

# Occupations Shape Retirement across Countries

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# Occupations Shape Retirement across Countries

## Abstract

We study how occupations shape 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 highly predictive of aggregate retirement behavior across 45 countries. Our findings suggest that events affecting occupational structure, such as skill-biased technological change or international trade, have consequences for aggregate retirement behavior and social security systems.

JEL-Codes: E240, H550, J140, J240, J260, J820.

Keywords: retirement, occupational distribution, cross-country analysis.

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## 1 INTRODUCTION

When to retire is one of the most important economic choices individuals make over their lifetime. At the aggregate level, retirement behavior has important consequences for a country's fiscal balance via tax revenue and social security spending. In this paper, we shed new light on the role of occupations for retirement. We show that occupation is a key predictor of retirement age at the individual level, and as a consequence, retirement behavior across countries is decisively shaped by the occupational composition of the workforce.

**Figure 1: Retirement Ages across Occupations**



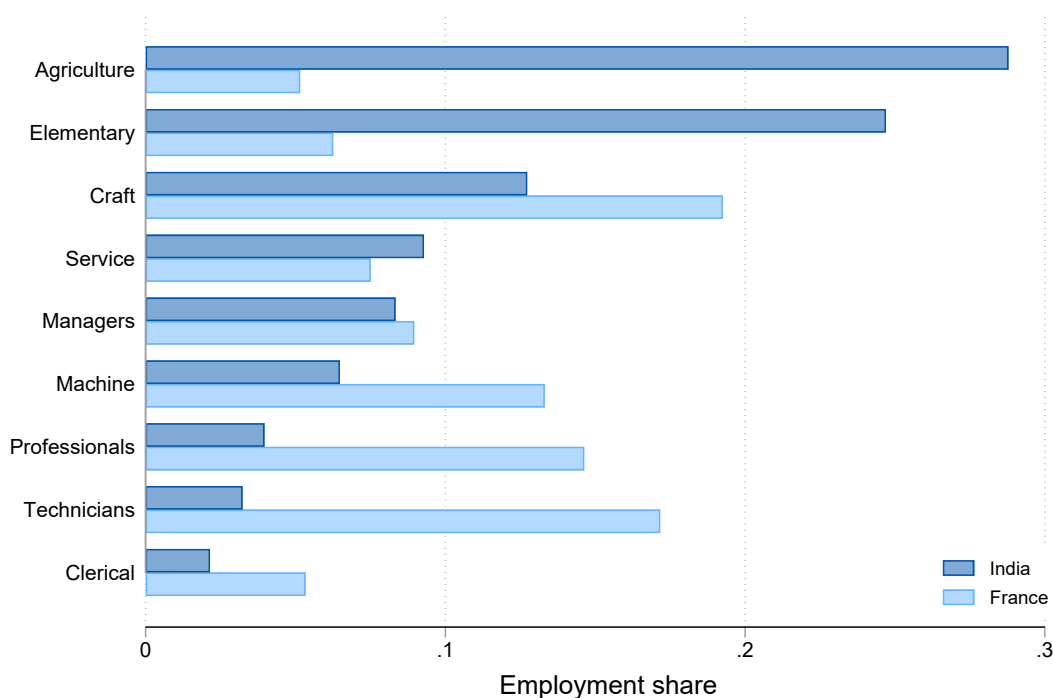
*Notes:* The figure shows the average retirement age of U.S. workers between 1990 and 2015 by four-digit occupation (2010 IPUMS/Census codes). Occupations are ranked along the horizontal axis from highest to lowest retirement age. See Appendix Table B3 for the full list of occupational retirement ages.

We proceed in three steps. First, we provide evidence of large occupational differences in individual retirement behavior among U.S. workers. Figure 1 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 between from 55 to more than 70

years.<sup>1</sup> 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 predicted retirement ages based on occupations 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. 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 across occupations are to a large extent universal across settings rather than being the product of a specific institutional environment.

**Figure 2: Occupational Composition: France vs. India**



*Notes:* The figure shows the share of the labor force working in broad occupational categories (1-digit ISCO08 codes) for the case of two countries, France and India, in 2010.

In the third and final step, we document the aggregate consequences of these find-

<sup>1</sup>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.

ings: occupational composition can explain a substantial portion of differences in retirement behavior across countries. Figure 2 illustrates the cross-country variation in occupational composition for the case of two countries, France and India. French workers are more likely to be in technical, professional, machine operator and craft occupations, whereas larger shares of Indian workers are in 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. Figure 3 shows that across countries, actual retirement behavior is highly significantly correlated with the prediction based on occupational composition. Occupation-predicted retirement ages account for roughly one third of the cross-country variation in effective retirement ages. We show that this estimated 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.

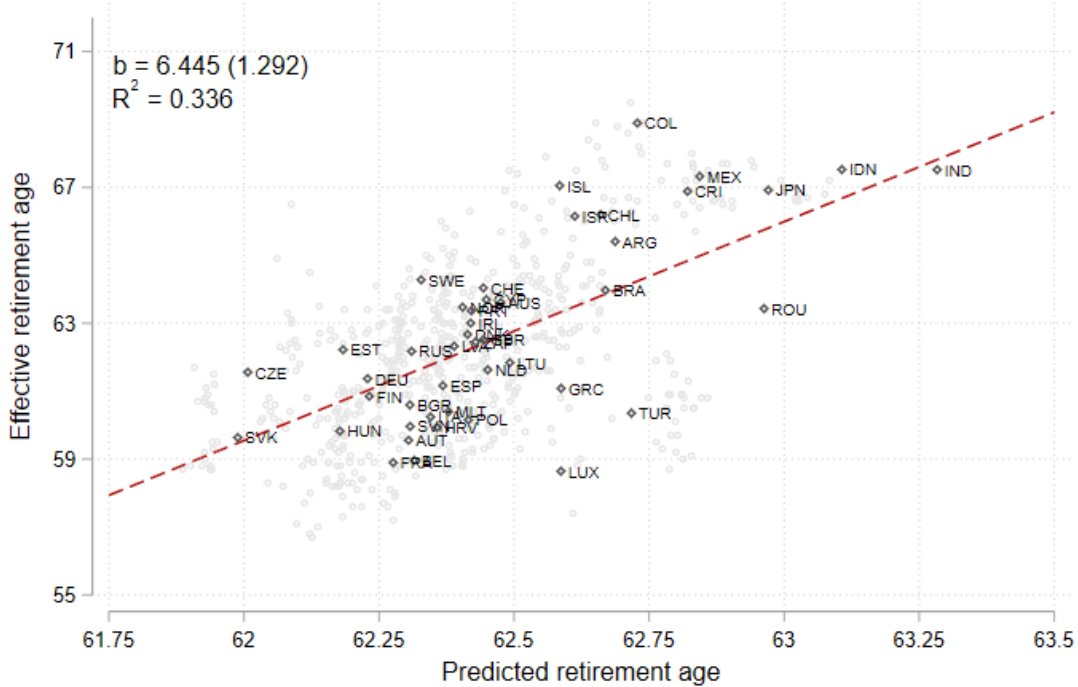
These results have implications for labor markets and social security systems. Shifts in occupational composition are at the heart of some of the most debated labor market trends in recent decades. For instance, skill-biased technological change affects the returns to different types of occupations, 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 results imply that skill-biased technological change can have important side effects on pension systems because occupational composition influences overall retirement behavior. 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 findings 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 the vast literature on retirement behavior. 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).<sup>2</sup> Besides these job characteristics, the literature also highlights the differential speed of knowledge obsolescence or human capital depreciation

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<sup>2</sup>The association between occupations and individual retirement is also investigated in other disciplines, including sociology (e.g. Hayward, 1986) and medicine (e.g. Karpansalo et al., 2002).

