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IZA DP No. 15700

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ISSN: 2365-9793

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IZA DP No. 15700 NOVEMBER 2022

ABSTRACT

Pension Reforms, Longer Working Horizons and Depression. Does the Risk of Automation Matter?*

We investigate the effect of postponing minimum retirement age on middle-aged workers' depression. Using pension reforms in several European countries and data from the SHARE survey, we find that depression increases with a longer work horizon, but only among workers employed in occupations with a relatively high risk of automation. We rule out alternatives to this risk, including job strenuousness, education, gender, and the degree of routinization of occupations. We explain our results with the higher job insecurity associated with occupations more exposed to automation.

JEL Classification: I1, J24, J26, O33

Keywords: pension reforms, depression, automation, SHARE

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* We are grateful to Roberto Nisticò and the audience at the NETSPAR Pension Day in Utrecht for comments and suggestions and to Glenda Quintini for providing some of the data used in this paper. Financial support from the Instituut Gak project "The role of pensions for career decisions" is gratefully acknowledged.

1. *Introduction*

Over the last decades, several European countries have introduced pension reforms that have tightened the minimum age requirements for pension eligibility, to cope with population aging and the increasing strains on the sustainability of the pension systems. Delaying pension eligibility, however, not only impacts on pension expenditure but also affects individual behavior before retirement, as treated individuals adjust to the observed changes in eligibility conditions, with effects that were probably not considered by policymakers when introducing these reforms.

Carta and de Philippis, 2021 and Hairault et al., 2010, have shown that changes in the minimum retirement age (MRA) modifies the extensive margin of individual labor supply quite before retirement. The intensive margin is also affected, as shown by Brunello, De Paola and Rocco, 2022, who examine the effects of a longer working horizon on individual sick leaves. Additional effects involve training (Brunello and Comi, 2015; Montizaan et al., 2010), health behaviors (Bertoni et al., 2018a), financial literacy (Angelini et al., 2009) and depression (Carrino et al., 2020; Grip et al., 2012).

This paper starts with an investigation of whether and how pension reforms affecting minimum retirement age have influenced depression among individuals aged 50 to 54, who did not experience changes in pension eligibility but faced an unexpected increase in their residual working horizon because of these reforms. Using data from 16 countries and 7 waves of the Survey on Health and Retirement in Europe (SHARE), we extend previous work by De Grip et al, 2012, and Carrino et al., 2020, by considering a much wider set of countries and pension reforms, thereby enhancing external validity.

Our key research question is whether the effects of an exogenous increase in the residual working horizon on depression vary with the degree of exposure to automation of different occupations. Our expectation is that workers in their early fifties with automatable jobs have more insecure jobs. For them, a longer residual working life may imply a higher likelihood that they lose their job before retirement, with potential negative effects on depression.

We estimate a difference-in-differences model where the treatment is the number of years to retirement eligibility and find that a one-year increase in this number leads to a close to 5 percent increase in our measure of individual depression. We also estimate a specification where we allow the effect of the treatment to vary depending upon whether the administered dose is equal to one year or to more than one year. With this more flexible specification, we find that the effect on depression is close to zero in the former case and close to 22 percent of the control group mean in the latter case. These findings are qualitatively like those by De Grip et al, 2012, and Carrino et al, 2020, but apply to a much broader sample of countries.

We also estimate the same specifications separately for individuals working in occupations with below and with above median automation risk and find that a longer residual working horizon has a positive and statistically significant effect on depression only among individuals employed in occupations with above median automation risk. For these individuals, we estimate that a one-year increase in the residual working horizon raises depression by 9.7 percent, almost twice the effect estimated for the entire sample. For the rest of the sample, the effect is small and not statistically significant.

After excluding that the uncovered heterogeneous effects are driven by differences in education, gender, job strenuousness and degree of job routinization, we explain our findings by arguing that workers employed in more automatable occupations face and perceive higher job insecurity, with negative consequences on depression. Using SHARE data, we document that workers employed in automatable jobs are more likely to report job insecurity, and that a longer work horizon increases the perceived job insecurity of those in automatable jobs. Using data from the German Socio-Economic Panel and the European Labor Force Survey, we respectively show that workers in occupations at high risk of automation are more likely to report that they fear job insecurity than those in low automation occupations, and that occupations with a higher share of workers at risk of automation display higher flows from employment to unemployment and out of the labor force.

From a policy perspective, these results are important because they indicate that the universal targeting of pension reforms may have unintended and negative consequences on the mental health of workers more at risk of losing their job later in their career due to automation. These negative consequences could perhaps be attenuated by providing early retirement windows for workers facing this risk or by introducing measures facilitating lifelong learning, that help middle aged workers to cope with the effects of automation, thereby reducing the impact on individual depression.

2. *Literature review*

Several studies examine the effects of retirement on mental health and depression *after* retirement. While Coe and Zamarro, 2011, show that retirement has a positive effect on health but not a significant effect on depression, Eibich, 2015; Fonseca et al., 2014, find that retirement may be protective against poverty and depression, and Heller-Sahlgren, 2017, presents evidence of a large and negative long-term impact of retirement on mental health. These effects may vary across groups. Belloni et al., 2016, for instance, show that retirement reduces depression for men but not for women, and Mazzonna and Peracchi, 2017, show that retirement has an immediate beneficial effect on both the mental and physical health of people working in more physically demanding jobs, and a negative effect on the rest of the work force.

Pension reforms that affect individual eligibility or benefits from retirement may also affect the mental health of individuals *before* they retire. Lindeboom et al, 2012, for instance, compare the mental health of Dutch workers aged 58 (who were affected by a policy change that reduced the replacement rate from 70% to 64% of average earnings) and 59 (who were unaffected by the policy) and find that depression rates in the older cohort were about 40 percent higher than in the younger cohort.[1]

More recently, Carrino et al, 2020, exploit a UK pension reform that increased women's state pension age for up to 6 years since 2010 and show that raising this age leads to an increase of up to 12 percentage points in the probability of depressive symptoms experienced by women aged 60 to 64, alongside an increase in self-reported medically diagnosed depression among women in a lower occupational grade. Their results suggest that these effects are driven by prolonged exposure to high-strain jobs characterized by high demands and low control.[2]

We contribute to this literature by investigating the effects of reforms affecting pension eligibility age in several European countries on the depression of individuals aged 50 to 54 who, because of the reforms, experienced an increase in their residual working horizon.

There is also a small literature that looks at the effects of automation on mental health. Patel et al., 2018, document the detrimental effects of automation risk on health (both physical and mental) in the US, using aggregate data (county-level) and focusing on the job insecurity mechanism. Blasco et al., 2022, use the French Working Condition Survey to construct an index of routine jobs, that they take

[1] Using the same reform, Montizaan et al., 2016; Montizaan and Vendrik, 2014, find strong and persistent effects on both job satisfaction and training participation by the treated.
[2] See also Atalay et al., 2019; Bertoni et al., 2018b; Bloemen et al., 2017; Hernaes et al., 2013; Shai, 2018.

as proxy of automation risk. They show that workers whose job is at risk of automation in the future are about four percentage points more likely to suffer at present from severe mental health disorders. Lordan and Stringer, 2022, on the other hand, study the impact of automatable jobs - defined as routine-task-intense- on life satisfaction and mental health. Using Australian data (HILDA), they find no effect on average but small negative effects in the industries with higher levels of automation risk.

We contribute to this literature by investigating whether the increase in the residual working horizon triggered by pension reforms that alter minimum retirement age affects individual depression differently depending on the degree of exposure of the current occupation to the risk of automation.

Why should a longer work horizon trigger the onset of depression for workers at high risk of automation? A potential channel that we explore in this paper is the higher risk of job loss, or perceived job insecurity. There is substantial evidence that job insecurity hampers physical and mental health (see Green, 2020). For instance, László et al., 2010, use SHARE data to estimate a significant and positive association between perceived job insecurity and poor self-assessed health, while Caroli and Godard, 2016, estimate negative causal effects of lower job protection on several measures of health using data for several European countries.[3]

3. Data

This paper uses release 8.0.0 of the first six waves of the Survey of Health, Ageing and Retirement in Europe – SHARE. SHARE is a longitudinal dataset collecting harmonized information on socio-economic status, health, social and family

[3] Additional evidence using longitudinal data from single countries is reported, for instance, by Moscone et al., 2016; Pirani and Salvini, 2015 for Italy, by Otterbach and Sousa-Poza, 2015 Otterbach and Sousa-Poza, 2016, for Germany, and by Cottini and Ghinetti, 2018, for Denmark.

networks for nationally representative samples of Europeans and Israelis aged 50+.[4]

Starting with Wave 1 in 2004, SHARE has collected so far eight biannual waves of interviews. While waves 1 (2004), 2 (2007), 4 (2011), 5 (2013), 6 (2015) and 8 (2020) are regular ones, asking respondents to report on their current situation, waves 3 (2009) and 7 (2017) are retrospective surveys, that use a life history calendar approach to reconstruct the main life events of respondents. Finally, two special CORONA surveys were fielded in 2020 and 2021 using computer-assisted phone interviews to monitor behaviors during the pandemic.

3.1. Sample selection

To assess the impact of policy-induced changes in the working horizon that occur across SHARE waves on individual depression, we organize our data in four blocks, each composed of two consecutive regular waves. Although SHARE has a panel component, we maintain the largest possible sample size by treating the data as repeated cross-sections. We do not consider the retrospective waves 3 and 7, when data on mental health were not collected, and avoid using wave 8, because the fieldwork was suddenly interrupted due to the outbreak of COVID-

[4] See Börsch-Supan et al. (2013) for methodological details. The SHARE data collection has been funded by the European Commission, DG RTD through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812), FP7 (SHARE-PREP: GA N°211909, SHARE-LEAP: GA N°227822, SHARE M4: GA N°261982, DASISH: GA N°283646) and Horizon 2020 (SHARE-DEV3: GA N°676536, SHARE-COHESION: GA N°870628, SERISS: GA N°654221, SSHOC: GA N°823782, SHARE-COVID19: GA N°101015924), and by DG Employment, Social Affairs & Inclusion through VS 2015/0195, VS 2016/0135, VS 2018/0285, VS 2019/0332, and VS 2020/0313. Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U.S. National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064, HHSN271201300071C, RAG052527A) and from various national funding sources is gratefully acknowledged (see www.share-project.org).

19. Since depression was collected using different survey instruments, we also exclude the CORONA surveys.

We group our data in four blocks, defined by waves W1 -W2, W2 -W4, W4 -W5 and W5-W6. As a result, some observations appear twice in the data. We only retain countries that are present in both waves of each block, as reported in Appendix Table A1. We also avoid that changes in pension eligibility rules alter not only each respondent's work horizon but also his/her retirement status by restricting our sample to individuals aged 50 to 54, younger than the minimum pension eligibility age in place in the countries that are present in our data during the period of interest, equal to 55 years. This initial sample consists of 26,083 observations.

To focus on individuals who are reasonably close to retirement, and for whom minimum pension eligibility rules are salient, we also drop respondents:

i) with less than 10 years of social security contributions, since they may be detached from work (1,885 observations);

ii) who started working before the age of 10 (23 observations);

iii) who report to be retired or eligible for special pension programs (i.e. invalidity, sickness, disability), since those programs have different rules (904 observations);

iv) who are already retired (1,337 observations);

v) who have a work horizon that is longer than 10 years at their first interview within each block (2,399 observations)[5];

[5] We also drop 285 observations from Israel, 295 from Italy and 98 from Greece since they satisfy special retirement programs (see appendix B), and thus have a residual working horizon equal to zero.

vi) for whom we observe missing values in the variables used in the analysis, that we describe hereafter (107 observations).

As a result of these sample selection criteria, our final sample consists of 18,750 observations, distributed across blocks as follows: 21.6 percent in block 1, 23,1 percent in block 2, 28.3 percent in block 3 and 27.0 percent in block 4.

3.2. Key variables and descriptive statistics

3.2.1 Outcomes

We capture depression with a clinical measure, the Euro-D scale (Prince et al. 1999), which was originally developed to harmonize data on late-life depression in Europe as part of the EURODEP collaboration. The scale considers current depression and adds up the following twelve symptoms – taken from the Geriatric Mental State (GMS)—as they are reported by the interviewee: depressed mood, pessimism, wishing death, guilt, lack of sleep, lack of interest, irritability, lack of appetite, fatigue, lack of concentration, lack of enjoyment and tearfulness. Its validation has shown adequate internal consistency.

