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Occupations and retirement across countries

Philip Sauré [a], Arthur Seibold [b,*], Elizaveta Smorodenkova [c], Hosny Zoabi [d]

[a] *Department of Economics, Johannes Gutenberg University Mainz, Germany*
[b] *Department of Economics, Ludwig-Maximilians University Munich, Germany*
[c] *Department of Finance, London School of Economics, United Kingdom*
[d] *The New Economic School, Russia*

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ABSTRACT

We study the role of occupations for individual and aggregate retirement behavior. First, we document large differences in individual retirement ages across occupations in U.S. data. We then show that retirement behavior among European workers is strongly correlated with U.S. occupational retirement ages, indicating an inherent association between occupations and retirement that is present across institutional settings. Finally, we find that occupational composition is an important predictor of aggregate retirement behavior across 45 countries. Our findings suggest that events affecting occupational structure, such as skill-biased technological change or international trade, can have consequences for aggregate retirement behavior and social security systems.

Introduction

The fiscal sustainability of old-age pension systems has become a growing concern around the world. A primary driver of the pressures on social security systems lies in demographic trends, notably rising life expectancy and declining birth rates. Compounding these issues is a long-running trend towards early retirement, which has only begun to reverse in recent years (Börsch-Supan and Coile, 2025). In response, researchers and policymakers have shown keen interest in understanding the factors that influence retirement behavior and strategies to encourage later retirement.

At the same time, there are large and persistent differences in observed retirement behavior across countries. Fig. 1 displays average retirement ages in 45 countries based on OECD data. The average retirement age for men in countries such as Colombia, Iceland, India and Japan ranges from 67 to 69 years, whereas in Belgium, France, and Luxembourg, the average worker retires between the ages 58 and 59. These differences in aggregate retirement patterns have significant implications for social security finances and economic performance more broadly.

In this paper, we put forward a new perspective on the cross-country variation in retirement behavior. We show that occupations are a key predictor of individual retirement ages and, consequently, countries' occupational composition is an important explanatory factor behind aggregate retirement patterns. These findings align with a rich, interdisciplinary body of literature that links occupations to health outcomes and labor market opportunities for the elderly. However, perhaps surprisingly, little systematic evidence exists on the role of occupations for individual and aggregate retirement up to date.

Our empirical analysis proceeds in three steps. First, we provide evidence of large occupational differences in individual retirement behavior among U.S. workers. Fig. 2 plots the distribution of retirement ages (defined as last job exit) by four-digit occupation based on CPS data. Occupational retirement ages span a large range from 55 to more than 70 years. For example, the average cement mason, concrete finisher and terrazzo worker retires at age 55.2, while editors, news analysts, reporters, and correspondents retire at 69.3 and barbers retire at 71.8. Our main analysis, which more formally predicts occupational retirement ages, suggests that much of this dispersion can indeed be attributed to occupational differences rather than other correlated characteristics of workers.

Second, we show that occupational retirement patterns of U.S. workers are highly predictive of individual retirement behavior in other countries. Using survey data from 18 European countries, we find a large positive correlation of individual retirement ages and U.S.

* Corresponding author at: Department of Economics, Ludwig-Maximilians University Munich, Germany.
E-mail addresses: philip.saure@uni-mainz.de (P. Sauré), arthur.seibold@econ.lmu.de (A. Seibold), e.smorodenkova@lse.ac.uk (E. Smorodenkova), hosny.zoabi@gmail.com (H. Zoabi).

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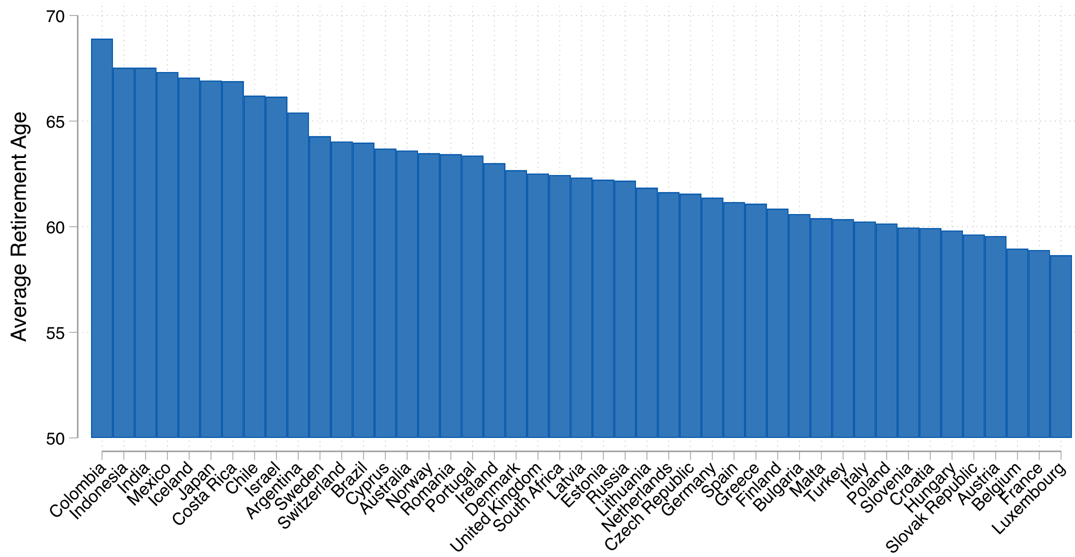

Fig. 1. Retirement ages across countries.
Notes: The figure shows the average retirement age across countries, pooled over the years 2000 to 2020. Average retirement ages are sourced from OECD data on "effective" retirement ages, defined as the average labor force exit age of workers aged 40 and older in a country.

