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Countries for Old Men:

An Analysis of the Age Pay Gap*

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Countries for Old Men: An Analysis of the Age Pay Gap*

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Abstract

This paper examines the widening pay gap between older and younger workers in high-income countries. Over the past four decades, the wages of older workers have grown significantly faster than those of younger workers, leading to a steep expansion in the age pay gap. Using detailed administrative data on 29 million workers across 3.5 million firms in Italy, along with data on 15.4 million workers from fourteen other countries, we analyze how workforce aging affects younger workers' career trajectories. Our findings are consistent with the existence of negative career spillovers: as older workers delay retirement and increasingly hold top jobs, many firms struggle to expand higher-ranked positions enough to preserve access for younger employees, pushing them into lower segments of the wage distribution. Consequently, younger workers increasingly enter the labor market at lower pay levels and experience slower wage growth after entry. They are also less likely to secure employment at higher-paying firms, which become progressively dominated by older workers. Cross-firm instrumental-variable regressions indicate that the deterioration in the career trajectories of younger workers is more pronounced in firms that have experienced more severe workforce aging. Finally, we argue that alternative explanations for these findings receive limited empirical support. These results underscore the challenges facing younger workers in aging economies and highlight the need for labor-market policies that balance the interests of both older and younger generations.

JEL Classification: J31, J21, M51, J11.
Keywords: workforce aging, wage growth, age pay gap, career spillovers, older workers, labor-market entry.

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Sintesi del lavoro:

Questo studio analizza l'allargamento del divario retributivo tra lavoratori giovani e anziani nei paesi ad alto reddito. Negli ultimi quattro decenni, i salari dei lavoratori anziani sono cresciuti molto più rapidamente di quelli dei giovani, portando a un marcato ampliamento del gap salariale per età. Utilizzando dati amministrativi su 29 milioni di lavoratori in 3,5 milioni di imprese in Italia, insieme a dati su 15,4 milioni di lavoratori provenienti da altri quattordici paesi, analizziamo come l'invecchiamento della forza lavoro influenzi le traiettorie di carriera dei giovani lavoratori. I nostri risultati sono coerenti con l'esistenza di spillover negativi sulle carriere: man mano che i lavoratori anziani posticipano il pensionamento e occupano sempre più posizioni apicali, molte imprese faticano ad espandere sufficientemente i ruoli di alto livello per garantire l'accesso ai più giovani, spingendoli verso le fasce più basse della distribuzione salariale. Di conseguenza, i giovani entrano sempre più spesso nel mercato del lavoro con salari più bassi e sperimentano una crescita salariale più lenta dopo l'ingresso. Hanno anche minori probabilità di essere assunti presso imprese che pagano meglio, le quali risultano progressivamente dominate da lavoratori anziani. Regressioni a livello di impresa che utilizzano uno strumento per l'invecchiamento della forza lavoro indicano che il peggioramento delle traiettorie di carriera dei giovani è più marcato nelle imprese che hanno sperimentato un invecchiamento più severo della forza lavoro. Infine, le spiegazioni alternative a questi risultati ricevono scarso supporto empirico. I nostri risultati evidenziano le sfide che i giovani lavoratori affrontano nelle economie in via di invecchiamento e sottolineano la necessità di politiche del lavoro che bilancino gli interessi delle generazioni più giovani e più anziane.

Parole chiave: Invecchiamento della forza lavoro, Crescita salariale, Divario retributivo per età, Spillover di carriera, Lavoratori anziani, Ingresso nel mercato del lavoro.

1 Introduction

In many high-income countries, the wages of older workers have been increasing much more rapidly than those of younger workers for several decades. For example, the pay gap between workers over 55 and those under 35 (hereafter, the *age pay gap*) increased by 61 percent in the United States between 1979 and 2018 and by 96 percent in Italy between 1985 and 2019. During the same period, the workforce has substantially aged, a trend driven in large part by longer working careers and improved life expectancy at older ages (Scott, 2023; Ashwin and Scott, 2025). In the United States, for example, the share of workers aged 55 or older increased by 88 percent, from 12.9 percent in 1985 to 24.3 percent in 2020, marking the largest growth among all age groups (Toossi and Torpey, 2017).

This paper studies how an increased stock of older workers affects the age pay gap. It is a standard economic belief that younger and older workers are imperfect substitutes in the production function (see, for example, Freeman (1979), Welch (1979), and Berger (1985)). Under this assumption, an increase in the relative supply of older workers should decrease the wages of older workers relative to those of younger workers, ultimately shrinking the age pay gap. However, since the age pay gap has instead widened, it has become evident that other factors must be responsible for the divergence in the wages of older and younger workers.

We propose an explanation for the concurrent trends of workforce aging and a widening age pay gap that centers on the limited availability of open slots in firms' hierarchies. During the past four decades, older workers have become more numerous and have substantially extended their careers. This shift has allowed them to accrue more tenure and experience, advancing further up the corporate ladder. Their ability to retain their jobs stems from factors extensively studied in the labor and personnel literature, such as backloaded wages (Lazear, 1979; Ke, Li, and Powell, 2018), knowledge spillovers (Sandvik et al., 2020; Cornelissen, Dustmann, and Schönberg, 2023), and, in some countries, employment protection laws (Bentolila and Bertola, 1990). In many cases, firms' growth has not kept pace with the increasing presence of older workers.[1] Consequently, firms have struggled to preserve promotion pathways for younger workers, who have faced increasing barriers to advancing into higher-ranked positions.

We empirically investigate the validity of this hypothesis using matched employer-employee administrative data from Italy with 312 million observations on 29 million workers across 3.5 million firms between 1985 and 2019. In Appendix B, we show that the main findings hold when we use administrative data from Germany and survey data provided by the Luxembourg Income Study for fourteen high-income countries, including the United States.

The data confirm that younger workers have indeed faced increasing struggles to reach higher segments of the wage distribution and higher-ranked jobs, in contrast to the trend experienced by older workers. In Italy, the likelihood of workers under 35 belonging to the top quartile of weekly

[1] While accommodating a growing presence of older workers, many firms in high-income economies have also faced dwindling growth prospects, due to declining labor productivity and GDP growth (Syverson, 2017).

wages declined by 34 percent from 1985 to 2019, while the probability for those over 55 increased by 32 percent. Moreover, between 1996 and 2019, the share of managerial roles held by under-35 workers fell from 8 percent to 3 percent, while that held by over-55 workers rose from 12 percent to 28 percent.

As predicted by our aging-fueled crowd-out explanation, the predominant driver of the widening age pay gap has been the opposite trajectories followed by younger and older workers along the wage distribution, rather than changes in the level of wages paid in different parts of the distribution or for different jobs. Building upon Bayer and Charles (2018), we compute the *pay rank gap*, which represents the portion of the age pay gap's expansion attributable to variation in the positions of younger and older workers in the wage distribution while keeping the level of real wages in the economy fixed at baseline. The data indicate that the deterioration in the pay rank of younger workers and the improvement in that of older workers accounted for 78 percent of the total growth in the age pay gap.

We then analyze when younger workers have started faring worse in their careers. Consistent with the increased concentration of older workers in higher-paying jobs, new entrants have started progressively lower in the wage distribution (64 percent of the total loss in pay rank), and their position in the wage distribution has started growing more slowly for several years after entry.

To draw a closer connection between workforce aging and its effects on younger workers, we leverage the employer-employee match in the Italian administrative data. Specifically, we regress the firm-level ten-year change in the pay rank of younger workers on the ten-year change in the share of workers aged 51–60 within the same firm for every starting year between 1985 and 2005, while also controlling for trends in firm age, firm size, and province. To address the potential endogeneity of the key independent variable, we instrument it with the firm-level difference between the share of workers aged 41–50 and the share aged 51–60 in the starting year. This instrument leverages cross-firm variation in exposure to workforce aging that arises from the natural aging process of workers who were already employed by each firm at baseline. The high tenure of workers over 40 suggests that cross-firm differences in this instrumental variable originate from personnel decisions made several years prior, rather than more recent firm responses to workforce aging.

The IV regressions confirm that the career paths of younger workers deteriorated significantly more within firms that experienced a larger increase in the share of older workers. For example, a one-standard-deviation increase in the share of workers aged 51-60 between 1995 and 2005 is associated with a 0.6-percentile lower growth (a 36 percent decline from the mean) in the pay rank of younger workers employed by the same firm during the same period, an effect size that is significant at the 1 percent level.

Moreover, our crowd-out explanation suggests that firms with more limited opportunities to add higher-ranked positions experience greater congestion at the top, making workforce aging particularly detrimental to younger workers. Supporting this view, the data reveal that firms with observable characteristics indicative of such constraints—such as older, larger firms with lower employment growth—exhibit a more pronounced increase in the age pay gap. Importantly, we find that the share of firms at a mature stage of their life cycle has expanded over time, resulting in more firms that face challenges in adding higher-ranked positions to their organizational structure.

Further evidence highlights another key dimension of firm heterogeneity: mean firm pay. Higher-paying firms, where older workers have been more likely to extend their careers, have experienced particularly severe congestion at the top. The consequences of this progressive entrenchment of older workers in higher-paying firms are twofold. Within firms, we establish that younger workers have shifted downward in the wage distribution of both lower- and higher-paying organizations, but the decline has been more pronounced in the latter. Across firms, younger workers have become more likely to secure employment in lower-paying organizations.

Finally, the paper examines other mechanisms that could account for the expanding age pay gap and the aging workforce: wage inequality, higher returns to experience and higher-level skills, sectoral and occupational shifts, domestic outsourcing, and changes in the characteristics of younger and older workers (for example, education). Overall, we find that these factors are not fully compatible with the characteristics of the growth in the age pay gap.

For example, if returns to experience and higher-level skills had increased, the wages of older, more experienced workers could have grown faster than those of younger workers. Similarly, wage inequality could have widened the age pay gap by increasing the distance between higher-paying jobs, which older workers predominantly hold, and lower-paying jobs, which younger workers predominantly hold. These factors would expand the age pay gap mainly by disproportionately increasing the level of wages in higher-paying jobs, amplifying the preexisting positive pay gap between older and younger workers. However, our findings indicate that the main driver of the widening age pay gap is the opposite movement of younger and older workers along the wage distribution. Unlike older workers, younger workers have faced increasing challenges in reaching higher-paying jobs, a pattern independent of whether wages in these positions have increased.

As an additional example, we also consider changes in the availability of different jobs. The decline in manufacturing (Charles, Hurst, and Notowidigdo, 2016; Charles, Hurst, and Schwartz, 2019), a sector in which less experienced workers once commanded relatively higher wages, may have widened the age pay gap by nudging younger workers toward sectors with lower starting wages. However, our results show a rather uniform expansion of the age pay gap across all two-digit sectors, both within and outside manufacturing.

Moreover, Deming (2021) shows that the share of decision-intensive occupations, in which more experienced older workers are more productive than less experienced younger workers, has been rising, steepening the wage curve over the life cycle. However, unlike the increased availability of decision-intensive jobs, we find that 88 percent of the age pay gap's expansion between 2012 (the first year with occupation data) and 2019 occurred within one-digit ISCO-08 occupation codes, rather than between them. This finding aligns with the conclusion in Acemoglu, Mühlbach, and Scott (2022) that the rise in the "age-friendliness" of jobs did not disproportionately benefit older workers.

In conclusion, this paper offers three main contributions. First, our results contribute to the literature that studies changes in younger workers' labor outcomes. Other papers (Rosolia and Torrini, 2007; Naticchioni, Raitano, and Vittori, 2016; Guvenen et al., 2022; Guaitoli and Pancrazi, 2023) use wages, total income, or lifetime income to show the deterioration of younger workers' careers.[2] We complement their findings by demonstrating the existence of an expanding age pay gap over a long period and across many countries, and by developing and empirically testing a theory about the origins of this expansion.

Second, this paper contributes to the literature that studies the interconnectedness of coworkers' career trajectories. Prior work has documented that limited career opportunities can generate negative career spillovers across coworkers in bureaucracies (Bertrand et al., 2020), sports (Brown, 2011; Gong, Sun, and Wei, 2017), firms in transitioning economies (Friebel and Panova, 2008), and privately owned firms in high-income economies (Lazear, Shaw, and Stanton, 2018; Bertoni and Brunello, 2021; Boeri, Garibaldi, and Moen, 2022; Ferrari, Kabátek, and Morris, 2025).

Within this branch of the literature, two papers are especially relevant for our analysis. Bianchi et al. (2023) shows that the Italian "Fornero reform," which unexpectedly increased the retirement age of older workers, led to a reduction in the wage growth of their younger coworkers. Using the Italian administrative data over a much longer time period, as well as labor-force survey data from a broader set of countries, this paper illustrates that the mechanism identified by Bianchi et al. (2023) explains the worsening of younger workers' careers long before (and after) the Fornero reform and in labor markets beyond Italy. Moreover, Mohnen (2025) analyzes U.S. data at the level of commuting zones to document that a smaller share of retirees is associated with higher youth unemployment in low-skill jobs. Our paper adopts a similar empirical strategy at the firm level, rather than the commuting-zone level, to show that extending the careers of older workers can negatively affect the wage growth of their younger coworkers, especially within firms with limited capacity to add higher-ranked positions.

Third, this paper explores the connection between the growth of the age pay gap and other wage trends and labor-market dynamics. We consider several explanations that are distinct from negative career spillovers, such as wage inequality (Piketty and Saez, 2003; Autor, Katz, and Kearney, 2008), changes in the returns to experience (Jones, 2009; Jeong, Kim, and Manovskii, 2015; Lagakos et al., 2018; Azoulay et al., 2020; Donovan, Lu, and Schoellman, 2023), skill-biased technological change (Autor, Katz, and Kearney, 2006; Acemoglu and Autor, 2011), cross-cohort changes in education and other observable characteristics (Fraumeni, 2015), the decline in manufacturing (Autor, Dorn, and Hanson, 2013; Charles, Hurst, and Schwartz, 2019; Acemoglu and Restrepo, 2020), the rise in the age-friendliness of occupations (Deming, 2021; Acemoglu, Mühlbach, and Scott, 2022), and domestic outsourcing (Goldschmidt and Schmieder, 2017; Drenik et al., 2023).

[2] Our findings also relate to the progressive decline in the mental health of young individuals (Blanchflower, Bryson, and Xu, 2024).

Overall, our analysis indicates that an explanation focused on negative career spillovers provides a better match for the characteristics of the widening age pay gap.

The rest of the paper is organized as follows. Section 2 describes the data and the initial evidence on the age pay gap. Section 3 develops a stylized model of the labor market with career spillovers and draws several testable predictions. Section 4 shows evidence of the slowdown in younger workers' careers that is consistent with the stylized framework. Section 5 draws a closer link between firm-level exposure to workforce aging and the worsening in younger workers' outcomes. Section 6 examines alternative explanations. Section 7 concludes.

2 The Widening of the Age Pay Gap

2.1 Italian Social Security Data

Our empirical analysis uses thirty-five years of confidential administrative data provided by the Italian Social Security Institute (INPS). This dataset comprises matched employer–employee records for the whole population of private-sector, nonagricultural firms with at least one salaried employee. The dataset combines individual-level information about workers, such as age and other demographic characteristics, wage, and contract type, with firm-level information, such as sector, location, and age.

In each year of the data, we restrict our analysis to workers who were at least sixteen years old, had worked at least six months, held a full-time contract, had earned strictly positive wages, and had not retired by December 31. We impose these restrictions to exclude workers with very short-lived job spells within each year.

This dataset allows us to employ two wage measures. First, we utilize the total yearly labor earnings, which include wages and bonus payments received by many Italian workers. Second, we compute weekly wages by dividing the yearly labor earnings by the number of working weeks. This new variable may conflate variation in hours worked and pay rates, but only if workers differ in the number of days they work within a week. Although this is possible, it is important to note that our analysis focuses on full-time employees, who therefore display little variation along this dimension. All measures of labor earnings are expressed in 2015 euros, using the conversion tables prepared by the OECD.[3] Moreover, they are winsorized at the 99.9$^{\text{th}}$ percentile to limit the influence of extreme outliers.[4]

In total, this dataset includes 312 million observations with information on 28.9 million full-time workers and 3.5 million firms between 1985 and 2019 (Table 1, Panel A).

[3] The tables can be downloaded from https://data.oecd.org/price/inflation-cpi.htm.

[4] We also cap the minimum real yearly earnings at €3,000 to eliminate a few observations with very low pay.

2.2 The Age Pay Gap in Italy

The Italian data indicate that the wages of older workers have grown at a much faster rate than those of younger workers for at least the past four decades. The difference between the mean log weekly wages of workers over 55 years old (hereafter, *O55 workers*) and workers under 35 years old (*U35 workers*) grew by 0.19 log points, a 96 percent increase from the level in 1985 (Figure 1, Panel A). This increase is only slightly larger (+0.2 log points) when we use yearly labor earnings, rather than weekly wages (Figure A1, Panel A).

This widening of the age pay gap has happened not only at the average, but rather at every point of the distribution of weekly wages (Figure A1, Panel C). For instance, the age gap increased by 0.2 log points at the 10$^{\text{th}}$ percentile, by 0.1 log points at the 25$^{\text{th}}$ percentile, by 0.14 log points at the median, by 0.25 log points at the 75$^{\text{th}}$ percentile, and by 0.18 log points at the 90$^{\text{th}}$ percentile.

This trend has led to a stark steepening in the age profile of wages (Figure 1, Panel B). Between 1985 and 2019, U35 workers experienced at most a 14-percent growth in real weekly wages, while O55 workers experienced wage increases between 33 percent for 56-year-olds and 53 percent for 65-year-olds.

While the age pay gap has widened, the workforce has aged significantly. The mean worker age increased by 19 percent from 35.8 years in 1985 to 42.7 years in 2019 (Table A1, Panel A, columns 1 and 2). Three main post-World-War-II demographic trends can explain this major aging of the workforce: (i) a decrease in the birth rate, (ii) an increase in life expectancy, and (iii) an increase in the minimum pension eligibility age.[5]

2.3 The Age Pay Gap in Other High-Income Countries

In addition to the Italian data, we have access to confidential employer-employee Social Security data for Germany, as well as labor survey data from the Luxembourg Income Survey (LIS) database for fourteen other high-income countries.[6] These data sources confirm that the widening pay gap between older and younger workers and the progressive aging of the workforce are not exclusive features of the Italian labor market (Table A1).

For instance, the age pay gap between O55 and U35 workers increased by 0.14 log points or 61 percent in the United States (1979-2018), by 0.04 log points or 41 percent in the United Kingdom (1979-2018), by 0.17 log points or 46 percent in Canada (1973-2018), and by 0.1 log points or 36 percent in Germany (1996-2017).

[5] According to the World Bank (`https://data.worldbank.org`, last accessed in April 2023), the birth rate in Italy decreased from 18.1 births per 1,000 people in 1960 to 7.3 births per 1,000 people in 2018, while life expectancy at birth increased by 21 percent from 1960 to 2018. In addition, the 1992 "Amato reform," the 2007 "Prodi reform," and the 2011 "Fornero reform" raised the minimum thresholds for pension eligibility for most workers in the private sector.

[6] These countries are Australia, Canada, Denmark, Finland, France, Germany, Greece, Israel, Netherlands, Norway, Spain, Switzerland, the United Kingdom, and the United States. Unlike the administrative data provided by the Institute for Employment Research (IAB), the German survey data from LIS originate from the Socio-Economic Panel (SOEP) managed by the German Institute for Economic Research (DIW Berlin).

During the same period, the mean workforce age increased by 12 percent in the United States (1979-2018), by 9 percent in the United Kingdom (1979-2018), by 2 percent in Canada (1973-2018), and by 9 percent in Germany (1996-2017).

In conclusion, the widening of the age pay gap is a pervasive phenomenon that transcends the Italian labor market. It is present in countries with more liberal economic institutions than the Italian ones (such as the United States, the United Kingdom, and Canada), in Northern European countries with extensive welfare states (such as Germany, Denmark, and Finland), as well as in other Southern European countries (such as Greece and Spain).

Beyond these initial facts, our analysis will show that the various databases lead to similar takeaways about the employment patterns of younger and older workers, based at least on the subset of empirical exercises we can replicate in multiple countries. Therefore, for brevity, the rest of the paper will focus on analyzing the Italian administrative data, the most extensive and detailed data source available to us, while Appendix B discusses the findings obtained using the other secondary datasets in more detail.

3 A Stylized Framework of Career Spillovers

In this section, we outline a stylized model of the labor market where higher-ranked jobs are limited, and workforce aging can harm the careers of younger workers. While the model is not intended for direct estimation, it generates predictions about key features of the widening age pay gap that we subsequently show in the data.

3.1 Setup With a Representative Firm

Production. There is a fixed supply of l_y younger workers and l_o older workers, who are homogeneous within each age group. The firm employs these labor inputs to perform a top job t and a bottom job b. Production occurs through the production function $AY\left(L_y, L_o\right)$, where A is a productivity shifter of the representative firm, $Y_{L_a} > 0$, and $Y_{L_a,L_a} < 0$ for all $a \in \{y, o\}$. Moreover, younger and older workers are complements in production: $Y_{L_y,L_o} > 0$. The inputs L_y and L_o are efficiency units of labor such that $L_a = \theta_{a,t} l_{a,t} + \theta_{a,b} l_{a,b}$, where $l_{a,j}$ is the number of workers in age group a and job $j \in \{t, b\}$, and $\theta_{a,j}$ measures their marginal productivity. We assume that $\theta_{a,t} > \theta_{a,b}$ for all a to make all workers more productive in the top job.

The introduction of career spillovers. In a frictionless labor market (Baker, Gibbs, and Holmström, 1994), an increase in the number of older workers would not restrict younger workers' access to top jobs. Younger workers who are qualified to obtain a promotion would either receive it at their firm or be poached by another firm. However, two features enable the emergence of these negative career spillovers in our model.

First, we assume that the wages and job allocations of incumbent older workers are stickier than those of younger new entrants. Various factors can explain this different degree of wage stickiness, such as backloaded wage schemes (Lazear, 1979; Ke, Li, and Powell, 2018), firm-specific human capital (Lazear, 2009; Gathmann and Schönberg, 2010), knowledge spillovers (Sandvik et al., 2020; Cornelissen, Dustmann, and Schönberg, 2023), and layoff costs (Bentolila and Bertola, 1990; Boeri and Jimeno, 2005; Saez, Schoefer, and Seim, 2023). Using the Italian administrative data, we estimate the passthrough of firm-level value-added shocks to the wages of younger and older workers (Lamadon, Mogstad, and Setzler, 2022). Consistent with our assumption, the results indicate that older workers's wages are significantly less responsive to negative firm-level shocks (Figure A2).[7]

In the model, we capture this notion by assuming that the firm cannot change older workers' wages and job allocations. The firm inherits older workers in each job before making any decisions in period 0. These *legacy workers* in job j are equal to $\rho_j l_{o,j}^{-1}$, where ρ_j is the retention rate in job j and $l_{o,j}^{-1}$ is the number of older workers in job j in period -1. The wages of older workers are also inherited from period -1 and are not renegotiable in period 0.

Second, we introduce the possibility that top jobs can be rationed. Specifically, we assume that the firm has K available slots at the top ($K = l_{o,t} + l_{y,t}$) and pays a quadratic administrative cost for its top jobs that is proportional to the parameter $c > 0$. Higher-ranked positions usually entail complex tasks, management responsibilities, and more autonomy to make consequential business decisions. So, when the firm adds a new higher-level position, it incurs a marginal cost cK as it carves out important tasks and responsibilities from its available organizational capacity to assign to the new position. This parametrization allows us to study a scenario in which the firm cannot create top jobs for all qualified younger workers, which aligns with the theoretical models and empirical findings discussed in Lazear, Shaw, and Stanton (2018) and Bianchi et al. (2023). The parameter c can be written as a function of aggregate economic growth so that macroeconomic trends can affect the cost of establishing new top jobs.

Wage formation and firm problem. The firm pays age-and-job-specific wages $w_{a,j}$. Following Acemoglu and Restrepo (2023), we assume that the top job pays an exogenous rent over the bottom job: $w_{a,t} = \mu_a w_{a,b}$, where $\mu_a > 1$ is the wedge between the top and the bottom job for age group a, and $w_{a,b}$ is the wage in the bottom job b for workers in age group a. Acemoglu and Restrepo (2023) shows that these rents can be microfounded by using efficiency wages to limit shirking or by introducing bilateral bargaining to capture the fact that jobs, for example, have different degrees of protection from unions.

The timing is as follows. First, the firm receives the legacy older workers from period -1. Then, given a set of age–and-job-specific wages, the firm decides how many younger workers to slot into the top and bottom jobs by equating the marginal revenue products of younger labor in the two positions to their marginal costs. Based on these decisions, the firm allocates the younger workers randomly between the top and bottom jobs until its labor demands in the two positions are satisfied. Finally, production is realized, and the firm pays all workers.

[7] Appendix C includes more details on these event studies.

The firm problem is to choose the number of younger workers in the bottom and top jobs that will maximize its profits, as follows:

$$\max_{l_{y,b},l_{y,t}} AY\left(L_y, L_o\right) - \sum_{a=y,o}\sum_{j=t,b} w_{a,j}l_{a,j} - \frac{c}{2}K^2.$$

Appendix D includes the full solution of the firm problem and all proofs for the following propositions. It also discusses several extensions of the baseline framework: (i) a different parametrization for the organizational cost of top jobs, (ii) endogenous labor supply, (iii) a more general production function with complementarity between workers in different jobs and age groups, and (iv) no exogenous rents in wages.

Comparative statics. Within this framework, we first examine how an increase in the number of older workers in top jobs inherited by the firm from period -1 affects the mean wage of younger workers.[8]

Proposition 1. *When $c > \bar{c} = A\left(\theta_{y,t} - \mu_y\theta_{y,b}\right) Y_{L_yL_o}\theta_{o,t}$, a larger cohort of legacy older workers in top jobs causes the following change in the average wage of younger workers ($\bar{w}_y$):*

$$\frac{\partial \bar{w}_y}{\partial l_{o,t}^{-1}} = \underbrace{\frac{1}{l_y}\left(\mu_y - 1\right) w_{y,b}\frac{\partial l_{y,t}}{\partial l_{o,t}^{-1}}}_{\textit{Career spillovers} <0} + \underbrace{\left[\frac{l_{y,t}}{l_y}\left(\mu_y - 1\right) + 1\right]\frac{\partial w_{y,b}}{\partial l_{o,t}^{-1}}}_{\textit{Wage level} >0}, \tag{1}$$

When the cost parameter c is above the threshold $\bar{c}$, which crucially depends on the degree of complementarity between younger and older workers, an increase in the number of older workers in top jobs exerts two opposite forces on the mean wage of younger workers.

First, the mean wage of younger workers decreases due to the lower likelihood of their holding top positions ($\partial l_{y,t}/\partial l_{o,t}^{-1} = \partial K/\partial l_{o,t}^{-1} - \rho_t < 0$), which is the core idea behind negative career spillovers. The presence of more older workers in top jobs induces the firm to add top slots to its organization due to the complementarity in production between younger and older workers. However, when the cost of establishing new top jobs is higher than the productivity gain generated by worker complementarity, the increase in the total number of top jobs is lower than the additional slots occupied by older workers. Hence, younger workers' access to top jobs is restricted.

Second, the mean wage of younger workers increases because the wages paid to younger workers in jobs at both levels increase. The positive contribution of this channel is twofold. Having more older workers directly increases the marginal revenue product of younger workers due to their complementarity. Prior research on demographic shifts in the workforce has mostly focused on this mechanism (Freeman, 1979; Welch, 1979; Berger, 1985). Moreover, these shifts decrease

[8] This exercise captures within our static framework the idea that the firm made prior hiring decisions while being myopic about future changes (i) in the relative size of worker cohorts, (ii) the retention rate of older workers, or (iii) the economic growth rate.

younger workers' efficiency units of labor by pushing them toward the bottom job, further increasing the marginal revenue product of younger labor.

In Appendix D, we show that an increase in the retention rate of legacy older workers (ρ_t)—a change that has taken place contemporaneously with an increase in the relative size of older cohorts—has similar opposite effects ($\partial l_{y,t}/\partial l_{o,t}^{-1} < 0$ and $\partial w_{y,b}/\partial l_{o,t}^{-1} > 0$) on the mean wage of younger workers.

Crucially, Proposition 1 generates several predictions that can be shown empirically.[9] First, younger workers face increasing difficulties in reaching higher-paying jobs.

Second, the overall effect of an increase in the supply of older workers on the mean wage of younger workers is ex-ante ambiguous. On the one hand, a negative effect stems from the less favorable positions of younger workers in the overall wage distribution and in firms' organizational hierarchies. On the other hand, younger workers' wages in different jobs increase. Therefore, if negative career spillovers are important, we should observe that the age pay gap has been widening primarily because the position of older and younger workers in the wage distribution has been diverging.

Third, although our framework does not have promotions, it is possible to infer Proposition 1' repercussions on the career progression of younger workers. Specifically, a decline in the probability of younger workers holding top jobs should stem from both (i) a lower probability of joining the labor market in higher-ranked positions, and (ii) a lower probability of being promoted to higher-ranked positions during early-career stages.

Proposition 2. *The magnitude of the negative career spillovers ($\partial l_{y,t}/\partial l_{o,t}^{-1} < 0$) increases with the organizational cost of top jobs (higher c).*

Proposition 2 indicates that younger workers' access to top jobs becomes more limited within firms that face more challenges in adding higher-ranked positions to their hierarchies. As shown by Bianchi et al. (2023), these firms are usually older and larger, and their workforce grows more slowly. They tend to be in a more mature stage of their life cycle and do not always have sufficient slack in their organizational capacity for the creation of new higher-ranked roles. Furthermore, the cost parameter c can be modeled as a decreasing function of the economic growth rate, therefore linking firm-level difficulties in expanding their hierarchies to macroeconomic trends (Appendix D).

3.2 Setup With Heterogeneous Firms

We now replace the representative firms with F heterogeneous firms to study how an increase in the supply of older workers affects the distribution of younger workers across higher-paying and lower-paying firms.

[9] It also helps explain why the age pay gap widened both when the large baby-boom cohorts entered the labor market in the late 1960s (Freeman, 1979; Welch, 1979) and when they reached later career stages. All demographic shocks have more negative effects on the employment opportunities of younger workers because older workers' wages are stickier.

On the labor-demand side, firms choose younger workers' wages in the bottom and top jobs. In line with Card et al. (2018) and Lamadon, Mogstad, and Setzler (2022), we assume that each firm is small and does not internalize the consequences of its actions on other firms. In this extension, the ratio of top and bottom wages is not equal to a fixed exogenous rent. Relaxing this assumption ensures that having more older workers in the economy can generate larger changes in younger workers' top-job wages in some firms and in their bottom-job wages in other firms, leading to firm-to-firm movements.

We further assume that the retention rates of older workers $\rho_{j,f}$ increase with the firm-level productivity shifter A_f. This assumption, which can be microfounded by directly modeling older workers' retirement choices, is consistent with prior empirical evidence on the positive correlation between worker retention and compensation levels (Antwi and Phillips, 2013; Ruffini, 2022).

Moreover, instead of being convex and continuous, the organizational cost has a discontinuity that guarantees that all firms face a binding constraint on the number of available top slots: $l_{o,t,f} + l_{y,t,f} = \overline{K}_f$. While making the computations more tractable, this parametrization also allows us to focus on the empirically relevant scenario in which firms are in a corner solution and cannot adjust the number of top slots over $\overline{K}_f$.

On the labor-supply side, we assume that worker i of age group $a \in \{y, o\}$ derives the following utility when working in job $j \in \{t, b\}$ and firm $f \in \{1, \ldots, F\}$:

$$U_{i,a,j,f} = \log\left(w_{a,j,f}\right) + \xi_{i,a,j,f},$$

where $\xi_{i,a,j,f}$ is worker i's idiosyncratic taste shock for firm f and job j. We assume that $\xi_{i,a,j,f}$ follows a type-1 extreme distribution with parameter $\sigma > 0$ and is not observed by firms. The parameter σ captures the degree of substitutability across firms and jobs in workers' preferences.