**Figure 3: Effective vs. Occupation-Predicted Retirement Age across Countries**



*Notes:* The figure shows the correlation of effective retirement ages and predicted retirement age based on occupations across countries. Effective retirement age is defined as the average actual retirement age of workers in a country. Predicted retirement age is computed based on a country's occupational composition as described in Section 2.2. 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.

as another potential mechanism behind varying retirement behavior across occupations (Bartel and Sicherman, 1993; Allen, 2001; Aubert et al., 2006; Ahituv and Zeira, 2011). Recently, Ameriks et al. (2020) and Hudomiet et al. (2021) document the importance of job flexibility in enabling labor supply at older ages, and Acemoglu et al. (2022) construct a measure of "age friendliness" based on textual descriptions of occupations.

More broadly, 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; Lalive et al., 2022; Gruber et al., 2022). These studies typically abstract from occupational differences in re-

tirement 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.<sup>3</sup>

Our contribution to the literature is threefold. First, we revisit the role of occupations for individual retirement behavior. Our approach departs from existing studies in that we systematically quantify retirement differences across fine-grained occupations, while remaining relatively agnostic about underlying mechanisms. 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 settings, which suggests that they are driven by inherent features of occupations. Third, we provide novel evidence that occupational composition shapes aggregate retirement behavior across countries. Despite far-reaching implications, this important stylized fact has received little attention in the literature so far.

The remainder of this paper is organized as follows. Section 2 describes the data sources and the empirical methodology, Section 3 reports individual-level and country-level results, and Section 4 discusses implications and concludes.

## **2 DATA AND METHODOLOGY**

We begin by describing our data sources and the empirical methodology.

### **2.1 Data**

#### **2.1.1 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 (OCC2010). Since individual retirement ages are not explicitly recorded, we

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<sup>3</sup>To our knowledge, the only exception is given by Coile et al. (2019) who consider very coarse occupation categories (blue-collar vs. white collar) 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.



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, and we drop occupations with less than five retirement incidents. This leaves us with 6,237 observed retirement incidents across 240 occupations. We also use information on state of residence, marital status and education levels. Appendix Table A1 presents summary statistics of the CPS data.

In order to validate our main retirement definition, 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.<sup>4</sup> Appendix Figure A1 shows that the two retirement age variables are almost perfectly correlated, with a slope coefficient close to one. This confirms that our main employment-based definition accurately captures retirement incidents.

### 2.1.2 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, 2022).<sup>5</sup> 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.<sup>6</sup> 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

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<sup>4</sup>We cannot use the HRS for our main analysis because fine-grained occupations are not available in this data.

<sup>5</sup>See Börsch-Supan et al. (2013) and Brugiavini et al. (2019) for methodological details of this dataset.

<sup>6</sup>The full correspondence tables are shown in Appendix Tables B1 and B2.

marital status, education levels, amount and type of income, and reported reason for retirement. Appendix Table A2 presents summary statistics of the SHARE data.

### 2.1.3 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 (PaG) Database (OECD, 2022a). PaG includes a number of retirement indicators for OECD and G20 countries. In particular, we use the information on country-level "effective" retirement ages, defined as the average age of workers' last labor force exit. The OECD generates this data based on their analysis of national labor force surveys. Appendix Table A3 summarizes effective retirement ages across countries.

**Other Variables.** In addition, we collect the following country-level variables from OECD databases (OECD, 2022b): 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. Table A4 shows summary statistics of the country-level data. In total, the data contains 822 observations spanning 45 countries. For most of the analysis, we exclude country-years with missing covariates, which leaves us with 621 observations.

## 2.2 Predicting Retirement Age Based on Occupations

### 2.2.1 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. We estimate the following regression:

$$R_i = \sum_o \theta_o D_{o(i)} + X_i' \gamma + e_i, \quad (1)$$

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:

$$\hat{R}_o = \hat{\theta}_o + \bar{R} \quad (2)$$

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 equation (1). Ideally, any variables influencing workers' occupational choice and retirement ages should be accounted for. However, we must be careful not to include "bad" controls which are outcomes of occupational choice. For instance, education may be an obvious confounder affecting the set of occupations available to an individual. But education may also be an outcome that workers choose with the aim of working in a certain occupation. Similarly, income is likely an outcome of occupational choice. Our approach to this issue is to remain relatively agnostic about the optimal choice of control variables. In the baseline specification, we only include state and year fixed effects and 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.

### 2.2.2 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 as

$$\hat{R}_c = \sum_o \omega_{o(c)} \hat{R}_o \quad (3)$$

where  $\omega_{o(c)}$  is the share of the labor force in  $c$  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.

## 2.3 Main Empirical Specifications

### 2.3.1 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:

$$R_i = \beta_0 + \beta_1 \hat{R}_{o(i)} + X_i' \delta + \varepsilon_i, \quad (4)$$

where  $R_i$  denotes retirement age of European worker  $i$ ,  $\hat{R}_{o(i)}$  is the occupation-predicted retirement age from equation (2),  $X_i$  is a vector of control variables and  $\varepsilon_i$  is an error term. Similarly to the prediction step, we include country and year fixed effects and marital status as control variables in the baseline specification, but we show that results are robust to including a host of additional characteristics.

### 2.3.2 Occupations and Retirement Across Countries

Ultimately, our goal is to test whether occupational composition can explain differences in retirement behavior across countries. We estimate the model

$$R_c = \alpha_0 + \alpha_1 \hat{R}_c + Z_c' \zeta + u_c, \quad (5)$$

where  $R_c$  is country  $c$ 's effective retirement age reported by the OECD and  $\hat{R}_c$  is the predicted retirement age based on occupational composition from equation (3).  $Z_c$  is a vector of country-level controls and  $u_c$  is an error term.

Equation (5) allows us to uncover the cross-country correlation of retirement behavior and occupational composition. To derive policy implications from our results, an important question is whether this correlation can be interpreted as a causal effect of occupational composition on aggregate retirement behavior. Providing a fully satisfactory answer to causal questions in cross-country data is notoriously challenging. Nevertheless, we attempt to account for some of the key confounding effects in our empirical analysis. 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.<sup>7</sup> This may lead the correlation to over- or under-state the causal effect of occupations on retirement. For instance, improvements in health over

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<sup>7</sup>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 likely entails changing occupational composition over the course of development.

the course of development may lead to later retirement, while income effects may lead to earlier retirement. To address these issues empirically, we collect a range of country-level characteristics proxying for key confounders, and we carefully investigate how controlling for these affects our results.

### 3 RESULTS

#### 3.1 Prediction Step

We begin by estimating equation (1), which allows us to obtain occupation-predicted retirement ages  $\hat{R}_o$  through equation (2). Predicted retirement ages vary strongly across occupations, similar to the distribution of average retirement ages by occupation shown in Figure 1. Indeed, the cross-occupation correlation between raw and predicted ages within the CPS data is 97.5%. As 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, Appendix Figure A2 summarizes predicted retirement ages by nine broad categories.<sup>8</sup> 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.

#### 3.2 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 equation (4) 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 af-

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<sup>8</sup>We use the broad occupational categories from Autor (2019) for this illustration.

ter 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.<sup>9</sup> Moreover, occupation-predicted retirement ages retain 62% of their explanatory power among European workers compared to an analogous in-sample estimation using CPS data.<sup>10</sup>

**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 controls	no	no	no	no	yes	yes
SHARE education controls	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 equation (4). 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. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Two 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 con-

<sup>9</sup>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.

<sup>10</sup>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. 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.

trol 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. One potential explanation for this result is that the retirement age distribution in Europe is more compressed, which might reduce differences across occupations. Indeed, the standard deviation of retirement ages is 7.4 years in the U.S. but only 4.5 years in Europe (see Appendix Tables A1 and A2). 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 equation (4). If anything, the presence of such measurement error would imply that we underestimate the predictive power of occupational retirement ages.

### 3.3 Occupations and Retirement Across Countries

Finally, we turn to the country-level results. Figure 3 in the introduction shows the correlation between countries' effective retirement age and the predicted retirement age based on occupational composition in a scatterplot. This corresponds to estimating equation (5) without country-level controls. The slope coefficient is positive and highly significant. The  $R^2$  of 0.34 indicates that occupational composition can explain around a third of the variation in retirement ages across the 40 countries contained in our data. While Figure 3 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 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.

