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

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Abstract

Drawing on expansive administrative and survey data, this study illustrates the growing wage disparity between older and younger workers in high-income countries. Our analysis pinpoints negative career spillovers as the driving factor, as an increasing number of older workers, higher retirement age, and constraints on firms' ability to create higher-ranked positions restrict younger workers' access to higher-paying roles. As older workers enjoy lengthier, successful careers, younger workers face lower initial wages, slower career progression, more frequent turnover with lesser financial gains, and decreased likelihood of working for higher-paying firms. We conclude by connecting these outcomes to broader labor-market trends.

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Keywords: wage growth, age wage gap, career spillovers, older workers, labor-market entry.

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1 Introduction

The workforce in many high-income countries is aging rapidly. 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.[1] This demographic shift starkly contrasts the one that took place after World War II. In the second half of the 1960s, the entry of the "baby-boom" cohort into the labor market led to a steep decline in the average worker age, coinciding with a slowdown in the growth of younger workers' wages. Prior studies (Welch, 1979; Freeman, 1979) have attributed these wage dynamics to the increased supply of younger workers under the assumption of imperfect substitutability between younger and older workers.

If we applied the same economic thinking to the current aging workforce, we would expect the increased number of older workers to reduce their preexisting wage advantage over younger workers. Instead, the current aging trend has coincided with an expanding *age wage gap*. For example, the wage gap between workers over 55 and those under 35 increased by 61 percent in the United States between 1979 and 2018 and 96 percent in Italy between 1985 and 2019.

This paper seeks to reconcile the apparent conflict between the widening age wage gap and the aging workforce. It leverages matched employer-employee administrative data from Italy and Germany with 347 million observations on 38 million workers across 3.7 million firms, along with information on 6.6 million workers from the Luxembourg Income Study for fourteen high-income countries. Our analysis of these expansive data emphasizes the role of negative career spillovers (Bianchi et al., 2023).[2]

In a frictional labor market, characterized by costly worker-firm separations and firm-level constraints in adding higher-ranked positions, improved career outcomes for older workers can come at the expense of younger workers' career progression.[3] Older worker's growing population and their longer careers allowed them to accrue more seniority, therefore progressing further along organizational hierarchies and occupying more higher-ranked positions for longer periods. These trends, together with declining economic growth, made it more difficult for firms to make room at the top of their hierarchies for younger workers, who experienced

[1] https://bit.ly/3eQmakN.

[2] In the rest of the introduction, we will usually focus on the results obtained using the Italian dataset because it is the most comprehensive and the only one that allows us to perform the full spectrum of tests included in this paper.

[3] Costly worker-firm separations can, for example, arise from knowledge spillovers (Cornelissen, Dustmann, and Schönberg, 2023), backloaded wages (Ke, Li, and Powell, 2018), or firm-specific human capital (Gathmann and Schönberg, 2010). Firm-level constraints in adding higher-ranked positions can stem from dwindling labor productivity and GDP growth (Syverson, 2017).

longer waiting times for promotions and slower career progression.

We highlight six main findings underscoring the importance of negative career spillovers. First, the widening age wage gap predominantly results from younger workers' increasing struggles to reach the upper segments of the wage distribution, a contrast to the trend experienced by older workers. In Italy, the likelihood of workers under 35 belonging to the top quartile of weekly wages declined by 34 percent from 1985 to 2019, while the probability of those over 55 increased by 32 percent. Moreover, 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.

Second, we propose a decomposition of the age wage gap's growth to quantify the impact of the divergent career trajectories of younger and older workers.[4] We identify two key components: the *rank gap* and the *distributional gap*. The rank gap, a direct implication of negative career spillovers, represents the portion of the age wage gap's expansion attributable to older workers surpassing younger workers in the wage distribution. The distributional gap, capturing broader changes to the support of the wage distribution, such as those caused by higher wage inequality, indicates that the age wage gap has expanded due to faster wage growth in segments of the wage distribution with a higher share of older workers, therefore amplifying their preexisting wage advantage. The rank gap was the primary factor driving the age wage gap's widening in nearly all countries in our sample. For example, it accounted for 78 percent of the total growth in Italy, 89 percent in the United States, 56 percent in Germany, and 77 percent in Canada.

Third, younger workers's careers have deteriorated both at and after labor-market entry. Consistent with the congestion of higher-paying jobs by older workers, new entrants have progressively started lower in the wage distribution, and have experienced slower wage growth for several years after entry. Our analysis focuses on the *wage rank loss* experienced by under-35 workers, rather than their loss in wage levels. The rank loss isolates shifts in under-35 workers' shares across vigintiles of the wage distribution, while keeping the support of the distribution itself fixed at baseline. In Italy, 86 percent of the total rank loss originates from a worse initial rank, while the remaining 14 percent arises from sluggish post-entry rank growth.

Fourth, in line with the existence of negative career spillovers, younger workers incurred positional losses in the wage distribution within both lower-paying and higher-paying firms. In contrast, older workers experienced large positional gains in all firms but those at the very top of the distribution of average firm wages. Within these higher-paying firms, the

[4] Bayer and Charles (2018) performs a similar decomposition for the black-white earning gap in the United States.

concentration of older workers increased disproportionately, negatively affecting the mean wage rank of all workers. For example, within firms in the top 5 percent of the distribution of mean wages in Italy, the share of over-55 workers increased by 28 percent between 1985 and 2019 (from 6 percent to 7.7 percent), while their wage rank declined by 0.33 log points. However, even within these higher-paying firms with extreme congestion, younger workers sustained larger positional losses. Therefore, the age wage gap widened within all firms, regardless of their mean pay level.

Rather than stemming from turnover events, the increased concentration of older workers within higher-paying firms originates from the fact that they were more likely to hold onto their positions in these firms. Compared to lower-paying firms, the mean age of over-55 workers in firms paying above-median wages increased by an additional 58 percent (+9 months vs. +5.7 months) from 1985 to 2019, and their mean tenure in 2019 was 61 percent higher (12.7 years vs. 7.9 years). Lower firm dynamism may have contributed to this trend by making jobs in higher-paying firms disappearing at progressively lower rates (Decker et al., 2014).

Fifth, the entrenchment of older workers in higher-paying firms has decreased the probability of younger workers securing employment in these firms. Confined to lower-paying firms and facing slower career progression, younger workers have increasingly relied on turnover for career advancement. In Italy, the share of under-35 workers experiencing a turnover event rose from 27 percent in 1985 to 44 percent in 2019. However, in line with increased congestion of higher-paying jobs and firms, younger workers' financial gains from firm-to-firm transitions have decreased. The average wage percentile increase associated with under-35 workers' turnover events declined by 34 percent, while the median gain fell by 67 percent.

Sixth, in line with the notion of negative career spillovers, the widening of the age wage gap was significantly larger among firms with more limited opportunities to add higher-ranked positions to their organizational hierarchies. Older, larger firms with lower employment growth found it particularly challenging to map out satisfactory career trajectories for younger worker. In Italy, for instance, the age wage gap rose by 0.24 log points among firms with below-median employment growth and by 0.17 log points among firms with above-median employment growth. This difference, equal to 38 percent of the average age wage gap's increase, is large in magnitude and statistically significant at the 1 percent.

Finally, the paper examines other mechanisms that could account for the expanding age wage gap, despite an aging workforce: wage inequality, higher returns to experience and higher-level skills, changes in the composition of younger and older workers, sectoral and occupational shifts. Overall, our analysis suggests that these factors are not fully compatible with the characteristics of the age wage gap's growth.

For example, if returns to experience and higher-level skills increased over time, wages of older, more experienced workers could have grown faster than those of younger workers.[5] However, under plausible assumptions about the correlation between wages, experience and skills, our analysis indicates that higher returns to these factors predominantly expands the age wage gap through a larger distributional gap, a conclusion that clashes with our prior findings.

We also consider changes in the availability of different jobs. The decline in manufacturing (Charles, Hurst, and Schwartz, 2019), a sector where less experienced workers could command relatively higher wages, may have widened the age wage gap by nudging younger workers toward sectors with lower starting wages. However, our results show a rather uniform expansion of the age wage gap across all 2-digit sectors, both within and outside manufacturing. Similarly, Deming (2021) shows that the employment share in 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, 88 percent of the age wage gap's expansion between 2012 (first year with occupation data) and 2019 occurred within 1-digit ISCO-08 occupation codes, rather than between them. This finding aligns with Acemoglu, Mühlbach, and Scott (2022)'s conclusion that the rise in age-friendly 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, 2014; Guvenen et al., 2022; Guaitoli and Pancrazi, 2022) use wages, total income, or life-time income to show the deterioration of younger workers' careers. We complement their findings by demonstrating the existence of an expanding age wage gap over a long period and across many countries and by testing different theories about the origins of this expansion.

Second, this paper contributes to the literature that studies the interconnectedness of coworkers' careers trajectories. Prior work has documented that limited career opportunities can generate negative career spillovers across coworkers in bureaucracies (Bertrand et al., 2018), sports (Brown, 2011; Gong, Sun, and Wei, 2017), firms in transitioning economies (Friebel and Panova, 2008), and privately owned firms in high-income economies (Bertoni and Brunello, 2020; Boeri, Garibaldi, and Moen, 2021; Mohnen, 2021; Bianchi et al., 2023; Ferrari, Kabátek, and Morris, 2023). Building upon these insights on negative career spillovers, our

[5] There is mixed evidence on the pattern followed by returns to experience. For example, Jones (2009) shows that they have increased in innovation-centric occupations due to a higher "burden of knowledge." However, beyond these specific jobs, Jeong, Kim, and Manovskii (2015)'s main takeaway is that a larger supply of older workers in the labor market decreased the price of experience.

analysis proposes an explanation that reconciles the widening age wage gap with the increased supply of older workers.

Third, this paper clarifies the connection between the growth of the age wage gap and other wage trends and labor-market dynamics. We consider several explanations alternative to negative career spillovers, such as wage inequality (Piketty and Saez, 2003; Autor, Katz, and Kearney, 2008), changes in the returns to experience (Jones, 2009; Azoulay et al., 2020; Jeong, Kim, and Manovskii, 2015), skill-biased technological chance (Acemoglu and Autor, 2011; Autor, Katz, and Kearney, 2006), change in workforce composition, the decline in manufacturing (Autor, Dorn, and Hanson, 2013; Charles, Hurst, and Schwartz, 2019; Acemoglu and Restrepo, 2020), the rise in age-friendly occupations (Deming, 2021; Acemoglu, Mühlbach, and Scott, 2022), and domestic outsourcing (Goldschmidt and Schmieder, 2017; Drenik et al., 2021).

2 The Data

2.1 Italian Social Security Data

Our empirical analysis uses 35 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 data, we restrict our analysis to workers who were at least 16 years old, had worked at least six months, held a full-time contract, had earned strictly positive wages, and had not retired. We impose these restrictions to weed out 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 the bonus payments received by many Italian workers.[6] 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 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.[7]

[6] The most common bonus payments are called the "thirteenth" and "fourteenth" salary. The thirteenth salary is a mandatory bonus payment given to employees at the end of December. The fourteenth salary is a voluntary bonus usually paid during the summer.

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

Moreover, they are winsorized at the 99.9^{th} percentile to limit the influence of extreme outliers.

In total, this dataset includes 312 million observations with information on 28,911,242 full-time workers and 3,532,905 firms between 1985 and 2019 (Table A1, Panel A).

2.2 Data for Other Countries

In addition to the Italian data, we have access to confidential employer-employee Social Security data for Germany from 1996 to 2017 provided by the Institute for Employment Research (IAB). This dataset combines (i) information from a sample of establishments with at least one employee subject to Social Security taxation (the IAB Establishment Panel) and (ii) information on workers coming from the Integrated Employment Biographies (IEB). Unlike the Italian Social Security data, the German dataset represents a snapshot of the labor market taken on June 30 of each year, rather than a comprehensive description of all labor-market events occurring throughout the year.

To measure the age wage gap, we use the daily wage associated with each individual's job spell yielding the highest earnings. This variable is expressed in 2015 euros using the conversion tables prepared by the OECD. Moreover, it is important to note that nominal earnings are top-coded. The cap varies annually, but is typically near the 95^{th} percentile. We select our sample by applying the same restrictions described in Section 2.1 for the Italian Social Security data.[8]

Moreover, we compute the age wage gap for other countries using survey data from the Luxembourg Income Survey (LIS) database. Among all 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. For each country, we compute changes in the age wage gap using yearly labor earnings, after converting them to 2011 purchasing-power-parity US dollars. Moreover, when feasible, we apply the same sample restrictions used on the administrative data from Italy and Germany.

Finally, it is worth noting that both the German data and the LIS database exhibit some limitations compared to the Italian INPS data and, therefore, can only replicate a subset of all empirical tests conducted with the Italian INPS data (see Table A2 for an overview). Within this subset, the various data sources produce similar results.

[8] Appendix A and Table A1 provide more details about the sample selection in each country.

3 The Widening of the Age Wage Gap

3.1 The Age Wage Gap in Italy

The Italian administrative data indicate that the mean worker age increased by 19 percent from 35.8 years in 1985 to 42.7 years in 2019 (Table 1, Panel A, columns 1 and 2). Three main post-World-War-II demographic trends can explain this stark aging of the workforce. First, 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.[9] Second, life expectancy at birth increased by 21 percent from 1960 to 2018, moving from 69.1 years to 83.3 years.[10] These two factors contributed to the increased aging of the population as a whole. Third, a series of pension reforms progressively increased the minimum age of eligibility for receiving public pensions, resulting in older workers spending more time in the labor force before retirement.[11]

While the Italian workforce has aged, the wages of older workers have grown at a much faster rate than those of younger workers. The difference between the mean log weekly wages of workers over 55 years old (thereafter, *O55 workers*) and workers under 35 years old (*U35 workers*) grew by 0.185 log points, a 96 percent increase from the level in 1985 (Figure 1, Panel A; Table 1, Panel A, columns 3 and 6).[12] This large widening of the age wage gap did not happen only at the average, but rather at every point of the distribution of weekly wages (Table 1, Panel A, columns 9 to 13). For instance, the age gap increased by 0.2 log points at the 10^{th} percentile, by 0.1 log points at the 25^{th} percentile, by 0.14 log points at the median, by 0.25 log points at the 75^{th} percentile, and by 0.18 log points at the 90^{th} percentile.

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

3.2 The Age Wage Gap in Other High-Income Countries

The aging of the workforce and the growing wage gap between older and younger workers are not limited to the Italian labor market.

[9] https://web.archive.org/web/20210219221740/https://data.worldbank.org/indicator/SP.DYN.CBRT.IN?end=2018&locations=IT&start=1960

[10] https://web.archive.org/web/20210219221923/https://data.worldbank.org/indicator/SP.DYN.LE00.IN?end=2018&locations=IT&start=1960

[11] In the last three decades, the 1992 "Amato reform," the 2007 "Prodi reform," and the 2011 "Fornero reform" successively raised the minimum thresholds for pension eligibility for most workers in the private sector.

[12] This increase is only slightly larger when using yearly labor earnings, rather than weekly wages (Figure 1, Panels C and D). In this case, the age wage gap grew by 0.2 log points between 1985 and 2019.

In Germany, the mean worker age increased by 9 percent between 1996 and 2017, while the age wage gap between O55 workers and U35 workers increased by 0.2 log points or 71 percent by 2007 and by 0.1 log points or 36 percent by 2017 (Table 1, Panel A). Unlike Italy, the widening of the age gap in Germany was concentrated around the 25$^{\text{th}}$ percentile (+0.34 log points) and the median (+0.1 log points) of the distribution of daily wages.