Proposition 3. *An increase in the market-wide number of older workers in top jobs has the following effects on younger workers' employment:*
a) Younger workers' employment level in top jobs declines in all firms, but this decrease is larger in magnitude in higher-productivity firms;
b) Younger workers' employment level in bottom jobs increases more in firms with higher percentage increases in the bottom-job wage.

Proposition 3 provides two additional predictions about cross-firm differences in negative career spillovers. First, an increase in the supply of older workers decreases younger workers' employment in the top jobs of all firms. Moreover, these negative career spillovers are larger in magnitude among higher-productivity firms. This conclusion follows from the distribution of older workers' retention rates. Since retention rates are higher among higher-productivity firms (where wages are also higher), an increase in the overall number of older workers leads to more restricted access for younger workers to the top jobs of these same firms.

Second, younger workers are more likely to move to firms in which bottom-job wages display higher percentage increases. A larger supply of older workers increases younger workers' wages in the bottom jobs due to the wage-level channel already discussed in Section 3.1. Proposition 3 further indicates that, while younger workers' employment in *top jobs* declines the most in higher-productivity firms, younger workers' employment in *bottom jobs* does not necessarily increase the most in that set of firms. In fact, there are parametrizations of the production function that ensure that the firms that experience the highest percentage increase in bottom-job wages are the least productive ones.

In short, more congestion in top jobs within higher-productivity and higher-paying firms can affect the distribution of workers between firms, generating a migration of younger workers toward the bottom jobs of lower-productivity and lower-paying firms. This hypothesis will find support in the data.

3.3 Summary

Our stylized framework highlights how an increase in the supply of older workers can lead to negative career spillovers for younger workers. It predicts that, when older workers become more numerous at the top of the wage distribution and firms' hierarchies, the following consequences will ensue:

1. Younger workers face increasing difficulties in reaching the top of the wage distribution, while the overall effect on their mean wage is ex-ante ambiguous.

2. The age pay gap widens primarily due to younger workers' positional losses and older workers' positional gains in the wage distribution.

3. Younger workers join the labor market lower in the wage distribution and experience slower growth in the years after entry.

4. Younger workers' positional losses are larger in firms that face more severe workforce aging and greater challenges in adding higher-ranked positions.

5. Younger workers face positional losses in both higher- and lower-paying firms, but these losses are more pronounced in the former.

6. More congestion in higher-paying firms can push younger workers toward lower-paying firms.

Each of these predictions receives empirical support, as we show in Section 4 and Section 5. We also discuss alternative interpretations of our empirical results in Section 6.

4 The Slower Career Progression of Younger Workers

One of our framework's core implications, which is defined by its first three empirical predictions, is that negative career spillovers contribute to widening the age pay gap by slowing down the career progression of younger workers. We start exploring these predictions in Section 4.1, which shows that younger workers have become progressively less likely to hold higher-paying positions. Section 4.2 proposes a formal decomposition to quantify the contribution of negative career spillovers to the increasing age pay gap. Finally, Section 4.3 shows that younger workers fared progressively worse both at and after labor-market entry. Appendix B.4 illustrates that these findings apply to other high-income countries.

4.1 The Position of Younger Workers in the Wage Distribution

Consistent with Prediction 1, younger workers have become less likely to reach the top of the wage distribution, whereas older workers have become significantly more represented at the top.

The probability of U35 workers belonging to the top quartile of the distribution of weekly wages decreased by 34 percent, from 15 percentage points in 1985 to 10 percentage points in 2019 (Figure 2, Panel A). This decline at the top of the distribution coincided with an increased probability of U35 workers being in the lowest quartile (+23 percent). In contrast, O55 workers experienced the opposite trend (Figure 2, Panel B). Their probability of being in the top quartile rose from 32 percentage points in 1985 to 37 percentage points in 2019, while their probability of being in the bottom quartile declined from 23 percentage points in 1985 to 18 percentage points in 2019.

This finding becomes even more pronounced when we examine vigintiles (Figure 2, Panel C). In stark contrast with the trend experienced by O55 workers, the share of U35 workers decreased nearly monotonically from the lowest to the penultimate vigintile between 1985 and 2019.

In addition to analyzing shifts along the wage distribution, we can look more closely at career trajectories within firms' hierarchies. The dataset provides information on the four official hierarchical levels in the Italian labor system: apprentices, blue-collar workers, white-collar workers, and managers. The last category includes managers ("*dirigenti*") and the so-called "*quadri*," who are high-ranked white-collar workers with important responsibilities and significant autonomy.[10] The percentage of managerial jobs held by U35 workers decreased from 8 percent in 1996 to 3 percent in 2019, while the share held by O55 workers more than doubled during the same period (Figure 2, Panel D).

4.2 The Change in Pay Rank

Using an empirical test similar to the one in Bayer and Charles (2018), we measure how much opposite movements of younger and older workers along the wage distribution have contributed to widening the age pay gap. Consistent with Prediction 2, the results indicate that the age pay gap has been increasing predominantly due to younger workers' positional losses and older workers' positional gains in the wage distribution.

[10] This analysis begins in 1996, rather than 1985, because the categorization of hierarchical levels changed after 1996. Specifically, the *quadri* category was introduced in 1996, and firms may have differed in whether they classified these positions as white-collar or managerial jobs before that year.

The change in the mean log wage of workers in age group a between years t and t' can be written as follows:

$$\Delta w_a^{t,t'} = \underbrace{\sum_v (s_{a,v,t'} - s_{a,v,t})\, \bar{w}_{v,t}}_{\text{Pay rank change}} + \underbrace{\sum_v s_{a,v,t}\, (\bar{w}_{v,t'} - \bar{w}_{v,t})}_{\text{Distributional change}} + \underbrace{\varepsilon_{\mathrm{a}}^{t,t'}}_{\text{Residual}} . \qquad (2)$$

In this equation, $s_{a,v,t}$ is the share of workers in age group $a \in \{\text{U35}, \text{O55}\}$, in vigintile v of the distribution of wages, and in year t, while $\bar{w}_{v,t}$ is the mean log wage in vigintile v and year t. Appendix E describes all the steps required to obtain this decomposition.

When $a = \text{U35}$, Equation (2) indicates that a change in the mean wage of younger workers comprises three components. First, the mean wage of younger workers can change due to variation over time in the share of younger workers in each vigintile of the wage distribution, while keeping the mean log wages in each vigintile fixed in the baseline year. This first component, the *pay rank* change, relates to the career-spillover portion of Equation (1): it isolates wage changes that arise exclusively from shifts along the wage distribution (for example, movements from higher-ranked to lower-ranked jobs), while the overall shape of the wage distribution remains unchanged.

Second, the mean wage of younger workers can change due to variation over time in the wages earned in different vigintiles of the distribution, while keeping the share of younger workers in each vigintile fixed at baseline. This second component, the *distributional change*, relates to the wage-level portion of Equation (1): it measures how much a change in the support of the wage distribution affects the mean wage of younger workers, while preventing them from moving along the wage distribution.

Finally, the third component is a *residual* resulting from the interaction between pay rank and distributional changes.

We first decompose the change in mean log weekly wages between 1985 and 2019 separately for U35 and O55 workers (Figure 3, Panel A). In line with Prediction 1, we find that the overall change in the mean wage of younger workers is the product of two opposing forces. On the one hand, the change in the pay rank is negative: abstracting from any change in the level of real wages paid in the economy, the movement of younger workers toward the bottom of the wage distribution decreased their mean wage by 0.09 log points. On the other hand, the distributional change is positive: when we keep younger workers in the same positions they held in 1985, changes in the level of wages paid in different parts of the pay distribution increased the mean wage of U35 workers by 0.24 log points.

In order to understand the contribution of these two channels to the widening of the age pay gap, we need to look at the same decomposition for O55 workers. Relative to U35 workers, older workers experienced an increase in pay rank (+0.06 log points) and a slightly larger distributional change (+0.27 log points). These conclusions hold if we decompose the change in mean wages for individual age bins (Figure 3, Panel B), suggesting that the classification we use for younger (U35) and older (O55) workers does not qualitatively affect the main findings.

Consistent with Prediction 2, we conclude that the age pay gap has been widening mainly due to opposing movements of younger and older workers along the wage distribution. To better visualize this result, we apply the decomposition in Equation (2) to the mean pay differential between younger and older workers (see Appendix E for the full derivation). By 2019, the gap in pay rank accounted for 78 percent of the total increase in the age pay gap between U35 workers and O55 workers (Figure 3, Panel C). Moreover, the pay rank gap was the primary driver of the widening in the age pay gap throughout the period under consideration, contributing between a minimum of 53 percent in 1987 and a maximum of 81 percent in 2004. These findings hold when we substitute yearly earnings for weekly wages (Figure A3).

As further discussed in Appendix B, out of the fourteen countries in our sample, the rank gap accounts for the majority of the increase in ten cases (Table A1, columns 7 and 8). For example, by the last year in the sample, the rank gap constituted 89 percent of the increase in the age pay gap in the United States, 56 percent in Germany (based on the administrative data), and 77 percent in Canada.

4.3 Entry Pay Rank and Pay Rank Growth

In this section, we show support for Prediction 3, which states that when the concentration of older workers in higher-paying positions increases, younger workers both (i) enter the labor market at lower segments of the wage distribution, and (ii) experience slower growth along the wage distribution after labor-market entry.

To study entry and post-entry conditions, we decompose the change in pay rank of U35 workers between year t and t' as follows:

$$\underbrace{\sum_{v} \left(s_{U35,v,t'} - s_{U35,v,t}\right) \bar{w}_{v,t}}_{\text{Pay rank change}} \approx \underbrace{\sum_{e\in[0,18]} s_{e,t} \cdot \sum_{v} \left[\left(s^{LME}_{e,t',v} - s^{LME}_{e,t,v}\right) \cdot \bar{w}_{v,t}\right]}_{\text{Change in entry pay rank}} + \underbrace{\sum_{e\in[0,18]} s_{e,t} \cdot \sum_{v} \left[\left(\Delta s^{t'-LME}_{e,t',v} - \Delta s^{t-LME}_{e,t,v}\right) \cdot \bar{w}_{v,t}\right]}_{\text{Change in pay rank growth}}, \quad (3)$$

where $e \in [0, 18]$ measures years of experience of U35 workers, $s_{e,t}$ is the share of U35 workers with e years of work experience in year t, $s^{LME}_{e,t,v}$ is the share of U35 workers with e years of work experience in year t in vigintile v *at the time of labor-market entry* (LME[11]), and $\Delta s^{t-LME}_{e,t,v} = s_{e,t,v} - s^{LME}_{e,t,v}$ is the change in the share of U35 workers with e years of work experience in year t in vigintile v between LME and year t. Appendix F describes all the steps required to derive this formula.[12]

[11] To reduce noise, LME is defined as the first three years of work rather than just the first year; accordingly, we stop the analysis in 2016 to ensure a consistent entry window across years.

[12] Equation (3) is not an exact decomposition because it keeps the share of U35 workers with e years of work experience fixed at time t ($s_{e,t}$). Fixing the distribution of work experience in a given year allows us to isolate changes in the

Equation (3) indicates that the change in younger workers' pay rank comprises two components. The first relates to the difference in the pay rank at *labor-market entry* of U35 workers between times t and t'. The second component assesses how the growth in the pay rank of U35 workers *after labor-market entry* changed between t and t'. In a plot of pay rank over the life cycle, the first term isolates changes in the intercept of the curve, while the second term represents changes in the slope for up to eighteen years after labor-market entry.

Consistent with Prediction 3, both entry rank and rank growth have contributed to decreasing the pay rank of younger workers (Figure 4, Panel A). By 2016, a progressively lower rank at entry represented 64 percent of the overall decline in the pay rank of U35 workers, slower growth in the pay rank in the eighteen years after entry accounted for 8 percent, while variation in the distribution of work experience made up the remaining 28 percent.

This result is robust to alternative specifications. First, the main finding holds if we replace $s_{e,t}$ in Equation (3) with $s_{e,,t'}$, the share of U35 workers with experience e at endline. This robustness check shows that the choice of the reference year for the distribution of job experience is not consequential. Second, the result is quantitatively similar if we decompose the change in the pay rank of U30 workers, rather than U35 workers, over a longer time period (Figure 4, Panel B). The main analysis starts in 1995, one of the first years with information on the entry wage for many U35 workers. Focusing on U30 workers, who, on average, have shorter past job histories, allows us to extend the sample back to 1990 without modifying our conclusions.

5 Firm-Level Evidence on the Effects of Workforce Aging

This section uses the employer-employee match in the Italian administrative data to document the heterogeneity in the widening of the age pay gap across firms. Specifically, Section 5.1 uses 2SLS regressions to establish a direct connection between firms' exposure to workforce aging and the career outcomes of younger workers. Section 5.2 examines how firm characteristics that are likely to be associated with constraints in adding higher-ranked positions—such as firm size, age, and employment growth—relate to changes in the age pay gap. Finally, Section 5.3 investigates how workforce aging affects the sorting of younger workers across firms.

5.1 The Effects of Firm-Level Workforce Aging on Younger Workers' Careers

This section establishes a direct connection between firms' exposure to workforce aging and changes in the outcomes of younger workers. Specifically, we exploit variation across firms in the degree of workforce aging to explore its effects on the labor outcomes of younger workers and on the age pay gap. We model this relationship using the following first-difference regression equation:

$$\Delta_{10} y_f = \alpha + \beta \Delta_{10} s_f^{(51-60)} + X_f' \gamma + \epsilon_f, \tag{4}$$

movements of younger workers along the wage distribution from changes in their mean tenure. Robustness checks indicate that the results hold under different reference years.

where Δ_{10} represents the ten-year change in firm-level variables between t and $t+10$ for $t \in [1985, 2005]$.[13] Standard errors are clustered at the province level.

The dependent variable y_f measures labor-market outcomes of U35 workers, such as their mean pay rank, or the age pay gap in firm f. The primary explanatory variable, $s_f^{(51-60)}$, is the share of firm f's workforce aged 51 to 60. At least in the baseline analysis, we define older workers as those aged 51-60, rather than 56-64 (O55), so that older workers (particularly, older men) are always below the minimum retirement age required to access a public pension during the period under study. However, we later show that the results are highly robust to alternative definitions of workforce aging.

The vector X_f' includes baseline controls, such as province fixed effects, firm age, and firm size. Because the model uses first differences, it naturally accounts for any time-invariant firm-level characteristics, analogous to including firm or sector fixed effects. Moreover, the parameter γ captures differential trends associated with the covariates in X_f'.

When y_f represents the outcomes of U35 workers (rather than the age pay gap), we stack the data so that the outcomes of U35 and O55 workers appear as separate observations in each year.[14]

The main coefficient of interest, β, measures whether workforce aging affects younger workers' career trajectories. However, estimating β via OLS could lead to biased findings if unobserved firm-specific shocks influence both workforce aging and the outcomes of U35 workers.

An instrumental variable. To tackle the potential endogeneity of the OLS estimate of β, we use an instrumental variable (IV) that relies on the firm-level age distribution of mid-career workers at baseline.

Specifically, we construct an instrument that predicts changes in workforce aging based on the share of employees who (i) were already present in firm f at the start of each ten-year period, and (ii) could join the 51-60 age group over the next ten years. The instrument is defined as:

$$\widetilde{\Delta}_{10} s_f^{(51-60)} = \left(s_{f,t}^{(41-50)} - s_{f,t}^{(51-60)} \right),$$

where $s_{f,t}^{(41-50)}$ denotes the share of firm f' workers aged 41–50 in year t.

This approach isolates changes in workforce aging that are driven exclusively by the natural age progression of employees who were already employed by each firm at baseline, rather than recent firm-level shocks or hiring decisions.[15]

For each ten-year change, the sample consists of all firms that had at least one U35 worker at t and $t+10$, and at least one worker over 40 at t. While these restrictions exclude a large number of short-lived firms from the analysis, the sample retains a substantial share of the Italian workforce.

[13] To limit noise, we compute firm-level values for each year x as three-year averages from x to $x+2$.

[14] Formally, this revised equation is $\Delta_{10} y_{a,f} = \alpha + \beta \Delta_{10} s_f^{(51-60)} + \gamma \Delta_{10} s_f^{(51-60)} \cdot \text{U35}_a + \delta \text{U35}_a + X_f' \theta + \epsilon_{a,f}$, where the subscript a denotes the age group, and U35_a is a dummy variable equal to 1 for U35 workers.

[15] Mohnen (2025) employs a similar approach to study the effects of differences in retirement rates across US commuting zones on youth employment.

For example, the sample includes 40 percent of the workforce when $t = 1985$, 39 percent when $t = 1995$, and 41 percent when $t = 2005$.

Validity of the instrument. The validity of this IV relies on two key properties: its relevance and its exogeneity.

First, the instrumental variable is strongly correlated with the endogenous variable. The first-stage regression demonstrates a large, positive, and statistically significant relationship between the projected ($\widetilde{\Delta}_{10}s_f^{(51-60)}$) and actual ($\Delta_{10}s_f^{(51-60)}$) changes in the share of older workers (Figure A4, Panel A). For example, a 1-standard-deviation (+18 percentage points) increase in $\widetilde{\Delta}_{10}s_f^{(51-60)}$ in 1985 is associated with a 0.7-standard-deviation (+11 percentage points) increase in the actual share of workers aged 51-60 between 1985 and 1995, an effect that is statistically significant at the 1 percent level. The first-stage effect becomes even larger over time. Moreover, the Kleibergen-Paap F-statistics exceed the conventional threshold of ten by multiple orders of magnitude in all our 2SLS regressions, indicating a strong first stage and mitigating concerns about weak instruments.

Second, the exogeneity assumption requires that the *projected* change in workforce aging at time t influences the change in younger workers' outcomes or the age pay gap between t and $t + 10$ only through its effect on the *actual* change in workforce aging over the same ten-year period.

Supporting this assumption, we observe that many workers aged 41–50 in 1985 were hired at least a decade earlier. Specifically, in 1985, 47 percent of workers in this age group had at least ten years of tenure with their employer, and 63 percent had at least seven years of tenure (Figure A4, Panel B).

Hence, unlike $\Delta_{10}s_f^{(51-60)}$, which may reflect recent shocks or firm-level decisions, the IV primarily captures historical hiring patterns that precede year t by a significant margin. For example, a negative firm-level shock at $t + 3$ might influence $\Delta_{10}s_f^{(51-60)}$ by increasing the retention of experienced workers and reducing younger workers' pay. However, $\widetilde{\Delta}_{10}s_f^{(51-60)}$ is largely determined at t by choices often made no later than $t - 10$ and therefore is unlikely to be related to such shocks.

Main results. Our analysis indicates that firms experiencing greater workforce aging have seen more pronounced losses in younger workers' pay ranks.

We begin by showing this finding using only the raw data. For each firm in the sample, we compute the change in the age pay gap, the mean pay rank of U35 workers, and the projected workforce aging ($\widetilde{\Delta}_{10}s_f^{(51-60)}$) for three ten-year periods (1985-1995, 1995-2005, and 2005-2015). The resulting reduced-form correlations, visualized through binned scatter plots (Figure 5), reveal a negative and linear relationship between the projected workforce aging at year t and shifts in U35 workers' mean pay rank between t and $t + 10$, while the relationship between the IV and changes in the age pay gap is positive.

Next, we move to the estimation of Equation (4). Both OLS and 2SLS estimates confirm that a higher degree of workforce aging is associated with worse outcomes for U35 workers, a result that holds consistently across all periods analyzed (Figure 6). If we consider the central ten-year period in our dataset (1995-2005), OLS estimates indicate that a 1-standard-deviation (+16 percentage points) increase in the share of workers aged 51–60 between 1995 and 2005 is associated with a 0.3-percentile lower growth (18 percent decline from the mean) in the pay rank of U35 employees and a 0.8-percentile higher growth (35 percent increase from the mean) in the pay rank gap between O55 and U35 workers during the same period (Table A2, Panel B).

After addressing the potential endogeneity of the OLS results, the 2SLS estimates show an even larger effect: a 1-standard-deviation increase in the share of older workers leads to a 36-percent lower growth in U35 workers' pay rank and a 66-percent larger widening of the age rank gap, both measured relative to the mean.

Robustness analysis. We conduct three sets of robustness checks to validate our findings (Figure A5).

First, we measure the dependent variables in log weekly wages, rather than in percentiles of each firm's pay distribution, and reach similar conclusions (Panels A and B).[16]

Second, we show that the results hold for alternative measures of workforce aging (Panels C and D). In this specification, the endogenous variable becomes the change in the share of workers aged 56 to 64 between t and $t+10$ ($\Delta_{10} s_f^{(56-64)}$), while the instrument changes accordingly to $\widetilde{\Delta}_{10} s_f^{(56-64)} = \left(s_{f,t}^{(46-55)} - s_{f,t}^{(56-64)}\right)$.

Third, the results remain consistent if we limit the sample to firms with at least six employees at time t, mitigating the influence of micro enterprises on the estimates (Panels E and F).

5.2 Evidence of Firm-Level Difficulties In Adding Higher-Ranked Positions

In this section, we show that Prediction 4, which indicates that the negative career spillovers are larger among firms with more difficulties in creating top positions, receives empirical support.

We first categorize firms based on their rate of employment growth (below and above median), their age (at most or above ten years old), and their size (thresholds at 50, 100, and 500 employees). Then, we compute changes in the pay rank and the age pay gap separately across these firm groups. If the data align with the predictions of the model, we expect to observe that the age pay gap increases more in lower-growth, larger, and older firms because their organizational hierarchies tend to be less flexible.

The data show that U35 workers experienced a substantial decline in their pay rank within all types of firms (Figure A6, Panel A). While the change in the pay rank is negative everywhere, Prediction 4 receives empirical support because U35 workers faced larger drops in their pay rank in larger firms with below-median growth in their workforce.[17]

[16] Building on the findings in Section 4.2, the baseline analysis uses pay rank to abstract from changes in the level of wages over time.

[17] One exception to Prediction 4 is that the decline in the U35 workers' pay rank is larger within younger firms. Nevertheless, the difference in the pay rank decline between younger and older firms is modest.

In line with these initial findings on the pay rank loss of younger workers, we also establish that the age pay gap has increased more in firms with less flexible hierarchies (Figure A6, Panel B). For example, the age gap in weekly wages increased by 0.24 log points within firms with below-median employment growth and by only 0.17 log points within firms with above-median employment growth. This difference is both economically and statistically significant: it is equal to 38 percent of the total increase in the age wage gap and is significant at the 1-percent level. Moreover, the age pay gap increased significantly more in firms that employed more workers and were more than ten years old.

Between 1985 and 2019, the labor market experienced an increase in the number of older firms, as well as an overall decline in economic growth (Figure A7). Even in the absence of workforce aging, our model indicates that firm aging and lower economic growth alone could have generated similar bottlenecks for the career progression of younger workers.

5.3 The Distribution of Workers Within and Between Firms

This section studies how negative career spillovers affect the allocation of younger and older workers across different types of firms. Consistent with Prediction 5, we find that the decline in the mean pay rank of younger workers has been larger in magnitude within higher-paying firms, where the number of older workers has increased the most. Moreover, consistent with Prediction 6, younger workers have become more likely to work for lower-paying firms, a pattern that has further widened the age pay gap.

We start by sorting workers into 100 percentiles or *firm groups* based on their firm's average log weekly wage, separately for each year in the sample (Machado and Mata, 2005). Next, for each year, we compute the mean percentile of U35 workers in the firm-group-specific distribution of log weekly wages. Finally, we measure the mean change in the percentile of U35 workers between 1985 and 2019 separately for each firm group. This process allows us to evaluate differences in the movement of younger workers along the wage distribution of lower-paying and higher-paying firms.

The data indicate that the mean percentile of U35 workers decreased in ninety-nine out of one hundred firm groups between 1985 and 2019 (Figure 7, Panel A). Moreover, as predicted by our framework, these positional losses were larger in magnitude among higher-paying firms. On average, U35 workers fell by 9 percentiles in the top decile of firm groups and by only 5 percentiles in the bottom decile.

Next, for each year we compute the share of younger workers in each firm group out of the total number of younger workers in the market. We repeat the same calculations for older workers. These variables allow us to establish two additional results. First, we find that older workers have become more likely to be employed in higher-paying firm groups (Figure 7, Panel B). From 1985 to 2019, O55 workers' share increased by 3.5 percentage points (a 29 percent gain relative to the 1985 level) in the top decile of firm groups and decreased by 2 percentage points in the bottom decile.[18]

Second, consistent with Prediction 6, younger workers have become more likely to find employment in lower-paying firm groups, which is a trend opposite to the one followed by older workers (Figure 7, Panel C). On average, the share of U35 workers decreased by 2 percentage points (a 26 percent loss relative to the 1985 level) in the top decile of firm groups and increased by 3 percentage points in the bottom decile.

6 Alternative Explanations

This section examines alternative mechanisms, distinct from negative career spillovers, that could explain why the wage growth of older workers has outpaced that of their younger counterparts. Our analysis indicates that while these factors represent important labor-market dynamics, they do not fully align with the observed trends in the age pay gap.

6.1 Wage Inequality and Higher Returns to Experience

The economic literature has documented a substantial rise in wage inequality in high-income economies (see, for example, Autor, Katz, and Kearney, 2008; Kopczuk, Saez, and Song, 2010; and Song et al., 2019). Historically, O55 workers have been more likely to occupy higher-paying jobs, which have experienced larger wage gains, whereas U35 workers have often been in lower-paying roles, which have experienced slower or stagnant wage growth. Therefore, higher inequality could have expanded the age wage gap by extending the support of the wage distribution.

Wage inequality, a multifaceted phenomenon with various labor-market and societal repercussions, has a core component that is directly addressed in Equation (2): the distributional gap. This gap quantifies the impact of variations in the mean wage levels across different vigintiles of the wage distribution (for example, rapid growth at the top and slow growth at the bottom), while the distribution of younger and older workers across vigintiles is held constant at baseline. However, as discussed earlier, the distributional gap explains only a minor portion of the age wage gap's expansion in both Italy (Figure 3) and other high-income countries (Table A1).

The same reasoning applies to trends in returns to experience and higher-level skills. The empirical evidence on the trajectory of returns to experience is mixed. On the one hand, Jones (2009) and Azoulay et al. (2020) document that scientific occupations and entrepreneurship have become more rewarding for experienced workers. Moreover, Lagakos et al. (2018) and Donovan, Lu, and Schoellman (2023) find that economic growth is positively associated with steeper returns to experience, which suggests that labor markets in growing economies may naturally move toward wider age pay gaps over time. On the other hand, outside of innovation-centric jobs, Jeong, Kim,

[18] In the model, this result requires both an increase in the market-wide number of older workers in top jobs and a larger increase in the retention rates of older workers in higher-paying firms than in lower-paying firms. Otherwise, if retention rates are higher among higher-paying firms and fixed over time, having more older workers in the economy can increase the number of older workers disproportionately in some firms but cannot affect the overall distribution of older workers across firms.

and Manovskii (2015) finds that an increased supply of older workers has led to a decrease in the price of experience, a trend that would have narrowed the age pay gap.

There is stronger agreement on the fact that returns to higher-level skills have increased in recent decades. Within the rich literature on skill-biased technological change (or SBTC; for an overview, see Acemoglu and Autor, 2011), Autor, Katz, and Kearney (2006) proposes a model in which new technology complements the nonroutine tasks integral to high-wage jobs and, therefore, is more beneficial to older workers, who are more likely than their younger coworkers to hold these positions. Beyond the evidence on SBTC, Deming (2021) shows that demand has risen for decision-making skills, which improve with experience and tenure, leading to higher market returns for these skills and increased wages for more experienced workers.

While higher returns to experience and skills have the potential to push the wages of younger and older workers further apart, they do so mainly through a larger distributional gap, which is a secondary source of the widening in the age wage gap. Given that older workers possess, on average, more experience and higher-level skills at baseline, an increase in the price for these factors widens the age pay gap predominantly by amplifying the preexisting wedge between the wages of older and younger workers, rather than by changing their relative positions in the wage distribution.[19] Bayer and Charles (2018) reaches similar conclusions when assessing the effects of rising returns to education on the racial wage gap in the United States.

6.2 Sectoral and Occupational Shifts

This section evaluates whether changes in job availability have played a central role in expanding the age wage gap. The overall evidence does not fully support this conclusion.

Decline in manufacturing. We first examine the decline in manufacturing jobs, which prior studies have linked to higher unemployment among younger, lower-skilled workers (Autor, Dorn, and Hanson, 2013; Charles, Hurst, and Notowidigdo, 2016; Charles, Hurst, and Schwartz, 2019; Acemoglu and Restrepo, 2020).

We first note that the decline in manufacturing started during the early 2000s, decades after the wages of older and younger workers started diverging. Moreover, if this hypothesis aligned with the data, the age pay gap should have predominantly expanded across sectors, as a result of younger workers' outflow from manufacturing. To test this prediction, we decompose the change in pay rank of younger and older workers between and within sectors. We start by dividing workers into 270 *sector groups*, one for each three-digit sector in the statistical classification of economic activities of the European Community (NACE Rev. 2). Then, within each three-digit sector group, we order workers in 200 equally sized groups (*worker groups*) based on their log weekly wage, yielding a total of 54,000 *sector-worker groups*.[20] This process allows us to isolate worker

[19] Appendix G includes a simple numerical exercise to further clarify this point.

[20] Appendix H includes more details on this decomposition.

movements along the pay distribution of each sector group (within-sector changes) from movements across sector groups (between-sector changes). The results indicate that only 2 percent of the widening in the pay rank of older and younger workers occurred between three-digit sectors (Figure A9, Panel A).

Moreover, we should observe a larger increase in the age pay gap in non-manufacturing sectors in which either the share of younger workers or their mean wage was lower at baseline. These sectors should have received lower-skilled younger workers who had become unable to find employment in manufacturing and were therefore willing to accept lower wages elsewhere. Yet, correlations between these baseline characteristics and the change in the rank gap at the two-digit sector level are statistically and economically insignificant (Figure A9, Panels B and C). For example, a one-standard-deviation (+1.4 percent) increase in the sectoral share of U35 workers in 1985 is associated with 0.0004-log-point lower growth in the rank gap from 1985 to 2019. Overall, the expansion of the age pay gap has been relatively homogeneous across all sectors, both within and outside manufacturing.

Occupational changes. Next, we explore whether the rise in decision-intensive occupations, which favor older workers due to their accrued experience, may have widened the age pay gap (Deming, 2021). This hypothesis implies that the age pay gap has mainly increased across occupations due to older workers transitioning into positions with higher rewards for experience.

To test this prediction, we decompose the increase in the pay rank between and within occupations. Similar to what we did with sectors, we allocate workers across 10 *occupation groups*, corresponding to each one-digit occupation in the International Standard Classification of Occupations (ISCO-08).[21] Within each group, we subdivide workers into vigintiles on the basis of their log weekly wage, resulting in 200 *occupation-worker groups*. Since 2012, the first year with occupation data, nearly all the growth in the pay rank gap between older and younger workers occurred within one-digit occupations (Figure A9, Panel D), contributing 81 percent of the total growth by 2015 and 88 percent by 2019.

Moreover, a larger supply of occupations with higher returns to experience should be associated with lower initial wages for labor-market entrants, but faster wage growth after entry. However, these trends, highlighted by Deming (2021) for pay *levels* over the life cycle, do not apply to the variation in pay *rank* across cohorts of younger workers, which is the primary driver of the expanding age pay gap. In line with what we expect from negative career spillovers, we have found that both the entry wage rank and the growth in the post-entry wage rank for U35 workers have declined over time, indicating a slowdown in younger workers' career progression for several years after entry (Figure 4). Thus, our analysis supports one of the main conclusions of Acemoglu, Mühlbach, and Scott (2022), namely, that the rise in the "age-friendliness" of jobs has not disproportionately favored older workers.