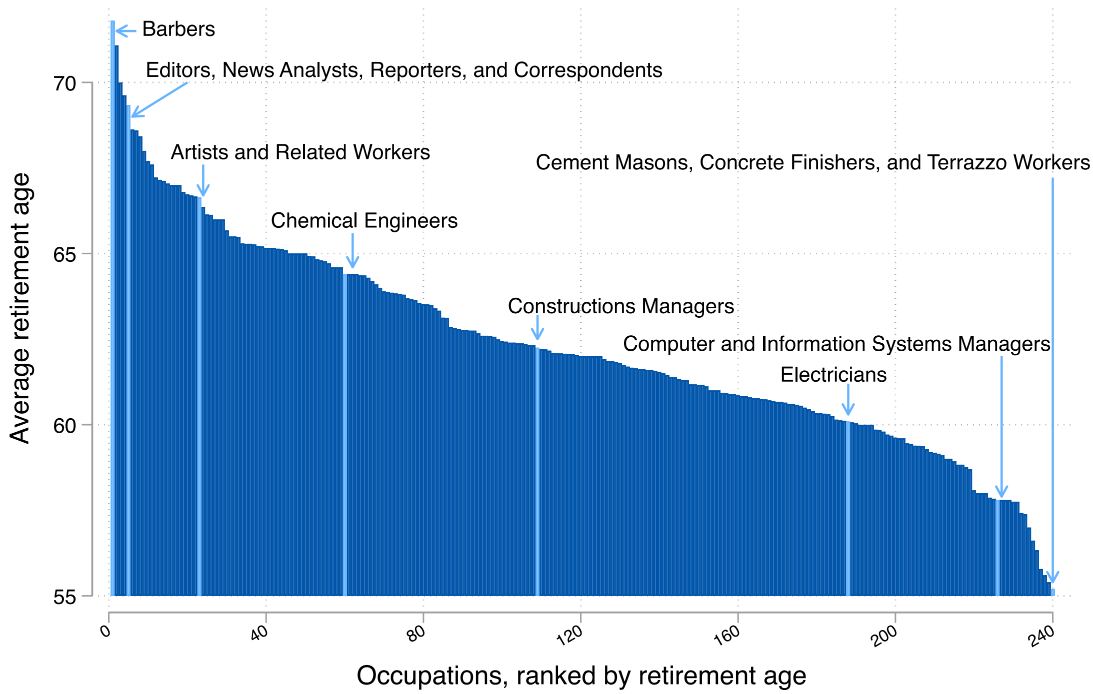

Fig. 2. Retirement ages across occupations.
Notes: The figure shows the average retirement age of U.S. workers between 1990 and 2015 by four-digit occupation (2010 IPUMS/Census codes). Occupations are ranked along the horizontal axis from highest to lowest retirement age. Light blue bars highlight selected occupations. See online Appendix Table C3 for the full list of occupational retirement ages.

occupational retirement ages. Occupation-predicted retirement ages retain almost two thirds of their explanatory power "out-of-sample" in the European data. This suggests that the underlying factors driving retirement differences are largely inherent to occupations, rather than being induced by specific institutional environments.

In the third and final step, we document the aggregate consequences of these findings: occupational composition can explain a substantial portion of differences in retirement behavior across countries. Fig. 3 depicts the cross-country variation in occupational composition. There are large differences, especially in the share of technical, professional, machine operator and craft occupations vs. elementary and agricultural occupations. We use data on occupational composition of 45 countries together with our occupation-predicted retirement ages in order to obtain predicted country-level retirement ages. Our main result is that, at the country level, actual retirement behavior is highly significantly correlated with the prediction based on occupational composition. We find that occupation-predicted retirement ages account for roughly one third of the cross-country variation in average retirement ages.

Our analysis yields novel descriptive evidence that occupations are a central predictor of retirement. Attaching a causal interpretation to cross-country results is of course notoriously difficult. Nevertheless, we provide suggestive evidence that our findings are not driven by

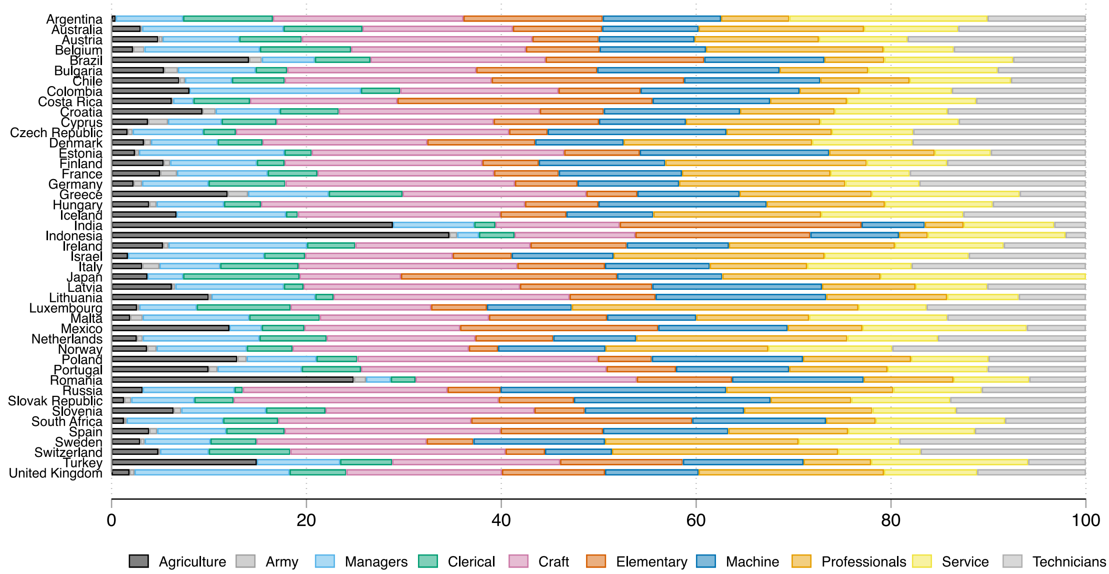

Fig. 3. Cross-country variation in occupational composition.
Notes: The figure shows the share of the labor force working in broad occupational categories (1-digit ISCO08 codes) across countries, pooled over our sample period.

two important types of confounding effects. First, we show that the estimated cross-country relationship is robust to controlling for an extensive set of country-level characteristics, including GDP per capita and proxies for education, health and labor market conditions. This suggests that omitted variables, for instance related to the level of economic development, cannot explain our findings. Second, in order to address concerns about potential reverse causality, we implement additional specifications exploiting variation in past occupational composition. We find that results are robust to using occupational structure up to 20 years prior to the outcome year, which makes the occurrence of reverse causality unlikely.