The LIS survey data allow us to observe these trends in many more countries (Table 1, Panel B). In all but one country in our sample (Israel), there has been an increase in the mean age of the workforce in recent decades.[13] For example, the mean workforce age increased by 12 percent in the United States, by 9 percent in the United Kingdom, by 2 percent in Canada, and by 6 percent in France.

Moreover, as observed in Italy and Germany, the labor earnings of O55 workers grew at a much faster pace than those of U35 workers in all fourteen countries in our sample. For instance, the age wage gaps 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 0.03 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 wage gap increased by 0.13 log points by 2013 in the United Kingdom and by 0.06 log points by 2007 in France.

Finland and Denmark are two other interesting case studies. These countries started at very low degrees of disparity between older and younger workers: in 1987, the age wage gap was only 0.04 log points in Finland and 0.16 log points in Denmark.[14] Then, their age gaps experienced a steep increase, growing by 0.21 log points and 0.19 log points, respectively, by the end of 2016.

In conclusion, the widening of the age wage 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 more developed welfare states (such as Germany, Denmark, Finland), as well as in other Southern European countries (such as Greece and Spain).

[13] Compared with other high-income economies, Israel's population, not just its workforce, has been growing at a much faster rate due to natural growth and international immigration (https://web.archive.org/web/20230420170222/https://www.cbs.gov.il/en/mediarelease/pages/2022/population-of-israel-on-the-eve-of-2023.aspx).

[14] In comparison, the age gap between O55 workers and U35 workers in 1987 was equal to 0.27 log points in Italy (INPS data) and 0.25 log points in the United States.

4 The Role of Career Spillovers

4.1 The Idea of Negative Career Spillovers

As shown in Section 3, the pay gap between older and younger workers has expanded in many high-income economies in recent decades, despite a substantial rise in the supply of older workers. Section 4 investigates whether negative career spillovers may explain this phenomenon.

Negative career spillovers, as initially defined by Bianchi et al. (2023), suggest that an increasing number of older workers with longer careers can lead to congestion in access to higher-paying positions for younger workers. Under this hypothesis, longer careers allow older workers to accrue more seniority and advance further up organizational hierarchies.[15] Consequently, a growing number of higher-ranked positions become occupied by older workers, relegating younger workers to lower-paying jobs and slower career growth due to prolonged wait times for accessing higher-paying roles.

In a frictionless labor market (Baker, Gibbs, and Holmström, 1994), a younger worker who is qualified to receive a promotion would not be hindered from it by older coworkers occupying higher-ranked jobs for a longer time, as her employer would create a new higher-level position or another firm would poach her. As outlined in Bianchi et al. (2023), two labor-market frictions are necessary for negative career spillovers.

First, firm separations must be costly to workers and/or firms. Various factors can make turnover costly, such as backloaded wages (Ke, Li, and Powell, 2018), team-based productivity (Hamilton, Nickerson, and Owan, 2003), firm-specific human capital (Lazear, 2009; Gathmann and Schönberg, 2010), knowledge spillovers (Cornelissen, Dustmann, and Schönberg, 2023), and layoff costs (Bentolila and Bertola, 1990). Regardless of the specific mechanism, prior work has documented that workers often receive a premium for longer tenure at their firm. In the context of career spillovers, this friction implies that older workers are incentivized to stay at their employers and reap the rents associated with their higher tenure, while younger workers cannot always accelerate their career growth by leaving their firms.

Second, some firms must face constraints in adding higher-level positions. In practice, firms in high-income economies may have experienced growing difficulties in expanding ranks, especially at the top, due to a decrease in labor productivity (Byrne, Fernald, and Reinsdorf, 2016; Syverson, 2017), GDP growth (Figure B1), and firm dynamism (Decker et al., 2014; Foster, Grim, and Haltiwanger, 2016). This friction implies that when older workers became more numerous and their careers became longer, firms' hierarchies were not sufficiently

[15] This idea is consistent with prior research on the crucial role of seniority in promotion decisions (Carmichael, 1983; Waldman, 1990; Prendergast and Topel, 1996; Li, Powell, and Ke, 2018).

flexible to create promotion paths toward top jobs for younger workers.

The following sections explore several empirical implications of negative career spillovers. Section 4.2 examines the different career paths of younger and older workers. Section 4.3 documents the widening of the age pay gap both within and between firms. Section 4.4 studies whether firms with more binding constraints in adding slots to their ranks exhibited larger increases in the age wage gap.

4.2 The Careers of Younger and Older Workers

The core implication of negative career spillovers posits that the age wage gap widened because the careers of younger workers worsened, while the careers of older workers improved.

4.2.1 Shifts along the wage distribution and firms' hierarchies

We begin by showing that younger workers have become less likely to reach the top of the wage distribution, while older workers have experienced the opposite trend. In Italy, 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). This trend becomes even more pronounced when examining vigintiles (Figure 2, Panel B), as the share of U35 workers decreased nearly monotonically from the lowest to the penultimate vigintile between 1985 and 2019.

In contrast, O55 workers experienced the opposite trend. Their probability of being in the top quartile of the distribution of weekly wages rose by 16 percent, from 32 percentage points in 1985 to 37 percentage points in 2019, while their probability of being at the bottom declined by 23 percent, from 23 percentage points in 1985 to 18 percentage points in 2019 (Figure 2, Panel C). Additionally, the share of O55 workers increased almost monotonically from the lowest to the next-to-highest vigintile (Figure 2, Panel D).

These opposite shifts of younger and older workers along the wage distribution translated into opposite career trajectories within firms' hierarchies. Here, we replace wages with information on the four main job levels in the Italian labor system: apprentices (*apprendisti*), blue-collar workers (*operai*), white-collar workers (*impiegati*), and higher-ranked workers and managers (*quadri* and *dirigenti*). The Italian INPS data contain information on workers' job levels from 1996. The percentage of managerial and higher-ranked jobs held by O55 workers more than doubled from 12 percent in 1996 to 28 percent in 2019, while the share held by U35 workers decreased from 8 percent to 3 percent during the same period (Figure B2, Panel A). Given that O55 workers were more likely to be managers at baseline, the progressive aging of the workforce could contribute to increasing the share of O55 managers. To address this issue, we divide the number of O55 managers by the total number of O55 workers, rather than by the total number of managers. After doing so, we observe the share of O55 managers among all O55 workers rising from 9 percent in 1996 to 11.5 percent in 2019, while the share of U35 managers shows little change over time (Figure B2, Panel B). Therefore, the shift of older workers into managerial jobs goes beyond the possible effect stemming from the overall aging of the workforce, indicating the existence of broader labor-market changes that improved older workers' career outcomes.

While more rarely attaining managerial jobs, U35 workers became more likely to hold apprenticeship positions, the lowest level of the hierarchical ladder (Figure B2, Panel C).[16] Specifically, their likelihood of being apprentices increased by 9 percentage points, from 6 percent of all U35 workers in 1996 to 15 percent of all U35 workers in 2019.

4.2.2 The rank wage gap

Next, we employ a decomposition of the age wage gap's widening to quantify the impact of shifts of younger and older workers along the wage distribution.

Two forces contributed to the age gap's widening. On the one hand, the overall shape of the wage distribution changed, favoring older workers. Specifically, U35 workers were more likely to be in segments of the distribution with lower wage growth, while the opposite trend held true for O55 workers. On the other hand, younger and older workers moved along the wage distribution in ways that benefitted the latter group. As previously shown, U35 workers fell toward the lower end of the wage distribution, while O55 workers ascended to the top. These movements did not necessitate changes to the overall shape of the wage distribution to widen the age gap. Negative career spillovers directly relate to this second force, as they depict opposing changes in younger and older workers' career trajectories. In contrast, the first force concerns broader alterations to the shape of the wage distribution, such as those resulting from increased wage inequality.

Using a framework similar to Bayer and Charles (2018), we propose a decomposition capable of quantifying these two components' contributions to the widening of the age wage gap. The change in the average log wage w between U35 workers and O55 workers and

[16] Apprenticeship positions are open-ended contracts that benefit from the same employment protection guaranteed to higher-ranked jobs. Therefore, they are associated with lower wages, but not necessarily with precarious work.

between years t and t' can be written as follows:

$$\Delta w_{O55}^{t,t'} - \Delta w_{U35}^{t,t'} = \underbrace{\sum_{v} \left(s_{O55,v,t} - s_{U35,v,t}\right)\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Distributional gap}} + \underbrace{\sum_{v} \Delta s_{O55-U35,v,t'-t} \cdot \bar{w}_{v,t}}_{\text{Rank gap}} + \underbrace{\varepsilon_{\text{O55-U35}}^{t,t'}}_{\text{Residual}}. \quad (1)$$

In this equation, $s_{a,v,t}$ is the share of workers in age group $a \in \{\text{U35}, \text{O55}\}$, vigintile v of the distribution of wages, and year t. $\Delta s_{O55-U35,v,t'-t} = (s_{O55,v,t'} - s_{O55,v,t}) - (s_{U35,v,t'} - s_{U35,v,t})$ 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'. Moreover, $\bar{w}_{v,t}$ is the mean log wage in vigintile v and year t. Appendix B.2 describes all the steps required to obtain this decomposition.

Equation (1) indicates that the widening of the age wage gap comprises three components. The first component represents variation over time in the average wages earned in different vigintiles of the distribution, while keeping the share of workers in all age groups and vigintiles fixed at baseline year t. This part is a pure *distributional gap,* measuring how much the change in the support of the wage distribution affected the wage gap between younger and older workers, while preventing individuals in both age groups from moving along the wage distribution. The second component represents variation over time in the difference between the shares of younger and older workers in each vigintile of the wage distribution, keeping the overall shape of the wage distribution fixed at baseline. This portion is a pure *rank gap,* arising entirely from shifts in the relative positions of younger and older workers along the wage distribution, while the distribution's support remains unchanged. An increase in the rank gap between older and younger workers is consistent with the existence of negative career spillovers. Finally, the third component is a *residual* resulting from the interaction between changes in shares and mean wages.

Using Italian administrative data, we decompose the age wage gap in log weekly wages between 1985 and 2019 to establish three main results. First, by 2019, the rank gap accounted for 78 percent of the total increase in the wage gap between U35 workers and O55 workers (Table 1, Panel A, column 7). Second, the rank gap was the primary driver of the age gap's widening throughout the period under consideration, contributing between a minimum of 53 percent in 1987 and a maximum of 81 percent in 2004 (Figure 3, Panel A). Third, substituting weekly wages with yearly earnings, the rank gap accounted for an even larger share of the age gap's increase (83 percent by 2019; Figure B3).

To further investigate the differences between the distributional gap and the rank gap, we decompose the change in mean wages over time separately for each age group (Figure 3, Panel B). These results indicate that the distributional gap increased the wages of both younger and older workers, albeit the increase was larger among O55 workers (+0.27 log points vs. +0.24 log points) because wages grew faster near the right tail of the distribution . Moreover, the rank gap contributed to decreasing the wages of younger workers (-0.09 log points) and to increasing the wages of older workers (+0.06 log points). This finding indicates that the movement of U35 workers between vigintiles of the wage distribution over time resulted in a decrease in their weekly wages, while the opposite occurred for O55 workers.[17]

Finally, we perform the decomposition in Equation (1) using German administrative data and the LIS survey data. Out of the fourteen countries in our sample, the rank gap accounts for the majority of the increase in ten cases (Table 1, 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 wage gap in the United States, 56 percent in Germany (based on the administrative data), and 77 percent in Canada.

In conclusion, these results align with the existence of negative career spillovers. The majority of the age gap's widening 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.

4.2.3 Entry rank and rank growth

In this section, we examine the early career paths of labor-market entrants, as negative career spillovers have two predictions about their trajectories. First, older workers' congestion of higher-paying positions should force younger workers to enter the labor market at lower sections of the wage distribution. Second, longer wait times for promotions should coincide with a slower wage growth after labor-market entry. We focus on younger workers' wage rank, rather than wage level, because variation in their relative position within the wage distribution is the main driver of the age wage gap's widening.

Next, we decompose the rank change of U35 workers between year t and t' as follows:

[17] This conclusion remains valid if we decompose the change in mean wages for individual age bins, instead of using only two age groups for younger and older workers (Figure 3, Panel C). This age-specific decomposition indicates that modifying the classification of younger (U35) and older (O55) workers does not qualitatively affect the main findings.

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

where $e \in [0, 18]$ measures years of experience of U35 workers (34-16=18), $s_{e,t}$ 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), 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 labor-market entry LME and year t. Equation (2) is not an exact decomposition of the change in wage rank of younger workers because it keeps the share of U35 workers with e years of work experience fixed at time t ($s_{e,t}$). Robustness checks indicate that the results hold under different assumptions. Appendix B.3 describes all the steps required to obtain this decomposition.

Equation (2) indicates that younger workers' change in wage rank comprises two components. The first, a change in *entry rank*, relates to the difference in the wage rank at labor-market entry between U35 workers at time t and t'. The second component, a change in *rank growth*, assesses how wage rank growth of U35 workers after labor-market entry changed between t and t'. In a plot of wage rank over the life cycle, the first term isolates changes in the intercept of the curve, while the second term depicts changes in the slope for up to eighteen years after labor-market entry.

To perform this decomposition, we use Italian administrative data, as it is the only dataset in our possession with information on the year of labor-market entry. Since INPS data first become available in 1974, we start this analysis in 1995, one of the first years with information on the entry wage for all U35 workers. To reduce noise, we compute the wage distribution at labor-market entry using the first three years of work, rather than just the first one.

The decomposition reveals four key findings. First, consistent with negative career spillovers, both entry rank and rank growth contributed to decrease the wage rank of younger workers (Figure 4, Panel A). Over time, U35 workers became more likely to start at lower vigintiles of the wage distribution and to experience slower rank growth after entry. By 2019, entry rank represented 86 percent of the overall decline in wage rank, while rank growth accounted for the remaining 14 percent. Second, the two components' relative importance changed over time. During the first years of the sample, the rank decline mainly resulted from slower post-entry rank growth, which accounted for 79 percent of the total rank loss by 2002. From 2003, a worsening entry rank became the primary driver of wage rank loss. Third, these results remain robust if Equation (2) holds the share of U35 workers with e years of work experience fixed at its value in the last year of the sample ($s_{e,,t'}$) (Figure 4, Panel B). Fourth, the results are qualitatively similar if we decompose the rank change for U30 workers, rather than U35 workers (Figure 4, Panels C and D). Focusing on U30 workers with shorter careers allows us to start the analysis in 1990. By 2019, a decline in entry rank accounted for 87 percent of the overall wage rank loss of U30 workers, while slower rank growth contributed the remaining 13 percent.

4.3 Age Gap Between and Within Firms

This section studies how negative career spillovers affected younger and older workers differently across internal and external labor markets. Older workers became more entrenched in higher-paying firms. *Within these firms*, heightened competition for top jobs lowered the average position in the wage distribution of all workers, including older ones. However, younger workers incurred larger positional losses that contributed to widening the overall rank gap. Within lower-paying firms, the age wage gap increased because older workers did not face increased competition for top jobs and improved their positions in the wage distribution, while younger workers sustained losses in wage rank. Moreover, the increased presence of older workers in higher-paying firms decreased younger workers' likelihood of finding employment in these firms, leading to large gains for older workers *between firms*.