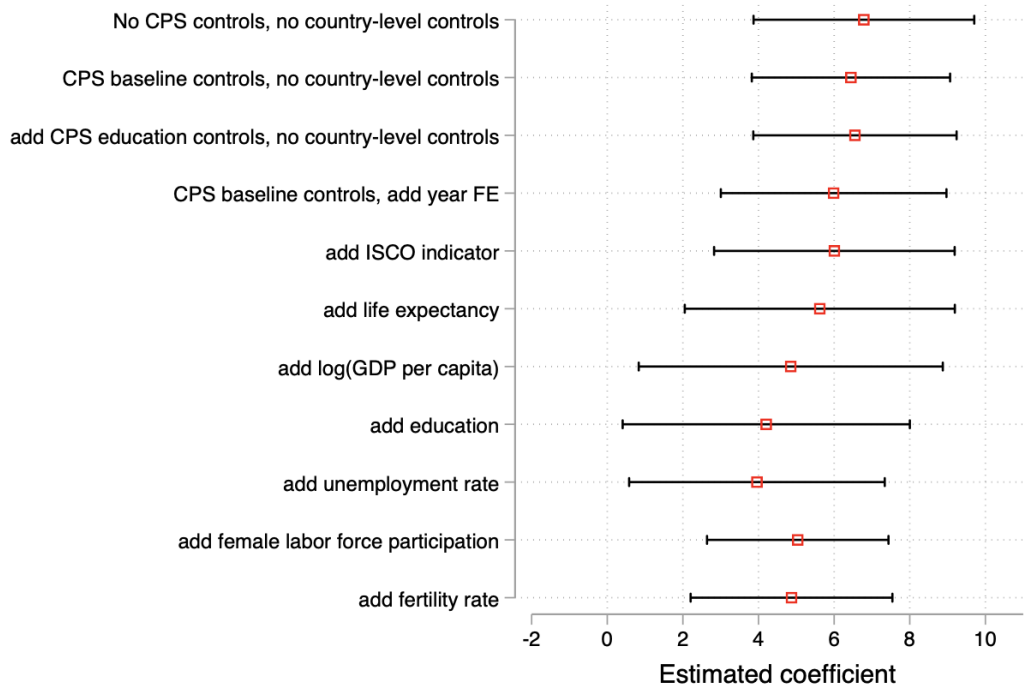
Figure 4 shows that these results are robust to including varying sets of control variables both in the individual-level prediction and in the country-level regressions. In the three specifications at the top, whether or not controls are included in the prediction using CPS data hardly changes the final country-level 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.<sup>11</sup> The fact that the estimated relationship remains large and significant suggests that we capture an inherent association

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<sup>11</sup>See Appendix Table A8 for details of these country-level regression results.

between retirement and occupational composition, rather than a spurious correlation driven by other differences across countries.

**Figure 4: Cross-Country Analysis: Robustness**



*Notes:* The figure shows robustness of our cross-country analysis to including varying sets of controls at the individual-level and at the country level. For each specification described by the respective row title, the figure shows the estimated correlation between countries' effective retirement and the predicted retirement age based on occupations. Red squares depict point estimates and black bars show 95% confidence intervals based on standard errors clustered at the country level.

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 a number of factors could actually exacerbate differences in aggregate retirement behavior relative to individual behavior within countries. First, endogenous institutional and policy responses could facilitate retirement behavior desired by a large number of individuals. For instance, 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. Since social security rules often apply to the workforce in



general, concessions to a share of workers may result in a broader shift towards early retirement ages. Second, 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 workers. In fact, similar patterns in aggregate vs. individual labor supply behavior have been observed in other contexts. For instance, an interesting 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 economic processes may well explain why the cross-country coefficients in Figures 3 and 4 exceed unity.

#### 4 DISCUSSION AND CONCLUSION

In this paper, we show that occupations are an important determinant of individual retirement decisions, and as a consequence, aggregate retirement behavior is shaped by the occupational composition of a country. These findings have a number of implications.

Perhaps the most important implication is that shifts in countries' occupational composition have side effects on social security systems. Indeed, some of the most extensively discussed events affecting labor markets 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 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 entail a positive fiscal externality on the government budget via longer periods of tax and contribution payments and shorter 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 ability to work at old age to retire earlier.<sup>12</sup> 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 predicted retirement ages based on occupational composition provide a natural benchmark for cross-country comparisons of 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 Figure 3. On the other hand, Germany and France have a very similar predicted retirement age based on occupational composition, 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. While we argue that our country-level results are robust to accounting for key confounders, this would help enable a clear-cut analysis of causal effects. 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.

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<sup>12</sup>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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ONLINE APPENDIX: ADDITIONAL FIGURES AND TABLES

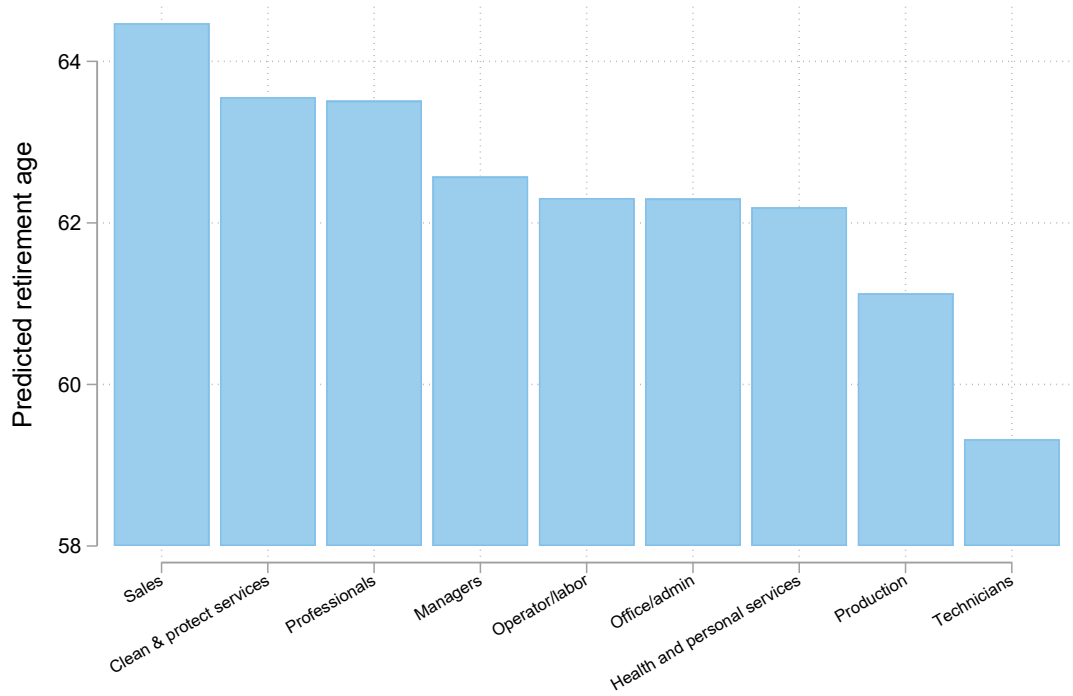
Figure A1: Validating Our Retirement Definition



*Notes:* The figure shows the correlation between our main retirement age definition and self-reported retirement age, using HRS data. Our main retirement definition, which we use to measure retirement ages in CPS data is based on job exits as described in Section 2. Each dot in the figure corresponds to one observation, and the red line depicts a linear fit. The figure also includes the estimated slope coefficient with its robust standard error in parentheses, and the  $R^2$  of the regression.



