corners of the graph.

Before summarizing the main findings of this study, we briefly consider an analysis of the validity of the hypotheses. Hypothesis H1 suggests that workers most impacted by AI are less likely to retire early. We observe that this is true when the occupation has both high AI advances and AI exposure. However, if either of these conditions is not met, hypothesis H1 may not hold true and the probability of early retirement may increase depending on the combination of the impact of AI advances and exposure, as well as worker characteristics. With respect to hypothesis H2, we can verify it based on the results presented in Figures 7.3, 7.6 and 7.7, and Table 7.7.

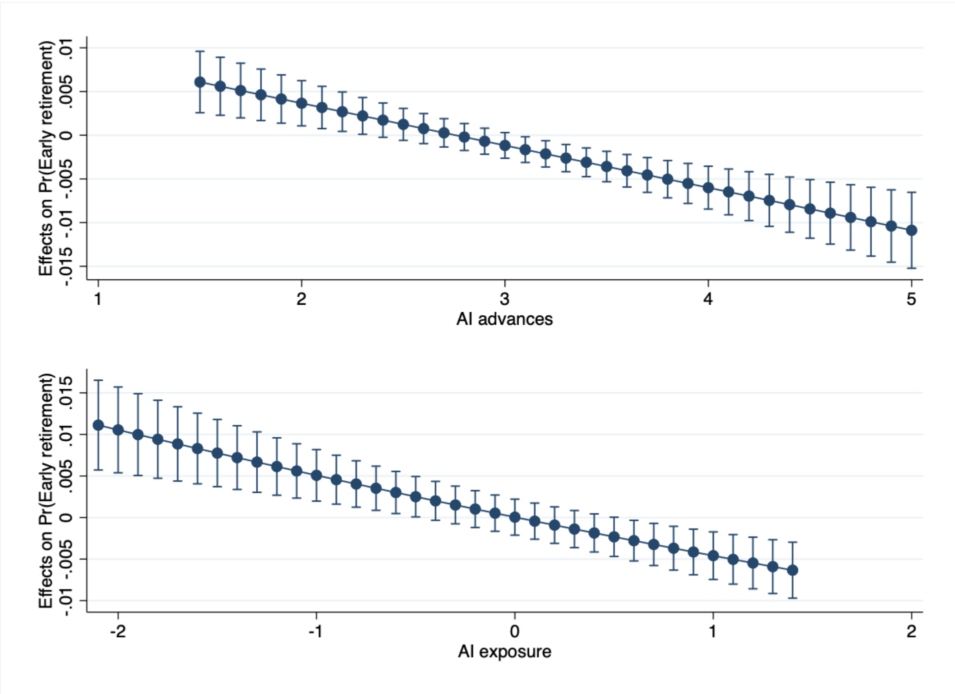

FIGURE 7.4: Interaction between AI advances and AI exposure

TABLE 7.8: Determinants of the ER transitions with special focus on the I-terrains - Logit estimations

Model	**XI**			**XII**			**XIII**			**XIV**			**XV**		
Predicted probability (y)	0.0534			0.0534			0.0534			0.0534			0.0534		
Independent variables (x)	$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat		$\frac{dy}{dx}/y\%$	z-stat	
Main regressors															
I-terrains (ref. HI terrain)															
Narrow AI definition	0.14	0.04		0.96	0.26		1.37	0.39		-0.98	-0.27		-1.01	-0.28	
Future AI applications	-9.81	-2.28	**	-5.92	-1.37		-2.06	-0.49		-5.06	-1.2		-5.50	-1.31	
AI terrain	-25.18	-7.25	***	-20.39	-5.84	***	-10.03	-2.77	***	-12.35	-3.37	***	-12.45	-3.39	***
Controls															
Female[a]	39.96	15.36	***	39.51	15.19	***	39.16	15.06	***	46.05	16.38	***	46.34	16.44	***
Age	34.98	73.15	***	34.83	72.82	***	34.92	73.01	***	35.21	73.67	***	35.28	73.61	***
With partner[a]	9.36	3.44	***	9.57	3.51	***	9.09	3.34	***	10.37	3.84	***	10.11	3.74	***
Health (ref. Excellent)															
Very good				7.84	2.02	**	7.63	1.95	*	8.01	2.05	**	8.06	2.06	**
Good				20.27	5.38	***	18.86	4.98	***	18.87	5.00	***	18.99	5.03	***
Fair				35.12	7.99	***	32.86	7.47	***	32.68	7.45	***	32.65	7.46	***
Poor				62.91	8.39	***	59.56	8.01	***	60.44	8.09	***	60.87	8.14	***
Ability to make ends meet (ref. With great difficulty)															
With some difficulty				9.43	2.05	**	9.57	2.12	**	7.72	1.70	*	8.30	1.83	*
Fairly easily				2.79	0.61		4.18	0.92		2.97	0.65		3.59	0.79	
Easily				4.00	0.83		7.45	1.55		5.61	1.16		5.97	1.24	
Education															
Tertiary education[a]							-25.63	-9.25	***	-26.63	-9.57	***	-26.79	-9.63	***
Job characteristics															
Job status (ref. Employee)															
Civil servant										18.33	6.33	***	17.98	6.21	***
Self-employed										-32.24	-9.97	***	-32.28	-9.96	***
Full time[a]										27.72	8.72	***	27.71	8.69	***
Sector (ref. Primary)															
Manufacturing and Construction										4.54	0.95		4.39	0.91	
Services										-13.57	-3.02	***	-13.90	-3.08	***
Macroeconomic variables															
GDP growth													-0.59	-1.05	
Harmonised unemployment rate													2.51	5.40	***
Old age pensions pps per capita													0.02	1.59	
Country dummies (ref. Spain)	Yes			Yes			Yes			Yes			Yes		
Wave dummies (ref. 2004)	Yes			Yes			Yes			Yes			Yes		
Log likelihood	-18,978.8			-18,906.1			-18,866.2			-18,731.5			-18,712.8		
#obs.	118,979			118,979			118,979			118,979			118,979		

Notes: * 0,1 > p ≥ 0,05; ** 0,05 > p ≥ 0,01; *** p < 0,01. [a] Dummy variable.

7.5 Conclusions

This chapter analyses the implications of the transformative digitalization in the ER decisions in Europe. To perform this analysis, using the SHARE as a base, we consider a variable collecting current AI advances (Felten et al., 2018) as a backward-looking AI vision and a variable collecting the AI exposure (Felten et al., 2021) as a forward-looking AI vision. In addition, we propose an occupational classification in 4 intelligence domains that imply the suitability of occupations in the intelligence dichotomy of human-artificial, collecting both the AI advances as a backward-looking AI vision and the AI exposure as the forward-looking vision.

We find that occupations characterized by high levels of AI advances and high levels of AI exposure are associated with a significant reduction in the probability of remaining in the workforce, both for individuals with higher education and those without. However, when these conditions are not present, the

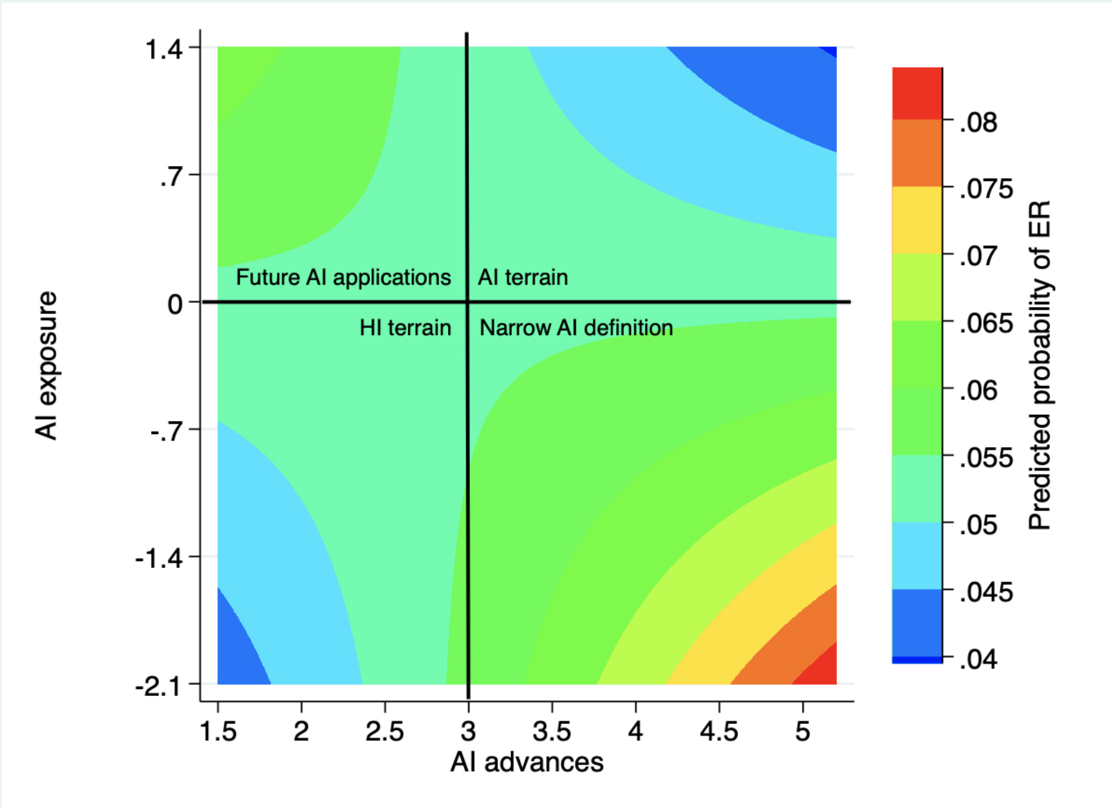

FIGURE 7.5: ER probability and I-terrains

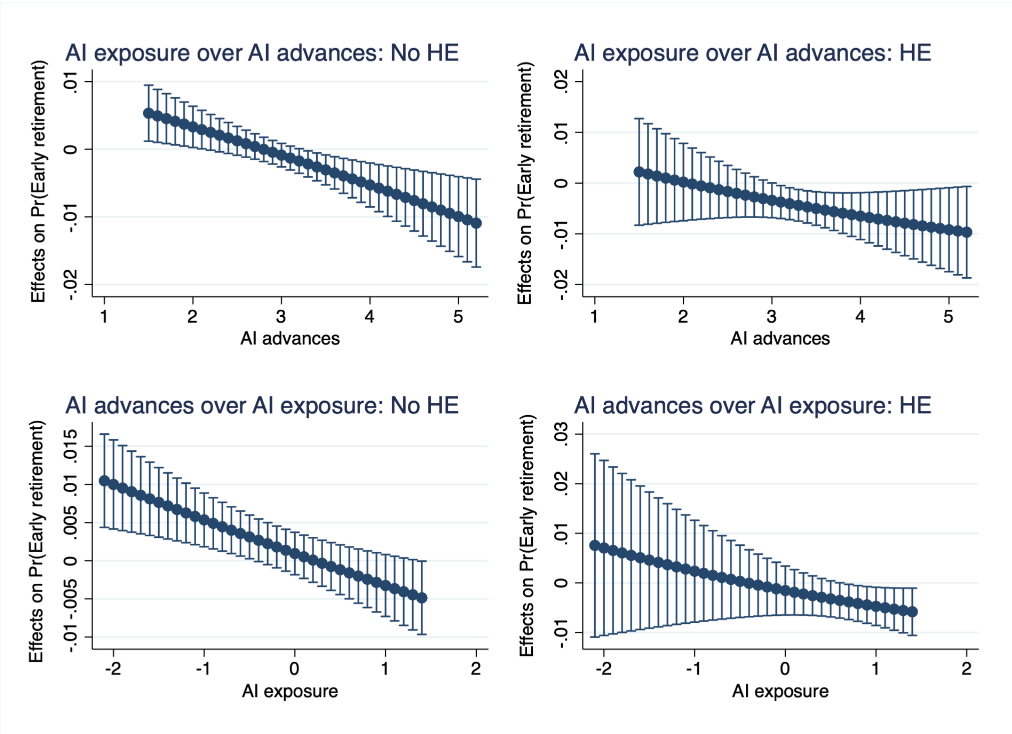

FIGURE 7.6: Interaction between AI advances and AI exposure at different education levels

impact of AI on the probability of ER depends on whether or not the individual has a higher education degree.

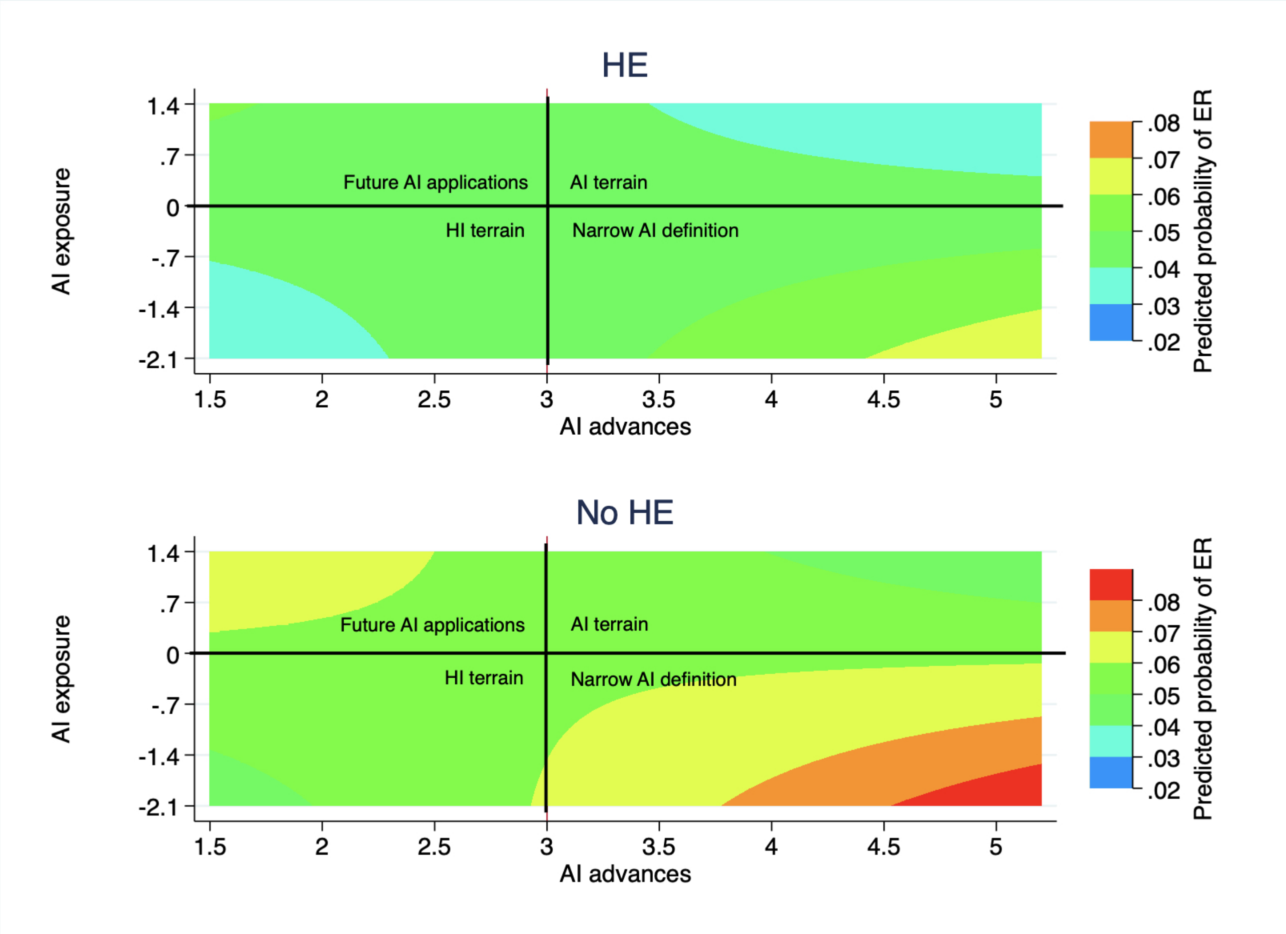

FIGURE 7.7: ER probability, I-terrains and education

Specifically, when we examine the impact of AI on retirement probabilities taking into account a continuous variable that measures the level of AI advances in each occupation, we observe that the current level of AI advances has a significant impact in reducing the probability of ER only for individuals with higher education degrees. In fact, for individuals without a higher education degree, the level of AI advances leads to a nonsignificant increase in the probability of ER, which causes this variable to have no significant effect when considering the entire sample. Similarly, when we examine the impact of AI on retirement probabilities taking into account a continuous variable that measures AI exposure, we observe that such AI exposure has a significant impact in reducing the probability of ER only for individuals with higher education degrees. In the case of individuals without a higher education degree, the impact is in the same direction, reducing the probability of ER, but is not significant.

Moreover, the interaction between the level of AI advances and AI exposure is particularly relevant since the impact of AI on the ER probability depends on both the current degree of advances and the expectations of future development An increase in the level of AI advances may increase or decrease the probability of ER, depending on the degree of AI exposure in the occupation. The same effect is observed in the opposite direction, indicating that an increase in AI exposure may increase or decrease the probability of ER, depending on the current level of AI advances.

The typological variable of I-terrains reveals that, in order to find a significant ER probability reduction from AI advances, a high AI exposure is needed. For a scenario in which there are high AI advances in an occupation but low expectancy of further development, there are not sufficient incentives to maintain a worker away from ER and the "wage effect" of the technological change (Ahituv and Zeira, 2011) would not be enough to prevent the worker from taking the ER decision. On the other hand, if we consider an occupation with low AI advances but high expectations of future developments, these incentives to keep the worker facing the development of this new technology are reduced since this worker does not have experience in this regard and it would be more efficient for this performance to be carried out by younger workers with a broader work horizon. Therefore, the incentives for workers to keep working longer in order to take advantage of the transformative side of the technological change are only significant in the scenario in which this worker is already experienced with AI (the occupation considered has experienced high AI advances) and there is high expectation of further AI implementations.

As AI continues to transform industries and workplaces, older workers may face unique challenges and opportunities. On the one hand, older workers may have more difficulty adapting to new technologies and may be at risk of being left behind as the job market evolves. On the other hand, older workers may have valuable skills and experience that can be leveraged in new ways with the help of AI. For instance, AI can assist older workers with tasks that may be physically demanding or require a high degree of precision. Additionally, older workers may have a wealth of institutional knowledge and problem-solving skills that can be combined with AI to drive innovation and improve business outcomes. However, it will be important for organizations to provide training and support for older workers to ensure they are equipped with the skills needed to work effectively with AI.

Tertiary education can play a critical role in helping older workers acquire the knowledge and skills they need to work effectively with AI and finding ways to add value in areas where AI cannot yet replace human judgment and creativity. This may involve retraining programs, continuing education courses, or even pursuing entirely new degree programs that are more relevant to the changing job market. At the same time, there is a need for educational institutions to adapt their curricula and teaching methods to better prepare students for the AI-driven future of work. This may involve incorporating AI-related topics into existing courses or even developing entirely new courses that focus specifically on AI and its applications in different industries.

Our research is not without limitations. One important limitation relies upon the assumption that the crosswalk between SOC-10 and ISCO-08 is perfect and the job content of an occupation in the US is the same as that of an occupation in any of the countries of our sample. This assumption has been made previously to adapt similar technological measures with the same source (see, for instance, Casas and Román, 2023; Crowley et al., 2021; Gardberg et al., 2020).

7.6 Appendix

TABLE A7.1: Descriptive statistics

	Total sample	**Switching to ER (S)**	**Non switching to ER (NS)**			
#obs. (#ind.)	118,979(17,573)	6,358(6,357)	112,621(17,002)			
Variable	Mean (S.D. overall)	Mean (S.D. overall)	Mean (S.D. overall)	Min	Max	Difference of means NS-S
Main regressors						
AI exposure	0.04 (0.96)	−0.03 (0.97)	0.04 (0.96)	-2.123	1.446	0.08 ***
AI advances	3.32 (0.63)	3.31 (0.62)	3.33 (0.63)	1.509	5.294	0.02 **
I-terrains	2.7 (1.15)	2.6 (1.13)	2.71 (1.15)	1	4	0.11 ***
HI terrain	17.76	19.03	17.68	0	1	-1.34 ***
Narrow AI definition	31.46	34.74	31.27	0	1	-3.5 ***
Future AI applications	13.24	13.38	13.23	0	1	-0.15
AI terrain	37.54	32.84	37.81	0	1	4.97 ***
Controls						
Female	0.514	0.483	0.516	0	1	0.03 ***
Age	55.4 (3.58)	59.2 (3.29)	55.2 (3.47)	50	66	-4.05 ***
With partner	0.799	0.807	0.799	0	1	-0.01
Health	2.8 (1.01)	3.0 (1.02)	2.8 (1.01)	1	5	-0.21 ***
Excellent	10.88	8.04	11.04	0	1	3 ***
Very good	23.78	19.28	24.04	0	1	4.75 ***
Good	40.39	40.83	40.36	0	1	-0.47
Fair	20.60	25.01	20.35	0	1	-4.66 ***
Poor	4.35	6.84	4.21	0	1	-2.63 ***
Ability to make ends meet	2.9 (0.97)	2.9 (0.97)	2.9 (0.97)	1	4	0.03 ***
With great difficulty	8.91	8.89	8.91	0	1	0.03
With some difficulty	26.89	28.61	26.79	0	1	-1.82 ***
Fairly easily	31.08	30.94	31.09	0	1	0.15
Easily	33.12	31.57	33.21	0	1	1.64 ***
Education						
Higher education	0.301	0.233	0.305	0	1	0.07 ***
Job characteristics						
Job status						
Employee	52.51	50.39	52.63	0	1	2.23 ***
Civil servant	36.77	40.59	36.55	0	1	-4.04 ***
Self-employed worker	10.73	9.01	10.82	0	1	1.81 ***
Full time	0.87	0.90	0.87	0	1	-0.03 ***
Sector						
Primary	8.12	9.30	8.05	0	1	1.24 ***
Manufacturing and Construction	24.17	28.48	23.92	0	1	-4.56 ***
Services	67.71	62.22	68.02	0	1	5.80 ***
Macroeconomic variables						
GDP growth	1.96 (3.42)	1.70 (3.57)	1.97 (3.41)	-14.8	11.9	0.27 ***
Harmonised unemployment rate	8.82 (4.38)	8.81 (4.63)	8.82 (4.36)	2.9	27.5	0.01
Old age pensions pps per capita	2041.4 (889.4)	2001.6 (851.1)	2043.7 (891.5)	504.7	3,929.8	42.11 ***

Note: [a] Tests of equality of means between observations not switching to early retirement (NS) and observations switching to early retirement (S); Ho: Mean (NS) – Mean (S) = 0; * 0,1 > p ≥ 0,05; ** 0,05 > p ≥ 0,01; *** p < 0,01.

Chapter 8

The influence of new technologies in the unemployment among older workers in Europe

8.1 Introduction

The greatest technological revolution in history promises to bring about radical changes in the world economy and in labour markets in particular. This important process of change remains covered in mystery in several respects like the degree to which new machines and human labour will be complements or substitutes in the production of existing tasks embedded in the production of goods and services (Jimeno, 2019). What seems clear is that this technological change promises to have particular effects for older workers (Battisti and Gravini, 2021).

In fact, the current technological revolution encompasses various technologies with different functionalities and characteristics that could affect work in different ways. Perhaps, this is the reason why numerous contradictory studies in this regard have arisen. On the one hand, some authors interpret the new technologies as labour destroyers (i.e., Frey and Osborne, 2017), as well as wage constrainers (i.e., Acemoglu and Restrepo, 2020a). On the other hand, other authors remark the labour friendly side of new technologies highlighting their capacity for labour productivity increase (i.e., Graetz and Michaels, 2018) and new jobs creation (i.e., Damioli et al., 2023). [1] Within this stream of thought, Brynjolfsson and Mitchell (2017) remarked that, although a profound change is coming, human roles remain being relevant for today's world mainly because we are very far away from general AI and machines cannot perform the full range of tasks that humans can do. [2] Furthermore, we can consider that the current technological change should itself be useful to solve many of the workplace issues that it may originate. [3]

Usually, literature generalizes the Fourth Industrial Revolution in the figure of a "robot" as a mix of Artificial Intelligence (AI) and Robotics. This reasoning has been employed in a number of macroeconomic studies to remark the drastic consequences for employment of these new "robots" (i.e., Berg et al., 2018; Lin and Weise, 2019). This general vision from the macroeconomic perspective is clearly denoting that a new technological wave will reduce labour time (by reducing the workday or jobs). However, from the microeconomic perspective, we can find that distinct individuals can be differently affected by new technologies in scales and measures, providing a large spectrum of affectation possibilities. In consequence, we can state that, although the labour-saving impact caused by new technologies has been

[1] The implications of robots adoption to productivity growth have been questioned by Cette et al. (2021), who analyze the contributions of robots to productivity growth in 30 OECD countries over 1975-2019 to conclude that robotization does not appear to be the source of a significant revival in productivity. Concretely, they find that the contribution of robots to productivity growth through capital deepening and TFP only appears to have been significant in Germany and Japan in the sub-period 1975-1995 and in several Eastern European countries in 2005-2019.

[2] Pettersen (2019) discusses aspects of knowledge work that cannot be easily replaced by AI.

