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

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Abstract

In the last three decades, the wages of older workers in many high-income countries have grown at a much faster rate than the wages of younger workers. This paper uses extensive data from multiple countries to provide an analysis of this age wage gap. First, the widening of the age wage gap stems from the increasing difficulty of reaching high-paying jobs experienced by younger workers. Second, a large share of the slowdown in the careers of younger workers occurred within firms. Third, differences in the appropriation of firm rents have been more important than worker characteristics in widening the age wage gap. The last portion of the analysis shows that the effects are larger for firms with greater constraints on adding higher-ranked jobs to their organization, which highlights the role of career spillovers in widening the age wage gap.

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1 Introduction

In the last three decades, the average age of the workforce increased in most high-income countries. In the United States, for example, the share of workers who were at least 55 years old increased by 88 percent, from 12.9 percent in 1985 to 24.3 percent in 2020, more than any other age group.[1] Similarly, in Italy, one of the main foci of our empirical analysis, the mean worker age increased by 19 percent, from 35.8 years old in 1985 to 42.7 years old in 2019. In many countries, this dramatic demographic shift was fueled by (i) a stark decrease in birth rates over time, (ii) a progressive increase in life expectancy, and (iii) an increase in retirement age. Moreover, the progressive aging of the workforce is projected to continue for the foreseeable future.

This is not the first time in recent history that workforce demographics have been rapidly changing. In the second half of the 1960s, the entry of the postwar "baby-boom" cohort into the labor market caused an opposite demographic shift in the workforce, leading to a large decrease in the average worker age. This change coincided with a slowdown in the growth of younger workers' wages relative to older workers' wages, which prior studies have attributed to a combination of (i) imperfect substitutability in production between younger and older workers, and (ii) an increase in the supply of younger workers relative to the stock of older workers (Welch, 1979; Freeman, 1979; Levine and Mitchell, 1988).

If we applied the same economic thinking to the progressive aging of the workforce that took place during the last three decades, we would expect the larger supply of older workers to have decreased their wage growth relative to the wage growth of younger workers. Instead, we establish that many high-income countries experienced the opposite trend: the *age wage gap* significantly widened in favor of older workers. Using both extensive administrative data and aggregate statistics, we find that the wage gap increased by 0.10 log points in favor of older workers in the United States (1985-2019), by 0.19 log points in Italy (1985-2019), by 0.10 log points in Germany (1996-2017), by 0.11 log points in the United Kingdom (1997-2019), and by 0.17 log points in Denmark (1997-2019).[2] Moreover, we establish that this trend cannot be simply explained by variations in the composition of older and younger workers. For example, we find that the previous results are robust to controlling for the progressive entry of women in the labor market, the increase in temporary contracts or foreign-born workers among younger workers, and for health improvements among older workers.

After establishing the existence of the age wage gap, this paper provides a comprehensive

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

[2] The exact definitions of younger and older workers for each country are in the notes of Figure B1. Whenever the data allow it, we define younger workers as those who were under 35 years old and older workers as those who were above 55 years old.

analysis of the widening of the gap, with particular emphasis on the role played by firms and their internal labor markets. This analysis leverages confidential employer-employee administrative data from Italy and Germany with 347 million observations on 38 million workers and 3.7 million firms. We also use survey data from the Current Population Survey for the United States in order to replicate the portion of the analysis that does not require matched employer-employee data. Overall, our results are qualitatively similar across these three different countries. In the rest of the introduction, we will focus on the results for Italian workers because the Italian dataset is the only one that allows us to perform the full spectrum of tests included in this paper.

We establish three main results about the wage gap between younger and older workers. First, careers mattered. The widening of the age wage gap is associated with a slowdown in the careers of younger workers, while the careers of older workers improved. Between 1985 and 2019, the probability of workers who were less than 35 years old being in the top quartile of the wage distribution decreased by 34 percent, while workers who were more than 55 years old became 16 percent more likely to be in the top quartile. Moreover, we find that the wage growth of new entrants in the labor market became progressively lower over time. Finally, we establish that the probability of younger workers holding managerial positions decreased by two thirds between 1985 and 2019, while that probability increased by 87 percent among older workers.

Next, we build upon this initial descriptive evidence by proposing a more formal decomposition of the wage change for each age group. Specifically, the wage change between 1985 and 2019 for each age subgroup can be divided into two separate parts: (i) a *ranking-shift* component that measures the change in wages that would have prevailed if younger and older workers had been allowed to move over time along the wage distribution, but with the support of the wage distribution remaining fixed in 1985; and (ii) a pure *wage-trend* or *wage-inequality* component that computes the counterfactual change in wages that would have prevailed if the average wages in different vigintiles of the distribution could vary over time, but the shares of younger and older workers along the wage distribution stayed constant at their 1985 levels. We find that the ranking-shift component accounted for up to 83 percent of the overall widening of the wage gap between workers over 55 years old and workers under 35 years old. In other words, rather than stemming from general trends in wage inequality, most of the variation in the age wage gap is due to younger and older workers moving in different directions along the wage distribution, which confirms the prior finding that the careers of younger workers worsened over time.

Second, careers within firms mattered. Within-firm factors played a central role in slowing down the careers of younger workers. Overall, they accounted for 51 percent of the gap in

1985, 61 percent in 2000, and 51 percent again in 2019. Since 2005, between-firm factors accounted for an increasing portion of the age wage gap, contributing to both decreasing the wage growth of younger workers and increasing the wage growth of older workers.[3]

Third, firms mattered. Differences in the appropriation of firm rents were more important than worker characteristics. We establish this result by estimating a two-way fixed-effect model that allows us to separate log wages into worker-specific and firm-specific effects (Abowd, Kramarz, and Margolis, 1999). The main result from this estimation is that differences in firm rents between 1985 and 2019, as well as differences between over-55 workers and under-35 workers, accounted for 69 percent of the overall increase in the age wage gap.

Moreover, we can further decompose this double difference into two parts: (i) a *wage-setting* component that compares differences in average firm rents between different age groups within the same set of jobs, and (ii) a *sorting* component that compares differences in average firm rents for the same age group across different jobs. Two main findings corroborate the previous results. First, even after accounting for worker characteristics, differences in internal wage-setting policies drove most of the age wage gap until 2005, especially in the set of firms in which under-35 workers were more likely to work. Second, sorting of under-35 workers in lower-rent firms and of over-55 workers in higher-rent firms became more prominent in the last fifteen years of data available.

The last portion of the paper provides a descriptive analysis of the economic factors that are compatible with the widening of the age wage gap. Overall, our findings are broadly consistent with the hypothesis that costly firm separations and the increasing inability of firms to add higher-ranked positions to their organizations (possibly due to a decrease in firm productivity and an increase in retirement age) generated negative career spillovers from older workers to younger workers (Bianchi et al., 2021). Older workers extended their careers and therefore started enjoying the rents associated with their higher-ranked positions for longer, while younger workers experienced a much lower wage growth, due to the increasing difficulty for them in reaching the top rungs of the job ladder. Consistent with this theory, we find that the widening of the age wage gap was larger among firms with more limited opportunities to promote their younger workers, that is, among older and larger firms with lower employment growth (Bennett and Levinthal, 2017). We also explore other plausible explanations, such as skill-biased technological change (SBTC), automation, unionization, selection into the labor market, and trends in the returns to education and job experience.

The contribution of this paper is twofold. First, it contributes to the literature that

[3] This final result is compatible with the increasing use of outsourcing (Goldschmidt and Schmieder, 2017). In the last fifteen years of data, younger workers became more likely to hold jobs that were progressively outsourced to lower-paying firms.

studies differences in labor outcomes between younger and older individuals. Rosolia and Torrini (2007) and Naticchioni, Raitano, and Vittori (2014) use Italian survey data to show that early-career wages decreased during the 1990s. Access to large-scale administrative data that match employers to employees allows us to complement their findings by studying the role of firms in driving the age wage gap. Moreover, we provide new descriptive results on plausible mechanisms that are compatible with these wage trends.

This paper also contributes to the broader literature that analyzes different trends in the level and variance of wages. Earlier work has used data from several countries to document the nature of the wage inequality (Autor, Katz, and Kearney, 2006; Autor, Katz, and Kearney, 2008; Card, Heining, and Kline, 2013; Song et al., 2019), as well as the wage gap between men and women (Card, Cardoso, and Kline, 2016; Bruns, 2019; Casarico and Lattanzio, 2020), between high-skill and low-skill workers (Katz and Murphy, 1992; Card and DiNardo, 2002; Acemoglu and Autor, 2011), between more educated and less educated workers (Goldin and Margo, 1992; Card and Lemieux, 2001; Goldin and Katz, 2009), and between workers in different racial groups (Bayer and Charles, 2018). We borrow similar techniques, such as Oaxaca-Blinder decompositions and AKM models, to focus on a less-well-known wage trend. Overall, our results show that the age wage gap differs from other types of wage gaps. For example, the increase in the wage gap between younger and older workers stems more heavily from (i) within-firm factors compared with the overall increase in wage inequality (Song et al., 2019), and (ii) differential appropriations of firm rents compared with the gender age gap (Card, Cardoso, and Kline, 2016).

Second, this paper contributes to the literature that studies the interconnectedness of the careers of coworkers (Hayes, Oyer, and Schaefer, 2006; Jäger and Heining, 2019). Within this broader literature, prior work has documented that limited career opportunities can generate negative career spillovers across coworkers in bureaucracies (Bertrand et al., 2018), academia (Borjas and Doran, 2012), sports (Brown, 2011; Gong, Sun, and Wei, 2017), firms in transitioning economies (Friebel and Panova, 2008), as well as privately owned firms in high-income economies (Bertoni and Brunello, 2020; Bianchi et al., 2021; Boeri, Garibaldi, and Moen, 2021). Two papers are especially relevant for our analysis. Bianchi et al. (2021) uses administrative data to show that an unexpected increase in the retirement age of older Italian workers reduced the wage growth of their younger coworkers. Moreover, Mohnen (2021) uses U.S. data at the level of commuting zones to document that fewer retirees are associated with higher youth unemployment in low-skill jobs. Our paper uses extensive worker-level administrative data from multiple countries to show that the widening of the age wage gap in the last three decades is compatible with the main takeaway of these prior studies: extending the careers of older workers can negatively affect the wage growth of their younger coworkers, especially within firms with limited ability to add higher-ranked positions.

2 The Data and the Age Wage Gap

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 consists of matched employer–employee records for the whole population of private-sector, nonagricultural firms with at least one salaried employee. The dataset combines individual-level information about workers, such as age and other demographic characteristics, wage, and type of contract, with information about the firm, such as sector, location, and age. In each year of data, we restrict our analysis to workers who were over 16 years old, had worked at least six months, had earned positive wages, and had not retired. We impose these restrictions to weed out workers with very short-lived job spells within each year. Unless otherwise specified, our analysis focuses on workers with full-time contracts, although we will include part-time workers in some robustness checks.

This dataset allows us to use two wage measures. First, we leverage the total yearly labor earnings. This variable includes wages, as well as the bonus payments that many Italian workers receive.[4] Using yearly earnings as a measure of wages presents a trade-off. On the one hand, they account for all returns to labor in a calendar year. On the other hand, a variation in yearly earnings may conflate changes in hours worked and pay rates. As an additional measure of earnings, we would like to isolate pay rates, but we do not directly observe them in the data. However, we can at least reduce the influence of labor-supply choices on labor earnings by moving to weekly wages. We compute them by dividing the yearly labor earnings by the number of working weeks.[5] 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 surely possible, it is important to note that most of our analysis focuses on full-time employees, who therefore display little variation along this dimension.

All measures of labor earnings, as well as any other monetary variables used in the analysis, are expressed in 2015 euros, using the conversion tables prepared by the OECD.[6]

[4] 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.

[5] Another advantage of this wage measure is that the number of working weeks is a key variable for computing pension eligibility. Therefore, this variable is recorded very accurately in the Social Security data.

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

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

Overall, 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 1, Panel A). Of all employees, 69 percent were male, 6 percent had temporary contracts, and 1 percent were not born in Italy. In addition, the average worker was 38 years old and had 18 years of experience in the labor market. On average, yearly earnings were €26,660 and weekly wages were €549. Manufacturing was the economic sector that employed the largest percentage of workers (37 percent), followed by services (32 percent) and construction (8 percent).

2.2 General Trends in the Age Wage Gap

Not surprisingly, our data indicate that the mean worker age increased by 19 percent from 35.8 years in 1985 to 42.7 years in 2019 (Figure 1, Panel A). Over the same period, the share of workers who were over 55 years old (thereafter, *O55 workers*) increased by 9.5 percentage points, while the share of workers who were under 35 years old (*U35 workers*) decreased by 22 percentage points (Figure 1, Panel B). As a direct consequence of their increasing number, O55 workers started receiving a larger share of the total wage bill at the expense of U35 workers (Figure A1). Specifically, the share of the wage bill earned by O55 workers increased from 5.7 percent in 1985 to 17.5 percent in 2019, while the share earned by U35 workers decreased from 41.2 percent to 19.7 percent.

Three main post-World-War-II demographic trends can explain the progressive 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.[7] Second, life expectancy at birth increased by 21 percent from 1960 to 2018, moving from 69.1 years to 83.3 years.[8] 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 at which workers became eligible to receive a public pension, inducing many older workers to spend more time in the labor force before retirement.[9]

While the workforce in Italy progressively aged, the wages of older workers grew at a much faster rate than the wages of younger workers. Specifically, the gap between the mean log weekly wages of O55 workers and U35 workers grew from 0.19 log points in 1985 to 0.38

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

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

[9] 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.

log points in 2019 (Figure 2, Panel A).[10] Moreover, the progressive widening of the age wage gap did not happen only at the average, but rather at every point of the wage distribution (Table A1). For example, the age gap in log weekly wages at the 10$^{\text{th}}$ percentile grew from 0.04 log points in 1985 to 0.24 log points in 2019, while the gap at the 90$^{\text{th}}$ percentile grew from 0.43 log points in 1985 to 0.61 log points in 2019. Similarly the age wage gap at the median increased from 0.13 log points in 1985 to 0.27 log points in 2019 (Figure A2, Panel A).

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 2, Panel B). As a consequence, the age profile of wages became much steeper over time.

2.3 Controlling for Compositional Changes

In this section, we test whether the widening of the age wage gap is associated with a change in the composition of the younger workforce and the older workforce. Overall, our analysis shows that the wages of older workers have grown at a much faster rate than the wages of younger workers even after controlling for changes in observable characteristics.[11]

To start, we find that the share of workers who (i) were born abroad or (ii) had temporary contracts increased more rapidly among U35 workers than O55 workers (Table A2, Panel A). Workers who were born abroad or had temporary contracts also tended to have lower-than-average wages (Table A2, Panel B). Therefore, these time trends could at least partially account for the widening age wage gap. We gauge their importance by computing the age wage gap on two different subgroups of workers who were not directly affected by these compositional changes: (i) workers who were born in Italy and (ii) workers with open-ended contracts. In both cases, the age wage gap computed on these subgroups tracks almost perfectly the age wage gap computed using observations from all workers in the sample (Figure A3 and Figure A4, Panel A). In short, two of the major changes in the composition of workers cannot explain the overall increase in the age wage gap.[12]

[10] We can obtain a similar finding by replacing weekly wages with yearly earnings (Figure A2, Panel A).

[11] In this section, we do not control for education because the Social Security data does not include usable information on this topic. However, Section 7 will use external data sources to discuss in more depth the possible role of education and experience.

[12] This analysis does not account for the changing selection among domestic workers and permanent workers. However, it should be noted that these two subgroups became less numerous over time among U35 workers. Therefore, it is plausible to assume that U35 workers within these two subgroups became more positively selected. As a consequence, this form of selection should bias the age wage gap downward rather than upward.

