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Technology, Labour Market Institutions and Early Retirement: Evidence from Finland

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Abstract

There are two major barriers to increasing employment of older workers. First, older workers engaged in codifiable, routine tasks are particularly prone to the risk of being displaced by computers and robots. Second, several countries have in place various labour market institutions that encourage early retirement, such as exceptional entitlements or looser criteria for unemployment and disability benefits applied to older individuals. We present evidence that these two factors reinforce each other to push older workers out of employment. We find that older workers who are more exposed to digital technologies are more likely to leave employment, and that this effect is significantly magnified when they are eligible to an extension of unemployment benefits until the earliest age for drawing old age pension. Furthermore, our findings imply that a policy reform that tightens the eligibility for the benefit extension would increase mostly the employment of older workers that are more exposed to digital technologies.

Keywords: Technological change, disability benefits, unemployment benefits, early retirement.

JEL classifications: H55, J26, J65, O33

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1. Introduction

Across many OECD countries, population ageing is posing a formidable challenge to medium- to long-run fiscal sustainability and economic growth. Furthermore, the shortage of qualified workers with relevant skills has become a common drag on economic growth, constraining productivity gains despite rapid technological progress (OECD, 2019a). Promoting longer working lives is essential for mitigating fiscal pressures from increasing pension and healthcare expenditures and addressing skill shortages. This need has become even more pressing in the aftermath of the economic crisis caused by the COVID-19 pandemic as countries face a large build-up of government debt and need to reboot economic growth.

There are two major barriers to increasing employment of older workers. First, older workers engaged in codifiable, routine tasks, may be particularly prone to being displaced by computers and robots (Autor, 2015). Indeed, their incentives to acquire new skills that would allow them to switch to tasks that are less likely to be automated are weak near retirement: because of their shorter remaining working lives, they (and their employers) would only obtain a low return on investments in new skills. They may thus choose to retire early when facing rapid technological change (Ahitiv and Zeira, 2011; Hægeland et al., 2007). Second, several OECD countries have in place various institutions that create strong incentives for early retirement. These include, for instance, exceptional entitlements or looser criteria for unemployment and disability benefits applied to older individuals. These two factors can reinforce each other to push older workers out of employment: older workers who are more exposed to new technologies are more likely to exit the labour market when they have access to these institutional pathways to early retirement. Alternatively, older workers who have access to early retirement pathways are more likely to use them when they are more exposed to technological change.

Finland offers a particularly interesting case for studying such interactions. On the one hand, Finland is a frontrunner in the adoption of new technologies. For instance, its business sector on average spent over 2% of GDP on R&D expenditure over the past decade, a share well above the OECD average. Finland is also considered as the most advanced European country in term of digitalisation of economic and social activities (European Commission, 2019). On the other hand, older workers in Finland lag significantly behind younger workers in skills that complement new technologies (OECD, 2020). The fast adoption of new technologies and the large inter-generational skills gaps suggest significant technology-driven pressure on employment of older workers. Indeed, at 67%, the employment rate of persons aged 55-64 is considerably lower in Finland than in its Nordic peers, where rates range from 72% to 77%. This large gap is rooted in early retirement pathways that persist in Finland but were scrapped long ago in other Nordic countries. In Finland, individuals aged 59 or older enjoy 100 working days longer entitlement to unemployment benefits than other age groups and can have their unemployment benefits extended from the age of 61 until they start drawing old-age pension (often dubbed as the unemployment tunnel). In addition, more lenient criteria that include non-medical factors are applied to individuals aged 60 and over for awarding disability benefits. These institutions generate strong incentives for early retirement (Kyyrä and Pesola, 2020; Kyyrä, 2015; Korkeamäki and Kyyrä, 2012).

By combining the rich employer-employee database that tracks an individual's outflow from employment into unemployment, disability and inactivity with novel occupation-level data that capture the exposure to new technologies, we find a significant interaction between technological change and the unemployment tunnel. For instance, while an individual aged 50 or more in occupations that are more exposed to technological change has higher probability of exiting employment, such risk is magnified when the individual gains access to the unemployment tunnel. For example, an older individual exposed to a one standard deviation higher than the average risk of automation is subject to about one percentage point higher probability of exiting employment (compared to individuals exposed to an average level of automation risks) every year, if he does not have access to the unemployment tunnel. However, this probability is 2 to 2.5 percentage points higher instead, if he has access to the unemployment tunnel. Furthermore, access to the unemployment tunnel increases the probability of exit by up to 2 percentage points even if the individual is only exposed to an average level of automation risk. The combined effect of higher automation risk and access to the unemployment tunnel therefore sums up to 4 percentage points higher probability of exit, which implies a 80% increase in probability of exiting employment for individuals aged 57-58.

The paper contributes to a large strand of literature on the impacts of technologies on employment, and to an equally large one on the employment effects of labour market institutions. Despite the common recognition that older workers are more vulnerable to technological change than younger workers, surprisingly few studies have explored the effect of new technologies on early retirement.[5] Furthermore, these studies have not explored how this effect can be magnified by labour market institutions like unemployment and disability benefits. This paper also has novel policy implications for OECD countries aiming to extend working lives in an age of rapid technological change, notably digitalisation. In particular, reforms that tighten access to early retirement pathways are essential for the inclusiveness of older workers in the future of work. Previous policy discussions stressed measures for upgrading workers' skills, particularly helping workers to acquire skills that complement new technologies (for example, OECD, 2019b). These include boosting training and learning opportunities throughout working lives, especially for workers more exposed to technological change. However, our findings indicate that the effectiveness of vocational training and continuous learning can be severely undermined if pathways to early retirement remain as they discourage older workers from taking up these training opportunities and instead induce them to exit the labour market.

The next section develops a conceptual framework on the interaction between technological change and early retirement pathways through a review of the relevant literature. It also provides a concise explanation of technology adoption in Finland and its institutional settings that have been acting as pathways to early retirement. Section 3 describes the data used for the analysis and presents simple statistical observations based on the combined dataset. It also provides a preliminary observation that the risk of being laid off temporarily or permanently increased disproportionally among older individuals more exposed to technological change in the wake of COVID-19 crisis. Section 4 sets up the empirical framework for the analysis and reports baseline findings as well as some robustness

[5] For instance, Lordan and Neumark (2018) reported that higher minimum wages increase the risk of job loss among old unskilled workers exposed to high automation risks.

analysis. It also illustrates through a simple simulation how exposure to technological change defines how employment of older workers responds to reform of the unemployment tunnel. The last section concludes and discusses policy implications.

2. Technology-induced early retirement and its interaction with institutions

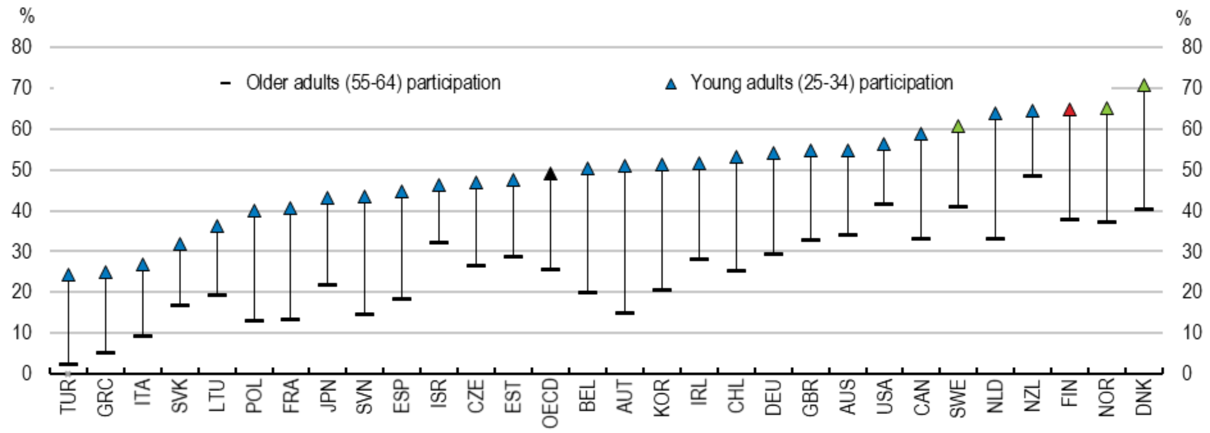
The effect of technological change on employment has been extensively researched. The past decades have seen a particularly extensive exploration of what is described as the "race between men and machine" (Brynjolfsson and McAfee, 2014), where workers engaging in tasks that can be codified are increasingly replaced by machines and computers, and therefore must acquire new skills so that they can switch to non-automatable jobs. The seminal work by Frey and Osborne (2013) estimated that about 47% of jobs in the United States are prone to high risks of automation, while subsequent studies using finer data reported somewhat lower estimates of 9 to 14% (Arntz, Zierhan and Gregory, 2016; Nedelkoska and Quintini, 2018). However, these estimations are based on the nature of the tasks performed and do not capture the possible heterogeneity in exposure to risk of automation across groups of workers. New technologies displace some workers engaging in automatable tasks while increasing the productivity of non-automatable tasks, thereby generating demand for workers with skills to perform the latter tasks (Acemoglu and Restrepo, 2019). The size of job opportunities created by new technologies is non-negligible. For instance, about half of employment growth over 1980–2015 in the US took place in occupations that underwent changes in job titles or tasks performed by workers (Acemoglu and Restrepo, 2018). However, some workers with lower capacity or willingness to acquire new skills are less likely to seize such job opportunities created by new technologies, and are therefore more prone to job loss as a result of technological change.

In general, older workers are particularly vulnerable to technological change. New technologies not only require a higher level of skills but also bias labour market demand toward specific types of skills while rendering other skills obsolete (Goos et al., 2014; Dickerson and Green, 2004). Older workers with less recent vintages of skills are particularly exposed to this risk of skills obsolescence[6]. At the same time, older workers participate less in job-related training than younger workers (Figure 1). This is because their shorter remaining careers do not allow older workers (or their employer) to recoup the upfront costs associated with investment in new skills (Ahituv and Zeira, 2011; Saint-Paul, 2009). Such a view is in line with the human capital theory, which emphasizes cost-benefit considerations in decisions to invest in human capital (Becker, 1964; Mincer, 1974)[7].

[6] Several studies report strong correlation between age and skills obsolescence (for example, Friedberg, 2003). In particular, Allen and De Grip (2011) suggested that workers employed in the same job for around more than 18 years suffer from the depreciation of their human capital, which outweighs the positive effect of experience on their productivity.

[7] It is commonly believed that learning ability deteriorates with age, and this may contribute to low take-ups of training opportunities by older workers. However, the evidence for lower learning capacity by older workers is mixed (see Peng et al., 2017).

Figure 1. Share of young adults and old adults in job-related trainings



Source: OECD (2019), Working Better with Age.