[3] For instance, as Mitchell and Brynjolfsson (2017) highlight, since technology will affect almost every occupation over the next 10-20 years, online education could enrich options for the retraining of displaced workers.

broadly studied from the macroeconomic point of view, literature lacks for microeconomic analysis focusing on specific technologies and workers.

This chapter emphasizes in this consideration of disaggregating the general vision of new technological impact on employment in order to identify different situations and elaborate proper policies helping concrete individuals to embrace the technological change through a peaceful path. Concretely, the effect of computerization, AI, ML and reorganization capacity on unemployment transitions among older workers in Europe is analysed. To the best of our knowledge, the novelty presented by this study is threefold: (i) analysing the impact of new technologies in the unemployment among older workers in Europe, (ii) considering the impact of AI in unemployment, and (iii) measuring the concrete effect of ML in unemployment.[4]

Following this introductory section, Section 2 will delve into the theoretical background that underpins our analysis, providing the necessary academic context and justifying our hypotheses. In Section 3, we describe the methods employed in the study, including details on the data, the sample, our estimation methods, and the measures. Our findings are then reported in Section 4, with a subsection dedicated to the specific influence of new technologies on unemployment and job status among older workers. This leads into Section 5, where we draw our conclusions from the study, providing a synthesis of our analysis and its implications.

8.2 Theoretical background

Every technological change implies winners and losers in labour markets, embedding both a labour-friendly and a labour-unfriendly side. While the appearance of new technologies displaces human labour from some tasks for which machine use results more efficient, other tasks are created in which humans have a competitive advantage respect to new equipment and there exists a positive capital-skill complementarity.

These two sides of every technological change have been identified by the literature in the case of digitalization. Defined as the transformation of business processes by leveraging digital technologies, digitalization is a conglomerate of old technological processes continuation and new technological paradigms disruption.

On the one hand, as the continuation of old technological processes, digitalization supposed the refinement of automation. Defined as the use or introduction of automatic equipment in a manufacturing or other process or facility, automation has been cohabiting with humans through all economic history. Nowadays, the natural evolution of automation technologies is reflected in the term computerization, defined as computerbased automation. This term, labelled by some authors as destructive digitalization (Fossen and Sorgner, 2019), includes the consideration of ML technologies and robotics (Frey and Osborne, 2017).

On the other hand, regarding the new technological paradigms, AI appears as a technology able to impact occupations unaffected by previous technological waves (Tolan et al., 2021; Acemoglu and Restrepo, 2018a). In fact, this new general purposed technology is likely to outperform humans in all tasks in the following century (Grace et al., 2018). Therefore, a debate has arisen about whether AI will complement or substitute human labour.

To date, a few studies have shown the AI potential for jobs creation, highlighting the labour-friendly side of this technology (Damioli et al., 2023; Acemoglu et al., 2022; Alekseeva et al., 2021; Yang, 2022). In line with these findings, some authors labelled AI as transformative digitalization. However, we must bear in mind that AI is a nascent technology in the first stages of development for which we have only observed its narrow dimension - computer software that relies on highly sophisticated algorithmic techniques to find patterns in data and make predictions about the future -, while its general look computer software that can think and act on its own - is yet a few years away to reality (Broussard, 2018).

[4]Although the term computerization includes robotics and ML, and the effect of computerization and robotics in unemployment has been covered by the literature, the concrete impact of ML has not been previously measured.

The specific analysis of AI impacts targeting older workers is particularly relevant if we consider that older workers are most exposed to AI than their younger counterparts if we take into account that high-skill occupations are most exposed to AI and these AI-exposed jobs predominantly involving high levels of education and accumulated experience are more likely to be performed by older workers (Webb, 2020). Although there is limited literature focusing specifically on the connection between AI advances and older workers, some research papers have discussed the broader implications of AI and automation on the workforce, which include potential impacts on older workers. For instance, Bessen (2019) discusses the role of demand in determining the impact of AI on jobs, suggesting that older workers in occupations with declining demand due to AI may face higher unemployment probabilities, but also highlights the potential for AI-driven growth in other sectors to create new job opportunities. As collected by Figure 8.1, the three technologies analysed in this study account not only for destructive and transformative digitalization but also for the interaction between them. While computerization has been equated to destructive digitalization, containing robotics and ML, AI has been equated to transformative digitalization, being ML an AI subtechnology.

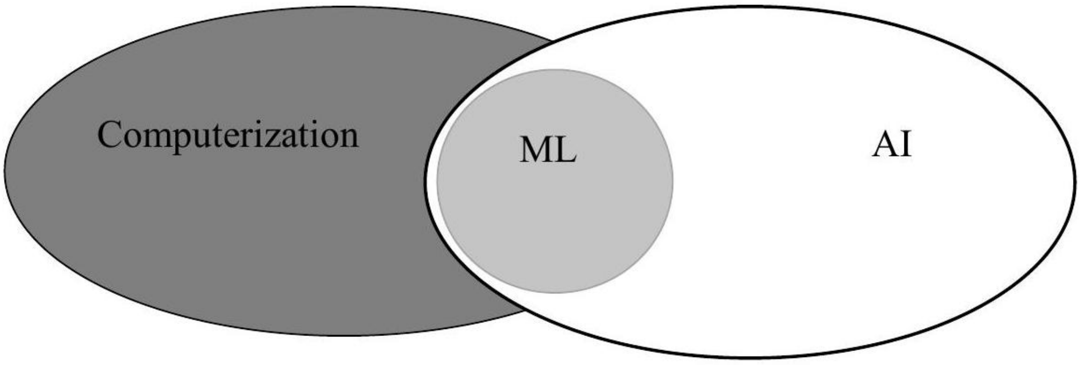

FIGURE 8.1: Venn diagram of computerization, *ML* and *AI*.

Older workers also experience the destructive and transformative effects of every technological change, although usually the destructive side is more pronounce for them due to a competitive disadvantage managing new technologies, which implies the deterioration of job prospects generating that this age group increasingly has more difficulties to adapt to technological progress (Schmidpeter and Winter-Ebmer, 2021). Indeed, literature has describe the ageing of the population as an augmenting-automation process, highlighting that ageing leads to greater industrial automation with a more intensive use and development of robots (Acemoglu and Restrepo, 2022) and concluding that computerization and population aging have large and statistically significant effects on employment growth (Phiromswad et al., 2022). This fact of older workers experiencing a greater hardship due to automation has been highlighted by economic literature since decades ago (see, for instance, Stern, 1955). The case of digitalization is extensive to many older people that find it difficult to navigate the digital sphere and to use online services, a phenomenon that has been labelled as "digital ageism" (Manor and Herscovici, 2021). In addition, while the labour-unfriendly side of every technological change is more pronounce for older workers, the transformative side is more reduced. For instance, capitalized software investment raises worker earnings at a rate that declines after the age of 50 , to about zero beyond 65 (Barth et al., 2022). In line with previous studies, we elaborate the Hypothesis H1 expecting to find that older workers at high computerization risk are more likely to become unemployed. This hypothesis of older workers at higher computerization risk experiencing higher unemployment probabilities can be supported by evidence from previous literature suggesting that older workers in occupations at high risk of computerization may face increased unemployment due to factors such as job polarization, reduced ability to adapt to new technologies, and lower engagement in training and skill development.

Autor and Dorn (2013) investigate the impact of computerization on the US labour market, highlighting that technological advances tend to disproportionately affect workers in routine and low-skilled jobs. Although their study does not specifically focus on older workers, they suggest that individuals in occupations with higher computerization risk, including older workers, are more likely to face unemployment due to job polarization.

Acemoglu and Restrepo (2020a) analyse the effect of industrial robots on local labour markets in the US, finding that the introduction of robots reduces employment and wages in affected industries. While the paper does not specifically concentrate on older workers, the results imply that workers in occupations with higher computerization risk, including older workers, may face higher unemployment probabilities.

Chui et al. (2016) discuss the potential for automation and computerization to displace human workers across various industries. They suggest that older workers in occupations at high risk of computerization may face higher unemployment probabilities due to their reduced ability to adapt to new technologies and the likelihood of their skills becoming obsolete. Nedelkoska and Quintini (2018) examine the relationship between automation and skill use, as well as its implications for worker training. The authors argue that workers at high risk of automation, which may include older workers, are less likely to engage in training and skill development. This lack of training makes them more vulnerable to unemployment.

Hypothesis H1: *Older workers at higher computerization risk have higher unemployment probabilities.*

The potential of AI for job creation has been documented by several studies (Acemoglu et al., 2022; Tschang and Almirall, 2021; Damioli et al., 2023; Alekseeva et al., 2021; Yang, 2022), therefore we present the Hypothesis H2 expecting to observe this transformative effect in the unemployment probabilities of older workers. Then, we expect that older workers in occupations with higher scores in AI advances are less likely to become unemployed. The hypothesis that older workers at occupations with higher AI advances have lower unemployment probabilities may appear counterintuitive, so we provide some concrete examples of potential scenarios where AI could support older workers and lead to lower unemployment probabilities. Brynjolfsson and McAfee (2014) argue that AI advancements can lead to the development of tools and systems that augment and support human labour rather than replace it. For example, AI-powered decision support systems or intelligent automation tools can help workers become more productive and efficient. In this context, older workers could benefit from the adoption of AI technologies, which might help them remain competitive in the labour market.

AI advancements in healthcare can lead to better health outcomes and well-being for older workers, as described by Topol (2019). Improved healthcare can enable older workers to maintain their health, extend their working lives, and reduce the likelihood of early retirement due to health issues. Goldin and Katz (2018) highlight that AI can play a significant role in personalized learning and skill development, allowing older workers to upskill or reskill more effectively. This could help older workers adapt to changing job requirements and reduce their unemployment probabilities. AI can also be used in job matching and employment services to help older workers find suitable job opportunities more efficiently, as illustrated by Marinescu and Wolthoff (2020). This could lead to better job market outcomes for older workers, thereby reducing their unemployment probabilities.

Hypothesis H2: *Older workers at occupations with higher AI advances have lower unemployment probabilities.*

ML is considered part of computerization and therefore a destructive digitalization technology. Therefore, we can expect that workers operating in occupations with higher suitability degrees to this technology are expectedly more likely to become unemployed, which lead us to the elaboration of our Hypothesis H3. According to Brynjolfsson and McAfee (2017) ML and related technologies may influence employment prospects across different demographic groups. Chui et al. (2016) suggests that older workers in routine and repetitive jobs, which are highly suitable for ML applications, may be more at risk of unemployment due to job displacement. Indeed, the measure provided by Frey and Osborne

(2017) takes into account advancements in ML and other digital technologies, then Hypothesis 1 and Hypothesis 3 must point logically in the same direction.

There is limited literature explicitly connecting older workers and machine learning (ML) suitability. The research on the impact of automation and digital technologies, which include ML as a key component, has focused primarily on the broader workforce without specifically targeting older workers. However, some studies explore the implications of automation and computerization on older workers, providing insights into their vulnerability to job displacement and the need for skill development. Arntz et al. (2016) suggesting that older workers are more likely to be affected by automation, including ML-driven technologies, than younger and more-educated workers. Tolan and Stone (2019) discuss the challenges that digital technologies, including ML, might bring to older workers, such as skill obsolescence or the need for retraining.

Hypothesis H3: *Older workers at occupations with higher ML suitability have higher unemployment probabilities.*

Autonomous equipment automate tasks, so the occupations highly composed by automatable tasks are those likely to disappear in the forthcoming years. Therefore, we expect that occupations with higher reorganization capacities are less likely to be taken over by new technologies. Accordingly, we state the Hypothesis H4 expecting that older workers in occupations with higher reorganization capacity are less likely to become unemployed since this reorganization capacity implies more possibilities to adapt the job content to new technologies.

The hypothesis that older workers at occupations with higher reorganization capacity have lower unemployment probabilities can be supported by the idea that occupations with greater adaptability can better accommodate the needs and skills of older workers. Caroli and Van Reenen (2001) found that organizations with greater reorganization capacity can better adapt to new technologies and market conditions, potentially leading to lower unemployment probabilities for workers, including older workers, as firms can reallocate tasks and retrain employees in response to changing circumstances.

Another study by Ilmakunnas and Ilmakunnas (2011) supports this hypothesis by examining the impact of age diversity in the workplace on productivity and profitability. They suggest that firms with higher reorganization capacity can better utilize the skills and experiences of a diverse workforce, including older workers, which can lead to improved productivity and potentially lower unemployment probabilities for these workers.

Cedefop (2018) further highlights the importance of reorganization capacity in addressing skill shortages and mismatches through findings from the European Skills and Jobs Survey. Occupations with higher reorganization capacity may offer better opportunities for older workers to acquire new skills and adapt to changing job requirements, reducing their unemployment probabilities. Moreover, a study by van Ours and Stoeldraijer (2011) on the relationship between age, wage, and productivity in Dutch manufacturing suggests that older workers can maintain their productivity levels in firms with higher reorganization capacity. In such firms, older workers may face lower unemployment probabilities as they can continue to contribute effectively to the organization. The aforementioned studies collectively suggest that older workers in occupations with higher reorganization capacity may face lower unemployment probabilities, as these occupations can better adapt to change and leverage the skills and experiences of older workers.

Hypothesis H4: *Older workers at occupations with higher reorganization capacity have lower unemployment probabilities.*

Employees, civil servants, and self-employed workers are differently exposed to the impacts of technology and face different labour market dynamics. Autor and Dorn (2013) find that the impact of new technologies on unemployment transitions may differ across job statuses, as employees in routine-intensive jobs might be more vulnerable to job displacement than civil servants and self-employed workers, who often have more job security or flexibility.

Bresnahan, Brynjolfsson, and Hitt (2002) indicate that the impact of new technologies on unemployment transitions might differ across job statuses, as employees, civil servants, and self-employed workers have varying degrees of exposure to technology-driven skill requirements and workplace reorganization. Moreover, Hipp, Bernhardt, and Allmendinger (2015) suggest that the effects of technology on unemployment transitions may differ for employees, civil servants, and self-employed workers due to variations in labour market regulations and protections across these job statuses. In summary, the studies collectively suggest that new technologies may affect the unemployment transitions of older workers differently based on their job status, with varying challenges and opportunities in adapting to technological changes leading to different unemployment probabilities and transitions. However, other factors, such as education levels, industry dynamics, and government policies, may also influence the relationship between new technologies and unemployment transitions for older workers across job statuses.

The aforementioned studies lead us to the specifications of the Hypothesis H5 indicating that the unemployment probabilities of older workers are differently impacted by new technologies depending on their job status.

Hypothesis H5: *New technologies affect the unemployment transitions of older workers differently depending on the job status.*

8.3 Methods

8.3.1 Data

We use the Survey of Health, Ageing and Retirement in Europe (SHARE), a research infrastructure developed from 2004 to the present day. This database, the largest panEuropean social science panel study providing internationally comparable longitudinal micro data which allow insights in the fields of public health and socio-economic living conditions of European individuals, accounts for 480,000 in-depth interviews with 140,000 people aged 50 or older from 28 European countries and Israel. From its beginnings, SHARE has released 8 waves.

8.3.2 Sample

Our sample covers 145,612 observations (from 16,697 individuals) from 40 to 66 years in the period 2004-2016. The retrospective modules of the SHARE make it possible to have data on an individual before entering the Survey, that is why even if the SHARE surveys people aged 50 or older, we can easily establish a sample that observes workers from the age of 40 harnessing the full potential of the data for our analysis. The geographical coverage is formed by 24 European countries: Austria, Germany, Sweden, Spain, Italy, France, Denmark, Greece, Switzerland, Belgium, Czech Republic, Poland, Hungary, Portugal, Slovenia, Estonia, Croatia, Lithuania, Bulgaria, Cyprus, Finland, Latvia, Romania and Slovakia.

This sample is constructed taking as a baseline the Job Episodes Panel. [5] Then, extra variables from waves 1, 2, 4, 5, 6 and 7 are merged. These added variables include information on physical health, financial status, and education. Finally, external information sources is added: the main explanatory variables at operational level containing technological measures and macroeconomic controls at country level (GDP and unemployment rate).

[5] https://doi.org/10.6103/SHARE.jep.710. See Brugiavini et al. (2019) and Antonova et al. (2014) for methodological details.

8.3.3 Estimation methods

Since transitions from employment to unemployment are analysed, logit models estimations are considered.

8.3.4 Measures

Dependent variable

Our main dependent variable is binary, taking value of 0 if the individual is working in periods t and $t+1$, and taking value of 1 if the individual is working in period t and unemployed in period $t+1$.

Independent variables

Main explanatory variables

Four technological measures for digitalization are considered: computerization probability (Frey and Osborne, 2017), advances in AI (Felten et al., 2018), suitability for ML (Brynjolfsson et al., 2018) and reorganization capacity (Brynjolfsson et al., 2018). [6] These four main explanatory variables have been obtained through a crosswalk between the Standard Occupational Classification (SOC-2010) and the International Standard Classification of Occupations (ISCO-2008).

Table 8.1 collects the descriptions of the main explanatory variables, while Table 2 shows their descriptive statistics and Figure 8.2 plots their histograms. Although these measures are calculated for different numbers of occupations, we consider only the occupations for which we can account for all the four digitalization measures so the effects of the different variables on labour is comparable. [7]

TABLE 8.1: Description of the main explanatory variables

Variable	**Description**	**Effect on employment**
Computerization probability [Frey and Osborne, 2017]	Probability that the occupation will be computerized in the time lap between 2023 and 2033.	Destructive
Advances in AI [Felten et al., 2018]	AI progress in the occupation from 2010 to 2015.	Transformative
Suitability for ML [Brynjolfsson et al., 2018]	Mean potential of tasks in the occupation to be took over by ML	Destructive
Reorganization capacity [Brynjolfsson et al., 2018]	Potential for reorganization, redesign and reengineering.	Transformative

Note: the term Destructive implies substitution to human labour while the term Transformative implies complementarity to human labour.

TABLE 8.2: Descriptive statistics of the main explanatory variables

[6] These measures have been previously used by Fossen and Sorgner (2021) to investigate the relationship of the new wave of digitalization of occupations with entry into different types of entrepreneurship.

[7] In particular, according to the SOC-10, computerization probability is provided for 702 occupations, advances in AI for 772 occupations, and suitability for *ML* and reorganization capacity for 964 occupations. Since the ISCO-08 is less disaggregated than SOC-10, after the crosswalk we account for 405 occupations with the 4 digitalization measures available.

	Computerization probability [Frey and Osborne, 2017]	Advances in AI [Felten et al., 2018]	Suitability for ML [Brynjolfsson et al., 2018]	Reorganization capacity [Brynjolfsson et al., 2018]
Mean	0.5	3.428	3.49	0.6
Median	0.532	3.466	3.486	0.599
S. D.	0.337	0.654	0.097	0.59
Minimum	0.0039	1.417	3.192	0.3949
Maximum	0.99	5.294	3.745	0.7996
# of observations	405	405	405	405

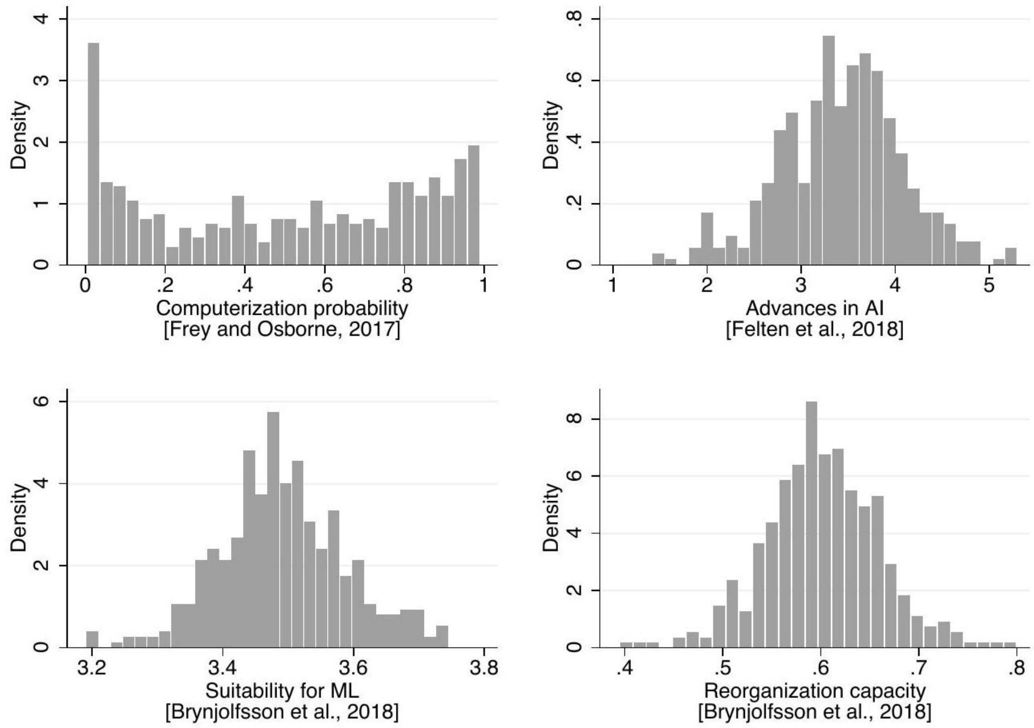

FIGURE 8.2: Histograms of the main explanatory variables

Control variables

As control variables we consider those widely covered and accepted by the literature about transitions to unemployment. Regarding the demographic characteristics, we consider gender, age, cohabitation status, health status in a range of 1 to 5 from excellent to poor health, and the financial situation measured as the ability to make ends meet measured on a scale of 1 to 4 from "with great difficulty" to "easily". Education is collected as a dummy variable that takes value 1 if the individual has higher education and 0 otherwise. [8] Regarding job characteristics, we control for (i) the job status, taking value 1 if the worker is an employee, 2 if civil servant and 3 if self-employed; (ii) the type of contract, that is collected in a dummy variable that takes value 1 if the job was always performed full time, 0 otherwise,

[8] We consider fundamental controlling higher education since Gardberg et al. (2020) find that the average automation probability of low-skilled workers is almost twice as high as of university graduates. Furthermore, these authors show that employment and wage shares of occupations with a higher automation risk have declined in Sweden over the period 1996-2013.

and, (iii) industry, considering the classic subdivision into primary, secondary (manufacturing and construction) and tertiary (services) sectors. Finally, country dummies, as well as macroeconomic variables (GDP growth and harmonized unemployment rates) are included. [9]

8.4 Results

Our main results are included in Tables 3 and 4. Table 8.3 includes 4 models that have as their main explanatory regressor one of the 4 technological variables considered. Specifically, Model I considers the automation probability as the main explanatory variable, while in Model II the main variable is AI advances, Model III encompasses ML suitability, and Model IV the reorganization capacity of the occupation. On the one hand, our results show that a higher automation probability and a higher suitability to ML lead to higher unemployment probabilities (verifying the Hypothesis H1 and H3), while on the other hand, we find that workers in occupations with higher levels of AI advances, as well as occupations with higher reorganization capacity, have lower unemployment probabilities (verifying the Hypothesis H2 and H4). [10]

As it can be observed in Table 8.3, workers in occupations with greater advances in AI have lower probabilities of becoming unemployed [11] while workers in occupations more adaptable to ML have greater probabilities of transitioning to unemployment. This is a striking fact as ML is a subfield of AI. What this information tells us is that, if we consider the aggregate of all AI subfields, this technology acts as a shield against unemployment. However, if the employment effect of ML -a specific subfield of AI- is isolated, we observe that the advancement of this technology makes workers in occupations adaptable to it increase their probability of being unemployed. This result may be an example of the complexity of the technological change that we are facing, in which a technology and a subfield of it can have completely opposite effects on specific aspects of the labour market.

Reinforcing recent evidence of occupation-level job tenure falling more in occupations at high risk of automation with a particularly pronounced effect among older workers (Georgieff and Milanez, 2021), we find that older workers at a higher computerization risk are more likely to become unemployed. Technological progress has been linked to inactivity among older workers, emphasizing the challenges faced by workers displaced by automation in finding alternative employment (Grigoli et al., 2022). Heywood et al. (2011), using German establishment data, discovered that establishments with jobs requiring computer use are less likely to hire older workers.

Hudomiet and Willis (2021) find evidence of computerization pushing numerous fulltime workers into part-time jobs while lowering their wages. Their results indicate that many older workers retired earlier than "normal" when computerization first permeated their occupations, suggesting that older workers nearing the end of their working lives may be forced into early retirement if it is not optimal for them to invest in human capital to compensate for their skills obsolescence.

[9] Table A1 collects the descriptive statistics of all measures included in our analysis. The mean age regarding observations in which a switch to unemployment is lower than the mean age of the total sample, since as workers get older, they are more propense to switch to inactivity instead of switching rather than to unemployment when they lose/leave their jobs. This also explains the low number of transitions to unemployment in the sample. Table A1 also indicates that unemployment among older workers is mainly a thing of poorer workers and the estimates in Table 8.3 corroborate that poorer workers have higher significant probabilities of going unemployed.

[10] Felten et al., (2021) also propose a measure for the AI future development expectation at occupation level. We do not find a significant association between this variable and the unemployment transitions of older workers in Europe, indicating that while AI advances play a significant role preventing unemployment of older workers, the expectations of further implementations of this technology does not directly influence the transition.