Our results have implications for labor markets and social security systems. Shifts in occupational composition are at the heart of some of the most debated labor market trends in recent decades. For instance, skill-biased technological change affects the returns to different types of occupations, and ultimately alters the occupational distribution of the workforce (Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Beaudry and Lewis, 2014; Autor, 2019; Acemoglu and Restrepo, 2022). Taken at face value, our findings imply that skill-biased technological change can have important side effects on pension systems when occupational composition adjusts. A similar logic can be applied to other sources of occupational change, such as international trade. Opening a country to trade exposes workers in different occupations to varying degrees of foreign competition, eventually affecting occupational composition (Artuç and McLaren, 2015; Curuk and Vannoorenberghe, 2017; Utar, 2018; Burstein et al., 2019; Traiberman, 2019). Again, our results may imply an easily overlooked side effect of trade-induced occupational change on retirement behavior, impacting the fiscal balance of social security systems.

This paper contributes to a rich literature on retirement behavior and its determinants. Most directly related to our work, a number of classic studies consider the influence of occupational characteristics, such as physical and mental strain, job autonomy, and the prevalence of unhealthy or undesirable working conditions, on individual retirement (e.g. Quinn, 1977, 1978; Filer and Petri, 1988; Mitchell et al., 1988).[1] Recently, Jacobs (2023) documents differences in disability and retirement patterns across broadly defined (blue collar vs. white collar) occupations and studies implications for social security design.

More generally, much of the recent retirement literature focuses on the impact of social security programs and pension reforms (Gruber and Wise, 2004; Coile and Gruber, 2007; Mastrobuoni, 2009; Behaghel and Blau, 2012; Brown, 2013; Staubli and Zweimüller, 2013; Manoli and Weber, 2016; Fetter and Lockwood, 2018; Seibold, 2021; Gruber et al., 2022; Lalive et al., 2023). These studies typically abstract from occupational differences in retirement behavior, or treat them as a potential confounder to be controlled for. Related to our cross-country analysis, there are also a number of macroeconomic studies examining how social security programs affect retirement across countries (Gruber and Wise, 1999; Erosa et al., 2012; Wallenius, 2013; Alonso-Ortiz, 2014; Laun and Wallenius, 2016; Coile et al., 2019). This prior work on aggregate retirement behavior considers factors such as health, income, education and tax policies, but provides little analysis of the role of occupational composition.[2]

Our contribution to the literature is threefold. First, we revisit the role of occupations for individual retirement behavior. While existing work tends to focus on specific mechanisms underlying occupational retirement patterns, we provide a systematic quantification of overall retirement differences across fine-grained occupations. In particular, our approach is complementary to Jacobs (2023) who provides a more structural analysis but considers very broad occupational categories. Second, combining individual-level data from the U.S. and 18 European countries, we show that a substantial portion of these retirement differences persists across institutional settings, which suggests that they are driven by inherent features of occupations. Third, we provide novel evidence that occupational composition matters for aggregate retirement behavior across countries. Despite far-reaching implications, this important stylized fact has received little attention so far.

[1] The association between occupations and individual retirement is also investigated in other disciplines, including sociology (e.g. Hayward, 1986; Hayward et al., 1989) and medicine (e.g. Karpansalo et al., 2002).

[2] To our knowledge, the only exception is given by Coile et al. (2019) who consider broadly defined (blue-collar vs. white collar) occupations as one potential factor explaining country-level labor force participation at old age. They find no significant impact across the nine countries in their data.

The remainder of this paper is organized as follows. Section "Conceptual Framework" presents a simple conceptual framework, Section "Data and Methodology" describes the data sources and the empirical methodology, Section "Results" reports individual-level and country-level results, and Section "Discussion and Conclusion" discusses implications and concludes.

Conceptual framework

We begin by presenting a simple conceptual framework of individual retirement decisions that helps us illuminate potential factors underlying occupational differences. We build on standard retirement models developed in the literature, e.g. by Laun and Wallenius (2015).

Lifetime utility of individual i is

$$U_i = \sum_{t=0}^{T} \beta^t \left[u\left(c_{it}\right) - g_o(h_{it}) l_{it}(1 - D_{it})\right] \tag{1}$$

where c_{it} is consumption in period t, $l_{it} \in [0, 1]$ is labor supply, and h_{it} is a vector of personal characteristics, which may include health, skills and task-specific knowledge (i.e., $h_{it} = (h_{it}^{health}, h_{it}^{skill}, \dots)'$). The function g_o, with $g_o(.) > 0$, captures how these characteristics affect disutility of labor in ways that may be specific to the individual's occupation o. D_{it} is a dummy that equals one if the individual is retired at time t, i.e., she does not work.

Individual i's budget constraint in period t is

$$c_{it} + a_{it+1} - (1 + r)a_{it} = w_{it} l_{it}(1 - D_{it}) + D_{it} b \tag{2}$$

where a_{it} are financial assets, r is the interest rate, w_{it} is the hourly wage, and b are generic pension benefits available to retired individuals.[3] We specify hourly wages as a function $w_{it} = \phi_o(h_{it})$, with $\phi_o(.) \geq 0$. Thus, wages are a function of the individual's productivity, which depends on personal characteristics in an occupation-specific manner. As shown in online Appendix B, individual optimality implies that i retires if and only if[4]

$$-g_o(h_{it}) + u'\left(c_{i0}\right)\left[\phi_o(h_{it}) - b\right] < 0 \tag{3}$$

Hence, higher disutility from work $g_o(h_{it})$ or lower productivity $\phi_o(h_{it})$ make individuals prone to retire. Similar effects arise due to higher lifetime income (which entails larger c_{i0}) conditional on current productivity, or higher benefits b.

This simple framework illustrates intuitively how various occupation-specific factors can influence retirement behavior. First, the extent to which deteriorating health increases disutility from work or decreases productivity likely varies across occupations. The more demanding an occupation is, the larger the additional disutility dg_o/dh^{health} and the productivity loss $d\phi_o/dh^{health}$ will be. Indeed, the degree of physical and mental demands of an occupation has been identified as an important driver of retirement in the literature (e.g. Quinn, 1978; Filer and Petri, 1988). Moreover, research in medicine and public health suggests that the types of tasks performed in an occupation may have a direct effect on individuals' health.[5] Second, several studies find that the speed of knowledge obsolescence and human capital depreciation, which vary across occupations, are among the factors determining older workers' employment prospects (Bartel and Sicherman, 1993; Allen, 2001; Aubert et al., 2006; Ahituv and Zeira, 2011). Our framework captures the occupation-specific productivity consequences of these dynamics through the function ϕ_o. Third, recent evidence suggests that occupations differ in their flexibility and other dimensions of "age friendliness" (Ameriks et al., 2020; Hudomiet et al., 2021; Acemoglu et al., 2022). Again, this variation in occupational features may lead to heterogeneous disutility from work, which in turn implies differential retirement patterns.