As the result of skill erosion and shorter working life horizons, older workers may respond to radical technological change by retiring early instead of investing in new skills (Ahituv and Zeira, 2011; Hægeland et al., 2007). For instance, Bartel and Sicherman (1993) found that the skill obsolescence of older workers lowers their productivity, which leads to early retirement. Using rich employee-employer data for Norway, Hægeland et al. (2007) reported that a firm's investment in new equipment and the introduction of new process technology increases the likelihood of early retirement by its employees. Other studies also found that the wage bill share of older workers is negatively correlated with the adoption of new technologies like ICT (Beckmann, 2007; Behaghel et al., 2014, Peng et al., 2017). On the other hand, technological change boosts productivity and thus wage levels, thereby encouraging older workers to remain in their jobs. This effect is found to dominate the retirement motive from skill obsolescence when technological change is large (Ahituv and Zeira, 2011; Burlon and Vilata-Bufí, 2016). Messe et al. (2014) found that technological change induces individuals to work longer in jobs with a higher probability of skill upgrading opportunities, which are associated with frequent on-the-job training. Therefore, the net impact of technological change on early retirement is a *priori* ambiguous.

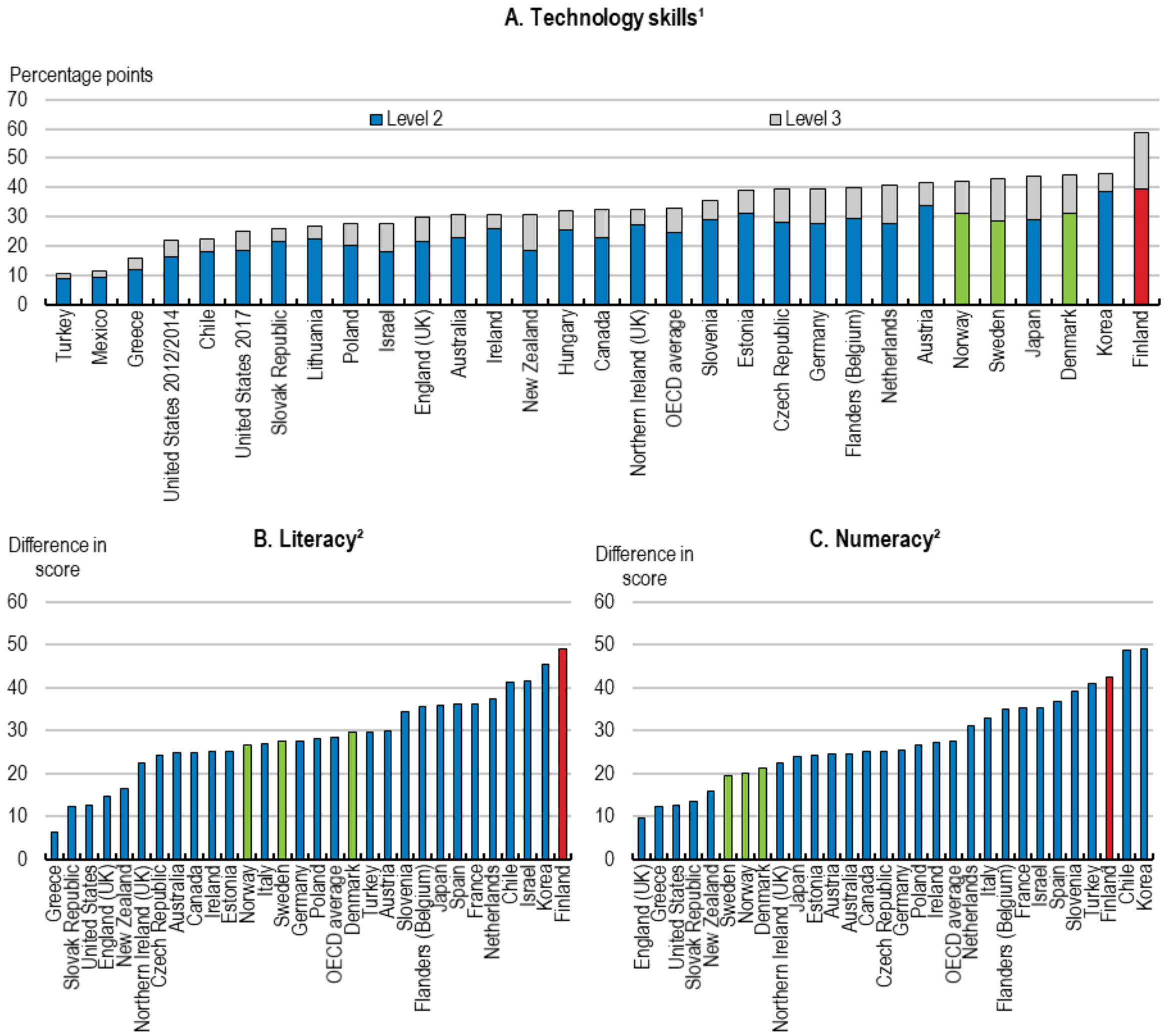
2.1 Institutional settings can reinforce technology-induced early retirement

The early retirement incentive generated by technological change can be reinforced by institutions that provide pathways to early retirement. For instance, many European countries provide longer entitlement periods for unemployment insurance benefits for the older unemployed. Eligible individuals may choose to leave their job to obtain more leisure time if the benefit scheme is sufficiently generous. Employers can also target dismissals at older employees who qualify for extended benefits. Older workers eligible for extended benefits are indeed found to enter unemployment at a higher rate (Winter-Ebmer, 2003; Kyyrä and Wilke, 2007; Tuit and van Ours, 2010; Baguelin and Remillon, 2014). Disability benefits are designed to provide insurance for employees' labour income against the risk of becoming disabled and incapable of regular work. In practice, they often distort labour supply (and demand in some cases) if their income replacement is very generous or the screening process for their eligibility is lenient. For instance, Autor and Duggan (2003, 2006) argued that institutional changes in disability benefits was one of the most important drivers of rapid growth in disability benefit rolls observed in the United States. Also, employers seeking to change the composition of the workforce at a time of stable or growing employment, when dismissals are difficult to justify, may encourage disability retirement of older workers (Korkeamäki and Kyyrä, 2012). Easy access to unemployment and disability benefits can tilt the conflicting effects of technological change in favour of early retirement. In other words, these institutions are more likely to encourage the early retirement of workers who are more exposed to technological change. To our knowledge, this paper is first to focus on the role of early retirement pathways in technology-induced retirement, although some studies did note the role of other institutions, such as collective wage bargaining or union density (for example, Peng et al., 2017).

2.2 Technological change and its implications in Finland

Finland is a highly innovative country and a frontrunner in adoption of digital technologies. Finland's Research and Development (R&D) expenditure amounted to 2.8% of GDP in 2018, a ratio that is higher than in most other OECD countries. In 2019, Finland ranked first in the European Commission's Digital Economic and Social Index (DESI) with 69.9 points, significantly outpacing the EU average of 52.5, indicating wide penetration of digital technologies in socio-economic activities. Finland also excels in mobile broadband, 5G readiness, digital public services, and human capital: its share of ICT specialists in the labour force stands at 7.2%, the highest among EU countries. Rigorous adoption of new technologies has resulted in strong demand for ICT skills. Almost 70% of Finnish companies report difficulty in filling vacancies for jobs requiring ICT skills, a share that is much higher than the EU average. Interestingly, the share of jobs at high risk of automation in Finland is relatively low compared with many OECD countries (Pajarinen and Rouvinen, 2014), which suggests that jobs in Finland are more intensive in non-routine tasks and ICT skills than in most other OECD countries. Rapid technological change in Finland is likely to generate strong pressure on older workers to retire early, especially when they need substantial investment in new skills to remain employable. Indeed, workers aged 55 to 64 in Finland comprise close to 40% of workers with very low literacy or numeracy skills, a share that is among the highest in the OECD (Musset, 2015). Also, the gap in information processing skills between 16-24 year-olds and 55-64 year olds is among the largest in the OECD (Figure 2).

Figure 2. Gaps in information processing skills between the youngest and oldest adults



1. Difference in shares of the youngest (25-34 year-olds) and oldest (55-65 year-olds) adults scoring at Level 2 or 3 in problem solving in technology-rich environment.
2. Difference in mean score between the youngest (25-34 year-olds) and oldest (55-65 year-olds) adults.

Source: OECD Survey of Adult Skills (PIAAC) (2012, 2015, 2018).

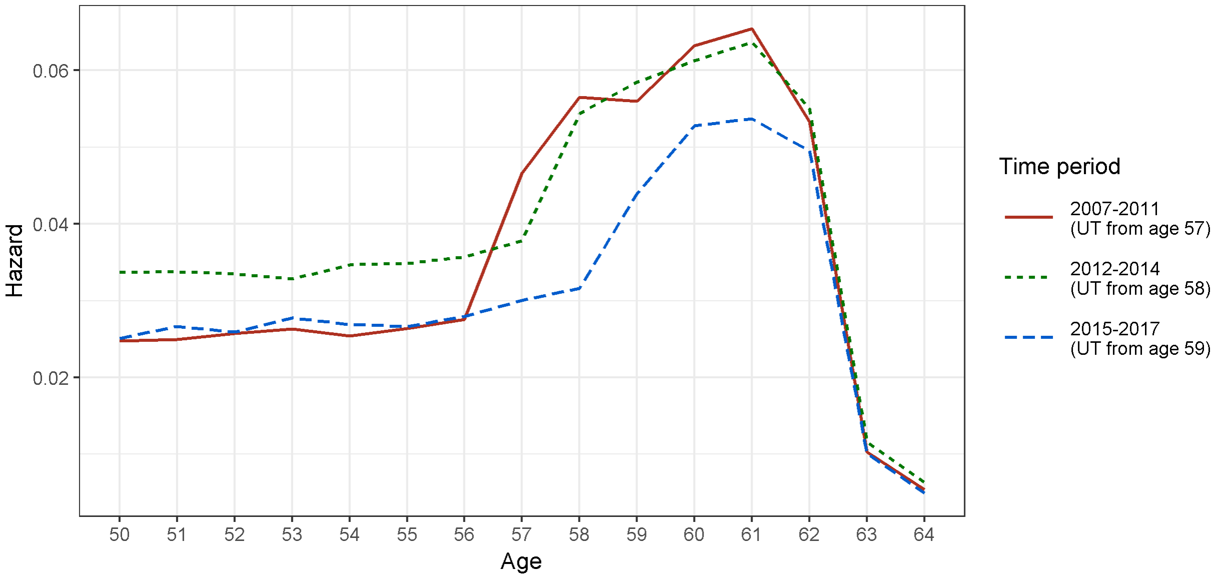
2.3 Institutional pathways to early retirement in Finland

The unemployment tunnel

Finland offers more generous unemployment and disability benefits for older workers than do other Nordic countries. For instance, individuals aged 58 years or more who worked at least five years in the past 20 years are entitled to receive unemployment benefits for a maximum of 500 weekdays, as opposed to 400 days for younger individuals. Furthermore, those aged 61 years or older when reaching their 500-days benefit limit can keep receiving benefits until the statutory retirement age of 65 or when they start drawing old-age pension, which currently can be taken from the age of 63 years and nine months. The combination of longer entitlement to regular unemployment benefits and the extension of unemployment benefits is often dubbed the unemployment tunnel. It provides a seamless flow of income to workers who become unemployed at the age of 59. The application of job search requirements for these older unemployed persons is lenient, making the unemployment tunnel an attractive pathway to early retirement (OECD, 2020).

