Technology, Labour Market Institutions and Early Retirement

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MOTIVATION

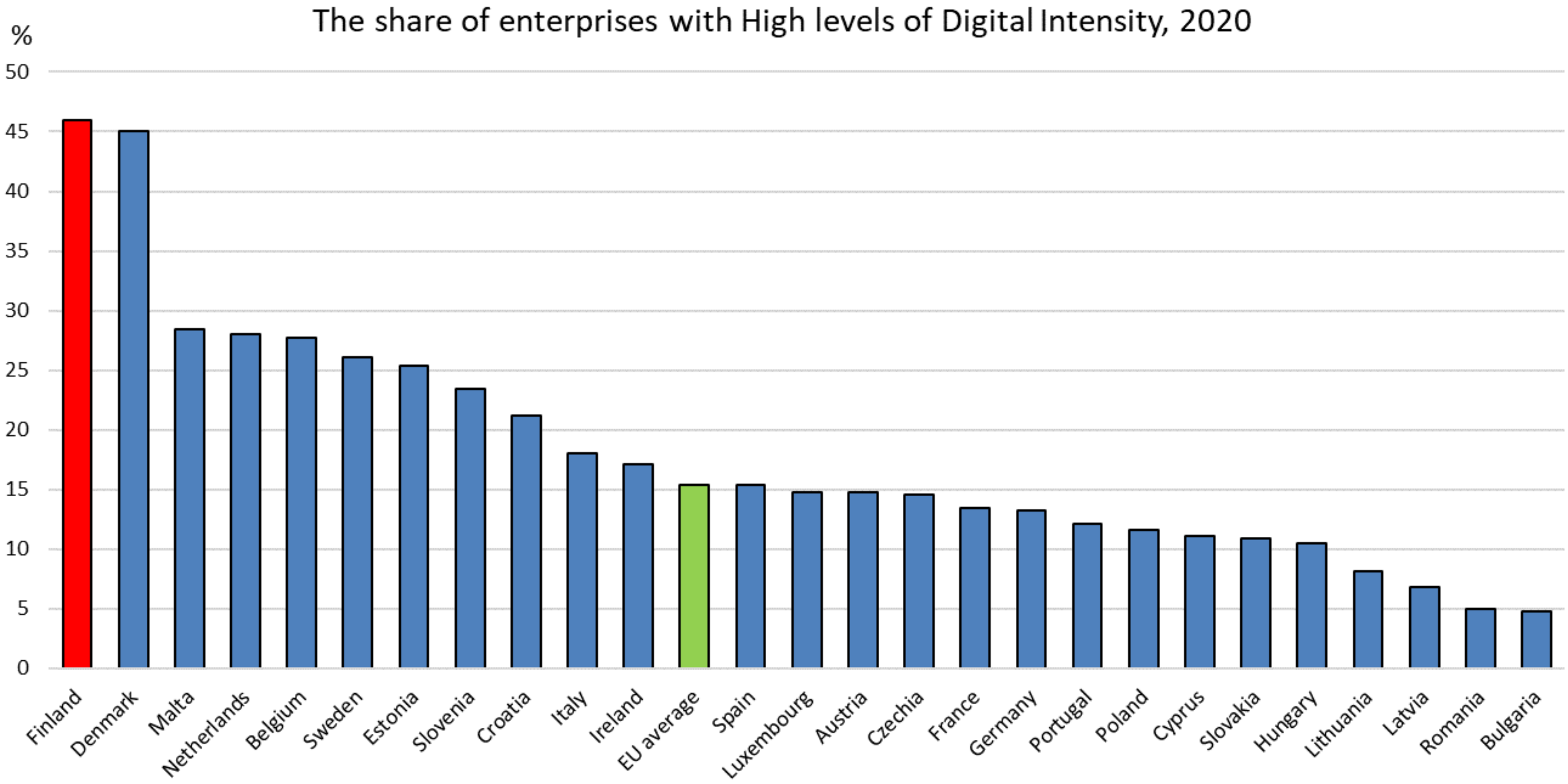
- Population ageing poses a formidable challenge to fiscal sustainability and economic growth.
- Promoting longer working lives is essential for mitigating fiscal pressures and alleviate labour shortages.
- Two important barriers to increasing employment of older workers.

1. **Technological changes**: skilled-biased technological changes displace workers engaged in codifiable, routine tasks. Old workers are more prone to such risks than younger workers as they have weaker incentives to update skills.
2. **Labour market institutions**: generous entitlements to unemployment benefits and/or looser criteria in granting disability benefits applied to older workers as well as early old age pension schemes encourage early retirement.

IN A NUTSHELL

- This paper explores how *technological changes* (digital technologies) interacts with an institutional pathway to early retirement (*the unemployment tunnel*) to push older workers out of employment.
- We match Finland's large employee-employer data with occupational-level indicators constructed by the OECD that capture exposure to digital technologies.
- We estimate the probability of an older individual exiting employment as a function of exposure to digital technologies, access to the unemployment tunnel and their interactions.
- We find that while higher exposure to digital technologies is associated with a higher risk of exiting employment, such risk is significantly magnified when the individual gains access to the unemployment tunnel: the combined effects of technological change and access to the unemployment tunnel amount to an 80% increase in the risk of exiting employment at age 57-58.
- Policy implication: reforms that tighten access to early retirement pathways are essential in ensuring inclusiveness of older workers in the future of work.