Other changes in the composition of the younger and older shares of the workforce are not likely to account for the age gap in wages. For example, it is true that younger workers became more likely to hold part-time contracts over time, which in turn could explain worse labor-market outcomes (Table A2). However, our baseline results in Section 2.2 already exclude part-time workers from the sample and, therefore, cannot be influenced by the disproportionate increase in part-time younger workers.[13]

Moreover, the increasing number of women entering the labor market could be an important factor if we assumed that (i) women had worse labor-market outcomes than men, and (ii) the entry of women was more prevalent among younger workers. Although the data support the hypothesis that women earned less than men (in our sample, 0.14 fewer log points in 2019), we do not find that the share of women increased more among U35 full-time workers (Table A2).[14] Therefore, this trend cannot account for the widening of the age wage gap. We can find further proof of this point by measuring the age wage gap using only men (Figure A3 and Figure A4, Panel B): within this subgroup, the age gap increased by 0.17 log points between 1985 and 2019, an increase closely matching the result obtained using both men and women.

Next, we explore the hypothesis that the higher wage growth among older workers may stem from substantial health improvements over time and therefore large increases in their productivity. If this theory fits the data, we should observe smaller effects in economic sectors that are less physically demanding. In these sectors, health improvements should translate into smaller productivity gains because poor health at baseline was plausibly a less binding constraint on longer careers. Following this logic, we compute the age wage gap using observations from either (i) sectors that are not designated by law as being physically demanding or (ii) sectors in which the share of the wage bill represented by payments to workers for injury and sick leaves is below the top quartile.[15] In both cases, the widening of the age wage gap is large and close to the baseline (Figure A3 and Figure A4, Panel C). In short, the data indicate that improvements in health among older workers do not appear to be central for explaining the widening of the age wage gap.

In a separate set of results, we control for all the previous worker characteristics simultaneously. We regress log weekly wages on a dummy variable for men, on one for domestic workers, on one for workers with temporary contracts, and on one for sectors that are not physically demanding, as well as on fixed effects for the province of residence. We run sepa-

[13]For completeness, we compute the age wage gap using both full-time and part-time workers, rescaling the observations from the latter group to be full-time equivalent (Figure A3 and Figure A4, Panel B). In this case, the age wage gap increased by 0.13 log points between 1985 and 2019.

[14]This result may be due to the fact that we focus on full-time workers.

[15]For more information about these definitions, see the notes of Figure A3 and Table A3.

rate regressions in each year, therefore allowing all previous coefficients to vary over time. We then use the residuals from these regressions to compute the age wage gap. After controlling for all these worker characteristics, the data still indicate that the age wage gap increased by 0.17 log points (Figure A3 and Figure A4, Panel D).

2.4 Age Wage Gap in Other High-Income Countries

In this section, we show that the widening gap in wages between younger and older workers is not specific to the Italian labor market. We prove this point by leveraging extensive administrative data from Germany as well as survey data and aggregate statistics from the United States, the United Kingdom, Denmark, Spain, and Canada. When pooled, the administrative data from Italy and Germany include 347 million observations with information on 38 million workers and 3.7 million firms (Table 1).

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) with (ii) information on workers coming from the Integrated Employment Biographies (IEB). Unlike the Italian Social Security data, the German dataset is a snapshot of the labor market taken on June 30 of every year, rather than a comprehensive description of all labor-market events that happened throughout the year.

To measure the age wage gap, we use the daily wage that is associated with each individual's job spell with the highest earnings. This variable is expressed in 2015 euros using the conversion tables prepared by the OECD. Moreover, it should be noted that nominal earnings are top-coded. The cap varies from year to year, but is usually close to the 95$^{\text{th}}$ percentile. We select our sample applying the same restrictions described in Section 2.1 for the Italian Social Security data.[16]

In Germany, the age wage gap increased steeply from 0.28 log points in 1996 to 0.49 log points in 2006 and then decreased to 0.38 log points in 2017 (Figure B1, Panel A). Although they followed different trajectories, the age wage gaps in Germany and Italy experienced a similar overall increase between 1996 and 2017: the gap increased by 0.07 log points in Italy and by 0.10 log points in Germany. Unlike the Italian gap, the German age wage gap widened mostly closer to the mean and the median of the distribution of daily wages, rather than at the very top and bottom (Table B1, Panel A).

Without administrative datasets, we can compute the age wage gap for other countries

[16] Appendix B.2 provides additional details about the German data and sample selection.

using publicly available survey data and aggregate statistics.[17] Remarkably, with the exception of Canada, which experienced a slightly U-shaped trend, the age wage gap followed the same increasing trend that we first observed in Italy (Figure B1, Panel B). This result holds even for countries like the United States and the United Kingdom with vastly different labor-market institutions. For example, in the United States, the gap in log mean wages moved from 0.16 log points in 1985 to 0.19 log points in 2002, always in favor of older workers. Then, it steeply increased to 0.33 log points in 2013, before shrinking slightly to 0.26 log points in 2019. The age gap widened even more at the very top and bottom of the wage distribution (Table B1, Panel B). In the United Kingdom, the age gap in log median wages increased from 0.15 log points in 1997 to 0.26 log points in 2019. The age wage gap in Spain started at 0.13 log points in 1998 and increased to 0.21 log points in 2018.

Denmark is another interesting case study. The country started at a much lower degree of disparity between younger workers and older workers than any other country in the sample: the age wage gap was equal to only 0.06 log points in 1997. Then, the age wage gap experienced a very steep increase over time, reaching 0.23 log points in 2019 and surpassing the levels observed in Spain and Canada.

In short, administrative data, labor-force surveys, and aggregate statistics reveal that the widening of the age wage gap is a phenomenon that transcended the Italian labor market. It was present in countries with much more liberal economic institutions than the Italian ones (like the United States and the United Kingdom), as well as countries with more or equally developed welfare states (like Germany and Denmark).

3 Decline in Careers of Younger Workers

In this section, we start decomposing the gap in wages between younger and older workers into meaningful components. The main takeaway of this analysis is that younger workers have faced increasing difficulties in reaching high-paying positions, while older workers have experienced the opposite trend. This slowdown in the careers of younger workers can account for most of the increase in the wage gap between U35 workers and O55 workers.

3.1 Descriptive Evidence on Careers of Younger Workers

The empirical evidence shows that younger workers became less likely to reach the top of the wage distribution. We can show this fact in several ways.

First, the probability of U35 workers being in the top quartile of the distribution of weekly wages decreased by 34 percent, moving from 15 percentage points in 1985 to 10 percentage points in 2019 (Figure 3, Panel A). This decrease at the top of the distribution

[17] Appendix B.3 provides more details about these data sources.

was accompanied by an increase in the probability of being in the bottom quartile. This finding becomes even starker if we move from quartiles to vigintiles (Figure 3, Panel B). In this case, we can observe that the share of U35 workers decreased almost monotonically from the lowest to the next-to-highest 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 increased by 16 percent, from 32 percentage points in 1985 to 37 percentage points in 2019, while their probability of being at the bottom decreased by 23 percent, from 23 percentage points in 1985 to 18 percentage points in 2019 (Figure 3, Panel C). Moreover, the share of O55 workers increased almost monotonically from the lowest to the next-to-highest vigintile (Figure 3, Panel D).[18]

This initial finding does not hold at the very top of the wage distribution (Figure C2). For example, between 1985 and 2019, the share of U35 workers in the top 1 percent and top 0.5 percent of the distribution of weekly wages slightly increased by 11 percent and 5 percent, respectively.[19] Therefore, it is important to remember that worse labor-market outcomes affected all younger workers except those within the top 5 percent of the wage distribution.

Second, the start of the careers of new entrants in the labor market became slower, showing progressively lower wage growth (Figure C3). Specifically, for U35 workers who entered the labor market for the first time between 1985 and 1989, the median weekly wage in the first year of work was equal to 79 percent of the median wage of all workers. After the first year, the median weekly wage of these new entrants grew until it became 94 percent of the median wage of all workers by the end of the sixth year of work.

However, if we plot this curve for U35 workers who entered the labor market *after* 1989, we observe two main changes. First, the wage in the first year of work became a lower proportion of the median wage of all workers. For example, for workers who entered the labor market for the first time between 2005 and 2009, their first median wage was only 75 percent of the median wage of all workers. Second, the wage growth during the first six years of work became lower. Among the workers who entered between 2005 and 2009, the median wage grew to only 89 percent of the median wage of all workers by the sixth year of work, failing to catch up to the higher levels experienced by workers who had entered the labor market before 2000.

Third, instead of focusing on wages, we can analyze changes in the type of positions held within firms. The share of managerial jobs held by O55 workers grew from 12 percent in 1996 to 28 percent in 2019, while the share of these jobs held by U35 workers decreased from 8

[18] Replacing weekly wages with yearly earnings does not change these results (Figure C1).

[19] Over the same period, the share of O55 workers in those quantiles decreased by 40 percent and 44 percent, respectively.

percent to 3 percent over the same period (Figure C4, Panel A).[20] This pattern could stem from the large increase in the number of O55 workers. In fact, if O55 workers were more likely to be managers at baseline, the progressive aging of the population could mechanically increase the share of O55 managers. To address this issue, we can 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 an increase in the share of O55 managers from 9 percent of all O55 workers in 1996 to 11.5 percent of all O55 workers in 2019, while the share of U35 managers shows little change over time (Figure C4, Panel B). In short, these findings indicate that the increased probability that O55 workers will hold managerial positions reflects a more structural change in the labor market, rather than just a mechanical shift in demographics.

3.2 Decomposition of the Age Wage Gap

So far, the descriptive evidence has pointed to a progressive slowdown of the careers of younger workers. In this section, we propose a more formal decomposition of the change in the age wage gap to control for general trends in wage inequality that have affected workers in all age groups.

Proposition 1. The change in the average log wage for age group a between years t and t' can be written as follows:

$$\Delta w_a^{t,t'} = \underbrace{\sum_v s_{a,v,t}\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Wage trend}} + \overbrace{\underbrace{\sum_v \left(s_{a,v,t'} - s_{a,v,t}\right)\bar{w}_{v,t}}_{\text{Ranking shift}} + \underbrace{\sum_v \left(s_{a,v,t'} - s_{a,v,t}\right)\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Ranking shift x Wage trend}}}^{\text{Total ranking shift}}. \tag{1}$$

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. Moreover, $\bar{w}_{v,t}$ is the mean log wage in vigintile v and year t.[21] For a given age or age group, the change in wages between two years can be written as the sum of three components. First, a portion of the wage change stems from variation over time in the average wages earned in different vigintiles of the distribution, keeping the share of workers in age group a and vigintile v fixed at baseline. We call this component the *wage trend*. Second, another portion of the wage change comes from variation over time in the

[20] The Social Security data allow us to identify workers with managerial or high-skill tasks starting in 1996. In the Italian system, these workers are called *dirigenti* and *quadri,* respectively.

[21] Appendix D describes all the steps required to obtain the decompositions included in this section.

shares of workers in age group a and vigintile v of the wage distribution, keeping the wage distribution fixed at baseline. We call this component the *ranking shift* to emphasize that it stems entirely from shifts along the wage distribution, while the support of the distribution is kept untouched. Third, the last portion of the wage change is a residual that comes from the interaction between the ranking shift and the wage trend. For example, it captures the fact that the share of workers in age group a may increase over time in the same vigintile in which average wages are increasing. Finally, we can group the second and third component on the right-hand side of Equation (1) to measure the total effect of a shift in ranking over time, because both parts contain changes in the share of workers in age group a who are in different vigintiles of the wage distribution.

Before we move to the results, it will be helpful to discuss how this decomposition relates to the previous findings reported in Section 3.1. Equation (1) indicates that the widening of the age wage gap can stem from two forces. First, U35 workers may have become more likely to be in the bottom vigintiles of the wage distribution, and vice versa for O55 workers (ranking shift). Second, U35 workers may have found themselves in parts of the distribution that experienced a lower growth in average wages, and vice versa for O55 workers (wage trend). The descriptive evidence that we presented in Section 3.1 suggested that the ranking-shift component played an important role in generating diverging wage trends between U35 workers and O55 workers.

Next, we report the decomposition from Equation (1) using log weekly wages between 1985 and 2019 (Figure 4, Panel A). At least three things are notable about these results. First, the wage-trend component increased the wages of all workers, including the younger ones. In other words, if we could allow average wages to change over time while blocking workers in different age groups from moving along the wage distribution, then all age groups would have experienced an increase in their real weekly wages.

Second, the ranking-shift component contributed to decreasing the wages of younger workers and to increasing the wages of older workers. This indicates that the movement of younger workers between vigintiles of the wage distribution caused a decrease in their weekly wages over time, while the opposite is true for workers who were at least 51 years old.[22] This finding is consistent with what we already established in Section 3.1, namely that U35 workers became more likely to be at the bottom of the wage distribution, while O55 workers became more likely to be at the top.

Third, if we focus on differences between younger and older workers, it is clear that the

[22]Moreover, the effect of the ranking shift is almost monotonically increasing with age. Therefore, when we focus on U35 workers, rather than on individual ages, we underestimate the wage losses of younger workers within the U35 category.

ranking shift was much more important than the wage trend in widening the age wage gap.

Proposition 2. In the next set of results, we decompose more directly the wage difference between U35 workers and O55 workers over time. This double difference can be written as follows:

$$\Delta w_{O55}^{t,t'} - \Delta w_{U35}^{t,t'} = \underbrace{\sum_v \left(s_{O55,v,t} - s_{U35,v,t}\right)\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Wage trend}}$$

$$+ \overbrace{\underbrace{\sum_v \Delta s_{O55-U35,v,t'-t}\bar{w}_{v,t}}_{\text{Ranking shift}} + \underbrace{\sum_v \Delta s_{O55-U35,v,t'-t}\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Ranking shift x Wage trend}}}^{\text{Total ranking shift}}. \qquad (2)$$

In this equation, $\Delta s_{O55-U35,v,t'-t}$ 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'. It can be rewritten as: $\Delta s_{O55-U35,v,t'-t} = (s_{O55,v,t'} - s_{O55,v,t}) - (s_{U35,v,t'} - s_{U35,v,t})$. We compute the components on the right-hand side of Equation (2) for every year between 1985 and 2019 using log weekly wages to establish three main results (Figure 4, Panel B). First, by 2019, the ranking shift accounted for 82 percent of the total wage gap between U35 workers and O55 workers. Second, the ranking-shift component has been the major driver of the wage gap throughout the period under consideration, contributing between 55 percent in 1987 and 83 percent in 2004. Third, if we replace weekly wages with yearly earnings, the ranking shift accounted for an even larger share of the gap (89 percent in 2019), suggesting that trends in the number of yearly working hours may have contributed to slowing down the careers of younger workers (Figure D1).

4 Age Gap Between and Within Firms

In this section, we investigate the role of internal and external labor markets by decomposing the overall age wage gap into a between-firm component and a within-firm component. This analysis allows us to assess whether younger workers became more likely to work for lower-paying firms or whether they started advancing more slowly than their older coworkers within the same set of firms.

4.1 Decomposition Between and Within Firms

We start by proposing a decomposition of the age wage gap in a given year into a between-firm component and a within-firm component.

Proposition 3. In year t, the difference in mean log wage between U35 workers and O55 workers can be written as follows:

$$\bar{w}_{O55,t} - \bar{w}_{U35,t} = \overbrace{\frac{1}{N_{O55,t}} \sum_{i \in O55} \bar{w}_{j(i),t} - \frac{1}{N_{U35,t}} \sum_{i \in U35} \bar{w}_{j(i),t}}^{\text{Difference between firms}} + \overbrace{\frac{1}{N_{O55,t}} \sum_{i \in O55} \Delta w_{i,j(i),t} - \frac{1}{N_{U35,t}} \sum_{i \in U35} \Delta w_{i,j(i),t}}^{\text{Difference within firms}} . \quad (3)$$

On the left-hand side of this equation, $\bar{w}_{O55,t}$ is the mean log weekly wage of O55 workers in year t, while $\bar{w}_{U35,t}$ is the mean log weekly wage of U35 workers in year t. On the right-hand side of the equation, $N_{O55,t}$ is the number of O55 workers in year t; $N_{U35,t}$ is the number of U35 workers in year t; $\bar{w}_{j(i),t}$ is the mean log weekly wage in year t within firm $j(i)$ in which individual i works; and $\Delta w_{i,j(i),t}$ is the difference between the log wage of worker i and the average log wage in firm $j(i)$ in year t ($\Delta w_{i,j(i),t} = w_{i,j(i),t} - \bar{w}_{j(i),t}$).[23] Equation (3) presents the wage gap as the sum of two components. The first element measures the differences in the average firm-level log weekly wages between firms that employ at least some O55 workers and firms that employ at least some U35 workers. This between-firm component captures the differential sorting of younger and older workers across higher-paying and lower-paying firms. The second element of Equation (3) measures the differences (i) between workers' log wages and the average log weekly wage in their firms, and (ii) between O55 workers and U35 workers. This within-firm component captures differences in the labor-market outcomes of younger and older workers relative to their coworkers.