4.3.1 Decomposition between and within firms

We start this analysis by decomposing the increase in the rank gap between and within firms. To this end, we adapt to our research question a framework first developed by Machado and Mata (2005).[18]

Initially, we sort workers into 100 percentiles or *firm groups* using their firm's average log weekly wage, separately for each year in the sample. Next, within each firm group, we sort workers into 500 quantiles or *worker groups* based on the difference between their weekly wage and the average weekly wage in their firm group. The outcome of this two-step process is the sorting of all workers into 50,000 equal-sized bins, which we call *firm-worker groups*.[19]

[18] Appendix B.4 provides more details on this decomposition.

[19] In theory, firm groups could coincide with firms themselves. However, in practice, many firms are not large enough to generate meaningful within-firm wage distributions. In most cases, this procedure still ensures that all coworkers are assigned to the same firm group. As a validity check, we compare the worker shares in different vigintiles of the distribution of weekly wages predicted by the sorting procedure to the actual shares observed in the raw data. As expected, the predicted and actual shares are nearly identical (Figure

This sorting allows us to rewrite the shares of workers in age group a, firm-worker group (f, e), and year t as follows:

$$s_{a,(f,e),t} = \underbrace{s_{a,f,t}}_{\text{Share of } a \text{ in } f} \cdot \underbrace{s_{a,(e|f),t}}_{\text{Share of } a \text{ in } e \text{ conditional on } f}. \tag{3}$$

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

Using Equation (3), we can rewrite the rank gap in Equation (1) as follows:

$$\underbrace{\sum_{v} \Delta s_{O55-U35,v,t'-t} \bar{w}_{v,t}}_{\text{Rank gap}} = \underbrace{\sum_{g\in(f,e)} \Delta s_{O55-U35,f,t'-t} \cdot \Delta s_{O55-U35,(e|f),t} \cdot \bar{w}_{g,t}}_{\text{Between firms}} + \underbrace{\sum_{g\in(f,e)} \Delta s_{O55-U35,f,t} \cdot \Delta s_{O55-U35,(e|f),t'-t} \cdot \bar{w}_{g,t}}_{\text{Within firms}} + \underbrace{\varepsilon^{t,t'}_{\text{O55-U35}}}_{\text{Residual}}. \tag{4}$$

The rank gap is the result of two counterfactual scenarios. First, a between-firm component identifies changes in the share of workers in age group a and firm group f between t and t', while keeping both (i) the distribution of workers within each firm-worker group and (ii) the mean wages in each firm-worker group fixed in the baseline year t. Under this scenario, workers of age group a can move across firm groups over time, but the within-firm distributions remain fixed. Second, a within-firm component isolates changes over time in the share of workers in age group a and worker group $(e|f)$, while keeping both (i) the distribution of workers across firm groups and (ii) the mean wages in each firm-worker group fixed in year t. In other words, workers in age group a can move within firm groups, but their allocation across firm groups stays fixed in year t. Finally, there is a residual component that is the product of the two previous changes in the worker shares.

In Italy, the rank gap increased both within and across firm groups (Figure 5, Panel A). The within-firm component was the main driver of the widening in the rank gap until 2004, and its magnitude remained large until 2019. From 2004, the between-firm component grew at a faster rate, contributing to 39 percent of the overall rank growth in 2004 and 62 percent in 2019. From 1985 to 2019, the rank gap grew by 0.06 log points within firm groups and by 0.09 log points between firm groups. These findings apply to Germany (Figure 5, Panel B). The rank gap increased both within and between firm groups, but the latter component

B4).

contributed more to the overall rank gap's growth starting from the late 90s. By 2017, the rank gap grew by 0.02 log points within firm groups and by 0.09 log points between firm groups.

In Italy, we further unpack these initial findings by decomposing the change in wage rank separately for U35 and O55 workers (Figure 5, Panel C). By 2019, younger workers experienced large losses in wage rank both within (-0.05 log points) and between (-0.04 log points) firm groups. In contrast, older workers benefited from rank gains both within and between firm groups, although the latter were significantly larger in magnitude; O55 workers' wage rank increased by 0.05 log points between firm groups and by only 0.01 log points within firm groups.

4.3.2 Rank change within firm groups

The large within-firm decline in wage rank for U35 workers is consistent with negative career spillovers. According to this hypothesis, the increased presence of older workers at the top of firms' hierarchies created roadblocks to their younger coworker's careers, confining them to lower segments of each firm's wage distribution.

To provide additional evidence on this point, we decompose the within-firm rank decline for U35 workers from 1995 to 2019 using Equation (2), which measures how much of this rank loss stems from worse conditions either at or after labor-market entry (Figure 5, Panel D). Within firm groups, younger workers experienced both a decline in their initial wage rank at labor-market entry and a much slower rank growth during the post-entry years. By 2019, lower entry rank accounted for 56 percent of the total within-firm rank loss, while more sluggish post-entry rank growth contributed the remaining 44 percent. In Section 4.2.3, the same decomposition revealed that worse entry rank was responsible for 86 percent of the *total* rank change (Figure 4, Panel B), suggesting that worse entry conditions must be associated with substantial rank losses between firm groups.

In contrast, older workers did not experience within-firm average gains symmetrical to the large losses incurred by younger workers. This finding fits the nature of negative career spillovers in internal labor markets. On the one hand, older workers improve their rank within firms by lengthening their careers and progressing further along organizational hierarchies. On the other hand, they become more numerous and increase congestion to higher-paying positions for all workers within a firm, including older workers themselves. The result is that the wage rank of the average older worker within each firm is subject to two opposing forces: longer careers and more time for career progression, but also more competition and crowding out from other older workers. The latter effect should prevail within firms in which the number of older workers increased the most.

To test this prediction, we measure changes in worker shares and wage rank across different firm groups. Firms are divided in twenty firm groups based on their mean log weekly wage, so that firms in groups 1 to 10 pay below-median mean wages, and firms in groups 11 to 20 pay above the median. As expected, older workers became more likely to be employed in higher-paying firm groups, while the opposite is true for younger workers (Figure 6, Panel A; Table B1, columns 1 and 2). From 1985 to 2019, O55 workers' share increased by 0.5 percentage points (or 9 percent over the 1985 level) in above-median firm groups. The increase was larger among the three highest-paying firm groups (for example, +1.7 percentage points in group 20), while the decline was steeper among the two lowest-paying groups (-1 percentage points in group 1 and -0.6 percentage points in group 2).

Consistent with more crowding out at the top of organizational hierarchies, the rank change *within firm groups* was smaller in above-median firm groups for all workers, including older ones (Figure 6, Panel B; Table B1, columns 3 and 4). As predicted by negative career spillovers, U35 workers' within-firm rank change was always negative, but larger in magnitude in higher-paying firm groups: the average rank loss was equal to 0.22 log points in groups 1 to 10 and 0.31 log points in groups 11 to 20. The same trend applies to older workers, although their rank change was positive within most firm groups. O55 workers gained positions in the wage distribution of below-median firm groups from 1985 to 2019, the same groups in which congestion was less severe. Within higher-paying firms, their rank change becomes progressively smaller before turning negative for the three highest-paying firm groups. On average, O55 workers' wage rank increased by 0.15 log points in below-median firm groups and decreased by 0.02 log points in above-median firm groups.

In summary, consistent with negative career spillovers, younger workers achieved worse placements in the wage distribution within all firm groups. These losses were larger in magnitude in firms in which the number of older workers increased the most, generating more severe bottlenecks to access higher-ranked positions. In contrast, older workers improved their positions in the wage distribution of firm groups in which the competition for top jobs from other older workers was lower. In these firms, they could extend their careers and progress further along organizational hierarchies. However, in higher-paying firm groups, the number of older workers and, therefore, competition for top jobs increased disproportionately, outweighing the benefits of longer careers, so that the average older worker experienced either a smaller positional gain or even a positional loss in the within-firm wage distribution.

4.3.3 Rank change between firm groups

As previously shown, older workers increased their presence within higher-paying firms, especially at the very top of the distribution of firms' mean wages. While increasing competition for top jobs *within firms*, this trend was also the main driver of the substantial rank gains older workers incurred *between firm groups* (Figure 5, Panel B).

This section investigates how older workers became more likely to work for higher-paying firms. One possibility is that O55 workers became progressively more likely to move to higher-paying firms, but data on tenure do not support this hypothesis (Table B1, columns 5 and 6). In 2019, O55 workers had a high average tenure within higher-paying firms: on average, 12.7 years of continuous employment in firms with mean wages above the median. Moreover, their tenure in above-median firm groups was 61 percent higher than that in below-median firm groups (7.9 years), further indicating that they did not recently move in large numbers to higher-paying firms. In addition to examining tenure levels in 2019, we can observe tenure changes between 1985 and 2019. Over this period, tenure decreased across all firm groups, but the decline was smaller in magnitude in firms paying above-median wages: the share of O55 workers with at least three years of tenure declined by 13.7 percent in lower-paying firms and by only 2.1 percent in higher-paying firms.[20]

Rather than from turnover, the increased presence of older workers at the top of the distribution of firms' mean wages stems from their higher likelihood of preserving their positions in these organizations. After all, longer careers are a more attractive option when returns from labor are higher. In addition to trends in tenure, this hypothesis is supported by information on older workers' age (Table B1, column 7). Consistent with the idea that older workers were more likely to postpone retirement within higher-paying firms, we observe that O55 workers' mean age disproportionately increased in firms paying above-median wages. From 1985 to 2019, O55 workers' mean age increased by 1.3 percent (or 9 months) in higher-paying firms and by only 0.8 percent (or 5.7 months) in lower-paying firms.

This progressive entrenchment of older workers in higher-paying firms was aided by the fact that firms with above-median wages experienced larger increases in lifespan (Table B1, column 8). From 1985 to 2019, firms paying above-median wages incurred a 104-percent increase in mean age, while other firms's mean age increased by 80 percent. In other words, older workers may have been able to hold their jobs in higher-paying firms for longer also because these positions started disappearing at a lower rate over time. In line with these findings, Decker et al. (2014) has documented a decline in firm turnover driven by lower entry rates of younger firms and lower exit rates of older firms. So, not only higher-paying firms became older, allowing older workers to retain their positions for longer, but startups, which are more likely to hire younger workers and pay them higher wages (Ouimet and Zarutskie, 2014), became rarer.

[20]We do not use mean tenure for this analysis because this variable is left censored for some workers at the start of the sample.

Then, according to negative career spillovers, the increased presence of older workers in higher-paying firms decreased younger workers' probability of finding employment in these firms, widening the rank gap between firm groups. As previously shown, younger workers became less likely to be in higher-paying firm groups (Table B1, column 1). Moreover, consistent with negative career spillovers, slower career progression within firms induced more younger workers to resort to turnover. However, older workers' congestion of higher-paying firms decreased younger workers' gains from turnover, because an increasing number of higher-ranked jobs became unavailable.

We establish three main findings on U35 workers' turnover. First, younger workers became increasingly more likely to experience turnover: U35 workers' share with a turnover event increased from 27 percent in 1985 to 44 percent in 2019 (Figure 7, Panel A). Second, younger workers became more likely to find employment in firms with higher turnover, while older workers experienced the opposite trend (Figure 7, Panels B and C). The share of U35 workers employed by firms with the highest share of turnover events increased by 35 percent by 2019, while O55 workers' share in the same firms decreased by 21 percent. Third, in spite of higher turnover, younger workers incurred lower gains from moving to other firms (Figure 7, Panel D). For example, the average gain in the wage percentile associated with a turnover event decreased by 34 percent, while the median gain declined by 67 percent. Over the same period, U35 workers' share with a positive change in wage percentile following a move decreased by 6 percent, a pattern that is consistent with both higher rates of involuntary turnover and increased willingness of trading higher current wages for better future career progression.

4.4 Heterogeneities Across Firms

Bianchi et al. (2023) shows both theoretically and empirically that one of the requirements for negative career spillovers is that firms need to face constraints in adding higher-ranked positions to their organizational hierarchies. If not, all workers who deserve a promotion can receive one, and more older workers with longer careers in top jobs cannot impede the progression of their younger coworkers.

In this section, we test whether the age wage gap increased more in firms that are more likely to face these constraints. Specifically, 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 age wage gap separately across these firm groups. If the data align with the existence of negative career spillovers, we expect to observe that the age wage gap increased more in larger and older firms in a mature stage of their life cycle, when organizational hierarchies become less flexible.

In Italy, the widening of the age wage gap was large within all types of firms (Figure B5, Panel A). Moreover, consistent with negative career spillovers, the magnitude of the age-wage-gap increase is significantly larger in magnitude among firms that are more likely to face constraints in adding higher-rank positions to their hierarchies. Specifically, the age gap in weekly wages increased by 0.24 log points within firms with below-median employment growth, while it increased 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 (0.185 log points) and is significant at the 1 percent level. Moreover, the age wage gap increased significantly more in firms that were more than ten years old and employed more workers.

These results also suggest why negative career spillovers may have become more prevalent over time. Given that older firms have become more common in many high-income economies (Figure B5, Panel B for Italy; Decker et al. (2014) for the U.S.), there are now many more organizations that are less likely to freely add higher-ranked jobs to their hierarchies.

5 Alternative Explanations

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

5.1 Wage Inequality

The economic literature has documented a substantial rise in wage inequality in high-income economies (for example, Piketty and Saez (2003) and Autor, Katz, and Kearney (2008)). Historically, O55 workers were more likely to occupy higher-paying jobs, which were subject to higher increases in mean wages, whereas U35 workers were often in lower-paying roles, which experienced smaller or no increases in mean wages. 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 (1). The distributional gap within this equation isolates the effect of changes in the wage distribution's support on the overall age wage gap, including those changes associated with higher wage inequality. Specifically, it quantifies the impact of variations in mean wages 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 can only account for a minor portion of the age wage gap's expansion in most high-income countries, suggesting that one of the core features of wage inequality does not play a central role (Table 1, column 8).

5.2 Higher Returns to Experience and Higher-Level Skills

In this section, we examine whether trends in the returns to experience and higher-level skills may have contributed to widening the age wage gap.

The evidence on the recent trajectory followed by returns to work experience is mixed. On the one hand, prior work has documented that specific occupations became more rewarding for experienced workers. For example, Jones (2009) shows that many academic and scientific tasks have grown more complex, necessitating more advanced skills. This increased "burden of knowledge" has prompted many inventors to extend their investment in education, thereby delaying the peak of their labor earnings. Azoulay et al. (2020) presents similar findings for entrepreneurs. On the other hand, outside of this set of innovation-centric jobs, the progressive aging of the workforce should have lowered returns to experience for the average worker. For example, Jeong, Kim, and Manovskii (2015) shows that an increased supply of older workers led to a decrease in the price of experience, a trend that would have narrowed the age wage gap.

There is stronger agreement in the literature on the fact that returns to higher-level skills have increased in recent decades. Within the rich literature on skill-biased technological change (SBTC; for an overview, see Acemoglu and Autor (2011)), Autor, Katz, and Kearney (2006) proposes a model in which new technology complements the non-routine tasks integral to high-wage jobs, thus increasing these tasks' value. Older workers, who are more likely than their younger coworkers to engage in these non-routine tasks and occupy higher-paying positions due to their experience, were particularly well-positioned to benefit from recent technological advancements. Beyond the evidence on SBTC, prior papers have documented shifts in the labor-market's demand for higher-level skills. For example, Deming (2021) shows that the demand for decision-making skills, which improve with experience and tenure, has risen, leading to higher market returns for these skills and increased wages for more experienced workers.