The main goal behind our empirical analysis will be to measure the *overall* importance of occupations for individual and aggregate retirement behavior. The model presented in this section highlights that this overall role likely reflects a combination of potential mechanisms.[6] We view our approach as complementary to existing literature that largely focuses on particular channels of occupational influence.

Data and methodology

Data

Individual-level data: U.S.

Our first main source of individual-level data is the Current Population Survey (CPS), a monthly household survey administered by the U.S. Census Bureau. We use the harmonized version IPUMS-CPS (Flood et al., 2022). CPS contains information on employment and demographic characteristics of individuals. Fine-grained four-digit occupations are reported according to the harmonized IPUMS classification based on 2010 Census occupation codes. Since individual retirement ages are not explicitly recorded, we infer the time of retirement based on employment variables. In particular, we define a retirement event if (i) a worker is aged between 50 and 80, (ii) reports not to be in the labor force, and (iii) worked more than 45 weeks in the previous year. We focus on male workers retiring in the years 1990 to 2015. In order to limit measurement error in the prediction step, we drop occupations with less than five retirement incidents. This leaves us with 6237 observed retirement incidents across 240 occupations. We also use information on state of residence, marital status and education levels. Online Appendix Table A1 presents summary statistics of the CPS data.

Defining retirement through employment exits is a common approach in the literature. However, a potential drawback of this definition is that it does not differentiate between voluntary retirement and involuntary separations, nor does it account for re-entries into the labor force. This may be a particular issue in the U.S., where retirement and pension claiming are less closely linked and re-entries are more common, compared to European countries. Thus, in order to validate our main retirement variable, we additionally use data from the Health and Retirement Study (HRS). Specifically, we use the RAND-HRS data, a subset derived from all survey waves (HRS, 2022). HRS contains all variables necessary to construct retirement ages analogous to our main definition in the CPS data, but respondents also explicitly report whether they are retired.[7] Online Appendix Figure A1 shows that the two retirement age variables are almost perfectly correlated, with a slope coefficient close to one. This suggests that our main employment-based definition accurately captures retirement incidents.

[3] In practice, non-working individuals may receive various benefits, including old-age pensions, unemployment benefits, or disability benefits. The rules governing these benefits, and the degree to which retirement and benefit claiming are linked, vary across countries. Since our focus is not on analyzing the impact of these policies, we do not explicitly model different types of benefits and abstract from variations over time, across individuals, and between countries.

[4] Note that in this stylized model, retirement in period t does not preclude later re-entry into the labor force.

[5] A number of studies in medicine and public health document that occupations are associated with large differences in physical and mental health. For instance, Hinkle et al. (1968) show that the risk of heart disease is influenced by occupations. Similar results are provided by Rushton et al. (2010), Eguchi et al. (2017) and García et al. (2023) for cancer, by Lee et al. (2021) for knee osteoarthritis, by Ettman et al. (2022) for depression, and by Chan et al. (2021) for brain network decline.

[6] In addition, there may be feedback effects and interactions between these mechanisms. For instance, individual health may depend on a worker's past and present occupation. Our model abstracts from these more complex interrelations for simplicity.

[7] Note that we cannot use the HRS for our main analysis because fine-grained occupations are not available in this data.

Individual-level data: Europe

Our second main dataset is the Survey of Health, Ageing and Retirement in Europe (SHARE), an annual survey of individuals aged 50 and above in European countries (SHARE, 2019).[8] We mainly use the information from survey waves 1 and 6 as these include occupations and the variables necessary to identify retirement ages. We also utilize the employment history data from wave 7 to more precisely identify retirees' former occupations, and waves 2, 4 and 5 to obtain some control variables. Depending on the wave, occupations are reported according to the 1988 or 2008 International Standard Classifications of Occupations (ISCO-88 or ISCO-08). To map occupations between CPS and SHARE, we generate correspondence tables between the 2010 IPUMS/Census classification and ISCO-88/ISCO-08.[9] In wave 1, we calculate retirement ages as the age of last job exit for individuals who report to be retired. In wave 6, the year of retirement is directly observed. For consistency with the CPS data, we restrict the sample to male workers who retired after 1990 and whose retirement age is between 50 and 80. The final sample consists of 13,696 retirees across 18 countries (Austria, Belgium, Croatia, Czechia, Denmark, Estonia, France, Germany, Greece, Israel, Italy, Luxembourg, Netherlands, Portugal, Slovenia, Spain, Sweden and Switzerland). We also use information on marital status, education levels, and amount and type of income. Online Appendix Table A2 presents summary statistics of the SHARE data.

Country-level data

We combine a number of data sources at the country level.

Occupational composition. We retrieve data on occupational shares of the workforce from the International Labor Organization (ILO, 2022). This data is available at the level of two-digit ISCO-88 or ISCO-08 occupations. To map occupations between the CPS and the country-level data, we again use our correspondence tables between the 2010 IPUMS/Census classification and ISCO-88/ISCO-08. Since ISCO occupations are coarser, we include weights based on the number of observations in the CPS when we aggregate information to the country-level.

Retirement age. We collect data on retirement across countries from the OECD Pensions at a Glance Database (OECD, 2022b). In particular, our measure of the country-level average retirement age is the "effective" retirement age, which the OECD defines as the average age of workers' last labor force exit. The OECD generates this data based on their analysis of national labor force surveys.[10] Online Appendix Table A3 summarizes average retirement ages across countries.

Other variables. In addition, we collect the following country-level variables from OECD databases (OECD, 2022a): male life expectancy at age 65, GDP per capita, fraction of men aged 55 to 64 with tertiary education, male unemployment rate, female labor force participation, and fertility rate. Online Appendix Table A4 shows summary statistics of the country-level data. In total, the main data contains 822 observations spanning 45 countries in the years 2000 to 2020. For most of the analysis, we exclude country-years with missing covariates, which leaves us with 621 observations.