The effect of the unemployment tunnel on employment of the older working age group is apparent. The risk of unemployment (share of workers flowing out of employment to unemployment) spikes around two years before reaching the eligibility age for extended unemployment benefit (Figure 3). The eligibility age for extended unemployment benefit has been raised several times in the past, from 55 before 1997 for all workers to the current 61 in 2014. Consequently, the age at which individuals can enter the unemployment tunnel increased from 57 in the years 2007-2011 to 58 in the years 2012-2014, and 59 in the years 2015-2017. These reforms have pushed back the timing of the sharp rise in unemployment risk, effectively lengthening the working lives of older workers (Figure 3). The 2005 reform, which raised the entry age from 55 to 57, is estimated to have increased employment of private-sector workers by 7 months over a 10-year period between the age of 54 and 63 (Kyyrä and Pesola, 2020). The eligibility age to extended unemployment benefits will be raised to 62 in 2023 for those born in 1961 or after. For these individuals, access to the unemployment tunnel will only be possible from age 60. In December 2020, the government decided that the unemployment tunnel will be gradually abolished altogether, so that people born in 1965 or after will not be eligible for extended unemployment benefit anymore.

Figure 3. The unemployment inflow by age and time period



Source: computation by authors

Special criteria for disability benefits for older workers

In Finland, more lenient eligibility criteria for disability benefits, including non-medical factors, are applied to applicants aged 60 or more. This results in the inflow into disability benefits soaring at age 60. Disability benefit applicants aged 60 and over are rarely rejected, and they tend to receive disability pension until retirement because they are much less likely to be rehabilitated than younger individuals on disability benefits (Aho et al., 2018; OECD, 2020). This makes disability benefit an effective alternative pathway to early retirement. For instance, applications for disability benefits soared in 2018 when the so-called Activation Model, which cuts unemployment benefits in case job search or training requirements were not fulfilled (Laaksonen, Rantala and Salonen, 2019), was implemented, not least because unemployed jobseekers with a pending disability benefit application were exempt from this sanction.

Flexible retirement age for old-age pension

Finland's statutory retirement age is 65, but the pension reform in 2005 introduced a flexible retirement age from 63 to 68 years. While this reform was intended to extend working lives beyond 65, it turned out to have the opposite effect, as the introduction of a flexible retirement age was effectively treated as lowering the full retirement age to 63 years. Gruber et al. (2019) report that retirement probabilities in the age range that was suddenly eligible for flexible retirement increased by 40% or more in 2005 from levels in 2004 despite only a modest increase in incentives to retire before age 65. The government responded in its 2017 pension reform by deciding to raise the minimum retirement age gradually from 63 to 65 by 2025 and link the minimum retirement age to life expectancy from 2030 onwards.

3. Data description and statistical observation

For the purpose of the empirical analysis, this paper combines rich employer-employee microdata with occupation-level data capturing the exposure of workers to technological change.

3.1 Employee-employer dataset

We exploit a large employee-employer dataset compiled by combining data from Statistics Finland's FOLK modules. The FOLK modules contain information combined from several administrative registers. They include a wide range of information on individuals' demographic and socioeconomic characteristics including education, income, labour market outcomes, housing and family. The dataset covers all persons belonging to the population in Finland since 1987 (approximately 5 million individuals/year). It contains individual-level information on all employment relationships during the last week of the year. This information includes, for example, employees' occupational status and industry. This allows monitoring transitions into and out of employment or the labour market. We focus on individuals between the ages of 50 and 64 who were employed in the private sector in the years 2007-2017, and require that they were employed in the same firm over the past two years. The resulting sample contains 661,821 individuals and over 3.1 million individual-year observations.

3.2 Data on exposure to technological change

This paper uses three indicators that capture the exposure of each occupation to technological change. All three indicators are constructed based on individual-level data from the O*ECD Survey of Adult Skills* (PIAAC). PIAAC tests the cognitive information-processing skills of adults along three dimensions: literacy, numeracy and problem solving in technology-rich environments. In addition, the survey measures how often people perform several tasks, including reading, writing, numeracy, using ICTs and problem solving, which require the cognitive skills assessed through the tests. It also includes information on how often workers perform other tasks, such as those related to management, communication, organisation and planning, and physical work.

The risk of automation

The risk of automation was first estimated by Frey and Osborne (2013) based on an assessment by experts on the risk of automation of tasks involved in a subset of occupations in the United States. The assessment identified the so-called bottlenecks to automation – i.e. the tasks that are difficult to automate because they involve a high degree of: social intelligence, such as the ability to effectively negotiate complex social relationships, including caring for others or recognizing cultural sensitivities; cognitive intelligence, such as creativity and complex reasoning; and perception and manipulation, such as the ability to carry out physical tasks in an unstructured work environment. These bottlenecks were then used to infer the risk of automation for occupations that were not assessed by the experts and for other countries than the United States. Nedelkoska and Quintini (2018) applied the approach by Frey and Osborne (2013) on individual-level data from PIAAC. They matched the information on tasks performed by individuals to bottlenecks to automation identified by Frey and Osborne (2013) and estimated the risk of automation for each job. Their method is more granular than the one by Frey and Osborne (2013) which estimated automation risks at the level of 2-digit occupation specified in O*NET. In particular, Nedelkoska and Quintini (2018) incorporated a considerable variation in the tasks within jobs classified under a same occupation, and therefore large differences in the shares of automatable tasks among jobs classified within in a same occupation. For the purpose of the analysis, this paper averages estimated job-level risks of automation for each occupation.

The intensity of routine tasks

Drawing on the observation that easily codifiable routine tasks are more likely to be automated, Marcolin, Miroudot and Squicciarini (2016) constructed an index capturing the intensity of routine tasks, building on four questions in PIAAC that capture the extent to which one's job is codifiable and sequentiable. They are: "To what extent can you choose or change the sequence of your tasks?" (Sequentiability); "To what extent can you choose or change how you do your work?" (Flexibility); "How often does your current job involve planning your own activities?" (Planning); and "How often does your current job involve organising your own time?" (Self-organisation). Answers to each question range from 1 to 5, with 5 corresponding to "Not at all" or "Never" and 1 to "To a very high extent" and "Every day" depending on the question. The index was constructed as a weighted average of scores to the five questions. A higher (lower) value of the index corresponds to a higher (lower) intensity of routine (non-routine) tasks.

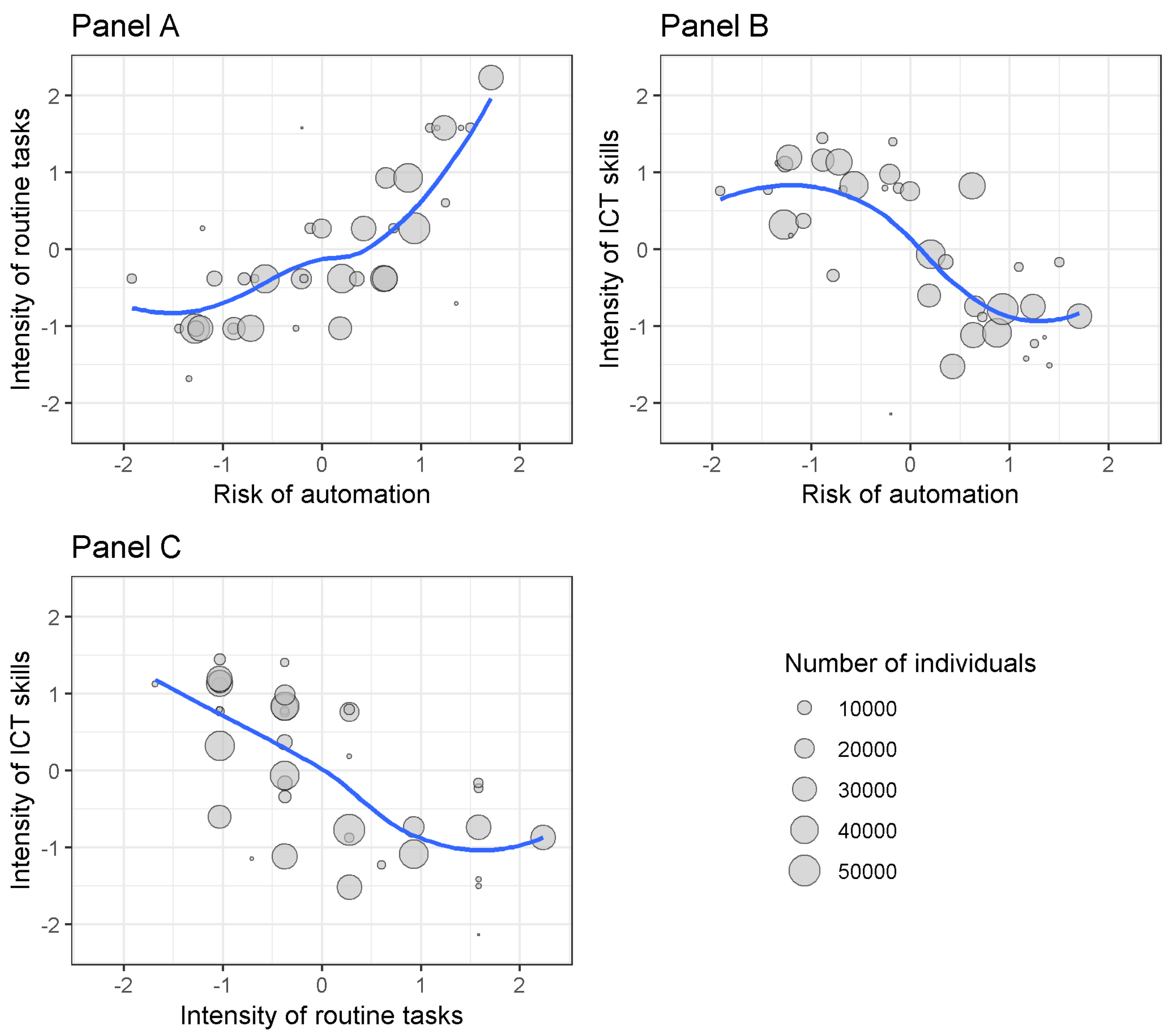
The intensity of ICT skills use

Tasks that require high intensity of ICT skills are likely to be complementary rather than substitutable with digital technologies. Grundke et al. (2017) constructed an index of ICT intensity of jobs by summarising PIAAC questions that capture types of tasks workers perform on the job and hence presumably the skills they may develop. These questions ask about the frequency of tasks associated with ICT use, from reading and writing emails to using word-processing or spreadsheet software, or a programming language. Answer to each of these items are scaled from 1 ("Never") to 5 ("Every day"). The ICT skill index based on these answers measures the frequency of ICT-related tasks, with a higher score associated with a higher frequency of performing the underlying tasks on the job.