While higher returns to experience and higher-level skills have the potential to push the wages of younger and older workers further apart, they should do so mainly through a larger distributional gap, a channel that Section 4.2.1 identified as a minor source of the widening in the age wage gap.[21]

[21] Bayer and Charles (2018) reaches a similar conclusion about the effect of rising returns to education on the black-white wage gap in the United States.

To clarify this point, 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 the labor contracts. Though simple, this equation becomes a standard Mincerian earning function if x is replaced with schooling and a quadratic polynomial of labor-market experience. It also relates to the popular AKM model (Abowd, Kramarz, and Margolis, 1999) as x could include both firm-specific and worker-specific fixed effects. A crucial feature of this wage equation is the unequal distribution of the variable x between younger and older workers. 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, variable ε^t_i is equally distributed across both worker categories.[22]

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 wage gap. We then utilize Equation (1) to decompose this increase into a larger rank gap and a larger distributional gap.

Without ε^t_i, x is the sole determinant of individual wages. When its unit price β_1 increases, the resulting expansion of the age wage gap stems entirely from a larger distributional gap between older and younger workers. (Figure B6, Panel A).

With ε^t_i, differences in x account for a smaller share of wage variation (Figure B6, Panel B). Following an increase in the price of x, the age wage gap increases, but the contribution coming from the distributional gap declines as the standard deviation of ε^t_i grows. When the standard deviation of ε^t_i is sufficiently large, the rank gap accounts for most of the age wage gap's widening.

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^t_i), a higher price of x increases the age wage gap mainly by moving the two tails of the wage distribution further apart (larger distributional gap). For example, given that older workers are on average more experienced than younger workers, a higher price of experience widens the age wage 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 though which a higher price of x widens the age wage

[22] We calibrate the wage equation to match five key moments from the first sample year of the Italian administrative data. Appendix B.5 includes more details.

gap depends on the relationship between x and wages. When the R^2 between x and wages is larger, the wage distributions of younger and older workers are less overlapped, and the same conclusions discussed for the case without ε_i^t apply. Conversely, when the R^2 between x and wages is smaller, the wage distributions of younger and older workers are more overlapped. In this case, a higher price of 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 age wage gap's widening primarily arises from a larger rank gap depends on the correlation between these variables and wages at baseline. Using Italian administrative data in 1985, we regress log weekly wages on a quadratic polynomial of labor-market experience and dummies for the four main job levels in the Italian labor market as a proxy for skills. Both the R-squared and adjusted R-squared equal 0.31 when including all full-time workers with open-ended contracts and drop to 0.26 when the sample is narrowed to 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 age wage gap through the distributional gap, a conclusion at odds with the empirical evidence in Section 4.2 (Table 1, columns 7 and 8).

5.3 Changes in the Composition of Younger and Older Workers

This section explores whether changes in the composition of younger and older workers have contributed to the age wage gap's expansion. We focus on factors, such as the share of temporary or foreign-born workers, that are typically associated with below-average wages and may have risen more rapidly among U35 workers. Our analysis, however, reveals that older workers' wages have outpaced those of younger workers even after controlling for these socio-economic trends.

Whenever these variables are available in the administrative and survey data under our control, we regress log wages on gender (a male dummy), nationality (a dummy for nonimmigrant workers) or race (a dummy for white workers in the United States), contract length (a dummy for temporary contracts), education (a dummy for college education), and health (a dummy for disability status). We estimate distinct regressions 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 wage gap.

Controlling for these characteristics does not substantially reduce the age wage gap's growth (Table B2, columns 1 to 14). For example, the Italian administrative data allow us to control for gender, nationality, and contract length. The residual wages indicate that the age wage gap rose by 0.16 log points, only 13.5 percent less than the unconditional gap increase.

This pattern remains broadly consistent across other countries in our sample. Out of 59 measurements with controls, the age wage gap's increase is less than half of the uncontrolled gap expansion without controls in only three cases.

We now 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 markets. Previous studies indicate that this form of selection could be negatively correlated with older workers' earning potential, therefore narrowing the age wage gap (Munnell, Sanzenbacher, and Rutledge, 2018; Kolsrud et al., 2021). We provide further evidence that selection into retirement is not a primary driver of the age wage gap's growth by limiting our O55 workers' group to male employees aged between 56 and 60. The rationale for this test is that men's minimum retirement age was already at least 60 years at the start of our sample in all but two countries in our sample (Table B3). 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 wage gap remains largely unaltered (Table B2, column 15).

5.4 Sectoral and Occupational Shifts

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

We first investigate secular sectoral shifts away from manufacturing. Prior studies have documented that the decline in manufacturing jobs contributed to unemployment among younger workers with lower skills (Autor, Dorn, and Hanson, 2013; Charles, Hurst, and Schwartz, 2019; Acemoglu and Restrepo, 2020). Therefore, the disappearance of jobs where younger workers could earn relatively higher wages may be related to the widening age wage gap.

If this hypothesis aligns with the data, the age wage gap should predominantly expand across sectors, as a result of younger workers's outflow from manufacturing. To test this prediction, we modify Equation (4) to decompose the change in rank gap between and within sectors. This procedure slightly differs from the decomposition between and within firms in two ways. First, instead of forming 100 firm groups, we create 270 *sector groups*, one for each 3-digit sector in the statistical classification of economic activities of the European Community (NACE Rev. 2). Second, we form 200 worker groups within each 3-digit sector, yielding a total of 54,000 *sector-worker groups*.[23] The results indicate that the majority of the rank gap's increase occurred within 3-digit sectors (Figure B7, Panel A), accounting for 68 percent of the total growth in the rank gap by 2019.

Moreover, we should observe a larger increase in the age wage gap in non-manufacturing

[23] We limit worker groups to 200 per sector to ensure sufficient observations in each worker-sector group.

sectors where either the share of younger workers or their mean wage was lower at baseline. These sectors should have received lower-skilled younger workers who became unable to find employment in manufacturing and were willing to accept lower wages elsewhere. On the contrary, the correlation between the widening of the age wage gap and these two baseline characteristics at the 2-digit sector level is both statistically and economically insignificant (Figure B7, 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, an effect size equal to just 0.2 percent of the standard deviation of the rank gap's increase. More generally, the expansion of the age wage gap is relatively homogeneous across all sectors, both within and outside manufacturing.

Next, we examine trends in the availability of jobs offering higher returns to experience. As previously discussed, Deming (2021) shows that the employment share in decision-intensive occupations, where older workers have an advantage due to their accrued experience, has been on the rise since the 1970s. Therefore, the growing supply of these occupations may have improved older workers' employment opportunities, widening the age wage gap.[24]

This hypothesis implies that the age wage gap mainly widened across occupations due to older workers transitioning into positions with higher rewards for experience. To test this prediction, we modify Equation (4) to decompose the increase in rank gap between and within occupations. We create 10 *occupation groups*, corresponding to each 1-digit occupation in the International Standard Classification of Occupations (ISCO-08).[25] Within each group, we subdivide workers in vigintiles, resulting in 200 *occupation-worker groups*. From 2012, the first year with occupation data, nearly all the rank gap's growth occurred within 1-digit occupations (Figure B7, Panel D), contributing 81 percent of the total growth by 2015 and 88 percent by 2019.

Moreover, our prior findings on the post-entry wage rank growth of U35 workers allow us to examine a second prediction. Specifically, 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. The increasing scarcity of jobs for inexperienced workers worsens entry conditions, but the wage curve steepens after entry due to more occupations offering higher rewards for experience. However, these trends, highlighted by Deming (2021) for wage *levels* over the lifecycle, do not apply to the variation in wage *rank* across cohorts of younger workers, the primary driver of the expanding age wage gap. In line with the existence of negative career spillovers, we have found that both the entry wage rank and

[24]This phenomenon is related, but different from an increase in the returns to higher-level skills and experience (discussed in Section 5.2).

[25]One of these 1-digit occupations isolates the decision-making intensive managerial jobs.

the post-entry wage rank growth for U35 workers declined over time, indicating a slowdown in younger workers' career progression for several years after entry (Figure 4). Thus, our analysis resonates with Acemoglu, Mühlbach, and Scott (2022)'s conclusion that the rise in age-friendly jobs has not disproportionately favored older workers.

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 B8, Panel A), domestic outsourcing could contribute to the widening age wage gap.

If domestic outsourcing were a primary factor, the rank gap should have predominantly increased between sectors. Goldschmidt and Schmieder (2017) documents that outsourced jobs have gradually moved to business-service firms concentrated in a limited number of sectors. However, we have already established that 68 percent of the rank gap's increase by 2019 took place within 3-digit sectors, while only 2 percent occurred between sectors (Figure B7, Panel A).

In additional tests, we examine whether excluding sectors and firms most likely to be affected by domestic outsourcing decreases the expansion of the age wage gap. Specifically, we drop all workers in 3-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 B8, Panels B to D). Our main findings remain robust after these exclusions: the rank gap increased, and the majority of this increase occurred within sectors. Despite being an important labor-market phenomenon, domestic outsourcing does not appear to be a key driver of the growth in the age wage gap.

6 Conclusions

This paper leverages comprehensive administrative data on 38 million workers across 3.7 million firms in Italy and Germany, supplemented by survey data on 6.6 million workers from fourteen high-income countries. It demonstrates that over the past four decades, wages of older workers have been growing at a much faster rate than those of younger workers. In Italy, for instance, the wage gap between workers over 55 and those under 35 grew by 96 percent between 1985 and 2019, while in the United States it increased by 61 percent between 1979 and 2018.

Our analysis underscores the importance of negative career spillovers (Bianchi et al., 2023). In a frictional labor market, characterized by costly worker-firm separations and firm-level constraints on creating new higher-ranked positions, a growing population of older workers and delayed retirements result in older workers accruing more seniority, advancing further along organizational hierarchies, and maintaining higher-ranked jobs for longer periods. The increased presence of older workers at the top of firms' hierarchies hampers the career progression of younger workers.

We highlight five main findings describing older workers' congestion of higher-ranked positions. First, the expanding age wage gap primarily arises from younger workers' increasing difficulty in reaching the top segments of the wage distribution and higher-ranked job levels, a situation that contrasts with the experience of older workers. Here, we demonstrate that the predominant factor in the growth of the age wage gap is not older workers extending their preexisting wage lead, but rather their surpassing of younger workers in the wage distribution. Second, in line with greater congestion at the top, younger workers enter the labor market at progressively lower segments of the wage distribution and experience lower wage growth for many years after entry. Third, older workers are prolonging their careers for longer periods in higher-paying firms. Within these firms, congestion increased the most, pushing both younger and older workers, on average, toward lower portions of the wage distribution. This effect is more pronounced for younger workers, therefore widening the age wage gap even within firms with more severe congestion. Fourth, the entrenchment of older workers in higher-paying firms makes it increasingly difficult for younger workers to secure employment in these firms. Consequently, younger workers, confined to lower-paying firms and facing slower career progression, resort more frequently to turnover for career advancement, despite declining financial gains from these events. Fifth, as predicted by negative career spillovers, the age wage gap's growth is larger within firms that face more binding constraints on adding higher-ranked positions to their organizational hierarchies.

In conclusion, labor markets have witnessed a major wage transfer 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 are not always feasible to defer until later career stages.

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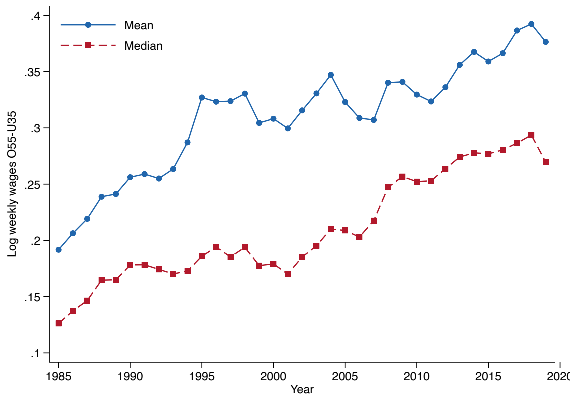
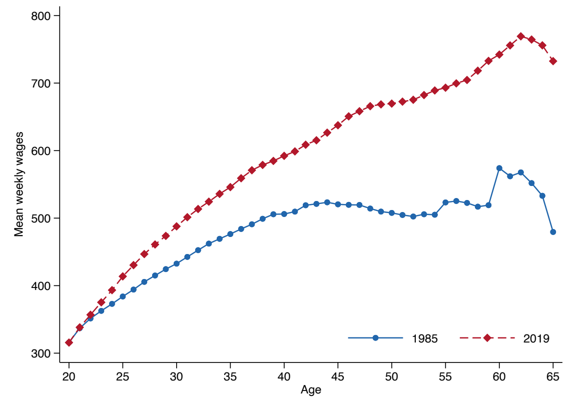
Figures and Tables

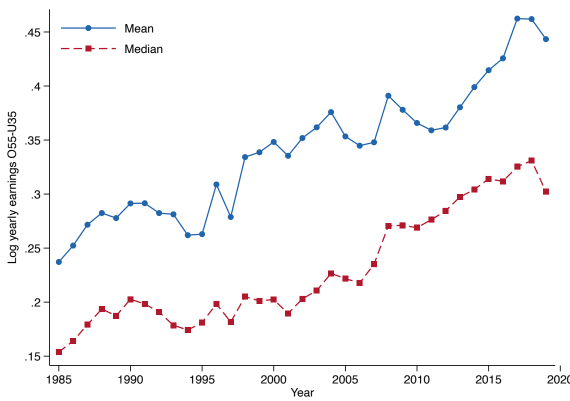
Figure 1: Age Gap in Weekly Wages and Yearly Labor Earnings



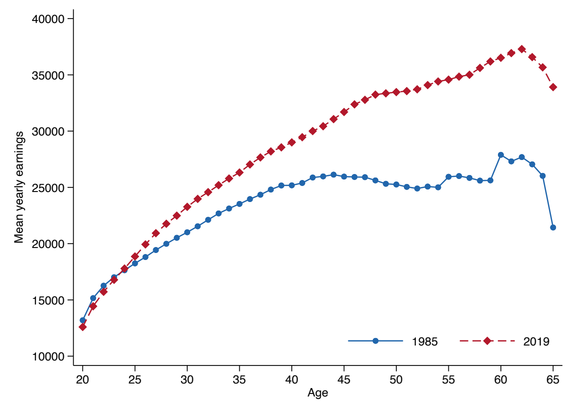
Panel A: Gap in log mean and median weekly wages



Panel B: Age profiles for mean weekly wages



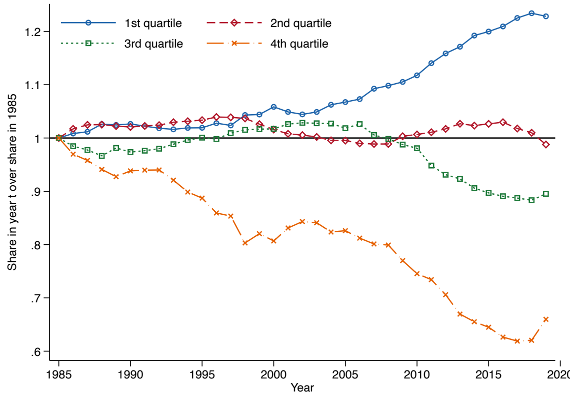
Panel C: Gap in log mean and median yearly earnings