[8] See Börsch-Supan et al. (2013) and Brugiavini et al. (2019) for methodological details of this dataset.

[9] The full correspondence tables are shown in online Appendix Tables C1 and C2.

[10] The effective retirement age is defined by the OECD as the average age of exit from the labor force for workers aged 40 and older, and a re-weighting procedure is applied in order to correct for compositional effects. This retirement age variable is well-suited for comparisons across countries and over time (see OECD, 2022b).

Predicting retirement age based on occupations

Occupation-predicted retirement age

In the first step of our analysis, we predict retirement ages based on occupations in the U.S. using the CPS data.[11] We estimate the following regression:

$$R_i = \sum_o \theta_o D_{o(i)} + X_i' \gamma + e_i, \tag{4}$$

where R_i is individual i's retirement age, $o(i)$ is i's occupation, D_o is a vector of occupation dummies, X_i are control variables, and e_i is an error term. We then define the *occupation-predicted* retirement age $\hat{R}_o$ as:

$$\hat{R}_o = \hat{\theta}_o + \bar{R} \tag{5}$$

where $\bar{R}$ is a re-scaling term we use in order to preserve the sample average retirement age in the prediction. Thus, the occupation-predicted retirement age isolates differences in retirement across occupations conditional on controls X_i.

An important issue in predicting occupational retirement ages is the choice of control variables to be included in Eq. (4). This matters to the extent that some omitted characteristics may be correlated with workers' occupational choices and retirement ages. In the baseline specification, we only include fixed effects for state and year of retirement as well as marital status in X_i. We then show that our main empirical results are robust to including an extensive list of additional controls both at the individual and the country level.

Predicted country-level retirement age

A key ingredient for our country-level analysis is the predicted retirement age based on a country's occupational composition. We predict country c's average retirement age in year t as

$$\hat{R}_{ct} = \sum_o \omega_{o(ct)} \hat{R}_o \tag{6}$$

where $\omega_{o(ct)}$ is the share of the labor force working in occupation o. Thus, the predicted country-level retirement age is a weighted average of occupation-predicted retirement ages $\hat{R}_o$, where weights are given by a country's occupational composition.

Main empirical specifications

Occupations and individual retirement

Our first "out-of-sample" test of the role of occupations asks whether U.S. occupation-predicted retirement ages can explain retirement behavior of individual European workers. Using SHARE data, we run the following regression:

$$R_i = \beta_0 + \beta_1 \ \hat{R}_{o(i)} + X_i' \delta + \varepsilon_i, \tag{7}$$

where R_i denotes retirement age of European worker i, $\hat{R}_{o(i)}$ is the occupation-predicted retirement age from Eq. (5), X_i is a vector of control variables and ε_i is an error term. Similarly to the prediction step, we include fixed effects for country and year of retirement as well as marital status as control variables in the baseline specification, but we show that results are robust to including a host of additional characteristics.

[11] We choose the U.S. as our benchmark setting to predict retirement ages for two main reasons. First, large-scale survey data is available that contains information on retirement and fine-grained occupations. Second, the U.S. labor market and retirement rules faced by many workers are relatively flexible, such that occupational differences manifest themselves clearly. In European countries, the retirement age distribution tends to be more compressed (see Section "Occupations and Individual Retirement").

Occupations and retirement across countries

To assess how much of the cross-country variation in retirement ages is due to occupational composition, we begin with a standard variance decomposition exercise. We compute:

$$\psi_t = 1 - VAR(R_{ct} - \hat{R}_{ct})/VAR(R_{ct}) \tag{8}$$

ψ_t measures the share of the variance in country-level average retirement ages R_{ct} explained by our occupation-based prediction $\hat{R}_{ct}$. ψ_t equals one if occupation-predicted retirement ages explain all of the variation in average retirement ages, and it is zero (negative) if R_{ct} and $\hat{R}_{ct}$ are uncorrelated (negatively correlated).

Our main cross-country specification allows for a more flexible relationship between R_{ct} and $\hat{R}_{ct}$. We estimate the regression

$$R_{ct} = \alpha_0 + \alpha_1 \hat{R}_{ct} + Z'_{ct}\zeta + \lambda_t + u_{ct}, \tag{9}$$

where Z_{ct} is a vector of country-level controls, λ_t is a year fixed effect, and u_{ct} is an error term. Compared to the simple variance decomposition above, Eq. (9) allows for additional flexibility in two ways. First, we include control variables. Second, we let the coefficient α_1 be determined by the data, which captures potential differences between the individual-level and country-level impact of occupations (see Section "Occupations and Retirement across Countries").

Eq. (9) enables us to examine the cross-country correlation between retirement behavior and occupational composition. This approach, in the spirit of a decomposition exercise, provides valuable insights in its own right. However, in order to derive policy implications, an additional question is whether this correlation can be interpreted as a causal effect of occupational composition on aggregate retirement behavior. To be clear, causality in this context would mean that a shock to a country's occupational structure leads to a change in retirement ages. Providing a fully satisfactory answer to causal questions in cross-country data is of course challenging. Nevertheless, we try to account for two important threats to causal identification. A first issue could be omitted variables biasing the results. In particular, a country's level of economic development likely influences its occupational composition and may affect retirement behavior via changing income, health, education, and family structure.[12] This may lead the correlation to over- or under-state the causal effect of occupations on retirement. For instance, improvements in health over the course of development may lead to later retirement, while income effects may lead to earlier retirement. To address this issue empirically, we collect a range of country-level characteristics, and we carefully investigate how controlling for these affects our results.

A second issue could be reverse causality. For instance, more workers may choose occupations amenable to working at old age in a country where late retirement is common. To address this issue, we implement alternative specifications using predictions based on a predetermined component of occupational composition. For this purpose, we replace $\hat{R}_{ct}$ with $\hat{R}_{c,t-l} = \sum_o \omega_{o(c,t-l)}\hat{R}_o$, where l is the lag length, in Eq. (9). The main idea behind this approach is that there is some path dependence in occupational composition, and thus past occupations should retain some explanatory power for current retirement patterns. However, current retirement patterns cannot affect past occupational composition, making reverse causality unlikely. Conceptually similar approaches are commonly used in studies involving changes in labor force composition (see e.g. Autor et al., 2013; Maestas et al., 2023). We use initial occupational composition up to 20 years prior to the outcome year for the lagged specifications, extending the country-level data up to the earliest available year 1992.