How are the three indicators related in Finland?

To ease interpretation and comparison between the indicators, all the indicators were standardised by subtracting the mean value across occupations and dividing by the standard deviation. It is useful to observe how closely the three indicators on exposure to technological change are related. Figure 4 explores the correlation between indicators for individuals between the ages of 50 and 64 who were employed in the private sector in the years 2007-2017. The size of circles indicates the number of observations for each data point. There is a positive, non-linear relationship between the risk of automation and the intensity of routine tasks. However, the relationship between the intensity of ICT skills and the risk of automation is more complex. It is particularly noteworthy that occupations with lowest intensity of ICT skills are not necessarily those with highest automation risks. This is most likely because these occupations are not the ones with the highest intensity in routine tasks that can be easily codified and thus replaced by computers and robots.

Figure 4. Scatter plot of exposure to technological change



Source: computation by authors

3.3 First look

Descriptive statistics

Based on the combined dataset, this section provides preliminary observations on the characteristics of older individuals exposed to technological change and a possible interaction between technological change and early retirement pathways. The first column of Table 1 reports statistics for the entire sample while other columns compare individuals in occupations with high or low exposure to technological change. The occupations with high automation risks, routine task intensity, as well as ICT skill intensity refer to those with positive values of standardised indicators of automation risk, routine task intensity and ICT skill intensity, respectively.

Table 1. Sample statistics by exposure to technological change

	All	Risk of automation		Intensity of routine tasks		Intensity of ICT skills	
		Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Sample means							
Age	56.0	55.9	56.1	56.0	56.1	56.1	56.0
Female	0.401	0.433	0.376	0.436	0.347	0.353	0.455
Married	0.637	0.690	0.594	0.665	0.592	0.591	0.686
Capital region	0.332	0.422	0.260	0.383	0.251	0.247	0.424
Education:							
Basic education	0.225	0.100	0.326	0.157	0.334	0.325	0.117
Secondary education	0.622	0.580	0.656	0.604	0.649	0.660	0.581
Tertiary degree	0.153	0.320	0.018	0.239	0.017	0.015	0.302
Industry:							
Agriculture, forestry and fishing	0.014	0.014	0.015	0.013	0.017	0.015	0.014
Mining and quarrying	0.004	0.003	0.004	0.002	0.006	0.005	0.003
Manufacturing	0.296	0.236	0.345	0.203	0.444	0.353	0.235
Power and water supply	0.026	0.030	0.022	0.027	0.024	0.022	0.030
Construction	0.072	0.048	0.092	0.093	0.039	0.093	0.049
Wholesale and retail trade	0.156	0.136	0.173	0.211	0.069	0.174	0.137
Transportation and storage	0.111	0.059	0.153	0.067	0.181	0.146	0.074
Accommodation and food services	0.025	0.009	0.038	0.034	0.012	0.040	0.009
Information and communication	0.056	0.099	0.021	0.079	0.019	0.017	0.098
Financial and insurance activities	0.056	0.113	0.011	0.048	0.069	0.003	0.114
Real estate activities	0.017	0.023	0.013	0.024	0.007	0.010	0.025
Professional and scientific activities	0.060	0.111	0.019	0.088	0.016	0.012	0.112
Administrative and support services	0.048	0.028	0.064	0.032	0.073	0.066	0.029
Education	0.008	0.013	0.004	0.012	0.002	0.003	0.013
Human health and social work activities	0.031	0.057	0.010	0.045	0.010	0.028	0.035
Arts, entertainment and recreation	0.006	0.008	0.005	0.007	0.004	0.004	0.008
Other services	0.010	0.011	0.009	0.012	0.007	0.008	0.011
Unkown	0.003	0.003	0.002	0.003	0.003	0.002	0.003
Panel B. Exit rates							
Overall exit rate	0.085	0.072	0.096	0.078	0.098	0.097	0.073
Unemployment	0.036	0.029	0.042	0.032	0.042	0.042	0.030
Disability	0.012	0.006	0.016	0.009	0.016	0.017	0.006
Inactivity	0.038	0.037	0.038	0.036	0.040	0.038	0.037
# of observations	3 119 580	1 391 511	1 728 069	1 910 509	1 209 071	1 622 275	1 497 305

Source: computation by authors

Panel A displays the mean value of various dummy variables indicating the characteristics of individuals as well as the industry they are employed in. For instance, it indicates that a larger share of women than men are in occupations with lower exposure to technological change, possibly due to their overrepresentation in the healthcare workforce. Also, a larger share of individuals living in the capital region are in occupations that are less likely be automated, less intensive in routine tasks and more intensive in ICT skills. Unsurprisingly, older individuals with low educational attainment, and to lesser extent with medium attainment, are overrepresented in occupations that are more exposed to digital technologies, while a larger share of individuals with tertiary education attainment are mostly in occupations that are less exposed. There are larger shares of individuals working in manufacturing, transportation and storage and construction sectors that are in occupations highly exposed to digital technologies, while the opposite holds for those working in information and communication industries and professional services.

Panel B displays the average probability of individuals exiting employment through early retirement pathways for occupations with high and low exposure to technological change. Overall, individuals in occupations with higher automation risk and intensity of routine tasks or low intensity in ICT skills have a two to three percentage point higher probability of exiting employment each year than do other individuals. This gap in the probability of job loss is accounted for in equal measure by higher probabilities of becoming unemployed or disabled. In contrast, the probability of individuals entering inactivity does not differ between two types of occupations.

The probability of exit from employment

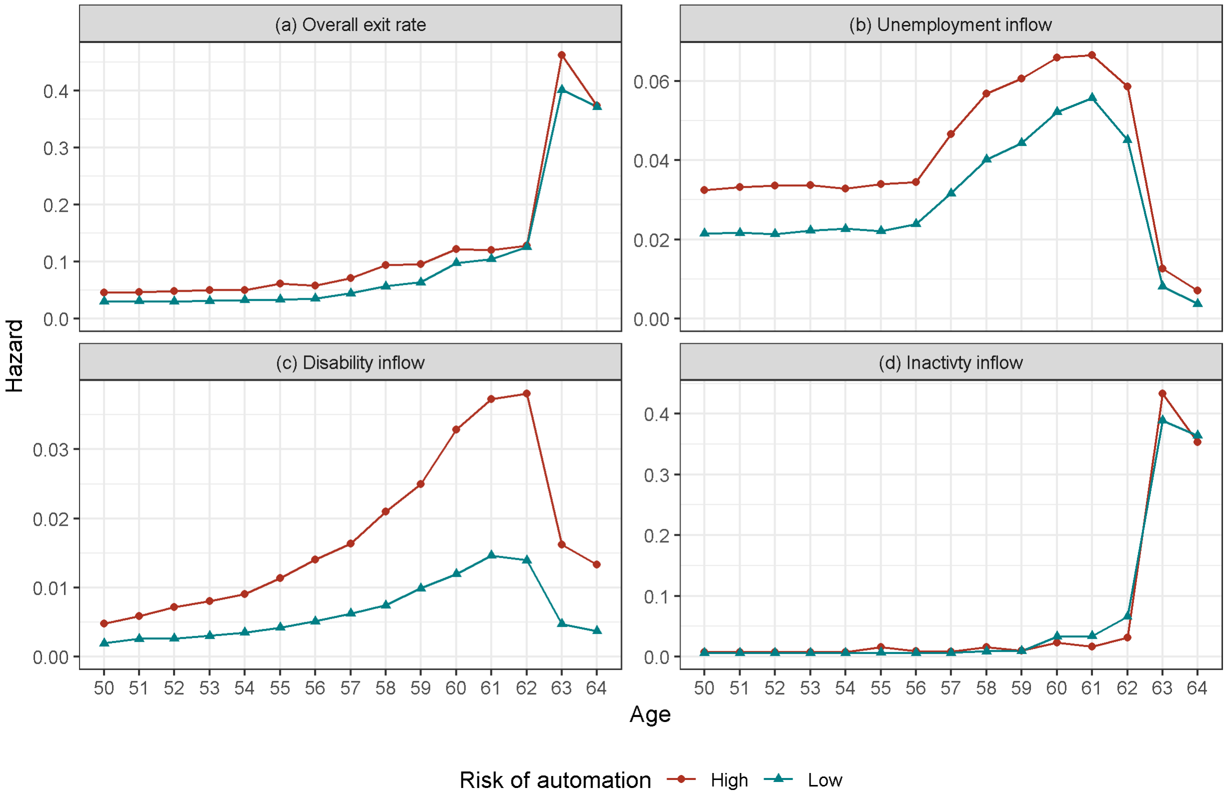
Figure 5 compares the average probability of exit from employment by individuals aged 50 and over between occupations with high automation risks and those with low automation risks, during the period 2007-2017. To shed light on the pathway to early retirement taken by the individual, probabilities of exit into unemployment, disability and inactivity are shown as well. The red line corresponds to individuals in occupations with high automation risks while the blue line corresponds to those in occupations with lower automation risks. The probability of exit is always higher among individuals in occupations with high automation risks (Panel A). The probability of exit spikes at the age 63 when individuals can access old-age pension. It is noteworthy that the spike is larger for individuals exposed to higher automation risks, due to the larger spike in risk of inflow into inactivity by this group at 63 (Panel D). This indicates that older individuals exposed to technological change are more likely to claim old-age pension as soon as it becomes available under the flexible retirement age system (see Section 3).

The unemployment risk is always higher for individuals in occupations with higher automation risks (Figure 5, Panel B). Moreover, the steeper slope of schedule implies that the unemployment risk increases faster with age for these individuals in their late-50s. The difference in the unemployment risk between individuals with high- and low automation risks is largest at the age of 59, when all individuals can access the unemployment tunnel. Also, the increase in unemployment risks from the age of 58 to 60 tends to be larger among occupations often characterised by codifiable routine tasks, such as office clerks and assembly individuals (Figure 6). Overall, individuals who are more prone to automation risks are more likely to flow into unemployment, especially when they are near the age where they can access the unemployment tunnel.

There is a stark difference in inflow into disability benefits between individuals in occupations with high and low automation risks, which increases dramatically when individuals reach their late-50s (Figure 5, Panel C). In particular, the gap widens sharply at the age of 60, when more lenient criteria for granting disability benefits are applied. However, such phenomenon could be driven at least partly by the conditions in occupations that are more prone to automation risks, such as physical stress.

