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

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ABSTRACT

This paper 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.

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, 2020) 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

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[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.

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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 1960 s and 1970 s 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).

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 paper 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 paper is organised as follows. Section "Literature review and hypotheses" presents the literature review and the main hypotheses of this study. Section "Data" collects the data used in the analysis. Section "Modelling approach" details the modelling approach. Section "Results" shows results. Section "Robustness checks" presents some robustness checks. Finally, Section "Conclusions" summarises the conclusions derived from this research.

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.

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 <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 (2020) 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 to 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 (2020), 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

[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.

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]

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, Baumann and Madero-Cabib (2021) find that early retirement is more frequent in social-democratic regimes (Denmark 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).

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 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

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

[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.

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).

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 computer-based work (Birdi et al., 1997). Older workers also show comparable performance on multiple telecommuting tasks to their younger colleagues (Sharit et al., 2004).

[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).

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 60 s. 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.

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 occupation-level 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

Table 1
Data levels and sources.

Data level	Data source
Microdata	
Early retirement decision, gender, age, cohabiting status, health, financial situation, education, job characteristics	SHARE (Eurofound)
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

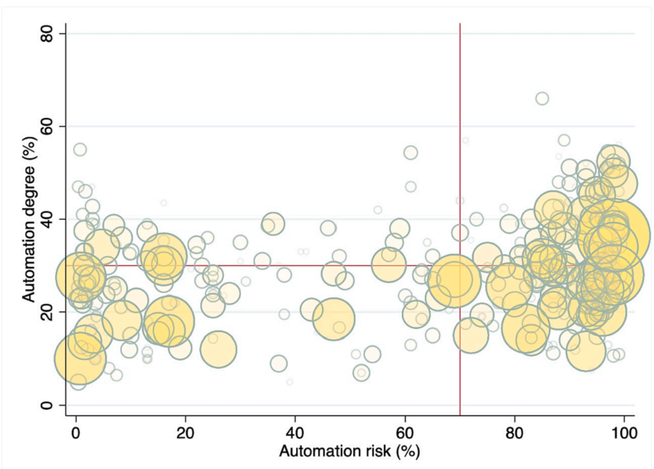

Fig. 1. Early retirement transitions and *A-terrains*. *Note*: Compiled by the authors from the SHARE data and considering the *A-terrains* classification.

Table 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)

Table 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	790	620	923	115	1,658	26
	(0.31)	(0.29)	(0.28)	(0.32)	(0.26)	(0.30)	%
CA	472	214	303	266	117	686	11
	(0.39)	(0.26)	(0.31)	(0.40)	(0.33)	(0.34)	%
RA	1,915	168	1,202	676	205	2,083	33
	(0.38)	(0.27)	(0.36)	(0.42)	(0.31)	(0.37)	%
AT	1,610	303	1,073	706	134	1,913	30
	(0.37)	(0.26)	(0.33)	(0.40)	(0.28)	(0.35)	%
Total	4,865	1,475	3,198	2, 571	571	6,340	100
	(0.37)	(0.28)	(0.33)	(0.37)	(0.30)	(0.34)	%
	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.

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 (Danø 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*.