[12] For instance, Imbs and Wacziarg (2003) argue that countries' productive structure diversifies at intermediate levels of development but then specializes again at high levels of development. This would likely entail changing occupational composition over the course of development.

To clarify, the methods we propose to deal with these challenges yield suggestive evidence on the potential significance of each issue. We do not claim that our cross-country findings imply causal effects. Identifying causal effects would require using some source of exogenous variation in occupational composition, which is outside the scope of this paper.

Results

Prediction step

We begin by estimating Eq. (4), which allows us to obtain occupation-predicted retirement ages $\hat{R}_o$ through Eq. (5). Predicted retirement ages vary strongly across occupations, similar to the distribution of average retirement ages by occupation shown in Fig. 2. Indeed, the cross-occupation correlation between raw and predicted ages within the CPS data is 97.5%. As online Appendix Table A5 shows, an F-test strongly rejects the null hypothesis of equal coefficients $\hat{\theta}_o$ across occupations. Occupations alone explain around 11% of the variation in retirement ages across individuals. Adding controls increases the R^2 of the prediction regression to 18%.

To provide a more concrete illustration of retirement behavior across occupations, online Appendix Figure A2 summarizes predicted retirement ages by nine broad categories.[13] On average, individuals in sales and professional occupations as well as in clean and protect services have the highest predicted retirement ages. Managers, office/administrative and operator/labor occupations are predicted to retire at intermediate ages, whereas workers in health and personal services, production and technician occupations are predicted to retire the earliest.

Occupations and individual retirement

Next, we assess whether U.S. occupation-predicted retirement ages can explain retirement behavior of individual European workers. Table 1 presents results from estimating Eq. (7) with varying sets of control variables both in the prediction step and in the main estimation step. Column (1) shows results without any controls, Column (2) includes CPS baseline controls in the prediction, Column (3) includes SHARE baseline controls in the main estimation, Column (4) includes baseline controls both in CPS and in SHARE, Column (5) additionally controls for detailed education categories in both datasets, and Column (6) adds an extended set of controls only available in SHARE, namely log income before retirement, a set of indicators for different types of income after retirement, and a set of indicators for retirement reasons. The estimated relationship between individual retirement ages and occupation-predicted retirement ages is positive and highly significant throughout all specifications. In terms of magnitude, a one-year increase in U.S. occupation-predicted retirement age is associated with a 0.47 to 0.53 years (5.6 to 6.1 months) increase in European workers' individual retirement age.[14] Moreover, occupation-predicted retirement ages retain 62% of their explanatory power among European workers compared to an analogous in-sample estimation using CPS data.[15] These

[13] We use the broad occupational categories from Autor (2019) for this illustration.

[14] Online Appendix Table A7 additionally reports individual-level regression results separately for each of the 18 countries included in our SHARE data. Similar to the main results from Table 1, the estimated relationship between individual retirement age and occupation-predicted retirement age is positive and below one within each country.

[15] For this comparison of explanatory power out-of-sample vs. in-sample, we require analogous results using the same occupational categories in the CPS data. Online Appendix Table A6 shows results from regressing individual retirement ages on ISCO88/08 occupation categories in the CPS. We obtain the relative explanatory power of 62% by dividing the R^2 from Column (1) of Table 1 by the R^2 from Column (1) of Table A6.

Table 1
Occupations and individual retirement ages.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: individual retirement age					
Occupation-predicted Retirement age	0.47*** (0.09)	0.47*** (0.09)	0.53*** (0.11)	0.53*** (0.12)	0.50*** (0.11)	0.51*** (0.11)
Observations	13696	13696	8551	8551	8551	5523
R^2	0.024	0.023	0.191	0.191	0.205	0.295
CPS baseline controls	No	Yes	No	Yes	Yes	Yes
SHARE baseline controls	No	No	Yes	Yes	Yes	Yes
CPS education control	No	No	No	No	Yes	Yes
SHARE education control	No	No	No	No	Yes	Yes
SHARE extended controls	No	No	No	No	No	Yes

Notes: The table shows results from regressing individual retirement ages of European workers on occupation-predicted retirement ages from U.S. data, as shown in Eq. (7). Across columns, different sets of control variables are included in the prediction step using CPS data and/or in the main regression using SHARE data. CPS baseline controls include year FE, state FE, and marital status. SHARE baseline controls include year FE, country FE, and marital status. CPS and SHARE education controls denote dummies for nine education categories in the respective dataset. SHARE extended controls include log(income) before retirement, a set of dummies for six different types of income after retirement, and set of dummies for 11 self-reported reasons for retirement. Standard errors clustered by country are shown in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

results indicate that occupational retirement patterns are similar in the U.S. and Europe, suggesting that the differences are not driven by a specific institutional setting.

Two further implications of these findings are worth noting. First, the relationship between individual retirement ages in Europe and occupation-predicted retirement ages from the U.S. is remarkably stable across columns in Table 1, despite strongly varying sets of control variables. Thus, individual characteristics such as education and income seem to confound retirement behavior across occupations less than possibly expected. In other words, observed retirement differences largely reflect inherent features of occupations. Second, we note that point estimates in Table 1 are generally below one. A potential explanation for this result is that the retirement age distribution in Europe is more compressed, reducing occupational differences. Indeed, the standard deviation of retirement ages is 7.4 years in the U.S. but only 4.5 years in Europe (see online Appendix Tables A1 and A2). One possible reason for this more compressed distribution is the closer link between retirement and pension claiming in Europe compared to the U.S., which may lead to more uniform retirement patterns. Another issue is that the estimated coefficients could be attenuated by measurement error. In particular, the crosswalk from IPUMS/Census occupations to ISCO codes could lead to some imprecision in the occupation-predicted retirement age variable in Eq. (7). If anything, the presence of such measurement error would imply that we underestimate the predictive power of occupational retirement ages.