Following Equation (3), we decompose the difference in log weekly wages between U35 workers and O55 workers separately for each year between 1985 and 2019 (Figure 5, Panel A). As already established in Section 2.2, the overall age wage gap increased over time. However, the sources of this increase were not consistent throughout that period. More specifically, we find that between 1985 and 2005 most of the increase in the wage gap can be attributed to within-firm factors. The within-firm component accounted for 51 percent of the gap in 1985, 56 percent in 1990, 58 percent in 1995, 61 percent in 2000, and 58 percent in 2005. In contrast, in the last fifteen years of data the importance of between-firm factors increased until they accounted for 49 percent of the age wage gap in 2019.[24]

In short, the data indicate that the internal labor markets played a primary role in widening the age wage gap. This result is in contrast with previous findings on wage inequality.

[23] Appendix E contains the full derivation of this result.

[24] All these findings hold if we divide workers into individual age groups (Figure 5, Panel B) or we use yearly earnings. (Figure E1)

For example, in the United States, Song et al. (2019) finds that the within-firm component can explain only 32 percent of the increase in the overall variance of wages between 1981 and 2013. In Italy, Briskar et al. (2020) finds that between-firm factors account for 62 percent of the whole wage dispersion. This discrepancy suggests that the factors behind the widening of the age wage gap differed from the factors that caused the more well-studied increase in wage dispersion.

We conclude this section by discussing a piece of descriptive evidence that corroborates the importance of the within-firm component. For several percentiles of the distribution of weekly wages, we compute three variables in 1985 and 2019: (i) the average log weekly wage of workers who were in that percentile, (ii) the average log weekly wage of all the older coworkers of U35 workers who were in that percentile, and (iii) the average log weekly wage of all the younger coworkers of O55 workers who were in that percentile. Then, we compute the difference in these three averages between 1985 and 2019 (Figure E2, Panel A).

If we exclude the percentiles at the very top and bottom of the distribution, in which the wage growth of workers within those percentiles was always larger than the wage growth of their coworkers, this analysis confirms that younger workers fared worse than their older colleagues. Between the 25th percentile and the 75th percentile, the older coworkers of U35 workers always experienced a higher wage growth compared to U35 workers in the percentile, while the younger coworkers of O55 workers always experienced a lower wage growth compared to O55 workers in the percentile.[25]

4.2 Counterfactual Analysis

Section 3.2 established that the ranking shift—that is, changes in the share of workers along the wage distribution, while the support of the distribution is kept fixed at baseline—accounted for most of the increase in the age wage gap between 1985 and 2019 (Figure 4, Panel B). In this section, we investigate how much of this ranking-shift effect happened within firms, rather than between them. For this purpose, we adapt to our specific research question a counterfactual exercise first developed by Machado and Mata (2005) and then further modified by Autor, Katz, and Kearney (2005) and more recently by Song et al. (2019).

In the first step, we sort workers into 100 percentiles based on their firms' average weekly wage, separately for each year in the sample. Next, within each of these 100 firm-based groups, we sort workers into 500 quantiles based on the difference between their weekly wage and the average weekly wage in their firm-based group. The result of this two-step process is the sorting of all workers into 50,000 equal-sized bins, which we call *firm-worker groups.*

[25] These findings are generally robust to using yearly earnings (Figure E2, Panel B).

The key feature of this sorting is that it allows us to rewrite the shares of workers in age group a, firm-worker group (f, e), and year t as follows:

$$s_{a,(f,e),t} = \underbrace{s_{a,f,t}}_{\text{Share of } a \text{ in } f} \cdot \underbrace{s_{a,(e|f),t}}_{\text{Share of } a \text{ in } e \text{ conditional on } f}. \tag{4}$$

Equation (4) rewrites the unconditional share of workers in age group a and firm-worker group (f, e) as 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 ($s_{a,(e|f),t}$).

Following Equation (4), Appendix F shows that it is possible to rewrite the total-ranking-shift component of Equation (2) as the sum of three elements: (i) a change over time in the share of workers in age group a and firm group f, while keeping the distribution of workers within each firm-worker group and the level of wages fixed; (ii) a change over time in the share of workers in age group a and firm-worker group $(e|f)$, while keeping the sorting of workers across firm groups f and wages fixed; and (iii) a residual.

The first component describes a counterfactual scenario that isolates the between-firm portion of the total ranking shift: younger and older workers were allowed to move across firms as they did in the data, but the internal ranking within each firm group stayed constant. The second component describes a different counterfactual exercise that focuses on the within-firm portion of the total ranking shift: workers could experience changes in their relative ranking within their firm group, but they could not move across firm groups.

We start this analysis by decomposing the total ranking shift between 1985 and 2019 separately for U35 workers and O55 workers (Figure 6, Panel A). We find that the within-firm component was the major driver behind the overall negative effect of the ranking shift among U35 workers; it accounted for 61 percent of the total. In contrast, the between-firm component was solely responsible for the overall positive effect of the ranking shift among O55 workers. Therefore, two distinct factors contributed to widening the difference in the ranking shift between younger and older workers: (i) younger workers moved toward the lower percentiles of the wage distribution mostly due to worse careers within their firms, and (ii) older workers improved their ranking in the wage distribution by moving to higher-paying firms.

We can show what effect prevailed by plotting the difference in total ranking shift between U35 workers and O55 workers, as well as between the year 1985 and year $t \in [1986, 2019]$ (Figure 6, Panel B). The data indicate that both the within-firm component and the between-firm component were important drivers of the difference in the ranking shift. In particular, within-firm factors were the predominant force until 2007, after which their influence decreased: they accounted for 51 percent of the total ranking shift in 1990, 79 percent in 2000, 40 percent in 2010, and 39 percent in 2019.

This late increase in the importance of between-firm factors is consistent with prior work that has studied the influence of outsourcing on labor markets (Goldschmidt and Schmieder, 2017). In fact, we find that younger workers became more likely to hold jobs that were outsourced to lower-pay firms (Figure F3, Panel A). As further proof of the role played by this outsourcing-driven sorting of workers, we also establish that between-firm factors accounted for a smaller share (-8 percentage points by 2019) of the increase in the age wage gap in sectors that were less exposed to the rise in outsourcing (Figure F3, Panel B).[26]

5 Age Gap in Firm Rents

Up to this point, we have established three main facts about the age wage gap. First, between 1985 and 2019, the wages of older workers grew at a much faster rate than those of younger workers. Second, the increasing inability of younger workers to reach the top of the wage distribution was the main source of this phenomenon. Third, a substantial portion of the slowdown in the careers of younger workers happened within firms, even though between-firm factors gained importance over time. All these prior results may have stemmed from differences in both firm-level wage premiums and worker-level characteristics. In this section, we focus on the role of firm premiums by leveraging for the first time the longitudinal component of the Social Security dataset.

5.1 A Model of Wages

We start by proposing a model of wage formation. The main goal of the model is to measure firm-level wage premiums for younger and older workers, distinguishing them from worker-level premiums and from the effect on wages of other observable characteristics of workers. For this purpose, we adapt to our empirical context the widely used AKM model, first popularized by Abowd, Kramarz, and Margolis (1999). Specifically, we estimate the following wage function:

$$w_{i,t} = \theta_i + \psi^{a(i)}_{j(i,t),p} + \beta^{a(i)} X_{i,t} + \varepsilon_{i,t}. \tag{5}$$

In Equation (5), the logged weekly wage of individual i in year t ($w_{i,t}$) is the sum of a worker-level fixed effect (θ_i), a fixed effect (also defined as firm rent or firm premium) for firm $j\,(i,t)$ that employs worker i in year t ($\psi^{a(i)}_{j(i,t),p}$), a quadratic function of age and experience ($X_{i,t}$),

[26] The classification of sectors that were more and less exposed to outsourcing follows Goldschmidt and Schmieder (2017). For more information, see the notes of Figure F3.

and time-varying unobserved factors ($\varepsilon_{i,t}$).[27]

Equation (5) deviates from the most basic AKM model in two ways. First, it is estimated separately for workers in age group $a \in \{U35, O55\}$.[28] Obtaining separate sets of firm fixed effects makes it possible to study whether U35 workers and O55 workers experienced a different appropriation of firm rents over time.

Second, instead of computing a single time-invariant fixed effect for each firm, we allow firm rents to vary every three years.[29] Specifically, we interact the time-invariant firm fixed effects with dummies that identify twelve consecutive three-year periods p.

Equation (5) is estimated for both U35 workers and O55 workers on the largest dual connected set. This is the largest set of firms connected by firm-to-firm transitions of both younger and older workers (Table G1). The estimation of Equation (5) allows us to compute the difference in firm rents (i) between U35 workers and O55 workers, and (ii) between 1985 and year $t \in [1986, 2019]$. To better assess the role played by firms, we further decompose the average difference in firm rents into two separate components: (i) sorting of younger and older workers between higher-rent and lower-rent firms, and (ii) wage-setting policies within firms. Specifically, we adapt to our empirical context the decomposition of firm fixed effects proposed by Card, Cardoso, and Kline (2016), as follows:

$$E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} \mid a(i) = \text{O55}\right) - E\left(\Delta_{t-1985}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{U35}\right) \tag{6}$$

$$= \underbrace{E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} - \Delta_{t-1985}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{O55}\right)}_{\text{Wage setting}} \tag{7}$$

$$+ \underbrace{E\left(\Delta_{t-1985}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{O55}\right) - E\left(\Delta_{t-1985}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{U35}\right)}_{\text{Sorting}}$$

$$= \underbrace{E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} - \Delta_{t-1985}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{U35}\right)}_{\text{Wage setting}} \tag{8}$$

$$+ \underbrace{E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} \mid a(i) = \text{O55}\right) - E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} \mid a(i) = \text{U35}\right)}_{\text{Sorting}}.$$

The first component of Equation (7) is the difference in firm rents (i) between 1985 and year t and (ii) between U35 workers and O55 workers, conditional on the set of firms that employ at least some O55 workers. This element measures differential trends in wage-setting

[27] Appendix G contains many more details about the estimation of this model.

[28] Following a similar process, Card, Cardoso, and Kline (2016) estimated gender-specific firm rents and Kline, Saggio, and Sølvsten (2020) estimated age-specific firm rents.

[29] Lachowska et al. (2019) and Engbom and Moser (2020) estimated a similar "time-varying" AKM model.

policies between U35 workers and O55 workers, that is, variation over time in their ability to appropriate firm rents in the same set of firms. The second component of Equation (7) measures the difference of firm rents among U35 workers (i) between 1985 and year t and (ii) between the set of firms that employ at least some O55 workers and the set of firms that employ at least some U35 workers. It measures how much the variation over time in the sorting of U35 workers across different firms affected the overall difference in firm rents between U35 workers and O55 workers. Moreover, it is possible to compute an alternative decomposition, in which the first component isolates differences in wage-setting policies in the set of firms that employ at least some *U35 workers*, and the second component measures sorting of *O55 workers* across different sets of firms (Equation (8)).

5.2 Normalization and Identification

In this section, we discuss several aspects related to the identification of the firm effects.

In the AKM model, firm rents are identified up to a normalization. Therefore, for the purpose of the estimation, we normalize firm rents for both U35 workers and O55 workers by excluding the fixed effect of the largest firm in the dual connected set. Therefore, all remaining firm effects measure the average difference in wages with respect to the excluded firm. However, as we discuss in more detail in Appendix G, this normalization does not have any effect on the results.[30]

Next, we point out another slight difference between Equation (5) and the most basic AKM model. As is well known, the firm premiums $\psi^{a(i)}_{j(i,t),p}$ are identified in the data using firm-to-firm transitions. However, in Equation (5), each firm j is the combination of a firm dummy and a period dummy. It follows that job moves are defined based on the firm-period pairs, rather than time-invariant firm dummies. In other words, there are two types of workers who matter for identifying the firm rents: (i) workers who moved across different firms within a period, and (ii) workers who stayed at a firm across different three-year periods.

Finally, we discuss the main pieces of evidence about the orthogonality condition needed to identify $\psi^{a(i)}_{j(i,t),p}$. There are three main threats to identification. First, job moves could be correlated with transitory firm shocks. Second, job moves could be driven by unobserved firm-worker match effects. Third, job moves could be correlated with transitory worker-level shocks. Each of these scenarios has clear implications for the trend of movers' wages just before and after firm-to-firm transitions. Therefore, we pool all job moves in the dataset and set up event studies that include two periods before and two periods after each firm-to-firm transition. We then study the pattern of the average log weekly wage around job moves for

[30] We always consider double differences of firm rents (i) between 1985 and year t and (ii) between U35 workers and O55 workers. Therefore, our comparisons always remove the normalization constant, making its definition inconsequential.

all "movers" in the data, separately for U35 workers and O55 workers. The analysis of these event studies reveals four main results (Figure G1 and Table G3).

First, the overall direction of wage changes around moves is consistent with the position of each firm in the distribution of weekly wages. Specifically, wages decreased among workers who moved to firms in a lower quartile of the distribution of mean wage, increased among workers who moved to firms in a higher quartile, and stayed roughly constant among workers who moved to firms in the same quartile.[31]

Second, there are not unusual positive spikes in mean wages just before an upward move or negative spikes just before a downward move. Therefore, the data do not support the hypothesis that many moves are correlated with transitory firm shocks.

Third, the wage gains from joining a higher-wage firm are roughly symmetric to the wage losses from joining a lower-wage firm. For example, among O55 workers, the average wage gain from moving from a firm in the bottom quartile to a firm in the top quartile was 6.5 percent, while the opposite average wage loss was 6.6 percent.

Fourth, there are not significant trends in mean wages during the periods that precede a firm-to-firm transition. Three quarters of the mean wage changes between period -2 and period -1 were less than 0.04 log points.

Taken together, these results indicate that cross-firm differences in firm premiums drive a large portion of the wage changes of movers. Consistent with prior work in this literature, this framework appears to fit the data well in spite of its somewhat strong assumptions. We refer the reader to Appendix G for many more details about the identification and for other robustness checks.[32]

5.3 Estimates of Wage Model

We estimate Equation (5) following the procedure outlined in Section (5.1) and obtain 617,024 firm effects associated with 7,411,175 U35 workers as well as 551,146 firm effects associated with 2,511,677 O55 workers (Table G2). We use these firm premiums to compute the double difference in Equation (6) and its two decompositions. This analysis leads to at least three main findings (Table 2).

First, differences between U35 workers and O55 workers in the appropriation of firm rents explain 69 percent of the widening in the age wage gap between 1985 and 2019. The importance of firm premiums followed an inverted U-shape: it started low, reached a peak

[31] As is customary in this type of analysis, the wages of movers are not used to divide firms into different quartiles.

[32] For example, we perform an analysis on the residuals of Equation (5) to assess the fit of the model, and also estimate a version of Equation (5) with job-match effects to test the sensitivity of the results to this modeling variation.

between 1997 and 2002, and then decreased until the end of the sample. These findings differ from those of prior work on wage trends. For example, Card, Cardoso, and Kline (2016) finds that differences in firm rents explain only 21 percent of the gender wage gap in Portugal between 2002 and 2009.[33] Similarly, previous papers on the gender wage gap have established that firm premiums account for 30 percent of the gap's recent growth in Italy (Casarico and Lattanzio, 2020) and for 15 percent of its growth in Germany (Bruns, 2019). Moreover, Card, Heining, and Kline (2013) finds that establishment fixed effects explain only 18.5 percent of the dispersion of log wages in West Germany between 1985 and 2009. Our analysis indicates that differences in the appropriation of firm premiums were more important than differences in worker characteristics in driving a wedge between the wages of younger and older workers. In short, this first finding corroborates the fact that firms have played a major role in widening the age wage gap.