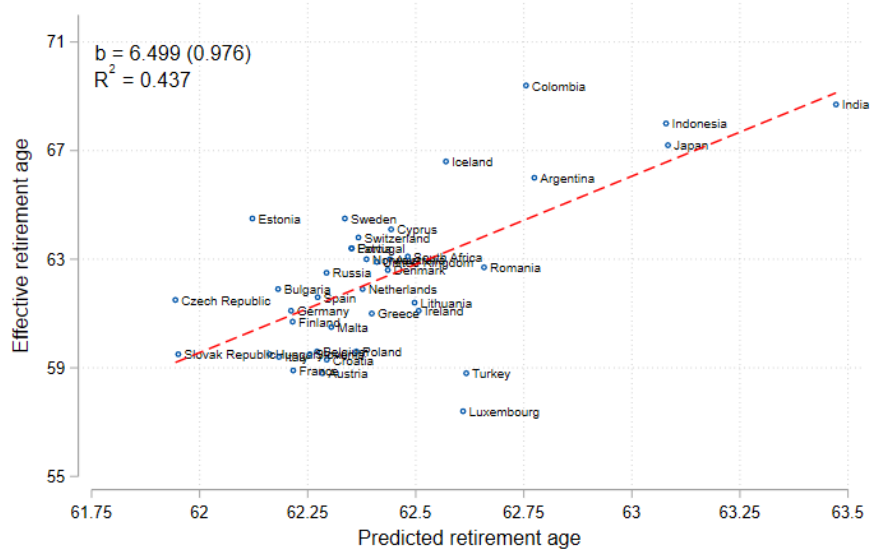
**Figure A2: Predicted Retirement Age by Broad Occupation**



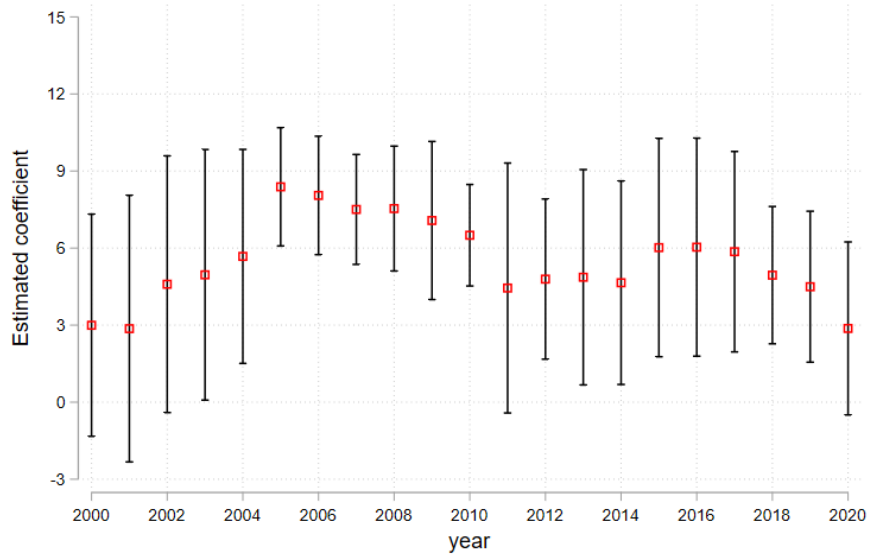
*Notes:* The figure shows predicted retirement ages by broad occupational categories. To aggregate occupations, we use the nine categories from Autor (2019).

**Figure A3: Cross-Country Results: Robustness over Time**

(a) Cross-Country Correlation in 2010



(b) Cross-Country Correlation Year-by-Year



Notes: The figure shows the cross-country correlation of effective retirement ages and predicted retirement age based on occupations over time. Panel (a) shows the correlation in 2010, the middle of our sample period. The figure includes the estimated slope coefficient  $b$  with its robust standard error in parentheses, and the  $R^2$  of the correlation. Panel (b) shows the estimated correlation in each year, where the red squares denote point estimates and the bars denote 95% confidence intervals.

**Table A1: Summary Statistics: CPS Data**

	(1)	(2)	3)	(4)
	mean	s.d.	min	max
Weeks worked last year	51.24	1.73	45	52
Retirement age	62.52	7.39	50	80
Retirement year	2003.40	7.48	1990	2015
Married	0.78	0.41	0	1
Education:				
Primary school (grades 1-4)	0.02	0.14	0	1
Some high school (grades 5-12)	0.19	0.39	0	1
High school diploma	0.32	0.47	0	1
Some college (1-2 years)	0.16	0.37	0	1
Associate degree	0.06	0.24	0	1
Some college (3-4 years)	0.01	0.10	0	1
Bachelor's degree	0.14	0.35	0	1
Some postgraduate studies (no degree)	0.00	0.06	0	1
Master's or Ph.D. degree	0.10	0.30	0	1
Observations	6237			

*Notes:* The table presents summary statistics for the U.S. Current Population Survey (CPS) data.

**Table A2: Summary Statistics: SHARE Data**

	(1)	(2)	(3)	(4)	(5)
	count	mean	s.d.	min	max
Age at time of survey	13696	69.95	6.80	51	94
Retirement age	13696	60.87	4.47	50	80
Retirement year	13696	2002.15	7.14	1990	2015
Married	8559	0.85	0.36	0	1
Education					
None	13655	0.05	0.21	0	1
Primary	13655	0.21	0.41	0	1
Lower secondary	13655	0.16	0.37	0	1
Upper secondary	13655	0.32	0.47	0	1
Post-secondary but non-tertiary	13655	0.03	0.18	0	1
Lower tertiary	13655	0.21	0.41	0	1
Upper tertiary	13655	0.01	0.10	0	1
Currently in education	13655	0.00	0.02	0	1
Other	13655	0.00	0.06	0	1
Log(income) before retirement	11563	7.19	1.31	0	41
Income after retirement (indicators)					
Life insurance	13655	0.01	0.12	0	1
Private pension	13655	0.04	0.20	0	1
Private health insurance	13655	0.00	0.04	0	1
Alimony	13040	0.00	0.02	0	1
Charitable support	13655	0.00	0.04	0	1
Reported reason for retirement					
Eligible for public pension	7918	0.58	0.49	0	1
Eligible for occupational pension	7457	0.08	0.27	0	1
Eligible for private pension	7457	0.03	0.16	0	1
Offered early retirement option	7918	0.14	0.35	0	1
Made redundant	7918	0.06	0.24	0	1
Own ill health	7918	0.12	0.33	0	1
Ill health of relative or friend	7918	0.01	0.09	0	1
To retire jointly with spouse or partner	7918	0.01	0.09	0	1
To spend more time with family	7918	0.03	0.16	0	1
To enjoy life	7918	0.06	0.23	0	1
Observations	13696				

*Notes:* The table presents summary statistics for the Survey of Health, Ageing and Retirement in Europe (SHARE) data.