Occupations and retirement across countries

Finally, we turn to the country-level results. In the simple decomposition from Eq. (8), we find that the occupational prediction accounts for 9.6% of the variance in country-level average retirement ages (pooling across all years). While these results are encouraging, in the following we focus on the results from the more general specification (9).

Fig. 4 graphically displays the correlation between countries' average retirement age and the predicted retirement age based on occupational composition. The figure corresponds to estimating Eq. (9) without country-level controls. The slope coefficient (α_1) is positive and highly significant. The R^2 of 0.34 indicates that occupational composition can explain around a third of the cross-country variation in retirement ages, when allowing for a data-driven slope. While Fig. 4 pools data for all years to maximize statistical power, this cross-country relationship is also present in annual cross-sections and remains quite robust over time. Illustrating this robustness, Panel (a) of online Appendix Figure A3 displays a scatterplot for the year 2010, the middle of our analysis period. The correlation is of similar magnitude and significance to the pooled specification. Panel (b) shows that the estimated coefficient remains positive and of similar size in each year between 2000 and 2020.

As discussed previously, giving a causal interpretation to these cross-country results is not straightforward. We present two pieces of additional evidence in order to address the most important confounding factors. First, the upper panel of Fig. 5 shows that results are robust to including varying sets of control variables both in the individual-level prediction and in the country-level regressions. In the three specifications at the top, whether or not controls are included in the prediction using CPS data hardly changes the final results. Moreover, adding an extensive set of country-level controls, including life expectancy, (log) GDP per capita, education, unemployment rates, female labor force participation, and fertility rates only reduces the estimated coefficient from 6.44 to 4.87.[16] The fact that the estimated relationship remains large and significant suggests that our cross-country results are not driven by omitted characteristics, including the level of economic development and associated factors.

Second, in order to address concerns about reverse causality, we implement specifications relying on past occupational composition in the prediction step, as described in Section "Main Empirical Specifications". Corresponding estimates are shown in the lower panel of Fig. 5. Note that the full set of country-level controls are included in all these specifications. For all lag lengths, we find highly significant coefficients between 3.74 and 4.56, which is similar to the fully controlled main specification. Moreover, the R^2 of the regression remains similar when using lag lengths up to 15 years, and only decreases to 0.21 at a 20-year lag.[17] This suggests that reverse causality is not a major driver of our baseline OLS results.

Country-level magnitudes. In the cross-country regressions, we generally find a coefficient larger than one. Taken at face value, this implies that occupational retirement differences are *magnified* at the country level compared to the individual level. This result may appear surprising at first glance, but in fact similar patterns in aggregate vs. individual labor supply behavior have been observed in other contexts. For instance, a parallel can be drawn to the literature estimating labor supply responses to taxes. Macroeconomic studies relying on cross-country variation tend to find much larger labor supply elasticities than microeconomic studies focusing on individuals within the same country (see e.g. Blundell and MaCurdy, 1999; Saez et al., 2009; Chetty, 2012). This pattern has been interpreted as labor market institutions facilitating choices desired by a large number of workers at the macro level, while individual choices are more constrained (Chetty et al., 2011). Similar mechanisms could exacerbate differences in aggregate retirement patterns relative to individual retirement behavior within countries. For example, one might expect countries with a large fraction working in occupations where late retirement is not feasible to put in place policies allowing for early retirement. In addition, when a large number of workers retire early for occupational reasons, this may affect social norms in a country, or peer effects might be exerted onto other individuals.

[16] The R^2 of the cross-country regression increases to 0.67 when including the full set of controls. See online Appendix Table A8 for detailed regression results.

[17] See online Appendix Table A9 for detailed estimation results using past occupational composition. Note that sample size decreases with the lag length, as data is not available for all countries in the earliest years.

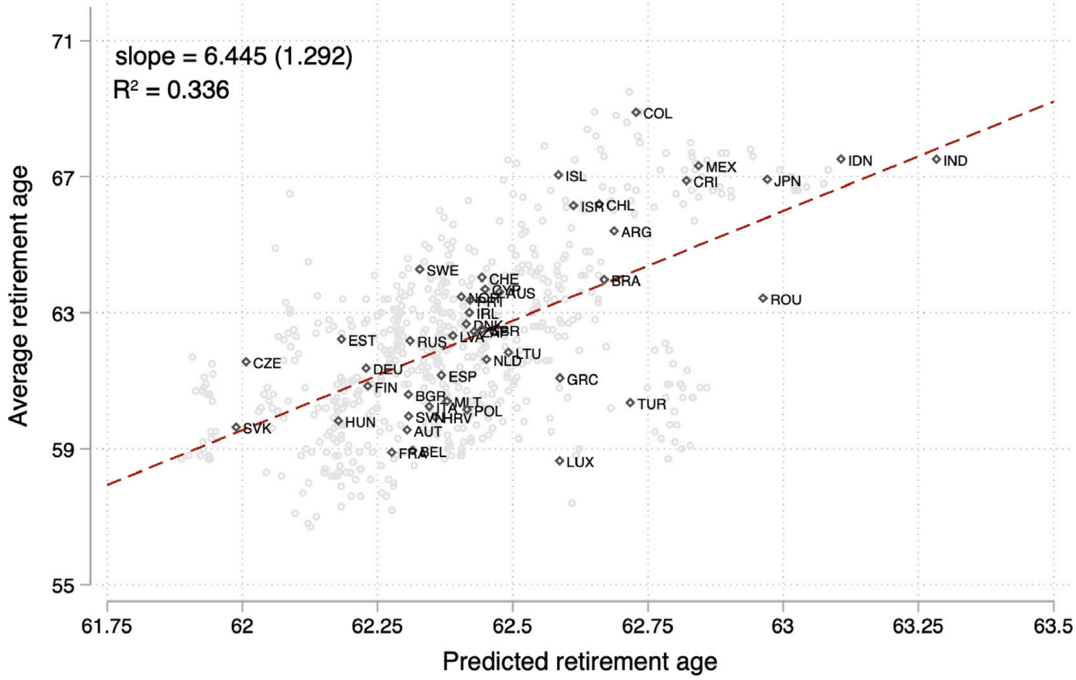

Fig. 4. Average vs. Occupation-predicted retirement age across countries.