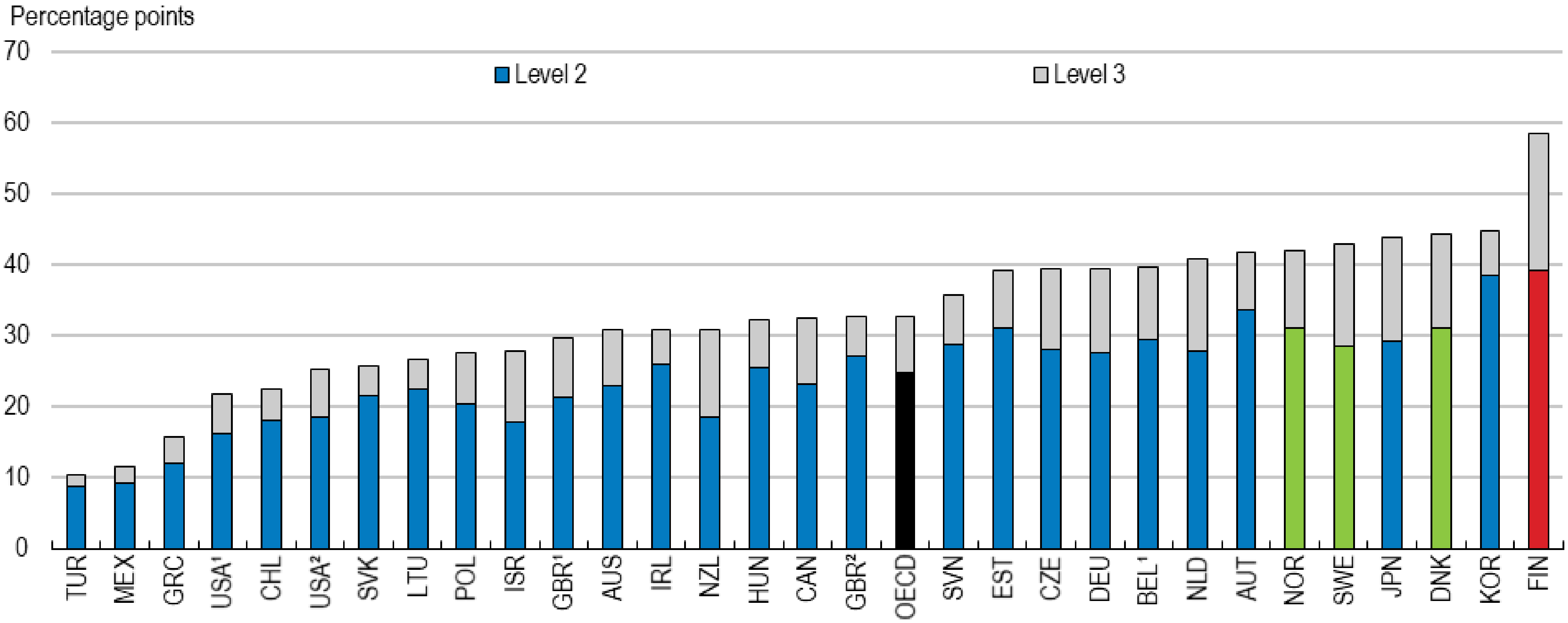
FINLAND IS THE FRONT RUNNER IN ADOPTION OF DIGITAL TECHNOLOGIES



Note: The Digital Intensity score is based on counting how many out of 12 technologies are used by each enterprise. High levels are attributed to those enterprises using at least 7 of the following 12 digital technologies: usage of internet by a majority of the workers; access to ICT specialist skills; fixed broadband speed > 30 Mbps; mobile devices used by more than 20% of employed persons; has a website; has some sophisticated functions on the website; presence on social media; does e-sales for at least 1% of turnover; exploit the B2C opportunities of web sales; pay to advertise on the internet; purchase cloud computing advanced services; send eInvoices.
Source: European Commission, Digital Scoreboard

INTER-GENERATIONAL GAPS IN DIGITAL SKILLS IS LARGE

Difference in Technological skills[1] between the youngest (25-34 year-olds) and oldest (55-65 year-olds) adults



Note: 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. Data for Belgium[1] correspond to Flanders, data for United Kingdom[1] correspond to England, data for United Kingdom[2] correspond to Northern Ireland, data for United States[1] correspond to data from 2012/2014 survey and data for United States[2] correspond to 2017.
Source: OECD Survey of Adult Skills (PIAAC) (2012, 2015, 2018).

THE UNEMPLOYMENT TUNNEL (UT) IN FINLAND

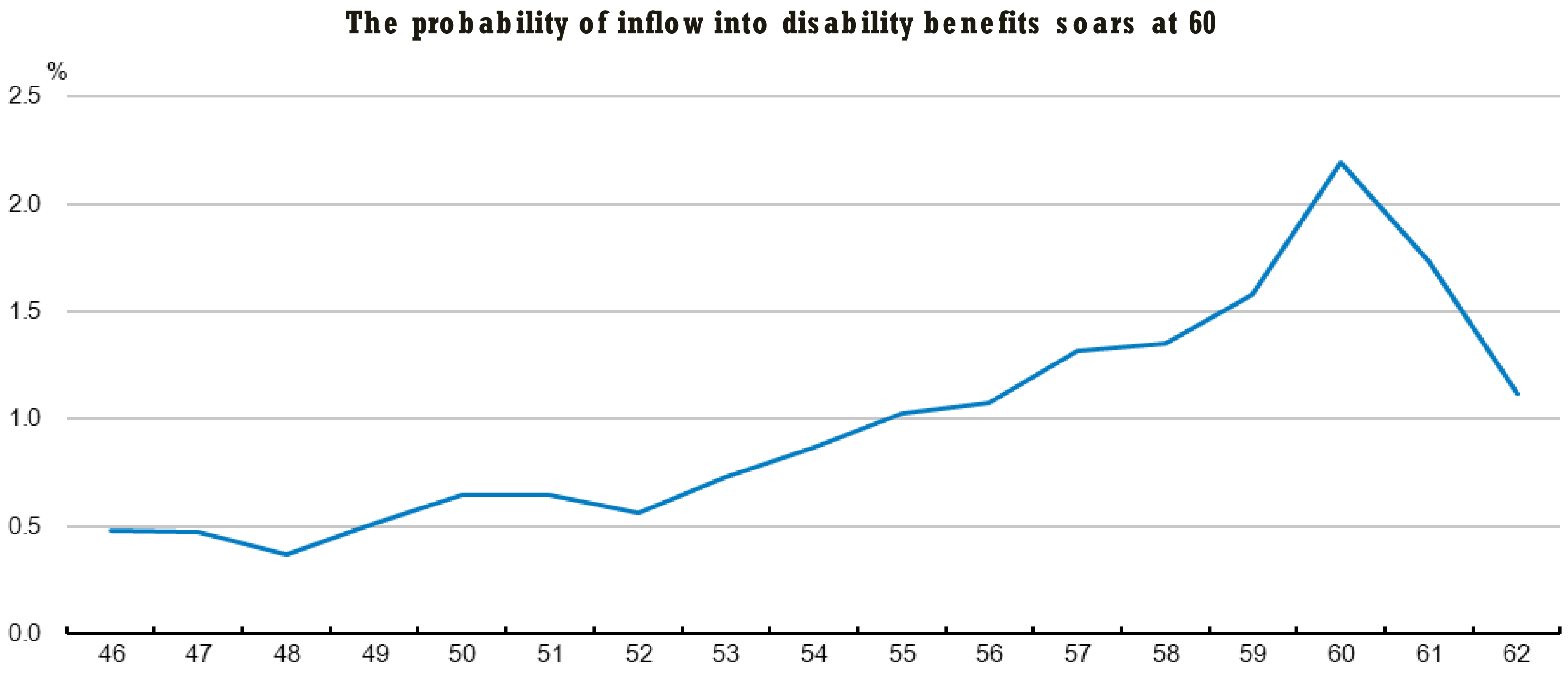
- UT is defined here as the combination of:
  - Longer entitlement to the unemployment benefit reserved for workers aged 58 or more (500 working days instead of 300 to 400 days for younger workers)
  - The extension of unemployment benefit until 65 (or when the individual starts drawing early old age pension) for unemployed aged 61 or more (62 from 2023).