Second, the decomposition in Equation (7) indicates that the sorting of U35 workers across firms accounted for 54 percent of the difference in firm premiums and, therefore, 37 percent of the increase in the age wage gap. The influence of this sorting pattern increased over time, accounting for all the differential appropriation in firm rents by 2019. In short, U35 workers became more likely to work in lower-premium firms over time, which in turn widened the wage gap with respect to older workers.

Third, the second decomposition in Equation (8) indicates that, in the set of firms in which U35 workers were more likely to work, differences in the effects of wage-setting policies on younger versus older workers accounted for 79 percent of the difference in firm premiums and 55 percent of the increase in the overall age wage gap. The influence of internal wage-setting policies peaked at 97 percent between 2000 and 2002 and then decreased to 57 percent between 2018 and 2019; this decrease coincided with an increase in the portion of the difference in firm premiums that could be explained by the sorting of O55 workers across firms.

Overall, the last two sets of results corroborate and expand the evidence from repeated cross-sections described in Section 4.2 and Figure 6.

5.4 Additional Evidence on Appropriation of Firm Rents

In this section, we provide an additional piece of evidence indicating that O55 workers were able to capture a significant portion of firm rents. Specifically, we estimate a series of event studies centered around positive and negative firm-level value-added shocks.[34] We then study

[33] However, it should be noted that Card, Cardoso, and Kline (2016) studies gender differences in the *level*, rather than the trend, of firm rents.

[34] Appendix G contains more details about the construction of this sample. In short, we measure the value-added shock for firm j as the year-to-year change in value added of firm j minus the average year-to-year

how the average wages of U35 workers and O55 workers who stayed at these firms for at least two years before and three years after the value-added shock changed in response to these shocks.

This analysis produces three main findings (Figure G3). First, the data do not show the existence of significant trends in wages before either a positive or a negative value-added shock. In other words, the shocks in period 0 do not seem to have been anticipated by wage changes. Second, as expected, a positive firm-level value-added shock is followed by an increase in average wages, and vice versa. Third, there are substantial differences in the way in which wages of U35 workers and O55 workers changed in response to value-added shocks. In the case of a 10-percent positive shock, the wages of O55 workers increased by 0.017 log points by the end of period 3, while the wages of U35 workers increased by only 0.003 log points. In the case of a 10-percent negative shock, the wages of U35 workers decreased by 0.005 log points by the end of period 3, while the wages of O55 workers decreased by only 0.003 log points. In conclusion, the main takeaway is that O55 captured a larger share of the positive shocks and were exposed to a smaller share of the negative ones.

6 Empirical Evidence Outside of Italy

In this section, we use administrative data from Germany, as well as CPS data from the United States, to replicate the previous analysis on the Italian data. It should be noted that not everything can be replicated due to data limitations. For example, the whole analysis in Section 5 can be performed only using the Italian Social Security dataset. The German dataset has only a sample of establishments, which makes it impossible to account for all firm-to-firm transitions. Moreover, the U.S. dataset is only a representative survey, which does not allow us to identify coworkers.

6.1 Germany

Overall, the analysis of the German data paints the same picture that we obtained using the Italian Social Security dataset.

First, we find that U35 workers became less likely to reach the top of the wage distribution (Figure H1, Panel A). Specifically, their probability of being in the top quartile of the distribution of daily wages decreased by 13 percent between 1996 and 2017, while their probability of being in the bottom quartile increased by 16 percent. In contrast, the probability of O55 workers being in the bottom quartile decreased by 18 percent, while their probability of being in the second and third quartiles increased by 24 percent and 18 percent, respectively

change in value added in the province and in the two-digit sector in which firm j operates. We then adapt to our setting a methodology described by Lamadon, Mogstad, and Setzler (2019) to set up event studies around value-added shocks.

(Figure H1, Panel B). However, unlike the situation we observed in Italy, O55 workers did not become more likely to be at the very top of the wage distribution; instead, they moved from the top and bottom tails toward the median.

Second, as we observed in Italy, most of the increase in the age wage gap stemmed from the ranking-shift component, rather than from changes in the average wages paid for different types of jobs (Equation (2)). The total-ranking-shift component accounted for 67 percent of the widening in the age wage gap in 2000, for 66 percent in 2010, and for 72 percent in 2019 (Figure H2, Panel A).

Third, most of the difference in log daily wages between U35 workers and O55 workers stemmed from within-firm factors (Figure H2, Panel B). For example, the latter accounted for 79 percent of the age wage gap in 2017. However, between-firm factors explained most of the *growth* in the age wage gap. This result from Germany matches the evidence from Italy, in which the primary source of growth in the age wage gap was within firms until 1995 and between firms from 2000 (Figure 5, Panel A).

Finally, we find that the ranking-shift component (Equation (2)) stemmed primarily from between-firm factors, although within-firm factors accounted for up to 46 percent in 2004 (Figure H3, Panel A). As we saw with Italian data, within-firm factors contributed to decrease the wages of U35 workers, while between-firm factors acted to raise the wages of O55 workers (Figure H3, Panel B).

6.2 United States

The analysis with U.S. data is limited by the fact that we have only a representative sample of the population (the Merged Outgoing Rotation Groups of the CPS). However, all the tests that we were able to replicate lead to similar conclusions about the nature of the age wage gap.

First, younger U.S. workers became less likely to reach the top of the wage distribution, and vice versa for older U.S. workers (Figure H4). The probability of U35 workers being in the top quartile of the distribution of weekly wages decreased by 17 percent between 1985 and 2019, while the probability of being at the bottom increased by 14 percent. In contrast, the probability of O55 workers being in the bottom quartile decreased by 7 percent, while the probability of being in the third and fourth quartiles increased by 6 percent and 1 percent, respectively.

Second, the ranking-shift component drove almost all the increase in the age wage gap in the U.S.: the total ranking shift accounted for 75 percent of the widening in the age wage gap between O55 workers and U35 workers that took place between 1985 and 2019 (Figure H5).

7 Forces Behind the Widening of the Age Wage Gap

We conclude our analysis with a descriptive discussion of mechanisms that may be consistent with the prior findings.

7.1 Career Spillovers From Older Workers to Younger Workers

In this section, we show that the age wage gap increased more among workers employed by firms that had more difficulty in adding higher-ranked positions. These results are broadly consistent with the idea that the success of older workers slowed down the wage growth of their younger coworkers, generating negative career spillovers and leading to a widening in the age wage gap.

In a completely frictionless labor market (Baker, Gibbs, and Holmström, 1994), younger workers who are qualified to receive a promotion cannot be blocked from it by the fact that older workers either stay longer in higher-ranked positions or receive higher wages. In fact, either their current firms would add a new higher-level job to the organization or other firms would intervene and poach those younger workers seen as deserving a promotion.

Two types of labor-market frictions are needed to generate negative career spillovers. First, firm separations need to be costly for the worker and/or the firm. The literature in organizational economics offers numerous explanations about why turnover can come at a cost. For example, firms may backload wages toward the end of workers' careers in order to use future promotions as a motivational device and to dissuade early turnover (Ke, Li, and Powell, 2018). The productivity of a worker could be affected by the composition of their current team and, therefore, may not be replicable in a different firm (Hamilton, Nickerson, and Owan, 2003). Moreover, the existence of firm-specific human capital may tie qualified workers to their current firms (Lazear, 2009; Gathmann and Schönberg, 2010), or firms may incur substantial monetary costs associated with laying off workers (Bentolila and Bertola, 1990).[35] Regardless of the specific mechanism that causes this friction, the consequence is that workers often receive a premium for staying longer at a firm.

Second, at least some firms need to face constraints in adding higher-level positions to their organizations. There are multiple factors that are not mutually exclusive which can explain both (i) the existence of such constraints and (ii) their growing influence. For example, the average firm may have faced increasing financial difficulties in expanding its ranks, as indicated by the progressive decrease in labor productivity (Syverson, 2017) and GDP

[35] These four examples are not an exhaustive list of plausible explanations. In fact, our analysis does not need to pick one specific mechanism either within or outside this short list, given that there is a growing amount of theoretical and empirical evidence highlighting the importance of this broad kind of friction in the labor markets.

growth (Figure I1) that most high-income countries have experienced in the last decades. Prior work has documented that economic conditions at the time of entry into the labor market can have long-lasting effects (Kahn, 2010). Therefore, this trend plausibly impacted the careers of new entrants more negatively than those of seasoned incumbents. Moreover, the progressive aging of the workforce and the increase in the retirement age imply that older workers stayed in their higher-ranked positions for longer, further blocking promotions of younger workers (Bianchi et al., 2021).

In practice, the combination of these frictions implies that negative career spillovers should be more prominent among firms that are growing less and are in a more mature stage of their life cycle.[36] These firms, in fact, may face more difficulties in creating new higher-ranked positions because they lack either sufficient monetary resources to promote all deserving workers or available tasks and responsibilities to assign to new managers. Consistent with this hypothesis, we show that the age wage gap increased more in firms that (i) experienced below-median growth in employment between 1985 and 2019, (ii) were at least ten years old, and (iii) employed more workers (Table I1, Panels A-C). Most of these differences are large in magnitude and statistically significant at the 1 percent level. Finally, we show that this type of firms has become more common over time, suggesting that career spillovers may have become more severe: the mean firm age increased by 35 percent from 11.9 years in 1985 to 16.1 years in 2019 (Figure I2).[37]

In short, we hypothesize that frictions in firm separations and increasing difficulty in creating higher-ranked jobs prevented firms from redistributing career opportunities from older workers to younger workers. In internal labor markets, this situation created opposite wage trends. Older workers kept accumulating tenure at the top of the wage distribution, enjoying the rents associated with their positions for longer. Younger workers experienced much lower wage growth, due to their increasing difficulty in reaching the top of the job ladder.

As a consequence of slower careers in internal labor markets, some younger workers could have decided to find better opportunities in the external labor market. Our data confirm that younger workers became increasingly more likely to have fragmented careers. If we exclude the peaks at the minimum retirement age, the share of older workers with a turnover event (voluntary or involuntary) either stayed constant or decreased over time (Figure I3). For example, among workers who were 60 years old, the share with a turnover event decreased from 35 percent in 1985 to 15 percent in 2019. Younger workers experienced the opposite

[36] This hypothesis is consistent with the theoretical framework in Bennett and Levinthal (2017).

[37] This finding is not due to censoring of firm age at the beginning of the sample. For each firm, we know the foundation year even when it predates the availability of Social Security data.

trend. For example, the share of 25-year-olds with a turnover event increased from 25 percent in 1985 to 52 percent in 2019. Interestingly, this increase in turnover may have been partially driven by the matching between younger workers and firms. In fact, we find that U35 workers became more likely to work for firms with a higher turnover rate, while O55 workers did not follow the same trend (Figure I4).

7.2 Education and Job Experience

As we already discussed in Section 2.3, the increase in the age wage gap is robust to controlling for changes in several observable characteristics: country of birth, type of contract, gender, province of residence, and improvements in health. We did not control for education because this information is available in the Italian Social Security data only for recent years and younger workers. In this section, we leverage several pieces of evidence to argue that trends in education and experience are not fully compatible with the increase in the age wage gap.

First, from a theoretical standpoint, it is not likely that recent trends in education were consistent with the widening of the age wage gap. In Italy, for example, university completion increased, albeit slightly, among younger cohorts (Figure I5). Therefore, the higher returns associated with college education should have pushed the wages of younger workers closer to those of older workers, rather than farther apart. Using survey data collected by the Bank of Italy, Rosolia and Torrini (2007) confirms that the trend in wages of younger and older workers have not been significantly affected by changes in education across cohorts and over time. Second, we use the German data, which include information about high-school completion, to show that the age wage gap widened among all workers, regardless of their education level (Figure I6).

Although our results may not be driven by changes in the returns to education, they could be related to changes in the returns to job experience. Specifically, earlier papers have shown that the productivity of inventors and entrepreneurs started peaking at a higher age over time (Jones, 2009; Azoulay et al., 2020). For these occupations, the returns to experience increased mainly because associated tasks became more complex and started requiring more skills. This increased "burden of knowledge" pushed more workers to lengthen their investment in education, thereby reducing their on-the-job-experience and postponing career advancements. At first glance, the fact that the age wage gap increased over time is consistent with this mechanism. We can show this point more directly by plotting the average weekly wage by years of experience both in 1985 and 2019 (Figure I7, Panel A). Weekly wages started plateauing around 15 years of experience in 1985, while they kept increasing until 23 years of experience in 2019.

Although trends in experience are certainly compatible with the widening of the age wage gap, two pieces of evidence limit its importance. First, we find that the age wage gap between O55 workers and U35 workers substantially increased even when we directly control for how many years U35 workers spent in the labor market (Table I1, Panel D). In fact, the age wage gap tended to be larger among U35 workers with more on-the-job experience. Therefore, it is not likely that the widening of the age wage gap was driven by an increasing number of U35 workers who had less on-the-job experience due to longer investments in education.

Second, we test whether experienced workers became more valuable over time. We divide economic sectors into two groups based on how much they relied on experience at baseline. Specifically, we compute the sector-level share of workers in the top decile of wages with at most five years of experience between 1985 and 1989.[38] Then, we compute the trend in the age wage gap, distinguishing between (i) the sectors with a share of low-experience and high-wage workers in the bottom quartile of the distribution and (ii) those in the rest of the economy. The idea is that an increase in the importance of experienced workers should have been less prominent within sectors that were already relying heavily on job experience at the beginning of the period under consideration, and vice versa. However, the data indicate that the age wage gap increased more in sectors with high reliance on experience at baseline (Figure I7, Panel B).

7.3 Other Factors

In this section, we discuss six remaining factors. First, the progressive increase in retirement age in most high-income countries may have changed the selection of older workers, leading to a higher share of high-wage individuals in the older workforce. However, prior work has documented that the workers who retire early tend to be negatively selected with respect to their labor-market outcomes and health (Munnell, Sanzenbacher, and Rutledge, 2018; Kolsrud et al., 2021). Therefore, a higher retirement age should have created a downward pressure on the wage growth of older workers, reducing the age wage gap. We can further show that selection among older workers does not drive the main findings by estimating the age wage gap between U35 male workers and male workers who were between 56 years old and 60 years old, rather than considering all O55 workers (Table I1, Panel E). The rationale for this test is that the retirement age for most men was at least 60 years old even at the beginning of the sample. Even when we focus on this more limited group of older workers, whose selection should not have changed as a result of higher retirement age, we find that the age wage gap substantially increased between 1985 and 2019.

[38] The 3-digit sector with the highest share of low-experience and high-wage workers is call centers and other business services.

Second, the progressive increase in youth employment and the decline in the number of new hires in the public sector may have pushed more low-skill younger workers into the private-sector labor market, increasing their wage dispersion and widening the age wage gap. However, the wage variance of new entrants was either constant or decreasing between 1985 and 2008, when these structural labor-market changes were taking place (Figure I8, Panel A).[39] Moreover, we also used survey data from the Bank of Italy's Survey of Household Income and Wealth (SHIW) to compute the age wage gap among all types of workers, including public servants and the self-employed. The age wage gap increased also in this sample, suggesting that our main findings based on only private-sector employees were not driven by hiring freezes in the public sector (Figure I8, Panel B). Alternatively, the increased age gap could have been the result of a brain drain, progressively depriving the Italian economy of its most talented younger workers (Anelli et al., 2021). However, our analysis showed that the widening of the age wage gap also happened in the United States and the United Kingdom, two countries that experienced a positive net migration of high-skill younger workers.