[11] Hunt et al. (2022) analyze the impact of AI-enabled technologies in organizations by applying a methodology based on the use of bespoke employer surveys to conclude that organizations introducing AI have higher rates of both job creation and destruction compared to organizations introducing non-AI technology.

TABLE 8.3: Determinants of the unemployment transitions

Model	I			II			III			IV		
Predicted probability (y)	0.0026635			0.0026604			0.0026593			0.0026565		
Independent variables (x)	$\frac{dy}{dx}/y$	z-stat		$\frac{dy}{dx}/y$	z-stat		$\frac{dy}{dx}/y$	z-stat		$\frac{dy}{dx}/y$	z-stat	
Main regressors												
Automation probability	0.82	4.36	***									
AI advances				-42.16	-4.31	***						
ML suitability							205.37	3.66	***			
Reorganization capacity										-200.69	-2.02	**
Controls												
Female [a]	-7.37	2.57	**	20.59	1.68	*	26.75	2.24	**	33.45	2.84	***
Age	-26.47	-5.64	***	-7.36	-5.65	***	-7.41	-5.68	***	-7.25	-5.56	***
With partner [a]	0.00	-1.82	*	-26.26	-1.81	*	-28.04	-1.91	*	-27.50	-1.88	*
Health (ref. Excellent)												
Very good	37.86	0.42		9.17	0.52		8.30	0.48		9.01	0.52	
Good	63.30	2.21	**	39.02	2.32	**	40.24	2.42	**	39.17	2.33	**
Fair	37.69	3.16	***	64.40	3.25	***	67.96	3.43	***	65.22	3.29	***
Poor	0.00	1.42		39.45	1.49		43.86	1.63		40.64	1.53	
Ability to make ends meet (ref. With great difficulty)												
With some difficulty	-127.52	-3.09	***	-91.57	-3.07	***	-101.84	-3.22	***	-96.65	-3.14	***
Fairly easily	-159.40	-4.11	***	-122.40	-4.01	***	-137.52	-4.25	***	-130.03	-4.14	***
Easily	-163.74	-5.09	***	-153.96	-5	***	-170.30	-5.23	***	-162.57	-5.13	***
Education												
Tertiary education	-1.43	-0.1		-4.48	-0.33		-20.15	-1.62		-14.94	-1.17	
Job characteristics												
Job status (ref. Employee)												
Civil servant	-45.23	-3.66	***	-47.50	-3.86	***	-51.53	-4.2	***	-50.54	-4.1	***
Self-employed	-68.11	-4.15	***	-70.52	-4.37	***	-76.07	-4.88	***	-75.05	-4.8	***
Full time [a]	1.02	0.06		5.06	0.31		-1.37	-0.08		-0.24	-0.01	
Sector (ref. Primary)												
Manufacturing and Construction	7.98	0.32		2.36	0.08		20.90	0.83		3.18	0.12	
Services	-13.38	-0.56		-30.82	-1.15		-12.30	-0.53		-22.48	-0.88	
Macroeconomic variables												
GDP growth	-2.44	-1.09		-2.42	-1.08		-2.43	-1.09		-2.45	-1.1	
Harmonised unemployment rate	1.81	0.87		1.93	0.93		1.70	0.82		1.77	0.86	
Country dummies (ref. Spain)	Yes			Yes			Yes			Yes		
Wave dummies (ref. 2004)	Yes			Yes			Yes			Yes		
Log likelihood	−2,459.8997			−2,460.6522			−2,463.7072			−2,468.6703		
#obs	145,612			145,612			145,612			145,612		

Notes: * 0.1 > p ≥ 0.05; ** 0.05 > p ≥ 0.01; *** p < 0.01. [a] Dummy variable

The results indicating that AI advances may reduce older workers unemployment probabilities can be related with the fact that the replacement of physically demanding tasks through the use of home-based communication and information technologies could potentially enable older workers to remain employed (Dropkin et al., 2016).

8.4.1 New technologies, unemployment and job status

In this section we consider the above models including the interaction between technological variables and job status. In this way, we analyse how the new technologies that make up the current technological wave affect in a differentiated way the probability of unemployment of employees, civil servants and the self-employed. Both Figure 8.3 and Table 8.5 are derived from the models in Table 8.4. Specifically, the up-left graph of Figure 8.3 and the rows on automation risk in Table 8.5 are obtained from Model V; the up-right graph of Figure 8.3 and the rows on AI advances in Table 8.5 are obtained from Model VI; the down-left graph of Figure 8.3 and the rows on ML suitability in Table 8.5 are obtained from Model VII; and the down-right graph of Figure 8.3 and the rows on reorganization capacity in Table 8.5 are obtained from Model VIII.

As we can observe in Figure 8.3 and Table 8.5, new technologies affect workers differently depending on their job status, which verifies the Hypothesis H5. Specifically, the probability of unemployment of

TABLE 8.4: Determinants of the unemployment transitions considering interaction between the technological measures and job status

Model	V			VI			VII			VIII		
Predicted probability (y)	0.0026617			0.0026568			0.0026571			0.0026572		
Independent variables (x)	$\frac{dy}{dx}/y$	z-stat		$\frac{dy}{dx}/y$	z-stat		$\frac{dy}{dx}/y$	z-stat		$\frac{dy}{dx}/y$	z-stat	
Main regressors												
Automation risk[a]	38.37	3.29	***									
High AI advances[a]				-38.71	-3.01	***						
High ML suitability[a]							33.98	2.86	***			
High reorganization capacity[a]										-19.43	-1.72	*
Controls												
Female[a]	30.40	2.57	**	25.55	2.11	**	28.37	2.37	**	35.91	3.06	***
Age	-7.29	-5.59	***	-7.32	-5.62	***	-7.37	-5.65	***	-7.32	-5.61	***
With partner[a]	-26.19	-1.8	*	-26.67	-1.83	*	-28.05	-1.91	*	-26.90	-1.85	*
Health (ref. Excellent)												
Very good	7.94	0.45		8.47	0.49		8.84	0.51		8.87	0.51	
Good	38.45	2.27	**	39.12	2.32	**	40.18	2.41	**	38.84	2.31	**
Fair	64.54	3.23	***	65.12	3.28	***	67.19	3.39	***	65.25	3.28	***
Poor	38.77	1.46		41.41	1.55		43.72	1.63		41.10	1.54	
Ability to make ends meet (ref. With great difficulty)												
With some difficulty	-97.19	-3.15	***	-94.66	-3.11	***	-100.47	-3.19	***	-97.11	-3.16	***
Fairly easily	-130.89	-4.16	***	-127.29	-4.09	***	-135.85	-4.23	***	-129.89	-4.13	***
Easily	-163.01	-5.13	***	-159.64	-5.09	***	-168.44	-5.2	***	-162.78	-5.13	***
Education												
Tertiary education[a]	-11.03	-0.83		-10.96	-0.83		-19.87	-1.6		-15.04	-1.18	
Job characteristics												
Job status (ref. Employee)												
Civil servant	-49.24	-4.02	***	-50.66	-4.13	***	-52.15	-4.25	***	-48.57	-3.8	***
Self-employed	-73.45	-4.61	***	-72.78	-4.33	***	-76.63	-4.92	***	-76.21	-4.86	***
Full time[a]	-0.68	-0.04		1.72	0.1		-0.37	-0.02		0.56	0.03	
Sector (ref. Primary)												
Manufacturing and Construction	4.50	0.18		3.58	0.13		20.91	0.84		5.83	0.22	
Services	-15.68	-0.64		-23.31	-0.91		-10.12	-0.44		-18.88	-0.76	
Macroeconomic variables												
GDP growth	-2.43	-1.09		-2.44	-1.09		-2.42	-1.08		-2.47	-1.1	
Harmonised unemployment rate	1.81	0.88		1.87	0.91		1.73	0.84		1.78	0.86	
Country dummies (ref. Spain)	Yes			Yes			Yes			Yes		
Wave dummies (ref. 2004)	Yes			Yes			Yes			Yes		
Log likelihood	-2,464.6429			-2,465.6987			-2,465.4628			-2,467.3924		
#obs	145,612			145,612			145,612			145,612		

Notes: * 0.1 >p ≥ 0.05; ** 0.05 >p ≥ 0.01; *** p< 0.01. [a] Dummy variable. All models presented in this table include interactions between the technological measure considered by the model and job status.

employees is the most affected by new technologies. While automation and ML increase the probability of unemployment for this group, advances in AI reduce it. On the other hand, these workers do not benefit significantly from a greater capacity to reorganize their occupations.

In fact, civil servants are the only workers who are benefited with lower unemployment probabilities when their occupations have a higher reorganization capacity. Furthermore, civil servants significantly reduce their unemployment probabilities when higher AI advances are produced in their occupations and they are not affected by the labourunfriendly side of computerization and ML.

Finally, we find that the self-employed are the group least affected by technological change with respect to the probability of unemployment. In particular, their unemployment probability only increases significantly (at a 10% of significance) when their occupation is associated with a high ML suitability.

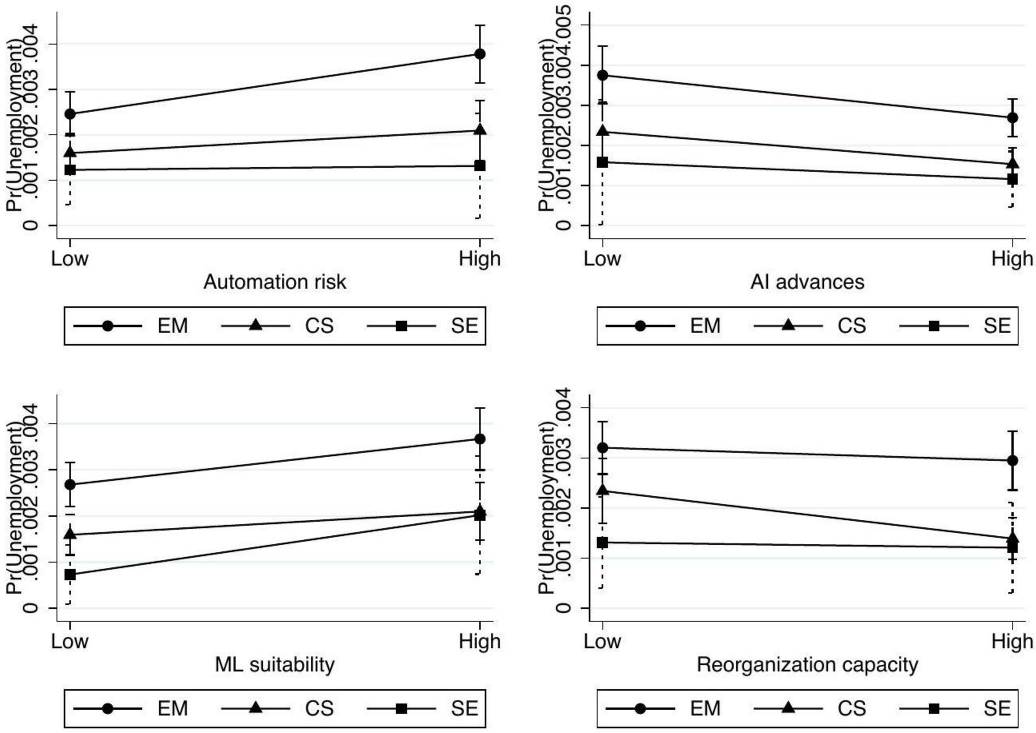

FIGURE 8.3: Unemployment probability, job status and new technologies

Note: Predicted probabilities and marginal effects are from models V-VIII in Table 8.5

TABLE 8.5: Predicted probabilities of unemployment and marginal effects by job status and technological effects.

		Predicted probability of unemployment			Marginal effect								
Technological measures		EM	CS	SE	EM			CS			SE		
					dy/dx	z-stat		dy/dx	z-stat		dy/dx	z-stat	
Automation risk	Low	0.0027	0.0017	0.0013	Ref.			Ref.			Ref.		
	High	0.0041	0.0023	0.0014	0.0015	3.19	***	0.0006	1.30		0.0002	0.20	
AI Advances	Low	0.0041	0.0025	0.0017	Ref.			Ref.			Ref.		
	High	0.0029	0.0017	0.0012	-0.0012	-2.45	**	-0.0009	-1.80	*	-0.0005	-0.57	
ML suitability	Low	0.0029	0.0017	0.0008	Ref.			Ref.			Ref.		
	High	0.0040	0.0023	0.0021	0.001	2.31	**	0.0005	1.24		0.0013	1.73	*
Reorganization capacity	Low	0.0034	0.0026	0.0014	Ref.			Ref.			Ref.		
	High	0.0032	0.0015	0.0013	-0.0002	-0.48		-0.001	-2.42	**	-0.0001	-0.18	

8.5 Conclusions

This chapter explores the consequences of the current technological change for the unemployment transitions of older workers, uncovering that different areas and subfields within the technological landscape may have varying effects on the unemployment probabilities of workers, with these effects further diverging among different types of workers.

Regarding computerization the negative effect on employment is expected and widely reported in the literature. For instance, Frey and Osborne (2017) reported that a significant proportion of jobs in various sectors are at risk of automation due to advances in computerization. Regarding the case of AI, we find a technology that acts as a shield serving as a protective factor against unemployment. A possible explanation is that AI technologies may complement and support human labour rather than replace it (Brynjolfsson & McAfee, 2014). However, the results also highlight that higher suitability to ML, a subfield of AI, increases unemployment probabilities. This finding is consistent with Acemoglu and Restrepo's (2018a) research, which indicates that ML advancements can displace jobs, particularly those requiring routine tasks, as ML algorithms become more efficient at performing these tasks.

Regarding the potential for reorganization of occupations, the results show that workers in occupations with higher reorganization capacity are less likely to transition to unemployment. This observation aligns with Caroli and Van Reenen's (2001) findings, which suggest that organizations with greater reorganization capacity can better adapt to new technologies and market conditions, resulting in lower unemployment probabilities for workers.

In addition to the heterogeneous effects of the various technologies, we emphasize that the impact of technological advancements on unemployment transitions varies depending on job status. In this context, employees are affected by all technological measures considered, except reorganization capacity, while civil servants are influenced only by AI advances and reorganization capacity. This differentiation in impact is supported by the work of Autor and Dorn (2013), who found that different types of workers are affected unevenly by technological change. Finally, self-employed workers are exclusively affected by ML suitability, a finding that can be further explored in future research to understand the unique challenges and opportunities faced by this specific group of workers.

In order to mitigate the adverse effects of technological change on older workers' unemployment transitions, labour market policies may need to be reformulated matching the necesities of the unveiled technological scenario. This reformulation of labour market policies aimed to help older workers navigating the digitalization technological wave should consider several aspects: (i) the promotion of lifelong learning and retraining programs, enhancing the employability of workers in the face of computerization, AI, and ML advancements (Schmidpeter & Winter-Ebmer, 2021; Dychtwald et al., 2004; Yamamoto, 1990); (ii) the encourage age-friendly workplace practices, ensuring that older workers can maintain their productivity in the face of technological change (Dropkin et al., 2016).; (iii) the strengthening of active labour market policies, mitigating the negative effects of technological change on labour force participation (Grigoli et al., 2020); (iv) the fostering of collaboration between government, industry, and educational institutions, ensuring that older workers have access to relevant training and education opportunities (van Ours & Stoeldraijer, 2011; Cedefop, 2018); and (v) the support to the development and adoption of complementary AI technologies, helping older workers to maintain their competitiveness in the labour market and reduce their unemployment probabilities (Brynjolfsson & McAfee, 2014).

8.6 Appendix

TABLE A8.1: Descriptive statistics

.	Total sample	Switching to unemployment	Non switching to unemployment		
#obs. (#ind.)	145,612(16,697)	377(362)	145,235(16,635)		
Variable	Mean (S.D. overall)	Mean (S.D. overall)	Mean (S.D. overall)	Min	Max
Automation probability	0.523 (0.35)	0.651 (0.32)	0.523 (0.35)	0.0039	0.99
High automation risk	0.391	0.533	0.390	0	1
AI advances	3.326 (0.63)	3.1 (0.59)	3.33 (0.63)	1.51	5.29
High AI advances	0.693	0.560	0.694	0	1
Suitability to ML	3.496 (0.1)	3.511 (0.1)	3.496 (0.1)	3.19	3.75
High suitability to ML	0.416	0.480	0.415	0	1
Reorganization capacity	0.594 (0.05)	0.583 (0.06)	0.594 (0.05)	0.395	0.8
High reorganization capacity	0.506	0.414	0.507	0	1
Female	0.540	0.637	0.540	0	1
Age	52.4 (5.3)	50.74 (4.93)	52.42 (5.30)	40	66
With partner	0.809	0.748	0.809	0	1
Health	2.9 (1.01)	3.2 (0.96)	2.9 (1.01)	1	5
Excellent	9.99	5.57	10	0	1
Very good	22.83	14.32	22.85	0	1
Good	41.30	41.64	41.30	0	1
Fair	21.12	31.30	21.10	0	1
Poor	4.75	7.16	4.75	0	1
Ability to make ends meet	2.91 (0.96)	2.46 (1.01)	2.9 (0.96)	1	4
With great difficulty	8.15	19.89	8.12	0	1
With some difficulty	26.28	33.42	26.26	0	1
Fairly easily	31.82	27.85	31.83	0	1
Easily	33.75	18.83	33.79	0	1
Tertiary education	0.308	0.223	0.308	0	1
Job status					
Employee	52.96	68.97	52.92	0	1
Civil servant	37.39	27.06	37.42	0	1
Self-employed worker	9.65	3.98	9.66	0	1
Full time	0.868	0.849	0.868	0	1
Sector					
Primary	6.31	6.63	6.31	0	1
Manufacturing and Construction	24.57	30.77	24.55	0	1
Services	69.12	62.60	69.14	0	1
GDP growth	2.10 (3.66)	1.79 (3.93)	2.10 (3.66)	-14.8	11.9
Harmonised unemployment rate	8.92 (4.19)	8.90 (3.84)	8.92 (4.19)	3.4	27.5

Chapter 9

Digitalization and Worker Mobility: Impact on Portuguese Labour Dynamics

9.1 Introduction

The world is undergoing one of the most significant technological revolutions in history. Digitalization is causing profound changes in all aspects of the economy - and, in particular, the labor markets. While certain digital technologies have an impact across all sectors, others likely affect specific occupations in distinct ways. Although technological advances often make the use of human labor inefficient for some tasks, they may also create new tasks in which labor has a comparative advantage (Acemoglu and Restrepo 2019).

Digitalization, defined as the transformation of business processes by leveraging digital technologies, has both a labor-unfriendly and a labor-friendly side (Montobbio et al. 2022). The labor-unfriendly side, labelled destructive digitalization, carries on the process of task automation started with the introduction of the first machines (Hitomi 1994). The labor-friendly side, dubbed transformative digitalization, relates to the rise of artificial intelligence (AI), a new general-purpose technology requiring human skills for its development.

Destructive digitalization has been equated in the literature to computerization, meaning job automation by means of computer-controlled equipment, including both machinelearning technologies and robotics (Frey and Osborne 2017). Frey and Osborne (2017) claim that 47% of US jobs are at high risk of computerization. Other studies make similar predictions. In a report about automation and computerization in Portugal, Duarte et al. (2019) predict the loss of about 40% of manufacturing jobs. [1]

On the other hand, the emergence of AI is at the center of the current industrial revolution. Occupations hitherto unscathed by automation are now susceptible to be impacted by AI (Acemoglu and Restrepo 2018a; Grace et al. 2018). This raises a debate about whether human work will be replaced or complemented by AI (Tschang and Almirall 2021). Recent studies have highlighted the labor-friendly side of AI. Acemoglu et al. (2022) document rapid growth in AI-related job vacancies and reduced hiring in non-AI positions, with no discernible impact on employment or wages. Alekseeva et al. (2021) document a major increase in the demand for AI skills between in the US economy. Damioli et al. (2022) and Yang (2022) find evidence of a positive and significant impact of AI patents on employment.

In this line, Fossen and Sorgner (2019) judge AI to be a transformative digitalization technology due to its complementarity with human labor. According to this destructivetransformative duality, they propose a systematic classification of occupations regarding the exposure to the destructive and transformative digitalization sides into four categories: "Rising Stars", "Machine Terrain", "Human Terrain", or "Collapsing Occupations" (Table 9.1).

[1] Other studies, however, downplay the negative impacts due in part to the use of different methodologies, focusing on the computerization of specific tasks rather than whole occupations. Arntz et al. (2016, 2017) find that the actual percentage of jobs at risk of automation in the OECD is about 9%.

TABLE 9.1: Effects of Digitalization on Occupations

	Low destructive effects	High destructive effects
High transformative effects	I. Rising stars occupations	II. Machine terrain occupations
Low transformative effects	III. Human terrain occupations	IV. Collapsing occupations

Source: Fossen and Sorgner (2019)

Computerization (destructive) and AI (transformative) are strictly related technologies, converging and jointly shaping a new pervasive knowledge base (Santarelli et al. 2022). This will result in a sizeable reconfiguration of labor, as many occupations disappear or change drastically while others emerge, taking advantage of the opportunities brought by the new technologies and knowledge. The reconfiguration implies new patterns of worker mobility across occupations, as previous technological changes have done.

General-purpose technologies (for example, computerization and AI) lead to high levels of occupation-to-occupation and sector-to-sector mobility (Gaggl et al. 2021). Bárány and Siegel (2020) show that most of this reallocation is due to occupation-specific technological changes, driving the decline of routine-intensive occupations and the mobility of displaced workers to different jobs (Blien et al. 2021). Sorgner (2017) finds that workers in occupations at high computerization risk are more likely to experience job loss, demotion, or reassignment to a job in a new field.

While the potential for digitalization to create and destroy jobs by making certain skills obsolete while promoting others has been the object of a variety of studies, worker mobility across the digitalization terrains is relatively unaddressed in the literature. Yet, labor mobility across sectors (and, likely, geographical spaces) will need to play a key role in minimizing adjustment costs to digital transformation and the spread of AI applications. Recognizing the need for, and enabling this mobility is necessary to curtail unemployment and preserve social inclusion and income redistribution. Research generating further insight on the trends associated with intersectoral labor mobility associated with AI and digitalization policymakers in industry and education would arguably benefit policymakers at the industrial, educational, and regional levels.

This chapter addresses this gap by studying labor mobility between occupations at different digitalization exposure levels, and how worker, firm and industry characteristics intervene in such moves. Specifically, we analyze how workers displaced from a job after firm closure move between occupations differently impacted by computerization and artificial intelligence in the Portuguese economy. The econometric analysis uses longitudinal linked employer-employee data and relies on multinomial models. By focusing on displaced workers, we attenuate possible selection effects that may arise from voluntary job mobility, thus improving the identification of the main effects. Portugal - a country with an aging, low-skill, low-wage workforce - may serve as a case study for extreme impacts of destructive digitalization due to its reliance on low-skill low labor that may be easily automatable. Portugal may also yield interesting conclusions on the transformative potential of AI, as it is undergoing a dramatic process of upskilling with a fast growing rate of individuals with higher education degrees.

We find that higher levels of human capital facilitate moves into occupations with high exposure to the transformative effects of digitalization, and especially so into rising star occupations where skilled workers find large complementarities with AI while being protected from the destructive side of digitalization because they perform tasks that are hard to automate. We also find a generalized move of women into the Machine Terrain, irrespective of the type of previous employment, while older workers tend to find re-employment in the same terrain from which they were displaced. In addition, our results point to a reshuffling process after a larger period spent without employment, where workers are less likely to return to their original terrain, sometimes improving their levels of exposure to digitalization but other times not.

Our study presents a detailed examination of the mobility processes of workers across occupations differently impacted by both the transformative and destructive sides of digitalization. The patterns observed are promising for the segment of workers who are able to take advantage of the transformative impacts of artificial intelligence, but may also unveil harder times for those who cannot break away from the destructive effects.

9.2 Background and hypotheses

The literature on the impact of technological progress on the labor market has traditionally focused on how new technologies displace and relocate workers (e.g., Acemoglu and Autor 2011; Acemoglu and Restrepo 2019), creating threats and opportunities for differently skilled workers. While the first studies of automation, job creation and destruction were theoretical and descriptive (e.g., Moos 1957; Atkinson and Stiglitz 1969; Leontief 1978, 1983), computational advances in data storage, processing and analysis have made detailed examination of the process possible (e.g., Dauth et al. 2017; Graetz and Michaels 2018; Jerbashian 2019; Feng and Graetz 2020; Domini et al. 2021; Downey 2021; FosterMcGregor et al. 2021).

The automation potential of new general-purpose technologies such as Robotization, Computerization and Artificial Intelligence (AI) is such that scholars are struggling to predict and map the expected impact of these technological changes on the workforce. To fulfil this purpose, Frey and Osborne (2017) develop a methodology based on the construction of occupational and task-based measures aiming to identify and document the potential impact of technological advances at the occupation level. The approach based on task- and occupation-specific measures of technological impacts has enabled researchers to account for Machine Learning suitability (Brynjolfsson et al. 2018), AI advances (Felten et al. 2018), AI progress (Felten et al. 2019), AI impacts (Webb 2020), and AI exposure (Felten et al. 2021) at the industry, labor, and income levels.