- The individual can thus access UT about 2 years before the eligibility age for the extension of unemployment benefit.

THE UNEMPLOYMENT TUNNEL ENCOURAGES THE EXIT FROM EMPLOYMENT

Note: The unemployment tunnel is defined here as the sum of 500 work days entitlement to the unemployment benefit and the extension of the unemployment benefit until up to the age of 65.
Source: computation by the authors.

THOSE AGED 60 AND OVER ENJOY MORE LENIENT CRITERIA FOR DISABILITY BENEFITS



Source: Ministry of Social Affairs and Health and Ministry of Finance (2019) Ikääntyneiden työllisyyden edistämiskeinoja valmistelevan työryhmän loppuraportti.

CONCEPTUAL FRAMEWORK: TECHNOLOGY-INDUCED EARLY RETIREMENT

- Skill-biased technological changes displace some workers but increase jobs that can capitalise on new technologies and the demand for workers with skills to perform such jobs.
- However, older workers are less likely to seize such job opportunities because:
  - They have smaller incentives to acquire new skills due to their shorter remaining careers (Ahituv and Zeira, 2011; Saint-Paul, 2009).
  - Older workers with less recent vintages of skills are exposed to the risk of skills obsolescence (Friedberg, 2003; Allen and De Grip, 2011).
- Older workers may thus respond to radical technological change by retiring early instead of investing in new skills (Ahituv and Zeira, 2011; Hægeland et al., 2007).
- However, technological change boosts productivity and thus wage levels, encouraging older workers to remain in their jobs (Ahituv and Zeira, 2011; Burlon and Vilata-Bufí, 2016).
- The net impact of technological changes on early retirement is thus *a priori* ambiguous.

INSTITUTIONAL PATHWAYS TO EARLY RETIREMENTCAN TILT THE EFFECTS OF TECHNOLOGICAL CHANGE IN FAVOUR OF EARLY RETIREMENT

- Rich evidence on the role of the unemployment tunnel as an early retirement pathway. (Kyyrä, 2015; Kyyrä and Pesola, 2020, Tuit and van Ours, 2010)
- Disability benefits as well (Autor and Duggan, 2006; Korkeamäki and Kyyrä, 2012)

Hypothesis:

- Older workers that are more exposed to technological change are more likely to retire early when they have access to early retirement pathways.
- Alternatively: older workers who have access to early retirement pathways are more likely to use it, when they are more exposed to technological changes

DATA: FINNISH EMPLOYEE-EMPLOYER (FOLK) DATASET

- Panel data covering all persons belonging to the population in Finland since 1987 (approximately 5 million individuals/year).
- Contains a wide range of information on individuals' demographic and socioeconomic characteristics including education, income, employment status, as well as occupation and the industry of employment.
  - Allows tracking each individual's 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.
  - We require that they were employed in the same firm over the past two years.
  - We exclude the self-employed from our sample.
- The resulting sample contains 661,821 individuals and over 3.1 million individual-year observations.
- We match this dataset with the indicators on exposure to digital technologies constructed by the OECD.