**Table A3: Effective and Predicted Retirement Age by Country**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	count	Effective Retirement Age				Predicted Retirement Age			
		mean	s.d.	min	max	mean	s.d.	min	max
Argentina	14	65.41	1.24	62.40	66.80	62.69	0.10	62.49	62.82
Australia	11	63.61	0.41	63.00	64.10	62.48	0.02	62.44	62.50
Austria	21	59.55	1.60	57.20	62.60	62.30	0.06	62.20	62.38
Belgium	21	58.96	1.02	57.30	60.90	62.32	0.10	62.18	62.46
Brazil	18	63.97	0.74	62.00	65.00	62.67	0.04	62.60	62.74
Bulgaria	21	60.60	2.82	56.00	64.80	62.31	0.09	62.16	62.42
Chile	8	66.20	0.90	65.10	68.00	62.66	0.08	62.56	62.76
Colombia	18	68.89	1.00	66.70	70.80	62.73	0.04	62.65	62.79
Costa Rica	13	66.88	0.58	65.70	68.00	62.82	0.04	62.71	62.88
Croatia	19	59.93	0.92	58.40	61.70	62.36	0.11	62.18	62.53
Cyprus	21	63.70	0.92	62.00	65.30	62.45	0.09	62.33	62.61
Czech Republic	21	61.56	0.82	60.40	63.10	62.01	0.08	61.91	62.10
Denmark	21	62.67	0.88	61.00	64.50	62.41	0.05	62.33	62.48
Estonia	21	62.22	2.25	58.20	66.50	62.18	0.10	62.04	62.31
Finland	21	60.85	1.45	58.90	63.50	62.23	0.06	62.16	62.32
France	21	58.90	0.71	58.20	60.40	62.28	0.11	62.15	62.42
Germany	21	61.37	1.02	60.00	63.40	62.23	0.06	62.13	62.35
Greece	21	61.08	0.37	60.50	61.80	62.59	0.23	62.33	62.86
Hungary	21	59.82	2.18	56.70	63.00	62.18	0.06	62.10	62.27
Iceland	21	67.05	0.92	65.70	68.90	62.58	0.09	62.45	62.73
India	5	67.52	0.73	66.90	68.70	63.28	0.12	63.18	63.47
Indonesia	4	67.52	0.68	66.80	68.20	63.11	0.02	63.08	63.13
Ireland	21	63.00	1.05	61.10	64.70	62.42	0.20	62.14	62.63
Israel	6	66.15	1.04	64.60	67.50	62.61	0.01	62.59	62.63
Italy	21	60.24	0.99	58.90	62.60	62.35	0.14	62.17	62.49
Japan	20	66.92	0.41	66.40	67.80	62.97	0.07	62.87	63.08
Latvia	21	62.32	1.63	59.00	66.30	62.39	0.07	62.23	62.47
Lithuania	21	61.84	1.11	60.10	63.40	62.49	0.08	62.31	62.60
Luxembourg	21	58.64	0.91	57.10	60.50	62.59	0.21	62.23	62.81
Malta	21	60.40	1.05	59.00	62.70	62.38	0.15	62.18	62.60
Mexico	8	67.32	0.49	66.20	67.70	62.84	0.03	62.81	62.89
Netherlands	21	61.63	1.53	59.50	64.20	62.45	0.11	62.33	62.60
Norway	21	63.47	0.88	62.10	64.90	62.40	0.05	62.35	62.51
Poland	21	60.15	0.87	59.30	62.20	62.42	0.05	62.34	62.51
Portugal	21	63.37	1.56	60.70	66.10	62.42	0.15	62.25	62.66
Romania	21	63.43	1.95	59.70	66.50	62.96	0.49	62.58	63.86
Russia	11	62.17	0.22	61.80	62.50	62.31	0.03	62.29	62.38
Slovak Republic	21	59.63	0.74	58.70	60.80	61.99	0.07	61.89	62.08
Slovenia	21	59.96	1.23	58.10	62.90	62.31	0.13	62.16	62.53
South Africa	21	62.45	1.13	60.40	64.30	62.43	0.04	62.33	62.48
Spain	21	61.16	0.46	60.30	61.70	62.37	0.16	62.19	62.57
Sweden	21	64.28	1.18	62.30	66.00	62.33	0.06	62.18	62.39
Switzerland	21	64.04	0.69	62.60	65.40	62.44	0.08	62.34	62.55
Turkey	17	60.35	1.09	58.80	62.10	62.72	0.10	62.57	62.83
United Kingdom	20	62.51	0.67	61.20	63.40	62.44	0.10	62.31	62.56

Notes: The table summarizes effective retirement ages and predicted retirement ages based on occupational composition by country.

**Table A4: Summary Statistics: Country-Level Data**

	(1)	(2)	(3)	(4)	(5)
	count	mean	s.d.	min	max
Effective retirement age	822	62.29	2.75	56	71
Predicted retirement age	822	62.44	0.26	62	64
ISCO08 classification used	822	0.50	0.50	0	1
Life expectancy at age 65 (men)	731	16.63	2.01	12	20
log(GDP per capita)	766	10.35	0.54	8	12
Tertiary education (men aged 55-64, %)	656	22.15	8.72	2	47
Unemployment rate (men)	797	8.11	4.71	2	28
Female labor force participation (%)	797	52.27	9.02	21	78
Fertility rate	822	1.65	0.34	1	3
Observations	822				

*Notes:* The table presents summary statistics of the country-level data.

**Table A5: Retirement Across Occupations in the U.S. (2010 IPUMS/Census Classification)**

	(1)	(2)	(3)	(4)	(5)
Dependent variable: individual retirement age					
Occupation dummies	yes	yes	yes	yes	yes
State FE		yes	yes	yes	yes
Year FE			yes	yes	yes
Marital status				yes	yes
Education controls					yes
Observations	6,237	6,237	6,237	6,237	6,237
$R^2$	0.109	0.118	0.125	0.177	0.184
F-test: joint significance of occupation dummies					
F-statistic	3.807	3.847	3.831	3.897	3.830
p-value	0.000	0.000	0.000	0.000	0.000

*Notes:* The table describes regression results based on equation (1), where we regress individual retirement ages in the U.S. on occupation dummies and control variables. Column (1) only includes occupation dummies, and Columns (2) to (5) subsequently add control variables as specified by the column titles. The lower panel of the table reports results from an F-test testing for the joint significance of the occupation dummies.

**Table A6: Retirement Across Occupations in the U.S. (ISCO-08 Classification)**

	(1)	(2)	(3)	(4)	(5)
Dependent variable: individual retirement age					
Occupation dummies	yes	yes	yes	yes	yes
State FE		yes	yes	yes	yes
Year FE			yes	yes	yes
Marital status				yes	yes
Education controls					yes
Observations	6,237	6,237	6,237	6,237	6,237
$R^2$	0.038	0.049	0.057	0.110	0.117
F-test: joint significance of occupation dummies					
F-statistic	6.666	6.464	6.588	6.778	6.133
p-value	0.000	0.000	0.000	0.000	0.000

*Notes:* The table shows regression results based on equation (1), where we regress individual retirement ages in the U.S. on occupation dummies and control variables. In order to make results comparable to Table 1, we use the ISCO-08 occupation classification instead of the 2010 IPUMS/Census classification. Column (1) only includes occupation dummies, and Columns (2) to (5) subsequently add control variables as specified by the column titles. The lower panel of the table reports results from an F-test testing for the joint significance of the occupation dummies.



**Table A7: Occupations and Individual Retirement Ages: Country-by-Country Results**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	AUT	BEL	HRV	CZE	DNK	EST	FRA	DEU	GRC
	Dependent variable: individual retirement age								
occupation-predicted retirement age	0.34*** (0.11)	0.67*** (0.12)	0.49*** (0.16)	0.23** (0.11)	0.19 (0.16)	0.18 (0.22)	0.59*** (0.13)	0.29*** (0.11)	0.77** (0.36)
Observations	821	1233	550	743	473	795	861	1153	898
R <sup>2</sup>	0.035	0.083	0.020	0.008	0.008	0.003	0.056	0.036	0.030
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	NLD	ISR	ITA	LUX	PRT	SVN	ESP	SWE	SWI
	Dependent variable: individual retirement age								
occupation-predicted retirement age	0.35 (0.30)	0.47** (0.21)	0.56*** (0.20)	0.42*** (0.13)	0.76** (0.35)	0.33*** (0.11)	0.27* (0.14)	0.35*** (0.11)	0.07 (0.14)
Observations	389	553	1172	296	140	909	1117	1072	494
R <sup>2</sup>	0.009	0.024	0.050	0.042	0.054	0.016	0.034	0.049	0.002

*Notes:* The table shows results from regressing individual retirement ages of European workers on U.S. occupation-predicted retirement ages. While the main Table 1 pools across countries, this table reports results separately for each country indicated by the column titles. The specifications shown include baseline CPS controls. Robust standard errors are shown in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

**Table A8: Effective vs. Predicted Retirement Age across Countries**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent variable: effective retirement age						
Predicted retirement age	6.44*** (1.29)	5.99*** (1.47)	6.01*** (1.57)	5.62*** (1.76)	4.85** (1.98)	4.20** (1.87)	4.87*** (1.31)
ISCO08 classification used			-0.06 (0.75)	-0.06 (0.74)	0.10 (0.81)	0.51 (0.77)	1.22* (0.63)
Life expectancy at age 65				0.13 (0.18)	0.30 (0.26)	0.33 (0.23)	0.26* (0.15)
log(GDP per capita)					-1.03 (1.07)	-1.90 (1.14)	-2.77*** (0.91)
Education						0.07* (0.03)	-0.00 (0.03)
Unemployment rate							-0.17*** (0.05)
Female labor force participation							0.14*** (0.02)
Fertility rate							0.49 (0.86)
Observations	621	621	621	621	621	621	621
R <sup>2</sup>	0.336	0.367	0.367	0.373	0.388	0.418	0.665
Year FE	no	yes	yes	yes	yes	yes	yes