Prince et al., 1999 find that reporting four or more symptoms (out of twelve) on the EURO-D scale is a reliable predictor of clinically-diagnosed depression. Consistently, Braam et al., 2005, suggests setting a threshold at four symptoms and define clinically significant depression when the EURO-D score is equal or greater than four. Following this literature, we define depression either with the original Euro-D scale or as a dummy equal to one if the scale is equal to four or higher, and to zero otherwise. As in Castro-Costa et al., 2008, we also use principal component analysis to extract from the twelve symptoms two orthogonal factors, affective suffering (A) and lack of motivation (M), with depressed mood, tearfulness, wishing death, lack of sleep, guilt, irritability, and fatigue loading mainly on the first factor, and pessimism, lack of interest, enjoyment and concentration loading mainly on the second. As shown in Table

1, respondents in our sample report on average 2.15 EURO-D symptoms, and 22.6 percent of them declare four or more symptoms.

3.2.2 Demographics

Table 1 shows that, in our sample, 57.6 percent of respondents are female. Average age is 52.7 and individual employment is distributed among the private sector (67.3 percent), the public sector (20.2 percent) and self-employment (12.5 percent). Finally, the percentage of individuals with at least two children is equal to 72.6.

3.2.3 The residual work horizon YTR

We estimate the individual residual working horizon by relying upon the information on employment histories that is contained in the Job Episodes Panel (JEP). This dataset was built using information from the retrospective SHARE waves 3 and 7 (see Brugiavini et al., 2019). The JEP is especially useful for our purpose as it allows us to reconstruct employment status as well as the years of social security contributions accumulated by individuals in each SHARE interview – a key ingredient to compute pension eligibility age. As shown in Table 1, respondents in our sample have accumulated on average 31.5 years of contribution.

We define the residual working horizon (YTR) as the number of years required to reach the minimum pension eligibility age, under the working assumption that employment continues in the future.[6] Depending on the country, pension eligibility age varies across cells defined by age, gender, years of paid social security contributions, sector of employment (for Italy), and number of children (for Czech Republic). Eligibility conditions also change over time, due to several social security reforms that took place in European countries during the sample

[6] See Carta and De Philippis, (2021), for a discussion of this assumption.

period (2004-15). These reforms affected 10 out of the 16 countries in the sample. We consider both old age and early retirement programs and consider as binding the minimum value of YTR computed using both criteria.

The variation in the definition of cells across countries is reported in Table 2, while detailed information on pension eligibility requirements is reported in Appendix B. As shown in Table 1, average YTR according to the pension eligibility rules in place in the baseline year of each block is 6.63 years. Its distribution is reported in Figure 1, showing that for most respondents YTR is above 5 years, which suggests that they are close enough to retirement to consider changes the pension eligibility ages as salient.

Conditional on the relevant variables, and most notably on age, YTR changes for each respondent across two consecutive waves composing each block because of variations in the minimum retirement eligibility age. The difference between the YTR obtained under the "old" and "new" rules – for constant values of age and the other eligibility criteria - is the treatment variable of interest for this study, or ΔYTR. For some countries in our sample, where pension eligibility depends both on years of contribution and on sector of employment at the time of retirement, we follow Carta and De Philippis, 2021, and assume that respondents do not change sector of employment.

Table 1 and Figure 2 report information on the distribution of ΔYTR in the sample. In total, 24.4 percent of respondents in our sample experience an increase in their residual work horizon across the two waves of a block, and the average change in the work horizon conditional on a positive change is equal to 1.535 years. Appendix Table A2 reports a summary of the countries and blocks where positive changes in the YTR are detected. The last row of the table also shows the share of the sample experiencing changes of YTR equal to 1, 2, 3 or 4 years (conditional on any change).

3.2.4 Automation risk

Our measure of automation risk is drawn from Nedelkoska and Quintini, 2018, and varies across two-digit ISCO-08 occupation codes (NQ2).[7] The indicator is based on the Survey of Adult Skills (PIAAC) for the years 2012 and 2015, and on the binary classification of occupation automatability proposed by Frey and Osborne, 2017. Nedelkoska and Quintini define three areas of "engineering bottlenecks" that prevent the automation of tasks and identify ten related skills, using individual data from PIAAC. The engineering bottleneck areas they consider, and the associated skills (within parentheses), are: *i)* perception manipulation (dexterity); *ii)* creative intelligence (problem solving, simple and complex); and *iii)* social intelligence (teaching, advising, planning for others, communication, negotiation, influence, selling). Using a logistic regression model, they show that all the ten skills are predictive of automatability. They also use this model to estimate individual-specific automation probabilities, that are then averaged by occupation. It turns out that the occupations with the highest mean probability of automation are in major ISCO-08 groups 9 (elementary occupations that do not require particular skills), 7 (craft and related trades workers) and 8 (operators and assemblers). As a sensitivity check, we also use as an alternative measure of automation, again from Nedelkoska and Quintini, 2018, that corresponds with the average country – specific share of workers in jobs with a risk of automation above 70%, using the 3-digit ISCO-08 classification of occupations (NQ3).

We merge these occupation - specific data with SHARE using the most recent and disaggregated ISCO-08 code available for each respondent, up to 2-digit for NQ2 and 3-digit for NQ3. If only coarser codes are available, we aggregate NQ2 and NQ3 at the corresponding level. We report the list of automation

[7] See Figure 4.3 of Nedelkoska and Quintini, 2018.

probabilities by occupation codes in Appendix B. We further define, for either measure, a binary variable equal to 1 if the value of automation is above the median across the distribution of occupations, and to 0 otherwise.

4. The empirical approach

As discussed in Section 3, pension eligibility requirements vary across countries by cells defined in terms of the criteria reported in Table 2 and have changed across interview waves due to pension reforms. We aim to identify the effect of changes in the years to retirement induced by pension reforms on depression by adapting the logic of the staggered difference-in-differences design to this context.

We proceed by considering pairs of successive waves – that constitute a block. The first wave is the baseline and the second one the end line. Our treatment variable is ΔYTR, or the change in YTR experienced by each respondent between the baseline and end line interview of each block due to changes in the pension rules that took place in the country where he or she lives during the same period. Within cells and blocks, the variation in ΔYTR is solely attributable to pension reforms, and hence we treat it as exogenous. Our difference-in-differences design compares changes in mental health across the baseline and end line wave of a block across respondents with different values of ΔYTR.

We aggregate the estimates obtained within each block in a single pooled estimate by following the approach championed by Cengiz et al., 2019. We stack the data for the different blocks and estimate the following model by ordinary least squares (OLS):

$$Y_{icwb} = \alpha_b POST_w + \beta_{cb} + \gamma \Delta YTR_{cb} \times POST_w + \varepsilon_{icwb} \quad (1)$$

In Equation (1), i, s, w, and b, stand for individual, cell, wave, and block, respectively, and Y_{icwb} is the outcome (depression). $POST_w$ is a dummy for the endline wave within each block, the effect of which (α_b) is allowed to vary by block.

For identification, we rely solely on the variation in ΔYTR between two consecutive waves within a cell of a block, that is generated by pension reforms. We isolate this source of variation by including cell-by-block-fixed effects β_{cb}. The coefficient of interest in Equation 1 is γ, that is associated with the interaction term $\Delta YTR_{cb} \times POST_w$ and is the difference-in-differences effect of a 1-year increase in the time to retirement on the outcome.

While equation (1) assumes a linear relationship between the change in the work horizon and the outcomes, we also consider a binary specification for the treatment, where our regressor becomes a dummy for ΔYTR>0, as well as a non-linear specification that compares respondents with $\Delta YTR_{cb} = 0$ with those with ΔYTR=1 and ΔYTR>1, respectively. We pool across the values of ΔYTR>1 because of the small share of individuals experiencing large increases in YTR, as reported in Figure 2. Finally, ε_{icwb} is an error term, and we allow for dependence of errors within cell-by-block groups by clustering standard errors at that level.

Considering that our empirical approach requires the inclusion of cell-by-block fixed effects, singleton cells populated by only one respondent will drop from the estimation sample. This is the case for 1,205 respondents in our sample, while the remaining 17,545 ones are grouped in 1,901 cells with a size ranging from 2 to 206 respondents, with a median size of 4 respondents and an average of 9.2. Descriptive statistics for this sample are reported in Appendix Table A3 and are overall comparable to the full sample. Excluded respondents belong to countries that use years of contributions as a criterion to determine pension eligibility (Austria, Spain, Italy, Greece, Belgium, Czech Republic and Estonia), as the inclusion of this criterion generates much finer cells. Excluded respondents are 3 percentage points more likely to be females, mildly younger (0.2 years on average) and have fewer years of contributions (3.5 years on average) than included ones, because the distribution of years of contribution has a thin left tail. Consistently, they are also 0.1 years farther from retirement at the baseline interview, and experience 0.4 years longer changes in ΔYTR. We shall bear these considerations in mind when discussing the external validity of our findings.

Before moving to the results, it is worth pointing out that our empirical approach considers blocks that only contain a single pre- and post-reform period. As a result, we can only estimate short-term effects, that materialize soon after the introduction of the reform. In a context where several pension reforms took place over a short period of time, this approach has the advantage that we cannot confound the long-run effects of a single reform with the short-run effects of successive reforms taking place in the same countries.

In addition, since we exploit the variation in ΔYTR along the intensive margin, the considerations about identification of treatment effects in difference-in-differences with continuous treatments discussed by Callaway et al., 2021 apply straightforwardly to our case. For instance, in our simple two-period setup, our non-linear estimator comparing trends for untreated respondents with ΔYTR=0 to those of respondents exposed to different levels of ΔYTR identifies the average treatment effect of that given treatment dose (ΔYTR=1 or ΔYTR>1) among units that receive it, under a standard parallel-trends assumption on untreated potential outcomes.

We test the validity of the parallel-trends assumptions using two placebo tests. First, we anticipate the timing of the implementation of pension reforms in each country by one block. Second, we randomly permute ΔYTR across cells-by-block groups 5,000 times. Both tests support the validity of the assumption.

5. Results

5.1 Baseline results

Table 3 reports our baseline estimates when we use the continuous EURO-D scale as well as the dummy for EURO-D>3 as outcomes. The results in column (1) show that, when we use a linear specification for the effect of ΔYTR, a 1-year change in years to retirement increases the number of EURO-D depressive symptoms by 0.1054, roughly 5 percent of the control group mean (2.139). When we adopt a binary specification for ΔYTR>0 – see column (2) - we obtain a similarly large but statistically insignificant effect. This is not surprising considering that roughly 70 percent of those with ΔYTR>0 have ΔYTR=1 and that the binary specification is artificially eliminating some variability in treatment intensity. The non-linear specification of column (3) is well supported by the data: the dose effect for ΔYTR=1 is close to zero and statistically insignificant, while the one for ΔYTR>1 is statistically significant and large in magnitude, being equal to 0.4718 symptoms or 22 percent of the control group mean (or 0.23 standard deviations).

The results that we obtain when coding EURO-D as a dummy taking a value 1 when it is above 3 and 0 otherwise are reported in columns (4) -(6). Treatment effects are in line but somewhat less precisely estimated than those reported in columns (1) -(3) due to the lower variability of the binary outcome. Overall, our results, that are based on a much broader set of countries, years, and pension reforms, are qualitatively consistent with those reported by De Grip et al., 2012, for Dutch workers exposed to a longer work horizon, and by Carrino et al., 2020, for English women.

5.2 Robustness and placebo tests

Before moving to the analysis of heterogeneous effects by automation risk, we present some sensitivities to our main results. A potential concern is that our sample is made up of countries that differ in their labor market and retirement institutions, and that the effects may be heterogeneous over time. Because of this, estimating a common effect of the treatment on outcomes can be restrictive. At the same time, estimating country- or block-specific effects is prohibitive for sample size reasons as well as because some countries do not experience pension reforms. To address this concern, in Figure 3 we report the distribution of the estimates that we obtain when we drop one country-by-block group at a time and conclude that they are very similar to the main estimates, shown by the red vertical lines. Furthermore, Appendix Tables A4 and A5 show the estimates that we obtain when we drop one country or block at a time, thereby assessing the sensitivity of single countries and time periods in determining the estimated effects. Again, the point estimates are remarkably stable across sub-samples.

Second, Table 4 reports the results of a placebo test carried out by anticipating the pension rules in place in each country by one block. The number of observations changes with respect to our baseline specification in Table 3 as we are forced to drop the last block of data. Results consistently show that, for both outcomes, there is no evidence of treatment effects when the reforms are anticipated or postponed, supporting the validity of our parallel-trends assumption.

Finally, the validity of the assumption of parallel trends is also confirmed by Figure 4, that reports the distribution of treatment effects that we obtain when we randomly permute ΔYTR across cells and blocks 5,000 times. The red vertical line is the observed treatment effect, which always lies to the right of the empirical critical values at the 10, 5 and 1 percentiles of these distributions – shown by the vertical grey lines – whenever the associated effect is significant in Table 3.