[21] One of these one-digit occupations isolates managerial jobs, which by definition are intensely focused on decision making.

Domestic outsourcing. Finally, we investigate the impact of domestic outsourcing. As demonstrated by Goldschmidt and Schmieder (2017), an increasing number of large firms have started outsourcing low-skill jobs to lower-paying business-service firms. Given that younger workers are more likely to occupy these progressively outsourced low-skill jobs (Figure A10, Panel A), domestic outsourcing could contribute to the widening age pay gap.

However, domestic outsourcing became more common during the 2000s, decades after the age pay gap had already started to widen. Moreover, if domestic outsourcing were a primary factor, the rank gap should have increased predominantly between sectors, but nearly all of the increase occurred within three-digit sectors.[22]

In additional tests, we drop all workers in those three-digit sectors identified by Goldschmidt and Schmieder (2017) as primary recipients of domestically outsourced jobs, as well as all workers employed by firms that have sold one or more business units (Figure A10, Panels B to D). Our main findings remain robust after these exclusions: the pay rank gap increased, and the majority of this increase occurred within sectors. Therefore, despite being an important labor-market phenomenon, domestic outsourcing does not appear to be a key driver of the growth in the age pay gap.

6.3 Changes in Education and Other Characteristics of Younger and Older Workers

This section explores whether cross-cohort differences in observable characteristics, such as education, have contributed to the expansion of the age pay gap. Overall, our analysis reveals that older workers' wages have outpaced those of younger workers even after controlling for many socio-economic factors.

We start by addressing trends in education. Prior work has documented that, in many countries, younger individuals tend to have substantially higher educational attainment than older individuals (Fraumeni, 2015). A concern related to this rise in education is that later U35 cohorts, having stayed longer in school, have on average less work experience than earlier U35 cohorts, so that the observed fall in their pay rank could be purely compositional. Therefore, we re-compute the change in pay rank by comparing equally experienced U35 workers and find that the outcomes of younger workers have deteriorated at any level of experience (Figure A11). Between 1985 and 2019, the pay rank of U35 workers decreased by 0.03, 0.05, and 0.12 log points at 1, 5, and 10 years of experience, respectively.

We then extend our focus to several other socio-economic factors. Whenever these variables are available in the administrative and survey data at our disposal, we regress log wages on (i) gender (a male dummy); (ii) nationality (a dummy for nonimmigrant workers), except for the United States, where the absence of nationality data induces us to use race instead (a dummy for white workers); (iii) contract length (a dummy for temporary contracts), (iv) education (a dummy for college education), and (v) health (a dummy for disability status). We estimate distinct regressions

[22] Goldschmidt and Schmieder (2017) documents that outsourced jobs have gradually moved to business-service firms concentrated in a limited number of sectors.

in each year and country, allowing coefficient estimates to vary over time and geography. We then use the residuals from these regressions to compute the age pay gap.

Controlling for these characteristics does not substantially reduce the growth in the age pay gap (Table A3, columns 1 to 14). This pattern remains broadly consistent across other countries in our sample. Out of 63 measurements with controls, only four cases manifest an increase in the age pay gap that is less than half of the gap expansion without controls.

We finally focus on the selection of older workers. The gradual increase in the retirement age may have altered the characteristics of older individuals remaining in the labor market. Previous studies indicate that this form of selection could be negatively correlated with older workers' earning potential, therefore narrowing the age pay gap (Munnell, Sanzenbacher, and Rutledge, 2018; Kolsrud et al., 2024). We provide further evidence that changing selection into retirement is not a primary driver of the growth in the age pay gap by limiting our O55 worker group to male employees aged between 56 and 60. The rationale for this test is that the minimum retirement age for men was already at least 60 years at the start of our sample in all but two countries in our sample (Table A4). By focusing on this narrower group of older workers, whose selection into retirement is less likely to have changed in recent decades, we find that the widening of the age pay gap remains largely unaltered (Table A3, column 15).

7 Conclusions

This paper uses comprehensive administrative data on 29 million workers across 3.5 million firms in Italy, supplemented by administrative and survey data on 15.4 million workers from fourteen high-income countries, to show that the wages of older workers have been growing at a much faster rate than those of younger workers over the past four decades.

Our analysis underscores the importance of interactions between the careers of older and younger workers in driving these trends. An aging workforce, delayed retirements, and slower economic growth have increased the representation of older workers at the top of firms' hierarchies. This shift has crowded out younger workers from higher-ranked positions, thus limiting their opportunities for advancement and wage growth.

We highlight four main findings related to these negative career spillovers. First, the expanding age pay gap stems primarily from the increasing difficulty younger workers face, relative to older workers, in reaching the top segments of the wage distribution and higher-ranked job levels, rather than from changes in the level of wages paid for different jobs. Second, as older workers are increasingly represented at the top, younger workers enter the labor market at progressively lower segments of the wage distribution and experience slower wage growth for many years after entry. Third, the growth in the age pay gap and the worsening career trajectories of younger workers are more pronounced within firms that experience greater workforce aging. Fourth, the increased presence of older workers in higher-paying firms makes it increasingly difficult for younger workers to secure employment in these organizations.

In conclusion, labor markets have witnessed a major redistribution of wages from younger to older workers. Future research should investigate the potential long-term implications of negative career spillovers beyond slowed career progression for younger workers. For example, lower early-career wages may deter some workers from purchasing durables, investing in real estate, or starting families, decisions that cannot always be deferred until later career stages.

References

Acemoglu, Daron and David H. Autor. 2011. "Skills, tasks and technologies: Implications for employment and earnings." *Handbook of Labor Economics* Vol. 4, 1043–1171. Elsevier Inc.

Acemoglu, Daron and Pascual Restrepo. 2020. "Robots and jobs: Evidence from us labor markets." *Journal of Political Economy*, 128(6): 2188–2244.

Acemoglu, Daron and Pascual Restrepo. 2023. "Automation and Rent Dissipation: Implications for Inequality, Productivity, and Welfare." Working paper, MIT.

Acemoglu, Daron, Nicolaj Søndergaard Mühlbach, and Andrew J. Scott. 2022. "The Rise of Age-Friendly Jobs." *Journal of the Economics of Ageing*, 23: 100416.

Antwi, James and David C. Phillips. 2013. "Wages and health worker retention: Evidence from public sector wage reforms in Ghana." *Journal of Development Economics*, 102: 101–115.

Ashwin, Julian and Andrew Scott. 2025. "A Bayesian Model of Later Life Mortality Trends and Implications for Longevity." *Working paper, London Business School*.

Autor, David H, David Dorn, and Gordon H Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review*, 103(6): 2121–2168.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2006. "The polarization of the U.S. labor market." *American Economic Review*, 96(2): 189–194.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. "Trends in U.S. Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics*, 90(2): 300–323.

Azoulay, Pierre, Benjamin F. Jones, J. Daniel Kim, and Javier Miranda. 2020. "Age and High-Growth Entrepreneurship." *American Economic Review: Insights*, 2(1): 65–82.

Baker, George P., Michael Gibbs, and Bengt Holmström. 1994. "The Internal Economics of the Firm: Evidence from Personnel Data." *Quarterly Journal of Economics*, 109(4): 881–919.

Bayer, Patrick and Kerwin Kofi Charles. 2018. "Divergent paths: A new perspective on earnings differences between black and white men since 1940." *Quarterly Journal of Economics*, 133(3): 1459–1501.

Bentolila, Samuel and Giuseppe Bertola. 1990. "Firing costs and labour demand: How bad is eurosclerosis?" *Review of Economic Studies*, 57(3): 381–402.

Berger, Mark C. 1985. "The Effect of Cohort Size on Earnings Growth: A Reexamination of the Evidence." *Journal of Political Economy*, 93(3): 561–573.

Bertoni, Marco and Giorgio Brunello. 2021. "Does a Higher Retirement Age Reduce Youth Employment." *Economic Policy*, 36(106): 325–372.

Bertrand, Marianne, Robin Burgess, Arunish Chawla, and Guo Xu. 2020. "The Glittering Prizes : Career Incentives and Bureaucrat Performance." *Review of Economic Studies*, 87(2): 626–655.

Bianchi, Nicola, Giulia Bovini, Jin Li, Matteo Paradisi, and Michael Powell. 2023. "Career Spillovers in Internal Labor Markets." *Review of Economic Studies*, 90(4): 1800–1831.

Blanchflower, David G, Alex Bryson, and Xiaowei Xu. 2024. "The Declining Mental Health Of The Young And The Global Disappearance Of The Hump Shape In Age In Unhappiness." *NBER Working Paper*, 32337.

Boeri, Tito and Juan F. Jimeno. 2005. "The effects of employment protection: Learning from variable enforcement." *European Economic Review*, 49(8): 2057–2077.

Boeri, Tito, Pietro Garibaldi, and Espen R. Moen. 2022. "In Medio Stat Victus: Labor Demand Effects of an Increase in the Retirement Age." *Journal of Population Economics*, 35(2): 519–556.

Brown, Jennifer. 2011. "Quitters Never Win: The (Adverse) Incentive Effects of Competing with Superstars." *Journal of Political Economy*, 119(5): 982–1013.

Card, David, Ana Rute Cardoso, Joerg Heining, and Patrick Kline. 2018. "Firms and labor market inequality: Evidence and some theory." *Journal of Labor Economics*, 36(S1): S13–S70.

Charles, Kerwin Kofi, Erik Hurst, and Mariel Schwartz. 2019. "The Transformation of Manufacturing and the Decline in US Employment." *NBER Macroeconomics Annual*, 33(1): 307–372.

Charles, Kerwin Kofi, Erik Hurst, and Matthew J. Notowidigdo. 2016. "The Masking of the Decline in Manufacturing Employment by the Housing Bubble." *Journal of Economic Perspectives*, 30(2): 179–200.

Cornelissen, Thomas, Christian Dustmann, and Uta Schönberg. 2023. "Knowledge Spillovers, Competition, and Individual Careers." *Working paper, UCL*.

Deming, David J. 2021. "The Growing Importance of Decision-Making on the Job." NBER Working Paper 28733.

Donovan, Kevin, Will Jianyu Lu, and Todd Schoellman. 2023. "Labor Market Dynamics and Development." *Quarterly Journal of Economics*, 138(4): 2287–2325.

Drenik, Andres, Simon Jäger, Pascuel Plotkin, and Benjamin Schoefer. 2023. "Paying Outsourced Labor: Direct Evidence from Linked Temp Agency-Worker-Client Data." *The Review of Economics and Statistics*, 105(1): 206–216.

Ferrari, Irene, Jan Kabátek, and Todd Morris. 2025. "Workplace Spillovers and Welfare Implications of Delaying Retirement." *Working paper, Marche Polytechnic University*.

Fraumeni, Barbara M. 2015. "Choosing a Human Capital Measure: Educational Attainment Gaps and Rankings." *NBER Working Paper 21283*.

Freeman, Richard B. 1979. "The Effect of Demographic Factors on Age-Earnings Profiles." *The Journal of Human Resources*, 14(3): 289.

Friebel, Guido and Elena Panova. 2008. "Insider Privatization and Careers: A Clinical Study of a Russian Firm in Transition." In *The Analysis of Firms and Employees: Quantitative and Qualitative Approaches*. , ed. Stefan Bender, Julia Lane, Kathryn L. Shaw, Fredrik Andersson, and Till von Wachter, 253–266. University of Chicago Press.

Gathmann, Christina and Uta Schönberg. 2010. "How general is human capital? A task-based approach." *Journal of Labor Economics*, 28(1): 1–49.

Goldschmidt, Deborah and Johannes F. Schmieder. 2017. "The Rise of Domestic Outsourcing and the Evolution of the German Wage structure." *Quarterly Journal of Economics*, 132(3): 1165–1217.

Gong, Jie, Ang Sun, and Zhichao Wei. 2017. "Choosing the Pond: On-the-Job Experience and Long-Run Career Outcomes." *Management Science*, 64(2): 860–872.

Guaitoli, Gabriele and Roberto Pancrazi. 2023. "Global Trends in Income Distribution Across Age Groups?" working paper, University of Warwick.

Guvenen, Fatih, Greg Kaplan, Jae Song, and Justin Weidner. 2022. "Lifetime Earnings in the United States over Six Decades." *American Economic Journal: Applied Economics*, 14(4): 446–479.

Jeong, Hyeok, Yong Kim, and Iourii Manovskii. 2015. "The price of experience." *American Economic Review*, 105(2): 784–815.

Jones, Benjamin F. 2009. "The burden of knowledge and the "death of the renaissance man": Is innovation getting harder?" *Review of Economic Studies*, 76(1): 283–317.

Ke, Rongzhu, Jin Li, and Michael Powell. 2018. "Managing Careers in Organizations." *Journal of Labor Economics*, 36(1): 197–252.

Kolsrud, Jonas, Camille Landais, Daniel Reck, and Johannes Spinnewijn. 2024. "Retirement Consumption and Pension Design." *American Economic Review*, 114(1): 89–133.

Kopczuk, Wojciech, Emmanuel Saez, and Jae Song. 2010. "Earnings Inequality and Mobility in the United States: Evidence From Social Security Data Since 1937." *Quarterly Journal of Economics*, 125(1): 91–128.

Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman. 2018. "Life Cycle Wage Growth Across Countries." *Journal of Political Economy*, 126(2): 797–849.

Lamadon, Thibaut, Magne Mogstad, and Bradley Setzler. 2022. "Imperfect competition, compensating differentials, and rent sharing in the US labor market." *American Economic Review*, 112(1): 169–212.

Lazear, Edward P. 1979. "Why Is There Mandatory Retirement?" *Journal of Political Economy*, 87(6): 1261–1284.

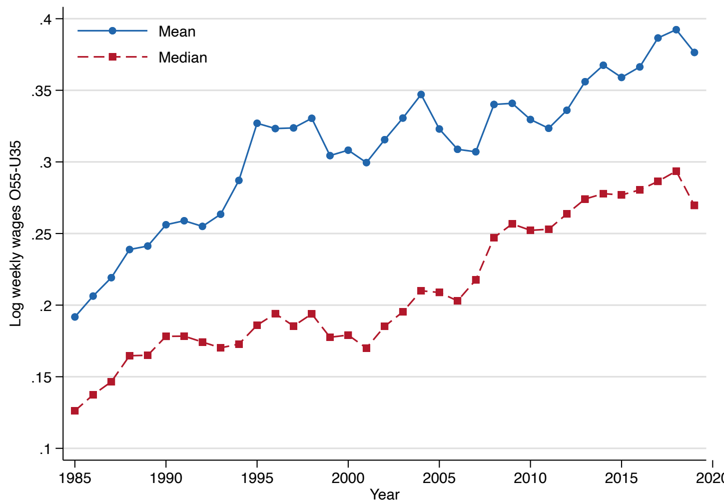
Lazear, Edward P. 2009. "Firm-Specific Human Capital: A Skill-Weights Approach Edward P." *Journal of Political Economy*, 117(5): 914–940.

Lazear, Edward P., Kathryn L. Shaw, and Christopher T. Stanton. 2018. "Who Gets Hired? The Importance

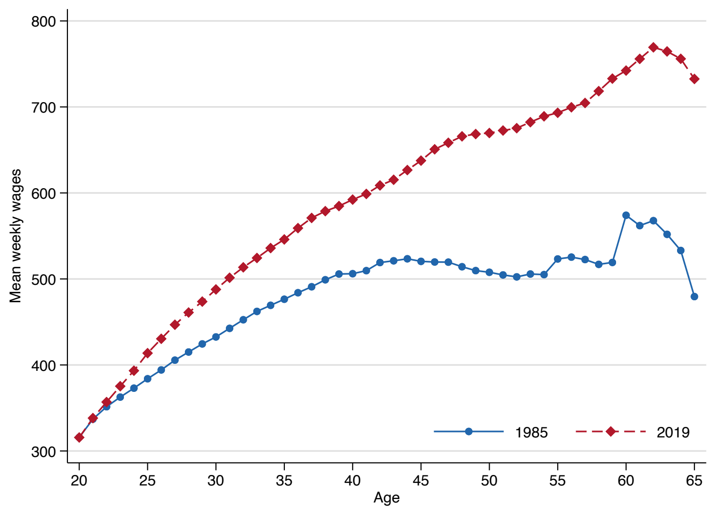
of Competition Among Applicants." *Journal of Labor Economics*, 36(S1): S133–S181.
Machado, José A.F. and José Mata. 2005. "Counterfactual decomposition of changes in wage distributions using quantile regression." *Journal of Applied Econometrics*, 20(4): 445–465.
Mohnen, Paul. 2025. "The Impact of the Retirement Slowdown on the U.S. Youth Labor Market." *Journal of Labor Economics*, 43(1): 203–246.
Munnell, Alicia H., Geoffrey T. Sanzenbacher, and Matthew S. Rutledge. 2018. "What causes workers to retire before they plan?" *Journal of Retirement*, 6(2): 35–52.
Naticchioni, Paolo, Michele Raitano, and Claudia Vittori. 2016. "La Meglio Gioventù: Earnings Gaps Across Generations and Skills in Italy." *Economia Politica*, 33(2): 233–264.
Piketty, Thomas and Emmanuel Saez. 2003. "Income Inequality in the United States, 1913-1998." *Quarterly Journal of Economics*, 118(1): 1–41.
Rosolia, Alfonso and Roberto Torrini. 2007. "The Generation Gap: Relative Earnings of Young and Old Workers in Italy." Bank of Italy Working Paper 639.
Ruffini, Krista. 2022. "Worker earnings, service quality, and firm profitability: Evidence from nursing homes and minimum wage reforms." *Review of Economics and Statistics*, 1–46.
Saez, Emmanuel, Benjamin Schoefer, and David Seim. 2023. "Deadwood Labor: The Effects of Eliminating Employment Protection." *NBER Working Paper*, 31797.
Sandvik, Jason J., Richard E. Saouma, Nathan T. Seegert, and Christopher T. Stanton. 2020. "Workplace Knowledge Flows." *The Quarterly Journal of Economics*, 135(3): 1635–1680.
Scott, Andrew J. 2023. "Working Life—Labor Supply, Ageing, and Longevity." In *The Routledge Handbook of the Economics of Ageing*. Chapter 18, 329–348. London: UK:Routledge.
Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom, and Till von Wachter. 2019. "Firming Up Inequality." *Quarterly Journal of Economics*, 134(1): 1–50.
Syverson, Chad. 2017. "Challenges to mismeasurement explanations for the US productivity slowdown." *Journal of Economic Perspectives*, 31(2): 165–186.
Toossi, Mitra and Elka Torpey. 2017. "Older workers: Labor force trends and career options." *Career Outlook*, May 2017.
Welch, Finis. 1979. "Effects of Cohort Size on Earnings: The Baby Boom Babies' Financial Bust." *Journal of Political Economy*, 87(5): S65–S97.

Figures and Tables

Figure 1: Age Gap in Weekly Wages



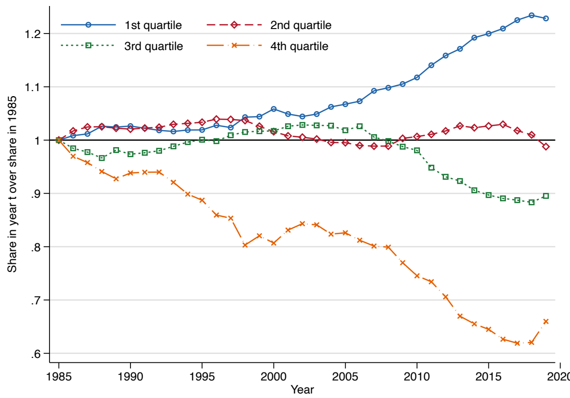
Panel A: Gap in log mean and median
weekly wages



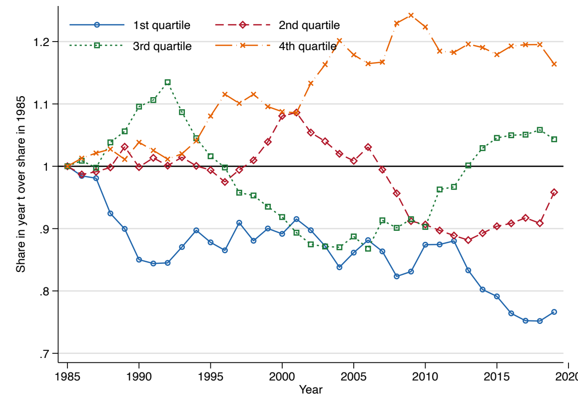
Panel B: Age profiles for
mean weekly wages

Notes: Panel A plots the gap between the log weekly wages of O55 workers and the log weekly wages of U35 workers from 1985 to 2019 for both mean and median wages. Panel B plots the mean real weekly wages (not logged) by age in 1985 and 2019.
Source: In each year, the data pool information about all workers who were at least 16 years old, had worked at least six months, had earned strictly positive wages, had full-time contracts, and had not retired by December 31. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (Italy).

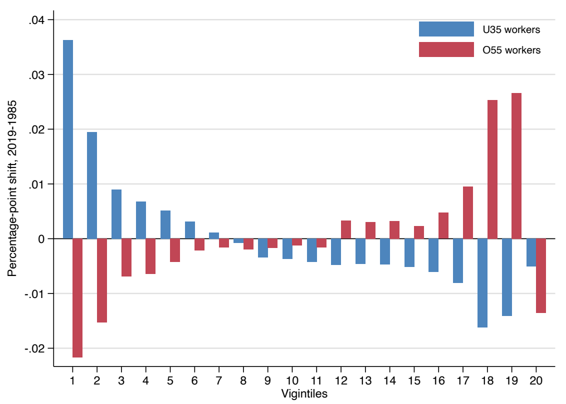
Figure 2: Positions in the Wage Distribution



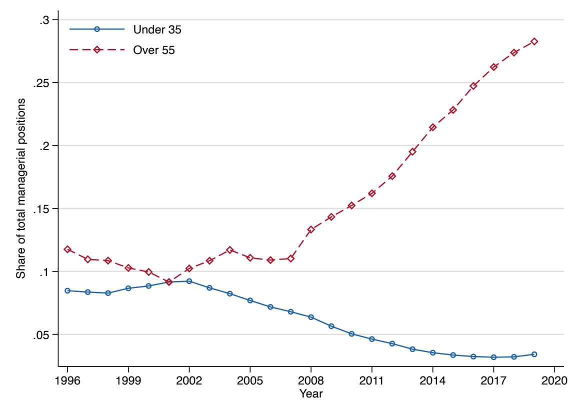
Panel A: U35 workers, quartiles



Panel B: O55 workers, quartiles



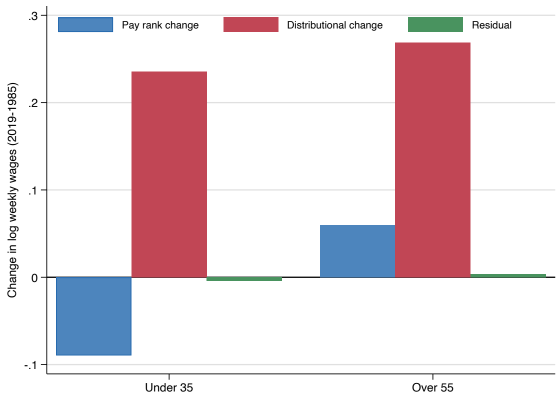
Panel C: Vigintiles



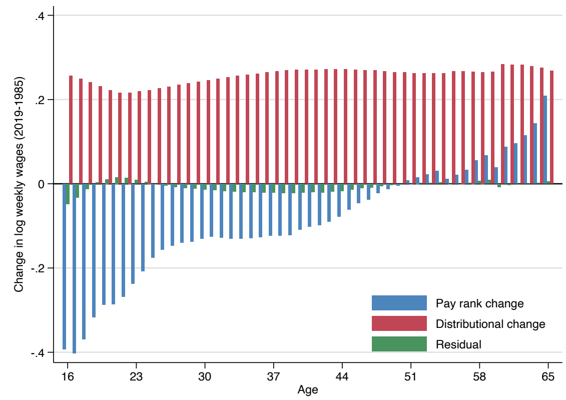
Panel D: Share of managerial jobs

Notes: Panel A (B) shows the ratio between the share of U35 (O55) workers in each quartile in year t and the share of U35 (O55) workers in the same quartile in 1985. Panel C plots the percentage-point difference in the share of U35 and O55 workers in each vigintile from 1985 to 2019. Panel D plots the share of total managerial jobs held by U35 and O55 workers for each year between 1996 (first year available) and 2019.
Source: In each year, the data pool information about all workers who were at least 16 years old, had worked at least six months, had earned strictly positive wages, had full-time contracts, and had not retired by December 31. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (Italy).

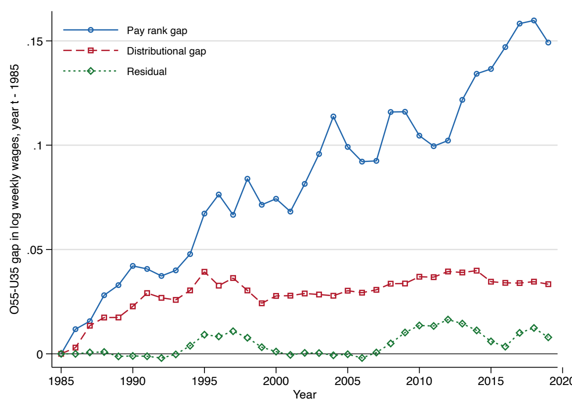
Figure 3: The Rank Change in Weekly Wages



Panel A: U35 and O55 workers,
2019-1985



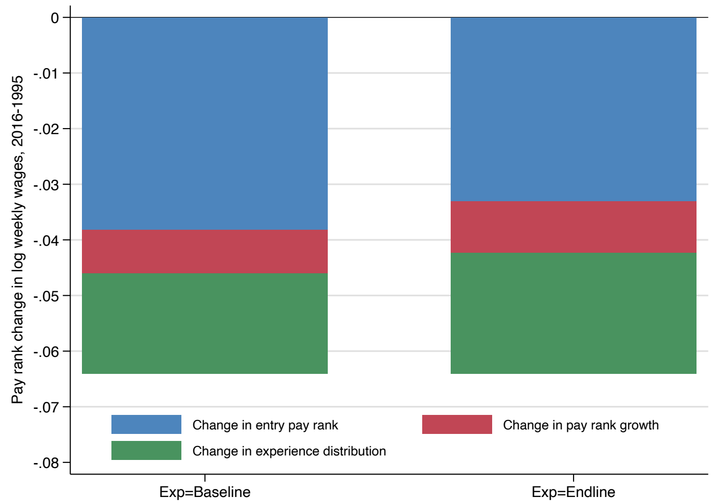
Panel B: All age groups,
2019-1985



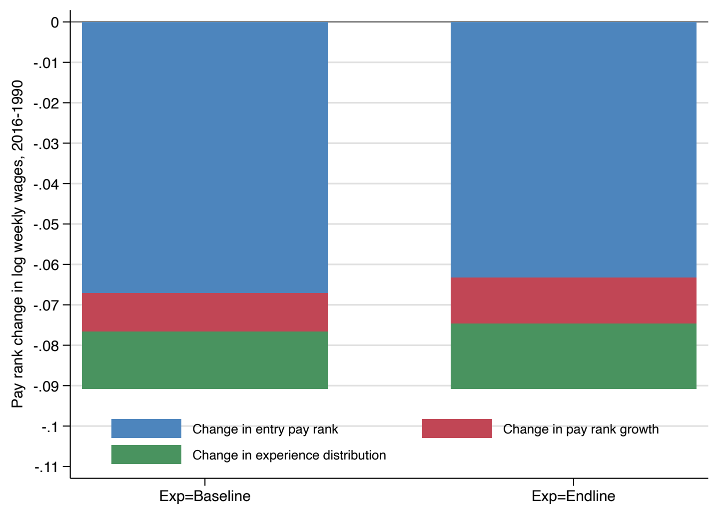
Panel C: O55 workers - U35 workers,
$t \in [1986, 2019] - 1985$

Notes: Panel A shows the decomposition of the change in the mean log weekly wages between 1985 and 2019 into the three components of Equation (2) for U35 workers and O55 workers. Panel B shows the same decomposition for individual age groups. Panel C shows the same decomposition for the change in the age pay gap between O55 and U35 workers from 1985 to each year $t \in [1986, 2019]$.
Source: In each year, the data pool information about all workers who were at least 16 years old, had worked at least six months, had earned strictly positive wages, had full-time contracts, and had not retired by December 31. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (Italy).

Figure 4: Entry Pay Rank and Pay Rank Growth



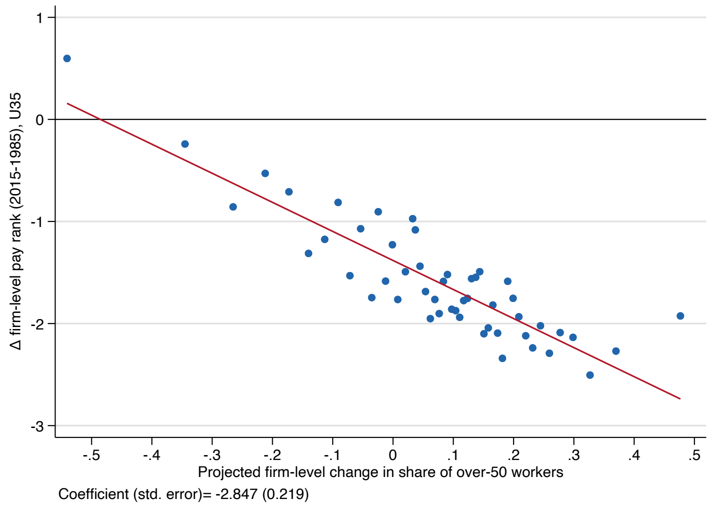
Panel A: U35 workers, 2016-1995



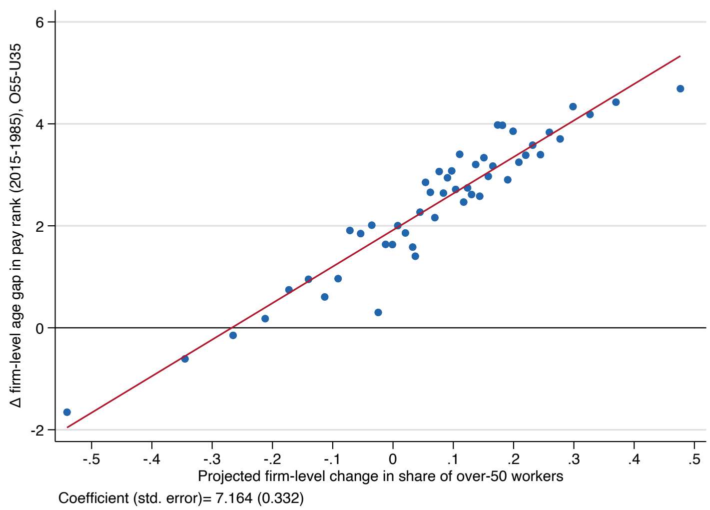
Panel B: U30 workers, 2016-1990

Notes: Panel A shows the decomposition of rank change in the distribution of log weekly wages for U35 workers from 1995 to 2016 into three components: (i) the change in pay rank at labor-market entry, (ii) the change in pay rank growth between labor-market entry and 2016, and (iii) residual variation in the distribution of work experience (Equation (3)). It shows this decomposition under two scenarios: the experience composition of U35 workers kept fixed in 1995 (Exp=Baseline) or 2016 (Exp=Endline). Panel B replicates the same decomposition for U30 workers between 1990 and 2016.
Source: In each year, the data pool information about all workers who were at least 16 years old, had worked at least six months, had earned strictly positive wages, had full-time contracts, and had not retired by December 31. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (Italy).