*Notes:* The table shows results from regressing effective retirement ages on predicted retirement ages across countries. Effective retirement age is defined as the average actual retirement age of workers in a country. Predicted retirement age is computed based on a country's occupational composition as described in Section 2.2. Column (1) shows the unconditional correlation, and Columns (2) to (7) subsequently add country-level control variables. Standard errors clustered at the country level are shown in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

**Table B1: Occupational Crosswalk: 2010 IPUMS/Census to ISCO-88**

<b>ISCO-88</b>	<b>2010 IPUMS/Census</b>
1	9800, 9810, 9820, 9830
11	10
12	30, 100, 110, 120, 130, 150, 160, 205, 300, 320, 360, 430
13	20, 220, 230, 310, 350, 420
21	1000, 1010, 1020, 1060, 1100, 1200, 1220, 1230, 1300, 1310, 1320, 1350, 1360, 1400, 1420, 1430, 1440, 1450, 1460, 1520, 1530, 1640, 1650, 1700, 1710, 1720, 1740, 1760, 1830, 7900
22	1620, 3000, 3010, 3050, 3210, 3230, 3240, 3250, 3260
23	2200, 2300, 2310, 2320, 2330, 2550
24	620, 700, 710, 730, 800, 820, 830, 840, 850, 900, 940, 1800, 1820, 1840, 2000, 2010, 2020, 2040, 2050, 2100, 2400, 2430, 2700, 2740, 2750, 2800, 2810, 2825, 2840, 2850, 3950, 4930
31	1050, 1410, 1540, 1550, 1560, 1600, 1920, 1930, 1960, 2900, 2920, 3200, 3720, 3750, 5800, 6200, 6660, 9000, 9030, 9040
32	1900, 1910, 1980, 3030, 3040, 3110, 3140, 3160, 3200, 3220, 3300, 3310, 3320, 3400, 3410, 3500, 3510, 3520, 3530, 3540, 3610, 3620, 3630, 3640, 3650, 6010, 8760, 9410
33	2340
34	410, 500, 510, 520, 530, 540, 560, 600, 720, 810, 860, 910, 930, 950, 1240, 2060, 2140, 2150, 2440, 2600, 2630, 2720, 2760, 2860, 2910, 3710, 3800, 3820, 3910, 4430, 4800, 4810, 4820, 4840, 4850, 4920, 5220, 5250, 5500, 5610, 5920
41	5000, 5110, 5120, 5140, 5150, 5165, 5200, 5230, 5260, 5330, 5340, 5520, 5540, 5550, 5600, 5620, 5630, 5700, 5810, 5820, 5840, 5850, 5860, 5900, 5910, 5940
42	4300, 4400, 4830, 5010, 5020, 5030, 5100, 5130, 5160, 5240, 5300, 5310, 5400, 5410, 5420
51	2540, 3600, 3700, 3730, 3740, 3900, 3930, 3940, 4000, 4010, 4040, 4150, 4200, 4320, 4340, 4350, 4460, 4500, 4510, 4520, 4540, 4600, 4610, 4620, 4640, 4650, 9050
52	4050, 4060, 4700, 4720, 4740, 4750, 4760, 4900, 4940, 4965, 9360
61	4210, 6005, 6100, 6120
Continued on next page	

**Table B1 (continued)**

<b>ISCO-88</b>	<b>2010 IPUMS/Census</b>
62	4210, 6005, 6100, 6120
71	4240, 6220, 6230, 6240, 6250, 6330, 6355, 6360, 6400, 6420, 6430, 6440, 6460, 6515, 6710, 6720, 6765, 6830, 7315, 7550
72	6210, 6500, 6520, 6530, 6700, 7000, 7010, 7020, 7030, 7100, 7110, 7120, 7125, 7130, 7140, 7150, 7160, 7200, 7210, 7220, 7240, 7260, 7300, 7320, 7330, 7350, 7360, 7410, 7420, 7540, 7560, 7630, 7740, 7930, 7940, 7950, 7960, 8000, 8010, 8030, 8060, 8130, 8140, 8210, 8220
73	7430, 8230, 8250, 8550, 8750, 8810, 8910, 8920
74	6040, 7800, 7810, 8330, 8350, 8400, 8450, 8500, 8510, 8540, 8710, 8740
81	6800, 6820, 6840, 7920, 8040, 8100, 8150, 8300, 8610, 8650, 8720, 8730, 8800, 8850, 8860, 8930, 8965, 9560
82	7700, 7710, 7720, 7730, 7750, 7830, 7840, 7850, 7855, 8200, 8320, 8340, 8410, 8420, 8460, 8530, 8600, 8620, 8630, 8640, 8830, 8940, 9310, 9650
83	6130, 6300, 6320, 6940, 9100, 9130, 9140, 9150, 9200, 9230, 9240, 9260, 9300, 9510, 9520, 9600
91	4030, 4120, 4130, 4140, 4220, 4230, 4250, 4420, 4530, 4950, 5510, 5530, 7340, 7510, 7610, 8310, 9350, 9610, 9720
92	6050
93	6260, 6600, 6730, 6740, 8950, 9240, 9620, 9630, 9640, 9750

**Table B2: Occupational Crosswalk: 2010 IPUMS/Census to ISCO-08**

<b>ISCO-08</b>	<b>2010 IPUMS/Census</b>
1	9800
2	9810
3	9820, 9830
11	10
12	20, 30, 100, 120, 130, 150, 300, 320, 360, 430
13	110, 140, 160, 205, 220, 230, 350, 420
14	310, 330
21	1200, 1220, 1230, 1300, 1310, 1320, 1350, 1360, 1400, 1420, 1430, 1440, 1450, 1460, 1520, 1530, 1610, 1640, 1650, 1700, 1710, 1720, 1740, 1760, 1830, 2360
22	3000, 3010, 3030, 3040, 3050, 3060, 3110, 3120, 3130, 3140, 3150, 3160, 3210, 3230, 3240, 3250, 3260
23	2200, 2300, 2310, 2320, 2330, 2340, 2550
24	620, 700, 710, 730, 800, 820, 830, 840, 850, 900, 940, 2825, 4930
25	1000, 1010, 1020, 1060, 1100, 7900
26	1800, 1820, 1840, 2000, 2010, 2020, 2040, 2050, 2100, 2400, 2430, 2700, 2740, 2750, 2760, 2800, 2810, 2840, 2850, 3950
31	1410, 1540, 1550, 1560, 1600, 1900, 1910, 1920, 1930, 1960, 3720, 3750, 6200, 6660, 7700, 8600, 8620, 8630, 8640, 9000, 9030, 9040, 9310, 9650
32	1980, 3200, 3220, 3300, 3310, 3320, 3400, 3410, 3500, 3510, 3520, 3530, 3540, 3610, 3620, 3630, 3640, 3650, 6010, 8760, 9410
33	410, 500, 510, 520, 530, 540, 560, 600, 720, 810, 860, 910, 930, 950, 1240, 3710, 3800, 3820, 3910, 4800, 4810, 4820, 4840, 4850, 4920, 5000, 5220, 5250, 5500, 5610, 5920
34	2060, 2140, 2150, 2440, 2720, 2860, 2910, 4000, 4010, 4430
35	1050, 2900, 2920, 5800
41	5150, 5700, 5810, 5820, 5860
42	4300, 4400, 4830, 5010, 5020, 5030, 5100, 5130, 5160, 5240, 5300, 5310, 5400, 5410, 5420
43	5110, 5120, 5140, 5165, 5200, 5230, 5330, 5340, 5520, 5600, 5620, 5630, 5840
44	5260, 5320, 5350, 5360, 5540, 5550, 5560, 5850, 5900, 5910, 5940
Continued on next page	