Third, as discussed earlier, the increase in the supply of older workers cannot explain the observed trend in wages. If anything, the ever increasing number of older workers, combined with the assumption of imperfect substitutability between younger and older workers[40], should have depressed growth in the wages of older workers and narrowed the age wage gap.[41]

Fourth, the degree of unionization of younger workers may have decreased over time, leading to more inequality between senior and junior workers. To test this hypothesis, we collected information on the sector-level number of members of CGIL, the largest Italian trade union. We use these data to compute the age wage gap separately for sectors with an above-median and below-median share of workers who were CGIL members in 1990, the first available year (Figure I9, Panel A). The sectors with a higher penetration of unions in 1990, which therefore may have become less unionized over time, experienced a smaller widening of the age gap. Therefore, the data do not support the hypothesis that a progressive decrease in the penetration of unions drove a large portion of these wage trends. However, a higher

[39] The wage variance increased only after the Great Recession, but it should be noted that the increase in the age wage gap started decades before 2008.

[40] This assumption is supported by the findings of Bianchi et al. (2021) and Boeri, Garibaldi, and Moen (2021).

[41] A related question is why this factor may have widened the age wage gap when the "baby-boom" cohort entered the labor market (Freeman, 1979). Most high-income countries experienced record-high GDP growth during the first twenty years after the end of WWII. Therefore, it is plausible to assume that not many firms were facing constraints in adding higher-ranked slots to their organizations (as discussed in Section 7.1)

degree of unionization at baseline may have contributed to shelter workers in these sectors from at least part of the increase in the age wage gap.

Fifth, skill-biased technological change (SBTC) could have widened the age wage gap in several ways. For example, the introduction of modern technology may have increased the productivity of older workers more than that of younger workers. However, the available evidence indicates that technological change tends to favor the careers of younger workers (Aubert, Caroli, and Roger, 2006), which suggests that this specific channel may not have played a major role in increasing the age wage gap. Alternatively, the rise in automation may have contributed to the disappearance of many routine jobs that were traditionally held by younger workers, thus slowing down their careers (Cortes et al., 2020). Using sector-level data on the per-worker number of industrial robots, we test this hypothesis by computing the age wage gap for sectors that experienced an above-median and a below-median growth in automation between 1993 and 2019 (Figure I9, Panel B). The age wage gap significantly widened in all sectors, but the increase was slightly larger in the industries in which robots became more common over time. In short, SBTC may have played a role in slowing down the careers of younger workers through the progressive automation of low-skill jobs.

Sixth, we already showed that outsourcing-driven sorting of workers accounted for a portion of the between-firm increase in the age wage gap in the last fifteen years of the data (Section 4.2). However, it does not explain the dramatic widening of the age wage gap within firms since 1985.

8 Conclusions

This paper uses extensive administrative data on 38 million workers and 3.7 million firms in Italy and Germany to show that the wages of older workers have been growing at a much faster rate than the wages of younger workers for at least the last three decades. The wage gap between workers who were at least 55 years old and workers who were less than 35 years old increased by 0.19 log points in Italy between 1985 and 2019 and by 0.10 log points in Germany between 1996 and 2017. We also use CPS survey data to show that the wage gap between older and younger workers increased by 0.10 log points in the United States between 1985 and 2019.

Our analysis reveals three main findings about the widening of the age wage gap. First, career patterns mattered. Most of the increase in the age wage gap came from the increasing difficulty experienced by younger workers in reaching the top of the wage distribution, rather than from changes in the wages paid for different jobs. Second, career patterns within firms mattered. A substantial portion of the slowdown in the careers of younger workers happened in the internal labor markets. In contrast, most of the wage growth experienced by older workers happened between firms. Third, firms mattered. After accounting for changes in worker characteristics, differences in the appropriation of firm rents explain over two thirds of the widening in the age wage gap.

Taken together, these results point to the importance of firms and their personnel policies in explaining the different wage trajectory of workers in different age groups. In a frictional labor market in which separations are costly and firms cannot always add higher-ranked jobs to their ranks, a progressive slowdown in firm productivity and a higher retirement age may have allowed older workers to hold top jobs for longer and thereby to appropriate an increasing share of firm premiums. Moreover, their presence slowed down the careers of their younger coworkers, who experienced lower wage growth and higher turnover as a consequence.

To conclude, labor markets have experienced a major transfer of wages from younger workers to older workers. Future research should investigate whether backloading wages at the end of working careers may have permanent consequences on the life of workers both at and outside of work. For example, lower earnings earlier in the life cycle may prevent some workers from purchasing durables, due to the fact that workers cannot use future wages as collateral. Moreover, lower earnings at career start may prevent some workers from making personal choices, such as having children, that cannot easily be postponed to the end of the life cycle.

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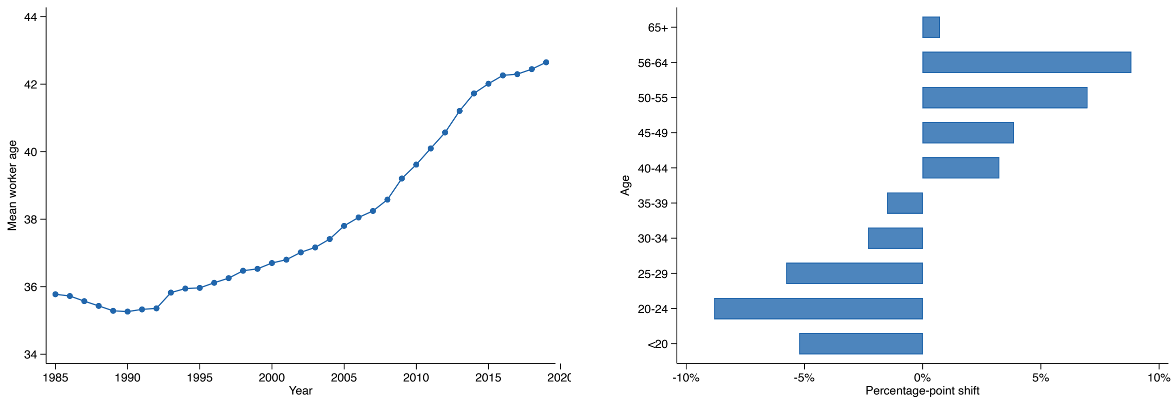
Figures and Tables

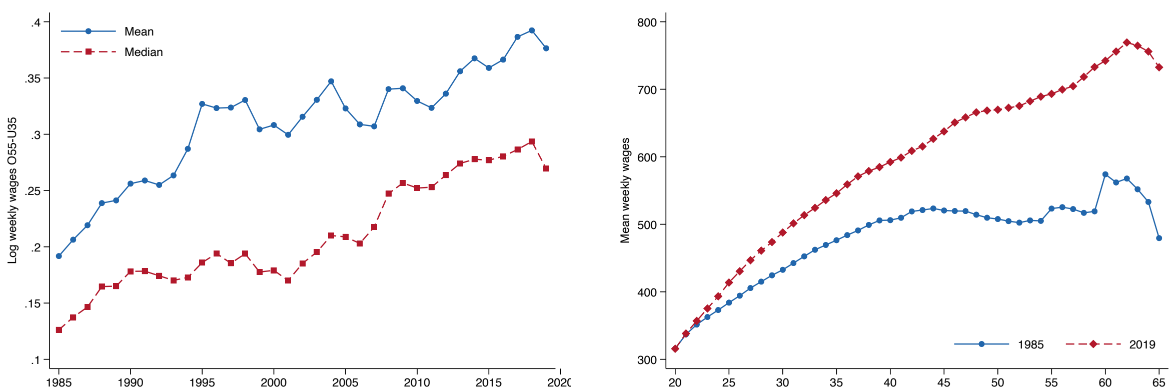
Figure 1: Aging of Workers



Panel A: Mean age   Panel B: $\Delta_{2019-1985}$ by age bins

Notes: Panel A plots the mean age of Italian workers by year. Panel B plots the percentage-point difference in the share of workers in each age bin between 1985 and 2019. For example, "+5%" indicates that the share of workers in that age bin increased by 5 percentage points between 1985 and 2019. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

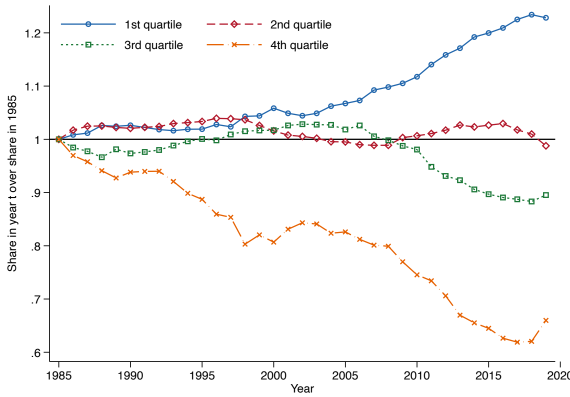
Figure 2: Age Gap in Weekly Wages



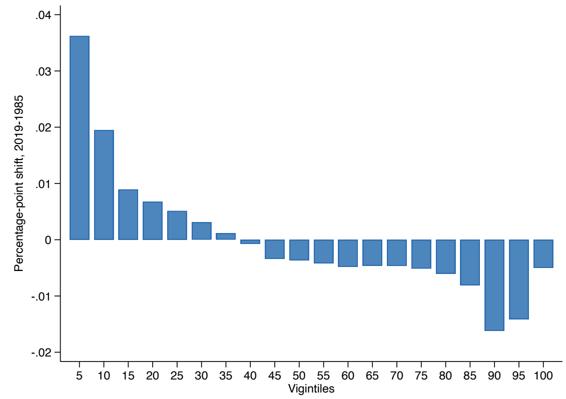
Panel A: Gap in log mean and median wages   Panel B: Age profiles (mean wages)

Notes: Panel A plots the gap between the log weekly wages of O55 workers and the log weekly wages of U35 workers between 1985 and 2019 for both mean and median wages. Panel B plots the mean real weekly wages (not logged) by age in 1985 and 2019. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

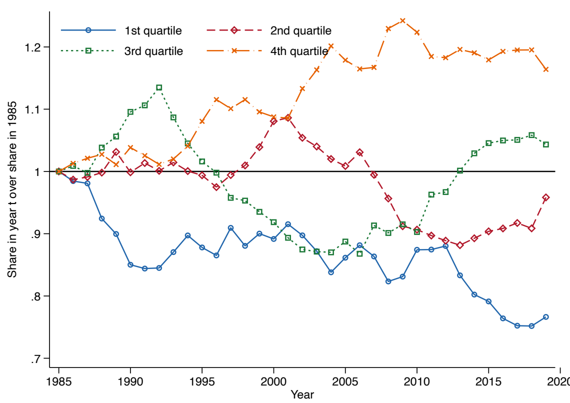
Figure 3: Shifts in Distribution of Weekly Wages



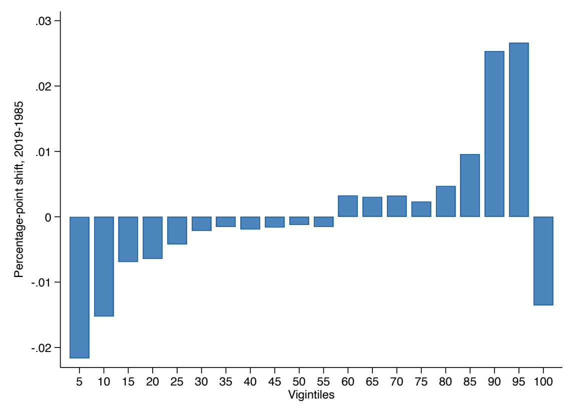
Panel A: U35 workers
Yearly change in quartiles



Panel B: U35 workers
$\Delta_{2019-1985}$ in vigintiles



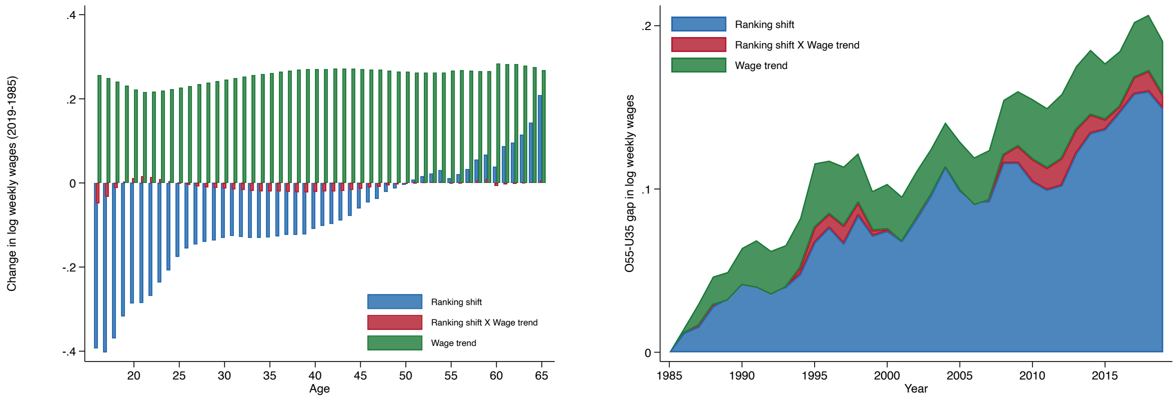
Panel C: O55 workers
Yearly change in quartiles



Panel D: O55 workers
$\Delta_{2019-1985}$ in vigintiles

Notes: These graphs show the changes in the shares of U35 and O55 workers in different parts of the distribution of weekly wages. Specifically, for each year, Panel A shows the ratio between the share of U35 workers in each quartile and the share of U35 in the same quartile in 1985. Panel B plots the percentage-point difference in the share of U35 workers in each vigintile between 1985 and 2019. For example, "0.05" indicates that the share of U35 workers in that vigintile increased by 5 percentage points between 1985 and 2019. Panel C and Panel D plot the same information for O55 workers. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure 4: Decomposition of Change in Weekly Wages

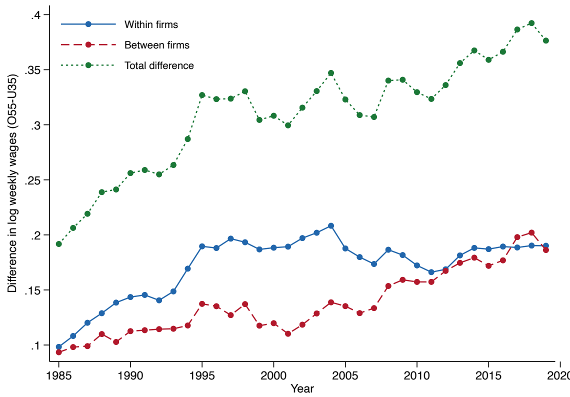


Panel A: 2019-1985 for all ages

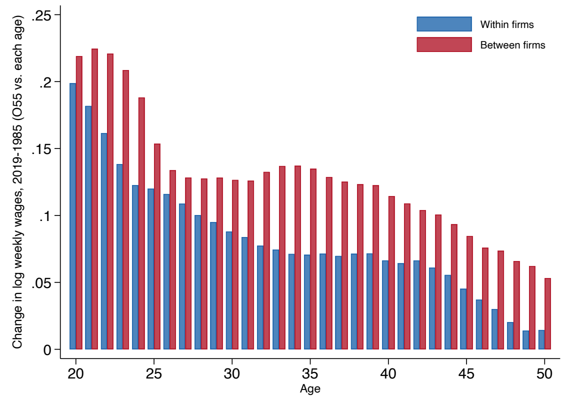
Panel B: O55 workers - U35 workers over time

Notes: Panel A plots the change in mean log weekly wages (decomposed into the three components of Equation (1)) between 1985 and 2019 for different age groups. Panel B plots the change in mean log weekly wages between O55 workers and U35 workers, as well as between 1985 and year $t \in [1986, 2019]$. This double difference is further decomposed into three components, following Equation (2). *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure 5: Difference in Weekly Wages Between and Within Firms



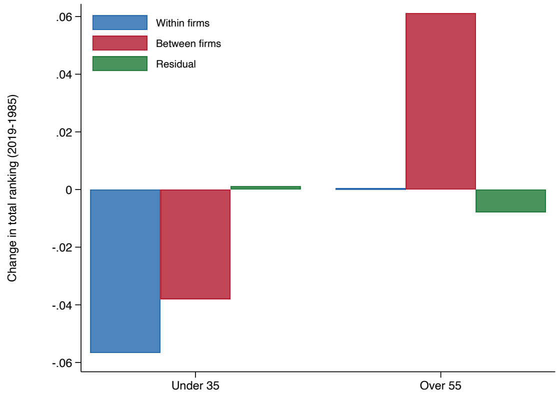
Panel A: O55 workers - U35 workers over time