Figure 5: Projected Workforce Aging and Age Pay Gap



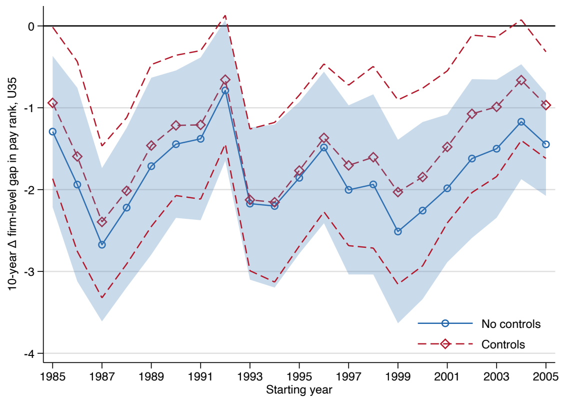
Panel A: U35 workers' pay rank



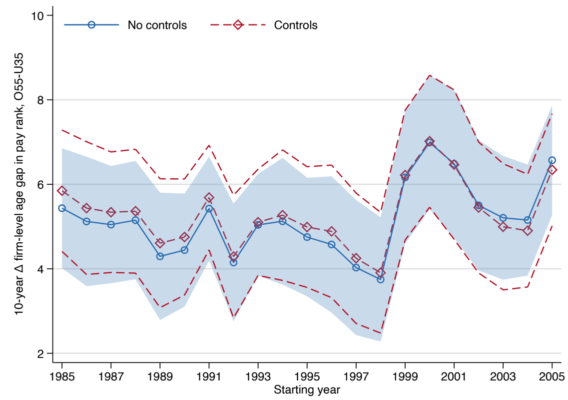
Panel B: Age pay gap

Notes: These figures show binned scatterplots that correlate firm-level changes in the pay rank of U35 workers (the pay rank is the mean percentile in a firm's pay distribution) or in the age pay rank gap (mean pay rank of O55 workers - mean pay rank of U35 workers) with firm-level projected changes in the share of workers over 50. In Panel A, the y-axis displays the firm-level change in the pay rank of U35 workers for three ten-year periods (1985-1995, 1995-2005, and 2005-2015), and the x-axis shows the firm-level difference between the share of workers aged 41-50 and the share of workers aged 51-60 at baseline (either 1985, 1995, or 2005). Panel B replicates the same analysis but uses the firm-level change in the age pay rank on the y-axis. Firm-level values for year x are computed as three-year averages over x and $x+2$. The sample includes firms that employed (i) at least one U35 worker in both baseline year t and endline year $t+10$, and (ii) at least one worker over 40 at baseline.
Source: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

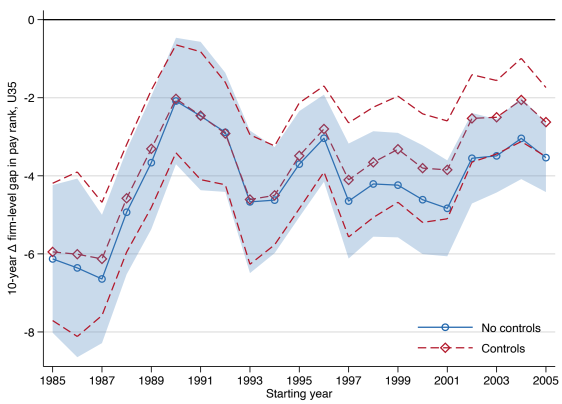
Figure 6: Firm-Level Workforce Aging, Rolling 10-Year Regressions



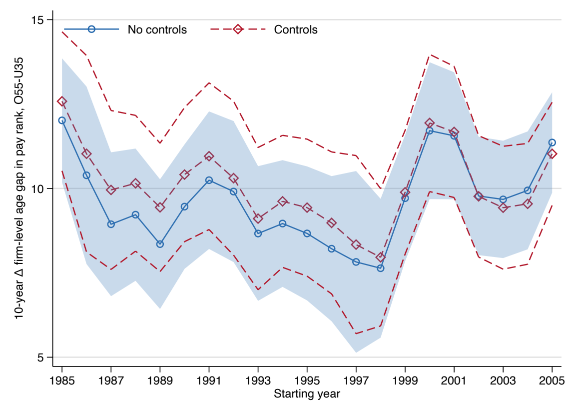
Panel A: OLS, U35 pay rank



Panel B: OLS, Age pay gap



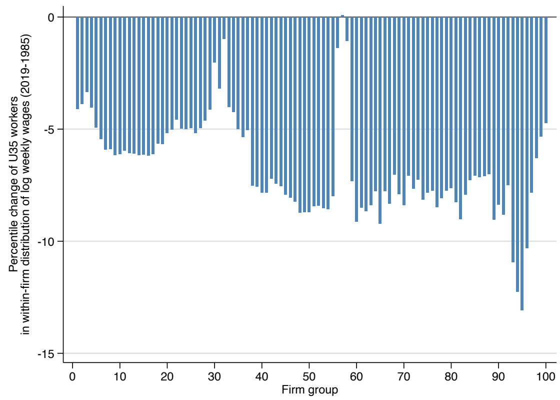
Panel C: 2SLS, U35 pay rank



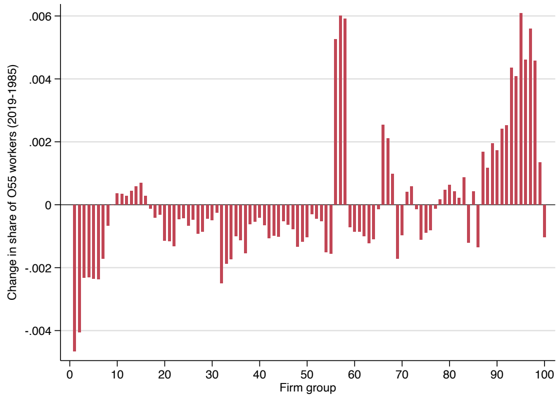
Panel D: 2SLS, Age pay gap

Notes: Each point on the x-axis represents the initial year of a ten-year rolling window used to estimate the correlation between changes in the outcomes of younger workers and workforce aging at the firm level. For example, the point labeled 1985 corresponds to regressions on the change from 1985 to 1995. Panel A regresses the Δ_{10} pay rank (the pay rank is the mean percentile in a firm's pay distribution) of U35 workers on the Δ_{10} share of workers aged 51-60. Panel B regresses the Δ_{10} age pay rank gap (mean pay rank of O55 workers - mean pay rank of U35 workers) on the Δ_{10} share of workers aged 51-60. Panels C and D modify these OLS regressions by instrumenting the Δ_{10} share of workers aged 51-60 with the difference between the share of workers aged 41-50 and the share of workers aged 51-60 at baseline. Controls include firm age, firm size, and province fixed effects, all observed at baseline. Firm-level values for year x are computed as three-year averages over x and $x + 2$. The sample includes firms that employed (i) at least one U35 worker in both baseline year t and endline year $t + 10$, and (ii) at least one worker over 40 at baseline. Standard errors are clustered at the province level.
Source: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

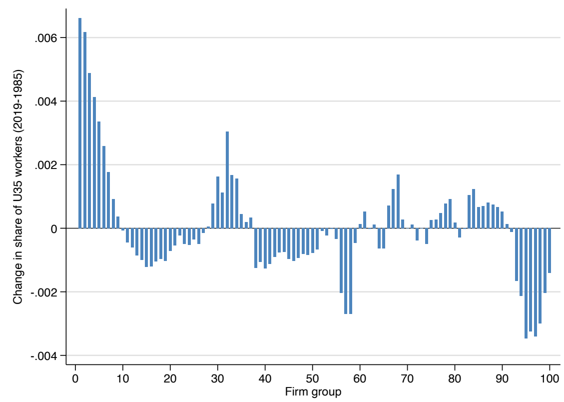
Figure 7: Distribution of Workers Within and Between Firms



Panel A: Position of U35 workers



Panel B: Share of O55 workers



Panel C: Share of U35 workers

Notes: Firm groups are one hundred groups that have the same number of workers and are ordered by ascending mean firm pay. Panel A shows the mean change in the percentile of U35 workers within the pay distribution of their firm group from 1985 to 2019. Panel B (Panel C) shows the change in O55 (U35) workers for each firm group from 1985 to 2019. To limit noise, the displayed values are averages computed using each group and its two adjacent firm groups (or one in the case of the first and last groups).
Source: In each year, the data pool information about all workers who were at least 16 years old, had worked at least six months, had earned strictly positive wages, had full-time contracts, and had not retired by December 31. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (Italy).

Table 1: Characteristics of Data Sources

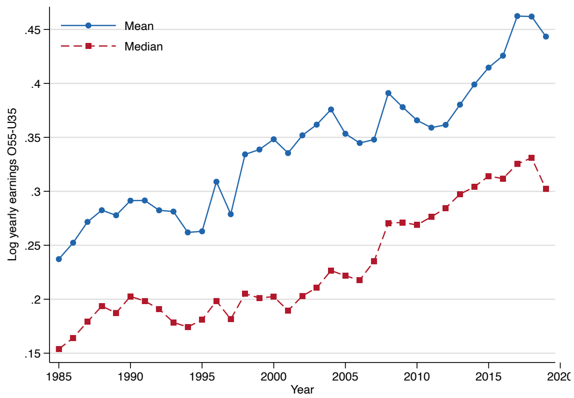
	# available years	# observations	# workers	# firms	Wage definition	Restrict to employees	Restrict to full time	Restrict working weeks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Employer-employee administrative data								
Italy (1985-2019)	35	312,065,728	28,911,242	3,532,905	Weekly	Yes	Yes	Yes
Germany (1996-2017)	22	35,092,712	8,865,294	127,782	Daily	Yes	Yes	No
Panel B: Survey data from the Luxembourg Income Study (LIS) Database								
Australia (1995-2018)	9	74,817	-	-	Yearly	Yes	Yes	No
Canada (1973-2018)	41	1,082,370	-	-	Yearly	Yes	Yes	Yes
Denmark (1987-2018)	12	1,319,502	-	-	Yearly	Yes	No	No
Finland (1987-2016)	9	79,119	-	-	Yearly	Yes	No	Yes
France (2002-2018)	17	488,398	-	-	Yearly	Yes	Yes	No
Germany (1994-2018)	25	198,138	-	-	Yearly	Yes	Yes	Yes
Greece (1995-2016)	7	25,887	-	-	Yearly	Yes	No	No
Israel (1979-2018)	22	129,914	-	-	Yearly	Yes	Yes	No
Netherlands (1983-2018)	13	64,589	-	-	Yearly	Yes	Yes	No
Norway (1986-2016)	9	894,042	-	-	Yearly	Yes	No	No
Spain (1993-2018)	23	158,300	-	-	Yearly	Yes	Yes	Yes
Switzerland (1982-2018)	15	74,382	-	-	Yearly	Yes	Yes	No
United Kingdom (1979-2018)	40	468,823	-	-	Yearly	Yes	Yes	No
United States (1979-2018)	40	2,265,013	-	-	Yearly	Yes	Yes	Yes

FOR PANEL A. *Source for Italy:* Database UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for Germany:* The German data come from the LIAB Linked Employer-Employee Dataset provided by the Institute for Employment Research.
FOR PANEL B. *Sources for Australia:* Survey of Income and Housing, Household Expenditure Survey (2004); Survey of Income and Housing (all other years). *Sources for Canada:* Survey of Consumer Finances (1973-1995); Survey of Labour and Income Dynamics (1996-2011); Canadian Income Survey (2012 and later). *Sources for Denmark:* sample based on administrative records; The Danish National Centre for Social Research, Statistics Denmark, Ministry of Finance, Ministry of Economic Affairs and the Interior, Ministry of Taxation. *Sources for Finland:* Income Distribution Survey (before 2004); SILC (2004 onwards). *Source for France:* Tax and Social Incomes Survey. *Source for Germany (LIS):* German Socio-Economic Panel. *Sources for Greece:* ECHP (1995, 2000); SILC (all other years). *Source for Israel:* Household Expenditure Survey. *Sources for Netherlands:* Amenities and Services Utilization Survey (1983, 1987, 1990); Socio-Economic Panel Survey (1993, 1999); SILC (all other years). *Sources for Norway:* Income Distribution Survey (2004 and before); Household Income Statistics (2007 and after). *Sources for Spain*: European Community Household Panel (1993-2000); SILC (2004 and later. *Sources for Switzerland:* Swiss Income and Wealth Survey (1982); National Poverty Study (1992); Income and Expenditure Survey (2000, 2002, 2004); SILC (all other years). *Sources for United Kingdom:* Family Expenditure Survey (1991 and earlier); Family Resources Survey (1994 and later). *Sources for United States:* CPS March Supplement (2001 and before); CPS Annual Social and Economic Supplement (2002 and later).

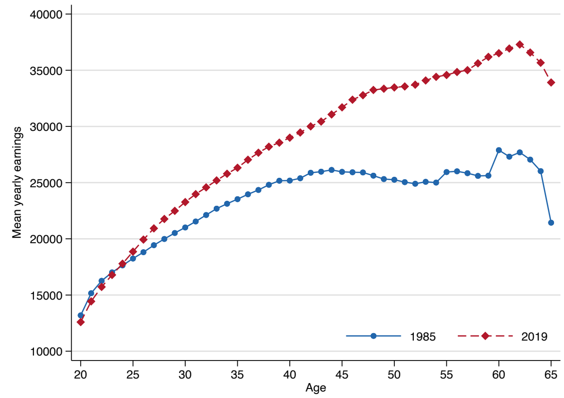
Appendix - For Online Publication

A Additional Results

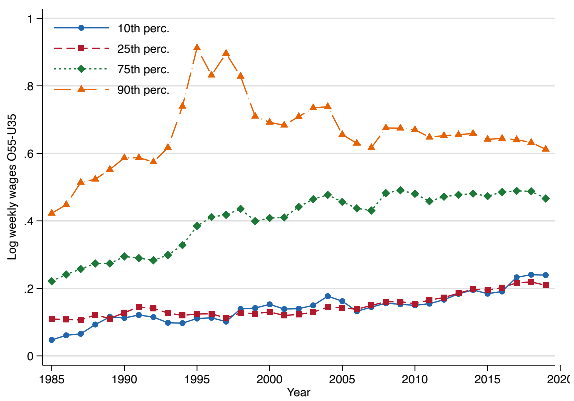
Figure A1: Age Pay Gap in Yearly Labor Earnings and at Various Percentiles



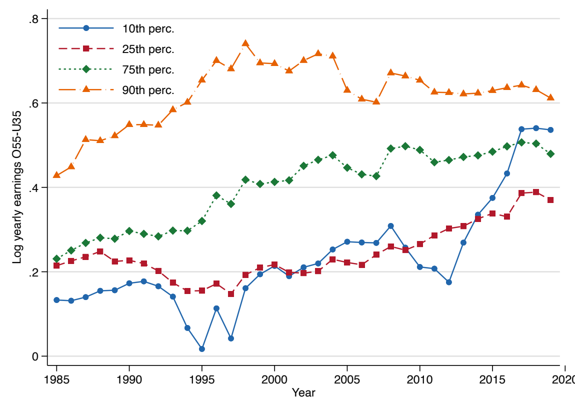
Panel A: Gap in log mean and median yearly earnings



Panel B: Age profiles for mean yearly earnings



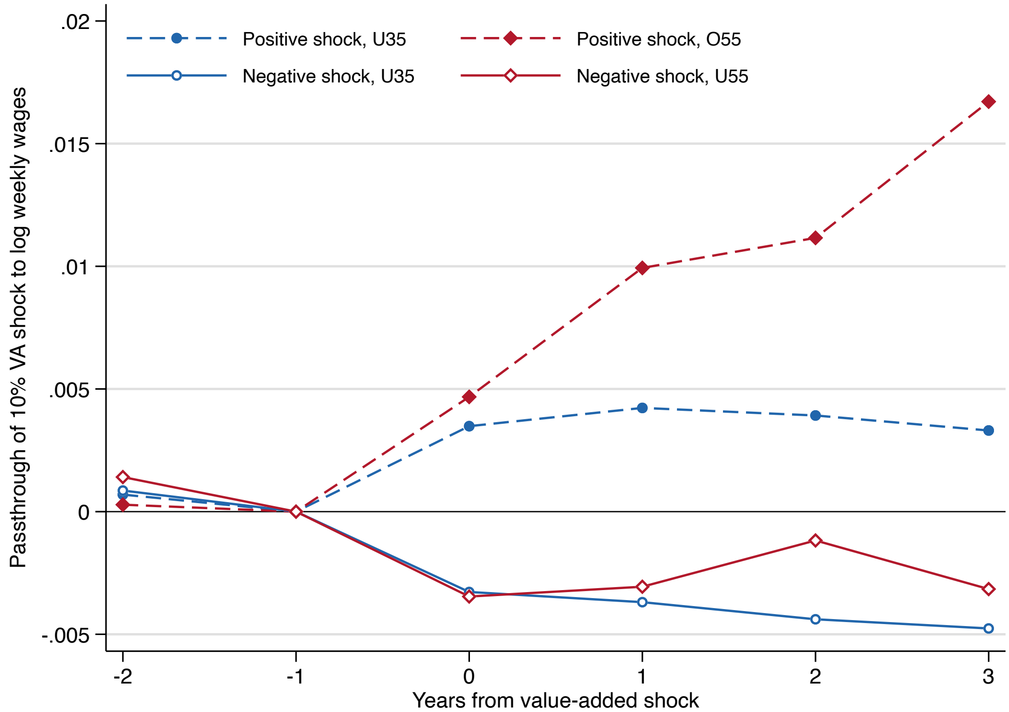
Panel C: Gap at various percentiles (weekly wages)



Panel D: Gap at various percentiles (yearly earnings)

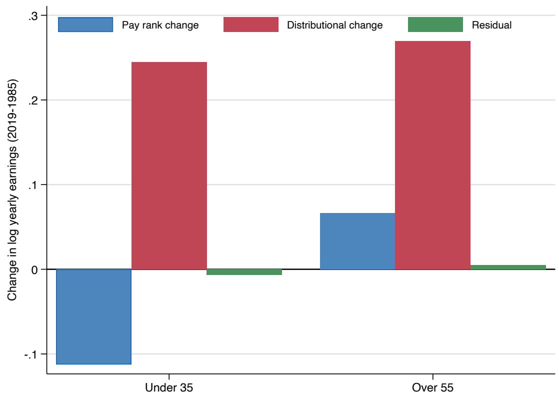
Notes: Panel A plots the gap between the log yearly earnings of O55 workers and the log yearly earnings of U35 workers from 1985 to 2019 for both mean and median wages. Panel B plots the mean real yearly earnings (not logged) by age in 1985 and 2019. Panels C and D plot the age pay gap (O55 workers - U35 workers) for weekly wages and yearly earnings, respectively, at various percentiles of the wage distribution. *Source:* In each year, the data pool information about all workers who were at least 16 years old, had worked at least six months, had earned strictly positive wages, had full-time contracts, and had not retired by December 31. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (Italy).

Figure A2: Wage Passthrough of Firm-Level Value-Added Shocks

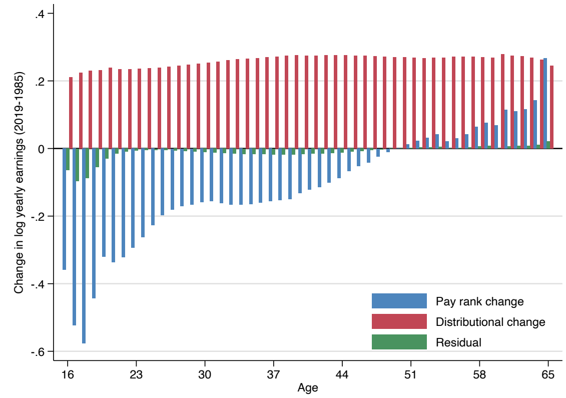


Notes: Each line shows the average effect on wages of U35 workers or O55 workers of either a positive 10-percent firm-level value-added shock or a negative 10-percent firm-level value-added shock. The dataset for the event study is created as follows. In each year t between 1998 and 2016, we compute the value-added shock from $t-1$ to t for each firm in the sample. The shock is the year-to-year change in value added minus the average year-to-year change in value added in a province and two-digit sector. We then divide firms into tertiles based on their value-added shock in year t. In the next step, we create event-study panels for each year t by (i) appending data from $t-2$ to $t+3$, (ii) keeping observations only from U35 workers and O55 workers, and (iii) computing the average log weekly wage and log value-added shock at the level of firms, age groups, and event periods. Next, we append these datasets and compute the average log weekly wage and value-added shock by tertiles of the distribution of value-added shocks in period 0, age groups, and event periods, weighting each firm-level data point by the firm's number of U35 workers or O55 workers. In the final step, we compute the change in log wages for U35 workers and O55 workers resulting from a positive shock, defined as the difference in value-added shock between the top tertile and the mid tertile. Similarly, we measure the wage change stemming from a negative value-added shock, leveraging the difference between the bottom tertile and the mid tertile.
Source: Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

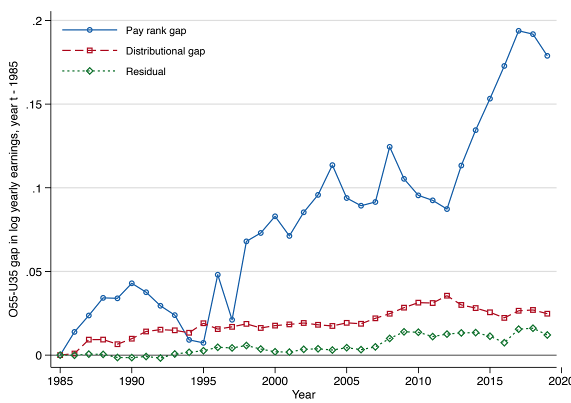
Figure A3: The Rank Change in Yearly Earnings



Panel A: U35 and O55 workers,
2019-1985



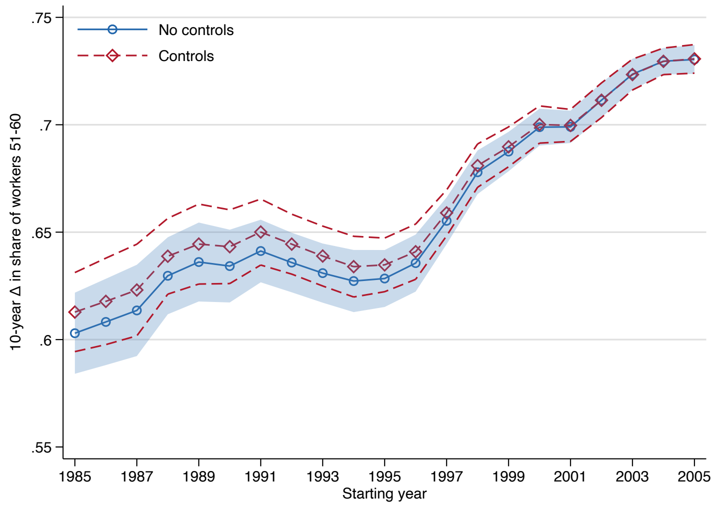
Panel B: All age groups,
2019-1985



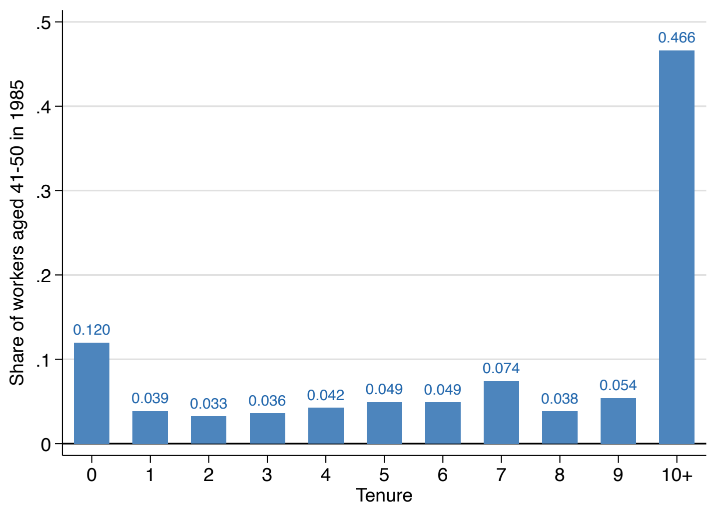
Panel C: O55 workers - U35 workers,
$t \in [1986, 2019] - 1985$

Notes: Panel A shows the decomposition of the change in the mean log yearly earnings between 1985 and 2019 into the three components of Equation (2). Panel B shows the same decomposition for individual age groups. Panel C shows the same decomposition for the change in the age pay gap between O55 and U35 workers from 1985 to each year $t \in [1986, 2019]$.
Source: In each year, the data pool information about all workers who were at least 16 years old, had worked at least six months, had earned strictly positive wages, had full-time contracts, and had not retired by December 31. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (Italy).

Figure A4: The Projected Workforce Aging



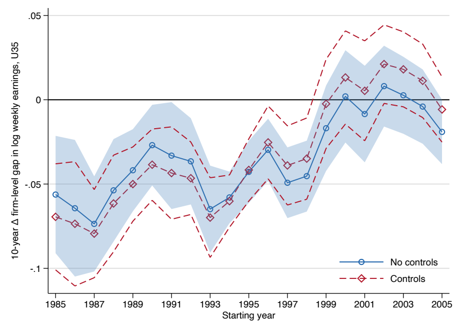
Panel A: First stage regressions



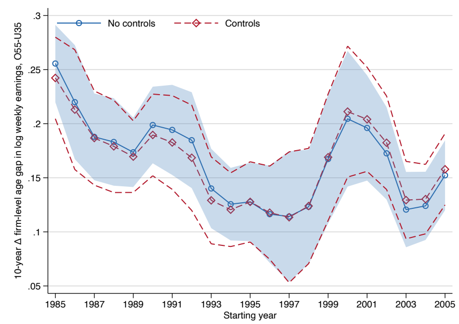
Panel B: Tenure distribution

Notes: In Panel A, each point on the x-axis represents the initial year of a ten-year rolling window used to estimate the correlation between the actual and projected workforce aging at the firm level. For example, the point labeled 1985 corresponds to regressions on the change from 1985 to 1995. The dependent variable is the Δ_{10} share of workers aged 51-60 (actual workforce aging), while the main explanatory variable is the difference between the share of workers aged 41-50 and the share of workers aged 51-60 at baseline (projected workforce aging). This regression is the first stage of the 2SLS Equation (4). Controls include firm age, firm size, and province fixed effects, all observed at baseline. Firm-level values for year x are computed as three-year averages over x and $x+2$. The sample includes firms that employed (i) at least one U35 worker in both baseline year t and endline year $t+10$, and (ii) at least one worker over 40 at baseline. Panel B shows the tenure distribution of workers who were between 41 and 50 years old in 1985 in Italy. The distribution of tenure is censored at 10 years. The sample includes the same subset of firms used to estimate the 1985 coefficient in Panel A.
Source: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

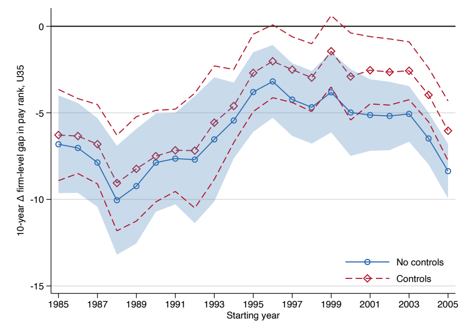
Figure A5: Robustness Checks, Rolling 10-Year Regressions



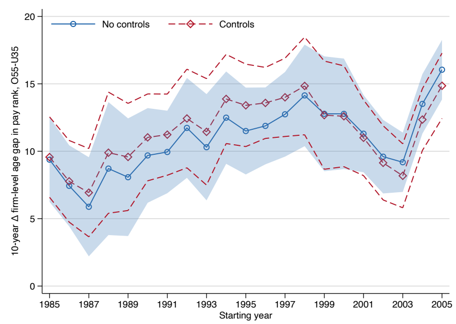
Panel A: 2SLS, U35 workers
Log weekly wages



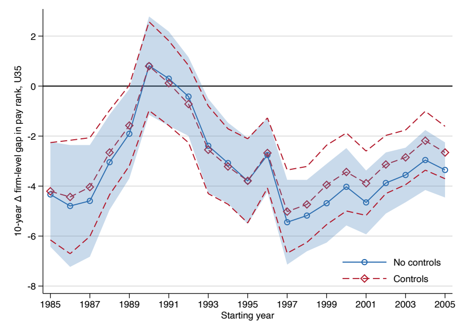
Panel B: 2SLS, O55-U35
Log weekly wages



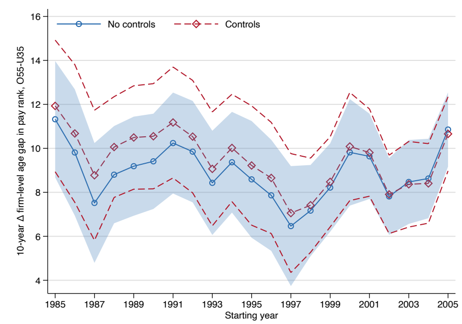
Panel C: 2SLS, U35 workers
$\Delta_{10} s_f^{(56-64)}$



Panel D: 2SLS, O55-U35
$\Delta_{10} s_f^{(56-64)}$



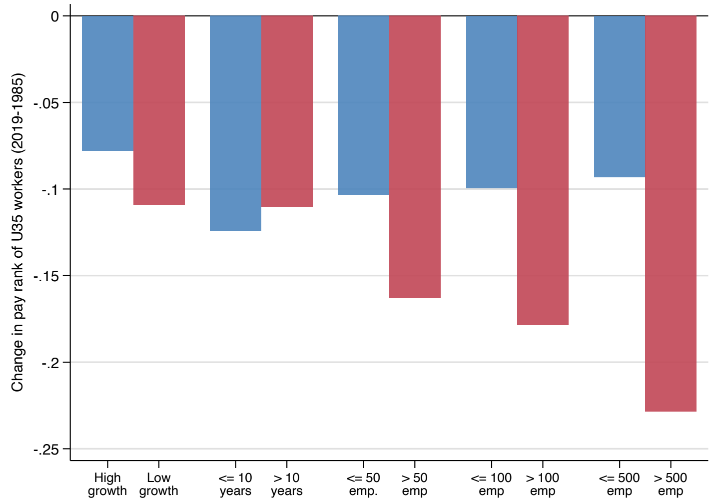
Panel E: 2SLS, U35 workers
Firms $\geq$ 6 employees



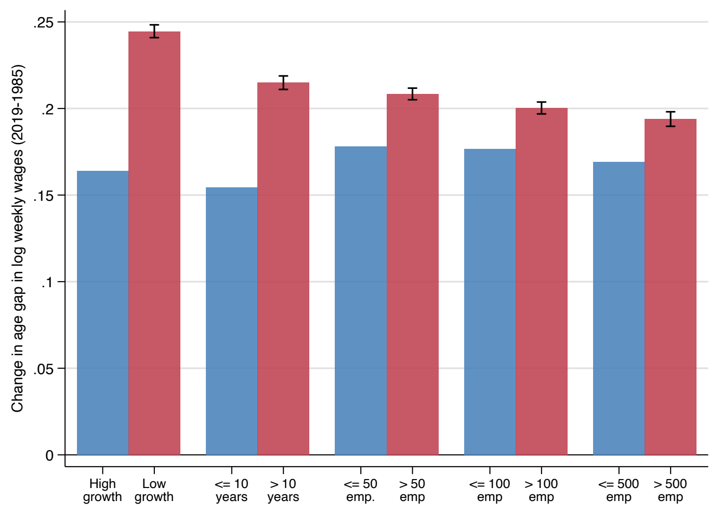
Panel F: 2SLS, O55-U35
Firms $\geq$ 6 employees