Manyika et al. (2017) analyze more than 2,000 work activities across 800 occupations discovering that about half of the carried out by human labor could potentially be automated by adapting currently available technologies. They conclude that, while less than 5 percent of all occupations can be automated entirely using demonstrated technologies, about 60 percent of all occupations have at least 30 percent of constituent activities that could be automated. Dengler and Matthes (2018) find that, if one assumes that entire occupations (composed of several tasks) are replaceable, approximately 47% of German employees experience an automation risk, but only 15% of German jobs are at risk when assuming that only certain tasks can be substituted. This last estimation downsizing the share of jobs at high computerization risk is closer to the one offered by Arntz et al. (2016 2017) arguing that only 9% of OECD jobs suffer from high automation risk.

Just as robotics and machine learning follow the natural evolution of skill-biased automation technologies, the appearance of AI seems to establish a new paradigm yet to be explored. This general-purpose technology is aimed to affect all forms of labor. Researchers believe that AI will outperform humans in many activities in the following years (Grace et al. 2018): for example, translating languages (by 2024), writing high-school essays (by 2026), driving a truck (by 2027), working in retail (by 2031), writing a bestselling book (by 2049), and working as a surgeon (by 2053). Furthermore, they predict a 50% chance of AI outperforming humans in all tasks in 45 years and automating all human jobs in 120 years. However, the fact that AI is going to outperform human labor does not necessarily imply its replacement. Many studies indicate multiple instances of high complementarity between human labor and AI (e.g., Alekseeva et al. 2021; Acemoglu et al. 2022; Damioli et al. 2022; Yang 2022). The AI revolution promises to bring multi-level changes to the economy. For instance, Adner et al. (2019) foresee qualitative - and not only quantitative - changes due to three fundamental processes underlying the actual digital transformation -representation, connectivity, and aggregation_- indicating that these processes will continue to push firms in all industries to create and capture value differently, develop new business models and ecosystems, manage new forms of intellectual property, grow scale and scope differently, and create new opportunities and challenges for organization design and management practices. Also in this line, Ciarli et al. (2021) argue that digitalization is often more about the displacement and deep transformation of activities and their organization than about a simple one-to-one replacement of jobs. Therefore, the term transformative digitalization has naturally arisen from and equated to AI.

Fossen and Sorgner (2019) develop a pioneering work focusing on the duality of digitalization, identifying automation through computerization as the destructive side (the negative effects, where technology mostly replaces human workers) and AI as the transformative side (the positive effects, complementary to labor, where human-machine interactions are extensive). They propose a typology of occupations according to these considerations, as shown in Table 9.1, mapping labor into four differentiated sections according to the digitalization effects upon occupations.

Specifically, these authors identify 'Human Terrain' occupations as being those suffering few or no impacts from both the destructive and the transformative sides of digitalization, and 'Machine Terrain' occupations as those highly affected by both sides of technological change. Additionally, they designate as 'Rising Stars' those occupations undergoing low negative impacts from destructive digitalization and high positive effects from transformative digitalization, while defining 'Collapsing Occupations' as those enduring strong negative impacts from destructive digitalization and low positive effects from transformative digitalization.

The literature seems to clearly establish that skills, experience, education and training play a relevant role on how new technologies displace and relocate workers. For the specific case of AI/digitalization, Fossen and Sorgner's technological terrains constitute a useful tool to analyze labor mobility. We therefore propose that, depending on individual characteristics such as formal education, skill levels, age, and work experience, workers being displaced from their jobs may be more likely to remain unemployed, find jobs in similar occupational terrains, or move to occupations that are more or less impacted by destructive and transformative digitalization. Depending on the interaction between workers' characteristics and digitalization, it is possible to formulate predictions regarding how such characteristics are likely to impact the mobility of displaced workers with reference to occupations where destructive and transformative digitalization play different roles.

First, we expect college-educated workers to be more likely to relocate to a rising star occupation, as collected by the second hypothesis. The argument behind this hypothesis is that technological progress raises the demand for educated workers (Autor et al. 1998). Indeed, computerization is associated with reduced labor input of routine manual and routine cognitive tasks, and increased labor input of nonroutine cognitive tasks, translating task shifts into education demand (Autor et al. 2003). Thus, we expect occupations more impacted by AI to increase the labor demand of workers with tertiary education and occupations more impacted by destructive digitalization to decrease the labor demand of workers with college education. We therefore propose that:

Hypothesis H1*: College-educated workers are more likely to move into a rising star occupation.*

Regarding task/occupation-specific skills, we expect workers in high-skilled occupations to have a high complementarity with transformative digitalization, as workers with college education, but a higher likelihood to complement destructive digitalization. The reason is based in the capital-skill complementarity assumption. In fact, macroeconomic models have presented automation as a process in which unskilled workers are displaced by the combination formed by equipment capital and skilled workers. Under this assumption, Krusell et al. (2000) explain the evolution of the skill premium in the 1970s US . Inspired by the work on 'skill-biased technological change' in which new technologies could lead to upskilling as machines substitute unskilled labor and require more skilled labor to operate and design them (Griliches 1969; Autor et al. 1998), [2] we propose that:

Hypothesis H2a*: High-skilled workers are more likely to leave the human terrain by moving to any other terrain more impacted by digitalization.*

[2] The skill-biased technological change assumption contrasts with the 'deskilling' hypothesis in which new technologies could lead to the substitution of skilled labor by machines that are operated by unskilled labour (Braverman 1974).

Hypothesis H2b: *High-skilled workers from occupations experiencing high transformative digitalization are likely to remain in the high transformative digitalization terrains.*

Firm- and industry-specific experience are important components of human capital that are likely to influence transitions within and across terrains. We expect that workers with experience in large firms should be more likely to be re-employed in the same terrain to take advantage of their previous experience. Employment in a large firm is likely to provide a positive signal regarding both firm- and industry-specific human capital that increases the chances of a displaced worker finding a job match in the same terrain. Large firms may also, through their human resource departments, provide guidance and support during the process of job relocation after displacement, thus facilitating relocation (Nyström 2018).

Similarly, employment in knowledge-based or high technology intensity sectors is likely to provide specific experience which will be more valued by firms in high tech sectors and rising star occupation terrains. These firms are more likely to provide formal training in new technologies that compensate for lower levels of formal education and offer a signal of the worker's specific skills. We therefore predict that:

Hypothesis H3a: *Workers from large firms are more likely to move to occupations in the same terrain.*
Hypothesis H3b: *Workers from knowledge/technology intensive firms are more likely to move to rising star occupations.*

Finally, we expect older workers to be less propense to switch terrains. The shorter the working life horizon is, the less the worker will relocate to a different terrain, since they will be looking for a relocation in the same occupation or in a similar occupation.

Charness (2006) argues that older workers will typically require up to twice as much time to master a new application or technology if it is weakly related to prior knowledge, so it is to be expected that they will try to relocate in the same terrain where they have some expertise and can find a competitive advantage relative to younger, more trained, cohorts of workers (Dychtwald et al. 2004). This behavior of older workers is not something specific from digitalization but a common reaction at any technological change, since older workers are less likely to have the requisite new skills and are often presumed to be less able to adapt (Adler 1988). Nevertheless, although this is not new, the competitive disadvantage of older workers managing new technologies is expected to be more pronounced in the digitalization technological change, since the relative deterioration of job prospects for older workers implies that this age group increasingly has more difficulties to adapt to technological progress (Schmidpeter and Winter-Ebmer 2021).

Hypothesis H4: *As workers age, they are more likely to stay in the same terrain and less likely to move across terrains.*

9.3 Data

To study worker mobility across occupations with different levels of exposure to digitalization, we use Quadros de Pessoal (QP), a linked employer-employee longitudinal dataset covering all Portuguese firms with at least one wage-earning employee. QP is assembled from a mandatory survey conducted yearly by the Portuguese Ministry of Employment and Social Security since 1985, containing an average of about 2.8 million workers in 300,000 firms per year. This dataset includes information on workers' occupation, education level, hierarchical level, gender and age, as well as wage earnings. For firms, QP provides the number of employees, geographical location and industrial sector of each establishment.

OECD's International Standard Classification of Occupations (ISCO) [3] indicates which tasks are demanded of workers within each specific hierarchical level, as well as which skills are required. In 2010 ,

[3] https://www.oecd-ilibrary.org/social-issues-migration-health/occupational-classification-isco88304441717388.

the occupation codes changed from the ISCO-88 to the ISCO-08 classification. The equivalence between the two classifications is not complete. Thus, to avoid issues of measurement error, and given that the focus of our work is on occupational mobility, our analysis covers the period between 2010 and 2019.

Regarding exposure to digitalization, we adapt Fossen and Sorgner's (2019) classification of occupations to consider two forward-looking measures of impacts of digitalization: transformative effects, and destructive effects. Occupations are then classified into four digitalization terrains: Rising Stars, Machine Terrain, Human Terrain, and Collapsing Occupations (see Table 9.1). [4] Occupational exposure to destructive impacts of digitalization originates from the computerization risks of occupations proposed by Frey and Osborne (2017), which captures the probability of workers in an occupation being replaced by computerization over the next decades. Exposure to the transformative impacts comes from Felten et al.'s (2021) index of predicted effects of artificial intelligence in the coming future. [5] Following Fossen and Sorgner (2019), an occupation is subject to high impacts of the destructive and transformative effects if its score is above the median.

Our sample is composed of paid employees who are at least 18 years old. Workers are censored once they reach 55 years old to exclude the possibility of a worker leaving an occupation into (early) retirement. We rely on an identification strategy of studying workers displaced by firm closure. The involuntary job mobility forced by the firm closure may mitigate selection effects of workers voluntarily switching jobs and/or occupations due to unobserved heterogeneity. This is especially true when we consider that the firm closure is likely due to firm performance rather than the productivity of a single (nonowner) employee. A similar strategy has been popularized in the labor economics literature by seminal works such as Gibbon and Katz (1991, 1992), Jacobson et al. (1993) and Neal (1995). Recent examples of this strategy include Castro-Silva and Lima (2022), Goos et al. (2021) and Schmidpeter and Winter-Ebmer (2021).

We observe the moment of firm closure to collect firm and worker characteristics (including original occupation), and then identify the moment the worker rejoins the dataset, registering the new occupation code and year of return. We cannot know the destination of workers who do not return to the dataset within the study period. This includes workers who are no longer present in the labor market during the study but may also include workers who move into sectors not covered by QP (namely, public administration). Some workers do not transition directly from one year to another; if they take longer than one year, we say they had a non-employment spell. [6] We exclude workers who do not return to the dataset until 2019 as we are only focused on job-to-job mobility. Because unobserved heterogeneity may play a role in finding a new job after displacement, we place no restriction regarding the time until workers find a new job. This should allow for enough heterogeneity in the skill level of workers in our sample. Additionally, controlling for time spent in non-employment should capture some of the diversity of skill levels. After applying the described restrictions as well as data cleaning, our working sample is composed of 412,897 worker-year observations of 382,164 distinct workers in 106,182 firms.

The dataset includes a categorical job-level variable that classifies workers according to their hierarchical position within the firm, task complexity and responsibility into eight levels determined by the

[4]See also Table A9.1 in Appendix for the top occupations in each terrain in terms of employment numbers.

[5]Fossen and Sorgner (2019) use Felten et al.'s (2018) backward-looking measure of the impacts of AI on occupations from 2010 to 2015. Since Frey and Osborne's (2017) measure is forward-looking, and given the more recent proposal by Felten et al. (2021), we believe the classification into digitalization terrains should also benefit from a forward-looking measure of AI impacts. For robustness, we have also used the original Felten et al. (2018) score for the classification and identified no major differences in results.

[6]"Non-employment" is an encompassing term that includes workers that left the dataset for a period of time of more than one year. Usually, these workers are unemployed, but they also might have been working as civil servants, or left the labor market entirely. Given the higher stability and benefits of civil service work relative to private employment (especially for the lower skilled), shifts from the public to the private sector are uncommon. Thus, our "non-employment" category is mostly composed of unemployed individuals. This can be confirmed using data from the Portuguese Labor Force Survey.

Portuguese law. [7] For the sake of parsimony, we summarize the variable into two classes: 1) high-skilled workers are those in the top four job-levels (managers, supervisors, team leaders and highly qualified professionals); 2) low-skilled workers are the bottom four levels (qualified and semi-qualified professionals, unskilled professionals, trainees and apprentices). We classify firms according to the technology and/or knowledge intensity of the industry they operate in, following Eurostat's industry level (NACE Rev. 2 codes) definition. Throughout the text, knowledge intensive firms or industries encompass both knowledge-intensive services firms and high (or mediumhigh) technology-intensive manufacturing firms.

Table 9.2 presents the transition matrix between digitalization terrains. The main diagonal of the transition matrix reveals significant path dependence, in the sense that most displaced workers will find employment in the same digitalization terrain they were in before displacement. The path dependence may be explained by specific sets of skills that make these workers more productive in similar jobs. There also seems to be some exchange between terrains with similar levels of transformative effects of digitalization.

TABLE 9.2: Transitions matrix: proportion by origin

	from Rising Stars	from Machine Terrain	from Human Terrain	from Collapsing Occupations	Total
to Rising Stars	71.46	12.52	4.06	3.80	18.03
to Machine Terrain	12.82	66.96	4.18	5.13	16.52
to Human Terrain	5.50	6.26	68.91	10.82	19.34
to Collapsing Occupations	10.22	14.26	22.86	80.25	46.11
Total	100.00	100.00	100.00	100.00	100.00

A relatively large proportion of workers in occupations with high exposure to the transformative effects will transition to an occupation with a similar level (12.8% of workers previously in Rising Stars occupations go to the Machine terrain, and 12.5% originally in the Machine Terrain switch to a rising star job). An identical pattern occurs for workers with low exposure to the transformative effects (e.g., 22.9% of workers displaced from the Human Terrain find employment in Collapsing Occupations). Downey (2021) offers a plausible explanation for this pattern, stating that middle-wage occupations' routine tasks targeted by automation technologies are only partially automated in the sense that these can be performed by less-skilled workers. Then, workers in the human terrain whose previous exposure to technology was relatively small may now switch to a collapsing occupation that has been partially automated. A possible alternative explanation for the high proportion of stayers in Collapsing Occupations may be that these workers lack the necessary human capital that allows them to step into the terrains less exposed to digitalization.

In Table 9.3 we present descriptive statistics for the main variables, across the different digitalization terrains at the moment of displacement. We can see how individuals in the four terrains differ in terms of skills. Close to 70% of workers in Rising Stars are highly skilled, with more than half holding at least a bachelor's degree.

[7] QP micro-data discriminates the hierarchy in the firm as seen in Table A9.2 in Appendix. The Table provides a description of the job levels and the corresponding tasks and skills required by each level. The hierarchical levels comprise three dimensions: the type of task and its complexity; the level of responsibility/authority; and the skills necessary to perform the corresponding job. The levels are defined by the Ministry of Labor questionnaire. All firms have to use these same levels when answering the survey. See Baptista et al. (2012) for further description.

TABLE 9.3: Descriptive statistics by original digitalization terrain

	Rising Stars	Machine Terrain	Human Terrain	Collapsing Occupations	All
College	0.52	0.24	0.04	0.02	0.16
	(0.50)	(0.43)	(0.20)	(0.15)	(0.36)
High Skills	0.69	0.28	0.12	0.05	0.22
	(0.46)	(0.45)	(0.33)	(0.21)	(0.41)
Female	0.51	0.64	0.40	0.44	0.48
	(0.50)	(0.48)	(0.49)	(0.50)	(0.50)
Age	36.46	35.59	38.12	36.51	36.64
	(8.35)	(8.64)	(9.57)	(9.72)	(9.31)
Above median age	0.32	0.29	0.43	0.37	0.36
	(0.47)	(0.45)	(0.49)	(0.48)	(0.48)
Tenure	5.92	5.69	4.97	4.55	5.07
	(6.72)	(6.91)	(6.47)	(6.39)	(6.58)
Years in non-employment	0.87	0.89	0.97	1.01	0.96
	(1.37)	(1.38)	(1.45)	(1.46)	(1.43)
Years in non-employment > 1	0.45	0.45	0.48	0.50	0.48
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Number of employees	471.40	428.84	296.14	305.24	355.18
	(1189.70)	(1214.50)	(1133.78)	(1120.77)	(1154.27)
Large firm (>=50)	0.44	0.39	0.32	0.27	0.33
	(0.50)	(0.49)	(0.47)	(0.44)	(0.47)
Knowledge intensive	0.50	0.39	0.18	0.11	0.24
	(0.50)	(0.49)	(0.38)	(0.31)	(0.43)
N	77,896	67,467	72,982	194,501	412,846

Mean values at moment of displacement (standard deviations in parentheses).

While workers in the Machine Terrain are also relatively skilled (but to a much lesser degree), those in the Human Terrain or Collapsing Occupations have very low levels of education and firm-specific skills. Workers previously in the Rising Stars or Machine Terrain categories also have longer tenures and spend less time in non-employment, in line with their higher ability levels. The proportion of workers previously in firms with 50 or more employees, and in knowledge-intensive firms decreases as we move from Rising Stars to Collapsing Occupations. [8] Women account for more than half of workers in rising star occupations and especially in the machine terrain where the share is around 64%. Our exploratory descriptive analysis points to a large gap in terms of skills and human capital consistent with the demands of the occupations in each terrain and with the degree of complementarity (or destructiveness) that digitalization has for jobs in the four occupation categories.

9.4 Empirical model

9.4.1 Transitions across digitalization terrains

We study transitions across digitalization terrains through multinomial logit models. With m possible transition destinations and m possible origins, the model specifies that the probability of worker i transitioning from digitalization terrain f to destination terrain d is given by:

[8] The average firm size (number of employees) in all categories is large for Portuguese standards. We note that some very large firms closed during this period (the largest of which had 7,604 employees), which results in a mean value that overstates the real size of closed firms. The median firm size at displacement is 15 employees, and the 75$^{\text{th}}$ percentile is 76 employees.

$$p_{ifd} = \frac{\exp\left(x_i'\beta_{fd}\right)}{\sum_{l=1}^{m}\exp\left(x_i'\beta_{fl}\right)}$$

Where d and f may be one of Rising Stars, Machine Terrain, Human Terrain, or Collapsing Occupations, $\mathbf{x_i}$ is the vector of regressors, and β_{fd} are the parameters to be estimated for each origin-destination pair. We thus estimate $m = 4$ multinomial models, one for each origin terrain. Each model is identified when one of the β_{fd} is set to zero. Our base case is when no transition occurs (the worker stays in the same terrain). The model coefficients are thus interpreted with respect to the no transition state.

For ease of interpretation, we compute average marginal effects on the probability of transition from f to d when a regressor changes. We focus on our main variables, namely college education, skill level, gender, age, years in non-employment, firm size class, and knowledge-intensity class. Our models include additional controls for worker and firm characteristics at the moment of displacement such as tenure, type of contract (permanent or not), part-time work, region and year dummies.

9.5 Results

9.5.1 Transitions across digitalization terrains

We begin by estimating the multinomial logit models for transitions across the four digitalization terrains, and then proceed with the computation of the marginal effects of the main regressors. The marginal effects are thus interpreted as the change in the probability of moving from one terrain to another when the regressor changes. We present separate tables for each of the main regressors. Table 9.4 shows the marginal effects of having a college degree compared to those without one, for each origin-destination pair.

TABLE 9.4: How college affects transitions

	from Rising Stars	from Machine Terrain	from Human Terrain	from Collapsing Occupations
To Rising Stars	0.201^{***}	0.088^{***}	0.062^{***}	0.114^{***}
	(0.004)	(0.004)	(0.006)	(0.005)
To Machine Terrain	-0.042^{***}	0.050^{***}	0.022^{***}	0.068^{***}
	(0.003)	(0.004)	(0.005)	(0.004)
To Human Terrain	-0.053^{***}	-0.045^{***}	0.054^{***}	-0.049^{***}
	(0.002)	(0.002)	(0.009)	(0.004)
To Collapsing Occupations	-0.107^{***}	-0.092^{***}	-0.138^{***}	-0.133^{***}
	(0.002)	(0.003)	(0.006)	(0.007)
N	77,896	67,467	72,982	194,501

Notes: Marginal effects from multinomial logit estimations (standard errors clustered at the worker level in parentheses). Regressions also control for high skills, gender, age, time in non-employment, tenure, permanent contract, part-time job, firm size, knowledge intensity, region and year dummies. $*p < 0.10$ $**p < 0.05$ $***p < 0.01$

Having college education always favors moves into rising star occupations more than to any other destination, whichever the previous occupation class was at the moment of displacement. This effect is especially strong for workers previously in rising stars occupations (20 percentage points). As a consequence, for workers in rising star occupations, higher education strongly reduces the probability of moves into other occupation classes. These results corroborate hypothesis 1 of this study, suggesting that digitalization and education interact influencing the occupation where the displaced workers' relocate.

College education also protects workers from moves into collapsing occupations as well as into the human terrain (except for those previously in the human terrain). In fact, one can argue that higher education promotes upgrading into occupations where AI will have high transformative effects, away from occupations where AI is less transformative. This is especially interesting for workers previously in collapsing occupations, where education increases the likelihood of moves to occupations with high transformative effects of AI (rising stars and machine terrain) at the expense of going into the human terrain or even staying in collapsing occupations. For many college-educated workers, displacement may be an opportunity for occupation upgrading.

The marginal effects of having a high skilled job are shown in Table 9.5. Workers in high skilled jobs follow a similar pattern to college-educated workers, albeit with less intensity. An exception are high skilled workers in the human terrain who may move into collapsing occupations instead of finding a new job in the human terrain. For workers previously in collapsing occupations, high skills increase the likelihood of upgrades into occupations with high transformative effects of AI (especially rising stars), or, to a much lesser extent, into the human terrain (0.6 p.p., small but significant at 10%). Results from Table 9.5 support hypotheses 2a and 2 b of this study. High degrees of human capital, be it education of firm specific skills, may protect workers from the high destructive effects of digitalization and benefit from complementarities with the transformative effects.

TABLE 9.5: How high skills affect transitions

	from Rising Stars	from Machine Terrain	from Human Terrain	from Collapsing Occupations
To Rising Stars	0.080^{***}	0.034^{***}	0.050^{***}	0.059^{***}
	(0.004)	(0.003)	(0.003)	(0.003)
To Machine Terrain	-0.028^{***}	0.057^{***}	0.009^{***}	0.024^{***}
	(0.003)	(0.004)	(0.003)	(0.003)
To Human Terrain	-0.017^{***}	-0.022^{***}	-0.101^{***}	0.006^{*}
	(0.002)	(0.002)	(0.006)	(0.004)
To Collapsing Occupations	-0.034^{***}	-0.069^{***}	0.041^{***}	-0.089^{***}
	(0.002)	(0.003)	(0.005)	(0.005)
N	77,896	67,467	72,982	194,501

Notes: Marginal effects from multinomial logit estimations (standard errors clustered at the worker level in parentheses). Regressions also control for high skills, gender, age, time in non-employment, tenure, permanent contract, part-time job, firm size, knowledge intensity, region and year dummies. $*p < 0.10 **p < 0.05 ***p < 0.01$

Results in Table 9.6 show that previous experience in a relatively large firm (more than 50 employees) strongly increases the likelihood of re-employment in the same terrain, while at the same time decreasing moves to any other destination, compared to workers displaced from firms with fewer than 50 employees. This provides support to hypothesis 3a of the study. Large firms often have well-specified organizational structures, where many workers have a well-defined set of tasks. Workers displaced from such firms may carry with them a signal of that specificity that hiring firms interpret as an indication of where the worker will better fit in the new organization.

Results in Table 9.7 show that workers displaced from knowledge/technology intensive industries are driven into rising stars occupations, except when they come from the machine terrain. They also move away from collapsing occupations. This provides partial support to hypothesis 3c. Presumably, in these industries there is a larger proportion of rising stars occupations and not much employment in collapsing professions.