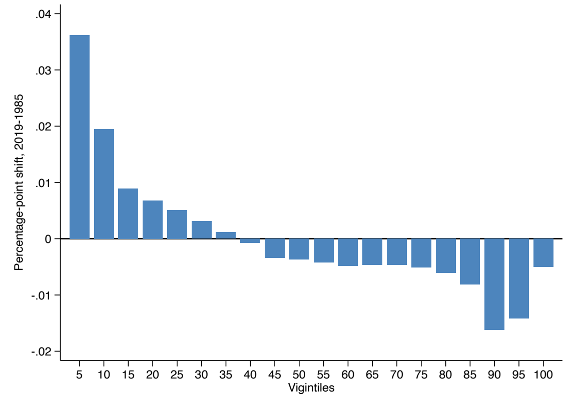
Panel D: Age profiles for mean yearly earnings

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. Panels C and D repeat this analysis for yearly labor earnings, rather than for weekly wages. *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

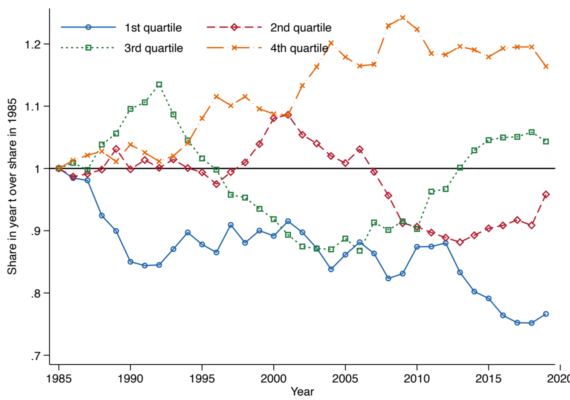
Figure 2: Worker Shares in Distribution of Weekly Wages



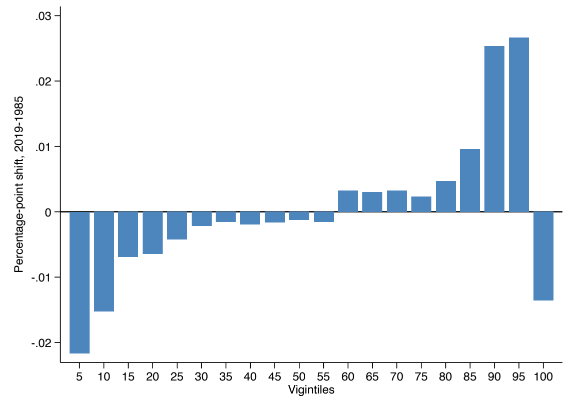
Panel A: U35 workers, quartiles,
$t \in [1986, 2019] - 1985$



Panel B: U35 workers, vigintiles
2019-1985



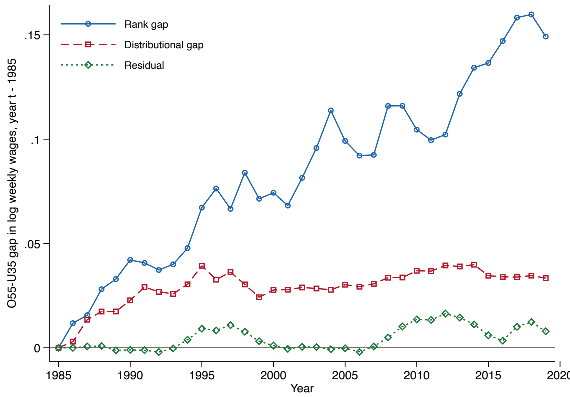
Panel C: O55 workers, quartiles
$t \in [1986, 2019] - 1985$



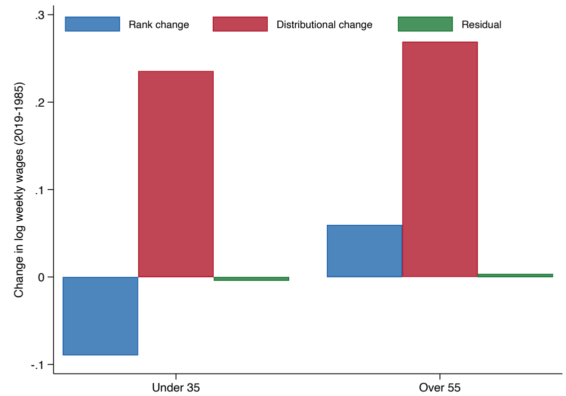
Panel D: O55 workers, vigintiles,
2019-1985

Notes: Panel A (C) 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 B (D) plots the percentage-point difference in the share of U35 (O55) workers in each vigintile from 1985 to 2019. For example, "0.05" indicates that the share of U35 or O55 workers in that vigintile increased by 5 percentage points between 1985 and 2019. *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

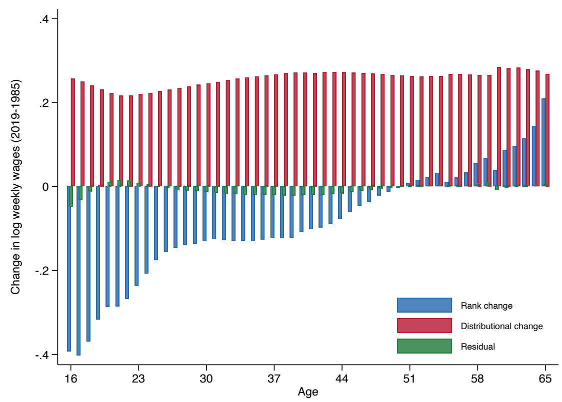
Figure 3: Decomposition of Change in Weekly Wages



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



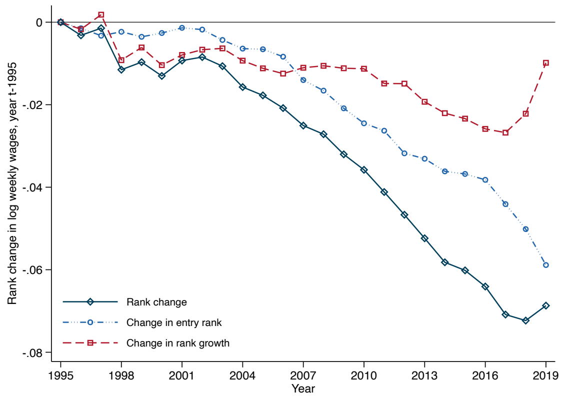
Panel B: 2019-1985,
two age groups



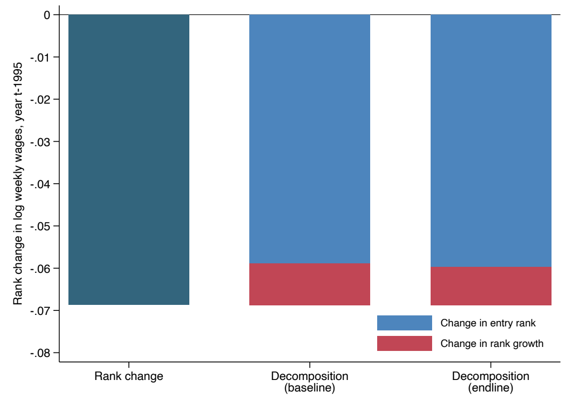
Panel C: 2019-1985,
individual age groups

Notes: Panel A shows the decomposition of the change in mean log weekly wages between O55 and U35 workers from 1985 to year $t \in [1986, 2019]$ into three components (Equation (1)). Panel B shows the decomposition of the change in mean log weekly wages between 1985 and 2019 separately for the two age groups (U35 and O55 workers). Panel C shows the same decomposition for individual age groups. *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

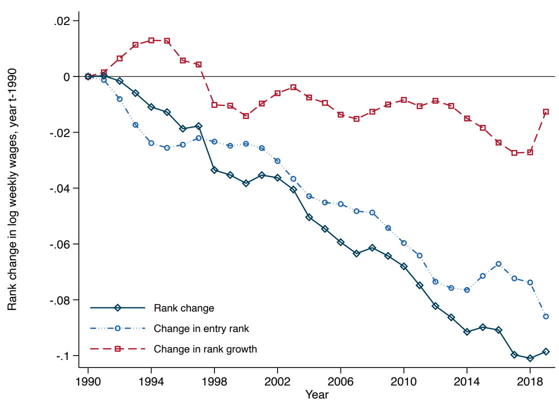
Figure 4: Entry Rank and Rank Growth



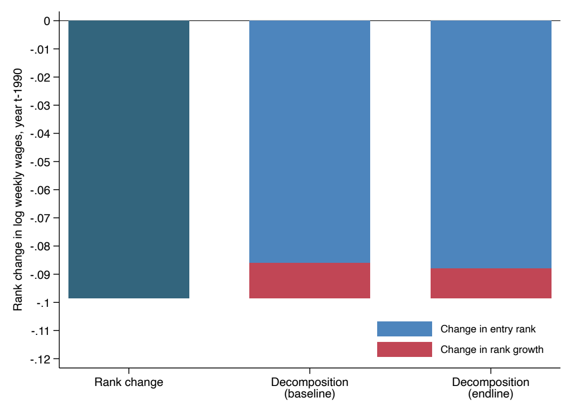
Panel A: U35 workers,
$t \in [1996, 2019] - 1995$



Panel B: U35 workers,
2019-1995



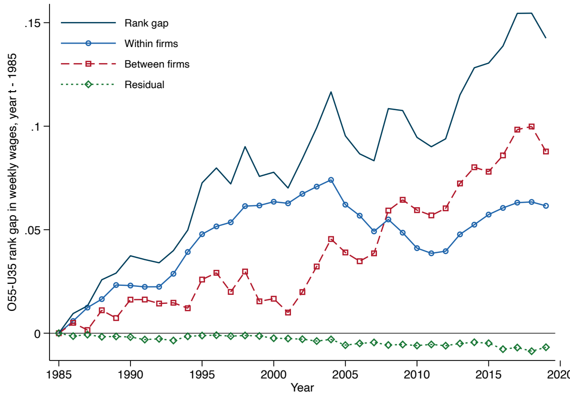
Panel C: U30 workers,
$t \in [1991, 2019] - 1990$



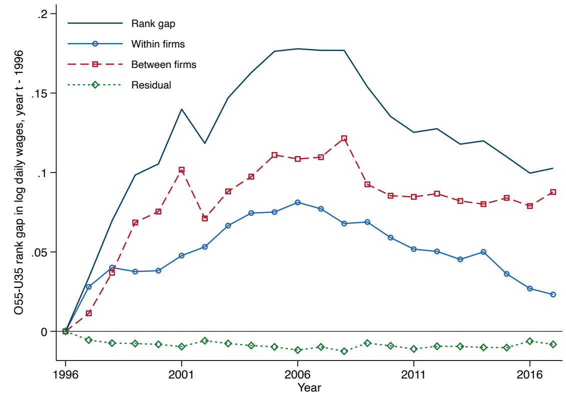
Panel D: U30 workers,
2019-1990

Notes: Panel A shows the decomposition of the rank change in the distribution of log weekly wages for U35 worker from 1995 to year t into two components: (i) the change in wage rank at labor-market entry and (ii) the change in rank growth between labor-market entry and year t (Equation (2)). Panel B shows the same decomposition between 1995 and 2019 under two scenarios; in one, the experience composition of U35 workers is kept fixed in 1995, while in the second, it is kept fixed in 2019. Panel C (D) replicates the decomposition in Panel A (B) for U30 workers and from 1990. *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1974-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

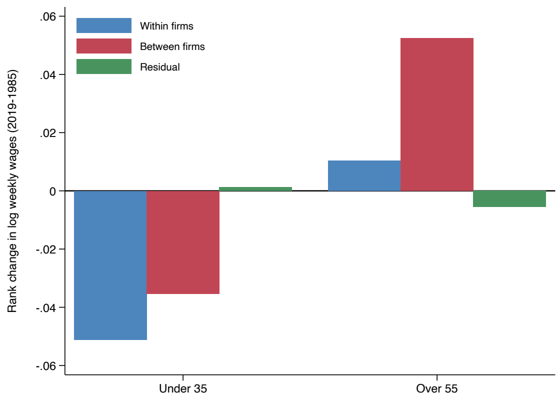
Figure 5: Increase in Rank Gap Between and Within Firms



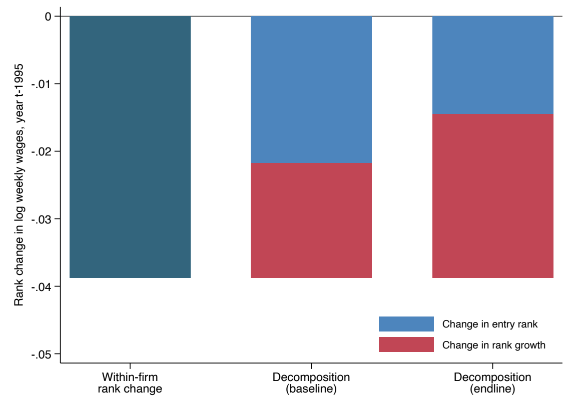
Panel A: Δ rank gap
between and within firms,
$t \in [1986, 2019] - 1985$ (Italy)



Panel B: Δ rank gap
between and within firms,
$t \in [1997, 2019] - 1996$ (Germany)



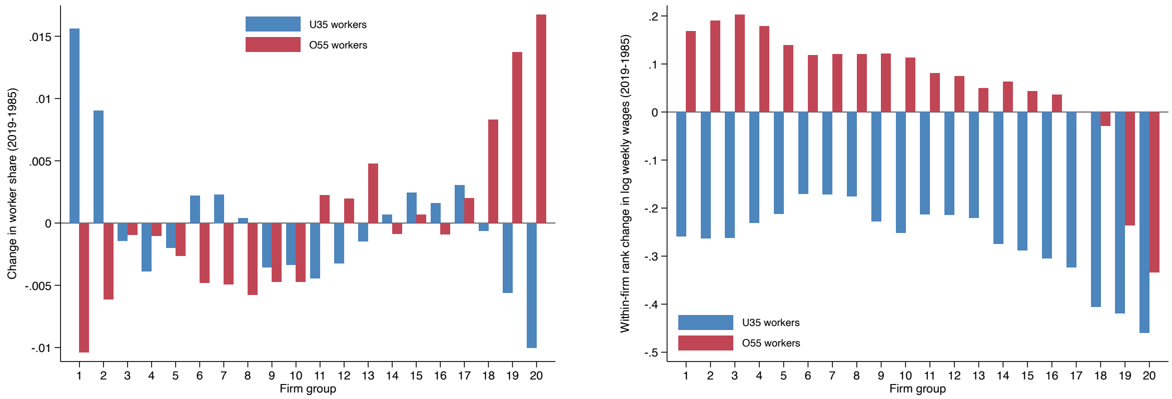
Panel C: Δ rank gap
between and within firms,
2019-1985 (Italy)



Panel D: U35 workers,
Δ rank gap within firms,
2019-1995 (Italy)

Notes: Panel A shows the decomposition of the change in rank gap in log weekly wages between O55 workers and U35 workers and between 1985 and year t into a within-firm component, a between-firm component, and a residual (Equation (4)). Panel B shows the decomposition of the change in rank gap in log daily wages between 1996 and 2017 in Germany. Panel C shows the decomposition of Italy's age wage gap in log weekly wages between 1985 and 2019 separately for U35 workers and O55 workers. Panel D decomposes the within-firm rank increase for U35 workers between 1995 and 2019 into a change in entry rank and a change in within-firm rank growth (Equation (2)). *Sources for Italy:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Sources for Germany:* 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 A.2.