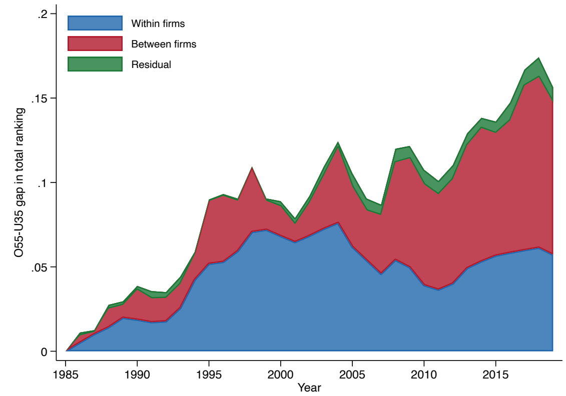
Panel B: O55 workers - each age, 2019-1985

Notes: Panel A plots the difference in log weekly wages (decomposed into the two components of Equation (3)) between O55 workers and U35 workers for each year between 1985 and 2019. "Between firms" computes the difference in average log weekly wages at the firm level. "Within firms" computes the difference in the average deviation of individual workers' weekly wages from the firm averages. Panel B plots the difference in log weekly wages between O55 workers and individual age groups and between 1985 and 2019. Again, this difference is decomposed into the same two components (Equation (3)). *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure 6: Decomposition of Total Ranking Shift



Panel A: Weekly wages
2019-1985 for U35 workers & O55 workers



Panel B: Weekly wages
O55 workers - U35 workers over time

Notes: Panel A decomposes the total-ranking-shift change in log weekly wages (Equation (1)) between 1985 and 2019 for U35 workers and O55 workers, separately. Panel B decomposes the total-ranking-shift change in log weekly wages between O55 workers and U35 workers and between year t and 1985. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table 1: Summary Statistics—Panel

	Panel A: Italian data (1985-2019)		Panel B: German data (1996-2017)		Panel C: USA data (1985-2019)	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
	(1)	(2)	(3)	(4)	(5)	(6)
Age	38.04	11.01	41.08	11.53	38.55	12.12
Male	0.69	0.46	0.70	0.46	0.59	0.49
Years in labor market	17.56	11.34	16.35	9.83	-	-
At least high school	-	-	0.23	0.42	0.51	0.50
Temporary contract	0.06	0.25	-	-	-	-
Foreign-born	0.01	0.09	0.07	0.26	0.18	0.38
Manufacturing	0.37	0.48	0.47	0.50	0.21	0.41
Services	0.32	0.46	0.20	0.40	0.50	0.50
Construction	0.08	0.28	0.03	0.16	0.07	0.25
Daily wages	-	-	100.83	43.03	-	-
Weekly wages	549.20	391.52	-	-	720.79	555.54
Yearly earnings	26,660.32	18,635.26	34,433.29	14,632.49	-	-
N. observations	312,065,728		35,092,712		2,664,026	
N. workers	28,911,242		8,865,294		-	
N. firms	3,532,905		127,782		-	

Notes: This table shows the worker-level summary statistics for the three main datasets that are available for this study. *Sources for Italy:* In each year, the data pools information about all workers who were over 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. Nominal earnings are top-coded using a year-specific threshold that is usually close to the 95$^{\text{th}}$ percentile. Details on the construction of these samples are in Appendix B.2. *Sources for United States:* The USA data come from the Merged Outgoing Rotation Groups (MORG) of the Current Population Survey (CPS), which we accessed from the National Bureau of Economic Research (NBER) at https://data.nber.org/morg/annual/. Details on the construction of these samples are in Appendix B.3.

Table 2: Decomposition of Double Difference in Firm Rents

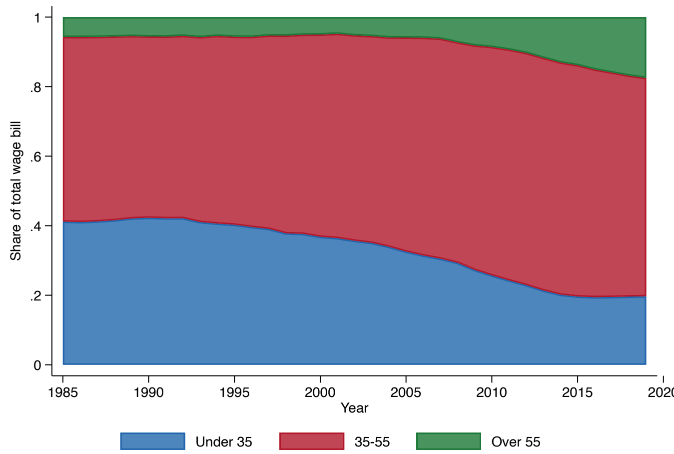
	All periods (1985-2019)	Period 1 (1985-1987)	Period 2 (1988-1990)	Period 3 (1991-1993)	Period 4 (1994-1996)	Period 5 (1997-1999)	Period 6 (2000-2002)	Period 7 (2003-2005)	Period 8 (2006-2008)	Period 9 (2009-2011)	Period 10 (2012-2014)	Period 11 (2015-2017)	Period 12 (2018-2019)
	(1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Δ_{t-1985} Gap (O55-U35) in log weekly wage	0.143	0.009	0.058	0.058	0.155	0.160	0.147	0.174	0.164	0.187	0.197	0.213	0.222
Δ_{t-1985} Gap (O55-U35) in firm rents (logs)	0.098	0.001	0.016	0.026	0.107	0.144	0.132	0.141	0.129	0.129	0.135	0.123	0.093
Δ_{t-1985} Gap (O55-U35) in firm rents (%)	0.685	0.093	0.270	0.442	0.689	0.898	0.898	0.809	0.790	0.688	0.685	0.576	0.419
Decomposition 1: Sorting with U35 effects and wage setting with O55 distribution													
Δ_{t-1985} Wage setting (logs)	0.045	0.000	0.015	0.020	0.096	0.110	0.114	0.098	0.068	0.045	0.022	-0.022	-0.057
Δ_{t-1985} Wage setting (% of Δ in firm rents)	0.462	-0.554	0.974	0.786	0.897	0.766	0.861	0.700	0.528	0.347	0.164	-0.180	-0.613
Δ_{t-1985} Sorting (logs)	0.053	0.001	0.000	0.006	0.011	0.034	0.018	0.042	0.061	0.084	0.113	0.145	0.150
Δ_{t-1985} Sorting (% of Δ in firm rents)	0.538	1.554	0.026	0.214	0.103	0.234	0.139	0.300	0.472	0.653	0.836	1.180	1.613
Decomposition 2: Sorting with O55 effects and wage setting with U35 distribution													
Δ_{t-1985} Wage setting (logs)	0.078	0.001	0.014	0.019	0.089	0.139	0.129	0.123	0.107	0.087	0.088	0.078	0.053
Δ_{t-1985} Wage setting (% of Δ in firm rents)	0.794	1.198	0.865	0.719	0.832	0.964	0.973	0.876	0.829	0.673	0.653	0.633	0.572
Δ_{t-1985} Sorting (logs)	0.020	0.000	0.002	0.007	0.018	0.005	0.004	0.017	0.022	0.042	0.047	0.045	0.040
Δ_{t-1985} Sorting (% of Δ in firm rents)	0.206	-0.198	0.135	0.281	0.168	0.036	0.027	0.124	0.171	0.327	0.347	0.367	0.428

Notes: This table shows the decomposition of the double difference in firm rents (difference over time and between U35 worker and O55 workers) into a wage-setting component and a sorting component. Decomposition 1 follows Equation (7), while decomposition 2 follows Equation (8). Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Online Appendix

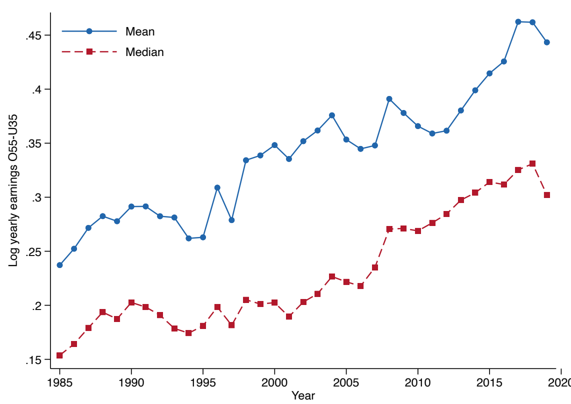
A Additional Evidence on Aging of Workforce and Age Wage Gap

Figure A1: Share of Total Wage Bill

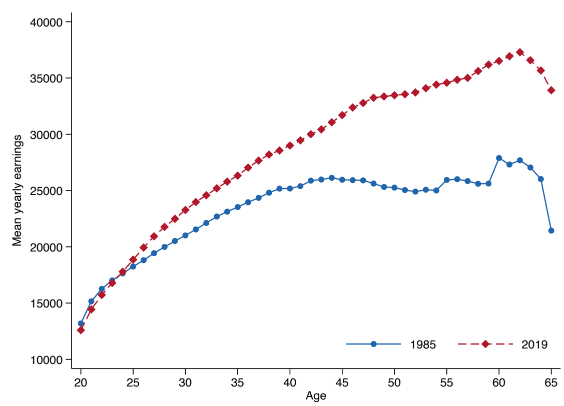


Notes: These graphs show the share of the total wage bill earned by workers in different age bins. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure A2: Age Gap in Yearly Earnings



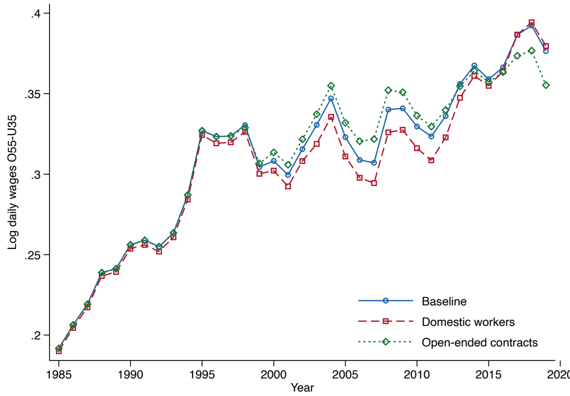
Panel A: Gap in log mean and median earnings



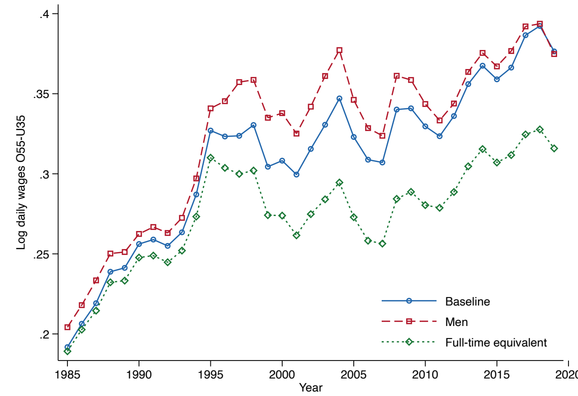
Panel B: Age profiles (mean earnings)

Notes: Panel A plots the gap between the log yearly earnings of O55 workers and the log yearly earnings of U35 workers between 1985 and 2019 for both mean and median earnings. Panel B plots the mean real yearly earnings (not logged) by age in 1985 and 2019. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

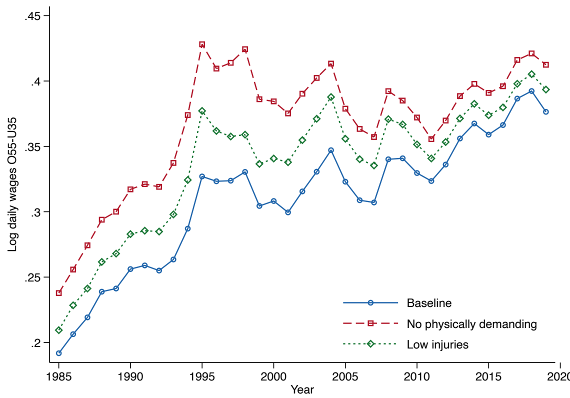
Figure A3: Mean Age Wage Gap Controlling for Compositional Changes



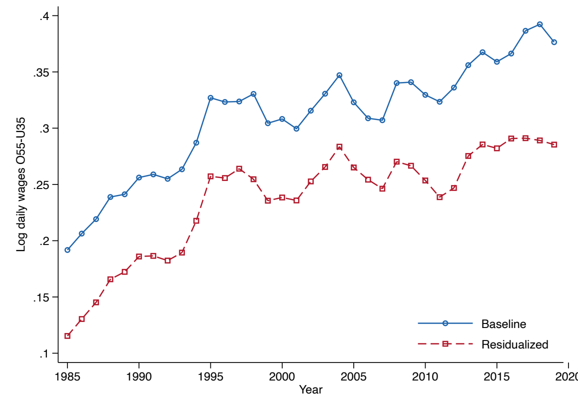
Panel A



Panel B



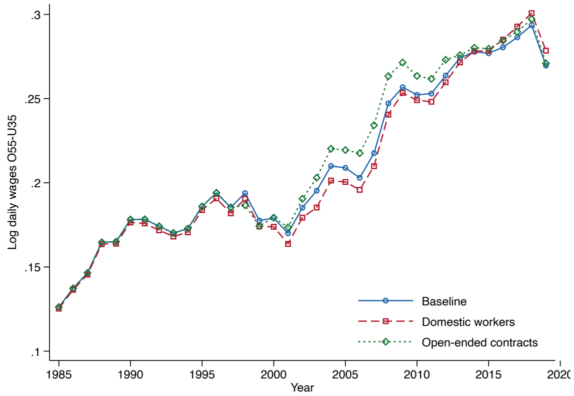
Panel C



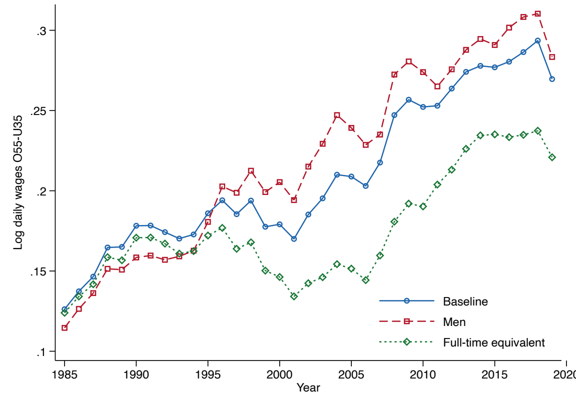
Panel D

Notes: Panel A plots the age gap in **mean** log weekly wages between O55 workers and U35 workers for domestic workers and for workers with open-ended contracts. Panel B plots the age wage gap for men and for full-time equivalent workers. Panel C plots the age wage gap for workers who are not in physically demanding jobs according to the Italian law and for workers who are in low-injury sectors according to the INPS data. Specifically, the occupations that are physically demanding ("*lavori usuranti*" in Italian) are defined by a decree of the Ministry of Labor (`https://www.gazzettaufficiale.it/eli/id/2018/02/26/18A01427/sg`). There are more details about this variable in the notes of Table A3. Moreover, we define the low-injury sectors as the 3-digit (NACE Rev. 2) sectors with a share of the wage bill paid for injury and sick leaves below the top quartile. Data on work leaves are available only starting from 2005. In Panel D, we first regress log weekly wages on the previous worker-level characteristics (domestic vs. foreign-born, open-ended vs. temporary contract, men vs. women, high-injury job vs. low-injury job), as well as province of residence. This regression is estimated separately in each year to allow the coefficients to change over time. Then, we use the estimated residuals from these wage regressions to compute the age wage gap. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