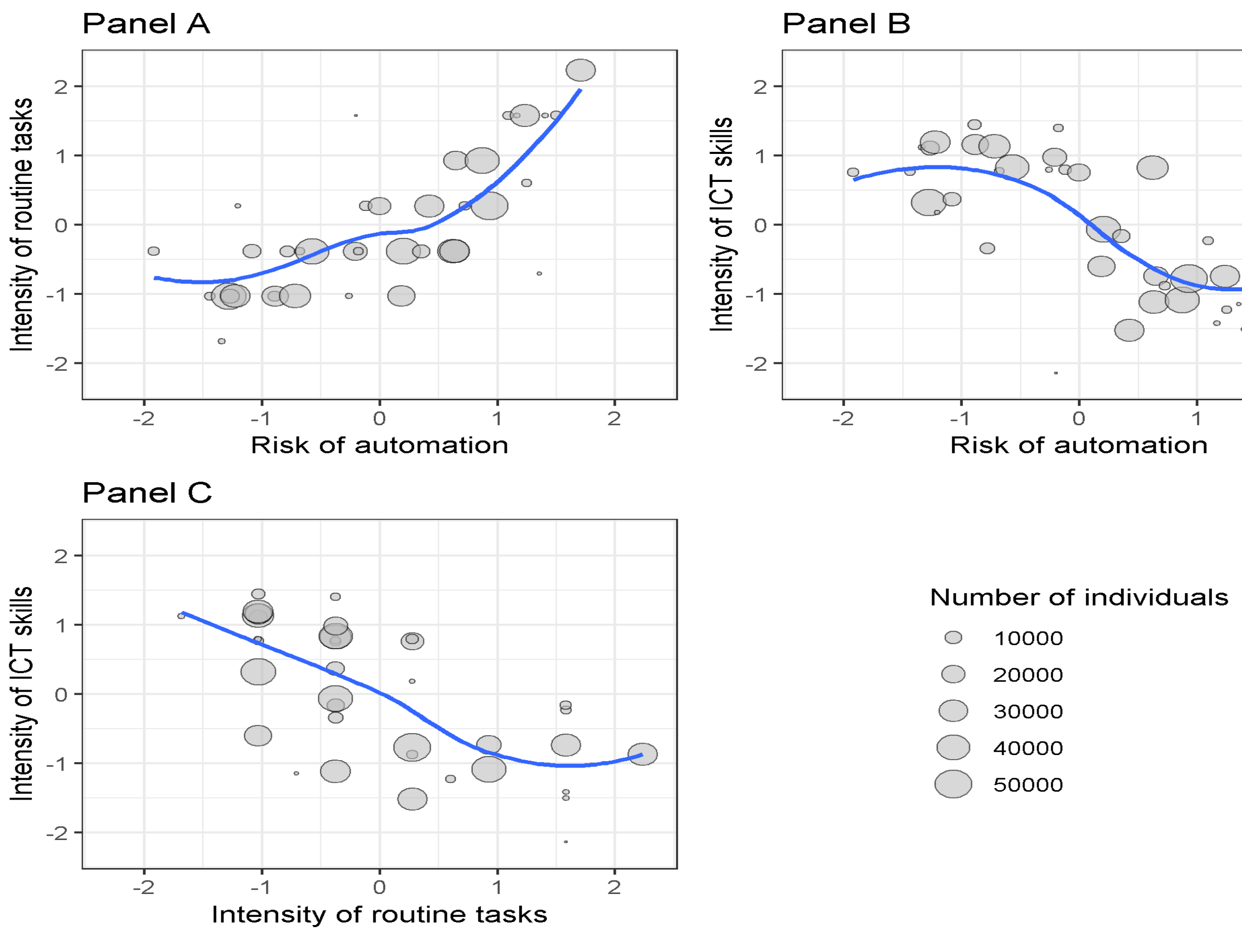
OECD DATA ON EXPOSURE TO DIGITAL TECHNOLOGIES

- Occupational-level indicators constructed based on individual-level data from the OECD Survey of Adult Skills (PIAAC).

1. **Automation risks** (Nedelkoska and Quintini, 2018): applied the approach by Frey and Osborne (2013) on individual-level data from PIAAC. 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.
2. **The intensity of routine tasks** (Marcolin et al., 2016): an index constructed from the weighted average of answers to questions in PIAAC capturing the extent to which an individual's job is codifiable and sequentiable (for example: "To what extent can you choose or change the sequence of your tasks?" or "How often does your current job involve planning your own activities?").
3. **The intensity of ICT skills use** (Grundke et al., 2017) : an index summarising the answers to PIAAC questions on the frequency of tasks associated with ICT use presumably requiring ICT skills, from reading and writing emails to using word-processing or spreadsheet software, or a programming language.

THREE INDICATORS ARE CORRELATED BUT IN COMPLEX WAYS

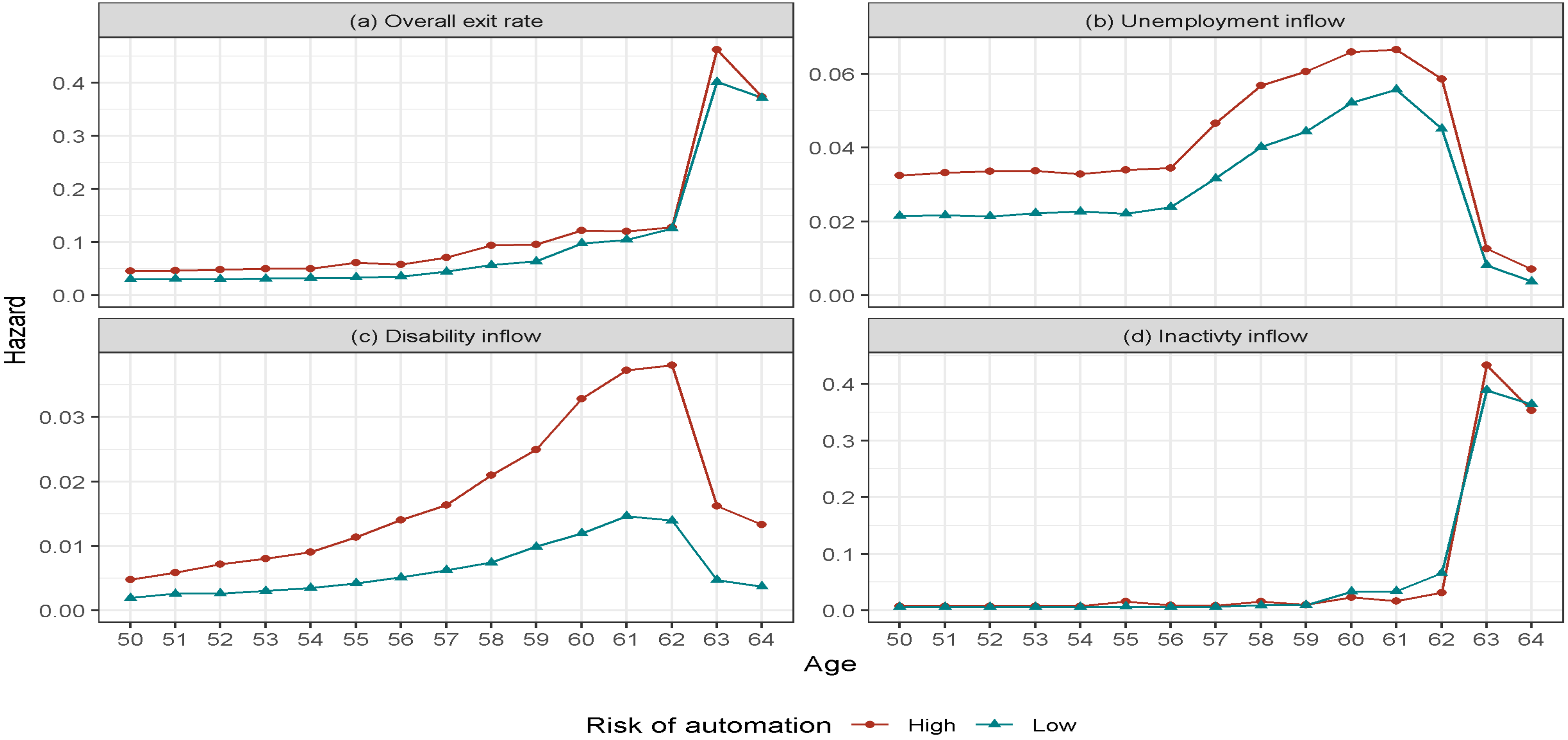
The correlation between indicators for individuals between the ages of 50 and 64 who were employed in the private sector in the years 2007-2017