5.3 Heterogeneous effects by levels of automation risk

We show in Tables 5 the heterogeneous effects of ΔYTR on the EURO-D (0-12) scale for respondents employed in occupations above and below the median risk of automation in the two-digit ISCO-08 automation classification (NQ2) defined in Section 3.[8]

The results indicate that a longer residual working horizon has a positive and statistically significant effect on depression only among individuals employed in occupations with above-median automation risk. As for Table 3, our estimates are highly statistically significant when using the linear and the non-linear specifications for ΔYTR, but imprecise with the binary specification. In all cases, the effects when the risk of automation is above median are about twice as large in magnitude as those reported in Table 3 for the pooled sample. Consistent with this finding, for respondents working in occupations with below median automation risk we estimate close-to-zero and insignificant effects of ΔYTR. The table also shows that, for the linear and non-linear specifications, the difference in the effects across samples are very significant from a statistical standpoint, with p-values well below 1 percent.

Appendix Table A6 replicates the estimates of Table 5 using the binary EURO-D>3 outcome variable, with findings that are wholly comparable to those of Table 5, both in terms of magnitude and of significance of the effects. Finally, results using the 3-digit ISCO-08 automation classification (NQ3) are reported in Tables A7 and A8 in the Appendix and are also qualitatively similar to the ones discussed in this section.

5.4 Mechanisms

Why should the risk of automation matter to explain the effect of a longer residual work horizon on depression? Our conjecture is that workers employed in more automatable occupations face higher job insecurity, and that pension

[8] The total sample size over the two sub-samples does not add up to the same number of observations reported in Table 3 because, after splitting the sample by automation level, some cell-by-block groups end up containing only one observation and drop from the estimation sample.

reforms force them to face this risk for a longer period, bringing in higher pressure and worse mental health.

SHARE includes a measure of self-reported job security ("My job security is poor"). We define a binary variable equal to 1 if the individual strongly agrees or agrees with the statement, and to 0 otherwise.[9] In the full sample, 21 percent of respondents report poor job security, and this share is higher among those in occupations with above-median automation risk (23.4 vs. 18.9 percent). We use this data to estimate the effect of the treatment on perceived job security for individuals in jobs that vary in their degree of automation risk. Our results in Table 6 indicate that – although the differences in the effects across occupations are not statistically significant due to the smaller sample size – a change in the years to retirement increases the perception of poor job security mostly among those exposed to a higher risk of automation.

We provide additional evidence on the association between the risk of automation, perceived job security and job turnover using data from the German Socio-Economic Panel and from the European Labor Force Survey. The German Socio-Economic Panel – SOEP – asks respondents about their perceived level of job security, using the following question: "Are you worried about your job security?". We code replies as a binary variable (insecurity) which takes value 1 if the respondent reports to be either "concerned" or "somewhat concerned", and to 0 if the respondent reports to be "not concerned". We retain the sample of respondents aged 50 to 54 and interviewed in 2011, the central year of our SHARE sample, and regress this binary variable on the NQ2 indicator of automation risk, clustering standard error by two-digit occupation level. We find that a 10 percent

[9] Unfortunately, from wave 5 onwards this question is not asked to respondents in refreshment samples and to longitudinal respondents who do not change their job. While we are forced to drop the former group, to avoid losing many observations we replace missing values with the last reported value of the binary variable for the latter group. Results without imputed values are qualitatively similar but less precise.

increase in the share of workers at risk of automation in an occupation is associated with a 9.5 percentage points higher share of workers reporting poor job security, an association that is significant at better than the 1 percent level. These findings further support our claim that higher automation risk is associated with higher job insecurity.

We also investigate whether occupations with a higher risk of automation are associated with higher worker flows from employment to unemployment or out of the labor force (net of retirement), using data from the 2011 wave of the European Labor Force Survey and considering individuals aged 50 to 54 and the countries in our working sample. These data include information on the current labor market status and on the status one year earlier. We compute each flow by adding up the transitions from employment one year earlier to current unemployment or out of the labor force, and by dividing the total by aggregate employment one year earlier.

We then regress these flows on country dummies and the NQ3 indicator of automation risk, clustering standard errors by three – digit occupations. We estimate that a 10 percent increase in the share of workers at risk of automation increases the outflow from employment to unemployment (out of the labor force) by 0.37 percent (0.33 percent), a statistically significant effect at the conventional levels of significance. Therefore, higher automation risk is not only associated with higher perceived job insecurity but also with higher outflow rates from employment into joblessness.

5.5 Other heterogeneous effects

Workers employed in highly automatable occupations may differ from those in less automatable occupations along other dimensions that could explain the effect of a longer work horizon on depression. Because of this, our findings that the positive effect of ΔYTR on depression occurs only for occupations with a relatively high risk of automation may be driven by other factors that correlate with automation risk. For instance, occupations at high risk of automation often involve physically demanding jobs. Workers in these jobs may suffer following pension reforms that increase the residual working horizon because they need to work longer in strenuous jobs rather than because of the risk of automation.

To address this concern, we notice that SHARE includes a question on whether the current job is physically demanding. Respondents can choose to strongly agree, agree, disagree, and strongly disagree. We compute the percentage who agree or strongly agree by occupation and compare the distribution of strenuous jobs and jobs at risk of automation (see Figure 5). As expected, the correlation is positive (0.345). However, 17.3 percent of the four-digit occupations have a below median risk of automation and an above median degree of strenuousness, and 18.9 percent have an above median risk of automation and a below median degree of strenuousness. Examples of the first group are shepherds, guards and distributors and examples of the second group are clerks, hotel front desk and repairers.

If our heterogeneous results by risk of automation were driven by the heterogeneity in the level of strenuousness, we should find that separate estimates by levels of strenuousness above and below median yield the same qualitative results as those reported in Table 5. Yet the estimates in Table 7 show that there is no statistically significant difference in the response of the outcome to the treatment according to the level of job strenuousness (comparable estimates for the binary EURO-D variable are in Appendix Table A9).

Another individual trait that correlates with automation risk is education: while 86 percent of respondents employed in low automation risk occupations have a high school or higher degree, this is true for only 63 percent of respondents in high automation risk occupations. We replicate our heterogeneity analysis distinguishing between respondents with and without a high school or higher degree in Table 8 for EURO-D (0-12) and in Appendix Table A10 for EURO-D>3. The results show no stark evidence of heterogeneous effects along these margins, suggesting that the results by automation risk do not reflect only differences in the education level of respondents in these groups.

Furthermore, given that males are more likely than females to hold a job in an occupation at high automation risk (53.4 vs. 47%), heterogeneous effects by gender are also reported in Table 9 for EURO-D (0-12) and in Appendix Table A11 for EURO-D>3, but reveal no significant heterogeneity by gender.

As explained in section 3.2.4, the measure of automation risk we use is constructed by predicting the automatability of job tasks based on skills measured at the individual level in the PIAAC survey. As a result, it differs from measures of task routinization that are coded using task descriptions at the occupation level (Acemoglu and Autor, 2011), which include for instance Mihaylov and Tijdens, 2019.

For each occupation code, ISCO provides a list of tasks and duties associated with that code. These authors construct a routine task intensity index for each 4-digit ISCO-08 occupation code by first constructing five measures of non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual tasks for 427 four-digit ISCO occupations, and by then combining the five routine indexes into a single measure of routine task-intensity (RTI index).

We plot this index against the risk of automation used in this paper in Figure 6. While most occupations (65 percent) have both an above (below) median risk of automation and an above (below) median degree of routinization, 13.2 percent have an above median RTI index but a below median automation risk, and 20.8 percent have above median automation risk but below median RTI index. The former group includes for example coding, proof reading and related clerks, and the latter group includes garbage and recycling collectors.

If our heterogeneous results by risk of automation were driven by the heterogeneity in the RTI index, we should find that separate estimates by RTI above and below the median yield the same qualitative results as those in Table 5. Table 10 for EURO-D (0-12) and Table A12 for EURO-D>3 in Appendix show that this is the case.

To discriminate between the two indices – automation risk vs. RTI index - we produce two separate tables: in Table 11 (and Appendix Table A13), we show the estimates by risk of automation for occupations with a lower than median RTI, and in Table 12 (and Appendix Table A14) we present the results by risk of automation for the occupations with a RTI above the median. Although the estimates are often imprecise because of the smaller sample size, we find that the effect of the treatment on depression is always higher in occupations at a higher risk of automation, independently of their level of routinization. We conclude that differences in our measures of automation are driving our results.

Finally, we experiment with an alternative definition of our outcome by following Castro-Costa et al., 2008, and using principal component analysis to extract from the twelve symptoms constituting the EURO-D index two orthogonal factors, affective suffering and lack of motivation, with depressed mood, tearfulness, suicidality, sleep disturbance, guilt, irritability, lack of appetite and fatigue loading mainly on the first factor, and pessimism, lack of interest, enjoyment and concentration loading mainly on the second.

We replicate our estimates in Table 5 using each factor as the dependent variable and find that the treatment has a statistically significant effect on affective suffering but not on lack of motivation. In addition, we find evidence that the effect of the treatment varies significantly with the automation risk only for the former factor (see Appendix Tables A15-A18).

Conclusions

Using data from 16 countries and 7 waves of the Survey on Health and Retirement in Europe (SHARE), we have started this paper by investigating whether changes in pension eligibility conditions influence the depression of middle-aged individuals aged 50 to 54, who have still a few years to go before retirement. Although this question is not new, we have extended previous work by De Grip et al, 2012, and Carrino et al., 2020, by considering a much wider set of countries and pension reforms, thereby enhancing external validity. Adopting a difference-in-differences model where the treatment is the number of years to retirement, we have found that a 1-year increase in this horizon leads to a close to 5 percent increase in the depression index.

Our key contribution to this literature has been the estimation of the effect of the treatment on depression separately for individuals working in occupations with below and above median automation risk. We have shown that a longer residual working horizon has a positive and statistically significant effect on depression only among individuals employed in occupations with above-median automation risk. For these individuals, we have estimated that a 1-year increase in the residual working horizon raises depression by 9.7 percent, almost twice the effect estimated for the entire sample. The effect is instead negligible for respondents employed in occupation with low automation risk.

We have argued that workers employed in more automatable occupations face and perceive higher job insecurity, with negative consequences on depression. Using data from SHARE as well as from the German Socio-Economic Panel and the European Labor Force Survey, we have shown workers' perception of job insecurity and actual flows out of employment are higher in automatable jobs.

Moreover, using SHARE we have shown that workers' self-rated job insecurity increases with their work horizon, and especially so for automatable jobs.

Since depression is associated with lowered work functioning, including absence from work, productivity impairment at work, and decreased job retention (see ILO, 2022), pension reforms that increase the residual working horizon can reduce productivity in the occupations more exposed to automation by fostering job insecurity and depression. The provision of early retirement windows for workers who lose their jobs late in their careers may help curb this negative side effect of pension reforms. Alternatively, measures that encourage lifelong learning may improve the ability to adjust to negative employment shocks, and therefore reduce depression before retirement.

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Tables and figures

Table 1. Descriptive statistics.

Variable	Mean	Std. Dev.
Outcomes:		
EURO-D (0-12)	2.152	2.062
EURO-D>3	0.226	0.418
Years To Retirement – YTR:		
Baseline YTR	6.635	2.466
ΔYTR>0	.244	0.430
ΔYTR – conditional on positive values (N=4,576)	1.535	0.992
Covariates determining cell:		
Age	52.660	1.148
Female	0.576	0.494
Self-employed	0.125	0.331
Civil servant	0.202	0.402
Private employee	0.673	0.469
Contribution years	31.498	5.943
No child	0.104	0.305
1 child	0.170	0.376
2 children	0.443	0.497
3/4 children	0.250	0.433
5 or more children	0.033	0.180
Observations	18,750	

Table 2. Variation in the definition of cells across countries

Criteria	Countries
Age	Denmark, Sweden, Netherlands, France
Age, gender	Germany, Israel, Luxembourg, Poland, Slovenia, Switzerland
Age, years of contribution	Spain
Age, years of contribution, gender	Austria, Belgium, Estonia, Greece
Age, years of contribution, gender, sector	Italy
Age, years of contribution, gender, number of children	Czech Republic

Table 3. Baseline estimates. The effect of a change in Years to Retirement (YTR) on depression

	(1) EURO-D (0-12)	(2) EURO-D (0-12)	(3) EURO-D (0-12)	(4) EURO-D >3	(5) EURO-D >3	(6) EURO-D >3
ΔYTR	0.1054***			0.0138		
	(0.0395)			(0.0088)		
$\Delta YTR > 0$		0.0808			0.0034	
		(0.0858)			(0.0177)	
$\Delta YTR = 1$			-0.0505			-0.0169
			(0.0939)			(0.0197)
$\Delta YTR > 1$			0.4718***			0.0638**
			(0.1448)			(0.0290)
p-value for joint significance of $\Delta YTR = 1$ and $\Delta YTR > 1$			0.003			0.041
Mean for control group	2.139	2.139	2.139	0.221	0.221	0.221
Observations	17,545	17,545	17,545	17,545	17,545	17,545
Clusters	1901	1901	1901	1901	1901	1901

Notes: each model includes wave-by-block and cell-by-block fixed effects. Standard errors within parentheses are clustered at the cell-by-block level. ***: p<0.01, **: p<0.05, *: p<0.1.