Notes: This figure shows three robustness checks for the 2SLS estimation of Equation (4). In Panels A and B, the dependent variables are measured in log weekly wages, rather than in percentiles of each firm's pay distribution. In Panels C and D, the endogenous variable becomes the change in the share of workers aged 56 to 64 between t and $t + 10$ ($\Delta_{10} s_f^{(56-64)}$), while the instrument changes accordingly to $\widetilde{\Delta}_{10} s_f^{(56-64)} = \left(s_{f,t}^{(46-55)} - s_{f,t}^{(56-64)}\right)$. In Panels E and F, we limit the sample to firms with at least six employees at time t. *Source*: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure A6: Age Pay Gap Across Different Firms



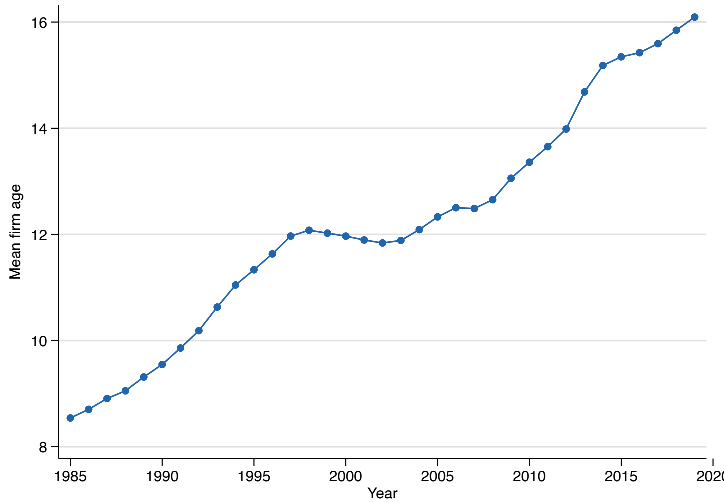
Panel A: Change in pay rank of U35 workers



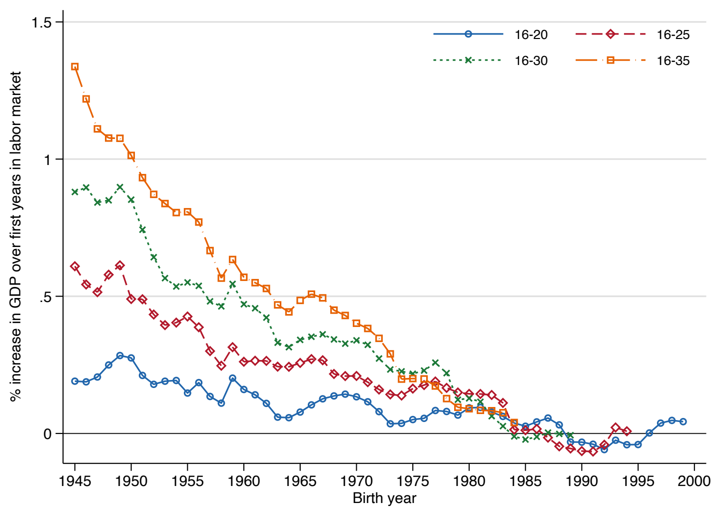
Panel B: Change in age pay gap

Notes: Panel A shows the change in the pay rank of U35 workers in the distribution of log weekly wages (Equation (2)) across different categories of firms. "High growth" and "Low growth" refer to firms' rates of workforce growth. We first compute the mean yearly employment growth within a three-year window (from $t - 3$ to t) for each firm and year in the sample. Firms with below-median mean employment growth are categorized as low-growth firms, while firms with above-median mean employment growth are categorized as high-growth firms. We also divide firms based on their age and workforce size. Panel B repeats the same analysis for the total change in the age pay gap between O55 workers and U35 workers. For each firm categorization, the vertical bars indicate 95-percent confidence intervals of the difference between the two group means. *Source:* In each year, the data pool information about all workers who were at least 16 years old, had worked at least six months, had earned strictly positive wages, had full-time contracts, and had not retired by December 31. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure A7: Firm Aging and GDP Growth



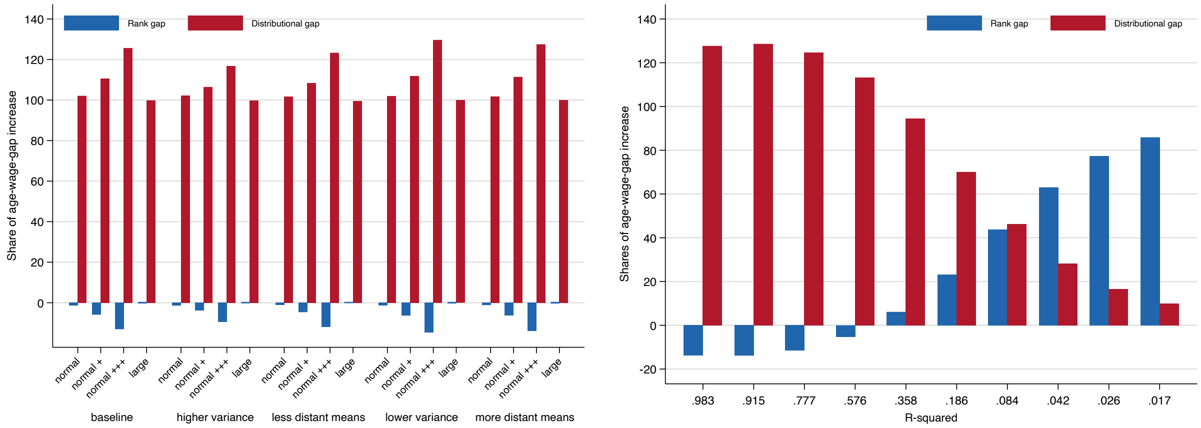
Panel A: Mean firm age



Panel B: GDP growth at labor-market entry

Notes: Panel A plots the mean age of firms between 1985 and 2019. Firm age is not right-censored at the beginning of the sample, because the foundation year is known even when it predates the start of the Italian Social Security data. Panel B computes the cumulative percentage change in GDP (in 2010 USD) over the first years in the labor market for individuals born in different years. For example, the data point for the variable "16-20" and birth year 1945 represents the percentage growth in GDP between 1961 (when individuals born in 1945 were 16 years old) and 1965 (when individuals born in 1945 were 20 years old).
Source for Italy: In each year, the data pool information about all workers who were at least 16 years old, had worked at least six months, had earned strictly positive wages, had full-time contracts, and had not retired by December 31. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for GDP data*: World Development Indicators by the World Bank, available online at https://databank.worldbank.org/reports.aspx?source=2&series=NY.GDP.MKTP.CD&country=, last accessed on April 21, 2023.

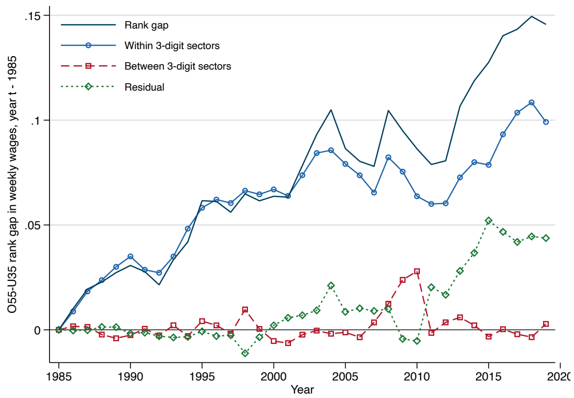
Figure A8: Simulating an Increase in Returns to Experience and High-Level Skills



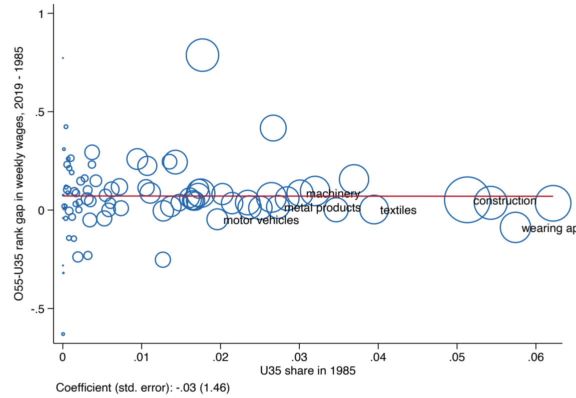
Panel A: $\sigma_\varepsilon^2 = 0$ Panel B: $\sigma_\varepsilon^2 > 0$

Notes: Wage in period t is computed using the following equation: $w_{i,a}^t = \beta_0 + \beta_1^t x_{i,a}^t + \varepsilon_i^t$. Under the baseline scenario, the variable x is distributed across younger (Y) and older (O) workers as follows: $x_{\mathrm{Y}}^t \sim N(4.9, 0.16)$ and $x_{\mathrm{O}}^t \sim N(5.1, 0.36)$. The share of older workers at t is 9 percent, while $\varepsilon_i^t \sim N(0, \sigma_\varepsilon^2)$. We chose this calibration to match five moments in the first available year of the Italian administrative data: the mean (5.9) and standard deviation (0.4) of the log weekly wages of U35 workers, the mean (6.1) and standard deviation (0.6) of the log weekly wages of O55 workers, and the ratio between O55 workers and U35 workers (0.09). In Panel A, $\sigma_\varepsilon^2 = 0$. The graph shows five scenarios and four simulations for each scenario. Under scenario "higher variance," the distributions of x have higher variance: $x_{\mathrm{Y}}^t \sim N(4.9, 0.20)$, $x_{\mathrm{O}}^t \sim N(5.1, 0.42)$ and $x_{\mathrm{Y}}^t \sim N(4.95, 0.16)$. Under scenario "less distant means," the difference in the means of x between younger (Y) and older (O) is smaller: $x_{\mathrm{Y}}^t \sim N(4.95, 0.16)$ and $x_{\mathrm{O}}^t \sim N(5.1, 0.36)$. Under scenario "lower variance," the distributions of x have lower variance: $x_{\mathrm{Y}}^t \sim N(4.9, 0.12)$ and $x_{\mathrm{O}}^t \sim N(5.1, 0.30)$. Under scenario "more distant means," the difference in the means of x is bigger: $x_{\mathrm{Y}}^t \sim N(4.85, 0.16)$ and $x_{\mathrm{O}}^t \sim N(5.1, 0.36)$. For each scenario, Panel A shows four simulations. "Normal" simulates an increase in β_1^t from 1 to 1.5. "Normal +" simulates the same increase in β_1^t and allows the share of older people to increase to 20 percent. "Normal +++" simulates the same increase in β_1^t and allows the share of older people to increase to 35 percent. "Large" simulates an increase in β_1^t from 1 to 2.5. For each simulation, Panel A calculates the increase in the age pay gap, and decomposes it using Equation (E.2). In Panel B, $\sigma_\varepsilon^2 > 0$. Under the "Baseline" scenario and the "Normal" simulation, Panel B shows the results of the decomposition in Equation (E.2) when the standard deviation σ_ε is allowed to increase from 0.05 to 0.5 in 0.05 increments. In this case, the standard deviations of x_{Y}^t and x_{O}^t decrease accordingly, until they reach 0.01. The x-axis shows the R^2 from the regressions of $w_{i,a}^t$ on $x_{i,a}^t$ for different values of σ_ε. All simulations were performed on 2,000,000 observations.

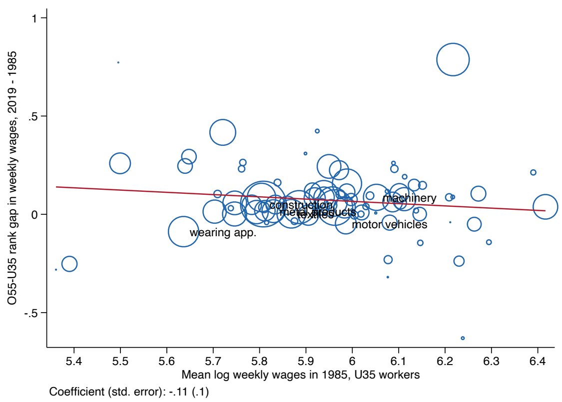
Figure A9: Sectoral and Occupational Shifts



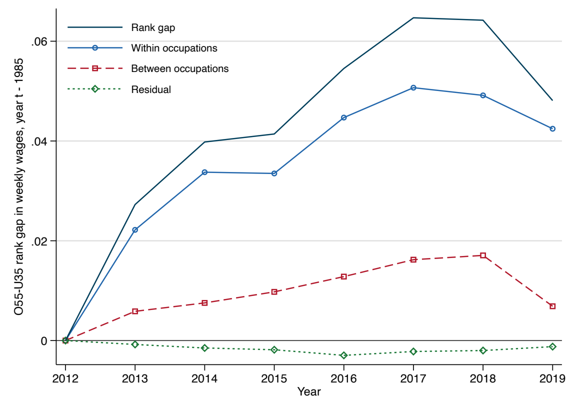
Panel A: Between and within
three-digit sectors



Panel B: Rank gap's increase
by U35 workers' share in 1985



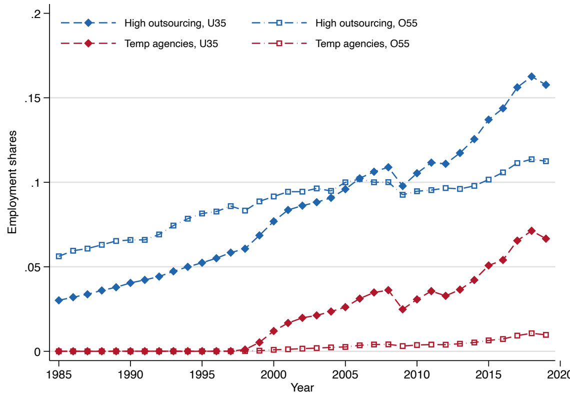
Panel C: Rank gap's increase by U35 workers'
mean log weekly wage in 1985



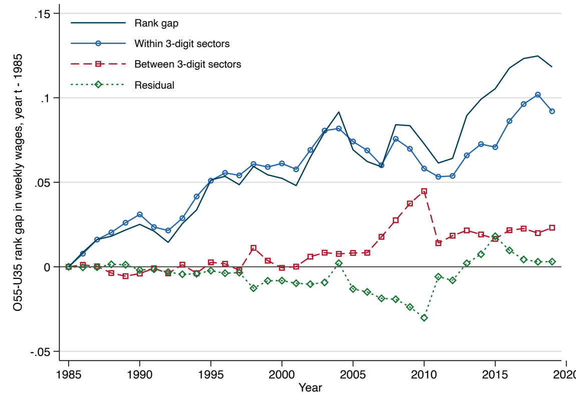
Panel D: Between and within
one-digit ISCO-08 occupations

Notes: In Panel A, the increase in rank gap in log weekly wages between O55 workers and U35 workers and between year *t* and 1985 is decomposed between and within three-digit sectors. Panel B plots the increase in the age gap in each two-digit sector against the sector-level share of U35 workers in 1985. Panel C plots the increase in the age gap in each two-digit sector against the sector-level mean log weekly wage of U35 workers in 1985. In Panels B and C, the size of each data point reflects the overall employment share (including both U35 workers and O55 workers) in each sector at baseline. Panel D shows the decomposition of the rank gap's increase between and within one-digit occupations. The ten one-digit occupations follow the categorization prepared by the International Standard Classification of Occupations (ISCO-08). In this panel, the analysis starts in 2012, the first year with occupation data.
Source: In each year, the data pool information about all workers who were at least 16 years old, had worked at least six months, had earned strictly positive wages, had full-time contracts, and had not retired by December 31. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (Italy).

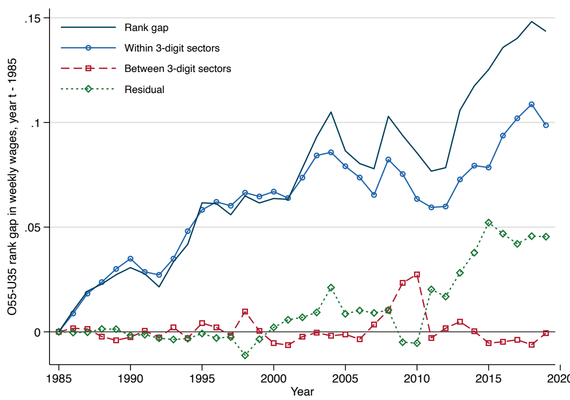
Figure A10: Domestic Outsourcing



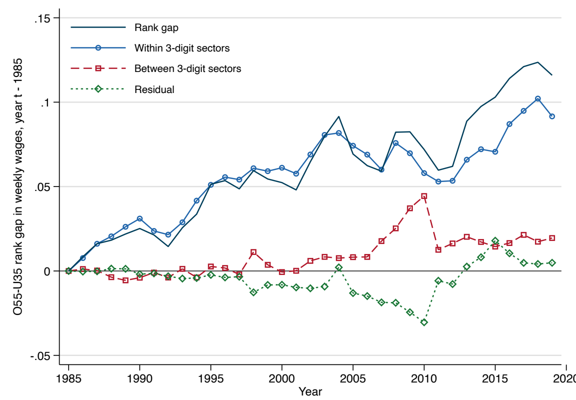
Panel A: Employment shares in high-outsourcing sectors



Panel B: Between and within three-digit sectors, no high-outsourcing sectors



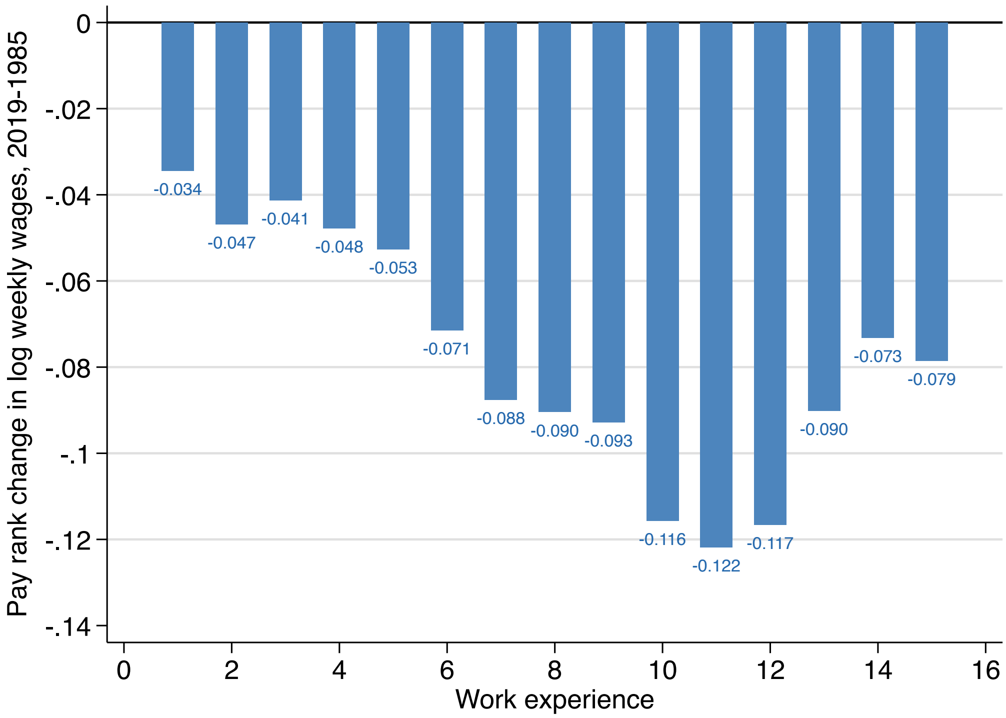
Panel C: Between and within three-digit sectors, no sales of business units



Panel D: Between and within three-digit sectors, no high-outsourcing sectors and sales of business units

Notes: Panel A shows the employment shares of U35 and O55 workers in three-digit sectors identified by Goldschmidt and Schmieder (2017) as being highly exposed to domestic outsourcing. "High-outsourcing" sectors are food, cleaning, security, logistics, and temp agencies (Table A-5 in Goldschmidt and Schmieder (2017)). The three-digit (NACE Rev. 2) corresponding codes are: 49.2, 49.4, 50.2, 50.4, 51.2, 52.1, 52.2, 56.2, 78.1, 78.2, 78.3, 80.1, 80.2, 80.3, 81.1, 81.2, 82.1, 82.2, 82.9. "Temp agencies" are sectors 78.1, 78.2, and 78.3. Panel B shows the decomposition of the rank gap's increase between and within three-digit sectors, excluding all high-outsourcing sectors and temp agencies. Panel C performs the same analysis, dropping all workers employed by firms that have sold at least one business unit (*cessione di ramo d'azienda* in Italian). Panel D drops high-outsourcing sectors, temp agencies, and all workers employed by firms that have sold at least one business unit.
Source: In each year, the data pool information about all workers who were at least 16 years old, had worked at least six months, had earned strictly positive wages, had full-time contracts, and had not retired by December 31. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (Italy).

Figure A11: Change in Pay Rank By Experience, U35 Workers



Notes: Each line shows the change in the pay rank (Eq. (2)) of log weekly wages between 1985 and 2019 for U35 workers with varying levels of work experience.
Source: In each year, the data pool information about all workers who were at least 16 years old, had worked at least six months, had earned strictly positive wages, had full-time contracts, and had not retired by December 31. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table A1: Workforce Aging and Age Pay Gap

	Change in mean worker age		Level and change in age pay gap at the mean						Change in age pay gap at various percentiles				
	last y. - first y.		first year	2007 - first y.	2013 - first y.	last year - first year			last year - first year				
	Δ years	Δ %	pay gap (log)	Δ pay gap (log)	Δ pay gap (log)	Δ pay gap (log)	Rank gap (%)	Distr. gap (%)	Perc. 10 (log)	Perc. 25 (log)	Median (log)	Perc. 75 (log)	Perc. 90 (log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Panel A: Employer-employee administrative data													
Italy (1985-2019)	6.87	19.21	0.192	0.115	0.164	0.185	78.32	17.52	0.192	0.100	0.143	0.245	0.190
Germany (1996-2017)	3.44	8.67	0.282	0.201	0.127	0.101	55.83	28.04	0.010	0.340	0.100	-0.010	-0.020
Panel B: Survey data from the Luxembourg Income Study (LIS) Database													
Australia (1995-2018)	5.66	16.22	0.039	0.166	0.183	0.177	80.01	7.23	-0.008	0.086	0.211	0.153	0.132
Canada (1973-2018)	0.92	2.38	0.056	0.384	0.314	0.273	77.19	4.63	0.383	0.314	0.246	0.270	0.246
Denmark (1987-2018)	6.46	17.36	0.157	0.252	0.321	0.267	105.62	0.12	0.467	0.331	0.165	0.159	0.182
Finland (1987-2016)	6.81	19.00	0.153	0.088	0.116	0.111	106.59	2.12	0.244	0.066	0.056	0.077	0.126
France (2002-2018)	2.24	5.74	0.374	0.062	0.002	0.029	40.36	45.44	0.260	0.062	-0.014	-0.041	-0.037
Germany (1994-2018)	3.77	9.82	0.448	0.162	0.175	0.084	48.40	48.98	0.030	0.166	0.131	-0.007	0.010
Greece (1995-2016)	2.95	7.51	0.278	0.294	0.218	0.180	100.75	3.40	0.130	0.202	0.202	0.206	0.206
Israel (1979-2018)	-3.16	-7.77	0.046	0.393	0.756	0.700	58.30	8.81	1.404	0.428	0.537	0.579	0.561
Netherlands (1983-2018)	3.40	9.09	0.314	0.380	0.428	0.226	7.69	73.48	0.555	0.259	0.077	-0.022	-0.009
Norway (1986-2016)	4.17	10.68	0.123	0.095	0.139	0.159	77.78	16.86	0.106	0.134	0.095	0.115	0.176
Spain (1993-2018)	4.98	12.88	0.189	0.265	0.330	0.509	60.99	15.56	0.668	0.532	0.391	0.444	0.440
Switzerland (1982-2018)	2.44	6.20	0.131	0.727	0.621	0.481	49.61	7.03	1.415	0.342	0.169	0.184	0.167
United Kingdom (1979-2018)	3.21	8.66	0.103	0.044	0.134	0.042	15.24	51.81	-0.182	-0.099	0.004	0.147	0.313
United States (1979-2018)	4.51	11.91	0.222	0.144	0.176	0.136	89.00	19.93	0.144	0.145	0.125	0.131	0.153

Notes: Columns 1 and 2 present the change in mean worker age. Column 3 shows the level of the age pay gap, defined as the difference in mean log wages between O55 workers and U35 workers, at baseline. In the case of Canada, Finland, and Israel, the older workers are classified as 55 years old or older, rather than older than 55 years old (due to the aggregation of the age variable in bins). The next columns show the age pay gap's growth between the first available year for each country and 2007 (column 4; 2008 for AUS), 2013 (columns 5; 2014 for AUS), or the last available year for each country (column 6). Columns 7 and 8 refer to the decomposition in Equation (E.2). Columns 9 to 13 show the change in the age pay gap at different percentiles. Appendix B and Table 1 provide more information about the wage variable and the sample restrictions in each country. *Source for Italy:* Database UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for Germany:* LIAB Linked Employer-Employee Dataset provided by the Institute for Employment Research. Details on the construction of these samples are in Appendix B.2. *Source for LIS data:* Luxembourg Income Study (LIS) Database, which we last accessed on 04/14/2023 at https://www.lisdatacenter.org/. More details are in Appendix B.3.

Table A2: Firm-Level Workforce Aging, Three 10-Year Periods

	U35 workers' pay rank				Age pay rank gap			
	OLS		2SLS		OLS		2SLS	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: 1985-1995								
$\Delta_{10}s_f^{(51-60)}$	-1.29***	-0.94**	-6.13***	-5.95***	5.44***	5.85***	12.02***	12.58***
	(0.47)	(0.47)	(0.95)	(0.89)	(0.72)	(0.72)	(0.94)	(1.04)
KP F-stat			2,005	2,005			4,010	4,356
Mean dep. var.	0.03	0.03	0.03	0.03	2.62	2.62	2.62	2.62
SD dep. var.	17.37	17.37	17.37	17.37	21.48	21.48	21.48	21.48
Mean $\Delta_{10}s_f^{(51-60)}$	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
SD $\Delta_{10}s_f^{(51-60)}$	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16
Mean $\widetilde{\Delta}_{10}s_f^{(51-60)}$	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
SD $\widetilde{\Delta}_{10}s_f^{(51-60)}$	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Obs.	101,204	101,204	101,204	101,204	50,602	50,602	50,602	50,602
Panel B: 1995-2005								
$\Delta_{10}s_f^{(51-60)}$	-1.86***	-1.77***	-3.70***	-3.49***	4.75***	4.99***	8.67***	9.43***
	(0.47)	(0.46)	(0.68)	(0.68)	(0.71)	(0.72)	(1.01)	(1.02)
KP F-stat			4,413	4,413			8,827	10,187
Mean dep. var.	1.56	1.56	1.56	1.56	2.29	2.29	2.29	2.29
SD dep. var.	17.23	17.23	17.23	17.23	22.09	22.09	22.09	22.09
Mean $\Delta_{10}s_f^{(51-60)}$	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
SD $\Delta_{10}s_f^{(51-60)}$	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16
Mean $\widetilde{\Delta}_{10}s_f^{(51-60)}$	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
SD $\widetilde{\Delta}_{10}s_f^{(51-60)}$	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Obs.	105,932	105,932	105,932	105,932	52,966	52,966	52,966	52,966
Panel C: 2005-2015								
$\Delta_{10}s_f^{(51-60)}$	-1.45***	-0.96***	-3.53***	-2.62***	6.57***	6.35***	11.36***	11.03***
	(0.32)	(0.33)	(0.44)	(0.45)	(0.66)	(0.67)	(0.76)	(0.77)
KP F-stat			23,226	23,226			46,452	47,348
Mean dep. var.	-2.14	-2.14	-2.14	-2.14	2.41	2.41	2.41	2.41
SD dep. var.	18.23	18.23	18.23	18.23	23.31	23.31	23.31	23.31
Mean $\Delta_{10}s_f^{(51-60)}$	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09
SD $\Delta_{10}s_f^{(51-60)}$	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17
Mean $\widetilde{\Delta}_{10}s_f^{(51-60)}$	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
SD $\widetilde{\Delta}_{10}s_f^{(51-60)}$	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Obs.	138,124	138,124	138,124	138,124	69,062	69,062	69,062	69,062
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Notes: This table highlights three ten-year regressions (1985-1995, 1995-2005, and 2005-2015) from Figure 6.
Source: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table A3: Age Pay Gap and Workforce Composition

	Baseline		Gender		Nationality		Contract length		Education		Disability		All		U35 vs. 56-60	
	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: Employer-employee administrative data																
Italy (1985-2019)	0.185	78.32	0.243	79.15	0.168	79.77	0.124	81.70	-	-	-	-	0.161	83.51	0.181	74.12
Germany (1996-2017)	0.101	55.83	0.112	64.79	0.093	58.48	-	-	0.137	25.59	-	-	0.146	35.02	0.133	73.10
Panel B: Survey data from the Luxembourg Income Study (LIS) Database																
Australia (1995-2018)	0.177	80.01	0.201	82.39	0.182	79.02	-	-	-	-	-	-	0.235	82.71	0.159	80.75
Canada (1973-2018)	0.273	77.19	0.323	74.95	0.293	77.92	-	-	0.271	76.03	-	-	0.309	72.70	0.302	72.56
Denmark (1987-2018)	0.267	105.62	0.281	98.71	0.237	108.27	-	-	0.263	107.41	-	-	0.239	102.50	0.297	104.57
Finland (1987-2016)	0.111	106.59	0.110	100.08	-	-	-	-	0.107	102.94	0.104	99.26	0.039	99.30	0.092	107.71
France (2002-2018)	0.029	40.36	0.033	42.79	0.034	48.93	-0.023	171.84	0.043	137.79	-	-	-0.026	5.82	0.001	30.08
Germany (1994-2018)	0.084	48.40	0.117	57.88	0.077	40.25	-0.028	182.60	0.113	67.15	0.101	83.07	0.058	54.72	0.129	63.89
Greece (1995-2016)	0.180	100.75	0.248	93.33	0.179	105.25	-	-	0.201	100.91	-	-	0.177	97.43	0.190	101.76
Israel (1979-2018)	0.700	58.30	0.745	57.67	-	-	-	-	0.602	61.87	-	-	0.612	60.79	0.639	54.99
Netherlands (1983-2018)	0.226	7.69	0.277	24.17	-	-	-	-	0.312	25.84	-	-	0.215	34.31	0.237	13.21
Norway (1986-2016)	0.159	77.78	0.178	64.62	-	-	-	-	0.178	76.84	0.139	76.45	0.166	57.48	0.123	68.95
Spain (1993-2018)	0.509	60.99	0.535	62.87	0.447	62.20	-	-	0.506	56.85	0.498	66.88	0.282	57.72	0.467	58.24
Switzerland (1982-2018)	0.481	49.61	0.472	53.87	0.442	53.61	-	-	-	-	-	-	0.304	54.68	0.355	28.05
United Kingdom (1979-2018)	0.042	15.24	0.093	51.95	-	-	-	-	-	-	0.046	98.83	0.142	50.52	0.035	10.65
United States (1979-2018)	0.136	89.00	0.163	78.08	0.112	94.02	-	-	0.111	100.39	-	-	0.127	82.41	0.098	88.36

Notes: "Gender" refers to a regression of log wages on a male dummy and calculates the age pay gap using the residuals from these regressions. "Nationality" uses a dummy for nonimmigrant workers as a regressor (a dummy for white workers in the United States is used instead to control for race). "Contract length" controls for temporary contracts. "Education" controls for college education. "Disability" controls for disability status. "All" simultaneously controls for all available worker characteristics in each country. "U35 vs. 56-60" computes the age pay gap between male workers aged between 56 and 60 and U35 workers. In the case of Canada, Finland, and Israel, the older workers are 55 years old or older, rather than older than 55 years old (due to the aggregation of the age variable in bins).
Source for Italy: Database UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for Germany:* LIAB Linked Employer-Employee Dataset provided by the Institute for Employment Research. *Source for survey data:* Luxembourg Income Study (LIS) Database, which we last accessed on 04/14/2023 at https://www.lisdatacenter.org/.