THE RISKS OF INFLOW INTO UNEMPLOYMENT AND DISABILITY BENEFITS ARE HIGHER FOR OLDER WORKERS MORE EXPOSED TO DIGITAL TECHNOLOGIES

The incidence of exit from employment by risk of automation

Average hazard rate, 2007-2017



Note: High risk of automation corresponds to occupations with higher than the average level of automation risks

EMPIRICAL STRATEGY

- Identify the impact of the unemployment tunnel by exploiting past reforms that pushed back the eligibility age for the extension of unemployed benefit.
  - People of same ages who were born in different years face exogenous variation in eligibility to the UT.
  - This allows us to identify the impact of the UT while including a full set of age and year fixed effects.

- We focus on the unemployment tunnel (UT) as we do not have the episode of the disability benefit reform in our sample period.

A LINEAR PROBABILITY MODEL

- We estimate the following model:

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

The dependent variable: the probability of exit from employment by individual *i* in an occupation *o* who is *k* years old at the end of year *t* after having been employed by the same employer in the last two years.

$\boldsymbol{Tech_{ot}}$: the standardised value of the indicator of exposure to digital technologies for occupation *o*

$\boldsymbol{UT_{ikt}}$: a dummy variable indicating individual *i*'s access to the unemployment tunnel in period *t*.

$\boldsymbol{X_{it}}$: a vector of control variables (age dummies, gender, educational attainment, marital status, area of residence, and year dummies)

- The coefficient β_1 on $Tech_{ot}$ captures the impact of one standard deviation higher exposure to digital technologies for individuals <u>*who do not have access to the unemployment tunnel*</u>.
- The coefficient β_2 on UT_{ikt} capture the effect of being eligible to the unemployment tunnel for individuals <u>*with an average exposure to technological change*</u>.
- The effect of one s.d. higher exposure to digital technologies on <u>individuals with access to the unemployment tunnel</u> is $\beta_1 + \beta_3$
- <u>The overall combined effects of technological change and the unemployment tunnel</u> are $\beta_1 + \beta_2 + \beta_3$

ISSUES IN EMPIRICAL ANALYSIS

- The occupation-level measures of exposure to digital technology do not have exogenous variation.
  - The relation between exposure to digital technologies and early retirement cannot be interpreted as causal.
  - The older workers in occupation more exposed to digital technologies can be more prone to retire early than those less exposed.
- The effect of higher exposure to digital technologies on exit rate may vary by age.
  - Add interactions between $Tech_{ot}$ and age dummies (to control for age-specific response by older workers to technological changes that are unrelated to UT).

ADDITIONAL ANALYSIS

- Aside the estimation of the probability of exiting employment, we also estimate the probabilities of inflow into unemployment, disability benefits and inactivity.
- Robustness analysis
  - Testing for "parallel trend" assumption: the exit rates of different age groups would have followed the same pattern in the absence of the UT.
  - Excluding the older groups who are always eligible for the UT from the comparison group to the 57- and 58-year-olds whose eligibility status changes due to the reforms
  - Logit model estimation
- Simulate the impact of reforms that tighten the access to UT on the probability of employment at old age, using the estimated coefficients
  - Observe the shifts in probability of remaining employed from the age 50 to 65.

RESULTS: AUTOMATION RISKS

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

SELECTED RESULTS WITH DIFFERENT INDICATORS

	(1)	(2)	(3)
Indicator of tech	**Risk of automation**	**Intensity in routine tasks**	**Intensity in ICT skills**
Outcome: Overall exit from employment			
Access to UT	1.757***	1.974***	1.952***
	(0.080)	(0.081)	(0.082)
Tech	0.887***	0.134	-0.789***
	(0.089)	(0.087)	(0.084)
Tech x UT	1.336***	1.670***	-1.126***
	(0.088)	(0.087)	(0.084)
Outcome: Inflow into unemployment			
Access to UT	1.503***	1.682***	1.668***
	(0.064)	(0.065)	(0.065)
Tech	0.312***	-0.098	0.071
	(0.073)	(0.071)	(0.067)
Tech x UT	1.109***	1.454***	-0.881***
	(0.073)	(0.072)	(0.068)
Tech x (Age - 58)	✓	✓	✓
Controls	✓	✓	✓
Specification	LPM	LPM	LPM