Table 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)		6,340 (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 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	0.488	93	26.34	RA
2	Bricklayers and related workers	7112	100	211	0.474	82	16.5	RA
3	Mail carriers and sorting clerks	4412	57	128	0.445	95	45.2	AT
4	Manufacturing labourers not elsewhere classified	9329	62	143	0.434	93	40.88	AT
5	Agricultural and industrial machinery mechanics and repairers	7233	77	181	0.425	88	20.78	RA
6	Motor vehicle mechanics and repairers	7231	67	162	0.414	93	11.6	RA
7	Electrical mechanics and fitters	7412	54	137	0.394	93	20.69	RA
8	Secondary education teachers	2330	115	297	0.387	0.78	10	HT
9	Heavy truck and lorry drivers	8332	94	252	0.373	79	25.5	RA
10	Secretaries (general)	4120	99	267	0.371	96	20	RA
11	Vocational education teachers	2320	56	151	0.371	26	12	HT
12	Accounting and bookkeeping clerks	4311	61	168	0.363	96	34.5	AT
13	General office clerks	4110	236	659	0.358	98	36.5	AT
14	Shopkeepers	5221	92	260	0.354	16	32	CA
15	Freight handlers	9333	68	193	0.352	85	31.5	AT
16	Accounting associate professionals	3313	104	310	0.336	98	34	AT
17	Primary school teachers	2341	109	324	0.336	17	18	HT
18	Cleaners and helpers in offices, hotels and other establishments	9112	123	380	0.324	69	26.67	HT
19	Car, taxi and van drivers	8322	66	209	0.316	98	28	RA
20	Managing directors and chief executives	1120	67	220	0.305	16	30	CA
21	Accountants	2411	58	192	0.302	99	47.67	AT
22	Administrative and executive secretaries	3343	55	184	0.299	86	30.5	AT
23	Shop sales assistants	5223	159	547	0.291	98	28	RA
24	University and higher education teachers	2310	63	218	0.289	3.2	15.4	HT
25	Subsistence crop farmers	6310	61	214	0.285	87	42	AT
26	Cooks	5120	78	274	0.285	96	24.8	RA
27	Nursing professionals	2221	108	391	0.276	0.9	27.47	HT
28	Domestic cleaners and helpers	9111	54	199	0.271	69	27	HT
29	Health care assistants	5321	74	286	0.259	47	18.5	HT
30	Child care workers	5311	67	278	0.241	8.4	18.25	HT

Note: ER: early retirement; HT: hands terrain; CA: collapsing automation; RA: rising automation; AT: automation terrain.

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 self-employed and employees (Zwier et al., 2021). In addition, transitions to self-employment at old ages have been documented as a bridge to retirement (Nolan and Barrett, 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:

Table 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.

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.*

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 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 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 paper 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

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

Table 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.

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 $t+1$ ($WO_t \rightarrow ER_{t+1}$) or (ii) remain as workers in period $t+1$ ($WO_t \rightarrow WO_{t+1}$). 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.

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*.[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]

[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.

Table 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.

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.

In order to combine both the forward-looking impact of automation upon occupations, and its backward-looking effect, the proposed