Table 4. Placebo test. Anticipating pension reforms by one wave

	(1) EURO-D (0-12)	(2) EURO-D (0-12)	(3) EURO-D (0-12)	(4) EURO-D >3	(5) EURO-D >3	(6) EURO-D >3
ΔYTR	-0.0103			0.0010		
	(0.0400)			(0.0130)		
$\Delta YTR > 0$		-0.0181			0.0042	
		(0.0998)			(0.0224)	
$\Delta YTR = 1$			-0.0145			0.0075
			(0.1173)			(0.0243)
$\Delta YTR > 1$			-0.0240			-0.0014
			(0.1433)			(0.0396)
p-value test joint significance $\Delta YTR = 1$ and $\Delta YTR > 1$			0.9821			0.9514
Observations	11,767	11,767	11,767	11,767	11,767	11,767
Clusters	1,255	1,255	1,255	1,255	1,255	1,255

Notes: each model includes wave-by-block and cell-by-block fixed effects. Observations for block 4 are dropped. Standard errors within parentheses are clustered at the cell-by-block level. ***: p<0.01, **: p<0.05, *: p<0.1.

Table 5. Heterogeneous effects of ΔYTR on EURO-D (0-12) by automation level of 2-digit ISCO-08 occupations (NQ2)

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable: EURO-D (0-12)	Below median automation	Above median automation	Below median automation	Above median automation	Below median automation	Above median automation
ΔYTR	0.0101	0.2068***				
	(0.0455)	(0.0671)				
p-value for equality across samples	0.0079					
$\Delta YTR > 0$			0.0161	0.1781		
			(0.1126)	(0.1297)		
p-value for equality across samples			0.3245			
$\Delta YTR = 1$					0.0125	-0.0395
					(0.1294)	(0.1332)
p-value for equality across samples					0.7734	
$\Delta YTR > 1$					0.0255	0.9207***
					(0.1730)	(0.2462)
p-value for equality across samples					0.0010	
p-value for joint equality across samples					0.0047	
Control group mean	2.039	2.2420	2.039	2.2420	2.039	2.2420
Observations	8,309	8,234	8,309	8,234	8,309	8,234
Clusters	992	1,265	992	1,265	992	1,265

Notes: each model includes wave-by-block and cell-by-block fixed effects. The p-value of the test for the joint significance of $\Delta YTR = 1$ and $\Delta YTR > 1$ is 0.987 in model (5) and 0.001 in model (6). Standard errors clustered at the cell-by-block level within parentheses. ***: p<0.01, **: p<0.05, *: p<0.1.

Table 6. Heterogeneous effects of ΔYTR on perceived poor job security by automation level of 2-digit ISCO-08 occupations (NQ2).

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable: EURO-D (0-12)	Below median automation	Above median automation	Below median automation	Above median automation	Below median automation	Above median automation
ΔYTR	0.0312	0.0534**				
	(0.0240)	(0.0265)				
p-value for equality across samples	0.5870					
$\Delta YTR > 0$			0.0453	0.0640*		
			(0.0382)	(0.0361)		
p-value for equality across samples			0.7160			
$\Delta YTR = 1$					0.0657*	0.0135
					(0.0376)	(0.0391)
p-value for equality across samples					0.3190	
$\Delta YTR > 1$					0.0555	0.2446***
					(0.0841)	(0.0909)
p-value for equality across samples					0.1740	
p-value for joint equality across samples					0.2120	
Control group mean	0.1890	0.2340	0.1890	0.2340	0.1890	0.2340
Observations	5,806	5,006	5,806	5,006	5,806	5,006
Clusters	755	840	755	840	755	840

Notes: each model includes wave-by-block and cell-by-block fixed effects. The p-value of the test for the joint significance of $\Delta YTR = 1$ and $\Delta YTR > 1$ is 0.987 in model (5) and 0.001 in model (6). Standard errors clustered at the cell-by-block level within parentheses. ***: p<0.01, **: p<0.05, *: p<0.1.

Table 7. The effects of ΔYTR on EURO-D (0-12) for occupations above and below median level of strenuousness

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable: EURO-D (0-12)	Below median stren.ness	Above median stren.ness	Below median stren.ness	Above median stren.ness	Below median stren.ness	Above median stren.ness
ΔYTR	0.1003*	0.1134				
	(0.0570)	(0.0791)				
p-value for equality across samples	0.9055					
$\Delta YTR > 0$			0.1419	0.0609		
			(0.1312)	(0.1390)		
p-value for equality across samples			0.6777			
$\Delta YTR = 1$					0.0778	-0.0887
					(0.1482)	(0.1447)
p-value for equality across samples					0.7734	
$\Delta YTR > 1$					0.3216	0.5835***
					(0.2217)	(0.2770)
p-value for equality across samples					0.5043	
p-value for joint equality across samples					0.5447	
Control group mean	0.205	0.244	0.205	0.244	0.205	0.244
Observations	8,646	7,736	8,646	7,736	8,646	7,736
Clusters	1,234	1,053	1,234	1,053	1,234	1,053

Notes: stren.ness: strenuousness. Each model includes wave-by-block and cell-by-block fixed effects. The p-value of the test for the joint significance of $\Delta YTR = 1$ and $\Delta YTR > 1$ is 0.513 in model (5) and 0.457 in model (6). Standard errors clustered at the cell-by-block level within parentheses. ***: p<0.01, **: p<0.05, *: p<0.1.

Table 8. Heterogeneous effects of ΔYTR on EURO-D (0-12) by education.

Outcome variable: EURO-D (0-12)	(1) Below high school	(2) High school or above	(3) Below high school	(4) High school or above	(5) Below high school	(6) High school or above
ΔYTR	0.1082	0.0917**				
	(0.1583)	(0.0434)				
p-value for equality across samples	0.923					
$\Delta YTR > 0$			0.1552	0.1026		
			(0.2573)	(0.0910)		
p-value for equality across samples			0.845			
$\Delta YTR = 1$					0.0540	0.0099
					(0.2723)	(0.0973)
p-value for equality across samples					0.876	
$\Delta YTR > 1$					0.4050	0.3938**
					(0.5213)	(0.1703)
p-value for equality across samples					0.984	
p-value for joint equality across samples					0.988	
Control group mean	2.429	2.041	2.429	2.041	2.429	2.041
Observations	3,727	12,993	3,727	12,993	3,727	12,993
Clusters	761	1404	761	1404	761	1404

Notes: each model includes wave-by-block and cell-by-block fixed effects. The p-value of the test for the joint significance of $\Delta YTR = 1$ and $\Delta YTR > 1$ is 0.7330 in model (5) and 0.0675 in model (6).). Standard errors clustered at the cell-by-block level within parentheses. ***: p<0.01, **: p<0.05, *: p<0.1.

Table 9. Heterogeneous effects of ΔYTR on EURO-D (0-12) by gender.

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable: EURO-D (0-12)	Females	Males	Females	Males	Females	Males
ΔYTR	0.1417**	0.0910				
	(0.0615)	(0.0605)				
p-value for equality across samples	0.612					
$\Delta YTR > 0$			0.1378	0.0324		
			(0.1161)	(0.1413)		
p-value for equality across samples			0.570			
$\Delta YTR = 1$					-0.0091	-0.1067
					(0.1255)	(0.1593)
p-value for equality across samples					0.633	
$\Delta YTR > 1$					0.6541***	0.3117
					(0.2192)	(0.2147)
p-value for equality across samples					0.315	
p-value for joint equality across samples					0.571	
Control group mean	2.489	1.720	2.489	1.720	2.489	1.720
Observations	10,022	7,405	10,022	7,405	10,022	7,405
Clusters	1208	833	1208	833	1208	833

Notes: each model includes wave-by-block and cell-by-block fixed effects. P-value for joint significance ($\Delta YTR = 1$) and ($\Delta YTR > 1$): 0.010 in model (5); 0.233 in model (6). Standard errors clustered at the cell-by-block level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 10. Heterogeneous effects of ΔYTR on EURO-D (0-12) for occupations above and below median level of index RTI

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable: EURO-D (0-12)	Below median RTI	Above median RTI	Below median RTI	Above median RTI	Below median RTI	Above median RTI
ΔYTR	-0.0057	0.0251*				
	(0.0121)	(0.0149)				
p-value for equality across samples	0.0965					
$\Delta YTR > 0$			-0.0124	-0.0066		
			(0.0274)	(0.0299)		
p-value for equality across samples			0.883			
$\Delta YTR = 1$					-0.0091	-0.0515
					(0.0314)	(0.0322)
p-value for equality across samples					0.336	
$\Delta YTR > 1$					-0.0216	0.1406***
					(0.0443)	(0.0478)
p-value for equality across samples					0.0136	
p-value for joint equality across samples					0.0208	
Control group mean	2.166	2.118	2.166	2.118	2.166	2.118
Observations	8,235	6,797	8,235	6,797	8,235	6,797
Clusters	1113	1062	1113	1062	1113	1062

Notes: each model includes wave-by-block and cell-by-block fixed effects. P-value for joint significance ($\Delta YTR = 1$) and ($\Delta YTR > 1$): 0.867 in model (5); 0.0166 in model (6). Standard errors clustered at the cell-by-block level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 11. Heterogeneous effects of ΔYTR on EURO-D (0-12) for occupations above and below median automation risk index RTI below median level.

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable: EURO-D (0-12)	Below median automation	Above median automation	Below median automation	Above median automation	Below median automation	Above median automation
ΔYTR	-0.0502	0.1771				
	(0.0561)	(0.1101)				
p-value for equality across samples	0.0492					
$\Delta YTR > 0$			-0.0791	0.1570		
			(0.1458)	(0.3000)		
p-value for equality across samples			0.456			
$\Delta YTR = 1$					-0.0835	-0.0246
					(0.1746)	(0.3310)
p-value for equality across samples					0.869	
$\Delta YTR > 1$					-0.0684	0.7457*
					(0.2122)	(0.4397)
p-value for equality across samples					0.0829	
p-value for joint equality across samples					0.220	
Control group mean	2.029	2.443	2.029	2.443	2.029	2.443
Observations	5,233	2,323	5,233	2,323	5,233	2,323
Clusters	681	468	681	468	681	468

Notes: each model includes wave-by-block and cell-by-block fixed effects. P-value for joint significance ($\Delta YTR = 1$) and ($\Delta YTR > 1$): 0.863 in model (5); 0.210 in model (6). Standard errors clustered at the cell-by-block level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

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Table 12. Heterogeneous effects of ΔYTR on EURO-D (0-12) for occupations at or above and below median automation risk and index of routinization RTI at or above median level.