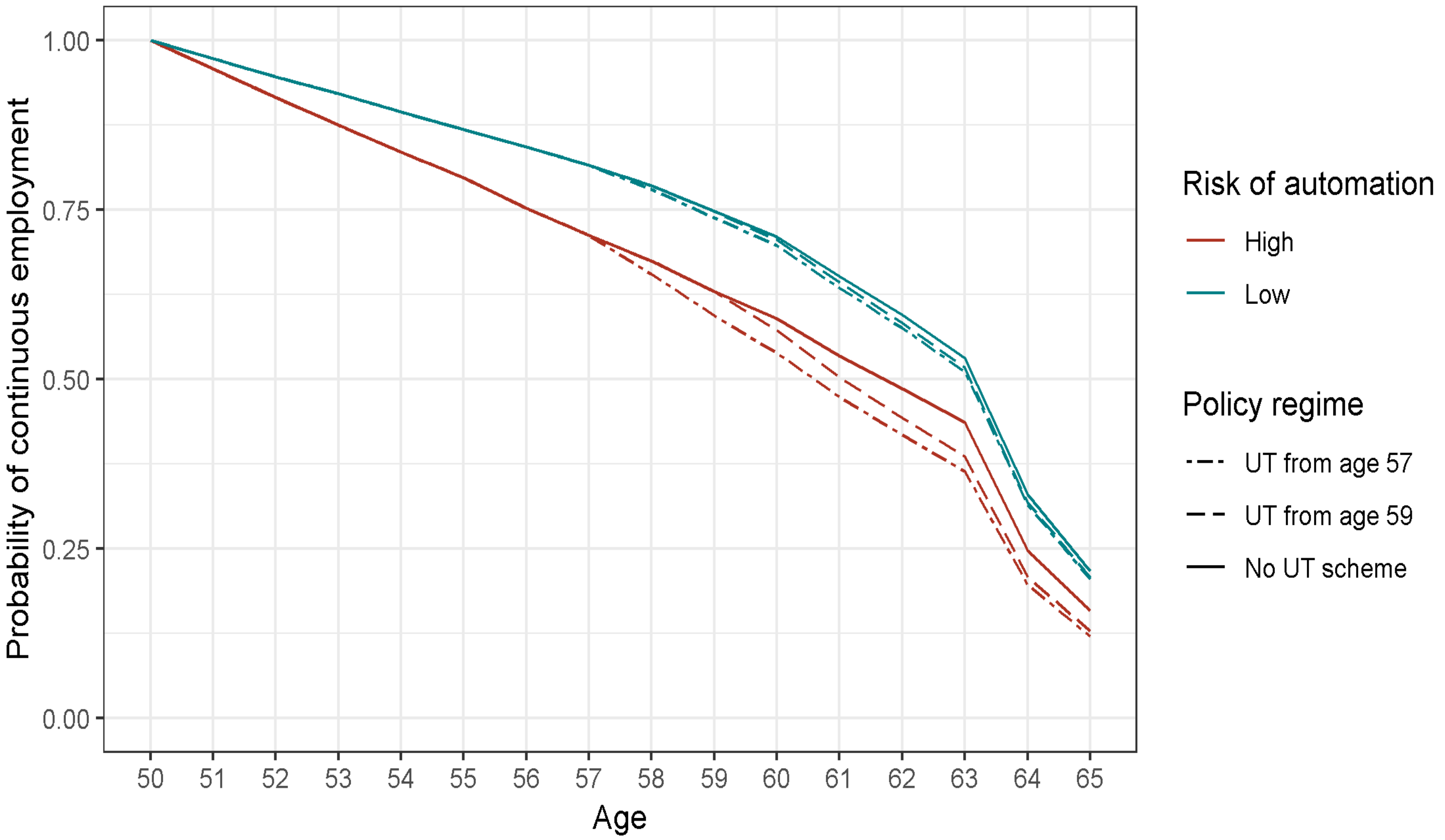
Note: All models include age and year dummies and control for gender, education, marital status and the region of residence. All coefficients and marginal effects are multiplied by 100 so they can be interpreted as percentage points. The average probabilities of exit from employment and inflow into unemployment, 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. *** corresponds to statistical significance at 1%.

SUMMARY OF ESTIMATION RESULTS

- **Evidence of technology-induced early retirement**: a standard deviation higher (lower) than the average automation risk (intensity in ICT skills) is associated with a little less than 1 percentage point higher yearly probability of an older worker exiting employment.
- **UT significantly enhances technology-induced retirement**: higher automation risks is associated with about 2 percentage points higher risk of outflow when older workers gain access to UT. Higher intensity in routine tasks is significantly associated with lower old age employment only when workers have access to UT.
- **The combined impacts of technological changes and UT are sizable**: since access to UT increases the exit probability of an older worker exposed to an average level of automation risks by 2 percentage points, the overall impacts amount to a 4ppts higher yearly probability of exiting employment (80% higher risk for workers aged 57-58).
- **The pathways of tech-induced early retirement**: inflow into disability benefits explains a quarter to a half of exit from employment by older workers with high exposure to digital technologies that do not have access to UT.

TIGHTENING ACCESS TO UT INCREASES MOSTLY THE EMPLOYMENT OF OLDER WORKERS EXPOSED TO HIGH AUTOMATION RISK

Probability a worker employed at age 50 being continuously employed



CONCLUSION

1. **Closing pathways to early retirement** is possibly the most important policy to increase old age employment under rapid technological changes. Older workers would have limited incentives to take up lifelong learning opportunities if labour market institutions that facilitate early retirement remain.
2. In December 2020, Finland decided to phase out the extension of unemployment benefits by 2025. This reform affects disproportionally specific types of older workers (low- to mid skilled male workers with higher exposure to technological changes). **Targeted training and job placement measures** will be needed to increase their employability.
3. High skilled workers are less responsive to UT. Policy efforts to **raise tertiary educational attainment** may go a long way to reduce technology-induced early retirement.
4. It would be important to evaluate the impacts of the large economic contraction during the COVID-19 pandemic on technology-induced early retirement.

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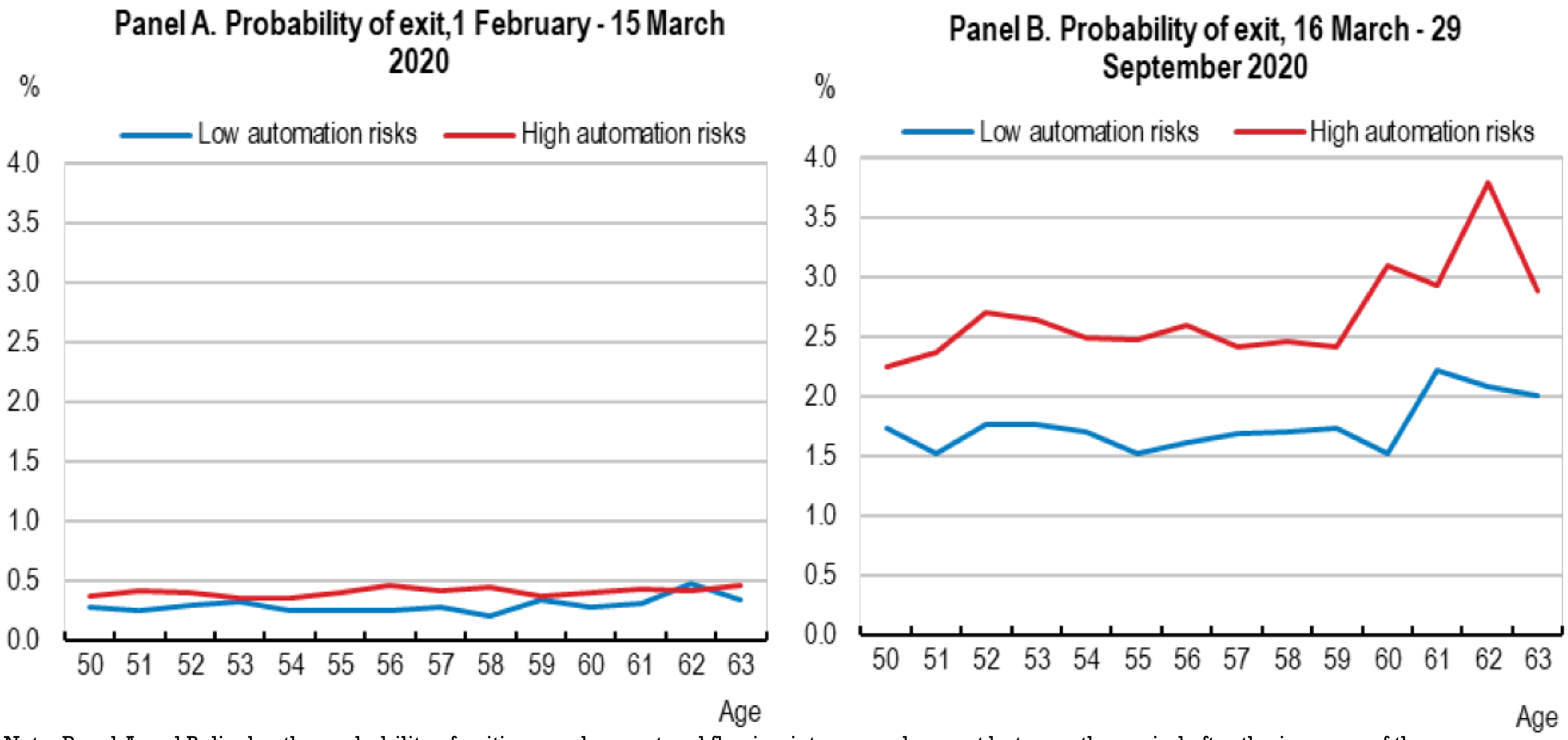
APPENDIX:
DID COVID-19 ACCELERATE TECHNOLOGY-INDUCED EARLY RETIREMENT?