Table A4: Men's Minimum Pensionable Age At Baseline

	Men's minimum pensionable age (1)	Data source (2)
Australia (1995-2018)	65 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089
Canada (1973-2018)	68 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089
Denmark (1987-2018)	67 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089
Finland (1987-2016)	65 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089
France (2002-2018)	60 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089
Germany (1994-2018)	63 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089
Greece (1995-2016)	57 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089
Israel (1979-2018)	65 years	https://www.oecd.org/els/public-pensions/PAG2013-profile-Israel.pdf
Italy (1985-2019)	55 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089
Netherlands (1983-2018)	65 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089
Norway (1986-2016)	67 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089
Spain (1993-2018)	65 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089
Switzerland (1982-2018)	65 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089
United Kingdom (1979-2018)	65 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089
United States (1979-2018)	65 years	Table 1.1, OECD's Pension at a Glance 2011, http://dx.doi.org/10.1787/888932372089

Notes: For each country, the table shows men's minimum pensionable age in the first available year of data. The main source is Table 1.1. from OECD's Pension at a Glance 2011, available online at http://dx.doi.org/10.1787/888932372089 (last accessed on May 11, 2023). Pensionable age is defined "as the age at which people can first draw full benefits (that is, without actuarial reduction for early retirement). (p.20)"

B Data Appendix

B.1 Italian Administrative Data

We use data on the Italian labor market between 1985 and 2019 provided by the Italian Social Security Institute (INPS). This dataset consists of matched employer–employee records for the whole population of private-sector, nonagricultural firms with at least one salaried employee. The dataset combines individual-level information about workers, such as age and other demographic characteristics, wage, and type of contract (full-time vs. part-time, open-ended vs. temporary), with information about the firm, such as sector, location, and age.

This dataset could be extended to include all years between 1974 and 1984 at the expense of having more limited information on the matching between workers and firms. Because the empirical analysis relies on having detailed information on the matching between workers and firms, we decided to focus on the post-1985 years. Figure B1 shows that the increase in the age pay gap followed a similar trend just before and after 1985, indicating that the exclusion of the earlier years is not likely to bias the analysis.

The INPS dataset represents a comprehensive summary of all the labor-market events that happened during a calendar year. For example, for the workers who moved to a different firm, the dataset displays two rows in the year of their move: one describes the contract with the "old" firm they left, while the other describes the contract with the "new" firm they joined. Similarly, for workers who received major internal promotions, the dataset displays two rows in the year of their promotions: one describes the contract with the "old" pre-promotion position, while the other describes the contract with the "new" post-promotion position.

For the purpose of the analysis, we need to reduce this very rich dataset with multiple worker-year observations to a more streamlined dataset with unique worker-year pairings. As it is common in this branch of the literature, we always keep the information associated with the spell with the highest wage.

Moreover, we restrict each year of data to workers who (i) were at least 16 years old, (ii) had worked at least six months, (iii) had earned strictly positive wages, (iv) held full-time contracts, and (v) did not retire within that year. We impose these restrictions to weed out workers with very short-lived job spells.

Next, we create two main wage variables. First, we create the total yearly labor earnings by summing the wages of all working spells associated with each worker in a year. In other words, although we process the data by retaining only the spell with the highest wage, the yearly earnings pool information from all working spells that are available in the raw employer-employee data. Second, we create a variable that is closer to pay rates: weekly wages. We compute them by dividing the labor earnings by the number of weeks in which each employee worked. The number of working weeks is a core input in the computation of the yearly contributions owed by each worker to Social Security. Therefore, this variable tends to have a low incidence of missing values and measurement errors. The weekly-wage variable uses information that comes exclusively from the working spell that we retained, that is, the spell with the highest wage during the year. Both measures of labor earnings are expressed in 2015 euros using the conversion tables prepared by the OECD.[23]

Unlike many administrative data providers in other countries, INPS does not winsorize earnings above the Social Security earnings maximum. The consequence is that the distribution of wages tends to be fairly skewed due to the presence of extreme outliers. For this reason, we winsorize both weekly wages and yearly earnings at the 99.9th percentile. Even after this winsorization, yearly earnings have very low values on the left tail of their distribution, indicating that our previous process was not able to weed out all short and inconsequential working spells. For this reason, we cap the minimum yearly earnings at €3,000 in real terms.

B.2 German Administrative Data

The data on the German labor market are available between 1996 and 2017 and are provided by the Research Data Centre (FDZ) of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB). We employ the Linked Employer-Employee Data from the *LIAB Cross-Sectional Model 2* (LIAB).[24] This dataset combines information from the IAB Establishment Panel with information from the Integrated Employment Biographies (IEB).[25] The former is an annual representative survey of establishments, while the latter contains information on all workers subject to

[23] The tables can be downloaded from https://web.archive.org/web/20201109004157/https://data.oecd.org/price/inflation-cpi.htm.

[24] Documentation can be fount at https://fdz.iab.de/en/Integrated_Establishment_and_Individual_Data/LIAB.aspx.

[25] Documentation on the IAB Establishment Panel is available at https://fdz.iab.de/en/FDZ_Establishment_Data/IAB_Establishment_Panel/IABBP_9319.aspx.

Social Security taxation. The LIAB dataset matches the individual biographies from the IEB to the sample of surveyed establishments in the IAB Establishment Panel.[26]

The LIAB has two important characteristics. First, information on employment and wages is available every year for the single reference date of June 30th. Therefore, the data represents a static snapshot of the labor market, rather than a comprehensive summary of all labor-market events. Second, although the data is available starting in 1993, the IAB Establishment Panel covers both East and West Germany starting only in 1996. For this reason, we focus on the period between 1996 and 2017 to avoid creating inconsistent time series.

For the purpose of our analysis, we have access to the variables coming from the Employee-History (BeH) module, which collects annual and end-of-employment notifications submitted to the Social Security Agencies about employees covered by Social Security and employees in marginal part-time employment. Information on temporary contract workers is available only starting in 2011.

To create a dataset that is as close as possible to the Italian one, we select employees who (i) were between 16 years old and 75 years old, (ii) had a full-time contract, and (iii) had earned strictly positive wages.[27] These restrictions reduce the sample from 12,451,266 workers to 8,865,294 workers.

As we discussed in Section B.1 for the Italian data, workers may appear more than once in a given year if they worked for more than one firm. We reduce the data to a single observation per worker in each year using the following procedure. For each worker, we compute earnings in a given job spell, multiplying the daily wage by the number of tenure days accumulated in the first semester of the year. We then select for each worker the job spell with the highest earnings in the year, and we attribute to the worker the daily wage earned in that spell. It should be noted that nominal earnings are top-coded at the Social Security earnings maximum, the threshold over which contributions to the Social Security are not owed. The cap varies from year to year, but is usually close to the 95th percentile. Finally, daily wages are expressed in 2015 euros using the conversion tables prepared by the OECD.

B.3 Survey Data for Other Countries

In this section, we provide more information about the survey data used to measure the age pay gap in all other countries. The data source is the Luxembourg Income Study (LIS) database, which we last accessed on April 14, 2023 at `https://www.lisdatacenter.org/`. The LIS database aggregates and harmonizes heterogeneous survey data from many different countries. A full list of the original data sources is in the notes of Table 1. Out of all the available countries in the LIS database, we focus on fourteen high-income economies with sufficiently long time series, a large number of observations, and stable sample sizes: Australia, Canada, Denmark, Finland, France, Germany, Greece, Israel, Netherlands, Norway, Spain, Switzerland, United Kingdom, and United States.[28]

In the analysis, we compute the age pay gap using the only wage variable that is consistently available across survey waves and countries: yearly labor earnings (`pilabour`). Before doing so, we convert nominal yearly labor earnings for all countries to 2011 purchasing-power-parity US dollars, using the conversion tables prepared by LIS (`https://www.lisdatacenter.org/resources/ppp-deflators/?highlight=ppp`).

Whenever possible, we apply the same sample restrictions used on the administrative data from Italy and Germany. Specifically, we restrict each year of data to workers who (i) were at least 16 years old, (ii) had earned strictly positive wages, (iii) were employees, (iv) had a full-time contract, and (v) had worked at least 20 weeks during the year. Restrictions (i) and (ii) can be imposed in every country and year, while restrictions (iii) to (v) require variables that are not available in every country. Table 1 lists all cross-country differences in the construction of the sample.

Finally, it should be noted that the LIS database is structured as repeated cross-sections. Therefore, it is not possible to use the LIS data to follow the same workers over time. Moreover, this data source never matches workers to firms.

B.4 Results Using Non-Italian Data

Changes in the age pay gap. As already discussed in the main text, the age pay gap has widened in all fourteen countries in our sample (Table A1, columns 3 to 8). For instance, the age pay gaps increased by 0.14 log points or 61

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[26] The IAB Establishment Panel covers between 4,265 and 16,000 establishments per year.

[27] Workers who are more than 75 years old are automatically excluded by the data provider.

[28] We initially considered nineteen high-income countries with long time series: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom, and United States. We dropped Austria, Belgium, Ireland, and Italy because they had a small number of U35 and O55 workers in each wave (on average, less than 1,000 people per wave). Moreover, we dropped some early survey waves for Australia, France, Norway, and Spain due to harmonization problems with the more recent years (for these countries, we kept all years that followed the last time their sample size shrank by at least 30 percent from the previous wave).

percent in the United States (1979-2018), by 0.04 log points or 41 percent in the United Kingdom (1979-2018), by 0.17 log points or 46 percent in Canada (1973-2018), and by 0.03 log points or 8 percent in France (2002-2018). Despite a smaller increase by 2018, both the United Kingdom and France saw much larger increases in previous years: the age pay gap increased by 0.13 log points between 1979 and 2013 in the United Kingdom and by 0.06 log points between 2002 and 2007 in France.

Three Scandinavian countries—Denmark, Finland, and Norway—provide interesting case studies. These countries started with very low degrees of disparity between older and younger workers: at baseline (in 1987 for Denmark and Finland and in 1986 for Norway), the age pay gap was only 0.16 log points in Denmark, 0.15 log points in Finland, and 0.12 log points in Norway. In comparison, the age gap between O55 workers and U35 workers in 1987 was equal to 0.27 log points in Italy and 0.25 log points in the United States. However, their age gaps then experienced a steep increase, growing by by 0.27 log points until 2018 in Denmark, by 0.11 log points until 2016 in Finland, and by 0.16 log points until 2016 in Norway.

Importance of pay rank gap. Out of the fourteen countries in our sample, the rank gap accounts for the majority of the increase in ten cases (Table A1, columns 7 and 8). For example, by the last year in the sample, the rank gap constituted 89 percent of the increase in the age pay gap in the United States, 56 percent in Germany (based on the administrative data), and 77 percent in Canada. In short, in most countries in our sample, the majority of the age gap's widening has stemmed from younger workers moving toward the bottom of the wage distribution and older workers moving toward the top, rather than from changes in the shape of the distribution itself.

Entry pay rank and pay rank growth. This analysis requires knowing the year of entry into the labor market for each individuals in the sample. This piece of information is available only in the Italian administrative data. Hence, this analysis can be performed only in Italy.

Firm heterogeneity. In this set of tests, we examine whether the age pay gap has increased more in the firms that possess observable characteristics that are more likely to be associated with difficulties in adding higher-ranked positions. These analyses require a match between workers and firms in the data. Therefore, they cannot be performed with the survey data from LIS because firm information is absent.

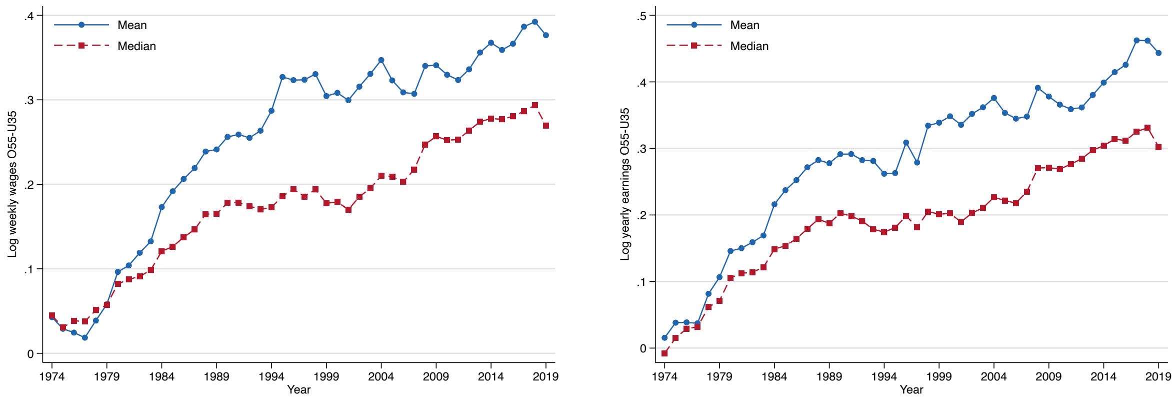
The German administrative data include firm information, but there are some limitations. First, it is not possible to classify all establishments as either high-growth or low-growth firms because the dataset is not a balanced panel. Second, it is not possible to identify older and younger establishments because the foundation year is not known. Therefore, out of the three variables used in the Italian administrative dataset, we can only use workforce size in the German administrative data. The results indicate that the same pattern identified in Italy applies to German firms (Figure B2): the age pay gap has increased significantly more in larger firms.

Finally, establishments do not usually remain in sample for ten years or longer. Hence, it is not possible to use the German admin data to successfully estimate Equation (4).

Distribution between and within firms. As discussed above, these tests cannot be performed with survey data from LIS due to the lack of information on firms. Moreover, the German administrative data comprise a small sample of establishments, a limitation that makes the process of dividing workers into one hundred percentiles based on their employers' mean wages too taxing.

Changes in workforce composition. The Italian administrative data, the German administrative data, and the LIS data all indicate that changes in the observable characteristics of younger and older workers do not seem to be responsible for a meaningful portion of the widening in the age pay gap (Table A3).

Figure B1: The Age Gap in Italy from 1974

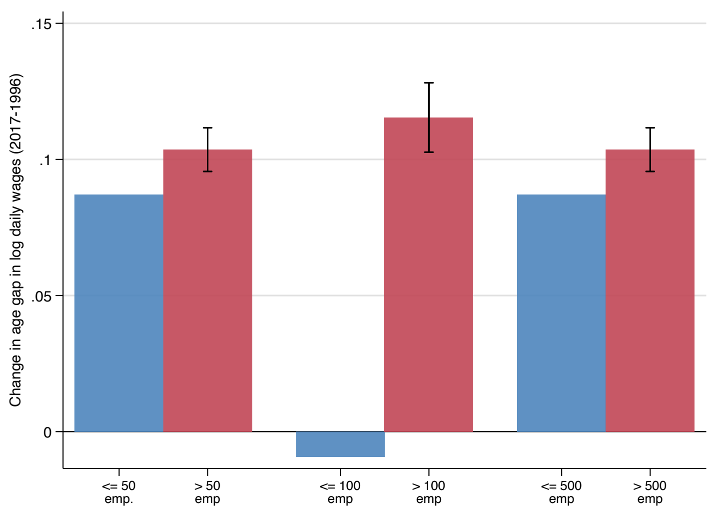


Panel A: Gap in log mean and median weekly wages

Panel B: Gap in log mean and median yearly earnings

Notes: Panel A plots the gap between the log weekly wages of O55 workers and the log weekly wages of U35 workers between 1974 and 2019 for both mean and median wages. Panel B repeats this analysis for yearly labor earnings, rather than for weekly wages.
Source: In each year, the data pool information about all workers who were at least 16 years old, had worked at least six months, had earned strictly positive wages, had full-time contracts, and had not retired by December 31. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (Italy).

Figure B2: Firm Heterogeneity—Germany



Notes: The figure depicts the change in the age pay gap in mean log weekly wages across different firm sizes.
Source: The German data come from the LIAB Linked Employer-Employee Dataset provided by the Institute for Employment Research. Details on the construction of these samples are in Appendix B.2.

Table B1: Empirical Analysis and Data Sources

	Δ pay gap	Pay rank gap vs. distributional gap	Entry pay rank vs. pay rank growth	Firm heterogeneity	Distribution between firms	Workforce composition
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Employer-employee administrative data						
Italy (1985-2019)	Yes	Yes	Yes	Yes	Yes	Yes
Germany (1996-2017)	Yes	Yes	No (no info on entry wage)	Partial	Small sample	Yes
Panel B: Survey data from the Luxembourg Income Study (LIS) Database						
Australia (1995-2018)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes
Canada (1973-2018)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes
Denmark (1987-2018)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes
Finland (1987-2016)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes
France (2002-2018)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes
Germany (1994-2018)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes
Greece (1995-2016)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes
Israel (1979-2018)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes
Netherlands (1983-2018)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes
Norway (1986-2016)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes
Spain (1993-2018)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes
Switzerland (1982-2018)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes
United Kingdom (1979-2018)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes
United States (1979-2018)	Yes	Yes	No (no info on entry wage)	No (no firm info)	No (no firm info)	Yes

Notes: "No (no firm info)" means that the data source does not match workers to firms. "No (no info on entry wage)" means that the data source does not include any information on the entry year of most workers. This missing information prevents us from assigning the initial wage to most workers in the sample. "Partial" is due to the fact that this analysis can be done reliably on the German dataset only with respect to firm size. "Small sample" refers to the fact that the small number of available establishments leads to small firm groups (percentiles based on mean firm pay) and noise in studying changes in the distribution of workers across these firm groups.

C Event Studies of Firm-Level Value-Added Shocks

In this section, we estimate a series of event studies centered around positive and negative firm-level value-added shocks. We then study how the average wages of U35 workers and O55 workers who stayed at these firms for at least two years before and three years after the value-added shock responded to these shocks.

To perform this analysis, we adapt an empirical process described by Lamadon, Mogstad, and Setzler (2022). In each year t between 1998 and 2016, we compute the value-added shock from $t-1$ to t for each firm in the sample. We limit this analysis to the period between 1998 and 2016 because (i) balance-sheet data containing information on value added are available only between 1996 and 2019, and (ii) two years before and three years after each event period are required to study pre-event and post-event trends. Specifically, the value-added shock for firm f is defined as the year-to-year change in value added for firm f minus the average year-to-year change in value added in the province and two-digit sector in which firm f operates.

We then divide firms into tertiles based on their value-added shock in year t. On average, firms in the top tertile experienced a positive 0.18-log-point value-added shock between $t-1$ and t, while firms in the bottom tertile experienced a negative 0.13-log-point shock.

Next, we create event-study panels for each year t by (i) appending data from $t-2$ to $t+3$, (ii) keeping observations only for U35 and O55 workers, and (iii) computing the average log weekly wage and log value-added shock at the firms, age group, and event period level.

Subsequently, we append these datasets and compute the average log weekly wage and value-added shock by tertiles of the distribution of value-added shocks in period 0, age groups, and event periods, weighting each firm-level data point by its number of U35 or O55 workers.

Finally, we compute the change in log wages for U35 and O55 workers that stems from a positive shock, defined as the difference in value-added shock between the top and middle tertiles. Similarly, we measure the wage change stemming for a negative value-added shock, leveraging the difference between the bottom and middle tertiles.

This analysis produces three main findings (Figure A2). First, the data do not show the existence of significant trends in wages before either a positive or a negative value-added shock. In other words, the shocks in period 0 do not seem to be anticipated by wage changes.

Second, as expected, a positive firm-level value-added shock is followed by an increase in average wages, and vice versa.

Third, there are substantial differences in the way in which wages of U35 workers and O55 workers responded to value-added shocks. In the case of a 10-percent positive shock, the wages of O55 workers increased by 0.017 log points by the end of period 3, while the wages of U35 workers increased by only 0.003 log points. In the case of a 10-percent negative shock, the wages of U35 workers decreased by 0.005 log points by the end of period 3, while the wages of U55 workers decreased by only 0.003 log points. In conclusion, the main takeaway is that O55 workers captured a larger share of the positive shocks and were exposed to a smaller share of the negative ones.

D Proofs of the Stylized Framework

Representative firm. The firm problem is

$$\max_{l_{y,b},l_{y,t}} AY\left(L_y, L_o\right) - \sum_{a=y,o}\sum_{j=t,b} w_{a,j}l_{a,j} - \frac{c}{2}K^2.$$

The first order conditions of the firm problem are

$$\begin{cases} AY_{L_y}\theta_{y,b} - w_{y,b} & = 0 \\ AY_{L_y}\theta_{y,t} - \mu_y w_{y,b} - cK & = 0. \end{cases}$$

In equilibrium:

$$\begin{cases} w^*_{y,b} & = AY_{L_y}\theta_{y,b} \\ w^*_{y,t} & = \mu_y AY_{L_y}\theta_{y,b} \\ K^* & = \frac{AY_{L_y}}{c}\left(\theta_{y,t} - \mu_y\theta_{y,b}\right). \end{cases}$$

The expression for K^* shows that $\left(\theta_{y,t} - \mu_y\theta_{y,b}\right) > 0$ to have an interior value of K^*.

Proof of Proposition 1. The bottom wage of younger workers responds to an increase in the number of older workers at the top as follows:

$$\frac{\partial w_{y,b}}{\partial l^{-1}_{o,t}} = A\theta_{y,b}\left(Y_{L_yL_y}\frac{\partial L_y}{\partial l^{-1}_{o,t}} + Y_{L_yL_o}\frac{\partial L_o}{\partial l^{-1}_{o,t}}\right).$$

The derivatives of the efficiency units of younger and older labor with respect to $l^{-1}_{o,t}$ are:

$$\begin{aligned} \frac{\partial L_y}{\partial l^{-1}_{o,t}} &= \theta_{y,t}\left(\frac{\partial K}{\partial l^{-1}_{o,t}} - \rho_t\right) - \theta_{y,b}\left(\frac{\partial K}{\partial l^{-1}_{o,t}} - \rho_t\right) = \left(\theta_{y,t} - \theta_{y,b}\right)\left(\frac{\partial K}{\partial l^{-1}_{o,t}} - \rho_t\right) \\ \frac{\partial L_y}{\partial l^{-1}_{o,t}} &= \theta_{o,t}\rho_t. \end{aligned}$$

We can rewrite the change in wages as follows:

$$\begin{aligned} \frac{\partial w_{y,b}}{\partial l^{-1}_{o,t}} &= A\theta_{y,b}\left(Y_{L_yL_y}\frac{\partial L_y}{\partial l^{-1}_{o,t}} + Y_{L_yL_o}\frac{\partial L_o}{\partial l^{-1}_{o,t}}\right) \\ &= A\theta_{y,b}\left[Y_{L_yL_y}\left(\theta_{y,t} - \theta_{y,b}\right)\left(\frac{\partial K}{\partial l^{-1}_{o,t}} - \rho_t\right) + Y_{L_yL_o}\theta_{o,t}\rho_t\right]. \end{aligned}$$

An increase in the supply of older workers causes negative career spillovers (or crowding out of younger workers from top spots) if $\frac{\partial l_{y,t}}{\partial l^{-1}_{o,t}} = \frac{\partial K}{\partial l^{-1}_{o,t}} - \rho_t < 0$, which implies that the total number of top jobs increases by less than the marginal increase in the supply of older workers at the top. A closer look at the derivative of K with respect to $l_{o,t}^{-1}$ reveals the conditions necessary for this situation to arise:

$$\begin{aligned}
\frac{\partial K}{\partial l_{o,t}^{-1}} &= \frac{A\left(\theta_{y,t}-\mu_y\theta_{y,b}\right)}{c}\left(Y_{L_yL_y}\frac{\partial L_y}{\partial l_{o,t}^{-1}}+Y_{L_yL_o}\frac{\partial L_o}{\partial l_{o,t}^{-1}}\right)\\
&= \frac{A\left(\theta_{y,t}-\mu_y\theta_{y,b}\right)}{c}\left[Y_{L_yL_y}\left(\theta_{y,t}-\theta_{y,b}\right)\left(\frac{\partial K}{\partial l_{o,t}^{-1}}-\rho_t\right)+Y_{L_yL_o}\theta_{o,t}\rho_t\right]\\
&= \underbrace{\frac{A\left(\theta_{y,t}-\mu_y\theta_{y,b}\right)}{c-A\left(\theta_{y,t}-\mu_y\theta_{y,b}\right)Y_{L_yL_y}\left(\theta_{y,t}-\theta_{y,b}\right)}\left[Y_{L_yL_o}\theta_{o,t}-Y_{L_yL_y}\left(\theta_{y,t}-\theta_{y,b}\right)\right]\rho_t}_{\text{Negative career spillovers if }<1}.
\end{aligned}$$

An increase in the supply of older workers limits younger workers' access to top jobs if the cost parameter c is above the following threshold:

$$c>\bar{c}=A\left(\theta_{y,t}-\mu_y\theta_{y,b}\right)Y_{L_yL_o}\theta_{o,t}>0.$$

This inequality indicates that the cost parameter c needs to be higher than the productivity gains for younger workers generated by the complementarity with older workers. The term on the right-hand side is greater than zero because $\left(\theta_{y,t}-\mu_y\theta_{y,b}\right)>0$. Consequently, when c meets the condition above, we can conclude that a larger supply of older workers at the top raises the bottom wage of younger workers:

$$\frac{\partial w_{y,b}}{\partial l_{o,t}^{-1}}=A\theta_{y,b}\left[Y_{L_yL_y}\left(\theta_{y,t}-\theta_{y,b}\right)\left(\frac{\partial K}{\partial l_{o,t}^{-1}}-\rho_t\right)+Y_{L_yL_o}\theta_{o,t}\rho_t\right]>0,$$

because $Y_{L_yL_y}<0$, $\left(\frac{\partial K}{\partial l_{o,t}^{-1}}-\rho_t\right)<0$, and $Y_{L_yL_o}>0$.

When $c>\bar{c}$, a larger supply of older workers at the top creates two opposing forces on the mean wages of younger workers: a negative positional loss and a positive increase in wage levels. To see this point, we consider the derivative of the mean wage of younger workers with respect to the number of older workers in top jobs:

$$\begin{aligned}
\frac{\partial \bar{w}_y}{\partial l_{o,t}^{-1}} &= \frac{\partial\left(\frac{l_{y,b}}{l_y}w_{y,b}+\frac{l_{y,t}}{l_y}w_{y,t}\right)}{\partial l_{o,t}^{-1}}\\
&= \frac{\partial\left(\frac{l_y-l_{y,t}}{l_y}w_{y,b}+\frac{l_{y,t}}{l_y}\mu_y w_{y,b}\right)}{\partial l_{o,t}^{-1}}\\
&= \frac{\partial\left(\frac{1}{l_y}\left(\mu_y-1\right)l_{y,t}w_{y,b}+w_{y,b}\right)}{\partial l_{o,t}^{-1}}\\
&= \underbrace{\frac{1}{l_y}\left(\mu_y-1\right)w_{y,b}\frac{\partial l_{y,t}}{\partial l_{o,t}^{-1}}}_{\text{Career spillovers}<0}+\underbrace{\left[\frac{l_{y,t}}{l_y}\left(\mu_y-1\right)+1\right]\frac{\partial w_{y,b}}{\partial l_{o,t}^{-1}}}_{\text{Wage level}>0}.
\end{aligned}$$

Proof of Proposition 2. Proposition 2 states that firms facing higher difficulties in adding top positions experience greater crowding out of younger workers from top jobs, therefore resulting in a more pronounced widening of the age pay gap.

We can illustrate this point by evaluating the firm's response around the threshold $\bar{c}$. When $c\leq\bar{c}$, more older workers at the top lead to an increase in the number of top slots that is at least equally large. Therefore, there are no positional losses for younger workers. Instead, when $c>\bar{c}$, the number of top jobs does not fully adjust to accommodate an increase in the number of older workers at the top. Thus, there is crowding out of younger workers in top jobs.

Beyond this threshold, we can evaluate the cross derivative of $\frac{\partial K}{\partial l_{o,t}^{-1}}$ with respect to c. We first start by simplifying the notation:

$$\begin{aligned}
B &= A\left(\theta_{y,t} - \mu_y \theta_{y,b}\right) > 0; \\
D &= \left(\theta_{y,t} - \theta_{y,b}\right) > 0; \\
den &= c - A\left(\theta_{y,t} - \mu_y \theta_{y,b}\right) Y_{L_y L_y}\left(\theta_{y,t} - \theta_{y,b}\right) = c - BDY_{L_y L_y} > 0; \\
\bar{c} &= A\left(\theta_{y,t} - \mu_y \theta_{y,b}\right) Y_{L_y L_o} \theta_{o,t} = BY_{L_y L_o} \theta_{o,t} > 0; \\
\frac{\partial Y_{L_y L_o}}{\partial c} &= Y_{L_y L_o L_y} \frac{\partial L_y}{\partial c} + Y_{L_y L_o L_o} \frac{\partial L_o}{\partial c} = Y_{L_y L_o L_y}\left(\theta_{y,t} - \theta_{y,b}\right) \frac{\partial K}{\partial c} = Y_{L_y L_o L_y} D \frac{\partial K}{\partial c}; \\
\frac{\partial Y_{L_y L_y}}{\partial c} &= Y_{L_y L_y L_y} \frac{\partial L_y}{\partial c} + Y_{L_y L_y L_o} \frac{\partial L_o}{\partial c} = Y_{L_y L_y L_y}\left(\theta_{y,t} - \theta_{y,b}\right) \frac{\partial K}{\partial c} = Y_{L_y L_y L_y} D \frac{\partial K}{\partial c}; \\
\frac{\partial K}{\partial c} &< 0.
\end{aligned}$$

Next, the derivative of K with respect to $l_{o,t}^{-1}$ can be expressed as

$$\begin{aligned}
\frac{\partial K}{\partial l_{o,t}^{-1}} &= \frac{A\left(\theta_{y,t} - \mu_y \theta_{y,b}\right)}{c - A\left(\theta_{y,t} - \mu_y \theta_{y,b}\right) Y_{L_y L_y}\left(\theta_{y,t} - \theta_{y,b}\right)} \left[Y_{L_y L_o} \theta_{o,t} - Y_{L_y L_y}\left(\theta_{y,t} - \theta_{y,b}\right)\right] \rho_t \\
&= \frac{B\left(Y_{L_y L_o} \theta_{o,t} - Y_{L_y L_y} D\right) \rho_t}{c - BDY_{L_y L_y}}.
\end{aligned}$$

The cross derivative becomes:

$$
\begin{aligned}
\frac{\partial^2 K}{\partial l_{o,t}^{-1}\partial c} &= \frac{B\rho_t}{(den)^2} \times \left\{ \left[\frac{\partial Y_{L_yL_o}}{\partial c}\theta_{o,t} - \frac{\partial Y_{L_yL_y}}{\partial c} D \right] \times den \right. \\
&\left. - \left(1 - BD\frac{\partial Y_{L_yL_y}}{\partial c} \right) \times \left(Y_{L_yL_o}\theta_{o,t} - Y_{L_yL_y} D \right) \right\} \\
&= \frac{B\rho_t}{(den)^2} \times \left\{ \left[Y_{L_yL_oL_y}\theta_{o,t} D\frac{\partial K}{\partial c} - Y_{L_yL_yL_y} D^2 \frac{\partial K}{\partial c} \right] \times \left(c - BDY_{L_yL_y} \right) \right. \\
&\left. - \left(1 - Y_{L_yL_yL_y} BD^2 \frac{\partial K}{\partial c} \right) \times \left(Y_{L_yL_o}\theta_{o,t} - Y_{L_yL_y} D \right) \right\} \\
&= \frac{B\rho_t}{(den)^2} \times \left\{ Y_{L_yL_oL_y}\theta_{o,t} D\frac{\partial K}{\partial c}\left(c - BDY_{L_yL_y} \right) - Y_{L_yL_yL_y} D^2 \frac{\partial K}{\partial c} c + Y_{L_yL_yL_y} Y_{L_yL_y} BD^3 \frac{\partial K}{\partial c} \right. \\
&\left. - \left(Y_{L_yL_o}\theta_{o,t} - Y_{L_yL_y} D \right) + Y_{L_yL_yL_y} Y_{L_yL_o}\theta_{o,t} BD^2 \frac{\partial K}{\partial c} - Y_{L_yL_yL_y} Y_{L_yL_y} BD^3 \frac{\partial K}{\partial c} \right\} \\
&= \frac{B\rho_t}{(den)^2} \times \left\{ Y_{L_yL_oL_y}\theta_{o,t} D\frac{\partial K}{\partial c}\left(c - BDY_{L_yL_y} \right) - Y_{L_yL_yL_y} D^2 \frac{\partial K}{\partial c} c \right. \\
&\left. - \left(Y_{L_yL_o}\theta_{o,t} - Y_{L_yL_y} D \right) + Y_{L_yL_yL_y} Y_{L_yL_o}\theta_{o,t} BD^2 \frac{\partial K}{\partial c} \right\} \\
&= \frac{B\rho_t}{(den)^2} \times \left\{ Y_{L_yL_oL_y}\theta_{o,t} D\frac{\partial K}{\partial c}\left(c - BDY_{L_yL_y} \right) \right. \\
&\left. - Y_{L_yL_yL_y} D^2 \frac{\partial K}{\partial c}\left(c - BY_{L_yL_o}\theta_{o,t} \right) - \left(Y_{L_yL_o}\theta_{o,t} - Y_{L_yL_y} D \right) \right\} \\
&= \frac{B\rho_t}{(den)^2} \times \left\{ Y_{L_yL_oL_y}\theta_{o,t} D\frac{\partial K}{\partial c}\left(c - BDY_{L_yL_y} \right) - Y_{L_yL_yL_y} D^2 \frac{\partial K}{\partial c}\left(c - \bar{c} \right) \right. \\
&\left. - \left(Y_{L_yL_o}\theta_{o,t} - Y_{L_yL_y} D \right) \right\}.
\end{aligned}
$$

This cross derivative is negative if

$$
\begin{aligned}
& Y_{L_yL_oL_y}\theta_{o,t} D\frac{\partial K}{\partial c}\left(c - BDY_{L_yL_y} \right) \\
& \qquad - Y_{L_yL_yL_y} D^2 \frac{\partial K}{\partial c}\left(c - \bar{c} \right) < Y_{L_yL_o}\theta_{o,t} - Y_{L_yL_y} D \\
& Y_{L_yL_oL_y}\theta_{o,t}\left(c - BDY_{L_yL_y} \right) \\
& \qquad - Y_{L_yL_yL_y} D\left(c - \bar{c} \right) > \frac{Y_{L_yL_o}\theta_{o,t} - Y_{L_yL_y} D}{D\frac{\partial K}{\partial c}} \\
& Y_{L_yL_oL_y}\theta_{o,t}\left(c - A\left(\theta_{y,t} - \mu_y\theta_{y,b} \right)\left(\theta_{y,t} - \theta_{y,b} \right) Y_{L_yL_y} \right) \\
& \qquad - Y_{L_yL_yL_y}\left(\theta_{y,t} - \theta_{y,b} \right)\left(c - \bar{c} \right) > \frac{Y_{L_yL_o}\theta_{o,t} - Y_{L_yL_y}\left(\theta_{y,t} - \theta_{y,b} \right)}{\left(\theta_{y,t} - \theta_{y,b} \right)\frac{\partial K}{\partial c}} < 0.
\end{aligned}
$$

The third derivatives of the production function, which control how the degree of complementarity between younger and older workers and the degree of substitutability among younger workers change with L_y, play an important role in this inequality.