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable: EURO-D (0-12)	Below median automation	Above median automation	Below median automation	Above median automation	Below median automation	Above median automation
ΔYTR	0.0110	0.2710***				
	(0.1006)	(0.0979)				
p-value for equality across samples	0.117					
$\Delta YTR > 0$			0.1177	0.2132		
			(0.2813)	(0.1827)		
p-value for equality across samples			0.788			
$\Delta YTR = 1$					0.1262	-0.1157
					(0.3318)	(0.1895)
p-value for equality across samples					0.543	
$\Delta YTR > 1$					0.0894	1.2536***
					(0.4774)	(0.3197)
p-value for equality across samples					‘0659	
p-value for joint equality across samples					0.147	
Control group mean	2.054	2.144	2.054	2.144	2.054	2.144
Observations	1,672	4,631	1,672	4,631	1,672	4,631
Clusters	331	833	331	833	331	833

Notes: each model includes wave-by-block and cell-by-block fixed effects. P-value for joint significance ($\Delta YTR = 1$) and ($\Delta YTR > 1$): 0.916 in model (5); 0.0001 in model (6). Standard errors clustered at the cell-by-block level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1. Distribution of baseline residual working horizon YTR

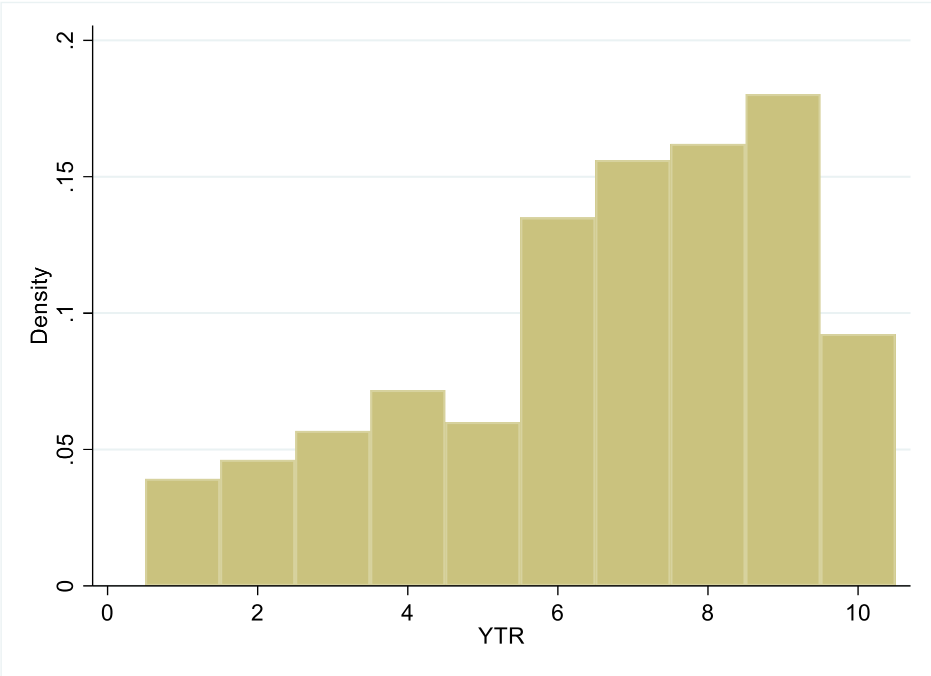


Figure 2. Distribution of policy-induced changes in residual working horizon ΔYTR

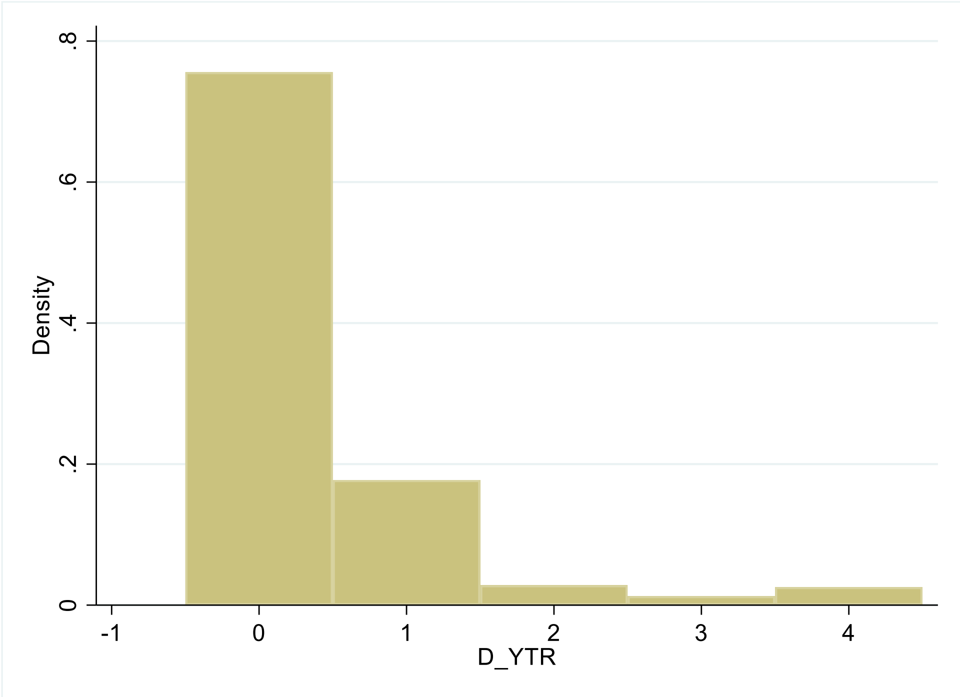
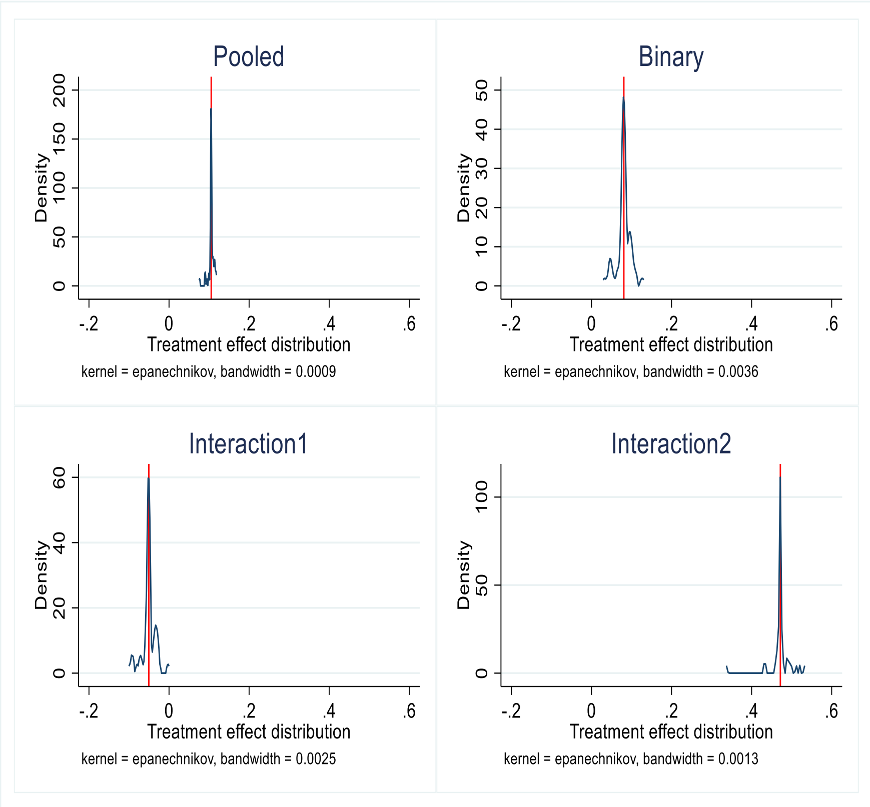


Figure 3. Distribution of treatment effects when one country-by-block group at a time is dropped from the sample

Panel a. EURO-D (0-12)



Panel B.

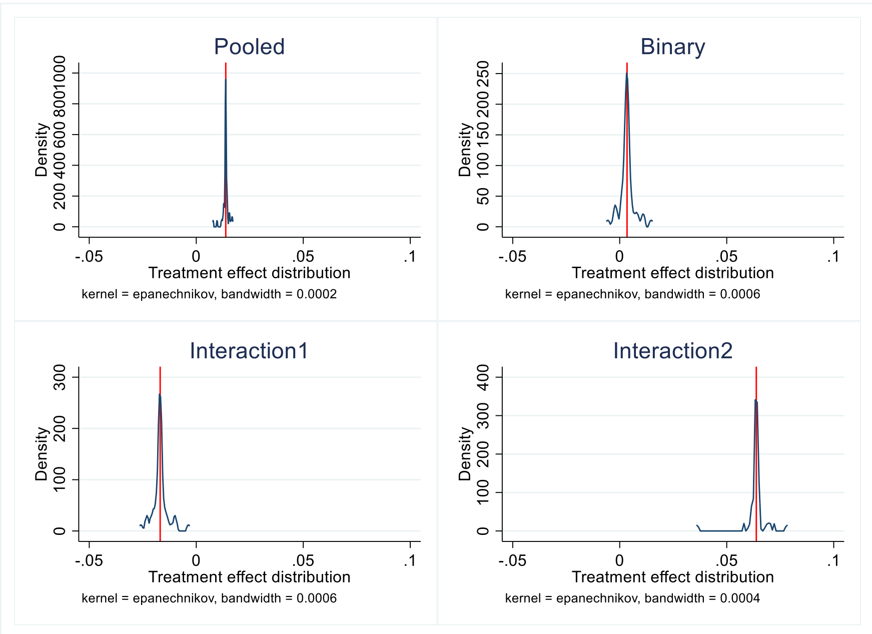
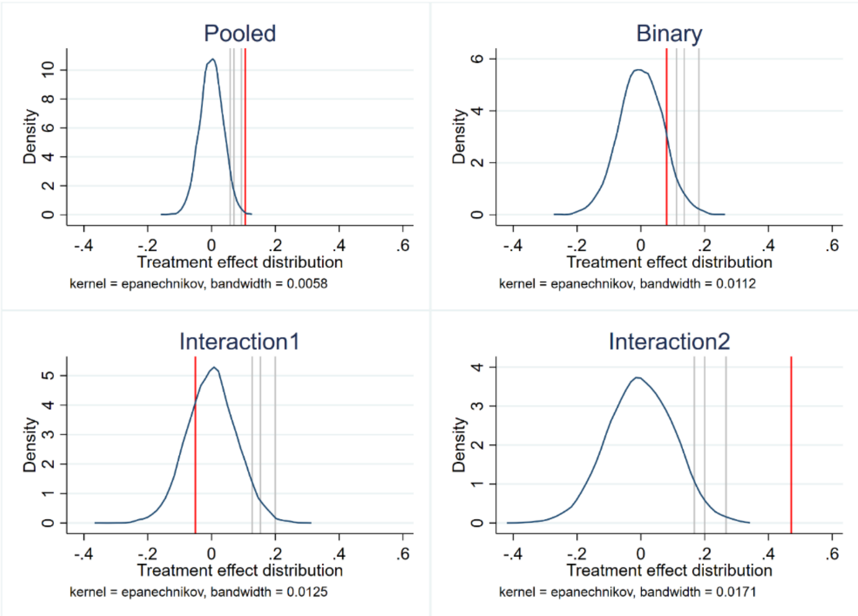


Figure 4. Distribution of treatment effects after 5,000 random permutations of ΔYTR across cells and blocks

Panel a. EURO-D (0-12)