HIGH FREQUENCY DATA

- Finland declared a State of Emergency on 16 March 2020 and activated confinement measures in the following days, including recommending that non-essential businesses close.
- The temporary layoff scheme, deployed extensively after 16 March, 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 monitored the inflow of Finnish workers into unemployment (including both temporarily and permanently layoffs) using high frequency (weekly) data from the public employment offices.
- We exploited these data for a preliminary observation on the relation between exposure to technological change and layoffs of older individuals.
- An important caveat is that some of the laid off individuals were furloughed and thus may had returned to their work.

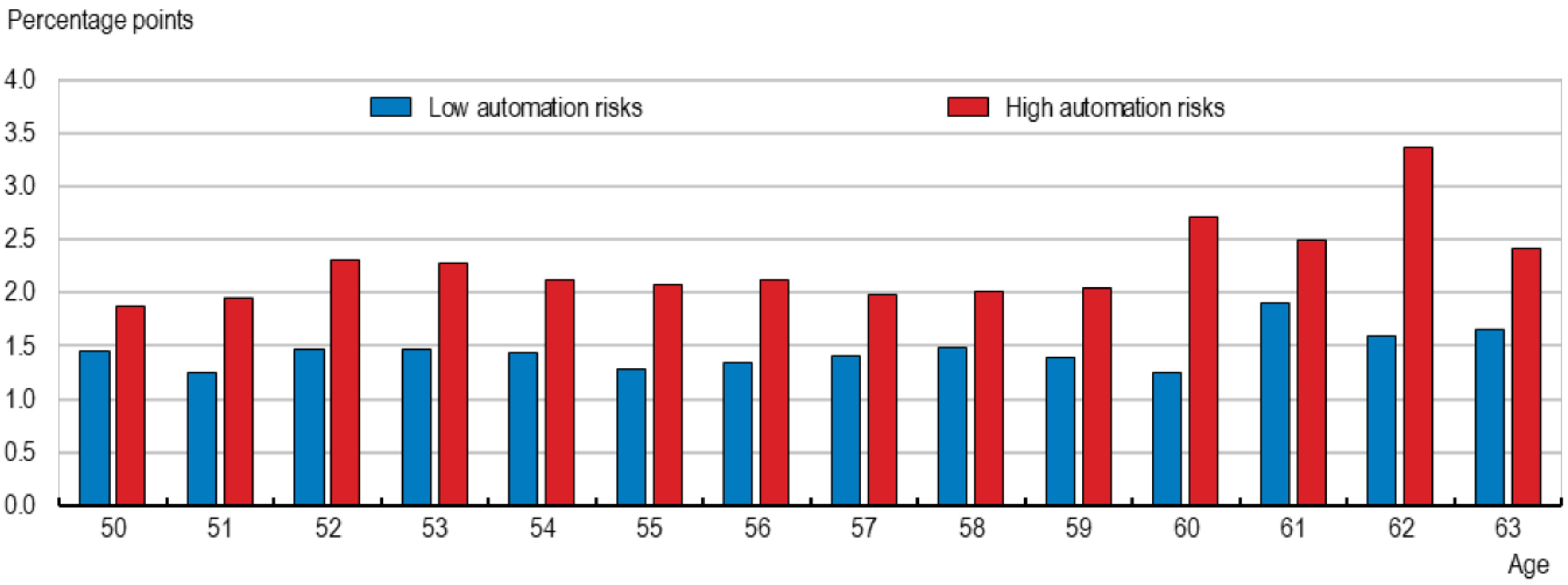
THE PROBABILITY OF EXITING EMPLOYMENT WAS HIGHER FOR OLDER WORKERS EXPOSED TO HIGHER AUTOMATION RISKS, ESPECIALLY AFTER THE LOCKDOWN



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.
Source: Helsinki Graduate School of Economics Situation Room; authors' computations.