TABLE 9.6: How working in a large firm ($>= 50$) affects transitions

	from Rising Stars	from Machine Terrain	from Human Terrain	from Collapsing Occupations
To Rising Stars	0.124^{***}	-0.039^{***}	-0.023^{***}	-0.002^{*}
	(0.003)	(0.003)	(0.002)	(0.001)
To Machine Terrain	-0.036^{***}	0.120^{***}	-0.018^{***}	-0.014^{***}
	(0.003)	(0.004)	(0.002)	(0.001)
To Human Terrain	-0.036^{***}	-0.023^{***}	0.100^{***}	-0.012^{***}
	(0.002)	(0.002)	(0.004)	(0.002)
To Collapsing Occupations	-0.052^{***}	-0.057^{***}	-0.058^{***}	0.028^{***}
	(0.002)	(0.003)	(0.003)	(0.002)
N	77,896	67,467	72,982	194,501

Notes: Marginal effects from multinomial logit estimations (standard errors clustered at the worker level in parentheses). Regressions also control for high skills, gender, age, time in non-employment, tenure, permanent contract, part-time job, firm size, knowledge intensity, region and year dummies. $*p < 0.10 * *p < 0.05 * * * p < 0.01$

TABLE 9.7: How working in a knowledge-/technology-intensive industry affects transitions

	from Rising Stars	from Machine Terrain	from Human Terrain	from Collapsing Occupations
To Rising Stars	0.102^{***}	0.004	0.027^{***}	-0.001
	(0.003)	(0.003)	(0.003)	(0.002)
To Machine Terrain	-0.041^{***}	0.098^{***}	0.008^{***}	0.009^{***}
	(0.002)	(0.004)	(0.002)	(0.002)
To Human Terrain	-0.006^{***}	-0.015^{***}	0.025^{***}	0.019^{***}
	(0.002)	(0.002)	(0.005)	(0.003)
To Collapsing Occupations	-0.055^{***}	-0.087^{***}	-0.061^{***}	-0.027^{***}
	(0.002)	(0.003)	(0.004)	(0.003)
N	77,896	67,467	72,982	194,501

Notes: Marginal effects from multinomial logit estimations (standard errors clustered at the worker level in parentheses). Regressions also control for high skills, gender, age, time in non-employment, tenure, permanent contract, part-time job, firm size, knowledge intensity, region and year dummies. $*p < 0.10 * *p < 0.05 * * * p < 0.01$

Results in Table 9.8 indicate that age increases the likelihood of staying in the same terrain revealing a degree of path dependence, thus supporting hypothesis 4 . This may be linked to accumulated experience in occupations in the origin terrain, as well as a reluctance of older workers to change occupations more drastically because of higher opportunity costs of changing combined with a higher costs of new skill acquisition. Through the years of experience, these workers' may have accumulated skills that are very specific to their origin terrain. This may be both a blessing and a curse. On one hand, it suggests these skills are still valuable, at least for those that find employment. On the other hand, older workers may lack the necessary skills to switch to occupations of the future.

To a lesser extent, age seems to facilitate moves into the human terrain reflecting older workers' somewhat more manual set of skills which are harder to replace by digitalization but enjoy fewer complementarities, coupled with the erosion of older workers' skills with technology and smaller payoffs from learning to use new technologies because of shorter career horizons (Ahituv and Zeira 2011). In

TABLE 9.8: How age (years) affects transitions

	from Rising Stars	from Machine Terrain	from Human Terrain	from Collapsing Occupations
To Rising Stars	0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
To Machine Terrain	−0.001***	0.002***	−0.002***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
To Human Terrain	0.000***	0.000***	0.005***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
To Collapsing Occupations	−0.001***	−0.002***	−0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
N	77896	67467	72982	194501

Notes: Marginal effects from multinomial logit estimations (standard errors clustered at the worker level in parentheses). Regressions also control for high skills, gender, age, time in non-employment, tenure, permanent contract, part-time job, firm size, knowledge intensity, region and year dummies. $*p < 0.10 **p < 0.05 ***p < 0.01$

addition, we observe that age reduces switches to Rising Stars or to the Machine Terrain from any other terrain, indicating that older workers are less likely to take advantage of AI developments. Instead, older workers displaced from an occupation at high computerization risk will be relocated in a similar occupation - also at high computerization risk - where their relocation learning efforts are smaller, or to a human terrain occupation where they are safe from automation. Battisti and Gravina (2021) suggest that older workers experience a higher complementarity degree with robots possibly because they are not performing challenging manual tasks (which are typically carried out by the middle-aged).

9.5.2 Other factors influencing transitions

We ran additional models in order to explore the effects of additional individual attributes on the transitions of displaced workers across occupational terrains. Results in Table 9.9 reveal that women are more likely to move into the machine terrain than men, regardless of origin. Women are, nonetheless, better able to avoid moving into collapsing occupations, as well as moving away from occupations with low transformative effects, although in this regard the difference to men is very small. Interestingly, women displaced from rising star occupations are penalized in moves to a new rising star job compared to men, instead finding employment in the machine terrain.

Once female workers are displaced from an occupation with high transformative digitalization effects (rising star occupations, machine terrain), they are less likely to relocate in an occupation with low transformative digitalization effects (human terrain, collapsing occupations). While other studies have highlighted that females are more affected by destructive digitalization, we show they are also more affected by transformative digitalization.

Workers undergoing a spell in non-employment after displacement tend to not return to the original occupation class, as evidenced by the main diagonal of Table 9.10. Instead, those that return to employment after more than a year without working are more likely to end up in collapsing occupations. A possible reason for this is related to depreciation of specific human capital depreciates which may occur while in non-employment. Continuous technological progress means that, while in non-employment, workers may not be able to keep up with new developments. Research in labor economics suggests that interrupted careers translate into depreciation of knowledge stocks, making workers less likely to return to the same types of occupations they held before displacement (Mincer and Ofek 1982).

TABLE 9.9: How gender (female) affects transitions

	from Rising Stars	from Machine Terrain	from Human Terrain	from Collapsing Occupations
To Rising Stars	-0.017^{***}	-0.022^{***}	0.003^{**}	0.006^{***}
	(0.003)	(0.003)	(0.002)	(0.001)
To Machine Terrain	0.047^{***}	0.076^{***}	0.008^{***}	0.033^{***}
	(0.002)	(0.004)	(0.002)	(0.001)
To Human Terrain	-0.011^{***}	-0.035^{***}	-0.005	0.001
	(0.002)	(0.002)	(0.004)	(0.001)
To Collapsing Occupations	-0.018^{***}	-0.019^{***}	-0.007^{*}	-0.040^{***}
	(0.002)	(0.003)	(0.003)	(0.002)
N	77,896	67,467	72,982	194,501

Notes: Marginal effects from multinomial logit estimations (standard errors clustered at the worker level in parentheses). Regressions also control for high skills, gender, age, time in non-employment, tenure, permanent contract, part-time job, firm size, knowledge intensity, region and year dummies. $*p < 0.10 * *p < 0.05 * * * p < 0.01$

TABLE 9.10: How a period of non-employment (dummy) affects transitions

	from Rising Stars	from Machine Terrain	from Human Terrain	from Collapsing Occupations
To Rising Stars	-0.100^{***}	0.055^{***}	0.009^{***}	0.019^{***}
	(0.003)	(0.003)	(0.002)	(0.001)
To Machine Terrain	0.028^{***}	-0.163^{***}	0.018^{***}	0.017^{***}
	(0.003)	(0.004)	(0.002)	(0.001)
To Human Terrain	0.028^{***}	0.038^{***}	-0.124^{***}	0.046^{***}
	(0.002)	(0.002)	(0.003)	(0.001)
To Collapsing Occupations	0.044^{***}	0.070^{***}	0.097^{***}	-0.083^{***}
	(0.002)	(0.003)	(0.003)	(0.002)
N	77,896	67,467	72,982	194,501

Notes: Marginal effects from multinomial logit estimations (standard errors clustered at the worker level in parentheses). Regressions also control for high skills, gender, age, time in non-employment, tenure, permanent contract, part-time job, firm size, knowledge intensity, region and year dummies. $*p < 0.10 * *p < 0.05 * * * p < 0.01$

Displaced workers coming from rising star occupations experience a downgrade in either the exposure to the destructive or the transformative effects (or both). But other workers (e.g., in the machine terrain or the human terrain) have a higher likelihood of finding employment in occupations with higher exposure to the transformative effects of AI, compared to workers who return to employment less than a year after displacement. A larger period spent searching for a job may increase the quality of employment matches and may allow workers to acquire new human capital necessary for reskilling for the jobs of the future.

Table 9.11 and Table 9.12 summarize the main findings from our multinomial transition analysis. For ensure robustness, we also ran our analysis on a sample where we drop the restriction of displaced workers, looking instead at the whole economy. The results are largely unaltered.

TABLE 9.11: Variables that positively affect transitions

	from Rising Stars	from Machine Terrain	from Human Terrain	from Collapsing Occupations
to Rising Stars	college, high skills, large firm, knowledge intensity	college, high skills, non-employment	college, high skills, female, non-employment, knowledge intensity	college, high skills, female, non-employment
to Machine Terrain	female, non-employment	college, high skills, female, age, large firm, knowledge intensity	college, high skills, female, non-employment, knowledge intensity	college, high skills, female, non-employment, knowledge intensity
to Human Terrain	age, non-employment	age, non-employment	college, age, large firm, knowledge intensity	high skills, age, non-employment, knowledge intensity
to Collapsing Occupations	non-employment	non-employment	non-employment	age, large firm

TABLE 9.12: Variables that negatively affect transitions

	from Rising Stars	from Machine Terrain	from Human Terrain	from Collapsing Occupations
to Rising Stars	female, non-employment	female, age, large firm	age, large firm	age, large firm
to Machine Terrain	college, high skills, age, large firm, knowledge intensity	non-employment	age, large firm	age, large firm
to Human Terrain	college, high skills, female, large firm, knowledge intensity	college, high skills, female, large firm, knowledge intensity	high skills, non-employment	college, large firm
to Collapsing Occupations	college, high skills, female, large firm, knowledge intensity	college, high skills, female, age, large firm, knowledge intensity	college, female, age, large firm, knowledge intensity	college, high skills, female, non-employment, knowledge intensity

9.6 Conclusions

This chapter analyzes the implications of digitalization for labor mobility by studying worker transitions among four occupational terrains distinctly exposed to digitalization as proposed by Fossen and Sorgner (2019). Using a sample of workers displaced due to firm closure, we estimated multinomial probability models of transitions from each of the four digitalization terrains into all four terrains, allowing us to better understand how worker mobility patterns are influenced by worker, firm and industry characteristics.

We find that having a college degree or a high level of firm specific human capital promotes moves into the transformative field of digitalization (and especially into rising star occupations), where these forms of human capital may find strong complementarities with artificial intelligence. We also find evidence of path dependence, in the sense that many displaced workers tend to return to the terrain from which they were displaced. However, individuals who spend at least one year out of employment are more likely to change their occupation drastically into a different digitalization terrain, some perhaps taking the opportunity to search for a better match while others may have to downgrade their employment expectations to worse jobs, namely into occupations collapsing due to high exposure to destructive digitalization and little to no positive interactions with the transformative effects of artificial intelligence.

These findings suggest a possible segmentation of the labor market. The segment of the highly skilled will occupy the jobs that benefit the most from newer technologies and experiencing almost none of the destructive effects, while a segment composed of less productive, often older, workers are pushed into collapsing occupations or, at best, into the human terrain performing manual jobs that, despite not yet being automated, are characterized by low wages, unstable employment interleaved with long period of unemployment. The path dependence described above is particularly damning to those in the collapsing jobs, as they struggle to find employment in more protected terrains and may find themselves in technological unemployment with an obsolete set of skills.

Future research could focus on how the effects of worker human capital (namely, education and skills) may differ between genders, age groups, firm size and knowledge intensity. This would allow a deeper comprehension of the role of human capital in determining transitions across occupations at different levels of transformative and/or destructive digitalization.

Our work points to opportunities for policy to guide both the training and the retraining (for example through formal education, short duration programs, or even on-the-job skills acquisition) of the workforce, preparing the labor supply for the jobs of the future. At the same time, measures for the protection of those negatively affected are needed, particularly during a transition period toward an economy based on newer, more sophisticated knowledge, as well as during periods between jobs where reskilling may be necessary.

9.7 Appendix

TABLE A9.1: Main occupations by digitalization terrain

Digitalization terrain	Occupation description	ISCO-08	Workers	% of employment
Rising Stars	Services Managers n.e.c.	1439	59,355	1.84
	Managing Directors and Chief Executives	1120	46,008	1.42
	Retail and Wholesale Trade Managers	1420	32,026	0.99
	Office Supervisors	3341	31,516	0.98
	Nursing Professionals	2221	30,798	0.95
Machine Terrain	Sales Workers n.e.c.	5249	125,845	3.90
	General Office Clerks	4110	122,489	3.79
	Clerical Support Workers n.e.c.	4419	39,153	1.21
	Accounting Associate Professionals	3313	22,868	0.71
	Accountants	2411	21,833	0.68
Human Terrain	Cleaners and Helpers in Offices, Hotels and Other Establishments	9112	124,936	3.87
	Heavy Truck and Lorry Drivers	8332	62,818	1.95
	Home-based Personal Care Workers	5322	41,840	1.30
	Car, Taxi and Van Drivers	8322	26,896	0.83
	Motor Vehicle Mechanics and Repairers	7231	23,721	0.73
Collapsing Occupations	Shop Sales Assistants	5223	83,609	2.59
	Waiters	5131	80,490	2.49
	Stock Clerks	4321	67,249	2.08
	Elementary Workers n.e.c.	9629	57,469	1.78
	Bricklayers and Related Workers	7112	46,832	1.45
Other	Crop Farm Laborers	9211	15,809	0.49
	Software and Applications Developers and Analysts n.e.c.	2519	12,533	0.39
	Sweepers and Related Laborers	9613	8,391	0.26
	Information and Communications Technology User Support Technicians	3512	7,399	0.23
	Mixed Crop and Livestock Farm Laborers	9213	6,595	0.20

Notes: n.e.c. = not elsewhere classified. Percentage of employment refers to share of total employment of occupation in 2019.

TABLE A9.2: Job (hierarchical) levels

Level	Tasks	Skills
8 - Top managers	Definition of the firm general policy or consulting on the organization of the firm. Strategic planning. Creation or adaptation of technical, scientific and administrative methods or processes.	Knowledge of management and coordination of firm's fundamental activities. Knowledge of management and coordination of the fundamental activities in the field to which the individual is assigned and that requires the study and research of high responsibility and technical level problems.
7 - Intermediary managers	Organization and adaptation of the guidelines established by the superiors and directly linked with the executive work.	Technical and professional qualifications directed to executive, research, and management work.
6 - Supervisors, team leaders, foremen	Orientation and supervision of teams, as directed by superiors, but requiring the knowledge of tasks.	Complete professional qualification with a specialization.
5 - Higher-qualified professionals	Tasks requiring a high technical value and defined in general terms by superiors.	Complete professional qualification with a specialization adding to theoretical and applied knowledge.
4 - Qualified professionals	Complex or delicate tasks, usually not repetitive and defined by superiors.	Complete professional qualification implying theoretical and applied knowledge.
3 - Semi-qualified professionals	Well defined tasks, mainly manual or mechanical with low complexity, usually routine and sometimes repetitive.	Professional qualification in a limited field or practical and elementary professional knowledge.
2 - Non-qualified professionals	Simple tasks, diverse and usually not specified, totally determined.	Practical knowledge and easily acquired in a short time.
1 - Apprentices, interns, trainees	Training for a specific task	Identical, but without practice, to the professional of the qualification level they will be assigned

Hierarchical levels as defined by Portuguese law - Decreto Lei 121/78 of July 2.

Part IV

A model for the circular economy

Chapter 10

The circular economy and the optimal recycling rate: A macroeconomic approach

10.1 Introduction

The debate on the "circular economy" (CE), as a new paradigm opposite to the standard "linear economy", has emerged from the necessity to deal with dwindling natural resources and the generation of waste through economic activity.[1] This issue has also attracted rising interest among scholars, although there is still a shortage of theoretical and empirical studies offering a better understanding of the consequences of incorporating the CE into the standard linear economy as a necessary step for correctly assessing the implications of CE driving policies. Several economies, such as the European Union (with Germany as the leading country), Japan and China, have incorporated the CE into their environmental and economic growth policies, considering the CE as one of the pillars of sustainable development (Geissdoerfer et al. 2017). Production and consumption activities in the economy are basically "linear", meaning that raw natural resources are used to produce final goods, and after their use in consumption or investment activities, waste is generated that needs to be managed. This is the so-called "take, make and waste" or "open-loop" approach to production. The CE is regarded as an instrument to mitigate the two main problems generated by the open-loop approach, specifically the depletion of natural resources and environmental damage, helping to "close the open-loop".

The paradigm of CE is gaining momentum as a strategy to improve the environmental quality and preserve natural resources. The role of natural resources in economics has regained prominence just when evidence of a damaged environment has emerged. Andrews (2015) situates the birth of the linear economy the "take-make-use-dispose" model of consumption in the Industrial Revolution and claims the necessity of a new economic model, in which the CE is called to play a central role in sustainability. Nowadays, there is an open debate among scholars on the relationship between the CE and sustainability, the different ways to promote the CE and the crucial sectors for implementation. Hu et al. (2018) analyze the efficiency of promoting the CE through legislation. Other authors focus on the idea of implementing taxes as an instrument to promote the CE. For example, Bahn-Walkowiak et al. (2012) analyze the effects of taxing construction materials. Pomponi and Moncaster (2017) highlight the necessity of using CE-driving policies in those sectors that consume more raw materials. Kirchherr et al. (2018) analyze the main barriers to the CE in European countries, concluding not only that technological barriers exist but also that the main barriers seem to be cultural: the lack of awareness among consumers and a company culture of reluctance to engage in the CE. George et al. (2015) conclude that the only possible way to improve the environmental quality is to increase the recycling rate as one of the pillars of the CE. Lin (2020) points out that waste has a non-zero value as it can be recycled and new material generated for new production/consumption activities.

In practice, economic activity (the production of consumption and investment goods) uses raw materials extracted from nature and produces a large variety of waste that could be reused for production purposes. Various of these waste products, such as metal, e-waste, paper, glass, plastic, batteries and

[1] For a definition of the CE, see for instance, Kirchherr et al. (2018), Korhonen (2018, a, b), and García-Barragán et al. (2019).

so on, can be recovered and re-manufactured. Even organic residuals can be transformed into fertilizers or energy generation fuel. The awareness of environmental and natural resources issues and the elaboration of policies to embrace the idea of the CE have become fundamental in China and Europe.[2] As McDowall et al. (2017) highlight, the conception of the CE differ between the two territories, being broader in China, which includes pollution and other environmental problems in the CE perspective. By contrast, the European focus is on waste, natural resources and opportunities for business. It is not surprising that the awareness about the necessity of the CE has emerged in China where, for example, the total amount of municipal solid waste reached 191.4 million tonnes in 2015, according to the National Bureau of Statistics of China (2016). In Europe, according to Eurostat (2021), the generation of municipal waste per capita rose to 489 kg in 2018 (municipal waste accounting for just 10% of the total waste generation).[3] Increasing the circularity of the economy is an issue that not only concerns governments, but also private firms as a managing strategy to maximize revenues. For instance, CE-related revenues represent around 15% of total revenues of the Philips company (Koninklijke Philips, 2019; 2020).

Data about waste generation and environmental exploitation highlight the necessity of an efficient recycling sector, together with a culture of negative externalities reduction and input re-use.[4] In this chapter, we adopt a broad view of the concept of recycling, including several activities distinct from producing recycled material and encompassing re-manufacturing activities and the re-usage of materials as well. That is, they include the aggregate of all secondary materials whether they need a recycling process or not. Indeed, the CE is a concept far beyond the recycling sector that to be implemented, needs to be accepted in daily life by every single economic agent, including households, firms and governments. The CE has become crucial for sustainable economic growth, (see Lin, 2020). All firms need to re-use their inputs as much as they can and make it easy for their customers to return the waste associated with the consumption of their products so that it can be re-integrated into the productive process. Consumers have to be conscious about the necessity of reducing waste, reusing products and recycling any waste that they produce. Finally, governments should give incentives to firms to use recycled materials instead of natural resources, as well as to consumers to favor their re-using and recycling processes. Lin (2020) studies sustainable growth from a CE perspective, highlighting the problems and limitations of the traditional linear economy which represents an economic growth system that is unsustainable in the long-run. Haas et al. (2015) estimate that the CE accounted for a very small fraction of the total economy in the year 2005, with a global 4 Gt/year (gigatonnes per year) of recycled waste material compared with a total of 58 Gt/year of raw natural materials. This represents around 6.5% of the total processed materials. However, we must take into account that almost half of the processed materials are energy, and, hence, are not available for recycling. Considering biomass, the circularity of the economy increases to 37%. These figures show that there is still considerable room to increase the circularity of the economy based on two pillars: an increase in recycling rates and an energy transition from fossil fuels to renewable energy sources.

Nonetheless, the CE has been neglected in standard macroeconomic analysis, which has traditionally only consider the linear economy.[5] Mainstream economics is dominated by the traditional "linear" economy, in which finite natural resources are extracted for production activities that are non-sustainable in the long-run and the generation of waste that deteriorates the environment. This chapter contributes

[2] Ghisellini et al. (2016) offer a measure of the concern about the CE around the world, and China emerges as the leading country. They review 89 case studies about the CE and then classify them by geographical location; 41 studies focus on China and 20 on the European Union (EU), meaning that, almost 70% of the surveyed studies about the CE refer to China.

[3] The World Bank estimates the figure to be around 2 billion tonnes of municipal solid waste annually. The United Nations estimates that the total solid waste in 2018 amounted to more than 10 billion tonnes.

[4] According to a behavioral study on consumers' engagement in the CE, elaborated by the European Commission, consumers keep things that they have owned for a long time (93%), recycle unwanted possessions (78%), and repair possessions if they break (64%).

[5] See Geissdoerfer et al. (2017) and Schroeder et al. (2018) for a review of the literature about the CE, its relationship with sustainability and the main topics studied in the literature related to the circularity issue.

to the literature by developing a standard neoclassical Dynamic General Equilibrium (DGE) model extended by the incorporation of the CE.[6] We depart from previous analyses in ecological economics or industrial ecology, and we use the tools of traditional mainstream neoclassical economics analysis as a prism to offer a new perspective on the CE. The chapter has a twofold purpose. First, we intend to study the economic and environmental implications of the CE from a macroeconomic point of view. Second, we aim to show that traditional neoclassical linear economic models can be transformed and used to study the CE to achieve a better understanding of this issue. The model considers a production function with raw materials as an additional input to capital and labor to produce final goods. Materials are a composite of natural resources (representing the linear economy) and recycled materials (the CE). The consumption of the final goods generates waste that can be recycled and reused in production. Given the presence of a negative externality (waste accumulation), the model is solved considering the socially-planned (optimal) allocation of resources. This integrated theoretical framework can be viewed as a representation of the evolution from a traditional linear economy to an economy in which the CE contributes to closing the open-loop of the former.

Consistent with the empirical evidence, quantitative simulations of the model reveal that, in the steady state, the optimal recycling rate representing the degree of circularity of the economy has a positive relationship with economic development. Furthermore, increasing the circularity of the economy is a necessary condition to increase social welfare in a growing economy. As output and consumption increase, more waste is generated, fostering the optimality of recycling activities. We find the existence of a steady-state hump-shaped relationship between the output and the stock of waste, which can be interpreted as the existence of an Environmental Kuznets Curve (EKC) in the presence of the CE. This EKC does not appear in the case of a linear economy, in which the relationship between the output and the stock of waste is always positive. This result shows the importance of the CE as a necessary transformation of the traditional economy to make economic growth compatible with environment preservation. The optimal social recycling rate positively depends on the damage of the stock of waste to households' utility and on the waste content of the final consumption goods. Among the potential policies to promote the CE, increasing the cost of natural resources or reducing the cost of recycled materials, we find that only the later contributes to increasing the circularity of the economy. As expected, a permanent positive technological shock reducing the cost of recycling increases recycling activities and output and reduces the stock of pollution. By contrast, simulation results from a permanent negative technological shock, increasing the cost of natural resources, are counterintuitive as this shock reduces the recycling rate and economic activity, and hence, does not contribute to the expansion of the CE.

The rest of the chapter is structured as follows. Section 2 elaborates an integrated macroeconomic model in which both linear and circular economies are present. Section 3 calibrates the parameters of the model and calculates the steady state of the economy. Section 4 presents some simulation results from the model and a sensitivity analysis of the key parameters. Section 5 offers a discussion of the results and their link with the results presented in the ecological economic literature and summarizes the main conclusions.

10.2 A macroeconomic model for the circular economy

The traditional macroeconomic modeling approach relies on the study of a "linear economy", in which inputs are used to produce a final output and some negative externalities, such as waste and pollution, are generated during the production process. Standard environmental macroeconomic models usually consider raw materials as an additional input to physical capital and labor, but they constitute a model representation of a linear economy, in which raw materials are used and waste is generated without any re-use. Materials are natural resources that can be either non-renewable or renewable. In a standard

[6] The standard neoclassical DGE model for a linear economy is introduced by Ramsey (1928) and later further developed by Cass (1965) and Koopmans (1965). Dasgupta and Heal (1974) developed a linear economy DGE model extended with the inclusion of natural resources. For a review of CE modeling approaches, see McCarthy et al. (2018).

linear economy, natural resources are transformed and used in production activities, and they finish as waste once the final good produced has been consumed or invested. Two key problems arise in a linear economy. First, natural non-renewable resources are depleted. Second, even when resources are renewable, a waste generation problem exists. However, the materials used in the production process, along with the existing technology, enable the recovery of a fraction of the total waste as well as its transformation into new materials. This is the case of the CE, in which waste products re-enter the production activities and, once the final goods have been consumed, are transformed again into waste, and so on. The macroeconomic model developed here encompasses the two fundamental aspects of the CE: it limits the harmful effects of the economic activity on the environment by reducing the stock of waste, and it mitigates the depletion of natural resources.

This section develops a CE model embedded in a standard neoclassical growth model for a linear economy. Waste is assumed to be generated by the consumption of final goods. Waste that is not recycled is accumulated into a stock of waste that negatively affects households' utility. The accumulation of waste can be reduced by increasing the recycling rate of waste (transforming waste into resources that can be used again in production activities). Our modeling strategy considers a view in which the CE refers to a wider set of activities leading to the re-use of materials in the economy (recycling, re-manufacturing, reusing, repairing, sharing, etc.). Given the existence of a negative externality, we consider a centralized economy in which a central planner maximizes social welfare to study the conditions for the first-best equilibrium. Given the presence of a negative externality, the planner solution will not be a decentralized equilibrium.