Panel B. EURO-D>3

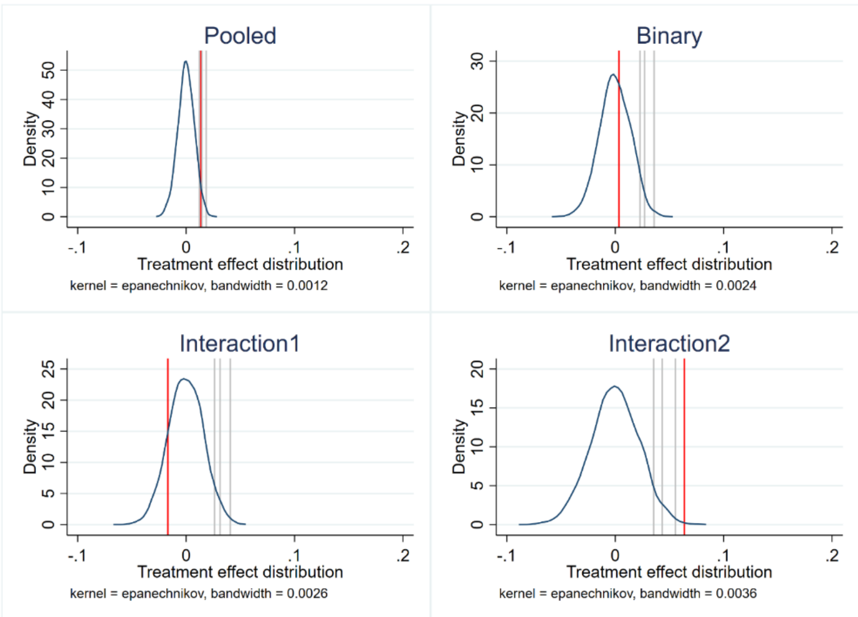


Figure 5. Risk of automation and share of strenuous jobs, by occupation

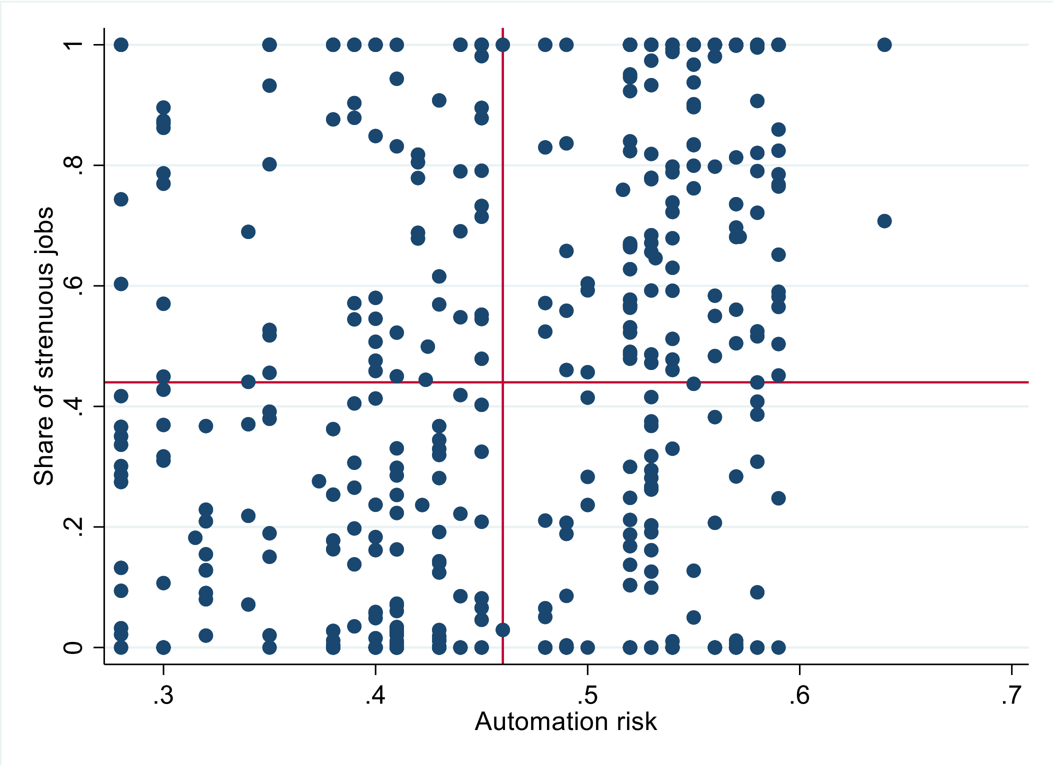
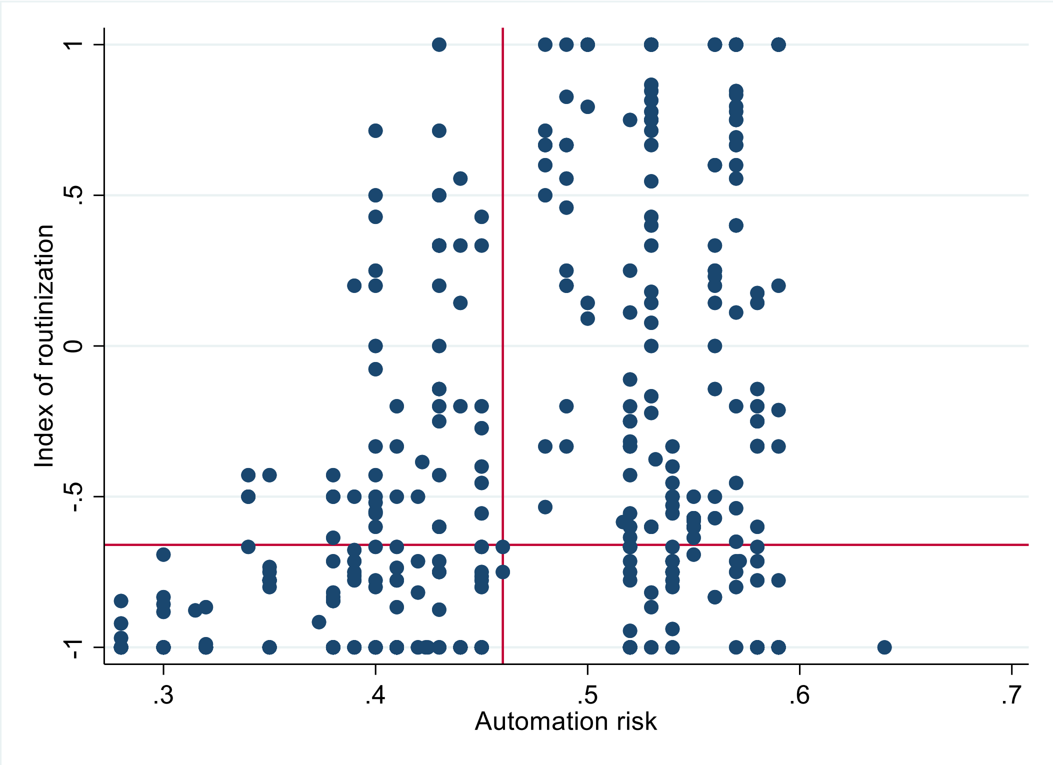


Figure 6. RTI index and risk of automation, by occupation



Appendix

A. *Additional tables*

Table A1. The presence of countries by wave

Wave 1	Wave 2	Wave 4	Wave 5	Wave 6
Austria	Austria	Austria	Austria	Austria
Belgium	Belgium	Belgium	Belgium	Belgium
Denmark	Denmark	Denmark	Denmark	Denmark
France	France	France	France	France
Germany	Germany	Germany	Germany	Germany
Italy	Italy	Italy	Italy	Italy
Spain	Spain	Spain	Spain	Spain
Sweden	Sweden	Sweden	Sweden	Sweden
Switzerland	Switzerland	Switzerland	Switzerland	Switzerland
Netherlands	Netherlands	Netherlands	Netherlands	
	Czech Republic	Czech Republic	Czech Republic	Czech Republic
		Estonia	Estonia	Estonia
		Slovenia	Slovenia	Slovenia
Greece	Greece			
	Poland	Poland		
			Luxembourg	Luxembourg
N=11	N=13	N=14	N=14	N=13

Notes: N: number of countries. Countries always present: Austria, Belgium, Denmark, France, Germany, Italy, Spain, Sweden and Switzerland. Countries present in only two consecutive waves: Greece, Poland and Luxembourg.

Table A2. Countries and blocks with changes is the residual work horizon

Positive change in YTR			
+1	+2	+3	+4
Block 1			
Austria			
Belgium			
Germany			
Italy			
Block 2			
Belgium			
Czech Republic	Czech Republic	Czech Republic	Czech Republic
Italy	Italy	Italy	
Block 3			
Austria			
Belgium	Belgium	Belgium	
Czech Republic			
Estonia			
Italy	Italy	Italy	Italy
Slovenia			
Spain	Spain	Spain	
Block 4			
Austria			
Belgium	Belgium		
Czech Republic			
			France
Italy	Italy		
Slovenia			
Sample share (conditional on ΔYTR>0)			
72.7%	11.6%	5.2%	10.5%

Table A3. Descriptive statistics in the estimation sample

Variable	Mean	Std. Dev.
Outcomes:		
EURO-D (0-12)	2.151	2.059
EURO-D>3	.225	.418
Years to retirement – YTR:		
Baseline YTR	6.627	2.483
Share with positive change in YTR (ΔYTR)	0.227	0.414
ΔYTR – conditional on positive values (N=1,825)	1.589	1.034
Covariates determining the cell:		
Age	52.674	1.141
Female	.574	.494
Self-employed	.12	.325
Civil servant	.205	.404
Private employee	.676	.468
Contribution years	31.721	5.746
No child	.105	.306
1 child	.166	.372
2 children	.445	.497
3/4 children	.25	.433
5 or more children	.033	.179
Observations	17,545	

Table A4. Baseline results on EURO-D (0-12) after dropping one country or block at a time

	Outcome variable: EURO-D (0-12)			
Regressor	ΔYTR	$\Delta YTR > 0$	$\Delta YTR = 1$	$\Delta YTR > 1$
Dropped country /block				
Austria	0.1154***	0.1182	-0.0262	0.4814***
	(0.0397)	(0.0911)	(0.1022)	(0.1449)
Belgium	0.1007**	0.0671	-0.0716	0.4891***
	(0.0399)	(0.0934)	(0.0999)	(0.1587)
Czech Republic	0.0918**	0.0663	-0.0654	0.4195***
	(0.0405)	(0.0891)	(0.0980)	(0.1473)
Denmark	0.1255***	0.1190	-0.0017	0.5173***
	(0.0416)	(0.0917)	(0.0984)	(0.1506)
Estonia	0.1243***	0.1458	0.0161	0.4888***
	(0.0400)	(0.0899)	(0.0992)	(0.1464)
France	0.1073*	0.0483	-0.0494	0.5194***
	(0.0638)	(0.0895)	(0.0956)	(0.2041)
Germany	0.0858**	0.0236	-0.1229	0.4199***
	(0.0402)	(0.0908)	(0.1002)	(0.1452)
Greece	0.1043***	0.0766	-0.0559	0.4705***
	(0.0395)	(0.0858)	(0.0937)	(0.1448)
Italy	0.0799*	0.0413	-0.0438	0.3837***
	(0.0437)	(0.0905)	(0.0963)	(0.1649)
Luxembourg	0.1135***	0.0959	-0.0363	0.4920***
	(0.0395)	(0.0859)	(0.0938)	(0.1451)
Netherlands	0.1061***	0.0826	-0.0491	0.4734***
	(0.0395)	(0.0860)	(0.0940)	(0.1448)
Poland	0.1054***	0.0807	-0.0506	0.4717***
	(0.0395)	(0.0858)	(0.0939)	(0.1448)
Slovenia	0.1047***	0.0836	-0.0824	0.4704***
	(0.0397)	(0.0930)	(0.1072)	(0.1453)
Spain	0.1097***	0.0828	-0.0582	0.5083***
	(0.0396)	(0.0867)	(0.0949)	(0.1445)
Sweden	0.1087***	0.0887	-0.0417	0.4780***
	(0.0397)	(0.0863)	(0.0943)	(0.1455)
Switzerland	0.1024**	0.0709	-0.0614	0.4643***
	(0.0399)	(0.0873)	(0.0952)	(0.1456)
Block 1	0.1080***	0.0880	-0.0649	0.4683***
	(0.0401)	(0.0932)	(0.1025)	(0.1452)
Block 2	0.1028**	0.0750	-0.0584	0.4906***
	(0.0414)	(0.0900)	(0.0971)	(0.1537)
Block 3	0.1145***	0.1621	0.0640	0.4127***
	(0.0423)	(0.1091)	(0.1234)	(0.1586)
Block 4	0.0862	-0.0075	-0.1308	0.5550**
	(0.0729)	(0.1076)	(0.1169)	(0.2589)

Notes: Notes: each model includes wave-by-block and cell-by-block fixed effects. Standard errors clustered at the cell-by-block level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A5. Baseline results on EURO-D>3 (0-12) after dropping one country at a time

	Outcome variable: EUROD>3			
Regressor	ΔYTR	ΔYTR > 0	ΔYTR = 1	ΔYTR > 1
Dropped country/block				
Austria	0.0167*	0.014	-0.0064	0.0665**
	(0.0087)	(0.0186)	(0.0211)	(0.0291)
Belgium	0.0124	-0.0022	-0.0257	0.0695**
	(0.0095)	(0.0201)	(0.0218)	(0.0345)
Czech Republic	0.0123	0.0007	-0.0206	0.0576*
	(0.0090)	(0.0185)	(0.0208)	(0.0296)
Denmark	0.0174*	0.0097	-0.0107	0.0717**
	(0.0092)	(0.0192)	(0.0209)	(0.0302)
Estonia	0.0163*	0.0145	-0.0037	0.0626**
	(0.0088)	(0.0183)	(0.0206)	(0.0293)
France	0.0109	-0.0021	-0.0161	0.0658*
	(0.0123)	(0.0179)	(0.0196)	(0.0367)
Germany	0.0105	-0.0077	-0.0309	0.0552*
	(0.0091)	(0.0187)	(0.0207)	(0.0292)
Greece	0.0137	0.0029	-0.0175	0.0637**
	(0.0088)	(0.0177)	(0.0197)	(0.0290)
Italy	0.0098	-0.0011	-0.0138	0.0499
	(0.0098)	(0.0185)	(0.0200)	(0.0332)
Luxembourg	0.0156*	0.0069	-0.0136	0.0684**
	(0.0088)	(0.0178)	(0.0197)	(0.0391)
Netherlands	0.0138	0.0034	-0.0169	0.0638**
	(0.0088)	(0.0178)	(0.0198)	(0.0290)
Poland	0.0139	0.0036	-0.0617	0.0641**
	(0.0088)	(0.0177)	(0.0197)	(0.0290)
Slovenia	0.0135	0.0009	-0.0263	0.0644**
	(0.0089)	(0.0196)	(0.0229)	(0.0291)
Spain	0.0146	0.0041	-0.0176	0.0695**
	(0.0088)	(0.0180)	(0.0200)	(0.0290)
Sweden	0.0140	0.0039	-0.0162	0.0642**
	(0.0088)	(0.0179)	(0.0198)	(0.0291)
Switzerland	0.0135	0.0026	-0.0178	0.0631**
	(0.0088)	(0.0179)	(0.0199)	(0.0291)
Block1	0.0143	0.0042	-0.0195	0.0632**
	(0.0089)	(0.0189)	(0.0211)	(0.0291)
Block 2	0.0152*	0.0051	-0.0171	0.0741**
	(0.0091)	(0.0186)	(0.0205)	(0.0303)
Block 3	0.0142	0.0173	0.0078	0.0416
	(0.0100)	(0.0223)	(0.0252)	(0.0356)
Block 4	0.0078	-0.0151	-0.0369	0.0844*
	(0.0149)	(0.0231)	(0.0255)	(0.0483)

Notes: Notes: each model includes wave-by-block and cell-by-block fixed effects. Standard errors clustered at the cell-by-block level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A6. Heterogeneous effects of ΔYTR on EURO-D>3 by automation level of 2-digit ISCO-08 occupations (NQ2).