Figure 6: Sorting of Older Workers and Change in Rank Gap

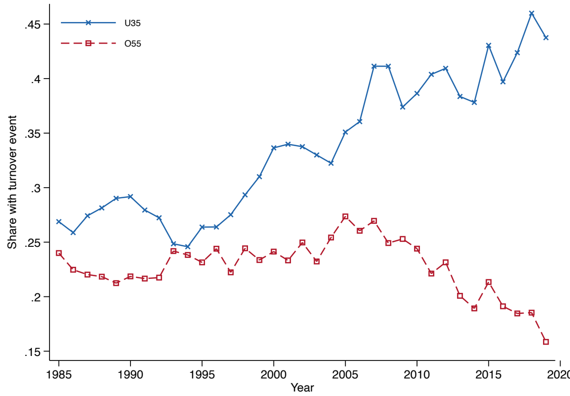


Panel A: Change in worker shares

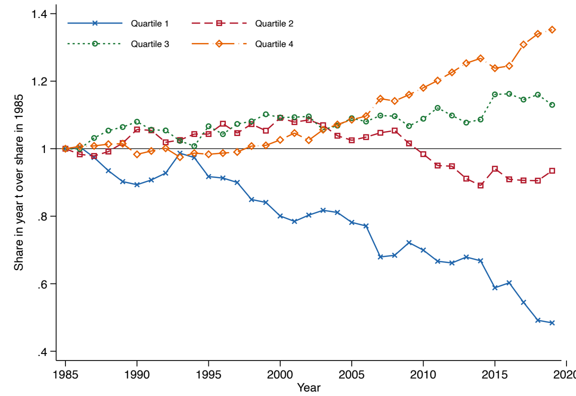
Panel B: Δ rank gap within firms

Notes: Panel A shows the variation in between-firm worker shares for each firm group from 1985 to 2019. Panel B shows the within-firm rank change separately for U35 workers and O55 workers in each firm group. Firm groups identifies different vigintiles of the distribution of mean firm-level weekly wages. To limit noise, the displayed values are averages computed using each group and its two adjacent firm groups (one in the case of the first and last group). *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

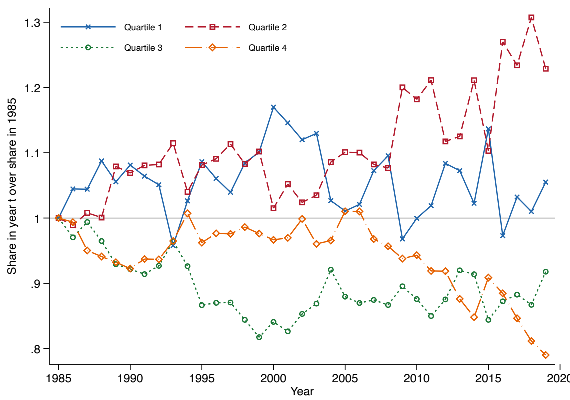
Figure 7: Turnover



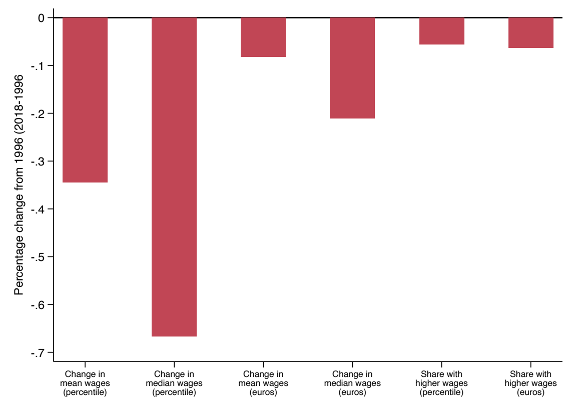
Panel A: Share of workers
with turnover events



Panel B: Shares of U35 workers
in firms with high/low turnover



Panel C: Shares of O55 workers
in firms with high/low turnover



Panel D: Features of
turnover events for U35 workers

Notes: Panel A plots the share of workers with a turnover event (voluntary or involuntary) separately for U35 workers and O55 workers. Panels B and C plot changes in the distribution of younger and older workers across firms with different turnover level. In each year, we divide firms into quartiles based on their workforce shares that experienced a turnover event (voluntary or involuntary). Then, Panel B (C) shows the change in the share of U35 (O55) workers in each quartile in percentage deviation from 1985 (1985=1). Panel D shows changes in the characteristics of U35 workers' turnover events. *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table 1: Workforce Aging and Age Wage Gap

	Change in mean worker age		Level and change in age wage gap at the mean						Change in age wage 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 %	wage gap (log)	Δ wage gap (log)	Δ wage gap (log)	Δ wage 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	0.200	0.100	0.140	0.250	0.180
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	0.040	0.379	0.227	0.174	77.02	4.89	0.229	0.212	0.150	0.193	0.187
Denmark (1987-2016)	6.45	17.33	0.157	0.252	0.321	0.185	136.71	-9.54	0.300	0.226	0.131	0.135	0.146
Finland (1987-2016)	6.81	19.00	0.044	0.188	0.222	0.214	102.73	5.87	0.455	0.239	0.130	0.121	0.136
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)	-2.92	-7.16	0.038	0.199	0.604	0.412	53.53	16.99	0.439	0.370	0.323	0.459	0.522
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 show the change in mean worker age. Column 3 shows the level of the age wage gap, the difference in mean log wages between O55 workers and U35 workers, at baseline. The next columns show the age wage 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 (1). Columns 9 to 13 show the change in age wage gap at different percentiles. Table A1 provides more information about the wage variable and the sample restrictions in each country. *Sources for Italy:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned positive wages, and did not retire. Database UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Sources for Germany:* 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 A.2. *Sources for LIS data:* The survey data in Panel B come from the Luxembourg Income Study (LIS) Database, which we last accessed on 04/14/2023 at https://www.lisdatacenter.org/. More details are in Appendix A.3.

Online Appendix

A Data Appendix

A.1 Italian Data

The data on the Italian labor market are available from 1985 to 2019 and are 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, 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. Due to the fact that 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 A1 shows that the increase in the age wage 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 display 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 display 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) worked at least six months, (iii) 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. This 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.[26]

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 tend to be fairly skewed, due to the presence of extreme outliers. For this reason, we winsorized both weekly wages and yearly earnings at the 99.9$^{\text{th}}$ percentile. Even after this winsorization, yearly

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

earnings have very low values on the left tail of their distributions, indicating that our previous process was not able to weed out all short and inconsequential working spells. For this reason, we cap the minimum of yearly earnings at €3,000 in real terms.

A.2 German 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).[27] This dataset combines information from the IAB Establishment Panel with information from the Integrated Employment Biographies (IEB).[28] The former is an annual representative survey of establishments, while the latter contains information on all workers subject to Social Security taxation. The LIAB dataset matches the individual biographies from the IEB to the sample of surveyed establishments in the IAB Establishment Panel.[29]

The LIAB has two important characteristics. First, information on employment and wages is available every year at the single reference date of June 30$^{\text{th}}$. 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) earned strictly positive wages.[30] These restrictions reduce the sample from 12,451,266 workers to 8,865,294 workers.

As we discussed in Section A.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 95$^{\text{th}}$ percentile. Finally, daily wages are expressed in 2015 euros using the conversion tables prepared by the OECD.

A.3 Data from Other Countries

In this section, we provide more information about the survey data that we used to measure the age wage 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

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

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

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

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

aggregates and harmonizes heterogeneous survey data coming from many different countries. A full list of the original data sources is in the notes of Table A1. 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.[31]

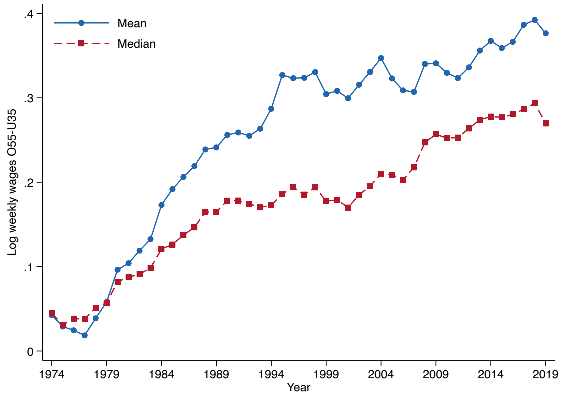
In the analysis, we compute the age wage gap using the only wage variable that is consistently available across survey waves and countries: yearly labor earnings (`pilabour`). Before doing so, we convert nominal yearly labor earnings for all countries to 2011 purchasing-power-parity US dollars, using 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) earned strictly positive wages, (iii) were employees, (iv) had a full-time contract, and (v) 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. Moreover, we winsorized the wave variables at the 99.9$^{\text{th}}$ percentile. Table A1 lists all cross-country differences in the construction of the sample.

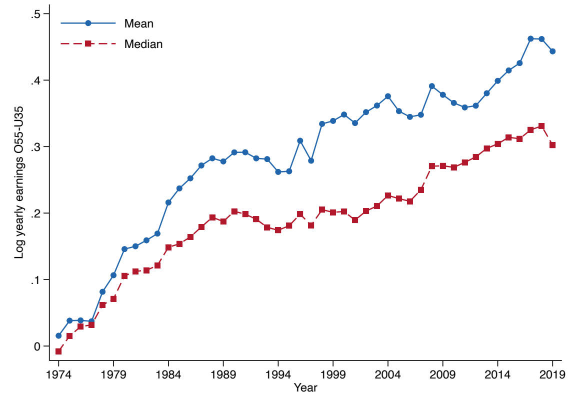
Finally, it should be noted that the LIS database is structured as repeated cross sections. Therefore, it is not possible to use the LIS data to follow the same workers over time. Moreover, this data source never matches workers to firms.

[31] 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, 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).

Figure A1: 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. *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1974-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table A1: 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 (1987-2016)	9	540,889	-	-	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	162,407	-	-	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

Sources for Italy: Database UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Sources for Germany:* The German data come from the LIAB Linked Employer-Employee Dataset provided by the Institute for Employment Research. *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). *Sources for France:* Tax and Social Incomes Survey. *Sources for Germany (LIS):* German Socio-Economic Panel. *Sources for Greece:* ECHP (1995, 2000); SILC (all other years). *Sources 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).

Table A2: Empirical Analysis and Data Sources

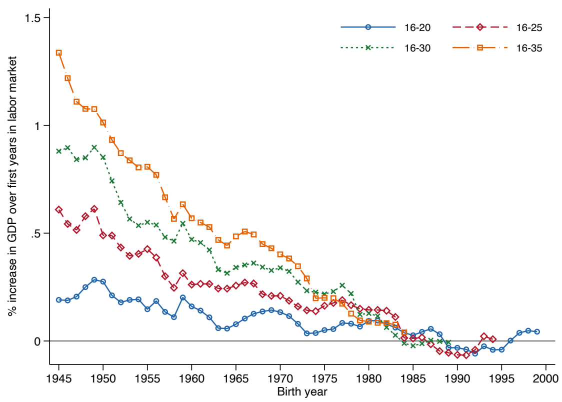
	Δ wage gap	Rank gap vs. distributional gap	Between/within firms and sectors	Entry rank vs. Rank growth	Firm Heterogeneity	Workforce composition
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Employer-employee administrative data						
Italy (1985-2019)	Yes	Yes	Yes	Yes	Yes	Yes
Germany (1996-2017)	Yes	Yes	Yes	No (no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

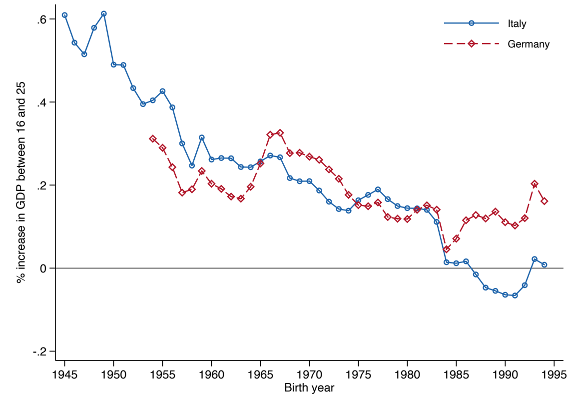
B Additional Results

B.1 Figures and Tables

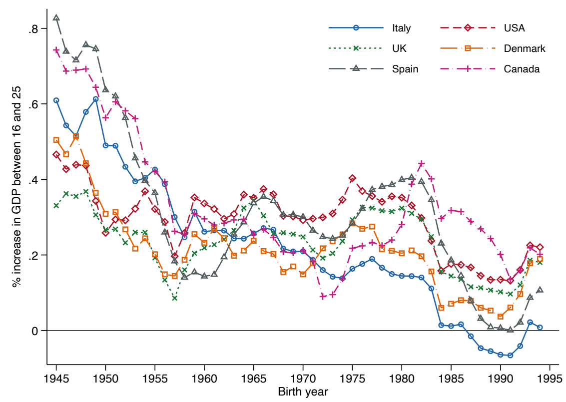
Figure B1: GDP Growth at Entry in Labor Market



Panel A: Italy



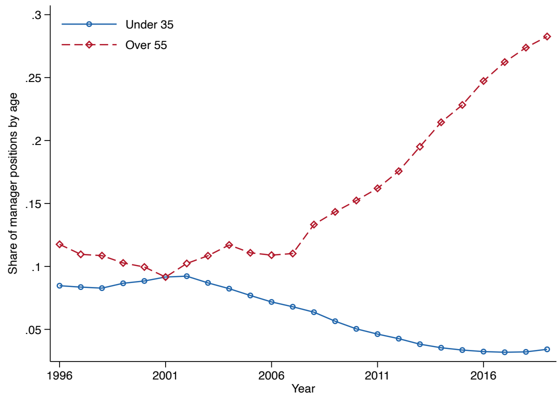
Panel B: Germany



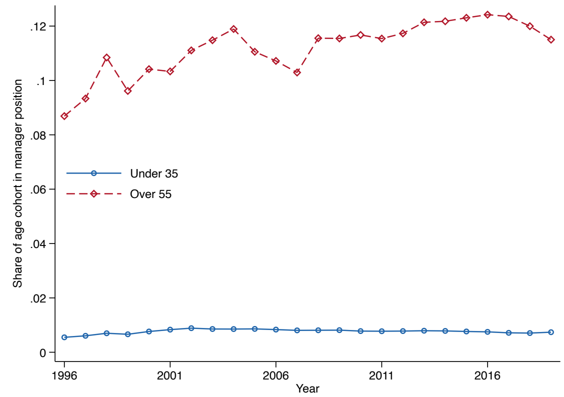
Panel C: Other countries

Notes: These figures compute the percentage change in GDP (in 2010 USD) over the first years in the labor market for individuals born in different countries and in different years. For example, in Panel A, the data point for the variable "16-20" and birth year 1945 computes 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). Panels B and C plot the GDP growth between 16 years old and 25 years old in different high-income countries. Sources: World Development Indicators by the World Bank, available online at `https://databank.worldbank.org/reports.aspx?source=2&series=NY.GDP.MKTP.CD&country=`, accessed on April 21, 2023.