Figure 5. The incidence of exit from employment by risk of automation

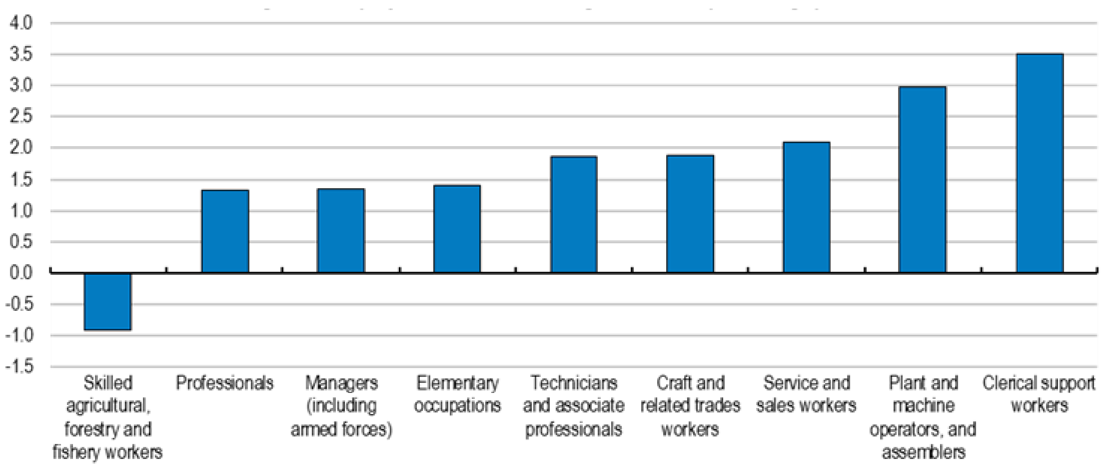
Average hazard rate, 2007-2017



Source: computation by authors

Figure 6. Changes in unemployment inflow rates between ages of 58 to 60 by occupation

Percentage points, 2015-2017



Source: computation by authors.

3.4 Did COVID-19 accelerate technology-induced early retirement?

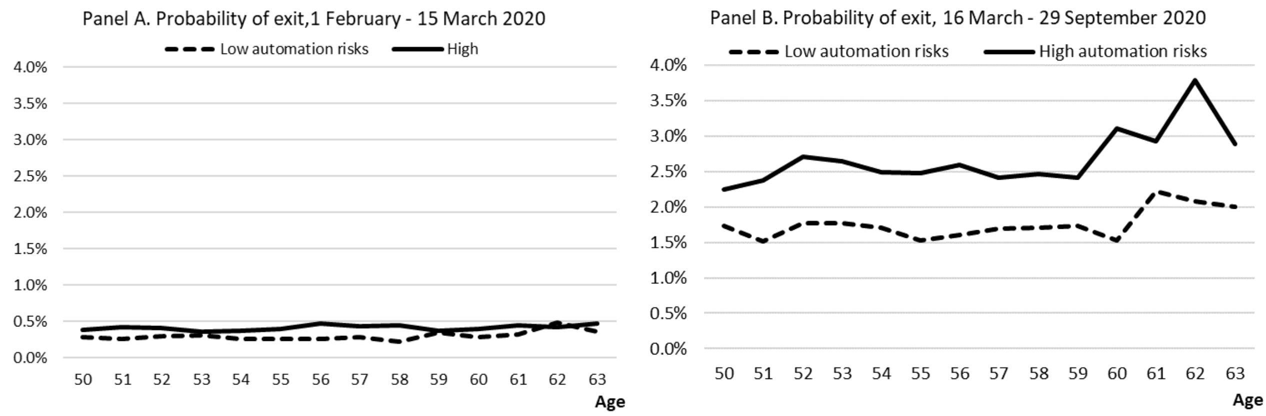
The COVID-19 pandemic in early 2020 brought about large economic contractions as individuals avoided situations with a high risk of catching the virus and countries shut down social and economic activities to contain the spread of the virus. Finland declared a State of Emergency on 16 March and activated confinement measures in the following days, including recommending that non-essential businesses close. Because of the pandemic, the economy had shrunk by 6.3% by mid-2020 from the last quarter of 2019. This economic contraction has not yet translated into a large increase in dismissal thanks to an extensive use of the temporary layoff scheme, which enabled employers to retain their employees while reducing their working hours and wages to zero for 90 days. The Helsinki Graduate School of Economics Situation Room monitors the inflow of Finnish workers into unemployment (including both temporarily and permanently layoffs) using high frequency data from the public employment offices.[8] We exploit these data for a preliminary observation on the relation between exposure to technological change and layoffs of older individuals.[9]

As in Figure 5, the probability of entering unemployment has been higher for individuals in occupations exposed to higher than average automation risks in 2020, although the difference widened significantly after 15 March when confinement measures were initiated (Figure 7, Panel A and B). The unemployment inflow increased more for individuals exposed to high automation risks after the confinement started, than those exposed to low automation risks (Panel C). This is more apparent when inflow rates before and after the initiation of confinement were first compared with the same period in 2019 to remove seasonal variations in unemployment that are unrelated to the COVID-19 crisis (Panel D). Panel D therefore illustrates the extent to which the excess probability of exit against 2019 increased after the confinement. The unemployment inflow increased disproportionally more for individuals exposed to high automation risks, at the ages of 59 (when they can access the unemployment tunnel), 60 (when more lenient criteria for awarding disability benefits apply) and 62 (a year before the eligibility age for early old-age pension). This suggests that some layoffs at those ages were motivated by technological change. However, as many of these laid-off individuals were furloughed and thus may return to their work, this is not conclusive evidence of the COVID-19 crisis accelerating early retirement induced by technological change.

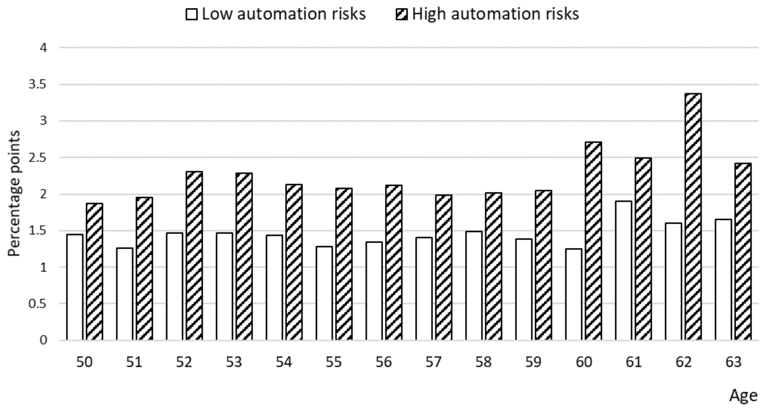
[8] See https://www.helsinkigse.fi/covid19-data-en/situation-room-report-8-10-2020-latest-developments-in-the-labor-market-households-and-firms/

[9] Note that this high-frequency data is different from the data we use for our empirical analysis.

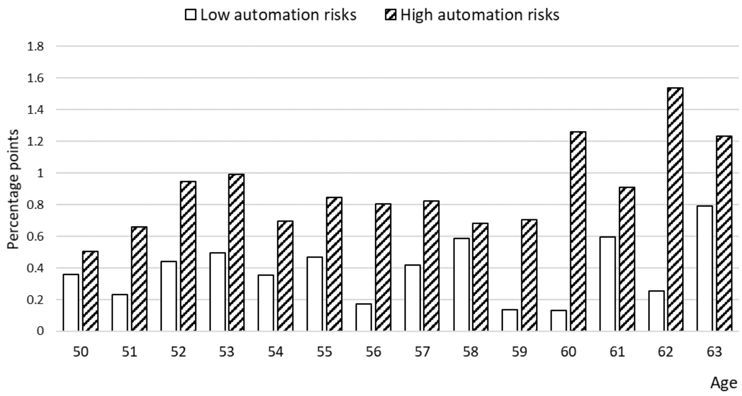
Figure 7. Unemployment inflow rates under the COVID-19 crisis



Panel C. Difference in the unemployment inflow rates, before and after 16 March 2020



D. Difference in the unemployment inflow rates against the same period last year, before and after 16 March 2020



Note: Panel A and B display the probability of exiting employment and flowing into unemployment between the period after the issuance of the State of Emergency on 16 March (16 March – 29 September 2020) and the period before (1 February – 15 March 2020) for older workers exposed to higher than average automation risks and those exposed to lower than average risks. Panel C displays the difference between before and after 16 March. Panel D controls for possible seasonal variation in unemployment inflow rates by differentiating the inflow rates in the two periods by those of corresponding periods in 2019, before differentiating the probabilities between the two periods.

Source: Helsinki Graduate School of Economics Situation Room; Authors' computation

4. Empirical analysis

In this section, we explore more formerly the interaction between exposure to technological change and institutional pathways to early retirement, namely the unemployment tunnel, within an empirical framework.

4.1 Estimation model and identification strategy

Our baseline model is a simple linear probability model with the dependent variable as the probability that an individual *i* exits employment at the end of the period *t* after having been employed by the same employer in the last two periods (*t-1* and *t-2*). In addition, we estimate models where the dependent variable is, respectively, (1) the probability of being unemployed, (2) the probability of receiving disability benefit, and (3) the probability of being outside the labour force for other reasons than disability at the end of period *t*.

The models are of the following form:

$$P(E_t = 0 | E_{t-1}, E_{t-2} = 1\,) = \alpha + \beta_1 Tech_{it} + \beta_2 UT_{it} + \beta_3 (Tech_{it} \times UT_{it}) + \delta X_{it},$$

Where the left-hand side is the probability of exits from employment as specified above. The second term on the right-hand side, $Tech_{it}$, is the standardised occupational-level indicator of exposure to technological change, which can be the automation risk, intensity in routine tasks, or intensity in the use of ICT skills in individual *i*'s occupation. The third term, UT_{it}, is a dummy variable for individual *i*'s access to the unemployment tunnel in period *t*. X_{it} is a vector of control variables that include age dummies, gender, educational attainment, marital status, residence, and year dummies intended to capture fluctuations in labour demand.

The effect of technological change on the probability of exit is captured by the coefficient β_1 on $Tech_{it}$, which equals the impact of one standard deviation higher exposure to technological change (as the result of the standardisation of all indicators) for individuals that do not have access to the unemployment tunnel. The corresponding effect of technological change on individuals with access to the unemployment tunnel is $\beta_1 + \beta_3$. The coefficient on the interaction term β_3 is expected to be positive and significant, except when $Tech_{it}$ is the intensity of ICT skills, in which case it is expected to be negative. The direct effect of access to the unemployment tunnel is captured by the coefficient β_2 on UT_{it} for individuals with an average exposure to technological change. This coefficient can be identified despite the model including a full set of the age and year dummies, thanks to the past reforms that raised the age at which individuals gain access to the unemployment tunnel for the cohorts born later and thus introduces exogenous variation in UT_{it}. Specifically, UT_{it} switches from 0 to 1 at age 57 in the years 2007-2011, at age 58 in the years 2012-2014, and at age 59 in the later years. The effect of the unemployment tunnel is then identified by differences in the exit probabilities at ages 57 and 58 in different years.