Notes: The figure shows the correlation of average retirement ages and predicted retirement age based on occupations across countries. Predicted retirement age is computed based on a country's occupational composition as described in Section "Predicting Retirement Age Based on Occupations". Labeled black dots denote time averages for each country, and gray dots denote country-year observations included in our main sample. The red dashed line depicts a linear fit. The estimated slope coefficient b with its standard error (clustered at the country level) in parentheses and the R^2 of the correlation are reported in the top left corner of the figure.

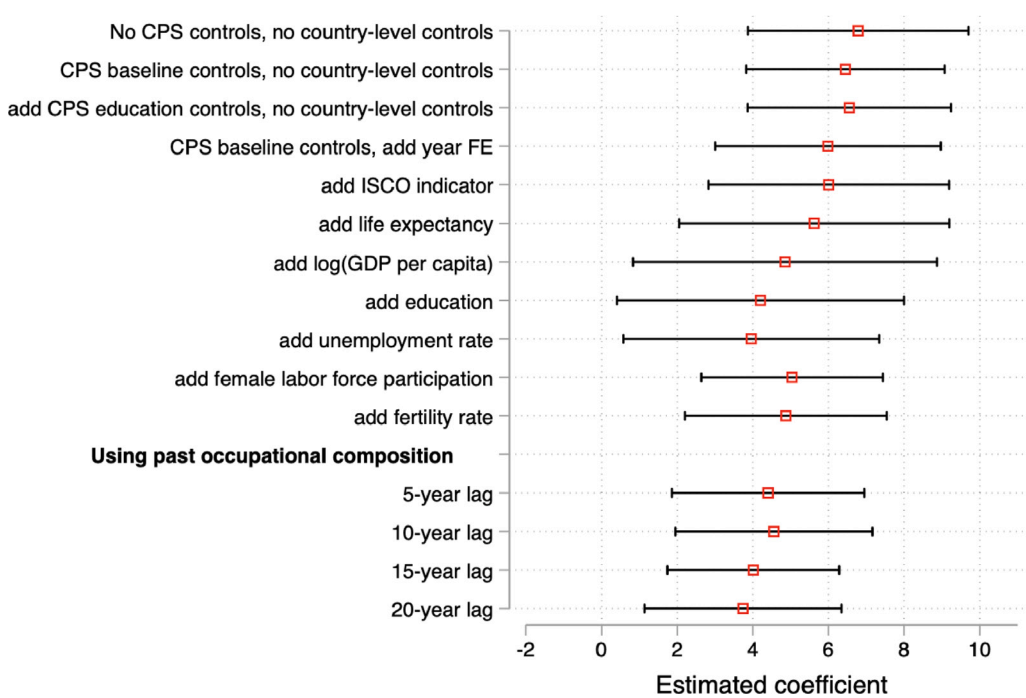

Fig. 5. Cross-country analysis: robustness.

Notes: The figure shows results from different cross-country regression specifications. For each specification described by the respective row title, the figure shows the coefficient from a regression of countries' average retirement age on the predicted retirement age based on occupations. The upper panel depicts OLS results including varying sets of controls at the individual-level and at the country level. The lower panel shows results from regressions using lagged occupational composition in the prediction step. The respective row title denotes the length of the lag used. All lagged specifications include the full set of country-level controls. In all rows, red squares depict point estimates and black bars show 95% confidence intervals based on standard errors clustered at the country level.

Discussion and conclusion

In this paper, we show that occupations matter for individual retirement decisions, and as a consequence, countries' occupational composition is strongly predictive of aggregate retirement behavior. These findings have a number of implications.

Perhaps the most important implication is that shifts in countries' occupational composition can have side effects on social security systems. Indeed, some of the most discussed labor market trends in the last decades entail occupational change. For example, skill-biased technological change leads to higher returns to skill and ultimately increases the share of workers in high-skill occupations (Autor et al., 2003; Acemoglu and Autor, 2011). As another example, opening countries to international trade can give rise to specialization in certain sectors and certain occupations (Utar, 2018; Traiberman, 2019). Our findings imply that such changes in occupational structure may influence aggregate retirement behavior, which in turn affects social security systems. For instance, if high-skill occupations tend to retire later, skill-biased technological change will generate a positive fiscal externality on the government budget by extending periods of tax and contribution payments and, to the extent that retirement and pension claiming are linked, shortening periods of pension benefit receipt. These important effects can be easily overlooked in the analysis of occupational change.

Second, our results speak to debates around the design of social security. Concerns are often voiced about the ability of individuals in certain occupations to work at old age. This point is underscored by the strong differences in retirement age across occupations emerging from our data. One way to address such concerns could be to allow retirement rules to vary across occupations. Indeed, some European countries have special pension schemes permitting workers in occupations with low work capacity at old age to retire earlier.[18] Our occupation-predicted retirement age measure may provide a valuable input to inform these debates.

Third, our analysis has implications for the interpretation of retirement behavior across countries. Our occupation-predicted retirement ages provide a natural benchmark for cross-country comparisons of average retirement ages. For instance, the average Japanese worker retires at 66.9 years over our sample period, while German workers retire at 61.4. Our findings imply that this large discrepancy can be almost entirely explained by differences in occupational composition between the two countries, as both lie close to the fitted line in Fig. 4. On the other hand, Germany and France have a similar predicted retirement age, but French workers retire already at age 58.9. Hence, the discrepancy must be explained by other factors such as retirement policies.

Finally, our work points at some potentially fruitful directions for future research. One promising avenue could be to identify and exploit sources of exogenous variation in occupational composition. This would enable a clear-cut analysis of causal effects and address key identification concerns we discuss in this paper. Another direction could be to apply our methodology to specific episodes of occupational change in order to derive concrete policy implications. For instance, future work could measure the long-run impact of opening a country to international trade on the social security system via changing retirement behavior, and examine how this alters the welfare effects of trade.

CRediT authorship contribution statement

Philip Sauré: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Arthur Seibold:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Elizaveta Smorodenkova:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Hosny Zoabi:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

We have no conflict of interest to declare.

Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeoa.2025.100561.

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[18] For example, special pension schemes for miners and pilots exist in a number of European countries (see Natali et al., 2016; König et al., 2021).

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