THE PROBABILITY OF EXITING EMPLOYMENT INCREASED MORE FOR OLDER WORKERS EXPOSED TO HIGHER AUTOMATION RISKS AFTER THE LOCKDOWN

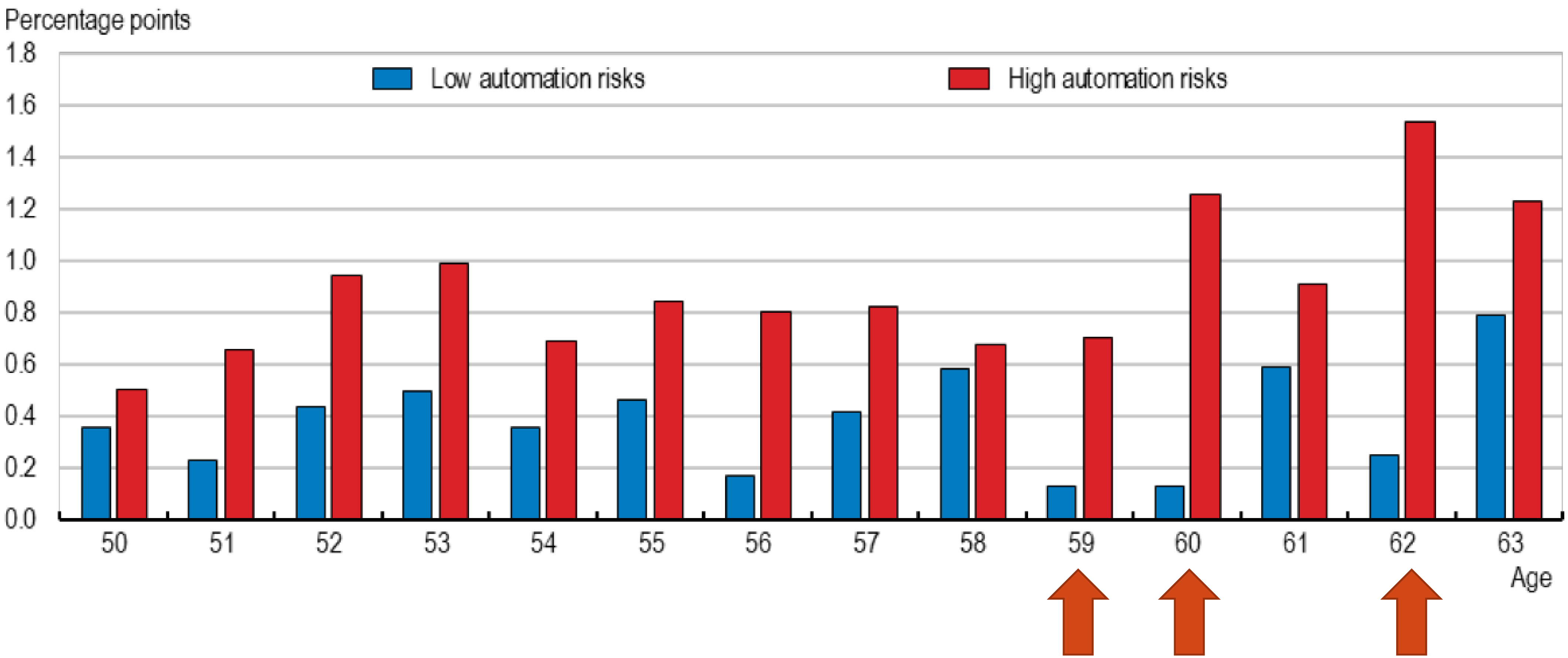
Difference in the probability of exiting employment, before and after 16 March 2020



Source: Helsinki Graduate School of Economics Situation Room; authors' computations.

ESPECIALLY WHEN CONTROLLED FOR POTENTIAL SEASONALITY

Difference in the probability of exiting employment, before and after 16 March 2020 (first differentiated against the 2019 level)



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.

Thank you!/Kiitos Paljon!

Additional slides

RESULTS: INTENSITY OF ROUTINE TASKS

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

RESULTS: INTENSITY OF ICT SKILLS

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

	Gender		Education			Time period		Industry	
	Female	Male	Basic	Secondary	Tertiary	2007–14	2012–17	Manuf.	Non-manuf.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Risk of automation									
UT	1.918***	2.151***	2.120***	1.959***	0.356	1.759***	1.548***	3.456***	1.274***
	(0.395)	(0.339)	(0.658)	(0.380)	(0.497)	(0.343)	(0.254)	(0.578)	(0.217)
Tech	1.369***	1.209***	0.350	1.138***	1.429***	1.934***	0.890***	0.831***	1.896***
	(0.275)	(0.417)	(0.529)	(0.312)	(0.369)	(0.434)	(0.314)	(0.261)	(0.594)
Tech × UT	0.550	1.464**	1.699	1.039	−0.799	0.625	1.586***	1.706**	−0.203
	(0.982)	(0.592)	(1.029)	(0.801)	(0.719)	(0.735)	(0.487)	(0.788)	(0.684)
Panel B. Intensity of routine tasks									
UT	2.006***	2.392***	2.367***	2.130***	0.299	1.843***	1.793***	3.505***	1.221***
	(0.332)	(0.310)	(0.390)	(0.297)	(0.593)	(0.292)	(0.284)	(0.483)	(0.192)
Tech	0.573**	0.537	−0.443	0.391	0.964**	0.938**	0.337	0.455*	0.989
	(0.279)	(0.487)	(0.571)	(0.332)	(0.413)	(0.435)	(0.350)	(0.252)	(0.728)
Tech × UT	0.759	1.704***	1.649**	1.314**	−0.852	1.050*	1.465***	1.816**	−0.298
	(0.745)	(0.574)	(0.752)	(0.653)	(0.724)	(0.614)	(0.557)	(0.722)	(0.505)
Panel C. Intensity of ICT skills									
UT	2.162***	2.390***	2.450***	2.182***	1.287	1.894***	1.834***	3.931***	1.336***
	(0.367)	(0.354)	(0.473)	(0.325)	(0.961)	(0.315)	(0.329)	(0.566)	(0.213)
Tech	−0.779***	−1.392***	−0.627	−1.049***	−1.154**	−1.524***	−0.997***	−0.670***	−1.475***
	(0.298)	(0.513)	(0.625)	(0.341)	(0.496)	(0.509)	(0.344)	(0.256)	(0.553)
Tech × UT	−1.202***	−1.366***	−1.464**	−1.225***	−0.353	−1.042**	−0.900**	−2.445***	−0.474
	(0.459)	(0.445)	(0.627)	(0.428)	(0.932)	(0.476)	(0.378)	(0.693)	(0.348)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Linear trends									

Notes: This table displays estimated coefficients of Equation (1) when the dependent variable is an overall exit from employment. All models include controls for gender, education, marital status and the region of residence. 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' calculations.