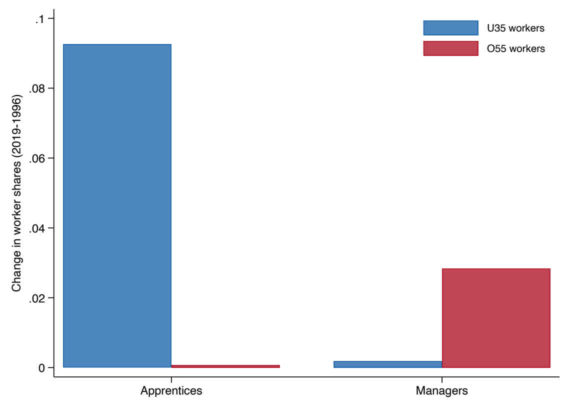
Figure B2: Changes in Job Levels



Panel A: Share of managerial jobs by age group



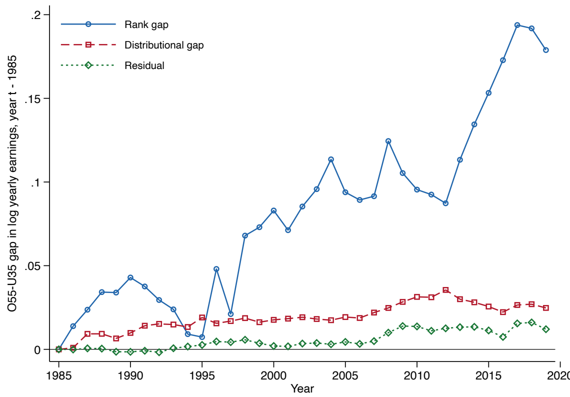
Panel B: Share of age group in managerial jobs



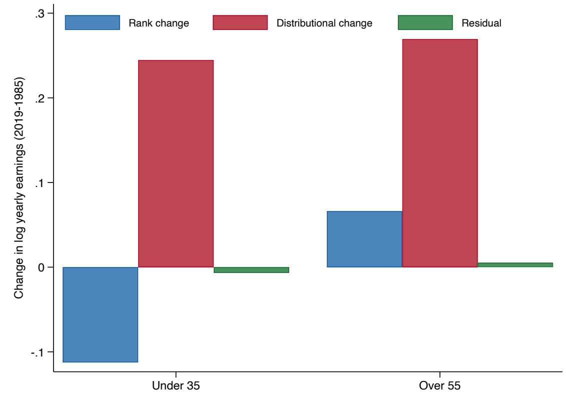
Panel C: Change in managerial and apprenticeship jobs

Notes: Panel A plots the share of managerial jobs held by workers in different age groups. For example, "0.1" means that 10 percent of all managerial jobs in a year are held by workers in a given age group (for example, U35 workers). Panel B plots the share of workers in each age group who hold a managerial position in a given year. For example, "0.1" means that 10 percent of workers in an age group are holding a managerial job in a year. Panel C shows the change in the share of managers and apprentices in each age group (same definition used in Panel B) from 1996 to 2019. *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

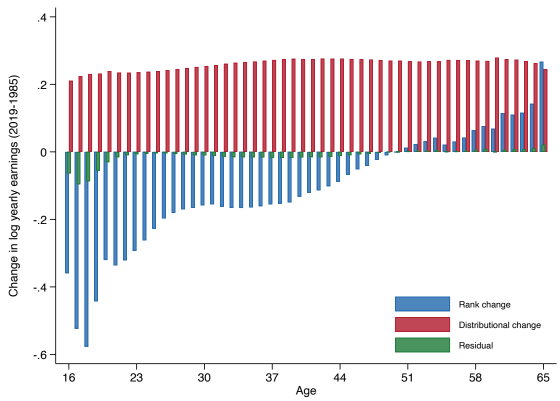
Figure B3: Decomposition of Change in Yearly Earnings



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



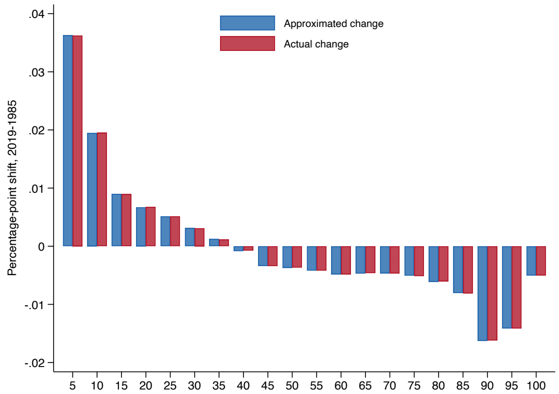
Panel B: 2019-1985,
two age groups



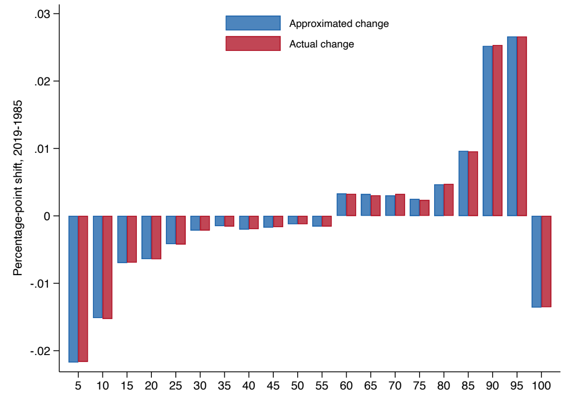
Panel C: 2019-1985,
individual age groups

Notes: Panel A decomposes the change in mean log yearly earnings between O55 and U35 workers from 1985 to year $t \in [1986, 2019]$ into three components (Equation (1)). Panel B separately decomposes the change in mean log yearly earnings between 1985 and 2019 for the two age groups (U35 and O55 workers). Panel C conducts the same decomposition for individual age groups. *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure B4: Actual Vs. Approximated Shares



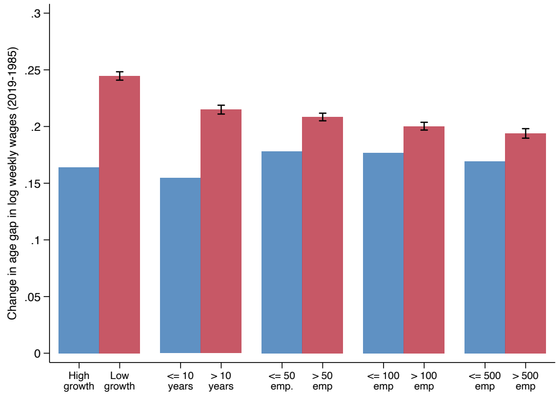
Panel A: U35 workers



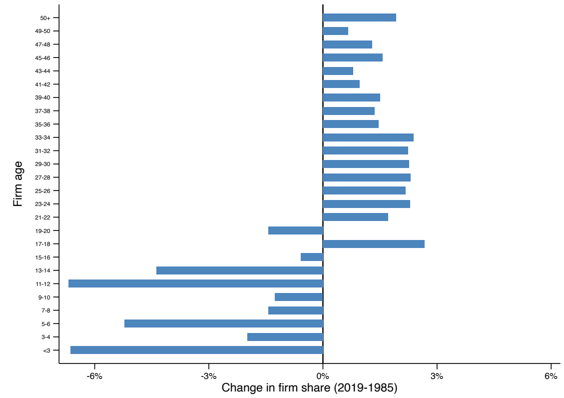
Panel B: O55 workers

Notes: These graphs show the percentage-point difference in the share of U35 workers (Panel A) or O55 workers (Panel B) in each vigintile of the distribution of weekly wages between 1985 and 2019. "Actual change" plots these differences using the raw distribution of weekly wages. "Approximated change" plots these differences using the distribution that arises from the sorting described in Section B.4. Specifically, workers are first sorted in 100 percentiles (firm groups) based on their firm's average weekly wages. Within each percentile, workers are then sorted in 500 quantiles (worker groups) based on the difference between their weekly wage and the average weekly wage in their firm group. Then, we use the distribution of the average weekly wages within the 50,000 firm-worker groups to compute the approximated changes between 1985 and 2019. Discrepancies between actual and approximated shares may arise due to the binning of workers in equally sized firm groups and firm-worker groups. The graphs show that these discrepancies are inconsequential. *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure B5: Firm Heterogeneity and Firm Age



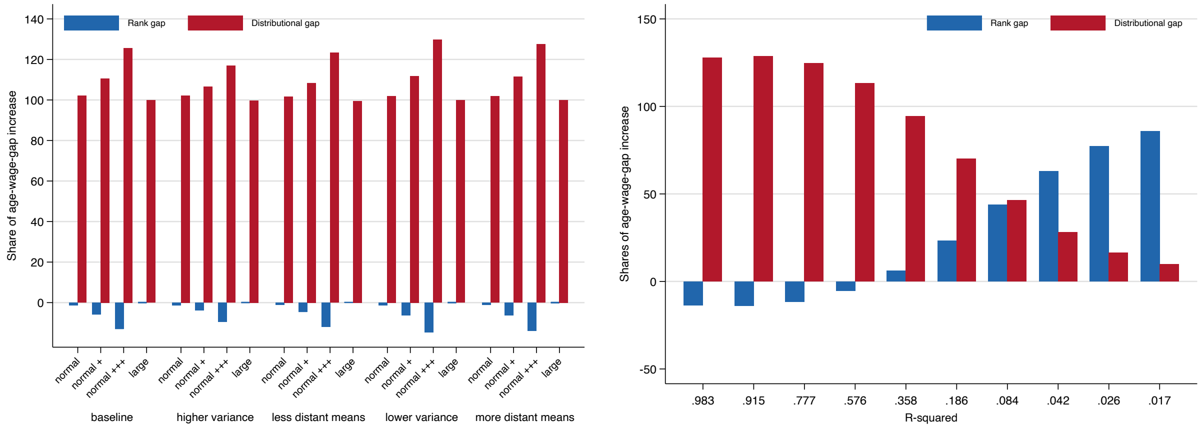
Panel A: Change in age wage gap, 2019-1985



Panel B: Change in firm age, 2019-1985

Notes: Panel A depicts the change in age wage gap in mean log weekly wages 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 high-growth firms. We also divide firms based on their age and workforce size. Panel B plots the percentage-point difference in the share of firms in each age bin 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 Social Security data. *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure B6: Simulating an Increase in Returns to Experience and High-Level Skills

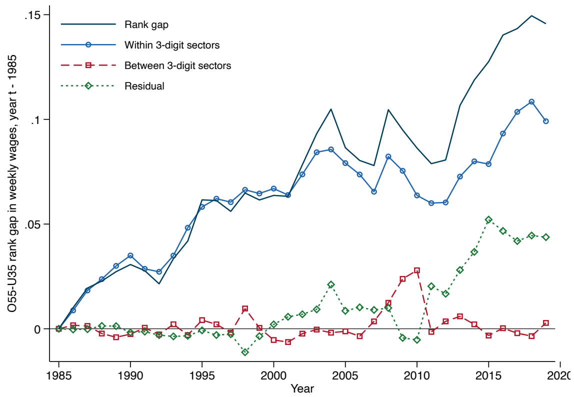


Panel A: $\sigma_\varepsilon^2 = 0$

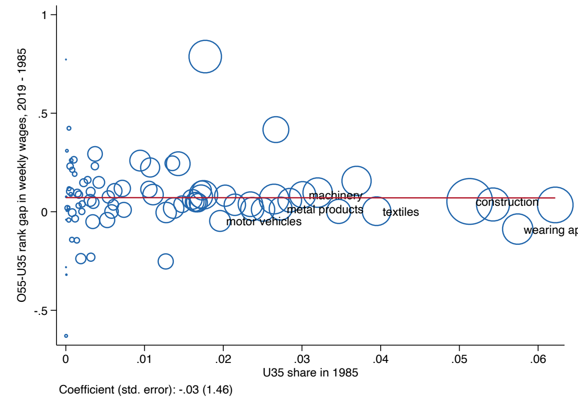
Panel B: $\sigma_\varepsilon^2 > 0$

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 wage gap, and decomposes it using Equation (1). 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 (1) 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.

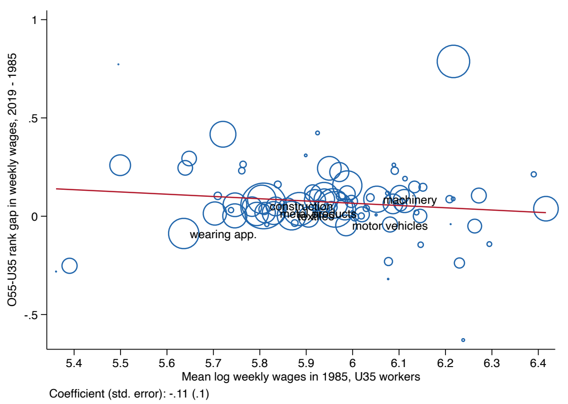
Figure B7: Sectoral and Occupational Shifts



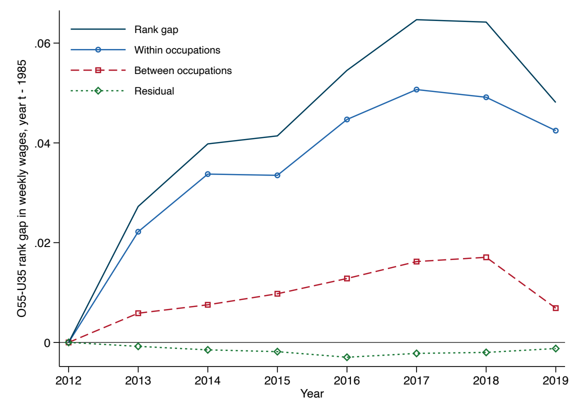
Panel A: Between and within 3-digit sectors



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



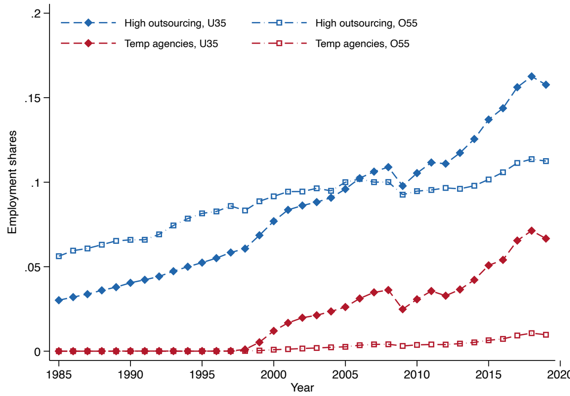
Panel C: Rank gap's increase by U35 workers' mean log weekly wage in 1985



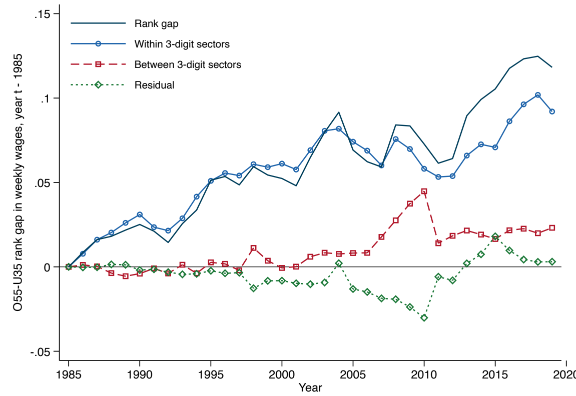
Panel D: Between and within 1-digit ISCO-08 occupations