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable: EUROD>3	Below median automation	Above median automation	Below median automation	Above median automation	Below median automation	Above median automation
ΔYTR	-0.0045	0.0331**				
	(0.0127)	(0.0132)				
p-value for equality across samples	0.0296					
$\Delta YTR > 0$			-0.0141	0.0271		
			(0.0244)	(0.0270)		
p-value for equality across samples			0.2500			
$\Delta YTR = 1$					-0.0111	-0.0065
					(0.0273)	(0.0284)
p-value for equality across samples					0.9050	
$\Delta YTR > 1$					-0.0220	0.1418***
					(0.0416)	(0.0471)
p-value for equality across samples					0.0066	
p-value for joint equality across samples					0.0230	
Control group mean	0.208	0.235	0.208	0.235	0.208	0.235
Observations	8,309	8,234	8,309	8,234	8,309	8,234
Clusters	992	1,265	992	1,265	992	1,265

Notes: each model includes wave-by-block and cell-by-block fixed effects. The p-value of the test for the joint significance of $\Delta YTR = 1$ and $\Delta YTR > 1$ is 0.8241 in model (5) and 0.0081 in model (6).). Standard errors clustered at the cell-by-block level within parentheses. ***: p<0.01, **: p<0.05, *: p<0.1.

Table A7. Heterogeneous effects of ΔYTR on EURO-D (0-12) by automation level of 3-digit ISCO-08 occupations (NQ3).

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable: EURO-D (0-12)	Below median automation	Above median automation	Below median automation	Above median automation	Below median automation	Above median automation
ΔYTR	-0.0193	0.1968***				
	(0.0496)	(0.0702)				
p-value for equality across samples	0.0150					
$\Delta YTR > 0$			-0.0728	0.1333		
			(0.1186)	(0.1334)		
p-value for equality across samples			0.249			
$\Delta YTR = 1$					-0.0941	-0.0771
					(0.1370)	(0.1338)
p-value for equality across samples					0.929	
$\Delta YTR > 1$					-0.0185	0.8657***
					(0.1877)	(0.2437)
p-value for equality across samples					0.00474	
p-value for joint equality across samples					0.0174	
Control group mean	1.977	2.265	2.039	2.2420	2.039	2.2420
Observations	7,143	9,421	8,309	8,234	8,309	8,234
Clusters	909	1346	992	1,265	992	1,265

Notes: each model includes wave-by-block and cell-by-block fixed effects. P-value for joint significance ($\Delta YTR = 1$) and ($\Delta YTR > 1$): 0.790 in model (5); 0.0009 in model (6). Standard errors clustered at the cell-by-block level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A8. Heterogeneous effects of ΔYTR on EURO-D>3 by automation level of 3-digit ISCO-08 occupations (NQ3).

Outcome variable: EUROD>3	(1) Below median automation	(2) Above median automation	(3) Below median automation	(4) Above median automation	(5) Below median automation	(6) Above median automation
ΔYTR	-0.0023	0.0262*				
	(0.0148)	(0.0136)				
p-value for equality across samples	0.182					
$\Delta YTR > 0$			-0.0134	0.0091		
			(0.0269)	(0.0267)		
p-value for equality across samples			0.559			
$\Delta YTR = 1$					-0.0168	-0.0221
					(0.0296)	(0.0277)
p-value for equality across samples					0.897	
$\Delta YTR > 1$					-0.0045	0.1176**
					(0.0483)	(0.0475)
p-value for equality across samples					0.0891	
p-value for joint equality across samples					0.216	
Control group mean	0.197	0.240	0.197	0.240	0.197	0.240
Observations	7,143	9,421	7,143	9,421	7,143	9,421
Clusters	909	1346	909	1346	909	1346

Notes: each model includes wave-by-block and cell-by-block fixed effects. P-value joint significance (ΔYTR=1) and (ΔYTR>1): 0.850 in model (5); 0.0215 in model (6). Standard errors clustered at the cell-by-block level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A9. The effects of ΔYTR on EURO-D>3 for occupations above and below median level of strenuousness.

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable: EURO-D (0-12)	Below median stren.ness	Above median stren.ness	Below median stren.ness	Above median stren.ness	Below median stren.ness	Above median stren.ness
ΔYTR	0.0116	0.0139				
	(0.0188)	(0.0105)				
p-value for equality across samples	0.921					
$\Delta YTR > 0$			0.0153	-0.0036		
			(0.0253)	(0.0293)		
p-value for equality across samples			0.632			
$\Delta YTR = 1$					0.0048	-0.0214
					(0.0294)	(0.0299)
p-value for equality across samples					0.536	
$\Delta YTR > 1$					0.0446	0.0586
					(0.0386)	(0.0636)
p-value for equality across samples					0.864	
p-value for joint equality across samples					0.801	
Control group mean						
Observations	8,646	7,736	8,646	7,736	8,646	7,736
Clusters	1,234	1,053	1,234	1,053	1,234	1,053

Notes: stren.ness: strenuousness. Each model includes wave-by-block and cell-by-block fixed effects. The p-value of the test for the joint significance of $\Delta YTR = 1$ and $\Delta YTR > 1$ is in model (5) and in model (6). Standard errors clustered at the cell-by-block level within parentheses. ***: p<0.01, **: p<0.05, *: p<0.1.

Table A10. Heterogeneous effects of ΔYTR on EURO-D>3 by education

Outcome variable: EUROD>3	(1) Below high school	(2) High school or above	(3) Below high school	(4) High school or above	(5) Below high school	(6) High school or above
ΔYTR	0.0225	0.0074				
	(0.0321)	(0.0092)				
p-value for equality across samples	0.651					
$\Delta YTR > 0$			0.0240	-0.0013		
			(0.0506)	(0.0190)		
p-value for equality across samples			0.628			
$\Delta YTR = 1$					0.0039	-0.0142
					(0.0519)	(0.0213)
p-value for equality across samples					0.739	
$\Delta YTR > 1$					0.0736	0.0389
					(0.1073)	(0.0319)
p-value for equality across samples					0.759	
p-value for joint equality across samples					0.909	
Control group mean	0.205	0.269	0.205	0.269	0.205	0.269
Observations	12,993	3,727	12,993	3,727	12,993	3,727
Clusters	1404	761	1404	761	1404	761

Notes: each model includes wave-by-block and cell-by-block fixed effects. The p-value of the test for the joint significance of $\Delta YTR = 1$ and $\Delta YTR > 1$ is 0.3320 in model (5) and 0.790 in model (6).). Standard errors clustered at the cell-by-block level within parentheses. ***: p<0.01, **: p<0.05, *: p<0.1.

Table A11. Heterogeneous effects of ΔYTR on EURO-D>3 by gender

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable: EUROD>3	Females	Males	Females	Males	Females	Males
ΔYTR	0.0240*	0.0066				
	(0.0130)	(0.0114)				
p-value for equality across samples	0.372					
$\Delta YTR > 0$			0.0133	0.0005		
			(0.0254)	(0.0257)		
p-value for equality across samples			0.731			
$\Delta YTR = 1$					-0.0144	-0.0070
					(0.0277)	(0.0293)
p-value for equality across samples					0.858	
$\Delta YTR > 1$					0.1103***	0.0156
					(0.0417)	(0.0402)
p-value for equality across samples					0.138	
p-value for joint equality across samples					0.297	
Control group mean	0.280	0.151	0.280	0.151	0.280	0.151
Observations	10,022	7,405	10,022	7,405	10,022	7,405
Clusters	1208	833	1208	833	1208	833

Notes: each model includes wave-by-block and cell-by-block fixed effects. P-value joint significance (ΔYTR=1) and (ΔYTR>1): 0.016 in model (5); 0.883 in model (6). Standard errors clustered at the cell-by-block level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A12. Heterogeneous effects of ΔYTR on EURO-D>3 for occupations at or above and below median level of Routine Task Intensity (RTI).

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable: EURO-D (0-12)	Below median RTI	Above median RTI	Below median RTI	Above median RTI	Below median RTI	Above median RTI
ΔYTR	-0.0057	0.0251*				
	(0.0121)	(0.0149)				
p-value for equality across samples	0.0965					
$\Delta YTR > 0$			-0.0124	-0.0066		
			(0.0274)	(0.0299)		
p-value for equality across samples			0.883			
$\Delta YTR = 1$					-0.0091	-0.0515
					(0.0314)	(0.0322)
p-value for equality across samples					0.336	
$\Delta YTR > 1$					-0.0216	0.1406***
					(0.0443)	(0.0478)
p-value for equality across samples					0.0136	
p-value for joint equality across samples					0.0208	
Control group mean	0.226	0.217	0.226	0.217	0.226	0.217
Observations	8,235	6,797	8,235	6,797	8,235	6,797
Clusters	1113	1062	1113	1062	1113	1062

Notes: each model includes wave-by-block and cell-by-block fixed effects. P-value for joint significance ($\Delta YTR = 1$) and ($\Delta YTR > 1$): 0.867 in model (5); 0.0017 in model (6). Standard errors clustered at the cell-by-block level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A13. Heterogeneous effects of ΔYTR on EURO-D>3 for occupations above and below median automation risk, within occupations below median level of the RTI index

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome variable: EURO-D (0-12)	Below median automation	Above median automation	Below median automation	Above median automation	Below median automation	Above median automation
ΔYTR	-0.0189	0.0359**				
	(0.0129)	(0.0177)				
p-value for equality across samples	0.00699					
$\Delta YTR > 0$			-0.0252	0.0519		
			(0.0311)	(0.0540)		
p-value for equality across samples			0.190			
$\Delta YTR = 1$					-0.0111	0.0280
					(0.0372)	(0.0619)
p-value for equality across samples					0.565	
$\Delta YTR > 1$					-0.0588	0.1293*
					(0.0465)	(0.0716)
p-value for equality across samples					0.0203	
p-value for joint equality across samples					0.0666	
Control group mean	0.204	0.269	0.204	0.269	0.204	0.269
Observations	5,233	2,323	5,233	2,323	5,233	2,323
Clusters	681	468	681	468	681	468

Notes: each model includes wave-by-block and cell-by-block fixed effects. P-value for joint significance ($\Delta YTR = 1$) and ($\Delta YTR > 1$): 0.444 in model (5); 0.196 in model (6). Standard errors clustered at the cell-by-block level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A14. Heterogeneous effects of ΔYTR on EURO-D>3 for occupations above and below median automation risk, within occupations at or above median level of the RTI index

Outcome variable: EURO-D (0-12)	(1) Below median automation	(2) Above median automation	(3) Below median automation	(4) Above median automation	(5) Below median automation	(6) Above median automation
ΔYTR	0.0210	0.0279				
	(0.0274)	(0.0185)				
p-value for equality across samples	0.852					
$\Delta YTR > 0$			0.0373	0.0025		
			(0.0599)	(0.0361)		
p-value for equality across samples			0.627			
$\Delta YTR = 1$					0.0165	-0.0425
					(0.0689)	(0.0388)
p-value for equality across samples					0.461	
$\Delta YTR > 1$					0.1070	0.1449**
					(0.1075)	(0.0595)
p-value for equality across samples					‘0.773	
p-value for joint equality across samples					0.718	
Control group mean	0.214	0.218	0.214	0.218	0.214	0.218
Observations	1,672	4,631	1,672	4,631	1,672	4,631
Clusters	331	833	331	833	331	833

Notes: each model includes wave-by-block and cell-by-block fixed effects. P-value for joint significance ($\Delta YTR = 1$) and ($\Delta YTR > 1$): 0.601 in model (5); 0.0182 in model (6). Standard errors clustered at the cell-by-block level in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A15. Effects of ΔYTR on affective suffering, in the full sample and by automation level of 2-digit ISCO-08 occupations (NQ2).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Outcome variable: Affective suffering	Full sample	Below median automation	Above median automation	Full sample	Below median automation	Above median automation	Full sample	Below median automatio n	Above median automation
ΔYTR	0.0575***	0.0050	0.1111***						
	(0.0198)	(0.0229)	(0.0339)						
p-value for equality across samples		0.0057							
$\Delta YTR > 0$				0.0516	0.0132	0.1029			
				(0.0442)	(0.0577)	(0.0672)			
p-value for equality across samples					0.295				
$\Delta YTR = 1$							-0.0155	0.0144	-0.0112
							(0.0483)	(0.0664)	(0.0690)
p-value for equality across samples								0.784	
$\Delta YTR > 1$							0.2517***	0.0098	0.4924***
							(0.0751)	(0.0886)	(0.1272)
p-value for equality across samples								0.0009	
p-value for joint equality across samples								0.0033	
Control group mean	-0.0063	-0.0543	0.0435	-0.0063	-0.0543	0.0435	-0.0063	-0.0543	0.0435
Observations	17,545	8,309	8,234	17,545	8,309	8,234	17,545	8,309	8,234
Clusters	1901	992	1265	1901	992	1265	1901	992	1265

Notes: each model includes wave-by-block and cell-by-block fixed effects. The p-value of the test for the joint significance of $\Delta YTR = 1$ and $\Delta YTR > 1$ is 0.0025 in model (7), in 0.974 model (8) and 0.0004 in model (9). Standard errors clustered at the cell-by-block level within parentheses. ***: p<0.01, **: p<0.05, *: p<0.1.