Proposition 1 with changes in retention rate and economic growth. Here, we demonstrate that an increase in the retention rate of older workers at the top and a decline in the economy-wide economic growth rate generate similar consequences for the mean wage of younger workers. Starting from an increase in the retention rate of older workers at the top, we derive that the bottom wage of younger workers change as follows:

$$\frac{\partial w_{y,b}}{\partial \rho_t} = A\theta_{y,b}\left[Y_{L_yL_y}\left(\theta_{y,t}-\theta_{y,b}\right)\left(\frac{\partial K}{\partial \rho_t}-l_{o,t}^{-1}\right)+Y_{L_yL_o}\theta_{o,t}l_{o,t}^{-1}\right].$$

An increase in the supply of older workers causes negative career spillovers (or crowding out of younger workers from top spots) if $\frac{\partial l_{y,t}}{\partial \rho_t} = \frac{\partial K}{\partial \rho_t} - l_{o,t}^{-1} < 0$, which holds when $c > A\left(\theta_{y,t}-\mu_y\theta_{y,b}\right)Y_{L_yL_o}\theta_{o,t}$. This is identical to the condition derived for an increase in the number of older workers at the top.

Furthermore, we can model c as a decreasing function of the economic growth rate: $c(g)$ with $c'(g) < 0$. Under the condition outlined above, a decline in g increases c and, therefore, lowers the response of K to a larger supply of older workers at the top, leading to more crowding out of younger workers in top positions.

Resource constraint. In this extension, the firm can demote x_o older workers from the top to the bottom jobs by paying a convex cost $c(x_o)$. We further assume that the marginal increase in demotions resulting from a larger supply of older workers in top jobs is lower than the retention rate in top jobs: $\partial x_o / \partial l_{o,t}^{-1} < \rho_t$. Moreover, we assume that top jobs incur an administrative cost κ per worker. The firm faces a constraint on the resources it can spend before production to (i) maintain top jobs and (ii) demote older employees to bottom jobs. This constraint is such that $\kappa \cdot \left(l_{o,t}+l_{y,t}\right)+c(x_o) \leq K$, where $l_{o,t} = \rho_t l_{o,t}^{-1} - x_o$ is the number of older workers employed in top jobs in the current period. The parameter K is the maximum amount of resources the firm can spend on higher-ranked positions and demotions.

The firm problem is to choose the number of younger workers in bottom jobs, the number of younger workers in top jobs, and the number of older workers to demote from top jobs in order to maximize its profits,

$$\max_{l_{y,t},l_{y,b},x_o} AY\left(L_y,L_o\right)-\sum_{a=y,o}\sum_{j=t,b} w_{a,j}l_{a,j}-\kappa\cdot\left(l_{o,t}+l_{y,t}\right)-c\left(x_o\right),$$

subject to the organizational constraint $\kappa \cdot \left(l_{o,t}+l_{y,t}\right)+c(x_o) \leq K$.

The FOCs are

$$\begin{cases} AY_{L_y}\theta_{y,b}-w_{y,b} & = 0 \\ AY_{L_y}\theta_{y,t}-w_{y,t}-(1+\lambda)\kappa & = 0 \\ AY_{L_o}\left(\theta_{o,b}-\theta_{o,t}\right)+\left(\mu_o-1\right)w_{o,b}+(1+\lambda)\left(\kappa-c_{x_o}\right) & = 0, \end{cases}$$

where λ is the multiplier on the organizational constraint and $c_{x_o} = \frac{\partial c(x_o)}{\partial x_o}$.

Under the scenario in which the constraint is binding, we have that

$$\frac{\partial l_{y,t}}{\partial l_{o,t}^{-1}} = -\rho_t + \partial x_o / \partial l_{o,t}^{-1} < 0$$

$$\frac{\partial l_{o,t}}{\partial l_{o,t}^{-1}} = \rho_t - \partial x_o / \partial l_{o,t}^{-1} > 0$$

$$\frac{\partial w_{y,b}}{\partial l_{o,t}^{-1}} = A\theta_{y,b}\left[Y_{L_yL_y}\frac{\partial l_{y,t}}{\partial l_{o,t}^{-1}}\left(\theta_{y,t}-\theta_{y,b}\right)+Y_{L_yL_o}\frac{\partial l_{o,t}}{\partial l_{o,t}^{-1}}\left(\theta_{o,t}-\theta_{o,b}\right)\right] > 0.$$

Therefore, we can retrieve Proposition 1.

When the constraint is not binding (NB), $\lambda = 0$. Then, $w_{y,b}^{NB}$ is equal to the marginal product of labor (of younger workers) in bottom jobs, $w_{y,t}^{NB} = \mu_y w_{y,b}^{NB}$, and the ratio between the marginal product of labor in top and bottom jobs is equal to μ_y. Without loss of generality, we can assume that when the organizational constraint is not binding, the firm sets $x_o^{NB} = 0$. Here, we assume that the firm optimized the allocation of older workers between the two job levels in period -1. Therefore, in the absence of an external financial constraint, it has no reasons to change the number of legacy workers in the top job in period 0.

When the constraint is binding (B), $\lambda > 0$. Relative to the nonbinding scenario, the firm assigns fewer younger workers to top jobs: $l_{y,t}^{B} < l_{y,t}^{NB}$. This result follows from the second FOC. We replace $w_{y,t}$ with $\mu_y Y_{L_y}\theta_{y,b}$, and then rewrite the equation as follows: $Y_{L_y}\left(\theta_{y,t}-\mu_y\theta_{y,b}\right)-(1+\lambda)\kappa = 0$. Since the second term becomes more negative when $\lambda > 0$, the first term needs to compensate by becoming more positive. Due to the concavity of the production function, a larger Y_{L_y} requires a lower L_y. Given that the model has full employment, a lower L_y requires $l_{y,t}^{B} < l_{y,t}^{NB}$ and

$l_{y,b}^{B} > l_{y,b}^{NB}$.

Beyond the comparison between the nonbinding and binding scenario, the same conclusions can be drawn when the binding constraint becomes tighter (lower K). We can combine again the first two first order conditions into the following equation: $Y_{L_y}\left(\theta_{y,t} - \mu_y \theta_{y,b}\right) - (1+\lambda)\,\kappa = 0$. The Lagrangian multiplier is the shadow price of the organizational constraint and is therefore decreasing with K. When K decreases, the second term becomes more negative. Therefore, the first term needs to compensate by becoming more positive. Hence, L_y decreases, leading to a lower $l_{y,t}^{B}$.

Hence, Proposition 2 holds in this model.

Endogenous labor supply. In this extension, we assume that the labor supply responds endogenously to the level of the bottom wage in the economy: $l_y^s\left(w_{y,b}\right)$ and $\frac{\partial l_y^s(w_{y,b})}{\partial w_{y,b}} > 0$.

The rest of the problem is unchanged. First, the firm receives the legacy older workers from period -1. Then, given a set of wages, the firm decides how many younger workers to slot in the top and bottom jobs by equating the marginal revenue products of younger labor in the two positions to their marginal costs. In equilibrium, the market clears so that the demand for younger workers equals their supply: $l_y^s\left(w_{y,b}\right) = l_y^d$. Then, the firm allocates the younger workers randomly between the top and bottom jobs until its labor demands in the two positions are satisfied. Finally, the production is realized, and the firm pays all workers.

The firm problem is to choose the total number of younger workers to employ and the number of top jobs that maximize its profits:

$$\max_{l_y^d, K} AY\left(L_y, L_o\right) - \sum_{a=y,o}\sum_{j=t,b} w_{a,j} l_{a,j} - \frac{c}{2}\cdot K^2$$

subject to

$$\begin{cases} l_{y,b} = l_y^d - K + l_{o,t} \\ l_{y,t} = K - l_{o,t}. \end{cases}$$

The FOCs are

$$\begin{cases} AY_{L_y}\theta_{y,b} - w_{y,b} & = 0 \\ AY_{L_y}\left(\theta_{y,t} - \theta_{y,b}\right) - \left(\mu_y - 1\right) w_{y,b} - cK & = 0. \end{cases}$$

In equilibrium:

$$\begin{cases} w_{y,b}^* & = AY_{L_y}\theta_{y,b} \\ w_{y,t}^* & = \mu_y AY_{L_y}\theta_{y,b} \\ K^* & = \frac{AY_{L_y}}{c}\left(\theta_{y,t} - \mu_y\theta_{y,b}\right). \end{cases}$$

The bottom wage of younger workers responds to an increase in the number of older workers at the top as follows:

$$\frac{\partial w_{y,b}}{\partial l_{o,t}^{-1}} = A\theta_{y,b}\left(Y_{L_y L_y}\frac{\partial L_y}{\partial l_{o,t}^{-1}} + Y_{L_y L_o}\frac{\partial L_o}{\partial l_{o,t}^{-1}}\right)$$

The derivatives of the efficiency units of younger and older labor with respect to $l_{o,t}^{-1}$ are:

$$\begin{aligned} \frac{\partial L_y}{\partial l_{o,t}^{-1}} &= \left(\theta_{y,t} - \theta_{y,b}\right)\left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t\right) + \theta_{y,b}\frac{\partial l_y^d}{\partial l_{o,t}^{-1}} \\ \frac{\partial L_o}{\partial l_{o,t}^{-1}} &= \theta_{o,t}\rho_t. \end{aligned}$$

We can rewrite the change in wages as follows:

$$\begin{aligned} \frac{\partial w_{y,b}}{\partial l_{o,t}^{-1}} &= A\theta_{y,b}\left(Y_{L_y L_y}\frac{\partial L_y}{\partial l_{o,t}^{-1}} + Y_{L_y L_o}\frac{\partial L_o}{\partial l_{o,t}^{-1}}\right) \\ &= A\theta_{y,b}\left[Y_{L_y L_y}\left(\theta_{y,t} - \theta_{y,b}\right)\left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t\right) + Y_{L_y L_y}\theta_{y,b}\frac{\partial l_y^d}{\partial l_{o,t}^{-1}} + Y_{L_y L_o}\theta_{o,t}\rho_t\right]. \end{aligned}$$

We can replace the derivative of the labor demand by using the market clearing condition:

$$\frac{\partial l_y^d}{\partial l_{t,o}^{-1}} = \frac{\partial l_y^s}{\partial w_{y,b}} \frac{\partial w_{y,b}}{\partial l_{t,o}^{-1}}.$$

The derivative of the bottom wage becomes

$$\begin{aligned}
\frac{\partial w_{y,b}}{\partial l_{o,t}^{-1}} &= A\theta_{y,b} \left[Y_{L_y L_y} \left(\theta_{y,t} - \theta_{y,b} \right) \left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t \right) + Y_{L_y L_y} \theta_{y,b} \frac{\partial l_y^s}{\partial w_{y,b}} \frac{\partial w_{y,b}}{\partial l_{t,o}^{-1}} + Y_{L_y L_o} \theta_{o,t} \rho_t \right] \\
&= \frac{A\theta_{y,b}}{1 - A\theta_{y,b}^2 Y_{L_y L_y} \frac{\partial l_y^s}{\partial w_{y,b}}} \left[Y_{L_y L_y} \left(\theta_{y,t} - \theta_{y,b} \right) \left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t \right) + Y_{L_y L_o} \theta_{o,t} \rho_t \right].
\end{aligned}$$

We then look at the derivative of K:

$$\begin{aligned}
\frac{\partial K}{\partial l_{o,t}^{-1}} &= \frac{A\left(\theta_{y,t} - \mu_y \theta_{y,b} \right)}{c} \left[Y_{L_y L_y} \left(\theta_{y,t} - \theta_{y,b} \right) \left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t \right) + Y_{L_y L_y} \theta_{y,b} \frac{\partial l_y^d}{\partial l_{o,t}^{-1}} + Y_{L_y L_o} \theta_{o,t} \rho_t \right] \\
&= \frac{A\left(\theta_{y,t} - \mu_y \theta_{y,b} \right)}{c} \left[Y_{L_y L_y} \left(\theta_{y,t} - \theta_{y,b} \right) \left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t \right) + Y_{L_y L_y} \theta_{y,b} \frac{\partial l_y^s}{\partial w_{y,b}} \frac{\partial w_{y,b}}{\partial l_{t,o}^{-1}} + Y_{L_y L_o} \theta_{o,t} \rho_t \right].
\end{aligned}$$

Before proceeding, we are going to simplify the notation:

$$\begin{aligned}
B &= Y_{L_y L_y} \left(\theta_{y,t} - \theta_{y,b} \right) < 0 \\
D &= Y_{L_y L_y} \theta_{y,b} \frac{\partial l_y^s}{\partial w_{y,b}} < 0 \\
E &= A\theta_{y,b} > 0 \\
F &= A\left(\theta_{y,t} - \mu_y \theta_{y,b} \right) > 0 \\
G &= Y_{L_y L_o} \theta_{o,t} > 0.
\end{aligned}$$

Therefore, we can rewrite the derivative of K as follows:

$$\begin{aligned}
\frac{\partial K}{\partial l_{o,t}^{-1}} &= \frac{A\left(\theta_{y,t} - \mu_y \theta_{y,b} \right)}{c} \left[Y_{L_y L_y} \left(\theta_{y,t} - \theta_{y,b} \right) \left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t \right) + Y_{L_y L_y} \theta_{y,b} \frac{\partial l_y^s}{\partial w_{y,b}} \frac{\partial w_{y,b}}{\partial l_{t,o}^{-1}} + Y_{L_y L_o} \theta_{o,t} \rho_t \right] \\
&= \frac{F}{c} \left[B \left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t \right) + D \frac{E}{1 - DE} \left[B \left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t \right) + G\rho_t \right] + G\rho_t \right] \\
&= \frac{F}{c} \left[\left(B + \frac{DE}{1 - DE} B \right) \left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t \right) + \left(G + \frac{DE}{1 - DE} G \right) \rho_t \right] \\
&= \frac{F}{c} \left[\frac{B}{1 - DE} \left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t \right) + \frac{G}{1 - DE} \rho_t \right] \\
&= \frac{F}{c} \left[\frac{B}{1 - DE} \frac{\partial K}{\partial l_{o,t}^{-1}} + \frac{G - B}{1 - DE} \rho_t \right] \\
&= \frac{c\,(1 - DE)}{c\,(1 - DE) - FB} \frac{F}{c} \frac{G - B}{1 - DE} \rho_t \\
&= \frac{F\,(G - B)}{c\,(1 - DE) - FB} \rho_t > 0 \\
&= \underbrace{\frac{A\left(\theta_{y,t} - \mu_y \theta_{y,b} \right) \left(Y_{L_y L_o} \theta_{o,t} - Y_{L_y L_y} \left(\theta_{y,t} - \theta_{y,b} \right) \right)}{c \left(1 - A\theta_{y,b}^2 Y_{L_y L_y} \frac{\partial l_y^s}{\partial w_{y,b}} \right) - A_f \left(\theta_{y,t} - \mu_y \theta_{y,b} \right) Y_{L_y L_y} \left(\theta_{y,t} - \theta_{y,b} \right)}}_{\text{Negative career spillovers if } <1} \rho_t > 0
\end{aligned}$$

There are negative career spillovers if the cost of top jobs is larger than the following threshold:

$$c > \bar{c} = \frac{1}{1 - A\theta_{y,b}^2 Y_{L_y L_y} \frac{\partial l_y^s}{\partial w_{y,b}}} A\left(\theta_{y,t} - \mu_y \theta_{y,b}\right) Y_{L_y L_o} \theta_{o,t} > 0,$$

which is equal to the $\bar{c}$ under fixed labor supply multiplied by a term that takes into account the endogenous response of younger workers to a change in the bottom wage. Then, both Proposition 1 and 2 hold in this extension.

More general production function. In this extension, we adopt a more general production function in which workers of different age groups and in different jobs are complements. The firm problem is to choose the number of younger workers in the bottom and top jobs that maximize its profits,

$$\max_{l_{y,b}, l_{y,t}} AY\left(l_{y,b}, l_{y,t}, l_{o,t}, l_{o,b}\right) - \sum_{a=y,o} \sum_{j=t,b} w_{a,j} l_{a,j} - \frac{c}{2} \cdot K^2.$$

We assume that $Y_{l_{a,t}} > Y_{l_{a,b}}$ for all a to make all workers more productive in the top job. However, we now have that $Y_{l_{a,j} l_{a',j}}$, $Y_{l_{a,j} l_{a,j'}}$,and $Y_{l_{a,j} l_{a',j'}}$ are all positive (Y is supermodular), while $Y_{l_{a,j} l_{a,j}}$ is still negative.

The FOCs are

$$\begin{cases} AY_{l_{y,b}} - w_{y,b} & = 0 \\ AY_{l_{y,t}} - \mu_y w_{y,b} - cK & = 0. \end{cases}$$

The optimal personnel choices are:

$$\begin{cases} w_{y,b}^* & = AY_{l_{y,b}} \\ w_{y,t}^* & = \mu_y AY_{l_{y,b}} \\ K^* & = \frac{A}{c}\left(Y_{l_{y,t}} - \mu_y Y_{l_{y,b}}\right). \end{cases}$$

The bottom wage of younger workers responds to an increase in the number of older workers at the top as follows:

$$\begin{aligned} \frac{\partial w_{y,b}}{\partial l_{o,t}^{-1}} &= A \frac{\partial Y_{l_{y,b}}}{\partial l_{o,t}^{-1}} \\ &= A\left[Y_{l_{y,b} l_{y,t}}\left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t\right) - Y_{l_{y,b} l_{y,b}}\left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t\right) + Y_{l_{y,b} l_{o,t}} \rho_t\right] \end{aligned}$$

The bottom wage of younger workers responds to an increase in the number of older workers at the top as follows:

$$\begin{aligned} \frac{\partial K}{\partial l_{o,t}^{-1}} =& \frac{A}{c}\left(\frac{\partial Y_{l_{y,t}}}{\partial l_{o,t}^{-1}} - \mu_t \frac{\partial Y_{l_{y,b}}}{\partial l_{o,t}^{-1}}\right) \\ =& \frac{A}{c}\left[Y_{l_{y,t} l_{y,t}}\left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t\right) - Y_{l_{y,t} l_{y,b}}\left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t\right) + Y_{l_{y,t} l_{o,t}} \rho_t\right] \\ & - \frac{A}{c}\mu_t\left[Y_{l_{y,b} l_{y,t}}\left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t\right) - Y_{l_{y,b} l_{y,b}}\left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t\right) + Y_{l_{y,b} l_{o,t}} \rho_t\right] \\ =& \underbrace{\frac{A\left[\left(Y_{l_{y,t} l_{y,b}} - Y_{l_{y,t} l_{y,t}} + Y_{l_{y,t} l_{o,t}}\right) - \mu_t\left(Y_{l_{y,b} l_{y,b}} - Y_{l_{y,b} l_{y,t}} + Y_{l_{y,b} l_{o,t}}\right)\right]}{c - A\left[\left(Y_{l_{y,t} l_{y,t}} - Y_{l_{y,t} l_{y,b}}\right) - \mu_t\left(Y_{l_{y,b} l_{y,t}} - Y_{l_{y,b} l_{y,b}}\right)\right]}}_{\text{Negative career spillovers if } <1} \rho_t. \end{aligned}$$

An increase in the supply of older workers limits younger workers' access to top jobs if the organizational cost of top jobs is above the following threshold:

$$c > \overline{c^*} = A\left[Y_{l_{y,t} l_{o,t}} - \mu_t Y_{l_{y,b} l_{o,t}}\right].$$

Unlike the baseline model, it is not sufficient for c to be above the threshold $\bar{c}$ to conclude that a larger supply of older workers at the top raises the bottom wage of younger workers:

$$\frac{\partial w_{y,b}}{\partial l_{o,t}^{-1}} = A\left[\underbrace{Y_{l_{y,b}l_{y,t}}\left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t\right)}_{<0} - \underbrace{Y_{l_{y,b}l_{y,b}}\left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t\right)}_{<0} + \underbrace{Y_{l_{y,b}l_{o,t}}\rho_t}_{>0}\right].$$

We also need to assume that

$$\begin{aligned}
Y_{l_{y,b}l_{o,t}}\rho_t &> \left(Y_{l_{y,b}l_{y,t}} - Y_{l_{y,b}l_{y,b}}\right)\left(\frac{\partial K}{\partial l_{o,t}^{-1}} - \rho_t\right) \\
Y_{l_{y,b}l_{o,t}} &> \left(Y_{l_{y,b}l_{y,t}} - Y_{l_{y,b}l_{y,b}}\right) \times \\
&\left(\frac{A\left[Y_{l_{y,t}l_{o,t}} - \mu_t Y_{l_{y,b}l_{o,t}}\right] - c}{c - A\left[\left(Y_{l_{y,t}l_{y,t}} - Y_{l_{y,t}l_{y,b}}\right) - \mu_t\left(Y_{l_{y,b}l_{y,t}} - Y_{l_{y,b}l_{y,b}}\right)\right]}\right) \\
c &> \frac{A}{\left(Y_{l_{y,b}l_{o,t}} + Y_{l_{y,b}l_{y,t}} - Y_{l_{y,b}l_{y,b}}\right)} \times \\
&\{\left(Y_{l_{y,b}l_{y,t}} - Y_{l_{y,b}l_{y,b}}\right)\left(Y_{l_{y,t}l_{o,t}} - \mu_t Y_{l_{y,b}l_{o,t}}\right) + \\
&Y_{l_{y,b}l_{o,t}}\left[\left(Y_{l_{y,t}l_{y,t}} - Y_{l_{y,t}l_{y,b}}\right) - \mu_t\left(Y_{l_{y,b}l_{y,t}} - Y_{l_{y,b}l_{y,b}}\right)\right]\} \\
&> \overline{c^*}B + D < \overline{c^*},
\end{aligned}$$

where

$$\begin{aligned}
B &= \frac{Y_{l_{y,b}l_{y,t}} - Y_{l_{y,b}l_{y,b}}}{Y_{l_{y,b}l_{o,t}} + Y_{l_{y,b}l_{y,t}} - Y_{l_{y,b}l_{y,b}}} < 1 \\
D &= \frac{A}{\left(Y_{l_{y,b}l_{o,t}} + Y_{l_{y,b}l_{y,t}} - Y_{l_{y,b}l_{y,b}}\right)} Y_{l_{y,b}l_{o,t}}\left[\left(Y_{l_{y,t}l_{y,t}} - Y_{l_{y,t}l_{y,b}}\right) - \mu_t\left(Y_{l_{y,b}l_{y,t}} - Y_{l_{y,b}l_{y,b}}\right)\right] < 0.
\end{aligned}$$

No exogenous rents. If we drop the assumption of exogenous rents in the top-job wages, the first order conditions indicate that, in equilibrium, the difference between the two wages should reflect differences in productivity and costs between the two positions, as follows: $w_{y,t}^* - w_{y,b}^* = AY_{L_y}\left(\theta_{y,t} - \theta_{y,b}\right) - cK^*$.

Given that the top wage now (i) is not automatically derived from the bottom wage, and (ii) depends on the number of younger workers at the top, there exist multiple combinations of top wages and numbers of younger workers in top jobs that satisfy the first order conditions. To restore the findings outlined in the baseline model, we need to replace the fixed labor supply with an endogenous labor supply that is an increasing function of the level of wages paid in the different jobs. This assumption ensures that changes in the level of wages lead to predetermined changes in the number of workers employed in different jobs. We further explore this scenario in an extension with heterogeneous firms.

Heterogeneous firms. The main differences from the baseline model are as follows. First, there are now F firms, but each firm is small and does not internalize the consequences of its actions on other firms. We further assume that $\rho_{j,f}$ increases with firm-level productivity A_f. Second, firms set wages for the bottom and top jobs, rather than taking them as given. Third, the ratio of top to bottom wages is not equal to a fixed rent and is not necessarily constant across firms. Fourth, we assume that $c(K)$ is 0 up to a threshold level $\overline{K}$ and then is ∞ beyond $\overline{K}$. In practice, this cost structure means that firms face a binding constraint on the number of top slots: $l_{o,t,f} + l_{y,t,f} = \bar{K}_f$. This parametrization makes the model more tractable and focuses the attention on the empirically relevant scenario in which the firm is in a corner solution and cannot adjust the number of top slots over $\bar{K}_f$.

The timing of the game is as follows. First, each firm receives legacy older workers from period -1. Then, each firm posts wage offers for its bottom and top jobs, and each younger worker joins the firm and job that maximizes her utility. Finally, the production is realized, and the firm makes payments to all workers.

The firm problem is to choose the wages in the top and bottom job in order to maximize its profits,

$$\max_{w_{y,t,f}, w_{y,b,f}} A_f Y\left(L_{y,f}, L_{o,f}\right) - \sum_{a=y,o}\sum_{j=t,b} w_{a,j,f} l_{a,j,f},$$

subject to

$$l_{o,t,f} + l_{y,t,f} \leq \bar{K}_f.$$

Each firm f also faces the following labor supply function for its job j:

$$l_{y,j,f} = \frac{\left(w_{y,j,f}\right)^{\frac{1}{\sigma}}}{\sum_{f=1}^{F} \sum_{j \in \{t,b\}} \left(w_{y,j,f}\right)^{\frac{1}{\sigma}}} l_y.$$

When a firm increases the wage paid in a given job, it anticipates the following change in labor supply:

$$\begin{aligned}\frac{\partial l_{y,j,f}}{\partial w_{y,j,f}} &= \frac{1}{\sigma} X_{y,j,f} \frac{\left(w_{y,j,f}\right)^{\frac{1}{\sigma}-1}}{\sum_{f=1}^{F} \sum_{j \in \{t,b\}} \left(w_{y,j,f}\right)^{\frac{1}{\sigma}}} l_y \\ &= \frac{1}{\sigma} \frac{l_{y,j,f}}{w_{y,j,f}}\end{aligned}$$

The denominator of the labor supply function does not change when the wage in firm f and job j increases because firms do not internalize the consequences of their own wage schedules on the market-wide level of wages. The firm's first order condition with respect to $w_{y,b,f}$ is:

$$\begin{aligned}A_f Y_{L_{y,f}} \theta_{y,b,f} \frac{1}{\sigma} \frac{l_{y,b,f}}{w_{y,b,f}} - w_{y,b,f} \frac{1}{\sigma} \frac{l_{y,b,f}}{w_{y,b,f}} - l_{y,b,f} &= 0 \\ w_{y,b,f} &= \underbrace{\frac{1}{1+\sigma}}_{\text{Markdown}} A_f Y_{L_{y,f}} \theta_{y,b,f}.\end{aligned}$$

The first order condition with respect to $w_{y,t,f}$ is:

$$\begin{aligned}A_f Y_{L_{y,f}} \theta_{y,t,f} \frac{1}{\sigma} \frac{l_{y,t,f}}{w_{y,t,f}} - w_{y,t,f} \frac{1}{\sigma} \frac{l_{y,t,f}}{w_{y,t,f}} - l_{y,t,f} & \\ -\lambda_f \frac{1}{\sigma} \frac{l_{y,t,f}}{w_{y,t,f}} &= 0 \\ w_{y,t,f} &= \underbrace{\frac{1}{1+\sigma}}_{\text{Markdown}} \left[A_f Y_{L_{y,f}} \theta_{y,t,f} - \lambda_f\right].\end{aligned}$$

In equilibrium, firms pay a markdown below the marginal revenue product of labor in both the bottom and top job.

Proof of Proposition 3. Next, we consider the effect of an increase in the economy-wide number of older workers on wages and the number of top slots. Specifically, we study a marginal increase in $l_{o,t}^{-1}$, the total number of older workers in top jobs in period -1. We assume that this increase affects all firms proportionately to the share of the total number of older workers they employ in top jobs. So, in firm f, a marginal increase in $l_{o,t}^{-1}$ increases period-0 older workers in top jobs by $\rho_{t,f} l_{o,t,f}^{-1}/l_{o,t}^{-1}$.