While the direct effect of UT_{it} is identified at ages 57 and 58, the effect of its interaction with technological change $Tech_{it}$ is determined by the average exit rates of all individuals of different ages with access to the unemployment tunnel. However, the effect of technological change on these individuals may change with age for reasons unrelated to the unemployment tunnel. For example, individuals exposed to high automation risks may respond differently to the lenient criteria for awarding disability benefits applied from the age 60 or to gradual deterioration of cognitive skills, compared to those exposed to low automation risks. Then, β_3 can reflect such effects even though it is not related to the unemployment tunnel. To mitigate this problem, we also estimate models that include interactions between $Tech_{it}$ and age dummies. In these models, β_3 captures only the interaction between technological change and the unemployment tunnel for individuals aged 57 and 58 who were directly affected by the past reforms. Thus, the identification of β_3 hinges only on the exogenous changes in the age when the unemployment tunnel becomes accessible, in a same manner as the identification of β_2.

A major advantage of the linear probability model is its ease in interpretability. Unlike in nonlinear probability models, the coefficients on UT_{it}, $Tech_{it}$ and their interaction can be interpreted directly as proxies of average marginal effects on the probability of exit from employment. On the other hand, a potential issue with the linear probability model is that the predicted probability can exceed 1 or be lower than 0. This can be problematic when we want to use the estimated parameter to simulate employment trajectories of older workers (see below). We therefore also estimate a logit model that addresses this issue and check if our baseline results remain robust.

4.2 Results

Tables 2 to 4 summarise the estimation results based on three different indicators of exposure to technological change. For the sake of brevity, the tables only report estimated coefficients on UT_{it}, $Tech_{it}$ as well as their interaction (β_1, β_2 and β_3). Panel A displays the estimated coefficients when the outcome is an overall exit from employment, while Panel B, C, and D display the estimates that correspond to models where the outcome is inflow into unemployment, disability and inactivity, respectively. Column 1 corresponds to a parsimonious model that only includes age and year dummies. Columns 2 to 4 correspond to models that also include interactions of $Tech_{it}$ with age dummies. Models in the last two columns control for gender, marital status, education and the region of residence. The parameters in Columns 1 to 3 are estimated by linear probability models, whereas the parameters in Column 4 are marginal effects estimated by a logit model with the same set of regressors as in Column 3.[10] All the parameters are multiplied by 100, so that they can be interpreted as percentage changes in the underlying exit probabilities. These changes can be interpreted in relation to the annual average probability of exiting employment and flowing into unemployment, disability or inactivity at age 57 to 58 (also multiplied by 100) shown in the brackets on the top of each panel.

[10] See Appendix A for the details of the computation of these marginal effects.

Table 2. The effects of risk of automation and access to the unemployment tunnel

	(1)	(2)	(3)	(4)
Panel A. Overall exit rate (mean 6.83)				
UT	1.777***	1.754***	1.757***	1.726***
	(0.081)	(0.080)	(0.080)	(0.082)
Tech	1.115***	1.260***	0.887***	0.895***
	(0.017)	(0.088)	(0.089)	(0.095)
Tech x UT	1.132***	1.297***	1.336***	1.369***
	(0.039)	(0.088)	(0.088)	(0.104)
Panel B. Unemployment inflow (mean 4.48)				
UT	1.563***	1.489***	1.503***	1.236***
	(0.065)	(0.064)	(0.064)	(0.061)
Tech	0.706***	0.452***	0.312***	0.229***
	(0.014)	(0.073)	(0.073)	(0.066)
Tech x UT	0.460***	1.098***	1.109***	1.056***
	(0.027)	(0.073)	(0.073)	(0.075)
Panel C. Disability infow (mean 1.35)				
UT	0.199***	0.246***	0.246***	0.243***
	(0.036)	(0.035)	(0.035)	(0.043)
Tech	0.289***	0.574***	0.407***	0.530***
	(0.007)	(0.039)	(0.040)	(0.058)
Tech x UT	0.612***	0.216***	0.235***	0.107*
	(0.015)	(0.039)	(0.039)	(0.059)
Panel D. Inactivity inflow (mean 1.00)				
UT	0.016	0.020	0.009	0.126***
	(0.036)	(0.036)	(0.036)	(0.040)
Tech	0.120***	0.234***	0.167***	0.230***
	(0.007)	(0.034)	(0.035)	(0.047)
Tech x UT	0.060**	-0.017	-0.008	-0.028
	(0.026)	(0.033)	(0.033)	(0.050)
Tech x (Age - 58)		✓	✓	✓
Controls			✓	✓
Specification	LPM	LPM	LPM	Logit

Note: All models include age and year dummies. Models in Columns 2 to 4 also include interactions between $Tech_{it}$ and age dummies, using 58-years-old as a reference group. Models in Columns 3 and 4 control for gender, education, marital status and the region of residence. Column 4 reports marginal effects estimated by the logit model. All coefficients and marginal effects are multiplied by 100 so they can be interpreted as percentage points. The average probabilities of exit from employment and inflow into unemployment, disability and inactivity at age 57-58 are indicated in the brackets on the top of each panel. The number of worker-year observations for each model is 3,119,580. Standard errors are clustered at the individual level. ***, ** and * correspond to statistical significance at 1%, 5% and 10% level, respectively.

Source: Authors' calculation

Table 3. The effects of intensity of routine tasks and access to the unemployment tunnel

	(1)	(2)	(3)	(4)
Panel A. Overall exit rate (mean 6.83)				
UT	1.965***	1.970***	1.974***	1.920***
	(0.081)	(0.081)	(0.081)	(0.081)
Tech	0.744***	0.525***	0.134	0.121
	(0.017)	(0.087)	(0.087)	(0.079)
Tech x UT	1.311***	1.640***	1.670***	1.524***
	(0.039)	(0.087)	(0.087)	(0.088)
Panel B. Unemployment inflow (mean 4.48)				
UT	1.643***	1.668***	1.682***	1.367***
	(0.065)	(0.065)	(0.065)	(0.060)
Tech	0.441***	0.075	-0.098	-0.139**
	(0.014)	(0.071)	(0.071)	(0.054)
Tech x UT	0.653***	1.446***	1.454***	1.216***
	(0.027)	(0.072)	(0.072)	(0.064)
Panel C. Disability infow (mean 1.35)				
UT	0.293***	0.286***	0.287***	0.2661***
	(0.037)	(0.037)	(0.037)	(0.043)
Tech	0.216***	0.380***	0.214***	0.244***
	(0.007)	(0.040)	(0.040)	(0.045)
Tech x UT	0.453***	0.206***	0.218***	0.0930**
	(0.016)	(0.040)	(0.040)	(0.046)
Panel D. Inactivity inflow (mean 1.00)				
UT	0.028	0.015	0.005	0.119***
	(0.036)	(0.036)	(0.036)	(0.040)
Tech	0.086***	0.069**	0.017	0.052
	(0.007)	(0.034)	(0.035)	(0.042)
Tech x UT	0.205***	-0.012	-0.002	-0.014
	(0.024)	(0.032)	(0.032)	(0.044)
Tech x (Age - 58)		✓	✓	✓
Controls			✓	✓
Specification	LPM	LPM	LPM	Logit

Note: All models include age and year dummies. Models in Columns 2 to 4 also include interactions between $Tech_{it}$ and age dummies, using 58-years-old as a reference group. Models in Columns 3 and 4 control for gender, education, marital status and the region of residence. Column 4 reports marginal effects estimated by the logit model. All coefficients and marginal effects are multiplied by 100 so they can be interpreted as percentage points. The average probabilities of exit from employment and inflow into unemployment, disability and inactivity at age 57-58 are indicated in the brackets on the top of each panel. The number of worker-year observations for each model is 3,119,580. Standard errors are clustered at the individual level. ***, ** and * correspond to statistical significance at 1%, 5% and 10% level, respectively.

Source: Authors' calculation

Table 4. The effects of intensity of ICT skills and access to the unemployment tunnel

	(1)	(2)	(3)	(4)
Panel A. Overall exit rate (mean 6.83)				
UT	1.950***	1.951***	1.952***	1.913***
	(0.081)	(0.082)	(0.082)	(0.080)
Tech	-1.164***	-1.198***	-0.789***	-0.729***
	(0.017)	(0.084)	(0.084)	(0.070)
Tech x UT	-0.219***	-1.126***	-1.126***	-0.830***
	(0.038)	(0.084)	(0.084)	(0.072)
Panel B. Unemployment inflow (mean 4.48)				
UT	1.636***	1.656***	1.668***	1.431***
	(0.065)	(0.065)	(0.065)	(0.059)
Tech	-0.619***	-0.133**	0.071	0.080
	(0.014)	(0.067)	(0.067)	(0.058)
Tech x UT	-0.020	-0.882***	-0.881***	-0.640***
	(0.025)	(0.068)	(0.068)	(0.060)
Panel C. Disability infow (mean 1.35)				
UT	0.293***	0.282***	0.283***	0.249***
	(0.037)	(0.037)	(0.037)	(0.042)
Tech	-0.342***	-0.579***	-0.467***	-0.419***
	(0.007)	(0.039)	(0.039)	(0.026)
Tech x UT	-0.702***	-0.284***	-0.283***	-0.096***
	(0.016)	(0.039)	(0.039)	(0.026)
Panel D. Inactivity inflow (mean 1.00)				
UT	0.021	0.013	0.001	0.115***
	(0.036)	(0.036)	(0.036)	(0.039)
Tech	-0.203***	-0.486***	-0.392***	-0.371***
	(0.007)	(0.036)	(0.037)	(0.020)
Tech x UT	0.503***	0.040	0.038	0.032
	(0.025)	(0.035)	(0.035)	(0.030)
Tech x (Age - 58)		✓	✓	✓
Controls			✓	✓
Specification	LPM	LPM	LPM	Logit

Note: All models include age and year dummies. Models in Columns 2 to 4 also include interactions between $Tech_{it}$ and age dummies, using 58-years-old as a reference group. Models in Columns 3 and 4 control for gender, education, marital status and the region of residence. Column 4 reports marginal effects estimated by the logit model. All coefficients and marginal effects are multiplied by 100 so they can be interpreted as percentage points. The average probabilities of exit from employment and inflow into unemployment, disability and inactivity at age 57-58 are indicated in the brackets on the top of each panel. The number of worker-year observations for each model is 3,119,580. Standard errors are clustered at the individual level. ***, ** and * correspond to statistical significance at 1%, 5% and 10% level, respectively.

Source: Authors' calculation

Looking at the parsimonious model in Column 1, access to the unemployment tunnel increases the probability of an individual with average exposure to technological change exiting employment by 1.8 to 2.0 percentage points every year depending on the indicator of technological change (Tables 2 to 4, Panel A). This increase is almost entirely accounted by a higher risk of inflow into unemployment: access to the unemployment tunnel increases the probability of such an individual flowing from employment to unemployment by 1.5 to 1.6 percentage points (Panel B), while it increases the probability of inflow into disability benefits only marginally, by around 0.2 to 0.3 percentage point (Panel C). There is no evidence that access to the unemployment tunnel increases the risk of inflow into inactivity. Looking at Column 2 to 4, the sizes of these direct impacts of the unemployment tunnel are stable across different model specifications and indicators of exposure to technological change.