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

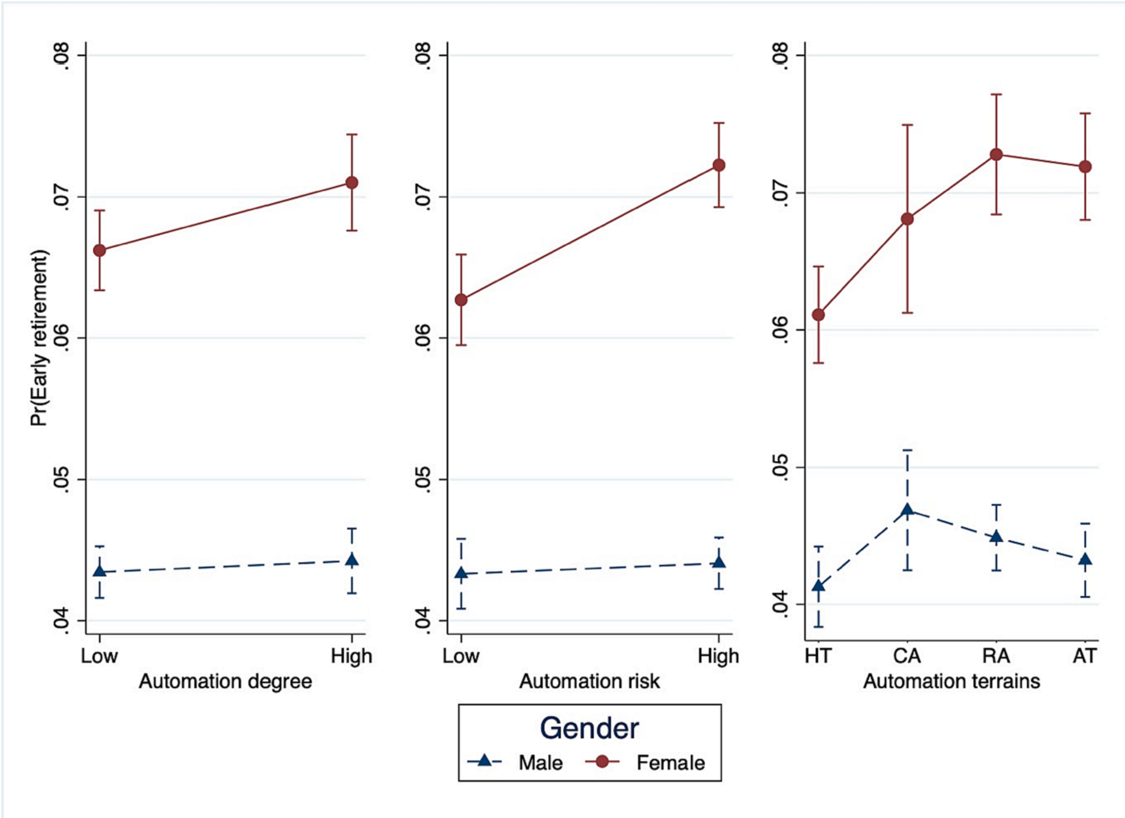

Fig. 2. Early retirement probability, automation and gender. *Notes*: Predicted probabilities and marginal effects from Table 9; HT: hands terrain; CA: collapsing automation; RA: rising automation; AT: automation terrain.

classification includes four different types of occupations, as summarised in table 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–, 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

[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.

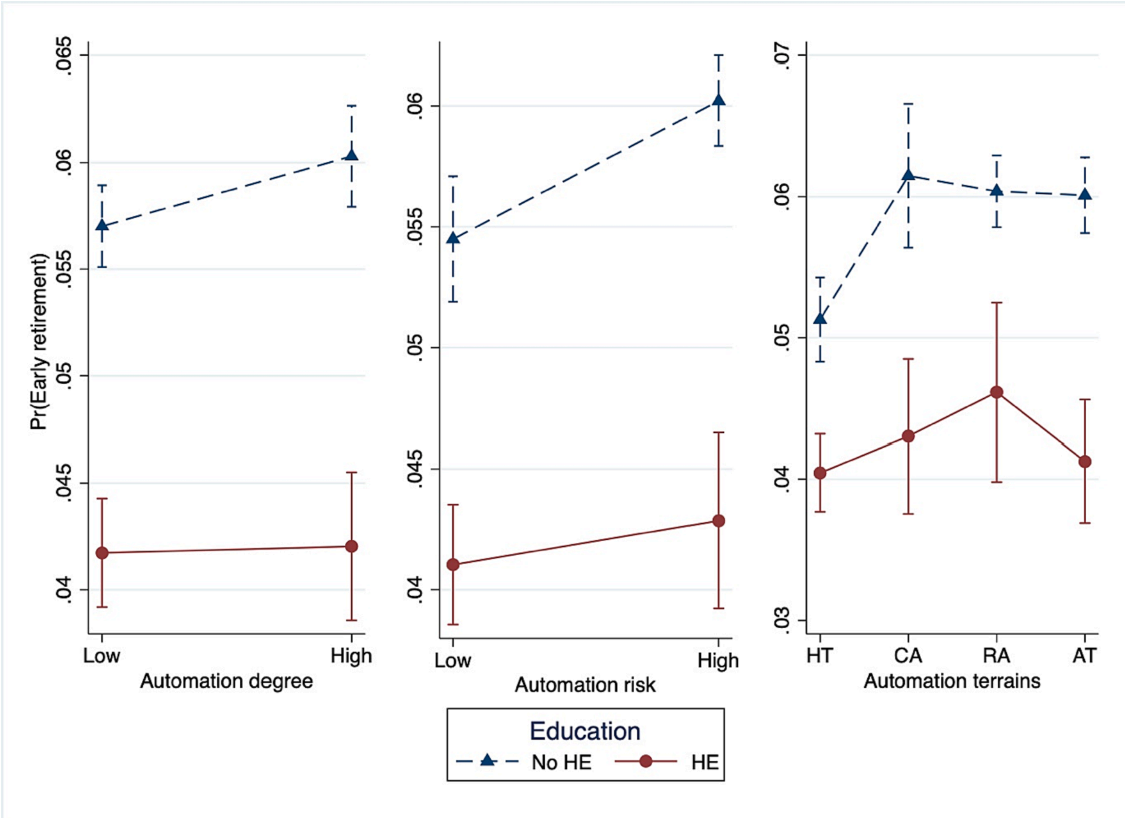

Fig. 3. Early retirement probability, automation and education. *Notes*: Predicted probabilities and marginal effects from Table 10; HE: higher education; HT: hands terrain; CA: collapsing automation; RA: rising automation; AT: automation terrain.