10.2.1 Households

We consider an economy populated by an infinitely-lived representative household with preferences regarding consumption, leisure and environmental quality. The instantaneous utility function is defined as:

$$U(C_t, L_t, Z_t) = \ln C_t - \theta \frac{L_t^{1+\frac{1}{\rho}}}{1+\frac{1}{\rho}} - \phi Z_t^{\chi} \tag{10.1}$$

where C_t is the consumption of goods and services, L_t is the labor and Z_t is the level of pollution generated by waste residuals from consumption activities that are assumed to be equal to the stock of waste. The parameter $\theta > 0$ represents the willingness to work, and ρ is the Frisch intertemporal elasticity of the labor supply representing the change in worked hours in response to a change in the equilibrium wage, given a constant marginal utility of wealth. Waste is considered to be a negative externality, reducing households utility function. The disutility produced by the accumulated waste stock is measured by the parameter ϕ. We assume that $U_Z < 0$ and $U_{ZZ} < 0$, indicating that, as waste is accumulated, its cost, in terms of utility, increases. The parameter $\chi > 1$ represents the elasticity of utility with respect to pollution.[7]

The resource constraint of this centralized economy is given by:

$$C_t + I_t + \Theta_n N_t + \Theta_v V_t = Y_t \tag{10.2}$$

[7]The model has been solved for alternative specifications of the households' utility function to check the robustness of the results to the particular specification of the utility function. First, we simplify expression (1) eliminating leisure (labor supply). We find that the optimal labor supply decision does not affect the results. Second, we use an alternative specification for the household's utility function given by,

$$U(C_t, Z_t) = \ln C_t + \theta \ln(H - Z_t)$$

where the constant H represents the initial endowment of environmental quality. As the stock of waste increases, the environmental quality declines and reduces utility. Again, we find that the results only change slightly using this alternative specification and, hence, the conclusions remain the same.

where I_t is investment, N_t represents natural resources[8], V_t denotes recycled materials, and Y_t is final output. Θ_n and Θ_v are technological parameters reflecting the real cost of natural and recycled material, respectively, which are assumed to be exogenously given. This resource constraint encompasses both the linear economy, in which natural extracted resources are used in production activities, and the circular economy, in which instead of new natural resources, recycled materials are used for production. The amount of recycled material depends on the recycling rate, whereas the amount of natural resources depends on the extraction rate.

We assume the following accumulation process for physical capital, K_t:

$$K_{t+1} = (1 - \delta_k)K_t + I_t \tag{10.3}$$

where δ_k $(0 < \delta_k < 1)$ is the physical capital depreciation rate.

10.2.2 Waste and recycling

The model considers the existence of a negative externality in the form of waste. We assume that waste is generated by the consumption of final goods.[9] Waste generated by consumption, X_t, is defined by the following function:

$$X_t = X(C_t) = \eta C_t^{\gamma} \tag{10.4}$$

where γ is the elasticity of X_t with respect to consumption[10], and η is the proportion of waste as a by-product of consumption. This parameter indicates the fraction of consumption that is transformed into waste (waste content per consumption unit). A prototype model for natural resources, but without the generation of waste, is provided by Dasgupta and Heal (1974).

We assume the following accumulation process for waste:

$$Z_{t+1} = (1 - \delta_z)Z_t + (1 - \mu_t)X_t \tag{10.5}$$

where Z_t is the stock of waste, δ_z is the decay rate of waste, and $0 < \mu_t < 1$ is the recycling rate. It is assumed that the cost of recycling is a constant and independent of the recycling rate. Furthermore, it is assumed that all kinds of waste can be recycled.[11] Therefore, recycled materials are produced according to:

$$V_t = \mu_t X_t \tag{10.6}$$

[8] The flow of natural material used in production, N_t, comes from the extraction of natural resources and the modeling strategy is close to that of André and Cerdá (2006). However, since we assume that natural resources can be both renewable and non-renewable and therefore that there is room for regeneration, we omit the modeling of this process so that our model focuses on circularity. In this sense, the fraction of income expended on both natural and recycled material is a function of the technological parameters Θ_n and Θ_v, which reflect all the real cost of natural and recycled material used in production.

[9] Alternatively, we can assume that waste is generated by consumption, investment, production activities or all of them. Nevertheless, the results presented in this chapter remain unchanged for these different modeling strategies.

[10] In the calibration of the parameters of the model (see next section) we assume that $\gamma = 1$.

[11] Alternatively, the waste accumulation law of motion can be defined as,

$$Z_{t+1} = (1 - \delta_z - \mu_t)Z_t + X_t$$

where the recycling rate represent the fraction of the stock of waste recovered each period. In this case, the recycling rate of the economy is not defined as the percentage of the current flow of waste recovered, but the percentage over the stock of waste. This alternative specification allows recycling not only waste of the present but also waste of the past. Nevertheless, both specifications produce similar results. Additionally, it is assumed that all kinds of waste can be recycled. However, it could be the case that not all kinds of waste are recyclable. This case could be considered by simply defining equation (6) in the text as,

$$V_t = \mu_t \psi X_t$$

where $0 < \psi \leq 1$, represents the fraction of waste recyclable. To keep the model as simple as possible we assume that $\psi = 1$.

In a linear economy, the recycling rate is equal to zero ($\mu_t = 0$), and hence, also $V_t = 0$. In this scenario, waste is accumulated over time depending on the relationship between the waste decay rate and the newly generated waste. On the other hand, if $\mu_t = 1$, the stock of waste is zero, and no negative externality exists as the flow of waste disappears instantaneously.

10.2.3 Production function

We use a standard Cobb-Douglas production function with three inputs: physical capital, labor and raw materials. This technology is given by:[12]

$$Y_t = A_t K_t^{\alpha_1} M_t^{\alpha_2} L_t^{1-\alpha_1-\alpha_2} \tag{10.7}$$

where Y_t is the aggregate output, A_t is a measure of total factor productivity (TFP), L_t collects labor services, K_t represents physical capital and M_t denotes the raw materials. α_1 represents the elasticity of output with respect to capital and α_2 is the elasticity of output with respect to raw materials. Materials used in production match an Armington aggregator of both virgin natural resources and recycled materials:

$$M_t = \left[\omega N_t^{\frac{\sigma-1}{\sigma}} + (1-\omega) V_t^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{10.8}$$

where ω is a distribution parameter and σ is the elasticity of substitution between natural resources and recycled material.[13] The degree of substitution between natural and recycled materials is not perfect. García-Barragán et al. (2019) assume that natural and recycled materials are not perfect substitutes between the quality losses of recycled material in subsequent recycling rounds. We do not consider that possibility, which would require a change in the recycling technology, and we simply assume that imperfect substitution applies equally to both types of material.

As it can be observed, the CE enters the aggregate production function in the form of materials along with the standard linear economy. The distribution parameter $1-\omega$ indicates the weight of the CE with respect to the linear economy. If $\omega = 1$, it means that the economy is fully linear, so all raw materials come directly from natural resources and all waste generated by consumption is accumulated into the existing stock of waste. For any value of $\omega < 1$, the CE comes into play, and a fraction of waste is transformed into recycled materials that can be used for production purposes. Hence, the circular part of the economy implies the existence of a material loop that contributes to a cleaner environment. Once raw materials are used in production activities, the consumption of the final goods generates waste that can be converted into new materials again and re-used for production activities.[14]

10.2.4 Central planner's welfare maximization problem

Given the existence of a negative externality, we consider the case of a planning problem, in which we assume the existence of a central planner who maximizes social welfare by choosing optimal values for the consumption, labor, capital stock, stock of waste and recycling rate. The central planner solves the

[12] This production function implies that the elasticity of substitution between inputs is unitary. Alternatively, we can assume a CES production function in which inputs are gross complements. However, the implications for the CE are similar, therefore, we decide to present the simplest specification.

[13] Solow and Wan (1976) investigate how the use of an exhaustible resource affects the production function and the shadow price of optimal extraction, concluding that relatively large variations in the availability of resources generate very small changes in the sustainable level of consumption.

[14] The idea of the CE is close to the carbon capture and sequestration technologies in environmental economics. Once waste or emissions are produced, some technologies can be used to mitigate the stock of pollution. They can also be reused to capture CO_2 for energy generation. The recycling of waste from consumption activities is based on a similar principle and implies that a fraction of the stock of waste is removed and re-used for production activities.

following problem,

$$\max_{\{C_t, L_t, K_{t+1}, \mu_t, Z_{t+1}\}} \sum_{t=0}^{\infty} \beta^t \left[\ln C_t - \theta \frac{L_t^{1+\frac{1}{\rho}}}{1+\frac{1}{\rho}} - \phi Z_t^{\chi} \right] \tag{10.9}$$

subject to the restriction given by (10.2), (10.3), (10.4), (10.5), (10.6), (10.7) and (10.8).[15] The full resolution of the central planner's maximization problem and the corresponding first-order conditions can be found in the technical appendix. From the first-order conditions, we find that the equilibrium condition for the optimal quantity of natural resources is given by:

$$\Theta_n M_t^{\frac{\sigma-1}{\sigma}} = \alpha_2 \omega Y_t N_t^{\frac{-1}{\sigma}} \tag{10.10}$$

The optimal investment decision is given by:

$$\frac{Y_{t+1} L_t^{\frac{1}{\rho}+1}}{Y_t L_{t+1}^{\frac{1}{\rho}+1}} = \beta \left[(1-\delta_k) + \alpha_1 \frac{Y_{t+1}}{K_{t+1}} \right] \tag{10.11}$$

Finally, the equilibrium condition for the optimal quantity of recycled material, indicating the optimal circularity of the economy, is given by:

$$\beta^{t+1} \phi \chi Z_{t+1}^{\chi-1} = \frac{\beta^t \theta L_t^{\frac{1}{\rho}+1}}{(1-\alpha_1-\alpha_2) Y_t} \left[\Theta_v - \alpha_2 (1-\omega) \frac{Y_t V_t^{\frac{-1}{\sigma}}}{M_t^{\frac{\sigma}{\sigma-1}}} \right] -$$
$$\frac{\beta^{t+1} \theta L_{t+1}^{\frac{1}{\rho}+1}}{(1-\alpha_1-\alpha_2) Y_{t+1}} \left[\Theta_v - \alpha_2 (1-\omega) \frac{Y_{t+1} V_{t+1}^{\frac{-1}{\sigma}}}{M_{t+1}^{\frac{\sigma-1}{\sigma}}} \right] (1-\delta_z) \tag{10.12}$$

Equilibrium conditions (10), (11) and (12) differ in several aspects from the equilibrium conditions resulting from the standard linear economy model. Expression (10) indicates that the optimal quantity of raw materials used in production activities is determined by the condition that equals the marginal productivity of natural material to the unit cost of raw material. Expression (11) represents the condition that equals the marginal value of consumption with the marginal value of investment, that is, the optimal consumption-saving decision. However, this equilibrium condition differs from the standard one in the fact that the intertemporal consumption marginal utility ratio is replaced by a combination of labor and output because of the introduction of the CE and that consumption generates waste. Indeed, expression (11) can be written as (see technical appendix),

$$\frac{C_{t+1} + \gamma X_{t+1} \left[\Theta_v - \alpha_2 (1-\omega) \frac{Y_{t+1} V_{t+1}^{-\frac{1}{\sigma}}}{M_{t+1}^{\frac{\sigma-1}{\sigma}}} \right]}{C_t + \gamma X_t \left[\Theta_v - \alpha_2 (1-\omega) \frac{Y_t V_t^{-\frac{1}{\sigma}}}{M_t^{\frac{\sigma-1}{\sigma}}} \right]} = \beta \left[1 - \delta_k + \alpha_1 \frac{Y_{t+1}}{K_{t+1}} \right] \tag{10.13}$$

which includes the intertemporal consumption ratio as in the linear economy model, plus a new term reflecting the fact that consumption produces waste and that the circular side of the economy transforms part of waste into recycled material reused again for production. Notice that the above equilibrium condition is equal to the standard optimal consumption path in the canonical linear economy model when waste produced from consumption is not considered $X_t = 0$. In our model, the optimal consumption

[15] This is the common solution approach adopted in the literature for solving environmental-economics models (see, for instance, Acemoglu et al. 2012; Acemoglu et al. 2016; Golosov et al. 2014). Given the presence of a negative externality, the planner solution will not be a decentralized equilibrium. The central planning outcome only coincides with a dynamic competitive market equilibrium in the absence of relevant distortions (Hassler and Krusell, 2018).

path is also affected by waste and the recycling rate reflected by the amount of recycled material. Finally, expression (12) represents the condition that equals the welfare cost of waste in terms of losses in household's utility with the difference between the marginal productivity and the cost of recycled material.

10.3 Calibration and steady state

This section presents the calibration of the parameters of the model. Since the model is composed of macroeconomic parameters and parameters related to recycling activities, we use different sources for this calibration. Macroeconomic parameters are calibrated from the real business cycle (RBC) literature, while parameters related to the waste generation process and recycling activities are obtained from different statistical sources and previous research. For some key parameters, we carry out a sensitivity analysis and simulate the model using a range of values given their uncertainty.

On the one hand, some of the parameters of the model are standard in macroeconomics. Therefore, we calibrate them by employing the standard values used in the literature. We set the intertemporal discount factor, β, to 0.97. The Frisch elasticity of labor, ρ, is fixed at 0.72. Given the value for labor elasticity, the willingness to work parameter, θ, is calibrated at 15.6 to produce a labor steady state value of 0.33. The capital depreciation rate, δ_k, is fixed at 0.07. The output-capital elasticity, α_1, is fixed at 0.3 and the output-labor elasticity, $1 - \alpha_1 - \alpha_2$, at 0.65. Given the assumption of constant returns to scale, these figures result in an output-material elasticity of 0.05.

On the other hand, the model includes parameters related to the waste generation process and recycling activities. The values of these parameters are not yet documented in the literature. We set the waste elasticity to consumption, $\gamma = 1$, assuming that every consumption unit involves an associated proportional waste product. The parameter η collects the share of waste in consumption. This parameter indicates the percentage of the waste remaining from each consumption unit, that is, the waste content in consumption goods. According to Eurostat (2021), each inhabitant of the EU uses 16 tonnes of materials per year, 6 tonnes of which become waste. Thus, we can establish a relationship between consumption and waste in the model by setting η to 6/16=0.375 and γ to 1. We calibrate $\sigma = 1.5$ to reflect the relationship of substitution between natural resources and recycled materials, both being far from perfect substitute inputs. In accordance with the Eurostat data, we set $\omega = 0.95$, so the share of circular materials is 11.7%, matching the circularity rate of the EU-27 countries.[16] The waste damage parameter to the utility function, ϕ, is calibrated as 0.5. The pollution damage to welfare is assumed to be a power function of the stock of pollution. Hence, the pollution elasticity parameter, χ, is fixed at 2. The values of these two parameters must adequately define the fraction of waste accumulation that ends up being harmful to household's welfare (representing a variety of factors, including negative effects on health, climate change, visual effects of landfills, garbage smells, etc.). To assign these values correctly, first, we explore all the possible paths along which residue can travel once it is produced. On the one hand, this waste can be recycled or reused, entering the CE system, and we assume that it would not cause any damage to the utility. Notice that the waste that follows the CE path is not collected in the variable representing the stock of waste. On the other hand, we have the waste that is not recycled or reused, which is accumulated in Z. This non-recycled or non-reused waste can follow different routes to landfill or incineration. In the EU, in 2018, more than half (54.6%) of the waste was treated in recovery operations: recycling (37.9% of the total treated waste), backfilling (10.7%) or energy recovery

[16]We must bear in mind that these data can significantly vary among countries. For example, the estimated circularity rate in France is 18.6% while it is only 1.6% in Ireland. Furthermore, it is assumed that parameters for the centralized economy are equal to those of the decentralized economy.

(6.0%). The remaining 45.4% was either landfilled (38.4%), incinerated without energy recovery (0.7%) or disposed of otherwise (6.3%).[17]

Having highlighted what waste treatment data looks like, we can explore what the empirical evidence shows about how the different methods of waste treatment can affect human health (and, therefore, utility). It is very difficult to establish exactly the relative importance of consumption levels and health status for a representative individual. Just as we assume that higher levels of consumption result in greater utility, we also assume that greater risk to health results in lower utility. Establishing a comparison with the work of Tomita et al. (2020), we can say that, if an individual can choose between being closer to or further away from a waste deposit, he will always choose to be as far away as possible. Tomita et al. (2020) find that residing within 5 km of a waste site in South Africa is significantly associated with asthma, tuberculosis, diabetes and depression.

We can also establish a comparison with macroeconomic models that take air pollution into account, since this type of pollution is more established in the literature as a negative externality and we can find several models describing it in that way. This relationship is direct when we highlight, for example, that waste incineration may result in emissions of air pollutants. Tait et al. (2015) conduct a systematic review of the health impacts of waste incineration in which a range of adverse health effects is identified, including significant associations with some neoplasia, congenital anomalies, infant deaths and miscarriage.

TABLE 10.1: Baseline calibration of the parameters

	Parameter	Definition	Value
Preferences	β	Discount factor	0.97
	θ	Labor weight	15.60
	ρ	Frisch elasticity parameter	0.72
Technology	α_1	Output-capital elasticity	0.30
	α_2	Output-material elasticity	0.05
	δ_k	Physical capital depreciation rate	0.07
	A	Total factor productivity	1.00
	Θ_n	Natural resource technology	1.00
	Θ_v	Recycled material technology	1.00
Waste	γ	Waste-consumption elasticity	1.00
	ϕ	Waste damage parameter	0.50
	χ	Pollution elasticity parameter	2.00
Circular Economy	ω	Natural resource share	0.95
	σ	Elasticity sources substitution	1.50
	η	Share of recyclable consumption waste	0.375
	δ_z	Waste stock decay rate	0.025

As we acknowledge that the calibration of these parameters can be subjective because there are not yet any solid data or empirical evidence about this, we present our results for different values to show how the calibration of these parameters can affect the final results. Finally, we assume an annual pollution stock decay rate, δ_z, of 2.5%. This corresponds to a life expectancy of 72 years. The degradation

[17] It is also important to pay attention to the different types of waste that are produced. In particular,4.4 % of waste produced in the EU during 2018 (101.7 million tonnes) was classified as hazardous waste. According to Eurostat, in 2018, 45.1% of the hazardous waste treated in the EU was recovered: 37.5% by recycling or backfilling and 7.6% by energy recovery. The remaining 54.9% was incinerated without energy recovery (5.7%), landfilled, in other words deposited into land or through land treatment and released into water bodies (32.8%), or disposed of in another way (16.2%).

time depends on the waste material, ranging from 3 months for paper tissues, napkins or an apple core to 1-2 years for a cigarette end, 10-100 years for an aluminum can for drinks, 100-1000 years for plastic and more than 10,000 years for polystyrene (US Department of Commerce). Finally, technological components are assumed to be exogenously given and are normalized to one. A summary of the benchmark calibrated parameters of the model is presented in Table 10.1.

10.3.1 Steady State

For readers' convenience, we report here the system of equilibrium equations in the steady state used to simulate the model.

$$Y = AK^{\alpha_1}M^{\alpha_2}L^{1-\alpha_1-\alpha_2} \tag{10.14}$$

$$M = \left[\omega N^{\frac{\sigma-1}{\sigma}} + (1-\omega)V^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{10.15}$$

$$I = \delta K \tag{10.16}$$

$$C = Y - I - \Theta_n N - \Theta_v V \tag{10.17}$$

$$X = \eta C^{\gamma} \tag{10.18}$$

$$\mu = \frac{V}{X} \tag{10.19}$$

$$Z = \frac{(1-\mu)X}{\delta_z} \tag{10.20}$$

$$L = \left(\frac{\left(\frac{1}{C} - \frac{\phi\chi Z^{\chi-1}}{\delta_z}\eta\gamma C^{\gamma-1}\right)(1-\alpha_1-\alpha_2)\,Y}{\theta}\right)^{\frac{\rho}{1+\rho}} \tag{10.21}$$

$$K = \frac{\alpha_1 Y}{\frac{1}{\beta} - 1 + \delta} \tag{10.22}$$

$$N = \left(\frac{\alpha_2\omega Y}{\Theta_n M^{\frac{\sigma-1}{\sigma}}}\right)^{\sigma} \tag{10.23}$$

$$V = \left(\frac{\alpha_2(1-\omega)\,Y}{\left(\Theta_v - \frac{\phi\chi Z^{\chi-1}(1-\alpha_1-\alpha_2)Y}{\theta L^{\frac{1}{\rho}+1}\delta_z}\right)M^{\frac{\sigma-1}{\sigma}}}\right)^{\sigma} \tag{10.24}$$

where we drop the time subscripts of variables to denote steady state values. The system of equations (10.14)-(10.24) contains 11 equations for 11 unknowns, $(C, I, L, K, Y, M, N, V, X, Z, \mu)$. The above system of steady state equations is numerically solved using a Newton-type algorithm.[18]

10.4 Results

Using the calibrated model, three simulation exercises are performed. First, we study the steady state relationship among the key variables of the model economy for a range of values of aggregate productivity. Second, we carry out a sensitivity analysis of the key parameters related to the CE. Finally, we simulate the effects of a permanent technological shock to each type of material.

[18]The codes are written in Matlab and are available from the authors on request.

10.4.1 Optimal recycling rate and output

First, we study the determinants of the optimal recycling rate and the factors driving the circularity of the economy. In our theoretical framework, the recycling rate is determined endogenously, resulting from the maximization of social welfare once the social cost of the accumulation of waste has been internalized. This optimal recycling rate in the centralized economy would be equivalent to the target recycling rate of policies promoting the CE in a market economy. Once the waste has been produced, the recycling rate determines the fraction of waste that is transformed into recycled material to be used again in production activities, while the remaining fraction is accumulated to the previous stock of waste. Empirical evidence (OECD, 2020) suggests that recycling rates are higher in developed economies than in developing economies, indicating that economic growth can also be a factor fostering the circularity of the economy. We test this empirical evidence by calculating steady states of the model economy for a range of values of total factor productivity (TFP). In particular, we simulate the model for a range of values for TFP, from 0.2 to 1.8. The baseline calibration of the model is fixed at a value for TFP of 1, which corresponds to a steady state output of 0.390.

Figure 10.1 plots the relationship between the steady-state output and the corresponding optimal recycling rate, stock of waste, and quantities for natural and recycled material. We start by studying the relationship between the optimal recycling rate and the level of output. The relationship between the output and the recycling rate is found to be always positive, indicating that the higher the level of output, the higher the optimal recycling rate. This steady-state relationship is obtained for alternative specifications of households' utility function. The function has an S-shaped form, reflecting that, once a certain level of output is reached, the transition from low to high recycling rates accelerates. When the output is high enough and the recycling rate is close to unity, further increases in output augment the recycling rate marginally. This result indicates that, as countries increase their output, the recycling rate that maximizes social welfare also increases and, therefore, a propensity to adopt a CE appears. Indeed, as the output grows, the waste generation increases along with the threat to the environment. Therefore, we should expect the recycling rate to be higher in developed countries than in developing countries given the greater environmental damage, with a general trend in increasing recycling activities and promoting the CE. Summing up, the model predicts a pattern of increasing circularity, as the only alternative to maximize social welfare in a growing economy to reduce the harmful effects caused by the linear economy.

Next, we study the relationship between the stock of waste and the output. Two opposite forces driving the relationship between these two variables emerge in the presence of the CE. On the one hand, as the output increases, the quantity of waste generated by consumption activities also increases, raising the stock of waste. On the other hand, as the output increases, the optimal recycling rate also increases, reducing the velocity of waste accumulation. In this context, the accumulation of waste critically depends on the circularity of the economy. We find the existence of a steady-state hump-shaped relationship between the output and the stock of waste, which can be interpreted as the existence of an Environmental Kuznets Curve (EKC) in the presence of the CE. This EKC does not appear in the case of a linear economy, in which the relationship between the output and the stock of waste is always positive. This result shows the importance of the CE as a necessary transformation of the traditional economy to make economic growth compatible with environment preservation. Bongers (2020) finds the existence of an EKC relationship between output and pollution when fossil fuel and renewable energy are considered as alternative energy sources, and a consequence of energy transition. In this theoretical framework, as the output increases, more renewable energy is used in production activities, thus reducing emissions. The mechanism from the CE found here is similar but operates through recycled material.