The estimated coefficient on $Tech_{it}$ in Column 1 of Table 2, Panel A, indicates that a risk of automation that is one standard deviation higher than the average increases the probability of an individual without access to the unemployment tunnel exiting employment by 1.1 percentage points every year. Similarly, a one standard deviation higher intensity in routine tasks increases the probability of exit by 0.7 percentage point (Table 3; Panel A), whereas a one standard deviation higher intensity of ICT skills decreases the exit probability by 1.2 percentage points (Table 4; Panel A). From panels B, C and D, more than a half of the increased probability of exit is through unemployment, while inflows into disability contribute about a quarter of the increase with inflows into inactivity contributing to an even smaller share.

The effect of technological change is magnified when an individual gains access to the unemployment tunnel. The coefficient on the interaction term in the Column 1 of Table 2, Panel A indicates that a one standard deviation higher risk of automation now increases the probability of exiting employment by 2.2 percentage points (the sum of β_1 and β_3). Similarly, a one standard deviation higher intensity of routine tasks increases the probability of exit by 2.1 percentage points (Table 3; Panel A; Column 1), while a standard deviation higher intensity of ICT skills decreases the exit probability by 1.4 (Table 4; Panel A; Column 1). Overall, the impact of higher exposure to technological change on exits from employment is nearly twice as large when an individual has access to the unemployment tunnel, confirming our conjecture that institutional pathways to early retirement reduce working lives in the face of technological change. It should also be noted that gaining access to the unemployment tunnel itself increases the probability of employment exit by 1.8 to 2 percentage points every year, as indicated by the estimate of β_2 in different model specifications. When incorporating this direct effect of the unemployment tunnel, the combined impact of technological change and the unemployment tunnel amounts to a 4-percentage point higher probability of exit. Since the average annual exit probability of an individual aged 57 or 58 without access to the unemployment tunnel is 5.1%, this implies an 80% increase in the probability of exit for them.

Comparing Columns 2 and 3 reveals that controlling for individuals' characteristics other than age reduces the coefficients on $Tech_{it}$, but has little effect on the coefficients of the interaction between $Tech_{it}$ and UT_{it}. For instance, a one standard deviation higher risk of automation would increase the exit probability by 0.9 percentage point in the augmented model (Table 2; Panel A; Column 3) instead of 1.3 percentage points in the parsimonious model (Column 2) for individuals without access to the unemployment tunnel but the impacts are similar between both models when they have access to unemployment tunnel (2.2 to 2.5 percentage points). This implies that among individuals with similar characteristics (for example, educational attainments), exposure to technological change becomes much more important when they can access the unemployment tunnel. This again underscores the significance of this institution in technology-induced early retirement.

Comparing Columns 3 and 4 shows that the estimates from the linear probability models are close to the marginal effects estimated from the corresponding logit models. The only exception is the effects of the unemployment tunnel on the inflow into inactivity, which are positive and significant in logit models whereas they do not significantly differ from zero in linear probability models (for example, see Table 2 Panel D). Overall, our findings are robust to different functional forms of the probability model.

The estimation results also depict an interesting early retirement strategy by older individuals exposed to technological change. When the unemployment tunnel is not available, individuals aged 58 change somewhat more their exits to disability than unemployment in response to the technological change. For instance, a one standard deviation higher risk of automation increases the disability inflow by some 0.4 to 0.6 percentage point, which is marginally larger than the increase in inflow into unemployment (the difference is not statistically significant – see Table 2; Panels B and C; Columns 2 to 4). However, a one standard deviation higher intensity in routine tasks increases the inflow into disability benefits by 0.2 to 0.4 percentage point, while not affecting the inflow into unemployment (Table 3; Panels B and C; Column 2 to 4). Also, the impact of higher intensity in ICT skills on inflow into unemployment is weak while that on inflow into disability is significant and non-negligible. These impacts of technological change on inflow into disability are substantial, given that the average probability of inflow into disability at ages 57 and 58 is only 1.4%.

When individuals can access the unemployment tunnel, the effects of technological change (the sum of β_2 and β_3) on inflows into unemployment are several times larger than those for disability benefits. Nevertheless, it is noteworthy that higher exposure to technological change increases the risk of inflow into disability significantly (up to threefold, depending on the model specification) when individuals can access the unemployment tunnel (Tables 2 to 4: Panel C). This is surprising as disability benefits are considered as an alternative pathway to early retirement (therefore a substitute) to the unemployment tunnel (see section 2). This evidence of strong positive spillovers from the unemployment tunnel to the disability inflow has not been reported by previous studies (such as Kyyrä, 2015; Kyyrä and Pesola, 2020).[11]

Table 5 reports additional estimation results for some subgroups. For the sake of brevity, we only show here the results for the overall exit rate. The estimation model corresponds that of the Column 2 of Table 2 to 4, which includes interactions between the exposure to digital technologies and age dummies, but not the controls. Columns 1 and 2 reveal that the interaction between higher exposure to digital technologies and access to the unemployment tunnel is a significant determinant of the exit from employment at old age for both male and female workers. However, its contribution seems weaker for women than for

[11] These previous studies covered earlier periods when individuals could access the unemployment tunnel under the age of 57. The chance of these relatively young cohorts in qualifying for disability benefits may have been small.

men, regardless of the measure of exposure to digital technologies used. When observed across educational attainments (Column 3 to 5), the coefficients on the interaction term between technological change and the unemployment tunnel are large and significant for older workers with basic and secondary education, who also see sizable increase in the probability of exiting employment when they access the unemployment tunnel. In contrast, older workers with tertiary education are less responsive to the unemployment tunnel and the coefficient on the interaction between technology and the unemployment tunnel is insignificant. Nevertheless, their exit is significantly driven by higher exposure to technological change. These results offer a new insight on the polarisation in the labour markets, where technological change is mainly blamed for the erosion of middle-skilled jobs (Goo et al., 2014). Our evidence suggests that labour market institutions may actually play an important role in loss of middle (and low) skilled jobs by promoting early exit from the labour market among the middle skilled workers highly exposed to technological change. While high skilled jobs are also subject to the technology-driven pressure, they are less frequently lost because high skilled workers respond less to the opportunities for early retirement.

Lastly, we separate our sample period into two periods and observe whether the role of technological change in driving old worker’s exit became more prominent in recent years (Column 6 and 7). Interestingly, the direct impact of higher exposure to digital technologies declined more recently, while the importance of the interaction with the unemployment tunnel increased.

Table 5. The effect of digital technologies and the unemployment tunnel on overall exit from employment

	Gender		Education			Time period	
	Female	Male	Basic	Secondary	Tertiary	2007-2014	2012-2017
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Risk of automation							
UT	1.672***	1.781***	1.651***	1.715***	0.693**	1.445***	1.513***
	(0.124)	(0.104)	(0.225)	(0.101)	(0.335)	(0.123)	(0.149)
Tech	1.366***	1.209***	0.365	1.148***	1.308***	1.908***	0.891***
	(0.155)	(0.108)	(0.257)	(0.117)	(0.327)	(0.162)	(0.112)
Tech x UT	0.783***	1.519***	1.882***	1.146***	0.293	0.753***	1.584***
	(0.153)	(0.108)	(0.247)	(0.117)	(0.333)	(0.141)	(0.178)
Panel B. Intensity of routine tasks							
UT	1.842***	2.041***	1.873***	1.923***	0.705*	1.581***	1.751***
	(0.128)	(0.106)	(0.203)	(0.102)	(0.374)	(0.125)	(0.152)
Tech	0.531***	0.535***	-0.451**	0.367***	0.825**	0.892***	0.338***
	(0.154)	(0.105)	(0.200)	(0.114)	(0.355)	(0.160)	(0.108)
Tech x UT	1.385***	1.719***	1.970***	1.612***	0.286	1.331***	1.464***
	(0.152)	(0.107)	(0.193)	(0.116)	(0.390)	(0.139)	(0.172)
Panel C. Intensity of ICT skills							
UT	1.823***	2.012***	2.148***	1.909***	0.371	1.568***	1.788***
	(0.130)	(0.105)	(0.201)	(0.101)	(0.461)	(0.126)	(0.154)
Tech	-0.824***	-1.408***	-0.633***	-1.093***	-1.173***	-1.575***	-0.998***
	(0.140)	(0.105)	(0.221)	(0.108)	(0.433)	(0.153)	(0.107)
Tech x UT	-0.924***	-1.180***	-1.360***	-0.913***	0.102	-0.809***	-0.899***
	(0.142)	(0.105)	(0.214)	(0.110)	(0.430)	(0.133)	(0.162)
Tech x (Age - 58)	✓	✓	✓	✓	✓	✓	✓
Controls							
Specification	LPM	LPM	LPM	LPM	LPM	LPM	LPM

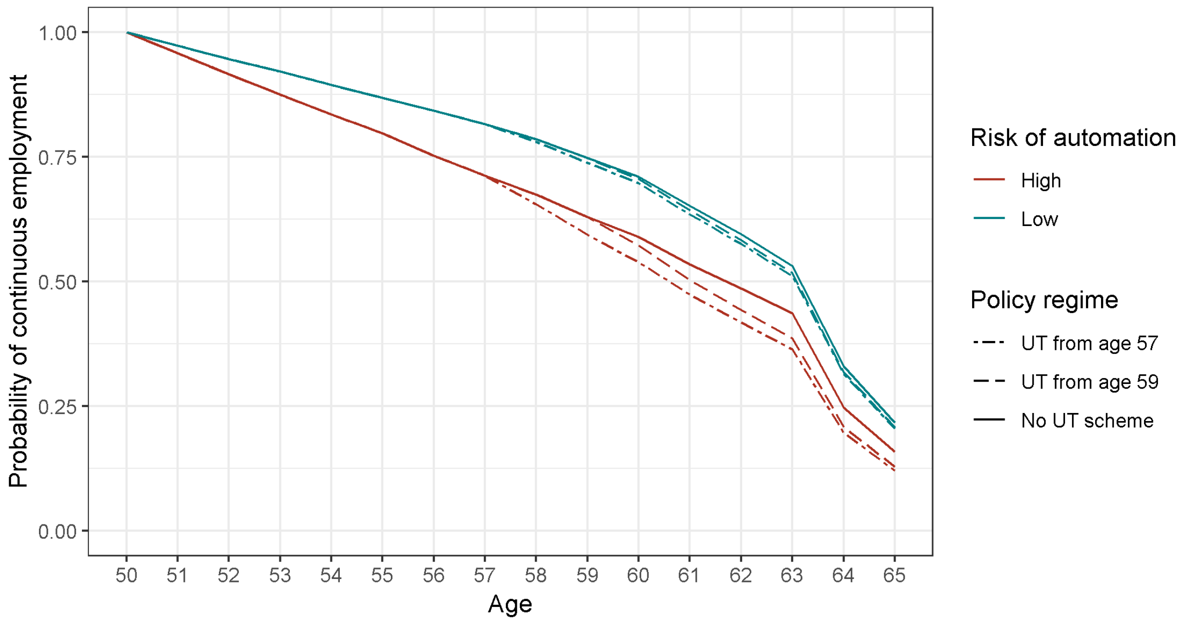
Note: All models include age and year dummies as well as interactions between $Tech_{it}$ and age dummies, using 58-years-old as a reference group. All coefficients are multiplied by 100 so they can be interpreted as percentage points. Standard errors are clustered at the individual level. ***, ** and * correspond to statistical significance at 1%, 5% and 10% level, respectively.