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 3-digit sectors (Equation (4)). Panel B plots the increase in the age gap in each 2-digit sector against the sector-level share of U35 workers in 1985. Panel C plots the increase in the age gap in each 2-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 1-digit occupations. The ten 1-digit occupations follow the categorization prepared by the International Standard Classification of Occupations (ISCO-08). Here, the panel starts in 2012, the first year with occupation data. *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

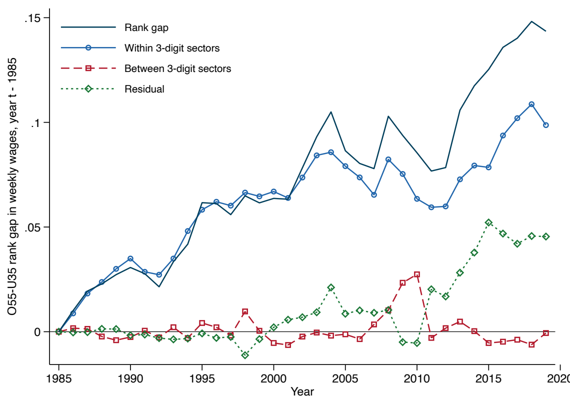
Figure B8: Domestic Outsourcing



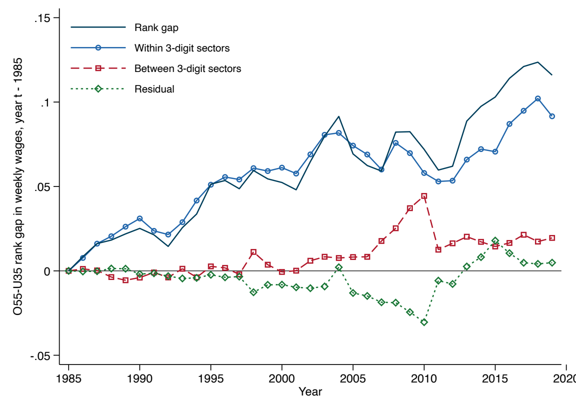
Panel A: Employment shares
in high-outsourcing sectors



Panel B: Between and within 3-digit sectors,
no high-outsourcing sectors



Panel C: Between and within 3-digit sectors,
no sales of business units



Panel D: Between and within 3-digit sectors,
no high-outsourcing sectors
and sales of business units

Notes: Panel A shows the employment shares of U35 and O55 workers in 3-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 3-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 3-digit sectors, dropping from the sample 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. *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1974-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table B1: Age Wage Gap and Firm Groups

	Change in worker shares		Change in within-firms wage rank		Tenure and age of O55 workers			
	U35 workers	O55 workers	U35 workers	O55 workers	Tenure in 2019	Δ tenure (%)	Δ age (%)	Δ firm age (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Group 1	0.016	-0.010	-0.259	0.168	4.369	-0.255	0.006	0.691
Group 2	0.009	-0.006	-0.263	0.190	6.142	-0.231	0.003	0.733
Group 3	-0.001	-0.001	-0.261	0.203	6.995	-0.151	0.001	0.828
Group 4	-0.004	-0.001	-0.230	0.178	7.761	-0.116	0.005	0.718
Group 5	-0.002	-0.003	-0.212	0.139	7.946	-0.131	0.006	0.693
Group 6	0.002	-0.005	-0.170	0.118	7.976	-0.126	0.009	0.750
Group 7	0.002	-0.005	-0.172	0.120	8.124	-0.129	0.012	0.829
Group 8	0.000	-0.006	-0.176	0.121	9.059	-0.106	0.013	0.904
Group 9	-0.004	-0.005	-0.227	0.121	9.879	-0.065	0.013	0.925
Group 10	-0.003	-0.005	-0.251	0.113	10.389	-0.060	0.012	0.939
Group 11	-0.004	0.002	-0.213	0.080	11.084	-0.038	0.012	0.994
Group 12	-0.003	0.002	-0.213	0.075	9.939	0.043	0.014	1.043
Group 13	-0.001	0.005	-0.220	0.049	11.719	-0.008	0.011	1.065
Group 14	0.001	-0.001	-0.274	0.063	13.074	-0.045	0.012	1.091
Group 15	0.002	0.001	-0.288	0.044	12.592	-0.037	0.011	1.112
Group 16	0.002	-0.001	-0.304	0.036	13.485	-0.024	0.010	1.116
Group 17	0.003	0.002	-0.323	0.001	15.656	0.045	0.011	1.103
Group 18	-0.001	0.008	-0.406	-0.028	15.391	0.039	0.014	1.098
Group 19	-0.006	0.014	-0.419	-0.236	10.750	-0.109	0.017	1.004
Group 20	-0.010	0.017	-0.460	-0.333	13.321	-0.079	0.016	0.803
Mean groups 1-10	0.002	-0.005	-0.222	0.147	7.864	-0.137	0.008	0.801
Mean groups 11-20	-0.002	0.005	-0.312	-0.025	12.701	-0.021	0.013	1.043

Notes: Firm groups identifies different vigintiles of the distribution of mean firm-level weekly wages. Columns 1 and 2 show variation in worker shares for each firm group from 1985 to 2019. Columns 3 and 4 show the within-firm rank change from 1985 and 2019 separately for U35 workers and O55 workers. Column 5 shows O55 workers' average years of continuous employment within the same firm in 2019. Column 6 shows the percentage change in the share of O55 workers with at least three years of tenure in each firm group from 1985 to 2019. Column 7 shows the percentage change in O55 workers' mean age from 1985 to 2019. Column 8 shows the percentage change in mean firm age from 1985 to 2019. To limit noise, the displayed values are averages computed using each group and its two adjacent firm groups (one in the case of the first and last group). *Sources:* In each year, the data pools information about all workers who were at least 16 years old, worked at least six months, earned positive wages, and did not retire. Database UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table B2: Age Wage 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)	0.100	55.83														
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)	0.174	77.02	0.224	77.37	0.194	78.67	-	-	0.191	187.68	-	-	0.231	72.88	0.194	80.34
Denmark (1987-2016)	0.185	136.71	0.195	126.48	0.175	141.67	-	-	0.180	136.16	-	-	0.169	127.38	0.187	137.94
Finland (1987-2016)	0.214	102.73	0.200	99.74	-	-	-	-	0.214	100.88	0.209	86.93	0.131	99.61	0.195	103.23
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)	0.412	53.53	0.451	55.72	-	-	-	-	0.351	56.40	-	-	0.371	59.13	0.574	53.52
Netherlands (1983-2018)	0.226	7.69	0.277	24.17	-	-	-	-	0.312	25.84	-	-	0.221	-53.53	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	51.95	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" regresses log wages on a male dummy and computes the age wage gap using the residuals from these regressions. "Nationality" uses a dummy for nonimmigrant workers as a regressor (white in the United States to control for race, instead). "Contract length" controls for temporary contracts. "Education" controls for college education. "Disability" controls for disability status. "All" simultaneously controls for all the worker characteristics available in each country. "U35 vs. 56-60" computes the age wage gap between male workers aged between 56 and 60 and U35 workers. *Sources for Italy:* Database UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Sources for Germany:* The German data come from the LIAB Linked Employer-Employee Dataset provided by the Institute for Employment Research. *Sources for survey data:* The survey data in Panel B come from the Luxembourg Income Study (LIS) Database, which we last accessed on 04/14/2023 at https://www.lisdatacenter.org/.

Table B3: 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 (1987-2016)	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.2 Equation (1)

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

$$\Delta w_a^{t,t'} = \underbrace{\sum_v s_{a,v,t}\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Distributional change}} + \underbrace{\sum_v \left(s_{a,v,t'} - s_{a,v,t}\right)\bar{w}_{v,t}}_{\text{Rank change}} + \underbrace{\sum_v \left(s_{a,v,t'} - s_{a,v,t}\right)\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Residual}}. \tag{B.1}$$

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:

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

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:

$$\Delta w_{O55}^{t,t'} - \Delta w_{U35}^{t,t'} = \underbrace{\sum_v \left(s_{O55,v,t} - s_{U35,v,t}\right)\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Distributional gap}} + \underbrace{\sum_v \Delta s_{O55-U35,v,t'-t}\bar{w}_{v,t}}_{\text{Rank gap}} + \underbrace{\sum_v \Delta s_{O55-U35,v,t'-t}\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Residual}}. \tag{B.2}$$

In this equation, $\Delta s_{O55-U35,v,t'-t} = \left(s_{O55,v,t'} - s_{O55,v,t}\right) - \left(s_{U35,v,t'} - s_{U35,v,t}\right)$. It 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 from the last two rows of Equation (B.1) by taking the difference for two age groups:

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

B.3 Equation (2)

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

$$\begin{aligned}
\underbrace{\sum_v \left(s_{U35,v,t'} - s_{U35,v,t}\right) \bar{w}_{v,t}}_{\text{Rank change}} &= \underbrace{\sum_{e\in[0,18]} s_{e,t'} \cdot \sum_v \left[s_{e,t',v}^{LME} \cdot \bar{w}_{v,t}\right]}_{\text{Change in entry rank—part 1}} \\
&\quad - \underbrace{\sum_{e\in[0,18]} s_{e,t} \cdot \sum_v \left[s_{e,t,v}^{LME} \cdot \bar{w}_{v,t}\right]}_{\text{Change in entry rank—part 2}} \\
&\quad + \underbrace{\sum_{e\in[0,18]} s_{e,t'} \cdot \sum_v \left[\left(s_{e,t',v} - s_{e,t',v}^{LME}\right) \cdot \bar{w}_{v,t}\right]}_{\text{Change in rank growth—part 1}} \\
&\quad - \underbrace{\sum_{e\in[0,18]} s_{e,t} \cdot \sum_v \left[\left(s_{e,t,v} - s_{e,t,v}^{LME}\right) \cdot \bar{w}_{v,t}\right]}_{\text{Change in rank growth—part 2}} .
\end{aligned} \tag{B.3}$$

There is one key difference between Equation (B.3) and Equation (2) in Section 4.2.3. In the full decomposition in Equation (B.3), 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 confound 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 in year t' and year t' was different. 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 baseline in year t (1995 for U35 workers and 1990 for U30 workers) or in 2019. This assumption allows us to rewrite Equation (B.3) as Equation (2) in Section 4.2.3.

B.4 Equation (4)

The rank change in Equation (B.1) can be rewritten as follows:

$$\begin{aligned}\sum_{v}\left(s_{a,v,t'}-s_{a,v,t}\right)\bar{w}_{v,t} \quad = \quad & \underbrace{\sum_{g\in(f,e)}\left(s_{a,f,t'}-s_{a,f,t}\right)s_{a,(e|f),t}\bar{w}_{g,t}}_{\text{Between firms}} \\ & + \underbrace{\sum_{g\in(f,e)}s_{a,f,t}\left(s_{a,(e|f),t'}-s_{a,(e|f),t}\right)\bar{w}_{g,t}}_{\text{Within firms}} \\ & + \underbrace{\sum_{g\in(f,e)}\left[\left(s_{a,f,t'}-s_{a,f,t}\right)\left(s_{a,(e|f),t'}-s_{a,(e|f),t}\right)\right]\bar{w}_{g,t}\,.}_{\text{Residual}}\end{aligned} \tag{B.4}$$

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 50,000 firm-worker groups and $\bar{w}_{g,t}$ is the average wage in firm-worker group g and year t.

This decomposition can be obtained using Equation (3). A change in the share of workers in age group a and firm-worker group $g=(f,e)$ between t and t' can be rewritten as follows:

$$\begin{aligned}s_{a,(f,e),t'}-s_{a,(f,e),t} &= s_{a,f,t'}\cdot s_{a,(e|f),t'}-s_{a,f,t}\cdot s_{a,(e|f),t} \\ &= s_{a,f,t'}\cdot s_{a,(e|f),t'}-s_{a,f,t}\cdot s_{a,(e|f),t}+\left(s_{a,f,t'}\cdot s_{a,(e|f),t}-s_{a,f,t'}\cdot s_{a,(e|f),t}\right) \\ &\quad +\left(s_{a,f,t}\cdot s_{a,(e|f),t'}-s_{a,f,t}\cdot s_{a,(e|f),t'}\right)+\left(s_{a,f,t}\cdot s_{a,(e|f),t}-s_{a,f,t}\cdot s_{a,(e|f),t}\right) \\ &= \underbrace{\left(s_{a,f,t'}-s_{a,f,t}\right)s_{a,(e|f),t}}_{\text{Between firms}}+\underbrace{s_{a,f,t}\left(s_{a,(e|f),t'}-s_{a,(e|f),t}\right)}_{\text{Within firms}} \\ &\quad +\underbrace{\left(s_{a,f,t'}-s_{a,f,t}\right)\left(s_{a,(e|f),t'}-s_{a,(e|f),t}\right)}_{\text{Residual}}.\end{aligned} \tag{B.5}$$

Then, the decomposition in Equation (B.4) can be obtained by multiplying all the three components in Equation (B.5) by $\bar{w}_{g,t}$ and by summing over the firm-worker groups g.

Using the same logic, we can rewrite the rank gap in Equation (1) as follows:

$$\underbrace{\sum_{v} \Delta s_{O55-U35,v,t'-t} \bar{w}_{v,t}}_{\text{Rank gap}} = \underbrace{\sum_{g \in (f,e)} \Delta s_{O55-U35,f,t'-t} \cdot \Delta s_{O55-U35,(e|f),t} \cdot \bar{w}_{g,t}}_{\text{Between firms}} + \underbrace{\sum_{g \in (f,e)} \Delta s_{O55-U35,f,t} \cdot \Delta s_{O55-U35,(e|f),t'-t} \cdot \bar{w}_{g,t}}_{\text{Within firms}} + \underbrace{\sum_{g \in (f,e)} \Delta s_{O55-U35,f,t'-t} \cdot \Delta s_{O55-U35,(e|f),t'-t} \cdot \bar{w}_{g,t},}_{\text{Residual}} \tag{B.6}$$

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 $\left(s_{O55,(e|f),t'} - s_{O55,(e|f),t}\right) - \left(s_{U35,(e|f),t'} - s_{U35,(e|f),t}\right)$.

B.5 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 $a \in \{\text{Younger, Older}\}$ 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 the 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, 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 wage gap. We then utilize Equation (1) to decompose this increase into a larger 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 $\beta_0 = 1$, $\beta^t_1 = 1$, $x^t_{\text{Y}} \sim N(4.9, 0.16)$ for younger workers, $x^t_{\text{O}} \sim N(5.1, 0.36)$ for older workers, and $\varepsilon^t_i \sim N(0, \sigma^2_\varepsilon)$. The variable ε^t_i has always 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 wage gap expands by 0.09 log points, a shift entirely attributable to a larger distributional gap (Figure B6, 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 wage 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 B6, Panel B). In practice, all else equal, 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 significantly with σ_ε. 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 $\sigma_\varepsilon = 0.5$ ($R^2 = 0.017$).

The key insight from this exercise is that the mechanism through which an increased price of x expands the age wage gap hinges on the role of x in explaining wage differences between younger and older workers. When the R^2 between x and wages is larger (lower values of σ_ε) and the wage distributions of younger and older workers are less overlapped, a rise in x's price pushes many high-earning older workers further ahead of younger workers, primarily widening the age wage gap by extending the wage distribution's right tail. Conversely, when the R^2 between x and wages is smaller (higher values of σ_ε) and the wage distributions of younger and older workers are more overlapped, a price increase of x is more likely to propel older workers past younger ones in the wage distribution, thereby expanding the rank gap.