**Table B2 (continued)**

<b>ISCO-08</b>	<b>2010 IPUMS/Census</b>
51	4040, 4110, 4150, 4200, 4320, 4340, 4350, 4460, 4500, 4510, 4520, 4540, 4620, 4640, 4650, 9050
52	4050, 4060, 4120, 4700, 4720, 4740, 4750, 4760, 4900, 4940, 4965, 9360
53	2540, 3600, 4600, 4610
54	3700, 3730, 3740, 3900, 3930, 3940
61	4210, 6005
62	6100, 6120
63	6100, 6120
71	6220, 6230, 6240, 6250, 6330, 6360, 6400, 6420, 6430, 6440, 6460, 6515, 6710, 6720, 6765, 7315, 7550
72	6210, 6500, 6520, 6530, 7000, 7140, 7150, 7160, 7200, 7210, 7220, 7240, 7330, 7350, 7360, 7540, 7560, 7630, 7740, 7930, 7940, 7950, 7960, 8000, 8010, 8030, 8060, 8130, 8140, 8210, 8220
73	7430, 8230, 8250, 8550, 8750, 8810, 8910, 8920
74	6355, 6700, 7010, 7020, 7030, 7040, 7100, 7110, 7120, 7125, 7130, 7260, 7300, 7320, 7410, 7420
75	4240, 6040, 6830, 7800, 7810, 7855, 8330, 8350, 8400, 8450, 8500, 8510, 8540, 8710, 8740
81	6800, 6820, 6840, 7830, 7840, 7850, 7920, 8040, 8100, 8150, 8200, 8300, 8320, 8340, 8410, 8420, 8460, 8530, 8610, 8650, 8720, 8730, 8800, 8830, 8850, 8860, 8930, 8940, 8965, 9560
82	7710, 7720, 7730, 7750
83	6130, 6300, 6320, 6940, 9100, 9130, 9140, 9150, 9200, 9230, 9240, 9260, 9300, 9510, 9520, 9600
91	4220, 4230, 8310, 9610
92	6050
93	6260, 6600, 6730, 6740, 8950, 9240, 9620, 9630, 9640, 9750
94	4030, 4130, 4140
95	4950
96	4250, 4420, 4530, 5510, 5530, 7340, 7510, 7610, 9350, 9720

**Table B3: Retirement Ages across Occupations in the U.S. (2010 IPUMS/Census Classification)**

<b>Occupation</b>	<b>Mean</b>	<b>N</b>
Barbers	71.80	5
Motor Vehicle Operators, All Other	71.08	12
Entertainment Attendants and Related Workers, nec	70.00	11
Social and Community Service Managers	69.63	8
Editors, News Analysts, Reporters, and Correspondents	69.33	6
Wholesale and Retail Buyers, Except Farm Products	68.63	8
Veterinarians	68.60	5
Mail Clerks and Mail Machine Operators, Except Postal Service	68.43	7
First-Line Supervisors of Landscaping, Lawn Service, and Groundskeeping Workers	68.00	5
Farmers, Ranchers, and Other Agricultural Managers	67.70	190
Pharmacists	67.60	10
Upholsterers	67.22	9
Management Analysts	67.15	52
Parking Lot Attendants	67.13	8
Property, Real Estate, and Community Association Managers	67.04	48
Tool and Die Makers	67.00	11
Community and Social Service Specialists, nec	67.00	6
Industrial Production Managers	67.00	5
Architects, Except Naval	66.80	5
Bookkeeping, Accounting, and Auditing Clerks	66.73	30
Clergy	66.70	57
Librarians	66.67	6
Artists and Related Workers	66.64	14
Personal Care Aides	66.36	11
Information and Record Clerks, All Other	66.14	7
Real Estate Brokers and Sales Agents	66.13	61
Forest and Conservation Workers	66.00	5
Billing and Posting Clerks	66.00	5
Parts Salespersons	66.00	9
Couriers and Messengers	65.68	28
Continued on next page		

**Table B3 (continued)**

<b>Occupation</b>	<b>Mean</b>	<b>N</b>
Cabinetmakers and Bench Carpenters	65.50	12
Receptionists and Information Clerks	65.50	10
Agricultural workers, nec	65.48	60
Office Clerks, General	65.29	17
Jewelers and Precious Stone and Metal Workers	65.29	7
Office and administrative support workers, nec	65.29	14
Compliance Officers, Except Agriculture	65.27	15
Musicians, Singers, and Related Workers	65.22	18
Lawyers, and judges, magistrates, and other judicial workers	65.21	43
Bakers	65.17	6
Counter and Rental Clerks	65.17	6
Bartenders	65.17	12
Secretaries and Administrative Assistants	65.14	14
Retail Salespersons	65.13	68
Electrical and electronics repairers, transportation equipment, and industrial and utility	65.10	10
Heating, Air Conditioning, and Refrigeration Mechanics and Installers	65.00	28
File Clerks	65.00	8
Sales and Related Workers, All Other	65.00	19
First-Line Supervisors of Gaming Workers	65.00	6
Religious Workers, nec	65.00	5
Brickmasons, Blockmasons, and Stonemasons	64.93	14
Physicians and Surgeons	64.91	47
Tailors, Dressmakers, and Sewers	64.83	6
Meter Readers, Utilities	64.80	5
Door-to-Door Sales Workers, News and Street Vendors, and Related Workers	64.78	27
Cost Estimators	64.71	7
Insurance Sales Agents	64.60	45
Pest Control Workers	64.60	5
Counselors	64.60	10
Advertising Sales Agents	64.40	10
Chemical Engineers	64.40	5

Continued on next page



**Table B3 (continued)**

<b>Occupation</b>	<b>Mean</b>	<b>N</b>
Personal Financial Advisors	64.40	5
Appraisers and Assessors of Real Estate	64.40	5
Sales Representatives, Wholesale and Manufacturing	64.37	115
Chief executives and legislators/public administration	64.36	64
Taxi Drivers and Chauffeurs	64.30	44
Weighers, Measurers, Checkers, and Samplers, Recordkeeping	64.20	5
Dentists	64.10	10
Aircraft Pilots and Flight Engineers	64.00	14
Securities, Commodities, and Financial Services Sales Agents	63.89	19
Other Teachers and Instructors	63.88	16
Butchers and Other Meat, Poultry, and Fish Processing Workers	63.86	35
Other Installation, Maintenance, and Repair Workers Including Wind Turbine Service Technicians, and Commercial Divers, and Signal and Track Switch Repairers	63.83	12
Designers	63.82	17
Purchasing Managers	63.80	10
Security Guards and Gaming Surveillance Officers	63.69	114
Bookbinders, Printing Machine Operators, and Job Printers	63.67	15
Postsecondary Teachers	63.64	36
Heavy Vehicle and Mobile Equipment Service Technicians and Mechanics	63.56	18
Mechanical Engineers	63.53	19
Civil Engineers	63.52	33
Janitors and Building Cleaners	63.49	322
Medical Assistants and Other Healthcare Support Occupations, nec	63.40	15
Computer Support Specialists	63.33	6
Grounds Maintenance Workers	63.13	85
Locomotive Engineers and Operators	63.13	8
Cashiers	62.86	43
Social Workers	62.82	17
Architectural and Engineering Managers	62.80	5
Computer, Automated Teller, and Office Machine Repairers	62.77	13
Writers and Authors	62.77	13
Construction workers, nec	62.75	8
Continued on next page		