Finally, we find that, as the output increases, the quantity of both natural and recycled material also increases. Nevertheless, the growth in the use of recycled material is higher than that of natural material,

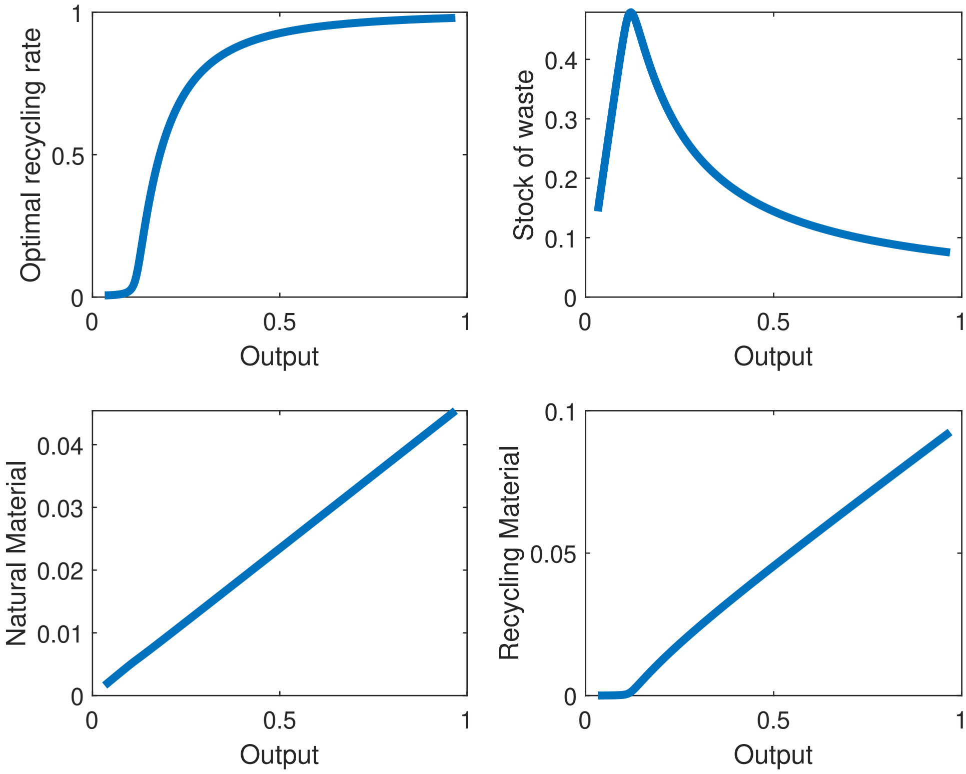

FIGURE 10.1: Steady state values as a function of output.

increasing the circularity of the economy. Although recycling activities increase the available quantity of material other than natural resources for production activities, economic growth increases the total demand for material, including both recycled and natural resources, notwithstanding the lower material intensity (the number of raw materials per unit of output) of the production process given the constant returns to scale technology. This implies that the CE can partially mitigate the problems provoked by the linear economy but cannot totally close the open-loop when the output grows. The increasing circularity of the economy does not completely eliminate the pressure on natural non-renewable resources, although it is a qualified solution to the problem of waste accumulation. From this point of view, circularity is the only way to mitigate waste accumulation in a growing economy and, therefore, a necessary but not sufficient condition for sustainable growth in an environment with finite non-renewable natural resources.

10.4.2 Sensitivity analysis

The results presented in the previous section were obtained by simulating the model using the benchmark calibration of the parameters (Table 10.1). However, little information is available for calibrating the parameters related to the CE, and we used ad hoc parameters with plausible values for the benchmark calibration. To check the robustness of the previous results, we carry out a sensitivity analysis by varying these parameters. In particular, the model has three key parameters for the CE: the waste damage to households' utility, ϕ, the waste content of consumption goods, η, and the elasticity of substitution between natural and recycled material, σ. For this sensitivity analysis, we solve the model by calculating steady states for a range of values of these three parameters. We use a range of values for the waste damage parameter from 0.15 to 1 (baseline value of 0.25). For the waste content of consumption, representing the fraction of consumption that transforms into waste, the selected range of values is from

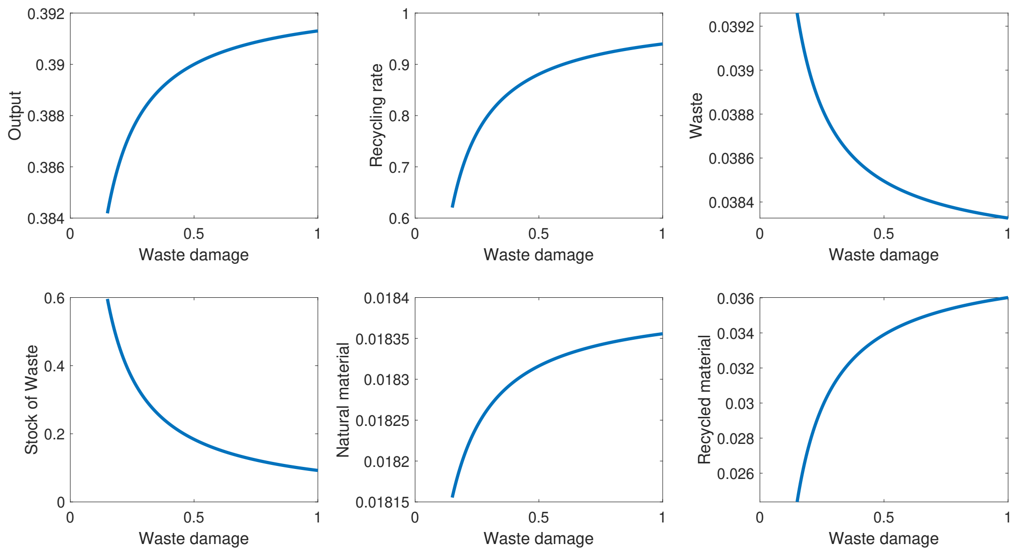

FIGURE 10.2: Sensitivity analysis: Steady state values as a function of the waste damage parameter.

0.1 to 0.5 (baseline value of 0.1). Finally, for the elasticity of substitution between natural and recycled material we choose a range of values from 1.01 to 10 (baseline value of 1.5).

Figure 10.2 plots the relationship between the recycling rate and the stock of waste as a function of the waste damage parameter. The waste damage parameter represents the cost, in terms of forgone utility, of the negative externality resulting from waste accumulation. As expected, as the waste damage parameter increases, the optimal recycling rate increases to compensate for the damage to households' welfare. The waste damage parameter to households' utility can be interpreted both as a negative externality to welfare and as reflecting concerns about the environment and the exploitation of natural resources. By contrast, the stock of waste has a negative relationship with the waste damage to households' welfare. This negative relationship is only possible in a circular economy, which implies that in the case of a linear economy as the waste damage parameter increases welfare declines without a strategy for waste stock abatement. As expected, as the waste damage parameter increases, the investment, capital stock and output increase. On the other hand, variables related to circularity (recycled material and recycling rate) are positively affected when the waste damage parameter increases.

A similar sensitivity exercise is carried out with respect to the parameter representing the waste content in consumption goods. Consumption goods differ in the waste that they generate. Furthermore, the waste content of consumption goods has been increasing over time. The use of plastic, glass, electronic components, batteries and so on, spreads at the same rate that the variety of consumption goods grows. The model predicts the existence of a steady-state positive relationship between the waste content in consumption goods and the optimal recycling rate. For an initial low value of waste content, the stock of waste is higher, in spite of a rising recycling rate. This result has different interpretations. On the one hand, it indicates that reducing the waste content of consumption goods would reduce the stock of waste, even with a low recycling rate. Therefore, a strategy should be to managing consumption goods disregarding, as much as possible, elements that, after consumption, become waste. This is the case of plastic (i.e., plastic wrap can be reduced), paper, etc. On the other hand, once the waste content of

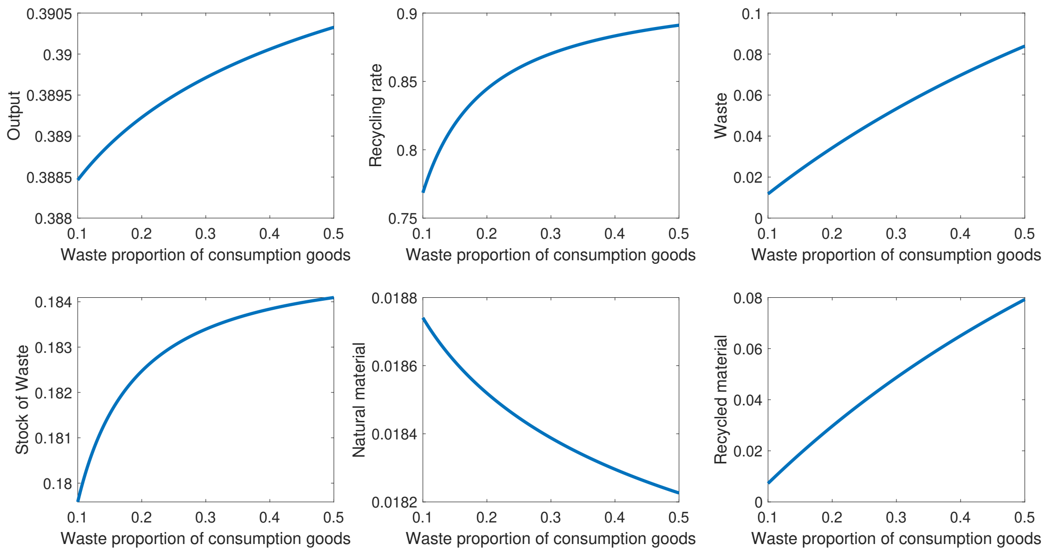

FIGURE 10.3: Sensitivity analysis: Steady state values as a function of the waste content in consumption parameter.

consumption goods reaches a threshold, the stock of waste remains almost constant as the recycling rate is high enough. This occurs when the fraction of waste content is above 10%, and the recycling rate is above 60%. This second interpretation means that the waste content in consumption goods should not be a problem once a high enough recycling rate is reached. On the other hand, as the waste content in consumption increases, the stock of waste also increases.

Finally, Figure 10.4 plots the results of a sensitivity analysis for the elasticity of substitution between natural and recycled material. Little change can be observed in the steady-state values when the elasticity of substitution is changed. Therefore, we conclude that the results obtained from the benchmark calibration of the model are not sensitive to the calibrated value for this parameter, and that they do not depend on the ease of substitution of natural with recycled material.

10.4.3 Technological change

Finally, we simulate a permanent change in the technology for material. In particular, we carry out two experiments: first, a permanent improvement in the technology for recycling material, which represents a permanent decline in the cost of recycling (a decline in the amount of output required per unit of recycled material), and second, a permanent deterioration in the technology for natural material, representing a permanent increase in the cost of natural material. It might be logical to think that both a decrease in the cost of recycled products and an increase in the cost of natural materials would boost the CE. However, we find that an increase in the cost of natural materials not only does not boost the CE but can even slightly slow it down.

The main results from these simulation exercises are shown in Figures 10.5 and 10.6. Figure 10.5 plots the transition dynamics from the initial steady state to the final steady state resulting from a permanent improvement in the technology for recycling material. The figure shows the transition path from the initial to the new (final) steady state, calculated as deviations from the initial steady state. This is done

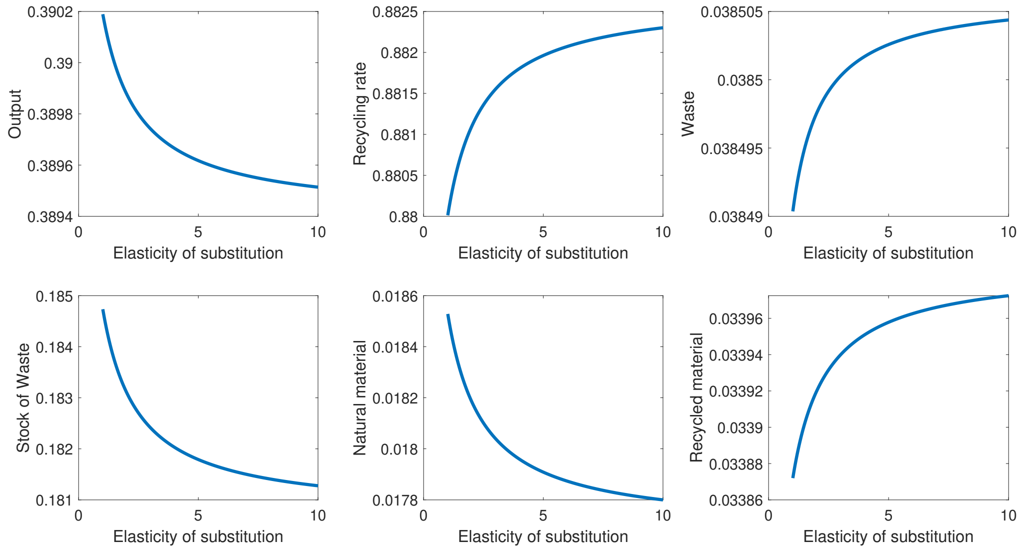

FIGURE 10.4: Sensitivity analysis: Steady state values as a function of the elasticity of substitution between natural and recycled material.

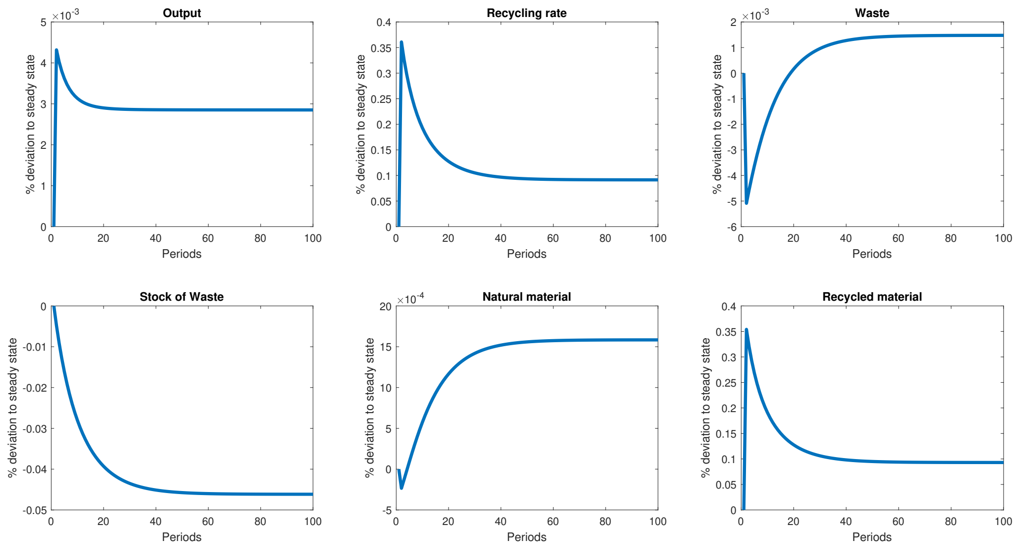

FIGURE 10.5: Technological change in recycling material: A permanent decline in Θ_v. Transition path to the new steady state as percentage deviation to the initial steady state.

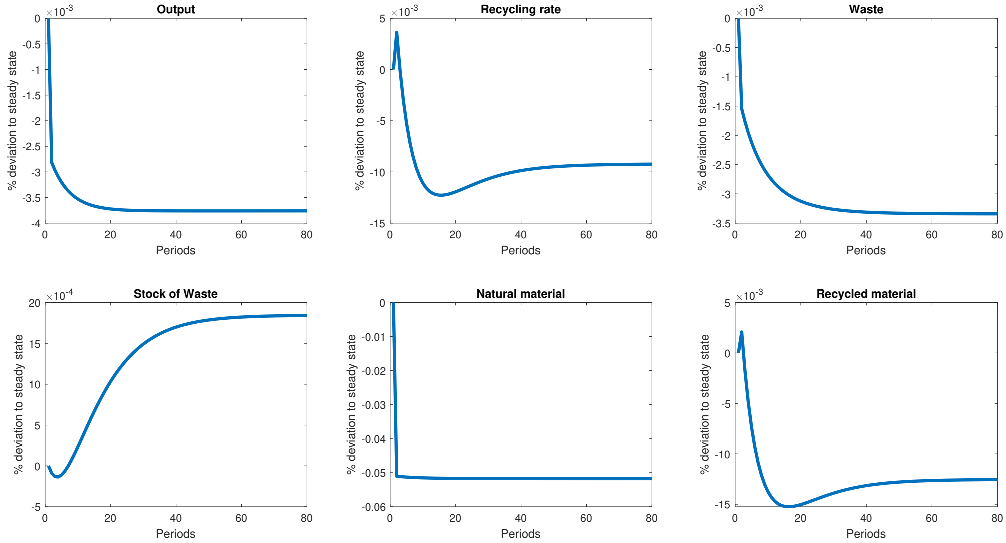

FIGURE 10.6: Technological change in recycling material: A permanent increase in Θ_n. Transition path to the new steady state as percentage deviation to the initial steady state.

by computing the perfect-foresight approximate solution of the non-linear model using the Klein (2000) solution method see the technical appendix. We simulate a 5% decline in the parameter Θ_v. The existence of an "overshooting" effect is observed for most of the variables as they increase on the impact, but later they adjust to the new steady state. The long-run effect on the output is positive, as expected. Indeed, the initial overshooting effect is explained by the fact that the increase in output leads to a rise, in the long-run, in the utilization of more natural resources. Natural resources decrease in impact as their cost relative to recycled material increases. However, the expansion of economic activity resulting from the shock leads to a greater demand for both recycled and natural material. Summing-up, the shock has positive effects on the CE side of the economy. As observed in Figure 10.5, both the recycling ratio and the use of recycled materials in production increase, while the stock of waste decreases. The generation of waste also declines in the impact, as the shock changes the optimal consumption/saving decision, increasing investment. However, after the initial decline, more waste is generated as consumption increases.[19] As recycled materials become less costly, a substitution effect of primary natural materials to recycled material in production activities is expected. However, there is also an income effect as reducing the cost of recycling increases the economic activity, expanding the demand for raw materials. Simulations show that, in the long-run, the income effect is larger than the substitution effect and, hence, the use of policies for expanding the CE does not guarantee a decay in the depletion rate of virgin natural resources.

Second, we study the case of a deterioration of technology (an increase in the cost) for natural resources. Figure 10.6 plots the transition dynamics from the initial steady state to the final steady state resulting from a permanent deterioration in the technology of natural material. We simulate a 5% increase in the parameter Θ_n. This shock has a negative effect on the output as the cost of using natural

[19] These results prove that, in principle, any policy designed to reduce the cost of recycling will have positive effects on the level of circularity of the economy and on social welfare. These results can be related to some extent with the case of a subsidy for recycling activities, although the use of taxes/subsidies provokes other effects on the economy not considered in our model. Kirchherr et al. (2018) take, as an example of this kind of intervention, the proposal of reducing the value-added tax (VAT) from 19% to 7% for any reparations as a measure to make reparations more attractive in Germany. This proposal was launched by Alliance 90/The Greens, a German environmental party.

material becomes higher, reducing the demand for raw material. However, we find that any policy increasing the cost of natural resources does not have positive effects on the circular economy but the opposite, increasing the deterioration of the environment. Indeed, the shock reduces the optimal recycling rate, increasing the stock of waste. It is true, that this shock reduces consumption and hence, the generation of waste. However, the decline in the recycling rate demonstrates that shocks that increase the cost of natural material do not help the circularity of the economy.

The economic intuition behind this counterintuitive result is the following. As we notice, the higher cost of natural resources increases production cost. As a consequence, output declines in the new steady state, resulting in a negative income effect. This negative income effect is larger than the substitution effect of natural resources by recycled material, resulting in a lower demand of both natural resources and recycled material compared to the initial steady state. The lower demand of recycled material decreases the recycling rate more than the observed decline in waste, leading to an increase in the accumulation of waste.

10.5 Discussion and conclusions

This chapter studies the optimal recycling rate in an economy with linear and circular production technologies from a macroeconomic perspective using standard tools in mainstream economics. The CE has traditionally been neglected in the construction of macroeconomic models, including those models that integrate environmental pollution and natural resource issues. This chapter fills this gap and incorporates the CE into an otherwise standard neoclassical optimal growth model. The CE enters the model in two different ways: mitigating the negative externality arising from waste accumulation, which has a negative impact on households' utility, and as an input-augmenting technology. We define a three-input production technology: capital, labor, and raw materials. Raw materials can be generated by the extraction of natural resources or by recovering and recycling waste. The first case represents a linear economy, whereas the second is representative of a CE. In our model, the two economies coexist, the aim of our research being to build a theoretical framework in which both the linear and the circular economy are present and interact with each other. The integration of the CE into an otherwise standard traditional linear economy model proves to be fruitful and leads to a number of interesting results about the implications of the CE in terms of social welfare, economic activity and the environment. Moreover, it is useful to identify proper policies to encourage the development of the CE and the relationship between the CE and economic growth. The analysis performed in the previous sections allows a direct comparison between the CE and the standard linear economy using the tools of mainstream economics. This integrated theoretical framework provides a number of insights.

First, we identify a positive relationship between the circularity of the economy and economic development, measured by output. This result indicates that the CE will expand as the level of output increases, as growing economies require the expansion of the CE as a necessary condition to turn economic growth into social welfare gains and to mitigate environmental deterioration (see Schroeder, Anggraeni and Weber, 2018). The model indicates that welfare maximization requires an increase in the circularity of the economy when the output is expanding. Otherwise, an increase in the output does not guarantee improved social welfare as the linear economy causes the environment to deteriorate. Therefore, the model reveals that the CE is fully consistent with sustainable development, contributing to the three pillars: economic, social, and environmental. Millar et al. (2019) argue that the CE cannot be understood as an optimal tool for sustainable development. While this is true, the CE can be viewed as a production model supporting sustainable development. This is consistent with the model's results, which show that the CE is a necessary but not sufficient condition for sustainable growth. The CE is adopted, not to solve all environmental and natural resource problems, derived from a linear conception of the economy, but as a strategy to mitigate those problems, by partially closing the open-loop of the standard linear production model. Schroeder et al. (2018) argue that the CE can contribute directly to attaining a high number of UN Sustainable Development Goals, while Geissdoerfer et al. (2017) highlight the differences and similarities between the CE and sustainability concepts. Millar et al. (2019) review the concepts of the CE and sustainable development and their relationship. The macroeconomic approach in this chapter contributes to that debate and shows that the economic, welfare, environmental and sustainable development implications of the CE are radically opposite to those of the linear economy. Lin (2020) points out the relationship between sustainable growth and CE and the importance of CE achieving the goal of sustainability, arguing that sustainable growth can be understood as an institutional arrangement of regenerating circular output in a sustainable way.

Second, the CE cannot solve all the environmental and natural resources exploitation problems generated by the linear economy. As pointed out by Millar et al. (2019), the CE can be interpreted as a positive contribution to a more environmentally sustainable model mitigating some of the problems produced by the linear economy. The CE can contribute to closing the "open-loop" on which the linear economy is based and, hence, promote economic growth by reducing its negative consequences for the environment and natural resources. Even in the case of 100% of energy being renewable and a recycling rate of 100%, the pressure on natural resources would exist in a growing economy. That is, full circularity of the economy would eliminate environmental quality damage but would not totally eliminate the pressure on the natural system. On the other hand, it is widely accepted that there is a relationship between the history of waste and climate change, and that CE policies should not only concern nowadays waste, but also the already accumulated waste in Earth, considering them as useful (new) factors of production and consumption. Korhonen et al. (2018a) identified six limits for the CE, including thermodynamics, spatial and temporal system boundaries, the limits posed by the physical scale of the economy, and the limits posed by path-dependency. These limits are also present in our model, in which the CE cannot be a substitute for the linear economy. Nevertheless, we show that the CE is essential for reducing the stock of waste and preserving the environment as output grows. Only in the presence of the CE is an EKC represented by a hump-shaped relationship between the output and the stock of waste obtained. Without increasing the circularity of the economy, economic growth leads to the accumulation of waste with adverse effects on social welfare from environmental deterioration. Lin (2020) proposes a Circular Economy National Income Accounting (CENIA) framework for measuring the contribution of CE to sustainable growth, where circular output representing the domestic demand for sustainable development is incorporated as a new component to the traditional definition of GDP.

Third, technological change, accounting for a reduction in the cost of recycling activities, improves the circularity of the economy and reduces the stock of pollution. Korhonen et al. (2018b) warn about the possibility of a "rebound" effect provoked by the expansion of the CE. The "rebound" effect is well-known in the energy literature and states that an increase in energy efficiency leads to an increase in energy consumption, reversing the initial positive effects of efficiency gains. The model developed here predicts no rebound effect from the CE, clearing the way for expanding the circularity of the economy. We find that expanding the CE has a positive effect on output, enhancing income growth without adverse effects on natural resource exploitation. This paves the way to the active use of this type of policies which augment the circularity of the economy as a strategy for sustainable long-run growth.

Finally, we find that any shock that increases the cost of natural material without directly affecting the rest of the economy is counterproductive for the CE and involves many adverse consequences for the economy. Although the relative price of recycled versus natural material declines, the optimal the optimal recycling rate decreases in response to the negative effects of this policy on output and consumption. Paradoxically, the decline in waste generation leads to an accumulation of the stock of waste, given the counter-reaction of the recycling rate. Therefore, while a shock increasing the cost of natural material would limit the natural resource depletion rate, it would provoke a deterioration of the environment by accumulating more waste at the same time as limiting the circularity of the economy.

10.6 Technical Appendix

This technical appendix presents the social planner maximization problem, the first order conditions for optimality, the algorithm for solving the steady state of the economy, and the procedure used to calculate the transition dynamics to the new steady state following a permanent technological shock.

10.6.1 The circular-linear economy model

We consider a CE model embedded in a standard neoclassical growth model for a linear economy. Waste is assumed to be generated by the consumption of final goods. Waste that is not recycled is accumulated into a stock of waste that affects negatively the households' utility.