Source: Authors' calculation

4.3 Simulating the impacts of reforms in the unemployment tunnel

In order to illustrate the combined effect of higher exposure to technological change and access to the unemployment tunnel, we use the estimated parameters to simulate how employment of older workers responds to reforms in the unemployment tunnel. We consider three different reform scenarios: (i) the unemployment tunnel is made available earlier, at the age 57, as it was during 2012-2014; (ii) it is made available at age 59 as it is now, and (iii) extended unemployment benefit is abolished. For each scenario, we compute the average probability of remaining employed from age 50 onwards for two groups of older workers, one subject to higher than average automation risks and another subject to lower than average risks. Figure 8 plots the probabilities corresponding to each scenario and group using the parameter estimates from the linear probability model that controls for individuals' characteristics and includes interactions between the automation risks and age dummies (Table 2; Column 3).

Figure 8. The probability of remaining employed under different UT policies based on the linear probability model



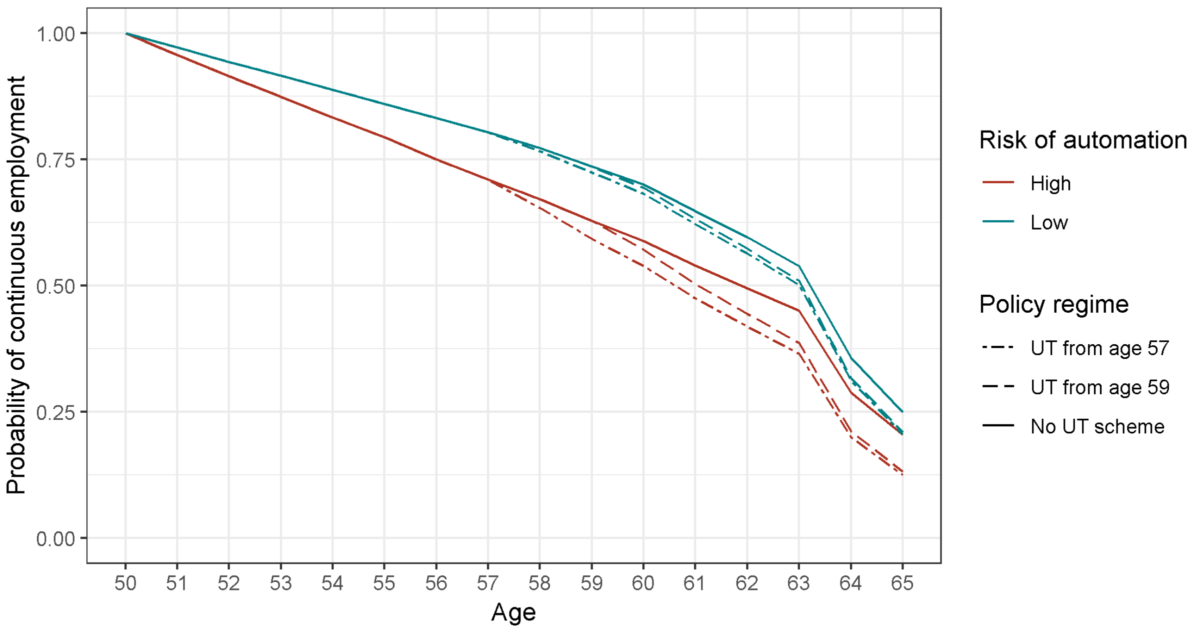
Note: Predicted probabilities are simulated using the estimated coefficients from the linear probability model in Column 3 of Table 2. See Appendix B for details.

Source: simulation by authors

Most notably, the probability of remaining employed declines markedly faster for older workers with high exposure to automation risks, resulting in a widening gap between the two groups. Furthermore, reforms in the unemployment tunnel significantly affect employment prospects of older workers exposed to high automation risks but not of those exposed to low automation risks. If the unemployment tunnel were available at age 57, older workers exposed to a high risk of automation would have a 16 percentage points lower probability of remaining employed at age 63 than those exposed to low automation risks. Raising the age at which the unemployment tunnel becomes available by two years narrows this gap in employment probability to 15 percentage points, while abolishing the unemployment tunnel altogether narrows the gap to 10 percentage points. These reductions in gaps are almost entirely driven by an increase in employment probability of older workers exposed to high automation risks. Simulations using the intensity of routine tasks or ICT skills instead of the risk of automation or based on models without controls or interaction between $Tech_{it}$ and age dummies produce similar results. They are available upon requests. The finding that the unemployment tunnel mainly reduces employment of older workers with high exposure to technological change is novel.

Simulation results are qualitatively similar when we replace the linear probability model with the logit model with the same set of regressors (Table 2, Column 4). The simulation based on the logit model generates larger gains in the probability of continuous employment when removing the unemployment tunnel than the simulation based on the linear probability model. The core finding that the unemployment tunnel mainly reduces employment of workers more exposed to technological change remains intact (Figure 9). Despite robustness to the functional forms of the probability function, the simulation results warrant some caution because they are based on the assumption that the effect of the unemployment tunnel on employment is constant from age 57 or 58 to 64. While the simulation based on the linear probability model imposes a constant additive effect on the exit probability, the one based on the logit model imposes a constant effect on the log-odds of the exit probability. While it is hard to say which assumption is more adequate, it is reassuring that both simulations produce qualitatively similar results.

Figure 9. The probability of remaining employed under different UT policies based on the logit model



Note: Predicted probabilities are simulated using the estimated coefficients from the logit model in the Column 4 of Table 2. See Appendix B for details.

Source: simulation by authors

5. Conclusion

This paper presents one of the first empirical evidence on the complementarity between exposures to new technologies, namely digital technologies, and pathways to early retirement, such as the extension of unemployment benefits reserved for older individuals, in reducing old age employment. Our hypothesis is that older individuals more exposed to technological change are more likely exit the labour market whenever they gain access to early retirement pathways than otherwise similar workers less exposed to technological change.

We find that an individual aged 50 or above in occupations that are more exposed to digital technologies has higher probability of exiting employment each year, and that this effect is magnified when this individual reaches the age when he can access the unemployment tunnel. For example, one standard deviation increase in the risk of automation from the average level is associated with 1.1 percentage points higher probability of an individual exiting employment, if he does not have access to the unemployment tunnel. However, the probability is 2.2 percentage points higher when the individual has access to the tunnel (Table 2; Panel A; Column 1). Furthermore, gaining access to the unemployment tunnel increases the exit probability of an individual exposed to an average level of risk of automation by 1.8 percentage points. All in all, the impacts of technological change and the early retirement pathway total to 4 percentage points, which implies a 80% increase in the probability of exiting employment for individuals aged 57-58. We then use these estimates to simulate the impact of reforms that tighten access to the unemployment tunnel and show that such reforms extend substantially the working lives of older workers exposed to high automation risks, but affect little those of individuals exposed to low automation risks.

This paper provides several implications for policy aimed at extending working lives. First, policies for preparing workers for the future of work, such as boosting lifelong learning opportunities, must go hand in hand with labour market reforms that remove disincentives for older workers to continue working. Otherwise, older workers will only have weak incentives to take up such training. There is even a risk that a prospect of easy access to early retirement pathways discourages younger cohorts of unskilled workers from investing in new skills. At the same time, labour market reforms often affect specific groups of workers disproportionally. This calls for complementary measures targeted at these groups to increase their employability. For instance, the recent policy decision to phase out the unemployment tunnel in Finland need to be coupled with a stronger employment service and highly tailored training programmes focused on workers with only compulsory education facing high automation risks. Lastly, it would be important to assess the impact of large economic contraction brought about by the COVID-19 pandemic on technology-induced early retirement, once sufficient data are available. While an extensive use of the temporary layoff scheme prevented mass unemployment in the wake of the economic contraction (OECD, 2020), the preliminary observation based on high-frequency data (section 3) suggests that exposure to new technologies and access to early retirement pathways played a non-negligible role in the layoffs of older workers. It is important that the scheme does not act as a fast track to early retirement by older workers with jobs that are not particularly vulnerable to the lockdown measures during the pandemic but relatively exposed to technological change.

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Appendix

A. Marginal effects for the logit model

The marginal effect of access to the unemployment tunnel (*UT*) is computed as

$$\frac{1}{N}\sum_{i=1}^{N}[P(UT = 1, Age = 58, Tech = 0, X_i) - P(UT = 0, Age = 58, Tech = 0, X_i)],$$

where $P(\cdot)$ is the probability of exiting employment as a function of *UT*, *Tech* and background characteristics, *N* is the total number of individuals in the sample, and X_i is a vector of background characteristics other than age for individual *i* (measured at the first year of observation). The term inside the square brackets is the change in the exit probability due to access to the unemployment tunnel by an individual *i* who is 58 years old and exposed to an average level of automation risks (therefore *Tech* = 0 due to the standardisation of the indicators of exposure to technological change). The marginal effect is obtained as an average of the individual-specific effects of *UT*.

The marginal effect of *Tech* is computed in a similar way but now setting *UT* to 0 and manipulating the value of *Tech*:

$$\frac{1}{N}\sum_{i=1}^{N}[P(UT = 0, Age = 58, Tech = 1, X_i) - P(UT = 0, Age = 58, Tech = 0, X_i)].$$

Finally, the marginal effect of the interaction between *UT* and *Tech* is computed as the following:

$$\frac{1}{N}\sum_{i=1}^{N}[P(UT = 1, Age = 58, Tech = 1, X_i) - P(UT = 0, Age = 58, Tech = 1, X_i)] \\ - \frac{1}{N}\sum_{i=1}^{N}[P(UT = 1, Age = 58, Tech = 0, X_i) \\ - P(UT = 0, Age = 58, Tech = 0, X_i)]$$

B. Simulating the probability of continuous employment

The average probability of remaining employed from the age of 50 up to age *K* for individuals who are exposed to a lower than average automation risks is computed as

$$S^0(K) = \frac{1}{N_0}\sum_{i|Tech<0}^{N_0}\prod_{k=50}^{K-1}[1 - P(UT(k), Age = k, Tech_i, X_i)]$$

Where $P(\cdot)$ is the probability of exit from employment at age *k*. $UT(k)$ is a dummy for having access to the unemployment tunnel at age *k*, which depends on the simulated policy scenario. The sum is taken over all individuals in occupations that are exposed to a lower than average level of automation risks. The variables *Tech* and X_i are held fixed at their first year values. The probability of continuous employment is computed in the same way for those who are exposed to a higher than average level of digital technologies.