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.

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.

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 A1 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 Fig. 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 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 %

[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.

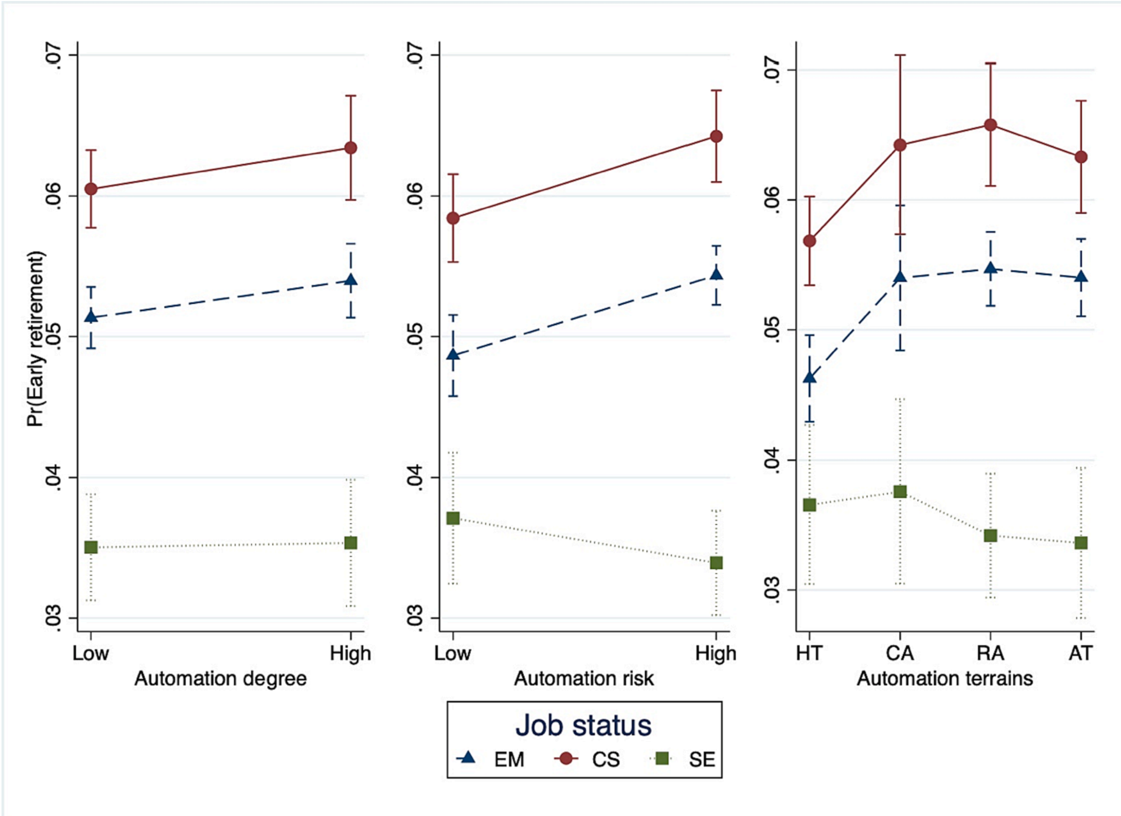

Fig. 4. Early retirement probability, automation and job status. *Notes*: Predicted probabilities and marginal effects from Table 11; EM: employee; CS: civil servant; SE: self-employed worker; HT: hands terrain; CA: collapsing automation; RA: rising automation; AT: automation terrain.

Table 9
Predicted probabilities of early retirement and marginal effects by gender.

Gender	Predicted probability of early retirement		Marginal effect of automation						Marginal effect of female				
	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	***

[a] Predicted probabilities and marginal effects are from a model similar to model V in Table 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 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 8 but including interaction term between A-terrains and gender.

from the *Rising automation terrain* and a 30 % from the *Automation terrain*.