Households

We consider an economy populated by an infinitely lived representative household with preferences over consumption, leisure, and environmental quality. The instantaneous utility function is defined as:

$$U(C_t, L_t, Z_t) = \ln C_t - \theta \frac{L_t^{1+\frac{1}{\rho}}}{1+\frac{1}{\rho}} - \phi Z_t^{\chi} \tag{A10.1}$$

where C_t is the consumption of goods and services, L_t is the labor and Z_t is the level of pollution generated by waste residuals from consumption activities that are assumed to be equal to the stock of waste. The parameter $\theta > 0$ represents the willingness to work, and ρ is the Frisch intertemporal elasticity of labor supply representing the change in worked hours change in response to a change in the equilibrium wage, given a constant marginal utility of wealth. Waste is considered to be a negative externality, reducing households utility function. The disutility produced by the accumulated waste stock is measured by the parameter ϕ. We assume that $U_Z < 0$ and $U_{ZZ} < 0$, indicating that, as waste is accumulated, its cost, in terms of utility, increase. The parameter $\chi > 1$ represents the elasticity of utility with respect to pollution.

The resource constraint is given by:

$$C_t + I_t + \Theta_n N_t + \Theta_v V_t = Y_t \tag{A10.2}$$

where I_t is investment, N_t represents natural resources, V_t denotes recycled materials, and Y_t is final output. Θ_n and Θ_v are technological parameters reflecting the real cost of natural and recycled material, respectively, which are assumed to be exogenously given.

We assume the following accumulation process for physical capital, K_t:

$$K_{t+1} = (1-\delta_k)K_t + I_t \tag{A10.3}$$

where δ_k $(0 < \delta_k < 1)$ is the physical capital depreciation rate.

Waste and recycling

The model considers the existence of a negative externality in the form of waste. We assume that waste is generated by the consumption of final goods. Waste generated by consumption, X_t, is defined by the following function:

$$X_t = X(C_t) = \eta C_t^{\gamma} \tag{A10.4}$$

where γ is the elasticity of X_t with respect to consumption, and η is a parameter concerning waste as a by-product of consumption. This parameter indicates the fraction of consumption that is transformed into waste (waste content per consumption unit).

We assume the following accumulation process for waste:

$$Z_{t+1} = (1-\delta_z)Z_t + (1-\mu_t)X_t \tag{A10.5}$$

where Z_t is the stock of waste, δ_z is the decay rate of waste, and $0 < \mu_t < 1$ is the recycling rate. Therefore, recycled materials are produced according to:

$$V_t = \mu_t X_t \tag{A10.6}$$

Production function

We use a standard Cobb-Douglas production function with three inputs: physical capital, labor and raw materials. This technology is given by:

$$Y_t = A_t K_t^{\alpha_1} M_t^{\alpha_2} L_t^{1-\alpha_1-\alpha_2} \tag{A10.7}$$

where Y_t is the aggregate output, A_t is a measure of Total Factor Productivity (TFP), L_t collects labor services, K_t represents physical capital and M_t concerns the raw materials. α_1 represents the elasticity of output with respect to capital and α_2 is the elasticity of output with respect to raw materials. Materials used in production match an Armington aggregator of both virgin natural resources and recycled materials:

$$M_t = \left[\omega N_t^{\frac{\sigma-1}{\sigma}} + (1-\omega)V_t^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{A10.8}$$

where ω is a distribution parameter and σ is the elasticity of substitution between natural resources and recycled material.

Centralized equilibrium

Given the existence of a negative externality, we consider the case of a planning problem, in which we assume the existence of a central planner who maximizes social welfare by choosing optimal values for the consumption, labor, capital stock, stock of waste and recycling rate. The central planner solves the following problem,

$$\max_{\{C_t, L_t, K_{t+1}, \mu_t, Z_{t+1}\}} \sum_{t=0}^{\infty} \beta^t \left[\ln C_t - \theta \frac{L_t^{1+\frac{1}{\rho}}}{1+\frac{1}{\rho}} - \phi Z_t^{\chi}\right] \tag{A10.9}$$

The central planner maximization problem can be defined using the following Lagrange auxiliary function:

$$\begin{aligned}
\mathcal{L} \quad = \quad & \sum_{t=0}^{\infty} \beta^t \left[\ln C_t - \theta \frac{L_t^{1+\frac{1}{\rho}}}{1+\frac{1}{\rho}} - \phi Z_t^{\chi}\right] \\
& -\lambda_{1,t} \left[\begin{array}{c} C_t + K_{t+1} - (1-\delta_k)K_t + \Theta_n N_t + \Theta_v V_t \\ -A_t K_t^{\alpha_1} \left[\omega N_t^{\frac{\sigma-1}{\sigma}} + (1-\omega)V_t^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\alpha_2\sigma}{\sigma-1}} L_t^{1-\alpha_1-\alpha_2} \end{array}\right] \\
& -\lambda_{2,t} \left[X_t - \eta C_t^{\gamma}\right] \\
& -\lambda_{3,t} \left[Z_{t+1} - (1-\delta_Z)Z_t - (1-\mu_t)X_t\right] \\
& -\lambda_{4,t} \left[V_t - \mu_t X_t\right]
\end{aligned} \tag{A10.10}$$

where β is the discount factor, and $\lambda_{i,t}$, $i = 1,2,3,4$ are Lagrange's multipliers. First order conditions for social welfare maximization are given by,

$$\frac{\partial \mathcal{L}}{\partial C_t} : \frac{\beta^t}{C_t} - \lambda_{1,t} + \lambda_{2,t}\eta\gamma C_t^{\gamma-1} = 0 \tag{A10.11}$$

$$\frac{\partial \mathcal{L}}{\partial L_t} : -\beta^t \theta L_t^{\frac{1}{\rho}} + \lambda_{1,t}(1-\alpha_1-\alpha_2)\frac{Y_t}{L_t} = 0 \tag{A10.12}$$

$$\frac{\partial \mathcal{L}}{\partial K_{t+1}} : -\lambda_{1,t} + \lambda_{1,t+1}\left[(1-\delta_k) + \alpha_1 \frac{Y_{t+1}}{K_{t+1}}\right] = 0 \tag{A10.13}$$

$$\frac{\partial \mathcal{L}}{\partial N_t} : -\lambda_{1,t}\left[\Theta_n - \alpha_2 \omega \frac{Y_t N_t^{\frac{-1}{\sigma}}}{M_t^{\frac{\sigma-1}{\sigma}}}\right] = 0 \tag{A10.14}$$

$$\frac{\partial \mathcal{L}}{\partial V_t} : -\lambda_{1,t}\left[\Theta_v - \alpha_2(1-\omega) \frac{Y_t V_t^{\frac{-1}{\sigma}}}{M_t^{\frac{\sigma-1}{\sigma}}}\right] - \lambda_{4,t} = 0 \tag{A10.15}$$

$$\frac{\partial \mathcal{L}}{\partial Z_{t+1}} : -\beta^{t+1}\phi\chi Z_{t+1}^{\chi-1} - \lambda_{3,t} + \lambda_{3,t+1}(1-\delta_z) = 0 \tag{A10.16}$$

$$\frac{\partial \mathcal{L}}{\partial X_t} : -\lambda_{2,t} + \lambda_{3,t}(1-\mu_t) + \lambda_{4,t}\mu_t = 0 \tag{A10.17}$$

$$\frac{\delta \mathcal{L}}{\delta \mu_t} : -\lambda_{3,t}X_t + \lambda_{4,t}X_t = 0 \tag{A10.18}$$

From first order conditions we obtain the following values for the Lagrange' multipliers:

$$\lambda_{1,t} = \frac{\beta^t \theta L_t^{\frac{1}{\rho}+1}}{(1-\alpha_1-\alpha_2)Y_t} \tag{A10.19}$$

$$\lambda_{2,t} = \frac{\beta^t}{\eta\gamma C_t^{\gamma-1}}\left[\frac{\theta L_t^{\frac{1}{\rho}+1}}{(1-\alpha_1-\alpha_2)Y_t} - \frac{1}{C_t}\right] \tag{A10.20}$$

$$\lambda_{2,t} = \lambda_{3,t} = \lambda_{4,t} \tag{A10.21}$$

where λ_1 represents the shadow cost of labor, λ_2 represents the shadow cost of waste, which is equal to the shadow price of the stock of pollution, λ_3, and equal to the shadow price of recycled materials, λ_4.

The shadow price of recycled material is given by:

$$\lambda_{4,t} = -\frac{\beta^t \theta L_t^{\frac{1}{\rho}+1}}{(1-\alpha_1-\alpha_2)Y_t}\left[1 - \alpha_2(1-\omega)\frac{Y_t V_t^{\frac{-1}{\sigma}}}{M_t^{\frac{\sigma-1}{\sigma}}}\right] \tag{A10.22}$$

Alternatively, Lagrange' multipliers can also be written as:

$$\lambda_{1,t} = \frac{\beta^t}{C_t + \gamma X_t\left[\Theta_v - \alpha_2(1-\omega)\frac{Y_t V_t^{-\frac{1}{\sigma}}}{M_t^{\frac{\sigma-1}{\sigma}}}\right]} \tag{A10.23}$$

$$\lambda_{2,t} = -\frac{\beta^t}{\gamma X_t + \frac{C_t}{\Theta_v - \alpha_2(1-\omega)\frac{Y_t V_t^{-\frac{1}{\sigma}}}{M_t^{\frac{\sigma-1}{\sigma}}}}} \tag{A10.24}$$

The optimal quantity of natural resources is given by:

$$\Theta_n M_t^{\frac{\sigma-1}{\sigma}} = \alpha_2 \omega Y_t N_t^{\frac{-1}{\sigma}} \tag{A10.25}$$

The optimal investment decision is given by:

$$\frac{C_{t+1} + \gamma X_{t+1}\left[\Theta_v - \alpha_2(1-\omega)\frac{Y_{t+1}V_{t+1}^{-\frac{1}{\sigma}}}{M_{t+1}^{\frac{\sigma-1}{\sigma}}}\right]}{C_t + \gamma X_t\left[\Theta_v - \alpha_2(1-\omega)\frac{Y_t V_t^{-\frac{1}{\sigma}}}{M_t^{\frac{\sigma-1}{\sigma}}}\right]} = \beta\left[1 - \delta_k + \alpha_1\frac{Y_{t+1}}{K_{t+1}}\right] \tag{A10.26}$$

which represents the optimal consumption path as combination of both the linear economy and the circular economy, under the presence of waste.

Finally, the equilibrium condition for the optimal quantity of recycled material, indicating the optimal circularity of the economy, is given by:

$$\beta^{t+1}\phi\chi Z_{t+1}^{\chi-1} = \frac{\beta^t \theta L_t^{\frac{1}{\rho}+1}}{(1-\alpha_1-\alpha_2)Y_t}\left[\Theta_v - \alpha_2(1-\omega)\frac{Y_t V_t^{\frac{-1}{\sigma}}}{M_t^{\frac{\sigma}{\sigma-1}}}\right] -$$
$$\frac{\beta^t \theta L_{t+1}^{\frac{1}{\rho}+1}}{(1-\alpha_1-\alpha_2)Y_{t+1}}\left[\Theta_v - \alpha_2(1-\omega)\frac{Y_{t+1}V_{t+1}^{\frac{-1}{\sigma}}}{M_{t+1}^{\frac{\sigma-1}{\sigma}}}\right](1-\delta_z) \tag{A10.27}$$

Then, the optimal quantity of recycled material depends directly on the difference between its price and its productivity in t and $t+1$ but also on how accumulated pollution affects the shadow price of consumption and how harmful is this pollution to welfare.

Steady State

For reader convenience, we report hereafter the system of equilibrium equations used to simulate the model.

$$Y = AK^{\alpha_1}M^{\alpha_2}L^{1-\alpha_1-\alpha_2} \tag{A10.28}$$

$$M = \left[\omega N^{\frac{\sigma-1}{\sigma}} + (1-\omega)V^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{A10.29}$$

$$I = \delta K \tag{A10.30}$$

$$C = Y - I - \Theta_n N - \Theta_v V \tag{A10.31}$$

$$X = \eta C^{\gamma} \tag{A10.32}$$

$$\mu = \frac{V}{X} \tag{A10.33}$$

$$Z = \frac{(1-\mu)X}{\delta_z} \tag{A10.34}$$

$$L = \left(\frac{\left(\frac{1}{C} - \frac{\phi\chi Z^{\chi-1}}{\delta_z}\eta\gamma C^{\gamma-1}\right)(1-\alpha_1-\alpha_2)\,Y}{\theta}\right)^{\frac{\rho}{1+\rho}} \tag{A10.35}$$

$$K = \frac{\alpha_1 Y}{\frac{1}{\beta} - 1 + \delta} \tag{A10.36}$$

$$N = \left(\frac{\alpha_2 \omega Y}{\Theta_n M^{\frac{\sigma-1}{\sigma}}} \right)^{\sigma} \tag{A10.37}$$

$$V = \left(\frac{\alpha_2 (1-\omega) Y}{\left(\Theta_v - \frac{\phi \chi Z^{\chi-1}(1-\alpha_1-\alpha_2)Y}{\theta L^{\frac{1}{\rho}+1} \delta_z} \right) M^{\frac{\sigma-1}{\sigma}}} \right)^{\sigma} \tag{A10.38}$$

where we drop the time subscripts of variables to denote steady state values. The system of equations (A10.28)-(A10.38) has 11 equations for 11 unknowns, $(C, I, L, K, Y, M, N, V, X, Z, \mu)$.

Solution algorithm

The above system of steady state equations have been numerically solved using the Newton-Raphson algorithm.[20] In particular, the steady-state solution algorithm is as follows. The steady state is defined by n equations with n unknowns: $F : R^n \longrightarrow R^n$. The solution for this problem consists in to find a vector $\hat{x} = (\hat{x}_1, ..., \hat{x}_n)$ of R^n such as $F : R^n \longrightarrow R^n$ should be $F(\hat{x}) = 0$. To run the algorithm we start from a guess solution, x_0. We start from a Taylor expansion function around an initial value x_n:

$$F(x) = F(x_n) + F'(x_n)(x - x_n) + \frac{F''(x_n)}{2!}(x - x_n)^2 + ...$$

That expression is then evaluated for different values, starting from the initial guess value, such as:

$$F(x_{n+1}) = F(x_n) + F'(x_n)(x_{n+1} - x_n) + \frac{F''(x_n)}{2!}(x_{n+1} - x_n)^2 + ...$$

The solution is given for the value that makes the Taylor expansion equals zero:

$$F(x_n) + F'(x_n)(x_{n+1} - x_n) + \frac{F''(x_n)}{2!}(x_{n+1} - x_n)^2 + ... = 0$$

If the Taylor expansion series is truncated in the second term (first order approximation), we have that:

$$F(x_n) + F'(x_n)(x_{n+1} - x_n) \simeq 0$$

The above approximation is closer to zero when the value would be closer to the true solution. Operating we obtain:

$$x_{n+1} = x_n - \frac{F(x_n)}{F'(x_n)}$$

and this is the so-called Newton-Raphson formulae. The procedure is iterative and consists in computing the above expression for the different approximations, step by step. In general, the first order Taylor expansion of the function F is:

$$F(x) \approx F(\overline{x}) + J(\overline{x})(x - \overline{x})$$

where $J(\overline{x})$ is the Jacobian matrix of F evaluated at $\overline{x}$:

$$J(\overline{x}) = \begin{bmatrix} F_{11}(\overline{x}) & F_{12}(\overline{x}) & ... & F_{1n}(\overline{x}) \\ F_{21}(\overline{x}) & F_{22}(\overline{x}) & ... & F_{2n}(\overline{x}) \\ ... & ... & ... & ... \\ F_{n1}(\overline{x}) & F_{n1}(\overline{x}) & ... & F_{nn}(\overline{x}) \end{bmatrix}$$

[20] Codes have been written in Matlab and are available from the authors upon request.

and where $F_{ij}(\overline{x}) = \frac{\partial F_i(\overline{x})}{\partial x_j}$. As $\overline{x}$ goes closed to the value x, the higher order terms go to zero. Given that we are looking for the zero value for equations $F(x)$, the above expression can be evaluated at $\hat{x}$ and thus, be written as:

$$\hat{x} \approx \overline{x} - J(\overline{x})^{-1}F(\overline{x})$$

Transition to the steady state

To compute the transition path (Figures 10.5 and 10.6 in the chapter) to the new steady state, we first compute the initial and the new (final) steady state using the previous algorithm, resulting from a permanent technological shock to natural resources and recycled material. Then, we use a perfect foresight simulation by solving the dynamic non-linear model using the Klein (2000) method, by computing the first order approximation solution to the non-linear rational expectation model. The Klein's solution method based on the use of a generalized Schur form to solve the linear approximation of the model, where the solution is a system of recursive equations.. Once the policy and transition functions are obtained as recursive equations, we simulate these policy and transition functions starting from the initial steady state until the change is the endogenous variables is zero, that is, to the point in which the new steady state have been reached. Figures 10.5 and 10.6 plots the transition path as deviation to the initial steady state.

Part V

Concluding remarks

Chapter 11

Conclusions, limitations and future research

The advent of automation and artificial intelligence has heralded a disruptive era in the global economy, transforming our understanding of labor markets, fiscal policy, and economic paradigms. This dissertation has advanced our understanding of the economic implications of the rapid proliferation of automation technologies for the global economy by examining the impact of adopting new autonomous technologies on economic outcomes, public finance, and social security. Through the careful examination of three interconnected perspectives - macroeconomic effects, fiscal impacts, and social security sustainability - a coherent picture emerges that underscores the profound economic shifts automation and AI are likely to bring about.

The synthesis of the macroeconomic perspective collected in Part II of the thesis (Chapters 2, 3, and 4) unearths critical insights into the factors that shape the impacts of these technologies on labour, government finances, and social security. The findings from these chapters call for a reevaluation of existing tax systems and social security financing in light of the increasing adoption of autonomous technology. While the integration of autonomous technologies can potentially transform economies by enhancing productivity and output, its consequences on labour markets, public finance, and social security sustainability require comprehensive policy responses. Policymakers, therefore, must navigate this evolving landscape with care, balancing the need for economic growth with the imperatives of social equity and fiscal sustainability. The ongoing debate around these issues points to the need for more comprehensive research and policy innovation in the face of accelerating automation. Future research should continue to explore the implications of alternative tax schemes and investigate the political feasibility of implementing such policies.

The advent of the fourth industrial revolution has thrust technology, particularly robotics and AI, into the spotlight as pivotal influencers in reshaping labour markets. Indeed, the digital age is catalysing a profound transformation in labour markets. This transformation, marking the fourth industrial revolution, wields the capacity to create, transform, and even eliminate occupations. Consequently, understanding their impact becomes paramount for economists, policymakers, and businesses, as they strive to navigate the future of work. As we navigate the complexities of digitalization, it is crucial to understand how these technological advancements are shaping occupations and influencing labour mobility and labour market transitions.

In essence, our work indicates that digitalization, while transformative, requires a nuanced understanding and continuous policy adaptations to ensure labour markets remain resilient, inclusive, and equitable. It is important to highlight that these transformations present both challenges and opportunities. The bifurcation observed in labour mobility patterns suggests a possible segmentation of the labour market. On one hand, the highly skilled segment will likely occupy jobs that interact positively with newer technologies, while the less productive or older workforce might be relegated to low-wage, unstable jobs, or worse, find themselves technologically unemployed with obsolete skills. On the other hand, there lies an opportunity for policies to guide workforce training and retraining, preparing the labour supply for future jobs and providing protection for those negatively affected during the transition.

The findings of this thesis highlight the importance of guiding the training and retraining of the workforce to prepare for the jobs of the future. Policy measures for the protection of those negatively affected are needed, particularly during the transition period toward an economy based on newer, more sophisticated knowledge, and during periods between jobs where reskilling may be necessary. Policy-makers have a crucial role in guiding workforce training and retraining efforts to prepare for the jobs of the future. By understanding the dynamic landscape of work and digitalization, researchers, policy-makers, and businesses can work together to create a sustainable, equitable, and prosperous future for all. The path to a future where technology and labour harmoniously coexist is fraught with challenges, but with continuous monitoring, adaptation, and the right policy measures, we can ensure a resilient labour market in the face of technological advancements.

Future research could delve deeper into the role of human capital across various demographics, firm size, and knowledge intensity, providing further insights into labour transitions in the face of transformative and destructive digitalization. This would enable a deeper understanding of human capital's role in determining transitions across occupations exposed to different levels of digitalization. By doing so, we can better prepare for an economy based on sophisticated knowledge, ensuring a prosperous future for all.

This dissertation also explores the effects of automation, AI, and machine learning (ML) on early retirement and unemployment transitions among older workers. The analysis reveals that the impact of these technological advancements varies depending on factors such as gender, education level, job status, and the specific technological domain in question. Furthermore, the results show that these technologies can both complement and substitute human labour, leading to differentiated outcomes for workers. These findings are of significant interest, given the rapid pace of technological change and its potential implications for the labour market and retirement decisions.

The rapidly evolving technological landscape is reshaping the labour market, impacting older workers' decisions regarding early retirement and unemployment transitions. It is critical that policy-makers, educators, and employers take proactive steps to address these changes, ensuring that older workers can continue to contribute to the workforce in meaningful and sustainable ways. Such interventions should not only focus on promoting education and training but also consider the diverse impacts of technological changes across different groups of workers, ensuring an inclusive approach to managing this digital transition.

In the context of early retirement, the findings suggest that workers with no higher education and high automation degree and/or risk are more likely to opt for early retirement, whereas individuals with higher education are less likely to do so. Moreover, women are more affected by automation in terms of early retirement transitions. In the case of AI, the impact on early retirement depends on the level of AI advances and exposure in each occupation, with tertiary education playing a critical role in shaping these effects. When examining unemployment transitions, computerization is found to have a negative effect on employment, while AI technologies can serve as a protective factor against unemployment. However, higher suitability to ML increases unemployment probabilities. Additionally, the impact of technological advancements on unemployment transitions varies depending on job status.

In light of these findings, the need for interventions to help older workers navigate the changing labour market is clear. Policies should aim to prevent early exits from the labour market, promote lifelong learning and retraining programs, encourage age-friendly workplace practices, and strengthen active labour market policies. Special attention should be given to providing adequate support for older workers in the face of increasing computerization, AI, and ML advancements. This includes fostering collaboration between government, industry, and educational institutions to ensure older workers have access to relevant training and education opportunities, as well as supporting the development and adoption of complementary AI technologies that can help older workers maintain their competitiveness in the labour market.

It is important to note that the research presented in this dissertation is subject to certain limitations. Particularly, the segment of the thesis encompassing Chapters 6 through 9 operates under the assumption that the job content of an occupation in the US is identical to that in the European countries of the sample, which presents a potential limitation. The crosswalk between SOC-10 and ISCO-08 is assumed to be perfect, which may not reflect the reality accurately. This assumption, while necessary for this analysis, may not fully capture the nuances and variations in job content and the influence of technological change across different countries and regions.

Despite these limitations, the dissertation provides valuable insights into the impact of automation, AI, and ML on the labour market and offers practical policy recommendations to address the challenges faced by older workers. Further research is required to refine our understanding of the complex interactions between technological changes and labour market dynamics. This would involve further exploration of the unique challenges faced by different worker groups and the potential of personalized policies in addressing these challenges.

Furthermore, Chapter 9 is currently undergoing a methodological enhancement overhaul, transitioning from cross-sectional analysis (i.e., investigating immediate outcomes post-displacement) to a panel data approach. This transformation implements multinomial logit models, endowed with correlated random effects, which, in theory, facilitate the overcoming of the Independence of Irrelevant Alternatives (IIA) issue. The proposed alteration would consider displacement as merely an identification tool, rather than solely observing the ensuing changes. It would be insightful to analyse the duration required for those individuals starting in unstable occupations to transition states, whether shifting to alternative occupational fields or transitioning into unemployment.

Chapter 10 of this thesis provides an essential exploration of the optimal recycling rate in an economy that incorporates both linear and circular production technologies from a macroeconomic perspective, using standard tools in mainstream economics. In the past, macroeconomic models have not accounted for the circular economy, even those that integrate environmental pollution and natural resource issues, and this dissertation fills this gap by integrating circular economy into a standard traditional macroeconomic neoclassical optimal growth model. The novel model incorporates the circular economy to counterbalance waste accumulation's negative externality and as an input-augmenting technology. Consequently, the model facilitates an integration of linear and circular economies, paving the way for a deep understanding of their interactions by providing a robust theoretical framework for understanding the intertwined relationship between economic growth, social welfare, environmental preservation, and the role of the circular economy. It offers valuable insights for future research and policymaking in our quest for sustainable development.

All in all, this thesis is biased by the availability of data on both autonomous technologies and the circular economy. For this reason, the exposed macroeconomic models are calibrated rather than estimated due to the lack of appropriate time series to make estimations. Although the IRF provides data on industrial robots, the concept of autonomous capital covered in the thesis encompasses a broader technological horizon including AI as well as intangible assets that are difficult to quantify. Therefore, the research developed in this thesis has the potential to be revisited and contrasted in greater depth as the availability of data on the topics analysed increases, allowing for more accurate analyses that provide more concrete evidence on the paradigms studied.

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