The marginal change in the bottom wage is as follows:

$$
\begin{aligned}
\frac{\partial w_{y,b,f}}{\partial l_{o,t}^{-1}} &= \frac{1}{1+\sigma} A_f \theta_{y,b,f} \left(Y_{L_{y,f} L_{o,f}} \frac{\partial L_{o,f}}{\partial l_{o,t}^{-1}} + Y_{L_{y,f} L_{y,f}} \left(\frac{1}{\sigma} \frac{l_{y,b,f}}{w_{y,b,f}} \frac{\partial w_{y,b,f}}{\partial l_{o,t}^{-1}} \theta_{y,b,f} + \frac{\partial l_{y,t,f}}{\partial l_{o,t}^{-1}} \theta_{y,t,f} \right) \right) \\
&= \frac{\frac{1}{1+\sigma} A_f \theta_{y,b,f} \left(Y_{L_{y,f} L_{o,f}} \frac{\partial L_{o,f}}{\partial l_{o,t}^{-1}} + Y_{L_{y,f} L_{y,f}} \frac{\partial l_{y,t,f}}{\partial l_{o,t}^{-1}} \theta_{y,t,f} \right)}{1 - \frac{1}{1+\sigma} \frac{1}{\sigma} A_f \theta_{y,b,f}^2 Y_{L_{y,f} L_{y,f}} \frac{l_{y,b,f}}{w_{y,b,f}}} \\
&= \frac{\frac{1}{1+\sigma} A_f \theta_{y,b,f} \left(Y_{L_{y,f} L_{o,f}} \theta_{o,t,f} - Y_{L_{y,f} L_{y,f}} \theta_{y,t,f} \right)}{1 - \frac{1}{1+\sigma} \frac{1}{\sigma} A_f \theta_{y,b,f}^2 Y_{L_{y,f} L_{y,f}} \frac{l_{y,b,f}}{w_{y,b,f}}} \rho_{t,f} \frac{l_{o,t,f}^{-1}}{l_{o,t}^{-1}} > 0
\end{aligned}
$$

The marginal change in the top wage is as follows:

$$
\frac{\partial w_{y,t,f}}{\partial l_{o,t}^{-1}} = \frac{\partial w_{y,b,f}}{\partial l_{o,t}^{-1}} \frac{\theta_{y,t,f}}{\theta_{y,b,f}} - \frac{1}{1+\sigma} \frac{\partial \lambda_f}{\partial l_{o,t}^{-1}}.
$$

We can conclude that the marginal change in the top wage is lower than that in the bottom wage and possibly even negative if $\frac{\partial \lambda_f}{\partial l_{o,t}^{-1}} > \frac{\theta_{y,t,f} - \theta_{y,b,f}}{\theta_{y,b,f}} (1+\sigma) \frac{\partial w_{y,b,f}}{\partial l_{o,t}^{-1}}$.

Next, we generate three additional predictions that will receive support from the empirical evidence. First, an increase in the market-wide number of older workers in top jobs disproportionately increases the number of older workers at the top of higher-paying and higher-productivity firms. This result stems from the fact that these firms have higher retention rates of older workers:

$$
\frac{\partial l_{o,t,f}}{\partial l_{o,t}^{-1}} = \rho_{t,f} \frac{l_{o,t,f}^{-1}}{l_{o,t}^{-1}},
$$

where $\rho_{t,f} > \rho_{t,f'}$ for $\forall f, f'$ such that $A_f > A_{f'}$. Moreover, if we assume that firms optimized the allocation of older workers in period -1, firms with higher productivity employ a higher share of the total number of older workers in the market because they have higher wages: $\frac{l_{o,t,f}^{-1}}{l_{o,t}^{-1}} > \frac{l_{o,t,f'}^{-1}}{l_{o,t}^{-1}}$ for $\forall f, f'$ such that $A_f > A_{f'}$.

Second, while the increase in the market-wide number of older workers in top jobs negatively affects younger workers' ability to reach top jobs in all firms, these negative career spillovers are larger within higher-paying and higher-productivity firms:

$$
\begin{aligned}
\frac{\partial l_{y,t,f}}{\partial l_{o,t}^{-1}} = \frac{\partial K_f}{\partial l_{o,t}^{-1}} - \frac{\partial l_{o,t,f}}{\partial l_{o,t}^{-1}} &< \frac{\partial l_{y,t,f'}}{\partial l_{o,t}^{-1}} = \frac{\partial K_{f'}}{\partial l_{o,t}^{-1}} - \frac{\partial l_{o,t,f'}}{\partial l_{o,t}^{-1}} \\
-\rho_{t,f} \frac{l_{o,t,f}^{-1}}{l_{o,t}^{-1}} &< -\rho_{t,f'} \frac{l_{o,t,f'}^{-1}}{l_{o,t}^{-1}},
\end{aligned}
$$

where $\rho_{t,f} > \rho_{t,f'}$ and $\frac{l_{o,t,f}^{-1}}{l_{o,t}^{-1}} > \frac{l_{o,t,f'}^{-1}}{l_{o,t}^{-1}}$ for $\forall f, f'$ such that $A_f > A_{f'}$.

Third, as a result of these negative career spillovers, younger workers are more likely to relocate toward firms that experience higher percentage increases in their bottom wage. We can see this result by considering the derivative of the ratio of the employment level of younger workers in the bottom jobs of two firms f and f':

$$
\begin{aligned}
\frac{\partial \frac{l_{y,b,f'}}{l_{y,b,f}}}{\partial l_{o,t}^{-1}} &= \frac{\partial}{\partial l_{o,t}^{-1}} \left(\frac{w_{y,b,f'}}{w_{y,b,f}} \right)^{\frac{1}{\sigma}} \\
&= \frac{1}{\sigma} \left(\frac{w_{y,b,f'}}{w_{y,b,f}} \right)^{\frac{1}{\sigma}-1} \frac{\frac{\partial w_{y,b,f'}}{\partial l_{o,t}^{-1}} w_{y,b,f} - \frac{\partial w_{y,b,f}}{\partial l_{o,t}^{-1}} w_{y,b,f'}}{\left(w_{y,b,f} \right)^2} \\
&= \frac{1}{\sigma} \frac{l_{y,b,f'}}{l_{y,b,f}} \left(\frac{\frac{\partial w_{y,b,f'}}{\partial l_{o,t}^{-1}}}{w_{y,b,f'}} - \frac{\frac{\partial w_{y,b,f}}{\partial l_{o,t}^{-1}}}{w_{y,b,f}} \right) > 0.
\end{aligned}
$$

This derivative is positive if

$$\frac{\frac{\partial w_{y,b,f'}}{\partial l_{o,t}^{-1}}}{w_{y,b,f'}} > \frac{\frac{\partial w_{y,b,f}}{\partial l_{o,t}^{-1}}}{w_{y,b,f}}.$$

In short, the employment of younger workers in the bottom job increases more in firm f' than in firm f if $\frac{\frac{\partial w_{y,b,f'}}{\partial l_{o,t}^{-1}}}{w_{y,b,f'}} > \frac{\frac{\partial w_{y,b,f}}{\partial l_{o,t}^{-1}}}{w_{y,b,f}}$.

It is possible for the percentage increase in the bottom wage to be larger among lower-productivity and lower-paying firms. We derive the necessary conditions below. Here, we assume that $\sigma = 1$ to simplify the calculations. We can rewrite the percentage change in the bottom wage as follows:

$$\begin{aligned}
\frac{\frac{\partial w_{y,b,f}}{\partial l_{o,t}^{-1}}}{w_{y,b,f}} &= \frac{\frac{1}{2}A_f\theta_{y,b,f}\left(Y_{L_{y,f}L_{o,f}}\theta_{o,t,f} - Y_{L_{y,f}L_{y,f}}\theta_{y,t,f}\right)}{1-\frac{1}{2}A_f\theta_{y,b,f}^2 Y_{L_{y,f}L_{y,f}}\frac{l_y}{\widetilde{w}}} \cdot \rho_{t,f}\frac{l_{o,t,f}^{-1}}{l_{o,t}^{-1}} \cdot \frac{1}{A_f Y_{L_{y,f}}\theta_{y,b,f}} \\
&= \frac{\frac{1}{2}\left(Y_{L_{y,f}L_{o,f}}\theta_{o,t,f} - Y_{L_{y,f}L_{y,f}}\theta_{y,t,f}\right)}{Y_{L_{y,f}}\left(1-\frac{1}{2}A_f\theta_{y,b,f}^2 Y_{L_{y,f}L_{y,f}}\frac{l_y}{\widetilde{w}}\right)} \cdot \rho_{t,f}\frac{l_{o,t,f}^{-1}}{l_{o,t}^{-1}},
\end{aligned}$$

where $\frac{\partial l_{y,j,f}}{\partial w_{y,j,f}} = \frac{l_{y,j,f}}{w_{y,j,f}} = \frac{l_y}{\widetilde{w}}$ and $\widetilde{w} = \sum_{f=1}^{F}\sum_{j\in\{t,b\}}\left(w_{y,j,f}\right)$. The partial derivative with respect to A_f increases the denominator, making it possible for lower-productivity firms to have larger percentage changes in the bottom wage. The total derivative would have to take into account that a different A_f affects the efficiency units of younger labor, therefore affecting the degree of substitutability and complementarity of younger and older workers.

We start by simplifying the notation:

$$\begin{aligned}
B &= \frac{1}{2}\rho_{t,f}\frac{l_{o,t,f}^{-1}}{l_{o,t}^{-1}} > 0 \\
D &= \frac{1}{2}A_f\theta_{y,b,f} > 0 \\
E &= \theta_{y,b,f}\frac{l_y}{\widetilde{w}} > 0 \\
den &= Y_{L_{y,f}}\left(1 - Y_{L_{y,f}L_{y,f}}DE\right) > 0.
\end{aligned}$$

The key derivatives are:

$$\begin{aligned}
\frac{\partial Y_{L_{y,f}L_{o,f}}}{\partial A_f} &= Y_{L_{y,f}L_{o,f}L_{y,f}}\theta_{y,b,f}\frac{l_{y,b,f}}{w_{y,b,f}}\frac{\partial w_{y,b,f}}{\partial A_f} = Y_{L_{y,f}L_{o,f}L_{y,f}}E\frac{\partial w_{y,b,f}}{\partial A_f} \\
\frac{\partial Y_{L_{y,f}}}{\partial A_f} &= Y_{L_{y,f}L_{y,f}}\theta_{y,b,f}\frac{l_{y,b,f}}{w_{y,b,f}}\frac{\partial w_{y,b,f}}{\partial A_f} = Y_{L_{y,f}L_{y,f}}E\frac{\partial w_{y,b,f}}{\partial A_f} < 0 \\
\frac{\partial Y_{L_{y,f}L_{y,f}}}{\partial A_f} &= Y_{L_{y,f}L_{y,f}L_{y,f}}\theta_{y,b,f}\frac{l_{y,b,f}}{w_{y,b,f}}\frac{\partial w_{y,b,f}}{\partial A_f} = Y_{L_{y,f}L_{y,f}L_{y,f}}E\frac{\partial w_{y,b,f}}{\partial A_f} \\
\frac{\partial w_{y,b,f}}{\partial A_f} &= > 0.
\end{aligned}$$

The percentage change in the bottom wage becomes

$$\begin{aligned}
\frac{\frac{\partial w_{y,b,f}}{\partial l_{o,t}^{-1}}}{w_{y,b,f}} &= \frac{\frac{1}{2}\left(Y_{L_{y,f}L_{o,f}}\theta_{o,t,f} - Y_{L_{y,f}L_{y,f}}\theta_{y,t,f}\right)}{Y_{L_{y,f}}\left(1-\frac{1}{2}A_f\theta_{y,b,f}^2 Y_{L_{y,f}L_{y,f}}\frac{l_y}{\widetilde{w}}\right)} \cdot \rho_{t,f}\frac{l_{o,t,f}^{-1}}{l_{o,t}^{-1}} \\
&= \frac{B\left(Y_{L_{y,f}L_{o,f}}\theta_{o,t,f} - Y_{L_{y,f}L_{y,f}}\theta_{y,t,f}\right)}{Y_{L_{y,f}}\left(1 - Y_{L_{y,f}L_{y,f}}DE\right)}.
\end{aligned}$$

The cross-derivative can be written as:

$$
\begin{aligned}
\frac{\partial \frac{\frac{\partial w_{y,b,f}}{\partial l_{o,t}^{-1}}}{w_{y,b,f}}}{\partial A_f} &= \frac{B}{(den)^2} \times \left\{ \left(\theta_{o,t,f} Y_{L_{y,f} L_{o,f} L_{y,f}} E \frac{\partial w_{y,b,f}}{\partial A_f} - \theta_{y,t,f} Y_{L_{y,f} L_{y,f} L_{y,f}} E \frac{\partial w_{y,b,f}}{\partial A_f} \right) \times den \right. \\
&- \left[Y_{L_{y,f} L_{y,f}} E \frac{\partial w_{y,b,f}}{\partial A_f} \left(1 - Y_{L_{y,f} L_{y,f}} DE \right) - DE Y_{L_{y,f} L_{y,f} L_{y,f}} E \frac{\partial w_{y,b,f}}{\partial A_f} Y_{L_{y,f}} \right] \\
&\left. \times \left(Y_{L_{y,f} L_{o,f}} \theta_{o,t,f} - Y_{L_{y,f} L_{y,f}} \theta_{y,t,f} \right) \right\} \\
&= \frac{BE \frac{\partial w_{y,b,f}}{\partial A_f}}{(den)^2} \times \left\{ \left(\theta_{o,t,f} Y_{L_{y,f} L_{o,f} L_{y,f}} - \theta_{y,t,f} Y_{L_{y,f} L_{y,f} L_{y,f}} \right) \times \left(Y_{L_{y,f}} - Y_{L_{y,f} L_{y,f}} Y_{L_{y,f}} DE \right) \right. \\
&- \left[Y_{L_{y,f} L_{y,f}} \left(1 - Y_{L_{y,f} L_{y,f}} DE \right) - DE Y_{L_{y,f} L_{y,f} L_{y,f}} Y_{L_{y,f}} \right] \\
&\left. \times \left(Y_{L_{y,f} L_{o,f}} \theta_{o,t,f} - Y_{L_{y,f} L_{y,f}} \theta_{y,t,f} \right) \right\} \\
&= \frac{BE \frac{\partial w_{y,b,f}}{\partial A_f}}{(den)^2} \times \left\{ Y_{L_{y,f} L_{o,f} L_{y,f}} Y_{L_{y,f}} \theta_{o,t,f} \left(1 - Y_{L_{y,f} L_{y,f}} DE \right) \right. \\
&+ Y_{L_{y,f} L_{y,f} L_{y,f}} Y_{L_{y,f}} \left(\theta_{o,t,f} Y_{L_{y,f} L_{o,f}} DE - \theta_{y,t,f} \right) \\
&\left. - Y_{L_{y,f} L_{y,f}} \left(1 - Y_{L_{y,f} L_{y,f}} DE \right) \right\}
\end{aligned}
$$

This cross-derivative is negative (therefore, employment of younger workers in bottom jobs increases more in lower-productivity firms) if:

$$
Y_{L_{y,f} L_{o,f} L_{y,f}} \theta_{o,t,f} + \quad Y_{L_{y,f} L_{y,f} L_{y,f}} \frac{\theta_{o,t,f} Y_{L_{y,f} L_{o,f}} DE - \theta_{y,t,f}}{1 - Y_{L_{y,f} L_{y,f}} DE} < \frac{Y_{L_{y,f} L_{y,f}}}{Y_{L_{y,f}}} \quad < 0.
$$

E Derivation of Equation (2)

The change in mean log wage for age group a between years t and t' can be written as follows:

$$
\begin{aligned}
\Delta w_a^{t,t'} = & \underbrace{\sum_v \left(s_{a,v,t'} - s_{a,v,t} \right) \bar{w}_{v,t}}_{\text{Pay rank change}} + \underbrace{\sum_v s_{a,v,t} \left(\bar{w}_{v,t'} - \bar{w}_{v,t} \right)}_{\text{Distributional change}} \\
& + \underbrace{\sum_v \left(s_{a,v,t'} - s_{a,v,t} \right) \left(\bar{w}_{v,t'} - \bar{w}_{v,t} \right)}_{\text{Residual}} . \qquad \text{(E.1)}
\end{aligned}
$$

In this equation, $s_{a,v,t}$ is the share of workers in age group a, vigintile v of the distribution of wages, and year t, while $\bar{w}_{v,t}$ is the mean log wage in vigintile v and year t. This decomposition can be obtained as follows:

$$\begin{aligned}
\Delta w_a^{t,t'} &= \sum_v s_{a,v,t'}\bar{w}_{v,t'} - \sum_v s_{a,v,t}\bar{w}_{v,t} \\
&= \sum_v s_{a,v,t'}\bar{w}_{v,t'} - \sum_v s_{a,v,t}\bar{w}_{v,t} + \sum_v s_{a,v,t'}\bar{w}_{v,t} - \sum_v s_{a,v,t'}\bar{w}_{v,t} \\
&= \sum_v \left(s_{a,v,t'} - s_{a,v,t}\right)\bar{w}_{v,t} + \sum_v s_{a,v,t'}\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&= \sum_v \left(s_{a,v,t'} - s_{a,v,t}\right)\bar{w}_{v,t} + \sum_v s_{a,v,t'}\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&\quad + \sum_v s_{a,v,t}\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) - \sum_v s_{a,v,t}\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&= \underbrace{\sum_v \left(s_{a,v,t'} - s_{a,v,t}\right)\bar{w}_{v,t}}_{\text{Pay rank change}} + \underbrace{\sum_v s_{a,v,t}\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Distributional change}} \\
&\quad + \underbrace{\sum_v \left(s_{a,v,t'} - s_{a,v,t}\right)\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Residual}}.
\end{aligned}$$

The gap in the average log wage between U35 workers and O55 workers, as well as between years t and t', can be written as follows:

$$\begin{aligned}
\Delta w_{O55}^{t,t'} - \Delta w_{U35}^{t,t'} &= \underbrace{\sum_v \Delta s_{O55-U35,v,t'-t}\bar{w}_{v,t}}_{\text{Pay rank gap}} + \underbrace{\sum_v \left(s_{O55,v,t} - s_{U35,v,t}\right)\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Distributional gap}} \\
&\quad + \underbrace{\sum_v \Delta s_{O55-U35,v,t'-t}\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Residual}}.
\end{aligned} \tag{E.2}$$

In this equation, $\Delta s_{O55-U35,v,t'-t} = \left(s_{O55,v,t'} - s_{O55,v,t}\right) - \left(s_{U35,v,t'} - s_{U35,v,t}\right)$ is the double difference in the share of workers in vigintile v (i) between O55 workers and U35 workers and (ii) between years t and t'. This decomposition can be obtained as follows:

$$\begin{aligned}
\Delta w_{O55}^{t,t'} - \Delta w_{U35}^{t,t'} &= \sum_v \left(s_{O55,v,t'} - s_{O55,v,t}\right)\bar{w}_{v,t} + \sum_v \left(s_{O55,v,t'} - s_{O55,v,t}\right)\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&\quad + \sum_v s_{O55,v,t}\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) - \sum_v \left(s_{U35,v,t'} - s_{U35,v,t}\right)\bar{w}_{v,t} \\
&\quad - \sum_v \left(s_{U35,v,t'} - s_{U35,v,t}\right)\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) - \sum_v s_{U35,v,t}\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&= \sum_v \left(\left(s_{O55,v,t'} - s_{O55,v,t}\right) - \left(s_{U35,v,t'} - s_{U35,v,t}\right)\right)\bar{w}_{v,t} \\
&\quad + \sum_v \left(\left(s_{O55,v,t'} - s_{O55,v,t}\right) - \left(s_{U35,v,t'} - s_{U35,v,t}\right)\right)\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&\quad + \sum_v \left(s_{O55,v,t} - s_{U35,v,t}\right)\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&= \underbrace{\sum_v \Delta s_{O55-U35,v,t'-t}\bar{w}_{v,t}}_{\text{Pay rank gap}} + \underbrace{\sum_v \left(s_{O55,v,t} - s_{U35,v,t}\right)\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Distributional gap}} \\
&\quad + \underbrace{\sum_v \Delta s_{O55-U35,v,t'-t}\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Residual}}.
\end{aligned}$$

F Derivation of Equation (3)

The exact formula of the decomposition of the rank change can be written as follows:

$$\underbrace{\sum_v (s_{U35,v,t'} - s_{U35,v,t})\, \bar{w}_{v,t}}_{\text{Rank change}} = \underbrace{\sum_{e\in[0,18]} s_{e,t'} \cdot \sum_v \left[s^{LME}_{e,t',v} \cdot \bar{w}_{v,t} \right]}_{\text{Change in entry rank—part 1}} - \underbrace{\sum_{e\in[0,18]} s_{e,t} \cdot \sum_v \left[s^{LME}_{e,t,v} \cdot \bar{w}_{v,t} \right]}_{\text{Change in entry rank—part 2}} + \underbrace{\sum_{e\in[0,18]} s_{e,t'} \cdot \sum_v \left[\left(s_{e,t',v} - s^{LME}_{e,t',v} \right) \cdot \bar{w}_{v,t} \right]}_{\text{Change in rank growth—part 1}} - \underbrace{\sum_{e\in[0,18]} s_{e,t} \cdot \sum_v \left[\left(s_{e,t,v} - s^{LME}_{e,t,v} \right) \cdot \bar{w}_{v,t} \right]}_{\text{Change in rank growth—part 2}} . \tag{F.1}$$

There is one key difference between Equation (F.1) and Equation (3) in Section 4.3. In the full decomposition in Equation (F.1), the experience composition of U35 workers is allowed to change from year t ($s_{e,t}$) to year t' ($s_{e,t'}$). Therefore, the two components of the decomposition can conflate two types of changes: (i) variation in entry rank and rank growth and (ii) variation in the experience distribution of U35 workers. For example, the change in entry rank can stem from the fact that the wage distribution at labor-market entry of workers under 35 differs between year t' and year t', or it can stem from the fact that U35 workers became either more or less experienced between t and t'.

In the main draft, we isolate the first channel. Therefore, we fix the experience distribution either at the baseline year t (1995 for U35 workers and 1990 for U30 workers) or at the endline year 2016. This assumption allows us to rewrite Equation (F.1) as Equation (3) in Section 4.3.

G Numerical Framework

Consider a simple wage function: $w^t_{i,a} = \beta_0 + \beta^t_1 x^t_{i,a} + \varepsilon^t_i$. Here, $w^t_{i,a}$ denotes the wage of worker i in age group $a \in \{\text{younger}, \text{older}\}$ in period t, $x^t_{i,a}$ represents the quantity of wage-enhancing factor x possessed by worker i in period t, β^t_1 is the unit price of factor x in period t, and ε^t_i refers to other characteristics correlated with wages. The variable x represents any worker characteristic associated with higher wages, such as experience, skills, education, job level, and other features of labor contracts. We assume that older workers posses on average a higher quantity of x, resulting in a higher mean wage for older workers at baseline—a fact corroborated by all available data sources. In contrast, the variable ε^t_i is equally distributed across both worker categories.

To simulate an increase in returns to experience or higher-level skills, we raise the price of the wage-enhancing factor x. Given that older workers possess, on average, a larger quantity of x, its price hike amplifies the age pay gap. We then utilize Equation (2) to decompose this increase into a larger pay rank gap and a larger distributional gap.

In the baseline scenario, we calibrate the wage equation to match five moments from the Italian administrative data in 1985: mean (5.9) and standard deviation (0.4) of log weekly wages of U35 workers, mean (6.1) and standard deviation (0.6) of log weekly wages of O55 workers, and the O55 to U35 workers ratio (0.09). In the wage function, we set $\beta_0 = 1$, $\beta^t_1 = 1$, $x^t_Y \sim N(4.9, 0.16)$ for younger workers, $x^t_O \sim N(5.1, 0.36)$ for older workers, and $\varepsilon^t_i \sim N(0, \sigma^2_\varepsilon)$. The variable ε^t_i always has mean 0, while its variance changes across different scenarios.

In the case of $\sigma^2_\varepsilon = 0$, x is the sole determinant of individual wages. When its unit price β_1 increases from 1 in period t to 1.5 in period t', the age pay gap expands by 0.09 log points, a shift entirely attributable to a larger distributional gap (Figure A8, Panel A). This finding holds if we increase the share of older workers in period t' to either 20 percent or 35 percent (matching the 2019 O55 to U35 workers ratio in Italy), and if β_1 rises to 2.5 instead of 1.5. Moreover, the distributional gap accounts for at least 99 percent of the age pay gap's widening under alternative assumptions for the distribution of x.

When $\sigma^2_\varepsilon > 0$, differences in x account for a smaller share of wage variation (Figure A8, Panel B). In practice, all else equal, the wage distributions of younger and older workers overlap more as the standard deviation of ε^t_i grows. Following a price increase of x from 1 to 1.5, the distributional gap's contribution declines as σ_ε increases. Specifically, the distributional gap accounts for 128 percent of the age gap's expansion if the standard deviation σ_ε equals 0.05 ($R^2 = 0.983$), 94 percent if $\sigma_\varepsilon = 0.25$ ($R^2 = 0.358$), and 10 percent if $\sigma_\varepsilon = 0.5$ ($R^2 = 0.017$).

This simple exercise provides two key insights for understanding the role of higher returns to experience and higher-level skills. First, in the absence of other factors (ε_i^t), a higher price for x increases the age pay gap mainly by moving the two tails of the wage distribution further apart (creating a larger distributional gap). For example, given that older workers are, on average. more experienced than younger workers, a higher price for experience widens the age pay gap by extending the preexisting wage advantage of older workers, rather than allowing older workers to overcome younger workers in the wage distribution. Second, in the presence of other factors, the main channel through which a higher price for x widens the age wage gap depends on the relationship between x and wages. When the R^2 of the regression of wages on x is larger, the wage distributions of younger and older workers overlap less, and the same conclusions discussed for the case without ε_i^t apply. Conversely, when the R^2 is smaller, the wage distributions of younger and older workers overlap more. In this case, a higher price for x is more likely to propel older workers past younger ones in the aggregate wage distribution, thereby expanding the rank gap.

In conclusion, whether higher returns to experience and skills align with the observation that the widening of the age pay gap primarily arises from a larger rank gap depends on the correlation between these variables and wages at baseline. Using Italian administrative data from 1985, we regress the log of weekly wages on a quadratic polynomial of labor-market experience and on dummies for the four main job levels in the Italian labor market as a proxy for skills. Both the R^2 and adjusted R^2 equal 0.31 when all full-time workers with open-ended contracts are included, and drop to 0.26 when the sample is restricted to only U35 and O55 workers. Given this degree of correlation, our numerical exercise indicates that higher prices for experience and higher-level skills would primarily widen the distributional gap, a conclusion at odds with the nature of the growth in the age pay gap.

H Decomposition Between and Within Sectors

The sorting described in Section A9 allows us to rewrite the shares of workers in age group a, in sector-worker group (f,e), and in year t as follows:

$$s_{a,(f,e),t} = \underbrace{s_{a,f,t}}_{\text{Share of } a \text{ in } f} \cdot \underbrace{s_{a,(e|f),t}}_{\text{Share of } a \text{ in } e \text{ conditional on } f} . \tag{H.1}$$

The unconditional share of workers in age group a and sector-worker group (f,e) is the product of (i) the share of workers in age group a and sector-group f ($s_{a,f,t}$) and (ii) the share of workers in age group a and worker group e conditional on being in sector group f ($s_{a,(e|f),t}$).

Then, the pay rank change in Equation (E.1) can be written as follows:

$$\begin{aligned}\sum_v \left(s_{a,v,t'} - s_{a,v,t}\right) \bar{w}_{v,t} \quad = \quad & \underbrace{\sum_{g\in(f,e)} \left(s_{a,f,t'} - s_{a,f,t}\right) s_{a,(e|f),t} \bar{w}_{g,t}}_{\text{Between sectors}} \\ & + \underbrace{\sum_{g\in(f,e)} s_{a,f,t} \left(s_{a,(e|f),t'} - s_{a,(e|f),t}\right) \bar{w}_{g,t}}_{\text{Within sectors}} \\ & + \underbrace{\sum_{g\in(f,e)} \left[\left(s_{a,f,t'} - s_{a,f,t}\right)\left(s_{a,(e|f),t'} - s_{a,(e|f),t}\right)\right] \bar{w}_{g,t}}_{\text{Residual}} .\end{aligned} \tag{H.2}$$

On the left-hand side of this equation, the average wage in vigintile of the distribution of weekly wages v and year t ($\bar{w}_{v,t}$) is multiplied by the change between t and t' in the share of workers in age group a and vigintile v. On the right-hand side, g identifies one of the 54,000 sector-worker groups and $\bar{w}_{g,t}$ is the average wage in sector-worker group g and year t.

This decomposition can be obtained from Equation (H.1). A change in the share of workers in age group a and sector-worker group $g = (f, e)$ between t and t' can be rewritten as follows:

$$
\begin{aligned}
s_{a,(f,e),t'} - s_{a,(f,e),t} &= s_{a,f,t'} \cdot s_{a,(e|f),t'} - s_{a,f,t} \cdot s_{a,(e|f),t} \\
&= s_{a,f,t'} \cdot s_{a,(e|f),t'} - s_{a,f,t} \cdot s_{a,(e|f),t} + \left(s_{a,f,t'} \cdot s_{a,(e|f),t} - s_{a,f,t'} \cdot s_{a,(e|f),t}\right) \\
&\quad + \left(s_{a,f,t} \cdot s_{a,(e|f),t'} - s_{a,f,t} \cdot s_{a,(e|f),t'}\right) + \left(s_{a,f,t} \cdot s_{a,(e|f),t} - s_{a,f,t} \cdot s_{a,(e|f),t}\right) \\
&= \underbrace{\left(s_{a,f,t'} - s_{a,f,t}\right) s_{a,(e|f),t}}_{\text{Between sectors}} + \underbrace{s_{a,f,t} \left(s_{a,(e|f),t'} - s_{a,(e|f),t}\right)}_{\text{Within sectors}} \\
&\quad + \underbrace{\left(s_{a,f,t'} - s_{a,f,t}\right) \left(s_{a,(e|f),t'} - s_{a,(e|f),t}\right)}_{\text{Residual}}.
\end{aligned}
\tag{H.3}
$$

Then, the decomposition in Equation (H.2) can be obtained by multiplying all the three components in Equation (H.3) by $\bar{w}_{g,t}$ and by summing over the sector-worker groups g.

Using the same logic, we can rewrite the rank gap in Equation (E.2) as follows:

$$
\begin{aligned}
\underbrace{\sum_{v} \Delta s_{O55-U35,v,t'-t} \bar{w}_{v,t}}_{\text{Rank gap}} &= \underbrace{\sum_{g \in (f,e)} \Delta s_{O55-U35,f,t'-t} \cdot \Delta s_{O55-U35,(e|f),t} \cdot \bar{w}_{g,t}}_{\text{Between sectors}} \\
&\quad + \underbrace{\sum_{g \in (f,e)} \Delta s_{O55-U35,f,t} \cdot \Delta s_{O55-U35,(e|f),t'-t} \cdot \bar{w}_{g,t}}_{\text{Within sectors}} \\
&\quad + \underbrace{\sum_{g \in (f,e)} \Delta s_{O55-U35,f,t'-t} \cdot \Delta s_{O55-U35,(e|f),t'-t} \cdot \bar{w}_{g,t}}_{\text{Residual}},
\end{aligned}
\tag{H.4}
$$

where $\Delta s_{O55-U35,f,t'-t}$ is $\left(s_{O55,f,t'} - s_{O55,f,t}\right) - \left(s_{U35,f,t'} - s_{U35,f,t}\right)$; $\Delta s_{O55-U35,(e|f),t}$ is $s_{O55,(e|f),t} - s_{U35,(e|f),t}$; $\Delta s_{O55-U35,f,t}$ is $s_{O55,f,t} - s_{U35,f,t}$; and $\Delta s_{O55-U35,(e|f),t'-t}$ is $\left(s_{O55,(e|f),t'} - s_{O55,(e|f),t}\right) - \left(s_{U35,(e|f),t'} - s_{U35,(e|f),t}\right)$.