Table A16. Effects of ΔYTR on lack of motivation, in the full sample and by automation level of 2-digit ISCO-08 occupations (NQ2).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Outcome variable: Affective suffering	Full sample	Below median automation	Above median automation	Full sample	Below median automation	Above median automation	Full sample	Below median automation	Above median automation
ΔYTR	0.0001	0.0187	-0.0104						
	(0.0158)	(0.0183)	(0.0363)						
p-value for equality across samples		0.526							
$\Delta YTR > 0$				-0.0350	-0.0126	-0.0439			
				(0.0276)	(0.0374)	(0.0484)			
p-value for equality across samples					0.625				
$\Delta YTR = 1$							-0.0573*	-0.0528	-0.0521
							(0.0294)	(0.0421)	(0.0472)
p-value for equality across samples								0.991	
$\Delta YTR > 1$							0.0311	0.0926	-0.0157
							(0.0532)	(0.0582)	(0.1222)
p-value for equality across samples								0.463	
p-value for joint equality across samples								0.760	
Control group mean	-0.0012	-0.0510	0.0505	-0.0012	-0.0510	0.0505	-0.0012	-0.0510	0.0505
Observations	17,545	8,309	8,234	17,545	8,309	8,234	17,545	8,309	8,234
Clusters	1901	992	1265	1901	992	1265	1901	992	1265

Notes: each model includes wave-by-block and cell-by-block fixed effects. The p-value of the test for the joint significance of $\Delta YTR = 1$ and $\Delta YTR > 1$ is 0.101 in model (7), in 0.094 model (8) and 0.545 in model (9). Standard errors clustered at the cell-by-block level within parentheses. ***: p<0.01, **: p<0.05, *: p<0.1.

B. *Automation data and pension eligibility rules*

Table B1. The NQ2 index for ISCO-08 two-digit occupations

Job title	ISCO-08 two digit	NQ2	High risk (binary)
Chief executives, Senior officials and Legislators	11	0.30	0
Administrative and Commercial Managers	12	0.32	0
Production and Specialized Services Managers	13	0.30	0
Hospitality, Retail and other Services Managers	14	0.34	0
Science and Engineering Professionals	21	0.41	0
Health Professionals	22	0.35	0
Teaching Professionals	23	0.28	0
Business and Administration Professionals	24	0.41	0
ICT Professionals	25	0.41	0
Legal, Social and Cultural Professionals	26	0.38	0
Science and Engineering Associate Professionals	31	0.40	0
Health Associate Professionals	32	0.45	0
Business and Administration Associate Professionals	33	0.43	0
Legal, Social, Cultural and Related Associate Professionals	34	0.39	0
ICT Technicians	35	0.44	0
General and Keyboard Clerks	41	0.53	1
Customer Services Clerks	42	0.49	1
Numerical and Material Recording Clerks	43	0.50	1
Other Clerical Support Workers	44	0.48	0
Personal Service Workers	51	0.54	1
Sales Workers	52	0.52	1
Personal Care Workers	53	0.42	0
Protective Services Workers	54	0.44	0
Market-oriented Skilled Agricultural Workers	61	0.55	1
Market-oriented Skilled Forestry, Fishery and Hunting	62	0.55	1
Subsistence Farmers, Fishers, Hunters and Gatherers	63	0.45	0
Building and Related Trades Workers	71	0.52	1
Metal, Machinery and Related Trades Workers	72	0.53	1
Handicraft and printing Workers	73	0.53	1
Electric and Electronics Trades Workers	74	0.52	1
Food Processing, Woodworking, Garment and other Craft	75	0.56	1
Stationary Plant and Machine Operators	81	0.57	1
Assemblers	82	0.59	1
Drivers and Mobile Plant Operators	83	0.58	1
Domestic, Hotel and Office Cleaners and Helpers	91	0.59	1
Agricultural, Forestry and Fishery Labourers	92	0.57	1
Labourers in Mining, Building, Manufacturing and Transport	93	0.59	1
Food Preparation Assistants	94	0.64	1
Street and Related Sales and Services Workers	95	0.46	0
Refuse Workers and other Elementary Workers	96	0.58	1

Table B2. The NQ3 index for ISCO-08 three-digit occupations

ISCO-08 3 digit	Share of workers in jobs at high risk of automation	ISCO-08 3 digit	Share of workers in jobs at high risk of automation	ISCO-08 3 digit	Share of workers in jobs at high risk of automation
111	0,0117954	321	0,2409792	633	0,228748
112	0,0062938	322	0,0638849	634	0,228748
121	0,0103557	323	0,433702	711	0,1804704
122	0,0114453	324	0,0301543	712	0,17897
131	0,0216297	325	0,0932058	713	0,1255862
132	0,035972	331	0,1132348	721	0,2613662
133	0	332	0,0563948	722	0,2313525
134	0,0061265	333	0,0630296	723	0,1121666
141	0,0611228	334	0,0507856	731	0,205528
142	0,0431567	335	0,06599	732	0,203777
143	0,0043835	341	0,0564344	741	0,1586326
211	0,048233	342	0,0442863	742	0,1148135
212	0,0128676	343	0,0352551	751	0,3264327
213	0,0234851	351	0,0896809	752	0,2332217
214	0,0386099	352	0,0689858	753	0,2737106
215	0,0246992	411	0,1855019	754	0,2260407
216	0,060853	412	0,1341695	811	0,1459166
221	0,0105621	413	0,3128336	812	0,3280365
222	0,0359737	421	0,0775609	813	0,2207289
223	0,0106665	422	0,1294441	814	0,2614146
224	0,0780193	431	0,1767748	815	0,2237703
225	0,0099995	432	0,1725551	816	0,2466649
226	0,0462001	441	0,1306377	817	0,3263959
231	0,0058712	511	0,043714	818	0,3070862
232	0,007197	512	0,2377662	821	0,235929
233	0,0102372	513	0,2711293	831	0,2859551
234	0,0245933	514	0,1058041	832	0,2360576
235	0,0117095	515	0,1598794	833	0,21828
241	0,0600348	516	0,0991194	834	0,2716971
242	0,0202258	521	0,1875188	835	0,3067455
243	0,0436894	522	0,1424954	911	0,2499833
251	0,0338064	523	0,3590768	912	0,189506
252	0,0445831	524	0,1768702	921	0,2763026
261	0,016812	531	0,0865778	931	0,3216618
262	0,0523336	532	0,0766956	932	0,3891996
263	0,00983	541	0,0996402	933	0,2141664
264	0,0729626	611	0,2048168	941	0,4229199
265	0,0333293	612	0,2017118	951	0,29408
311	0,0940201	613	0,2959017	952	0,29408
312	0,0375307	621	0,2172938	961	0,4297906
313	0,1462968	622	0,4801768	962	0,2799952
314	0,1213228	631	0,228748		
315	0,1603869	632	0,228748		

C. *Pension eligibility rules*

The requirements for retirement eligibility are mostly taken from Bertoni et al., 2021; "MISSOC | Mutual Information System on Social Protection"; OECD, 2015, 2013, 2011, 2009, 2007b, 2007a, and country-specific references.

Austria

Source: MISSOC

Old age retirement: 65 for males, 60 for females

Early retirement: in 2004: 61 for males and 56 for females. From 2006: 62 for males and 57 for females. From 2012: 63 for males and 58 for females. From 2014: 64 for males and 59 for females.

15 years of contribution are required for both old age and early retirement.

Belgium

Source: Angelini et al., 2009; Bertoni et al., 2021; OECD, 2013

Old age retirement: 65 for males. For females: 63 from 2003; 64 from 2006; 65 from 2009.

Early retirement: 60 for both from 1987; 61 for both from 2014. Required contribution years: 34 from 2004; 35 from 2005; 38 from 2013; 40 from 2015.

Czech Republic

Source: Bertoni et al., 2021; OECD, 2011, 2009

Old age: for males: 61 from 2008; 62 from 2009. For females the following table applies:

Table C.1 Retirement age

	0 child	1 child	2 children	3/4 children	5+ children

Up to 1999	55	55	55	55	55
From 2000 to 2002	56	56	56	56	56
From 2003 to 2006	59	58	57	56	55
From 2007 to 2011	60	59	58	57	56
From 2012 to 2014	61	60	59	58	57
From 2015 to 2018	62	61	60	59	58
From 2019	63	62	61	60	59

Early retirement: it is possible to anticipate up to two years before the normal retirement age. Contribution years are required: 25 in 2009; 35 from 2010.

Denmark

See: Bertoni et al., 2021; OECD, 2011

Old age: 65 from 2004 for both males and females

Early retirement: 60 for both males and females

Estonia

See: Bertoni et al., 2021; OECD, 2011

Old age: 63 for males. For females: 61 from 2010, 62 from 2013.

Early retirement: 60 for males. For females: 58 from 2010, 59 from 2013.

15 contribution years are required for both programs.

France

See: Bertoni et al., 2021; OECD, 2015

Old age: 60 from 1983. From 2011: 60 for those born before 1952, 61 for those born between 1953 and 1954, and 62 for those born since 1955.

Early retirement: 55 from 1981, 60 from 2015.

Germany

See: Bertoni et al., 2021; Mazzonna and Peracchi, 2017; OECD, 2009

Old age: 65 for both males and females until 2012, 67 from 2012.

Early retirement: 63 for males. For females 62 in 2004, 63 in 2006.

5 years of contribution are required for both programs.

Greece

See: Bertoni et al., 2021; OECD, 2009

Old age: 65 for males and 60 for females until 2012. For females: 65 in 2013. From 2014, 67 for males and 67 for females. 15 contribution years are required.

Early retirement: 60 until 2012, 62 from 2013. 35 years of contribution are required. One may retire regardless of age provided that he/she has 37 years of contribution.

Italy

See: Brunello and Comi, 2015; Carta and de Philippis, 2021; Chinetti, 2021

Old age: for males: 65 up to 2011. From 2011, 66. For females: 60 up to 2009. In 2010, 61 only for female working in the public sector, for the others 60. In 2013: 66 (public sector), 62 (private sector), 64 (self-employed workers). In 2015: 66 (public sector), 64 (private sector), 65 (self-employed workers). 20 contribution years are required.

Early retirement: in 2004: age 57 and 35 contribution years, 58+35 for self-employed workers. Or with 38 contribution years (39 for self-employed workers) regardless of age. in 2007: age 57 and 35 contribution years, 58+35 for self-employed workers. Or with 39 contribution years (40 for self-employed workers) regardless of age. in 2011: age 60 and 35 contribution years, 61+35 for self-employed workers. Or with 40 contribution years regardless of age. From 2013 regardless of age with 43 contribution years for males and 42 for females.

Luxembourg

See: Bertoni et al., 2021

Old age: 65 for both males and females.

Early retirement: for males 57 from 1993 onwards. For females 60 from 1993 onwards.

The Netherlands

See: Bertoni et al., 2021

Old age: 65 for both males and females until 2017, 66 afterwards.

Early retirement: 60 from 1975.

Poland

See: Bertoni et al., 2021

Old age: 65 for males and 60 for females.

Early retirement: 60 for males and 55 for females.

Slovenia

See: Bertoni et al., 2021; OECD, 2011

Old age: for males: 65 from 1993. For females: 63 from 2008, 65 from 2014

Early retirement: for males: 58 from 1993, 59 from 2015. For females: 56 in 2011, 57 in 2013, 58 from 2014, 59 from 2016.

Spain

See: Bertoni et al., 2021; OECD, 2013, 2011

Old age: 65 for both males and females. 15 contribution years are required.

Early retirement: 61 from 1994. Contribution years are required: 30 up to 2011, 33 from 2013.

Sweden

See: Bertoni et al., 2021

Old age: 65 from 1995.

Early retirement: 61 from 1998.

Switzerland

See: Bertoni et al., 2021

Old age: 65 for males. For females: 63 in 2004 and 64 from 2005

Early retirement: from 2001: 63 for males and 62 for females.