In Table 3, we can see the data associated with Fig. 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.

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 4 adds a deeper dimension with respect to Table 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

Table 10
Predicted probabilities of early retirement and marginal effects by education.

Education	Predicted probability of early retirement		Marginal effect of automation						Marginal effect of higher 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	***

[a] Predicted probabilities and marginal effects are from a model similar to model V in Table 6 but including interaction term between high automation risk and higher education dummy.
[b] Predicted probabilities and marginal effects are from a model similar to model X in Table 7 but including interaction term between high automation degree and higher education dummy.
[c] Predicted probabilities and marginal effects are from a model similar to model XV in Table 8 but including interaction term between A-terrains and higher education dummy. HE: higher education.

higher education.

Table 5 also complements Fig. 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<10 % of automation risk. In sum, the 30 occupations from Table 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.

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 6–8 collect fifteen estimations of logit models. Concretely, Table 6 considers the automation risk as the main regressor, Table 7 explores the effect of automation degree and Table 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.

The result of the first estimation in Table 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 Figs. 2–4 and Tables 9–11, we find differentiated effects for higher gender, education, job status.

Table 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 8 offers the results for the A-terrains as the main regressor, collecting the 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 6–8 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 <40 percent of men with the same education level.

Table 11
Predicted probabilities of early retirement and marginal effects by job status.

Job status	Predicted probability of early retirement			Marginal effect of automation								Marginal effect of 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	***

[a] Predicted probabilities and marginal effects are from a model similar to model V in Table 6 but including interaction term between high automation risk and job status dummies.
[b] Predicted probabilities and marginal effects are from a model similar to model X in Table 7 but including interaction term between high automation degree and job status dummies.
[c] Predicted probabilities and marginal effects are from a model similar to model XV in Table 8 but including interaction term between A-terrains and job status dummies. EM: employee; CS: civil servant; SE: self-employed worker.

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 9 and Fig. 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 of early retirement for men.

These results can be also observed in the different slopes for males and females in the graphs of Fig. 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 9. Furthermore, as we can observe in the right-graph of Fig. 2 and Table 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 9 and Fig. 2 allow us to conclude that hypotheses 2a and 2b 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 Fig. 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 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 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

[13] See, for instance, Consoli et al. (2016).

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 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 Fig. 3 and Table 10 is that, for middle-age workers, obtaining higher education implies getting a shield against early retirement caused by automation.

In the right-graph of Fig. 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 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 Fig. 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 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, Fig. 3 and Table 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 3a and 3b of this study, stating that workers with higher education are less likely to retire early than workers without higher education, independently of the automation process and maintaining their early retirement probabilities not significantly affected by automation.

Fig. 4 and Table 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 Fig. 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 4b. 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 Barrett, 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 Fig. 4 and Table 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 self-employed 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.

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 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 A3 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 A4, showing that, while logically the intention to retire early increases the

[14] The Table A2 in the appendix collects some occupations of the *hands terrain*.

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 A5 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.

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.

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.

[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.

[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.

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 self-employed 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 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.

CRediT authorship contribution statement

Pablo Casas: Conceptualization, Formal analysis, Methodology, Software, Validation, Data curation, Writing – original draft, Writing – review & editing, Supervision. **Concepción Román:** Conceptualization, Formal analysis, Methodology, Software, Validation, Data curation, Writing – original draft, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[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.

Appendix A

Table A1
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 A2
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 A3
Robustness check 1 - Determinants of early retirement transitions excluding self-employed workers.

Model	V.R1			X.R1			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[a]	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 A4
Robustness check 2 - Determinants of early retirement transitions and intention to retire early.

Model	XVI			XVII			XVIII			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: * $0.1 > p \geq 0.05$; ** $0.05 > p \geq 0.01$; *** $p < 0.01$. [a] Dummy variable.

Table A5
Robustness check 3 - Determinants of early retirement transitions – Years to statutory retirement age.

Model	XX			XXI			XXII		
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									

(*continued on next page*)

Table A5 (*continued*)

Model	XX			XXI			XXII		
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: * $0.1 > p \geq 0.05$; ** $0.05 > p \geq 0.01$; *** $p < 0.01$. [a] Dummy variable.

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