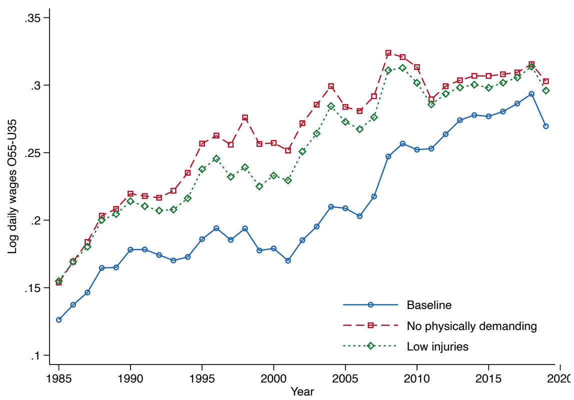
Figure A4: Median Age Wage Gap Controlling for Compositional Changes



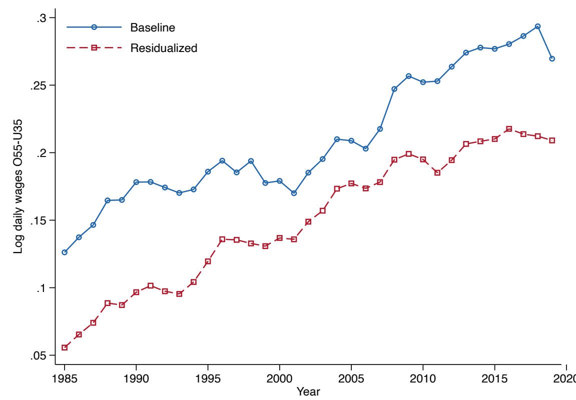
Panel A



Panel B



Panel C



Panel D

Notes: Panel A plots the age gap in **median** log weekly wages between O55 workers and U35 workers for domestic workers and for workers with open-ended contracts. Panel B plots the **median** age wage gap for men and for full-time equivalent workers. Panel C plots the **median** age wage gap for workers who are not in physically demanding jobs according to the Italian law and for workers who are in low-injury sectors according to the INPS data. Specifically, the occupations that are physically demanding ("*lavori usuranti*" in Italian) are defined by a decree of the Ministry of Labor (https://www.gazzettaufficiale.it/eli/id/2018/02/26/18A01427/sg). There are more details about this variable in the notes of Table A3. Moreover, we define the low-injury sectors as the 3-digit (NACE Rev. 2) sectors with a share of the wage bill paid for injury and sick leaves below the top quartile. Data on work leaves are available only starting from 2005. In Panel D, we first regress log weekly wages on the previous worker-level characteristics (domestic vs. foreign-born, open-ended vs. temporary contract, men vs. women, high-injury job vs. low-injury job), as well as province of residence. This regression is estimated separately in each year to allow the coefficients to change over time. Then, we use the estimated residuals from these wage regressions to compute the **median** age wage gap. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table A1: Summary Statistics—Labor Earnings by Age

Year	Age group	Mean	P10	P25	Median	P75	P90	N
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel A: Log weekly wages				
1985	< 35	5.88	5.37	5.73	5.92	6.10	6.30	3,962,051
1985	$[35, 55]$	6.12	5.67	5.92	6.10	6.33	6.63	3,692,858
1985	> 55	6.07	5.41	5.84	6.05	6.32	6.73	391,133
1985	All	6.00	5.47	5.81	6.01	6.22	6.49	8,046,042
1985	O55 - U35	0.19	0.04	0.11	0.13	0.22	0.43	
2019	< 35	6.02	5.62	5.87	6.05	6.24	6.48	2,582,209
2019	$[35, 55]$	6.32	5.87	6.05	6.25	6.55	6.89	5,564,765
2019	> 55	6.39	5.86	6.08	6.32	6.71	7.09	1,371,845
2019	All	6.25	5.80	5.99	6.20	6.49	6.84	9,518,819
2019	O55 - U35	0.37	0.24	0.21	0.27	0.47	0.61	
				Panel B: Log yearly earnings				
1985	< 35	9.69	8.97	9.44	9.81	10.02	10.23	3,962,051
1985	$[35, 55]$	10.00	9.34	9.79	10.03	10.27	10.57	3,692,858
1985	> 55	9.93	9.10	9.65	9.97	10.25	10.66	391,133
1985	All	9.84	9.11	9.61	9.91	10.15	10.43	8,046,042
1985	O55 - U35	0.24	0.13	0.21	0.16	0.23	0.43	
2019	< 35	9.82	9.04	9.60	9.95	10.16	10.40	2,582,209
2019	$[35, 55]$	10.20	9.61	9.95	10.18	10.49	10.83	5,564,765
2019	> 55	10.26	9.58	9.97	10.25	10.64	11.01	1,371,845
2019	All	10.10	9.41	9.86	10.12	10.42	10.77	9,518,819
2019	O55 - U35	0.44	0.54	0.37	0.30	0.48	0.61	

Notes: This table shows log weekly wages (Panel A) and yearly earnings (Panel B) (i) at different points of their distributions, (ii) in 1985 and 2019, and (iii) for different age groups. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table A2: Summary Statistics of Compositional Changes

	Age group	Foreign–born workers	Temporary workers (start in 1998)	Part-time workers	Women
	(1)	(2)	(3)	(4)	(5)
			Panel A: Shares		
Share in 1985	< 35	0.010	0.000	0.014	0.390
Share in 2019	< 35	0.164	0.225	0.333	0.340
$\Delta_{2019-1985}$ Share	< 35	0.154	0.225	0.319	-0.051
Share in 1985	> 55	0.006	0.000	0.011	0.174
Share in 2019	> 55	0.074	0.074	0.271	0.267
$\Delta_{2019-1985}$ Share	> 55	0.068	0.074	0.259	0.093
			Panel B: Gaps in mean log weekly wages		
Wage gap in 1985	All	-0.013	/	-0.013	-0.277
Wage gap in 2019	All	-0.242	-0.448	-0.249	-0.137
$\Delta_{2019-1985}$ Wage gap	All	-0.229	/	-0.236	0.140

Notes: Panel A shows the share of each subgroup within two age groups (U35 workers and O55 workers) and in two years (1985 and 2019). In this case "0.01" for foreign-born workers and U35 workers would indicate that 10 percent of U35 workers in that year were born outside of Italy. The share of workers with temporary contracts was equal to zero in 1985 because temporary contracts were introduced only in 1998 (d.lgs. 280/97 and 468/97). Panel B shows the gap in log mean weekly wages between these different subgroups of workers and their complement subsets. In the case of foreign-born workers, the gap is between foreign-born and domestic workers. In the case of temporary workers, the gap is between workers with temporary contracts and workers with open-ended contracts. In the case of part-time workers, the gap in between part-time and full-time workers. In the case of women, the gap is between women and men. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table A3: List of Physically Demanding Jobs

Job classification	Istat job code	Sector code (NACE Rev. 2)	Sector classification
(1)	(2)	(3)	(4)
Operai dell'industria estrattiva, dell'edilizia e della manutenzione degli edifici	6.1 - 8.4.1 - 8.4.2	05-06-07-08-09	Estrazione di minerali da cave e miniere
Conduttori di gru o di macchinari mobili per la perforazione nelle costruzioni	7.4.4.2 - 7.4.4.3 - 7.4.4.4	41.2-42.1-42.2-42.9-43.1-43.2-43.3-43.9	Costruzioni eccetto sviluppo di progetti immobiliari
Conciatori di pelli e di pellicce	6.5.4.1	15.1-15.2-14.1-14.2	Fabbricazione di articoli in pelle e simili + Confezione di articoli in pelle e pelliccia
Conduttori di convogli ferroviari e personale viaggiante	7.4.1.1 e personale viaggiante	49.1-49.2	Trasporto ferroviario
Conduttori di mezzi pesanti e camion	7.4.2.3	49.3-49.4-49.53.2-	Trasporto terrestre + attività di corriere
Personale delle professioni sanitarie infermieristiche ed ostetriche ospedaliere con lavoro organizzato in turni		86.1	Servizi ospedalieri
Addetti all'assistenza personale di persone in condizioni di non autosufficienza	5.4.4.3	87.1-87.2-87.387.9-88.1-88.9	Servizi di assistenza sociale residenziale e non residenziale
Insegnanti della scuola dell'infanzia e educatori degli asili nido	2.6.4.2	85.1	Istruzione prescolastica
Facchini, addetti allo spostamento merci e assimilati	8.1.3.1	52.1-52.2	Magazzinaggio e attività di supporto ai trasporti
Personale non qualificato addetto ai servizi di pulizia	8.1.4.1 - 8.1.4.3	97.0-81.2	Attività di pulizia + colf
Operatori ecologici e altri raccoglitori e separatori di rifiuti	8.1.4.5	38.1-38.2-38.3	Raccolta e smaltimento rifiuti
Operai dell'agricoltura, zootecnia e pesca	6.4.1 - 6.4.2 - 6.4.3 - 8.3.1 - 8.3.2	01-02-03	Agricoltura, silvicoltura e pesca
Pescatori della pesca costiera, in acque interne, in alto mare, dipendenti o soci di cooperative	6.4.5.2 - 6.4.5.3	03	Pesca
Siderurgici di prima e seconda fusione e lavoratori del vetro addetti a lavori ad alte temperature non già ricompresi tra i lavori usuranti di cui al dlgs n. 67/2011	7.1.2.1 - 7.1.2.2 - 7.1.2.3 - 7.1.3	24.1-24.2-24.3-24.4-24.5-23.1	Siderurgia e fabbricazione di vetro
Marittimi imbarcati a bordo e personale viaggiante dei trasporti marini ed acque interne	7.4.5 e personale viaggiante	50.1-50.2-50.3-50.4	Trasporto marittimo e per vie d'acqua

Notes: The law (decree of the Ministry of Labor available at https://www.gazzettaufficiale.it/eli/id/2018/02/26/18A01427/sg) defines physically demanding jobs ("*lavori usuranti*") using the classification of occupations by the Italian Institute of Statistics (columns 1 and 2). We created a crosswalk from the occupation codes to the sector codes (NACE Rev. 2 in columns 3 and 4) to link information on physically demanding jobs to the Social Security data.

B Data Appendix

B.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.

It 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, for workers with multiple working spells in a single year, we keep the information associated with the spell with the highest wage. For example, Kline, Saggio, and Sølvsten (2020) follows the same strategy with similar data.

Moreover, we restrict each year of data to workers who (i) were over 16 years old, (ii) worked at least six months, (iii) earned positive wages, and (iv) did not retire within that year. We impose these restrictions to weed out workers with very short-lived job spells. For the same reason, unless otherwise specified, our analysis focuses on workers with full-time contracts. However, we include part-time workers in a robustness check in Section 2.3.

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.

All measures of labor earnings, as well as any other monetary variable used in the analysis, are expressed in 2015 euros using the conversion tables prepared by the OECD.[42] Moreover, 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 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.

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

B.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).[43] This dataset combines information from the IAB Establishment Panel with information from the Integrated Employment Biographies (IEB).[44] 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.[45]

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. For this reason, we do not report this variable in Table 1.

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.[46] These restrictions reduce the sample from 12,451,266 workers to 8,865,294 workers.

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

B.3 Data from Other Countries

In this section, we provide more information about the survey data and aggregate statistics that we collected to measure the age wage gap in more countries.

For the United States, we leverage microdata from the Current Population Survey (CPS). Specifically, we use the Merged Outgoing Rotation Groups (MORG) of the CPS, which are "extracts

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

[44] Documentation on the IAB Establishment Panel is available at `https://fdz.iab.de/en/FDZ_Establishment_Data/IAB_Establishment_Panel/IABBP_9319.aspx`. Documentation on the IEB is not available online.

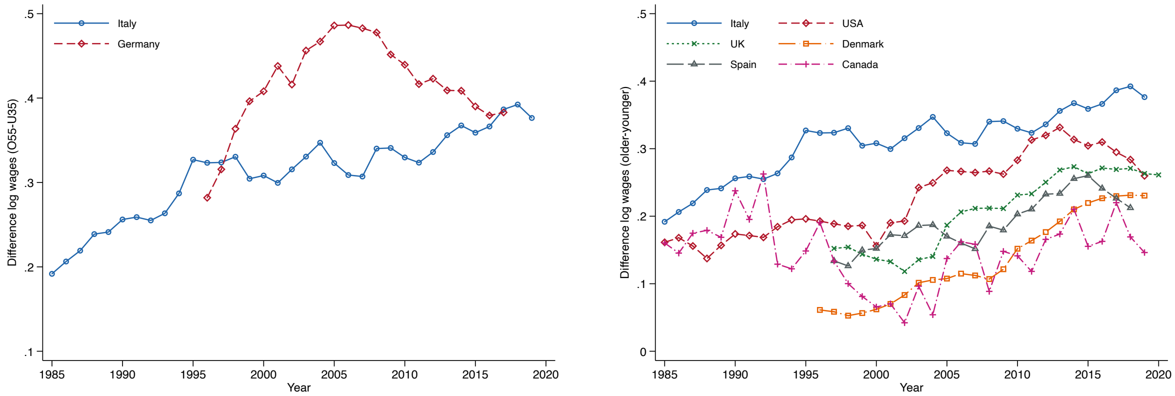
[45] The IAB Establishment Panel covers between 4,265 and 16,000 establishments per year.

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

of the Basic Monthly Data during the household's fourth and eighth month in the survey, when usual weekly hours/earnings are asked." We accessed these data from the National Bureau of Economic Research (NBER) at https://data.nber.org/morg/annual/. We impose the following restrictions to the sample in order to match as much as possible the characteristics of the Italian INPS data. First, we keep observations for workers employed full time by private organizations. Second, we keep observations from workers who were at least 16 years old. Third, we drop observations with imputed wages, as recommended by Hirsch and Schumacher (2004). The wage variable is the log of mean "weekly earnings," which is defined as earnings before taxes and other deductions. It includes any overtime pay, commissions, or tips usually received. In Figure B1 (Panel B), the younger workers are between 16 years old and 34 years old, while the older workers are above 55 years old. This classification exactly matches the one we implemented on the Italian data.

For the other countries, we only have aggregate statistics on wages of younger and older workers. For the United Kingdom, the data come from the Annual Survey of Hours and Earnings, which we accessed from the UK Parliament's House of Commons Library at https://commonslibrary.parliament.uk/research-briefings/cbp-8456/. The wage variable is the log of median "weekly pay," which is defined as the pay received from the employer's payroll for the pay period. The younger workers are between 22 years old and 29 years old, while the older workers are between 50 years old and 59 years old. For Denmark, the data come from StatBank Denmark, the statistical database maintained by the central authority of statistics in Denmark, which we accessed at https://statbank.dk/INDKP201. The wage variable is the log of mean "wages and salaries." The younger workers are between 30 years old and 34 years old, while the older workers are between 55 years old and 59 years old. For Spain, the data come from Instituto Nacional de Estadística, the Spanish Statistical Office, which we accessed at https://www.ine.es/dynt3/inebase/en/index.htm?padre=2129&capsel=2429#. The wage variable is the log of mean "annual net income." The younger workers are between 16 years old and 29 years old, while the older workers are between 45 years old and 64 years old. For Canada, the data come from the Survey of Labour and Income Dynamics of Statistics Canada, which we accessed at https://tinyurl.com/6mvxd23. The wage variable is the log of mean "wages, salaries, and commissions." The younger workers are between 25 years old and 34 years old, while the older workers are between 55 years old and 64 years old.