**Table B3 (continued)**

<b>Occupation</b>	<b>Mean</b>	<b>N</b>
Production, Planning, and Expediting Clerks	62.75	8
Purchasing Agents, Except Wholesale, Retail, and Farm Products	62.67	9
Supervisors of Transportation and Material Moving Workers	62.60	15
Medical and Health Services Managers	62.60	5
First-Line Supervisors of Sales Workers	62.59	211
Nursing, Psychiatric, and Home Health Aides	62.57	14
Pipelayers, Plumbers, Pipefitters, and Steamfitters	62.49	45
Maids and Housekeeping Cleaners	62.44	32
Economists and market researchers	62.43	7
Payroll and Timekeeping Clerks	62.40	5
Accountants and Auditors	62.40	55
Laborers and Freight, Stock, and Material Movers, Hand	62.38	140
Chemists and Materials Scientists	62.38	8
Other Business Operations and Management Specialists	62.36	11
Packers and Packagers, Hand	62.33	15
Sales Representatives, Services, All Other	62.32	22
Constructions Managers	62.25	36
First-Line Supervisors of Housekeeping and Janitorial Workers	62.21	19
Surveying and Mapping Technicians	62.20	5
Loan Interviewers and Clerks	62.17	6
Drafters	62.10	10
Driver/Sales Workers and Truck Drivers	62.08	338
Inspectors, Testers, Sorters, Samplers, and Weighers	62.08	62
Customer Service Representatives	62.07	27
Food Service and Lodging Managers	62.07	45
Financial Specialists, nec	62.06	17
Elementary and Middle School Teachers	62.04	27
Industrial Truck and Tractor Operators	62.00	44
Dredge, Excavating, and Loading Machine Operators	62.00	8
Millwrights	62.00	9
First-Line Supervisors of Farming, Fishing, and Forestry Workers	62.00	7
Food Preparation Workers	62.00	12
First-Line Supervisors of Food Preparation and Serving Workers	62.00	14

Continued on next page

**Table B3 (continued)**

<b>Occupation</b>	<b>Mean</b>	<b>N</b>
Managers, nec (including Postmasters)	61.92	370
Bus and Ambulance Drivers and Attendants	61.87	67
Engineers, nec	61.86	28
Actors, Producers, and Directors	61.83	6
Claims Adjusters, Appraisers, Examiners, and Investigators	61.80	5
Registered Nurses	61.75	8
Pumping Station Operators	61.70	10
Bill and Account Collectors	61.67	6
Electrical and Electronics Engineers	61.65	34
Human Resources, Training, and Labor Relations Specialists	61.63	19
Water Wastewater Treatment Plant and System Operators	61.63	8
First-Line Supervisors of Mechanics, Installers, and Repairers	61.61	38
Structural Iron and Steel Workers	61.60	5
Stationary Engineers and Boiler Operators	61.57	14
Machinists	61.54	37
Mining Machine Operators	61.50	8
Dishwashers	61.45	11
Fishing and hunting workers	61.40	5
First-Line Supervisors of Production and Operating Workers	61.38	81
Cleaners of Vehicles and Equipment	61.33	15
Maintenance and Repair Workers, General	61.30	56
Automotive Service Technicians and Mechanics	61.30	54
Computer Programmers	61.18	17
Welding, Soldering, and Brazing Workers	61.17	40
Painting Workers and Dyers	61.17	6
Clinical Laboratory Technologists and Technicians	61.17	6
Education Administrators	61.12	34
Refuse and Recyclable Material Collectors	61.00	8
Electrical Power-Line Installers and Repairers	61.00	7
Childcare Workers	61.00	8
Construction and Building Inspectors	60.93	15
Construction equipment operators except paving, surfacing, and tamping equipment operators	60.91	47
Continued on next page		

**Table B3 (continued)**

<b>Occupation</b>	<b>Mean</b>	<b>N</b>
Electrical, Electronics, and Electromechanical Assemblers	60.89	9
Operations Research Analysts	60.89	9
Financial Managers	60.86	35
Electric Motor, Power Tool, and Related Repairers	60.83	6
Photographers	60.83	6
Tax Examiners and Collectors, and Revenue Agents	60.80	5
Crushing, Grinding, Polishing, Mixing, and Blending Workers	60.78	9
Carpenters	60.77	93
Packaging and Filling Machine Operators and Tenders	60.75	12
Engineering Technicians, Except Drafters	60.74	23
Industrial and Refractory Machinery Mechanics	60.71	48
Stock Clerks and Order Fillers	60.68	57
Computer Operators	60.67	6
Software Developers, Applications and Systems Software	60.67	18
Sheet Metal Workers, metal-working	60.65	17
Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	60.60	10
Technical Writers	60.60	5
First-Line Supervisors of Construction Trades and Extraction Workers	60.58	60
Food preparation and serving related workers, nec	60.56	9
Life, Physical, and Social Science Technicians, nec	60.50	22
Managers in Marketing, Advertising, and Public Relations	60.45	20
Aircraft Mechanics and Service Technicians	60.40	15
Material moving workers, nec	60.33	9
Human Resources Managers	60.33	6
First-Line Supervisors of Office and Administrative Support Workers	60.32	34
Dispatchers	60.30	10
Painters, Construction and Maintenance	60.25	44
Assemblers and Fabricators, nec	60.15	53
Power Plant Operators, Distributors, and Dispatchers	60.13	8
Vehicle and Mobile Equipment Mechanics, Installers, and Repairers, nec	60.11	9
Electricians	60.09	65
Shipping, Receiving, and Traffic Clerks	60.07	46

Continued on next page

**Table B3 (continued)**

<b>Occupation</b>	<b>Mean</b>	<b>N</b>
Secondary School Teachers	60.04	25
Computer Control Programmers and Operators	60.00	5
Reservation and Transportation Ticket Agents and Travel Clerks	60.00	5
Correspondent clerks and order clerks	60.00	5
Personal Care and Service Workers, All Other	60.00	5
Public Relations Specialists	59.86	7
Computer Scientists and Systems Analysts	59.85	39
Network systems Analysts/Web Developers		
Industrial Engineers, including Health and Safety	59.80	5
Molders and Molding Machine Setters, Operators, and Tenders (Metal and Plastic)	59.71	7
General and Operations Managers	59.68	22
Cutting, Punching, and Press Machine Setters, Operators, and Tenders (Metal and Plastic)	59.63	8
Conveyor operators and tenders, and hoist and winch operators	59.60	5
Pressers, Textile, Garment, and Related Materials	59.60	5
Postal Service Mail Carriers	59.46	35
Other production workers including semiconductor processors and cooling and freezing equipment operators	59.43	60
Sheriffs, Bailiffs, Correctional Officers, and Jailers	59.39	18
Transportation, Storage, and Distribution Managers	59.38	13
Construction Laborers	59.37	84
Automotive Body and Related Repairers	59.29	7
Highway Maintenance Workers	59.20	5
Logging Workers	59.18	11
Cutting Workers	59.15	13
Military, Rank Not Specified	59.11	28
Railroad Brake, Signal, and Switch Operators	59.00	5
Drywall Installers, Ceiling Tile Installers, and Tapers	59.00	6
Postal Service Clerks	58.93	14
Ship and Boat Captains and Operators	58.83	6
Carpet, Floor, and Tile Installers and Finishers	58.83	12
Metal workers and plastic workers, nec	58.76	25

Continued on next page

**Table B3 (continued)**

<b>Occupation</b>	<b>Mean</b>	<b>N</b>
Waiters and Waitresses	58.70	10
Bus and Truck Mechanics and Diesel Engine Specialists	58.08	24
Roofers	58.00	8
Private Detectives and Investigators	58.00	6
First-Line Supervisors of Police and Detectives	58.00	15
Radio and Telecommunications Equipment Installers and Repairers	57.87	23
Crane and Tower Operators	57.83	6
Metal Furnace Operators, Tenders, Pourers, and Casters	57.80	5
Security and Fire Alarm Systems Installers	57.80	5
First-Line Supervisors of Fire Fighting and Prevention Workers	57.80	10
Computer and Information Systems Managers	57.80	5
Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	57.75	8
Supervisors, Protective Service Workers, All Other	57.75	8
Chefs and Cooks	57.42	45
Firefighters	57.39	18
Molders, Shapers, and Casters, Except Metal and Plastic	57.00	11
Telecommunications Line Installers and Repairers	56.62	13
Administrative Services Managers	56.33	6
Police Officers and Detectives	55.79	28
Diagnostic Related Technologists and Technicians	55.60	5
Woodworkers including model makers and patternmakers, nec	55.40	5
Cement Masons, Concrete Finishers, and Terrazzo Workers	55.20	5