Figure B1: Age Wage Gap in Different Countries



Panel A: Administrative data

Panel B: Surveys and Aggregate Statistics

Notes: These graphs show that the gap in wages between younger and older workers in different countries. Panel A leverages administrative data from 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 B.2. Panel B leverages data from surveys and aggregate statistics. The USA data come from the Merged Outgoing Rotation Groups (MORG) of the Current Population Survey (CPS), which we accessed from the National Bureau of Economic Research (NBER) at `https://data.nber.org/morg/annual/`. The wage variable is the mean of log "weekly earnings," which is defined as earnings before taxes and other deductions. It includes any overtime pay, commissions, or tips received. The younger workers are between 16 years old and 34 years old, while the older workers are above 55 years old. The UK data come from the Annual Survey of Hours and Earnings, which we accessed from the UK Parliament's House of Commons Library at `https://commonslibrary.parliament.uk/research-briefings/cbp-8456/`. The wage variable is the log of median "weekly pay," which is defined as the pay received from the employer's payroll for the pay period. The younger workers are between 22 years old and 29 years old, while the older workers are between 50 years old and 59 years old. The Danish data come from StatBank Denmark, the statistical database maintained by the central authority of statistics in Denmark, which we accessed at `https://statbank.dk/INDKP201`. The wage variable is the log of mean "wages and salaries." The younger workers are between 30 years old and 34 years old, while the older workers are between 55 years old and 59 years old. The Spanish data come from Instituto Nacional de Estadística, the Spanish Statistical Office, which we accessed at `https://www.ine.es/dynt3/inebase/en/index.htm?padre=2129&capsel=2429#`. The wage variable is the log of mean "annual net income." The younger workers are between 16 years old and 29 years old, while the older workers are between 45 years old and 64 years old. The Canadian data come from the Survey of Labour and Income Dynamics of Statistics Canada, which we accessed at `https://tinyurl.com/6mvxd23`. The wage variable is the log of mean "wages, salaries, and commissions." The younger workers are between 25 years old and 34 years old, while the older workers are between 55 years old and 64 years old.

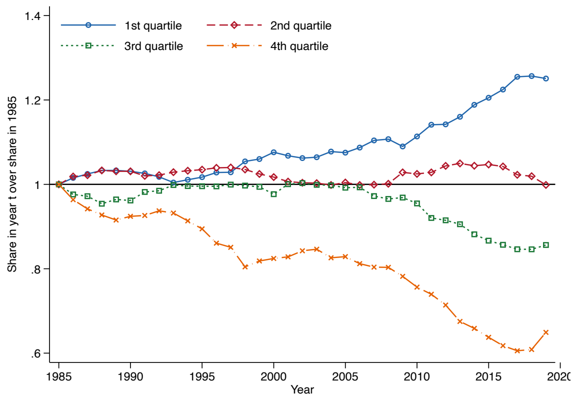
Table B1: Age Wage Gap in Germany and France

Year	Age group	Mean	P10	P25	Median	P75	P90	N
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel A: Germany (1996-2017), log daily wages				
1996	< 35	4.14	3.21	4.02	4.28	4.49	4.69	781,438
1996	> 55	4.42	3.93	4.20	4.45	4.74	4.90	199,714
1996	O55 - U35	0.28	0.72	0.18	0.17	0.25	0.21	
2017	< 35	4.44	3.54	4.08	4.60	4.91	5.15	320,950
2017	> 55	4.82	4.27	4.60	4.87	5.15	5.34	211,844
2017	O55 - U35	0.38	0.73	0.52	0.27	0.24	0.19	
				Panel B: USA (1985-2017), log weekly wages				
1985	< 35	5.67	5.01	5.30	5.67	6.03	6.36	50,003
1985	> 55	5.83	5.08	5.42	5.86	6.24	6.62	8,206
1985	O55 - U35	0.16	0.06	0.13	0.19	0.21	0.26	
2019	< 35	6.67	6.00	6.29	6.63	7.05	7.46	19,292
2019	> 55	6.93	6.17	6.49	6.91	7.43	7.90	10,618
2019	O55 - U35	0.26	0.18	0.20	0.27	0.38	0.44	

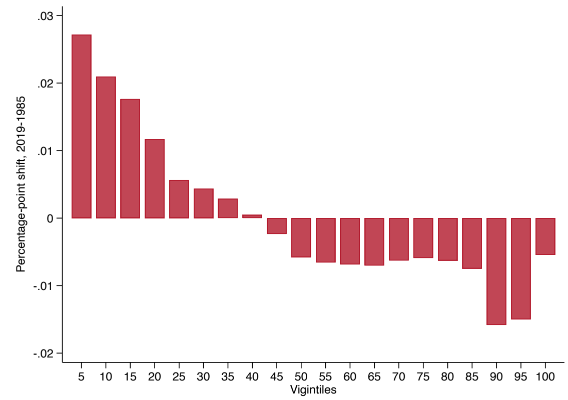
Notes: Panel A shows the age gap in log daily wages between 1996 and 2017 using German administrative data. Panel B shows the age gap in log weekly wages between 1985 and 2019 using USA survey data. *Sources:* In each year, the data pools information about all workers who were over 16 years old, had a full-time contract, and earned positive wages. *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 B.2. *Sources for United States:* The USA data come from the Merged Outgoing Rotation Groups (MORG) of the Current Population Survey (CPS), which we accessed from the National Bureau of Economic Research (NBER) at `https://data.nber.org/morg/annual/`. Details on the construction of these samples are in Appendix B.3.

C Additional Evidence on Careers of Younger Workers

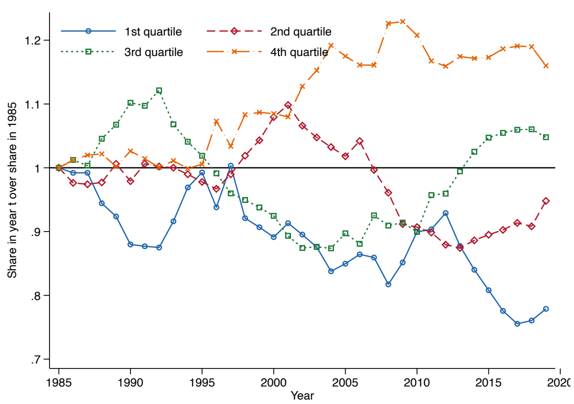
Figure C1: Shifts in Distribution of Yearly Earnings



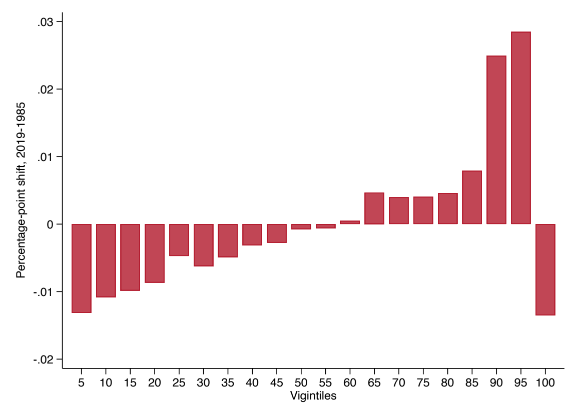
Panel A: U35 workers
Yearly change in quartiles



Panel B: U35 workers
$\Delta_{2019-1985}$ in vigintiles



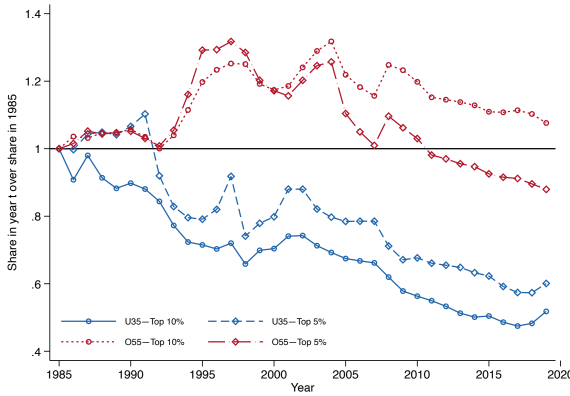
Panel C: O55 workers
Yearly change in quartiles



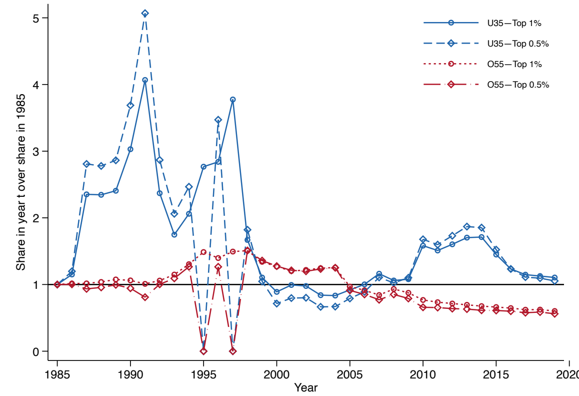
Panel D: O55 workers
$\Delta_{2019-1985}$ in vigintiles

Notes: These graphs show the changes in the shares of U35 and O55 workers in different parts of the distribution of yearly earnings. Specifically, for each year, Panel A shows the ratio between the share of U35 workers in each quartile and the share of U35 in the same quartile in 1985. Panel B plots the percentage-point difference in the share of U35 workers in each vigintile between 1985 and 2019. For example, "+0.5" indicates that the share of U35 workers in that vigintile increased by 5 percentage points between 1985 and 2019. Panel C and Panel D plot the same information for O55 workers. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

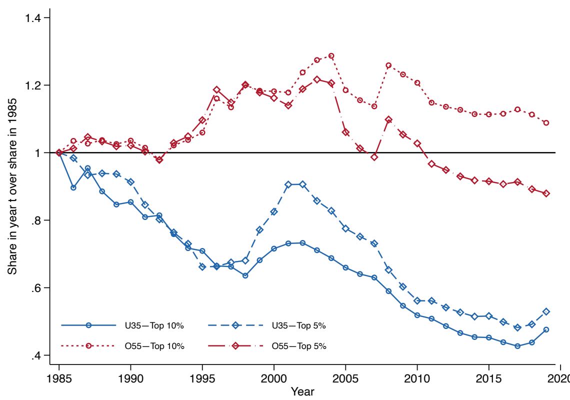
Figure C2: Probability of Holding Top-Paying Job



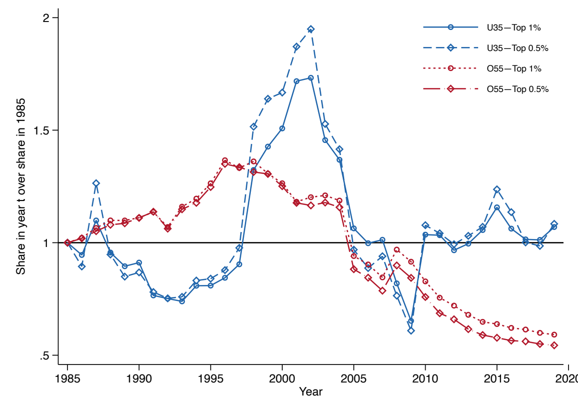
Panel A: Top 10% & Top 5%, weekly wages



Panel B: Top 1% & Top 0.5%, weekly wages



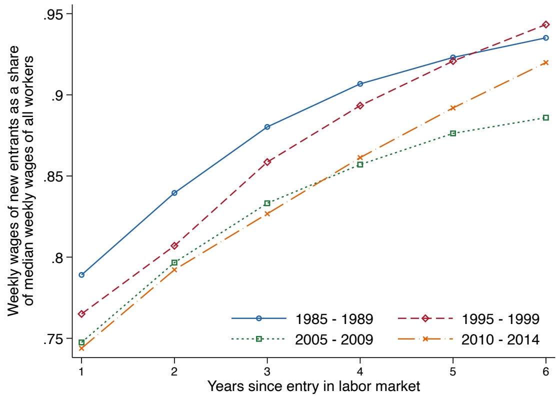
Panel C: Top 10% & Top 5%, yearly earnings



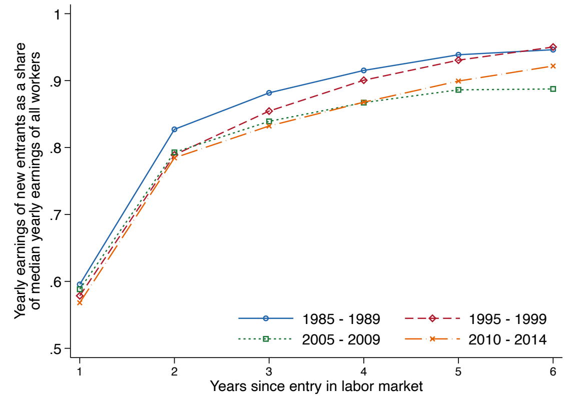
Panel D: Top 1% & Top 0.5%, yearly earnings

Notes: These graphs show the changes in the share of U35 and O55 workers at the top of distribution of labor earnings. All plots show the ratios between the share of workers in a given age cohort in year t and the share of workers in the same age cohort in 1985. For example, a "0.05" for "U35—Top 10%" means that the share of U35 workers in the top 10 percent of the distribution of labor earnings increased by 5 percent since 1985. Panel A focuses on the top 10 percent and top 5 percent of the distribution of weekly wages. Panel B focuses on the top 1 percent and top 0.5 percent of the distribution of weekly wages. Panel C focuses on the top 10 percent and top 5 percent of the distribution of yearly earnings. Panel D focuses on the top 1 percent and top 0.5 percent of the distribution of yearly earnings. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure C3: Wage Growth at Start of Careers



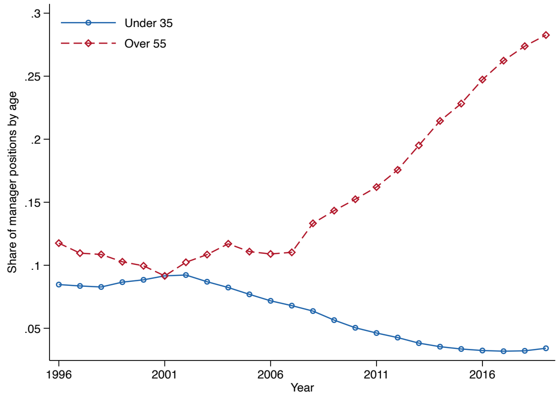
Panel A: Weekly wages



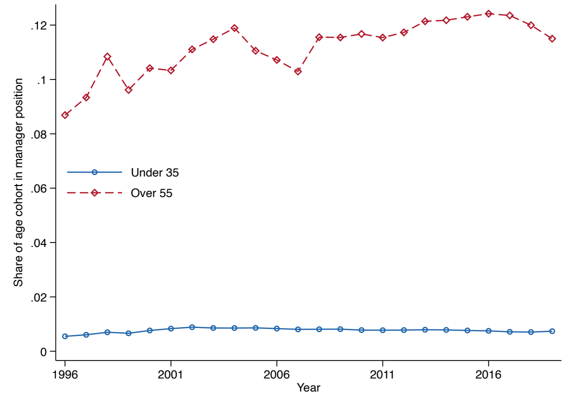
Panel B: Yearly earnings

Notes: In Panel A, each line plots the median of the ratios between the weekly wages of new entrants and the median weekly wage of all workers in the same year. For example, consider a worker who entered the labor market in 1985. We compute the ratio between their weekly wages in the first six years of their careers and the median weekly wages of all workers in the same six years. We repeat this computation for all workers who entered the labor market between 1985 and 1989. Then, the median of these ratios is used to plot the "1985-1989" blue line. Panel B plots the same median ratios using yearly earnings, rather than weekly wages. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Moreover, for this analysis, we consider only workers who were active in the labor market for the first six years after entry. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure C4: Probability of Holding Managerial Positions



Panel A: Share of manager jobs by age cohort



Panel B: Share of age cohort in manager jobs

Notes: These graphs show the trend in managerial positions by age cohorts. Panel A plots the share of manager jobs held by workers in different age cohorts. For example, "0.1" means that 10 percent of all managerial jobs in a year are held by workers in a given age cohort. Panel B plots the share of workers in each age cohort who hold a managerial position in a given year. For example, "0.1" means that 10 percent of workers in an age cohort are holding a managerial job in a year. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

D Decomposition of Change in Wage Gap

Proposition 1. The change in mean log wage for age group a between years t and t' can be written as follows:

$$\Delta w_a^{t,t'} = \overbrace{\underbrace{\sum_v \left(s_{a,v,t'} - s_{a,v,t}\right) \bar{w}_{v,t}}_{\text{Ranking shift}} + \underbrace{\sum_v \left(s_{a,v,t'} - s_{a,v,t}\right) \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Ranking shift x Wage trend}}}^{\text{Total ranking shift}} + \underbrace{\sum_v s_{a,v,t} \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Wage trend}}. \tag{D.1}$$

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.

Proof of proposition 1. This decomposition of the change in mean log wage for age group a between years t and t' can be obtained as follows:

$$\begin{aligned}
\Delta w_a^{t,t'} &= \sum_v s_{a,v,t'}\bar{w}_{v,t'} - \sum_v s_{a,v,t}\bar{w}_{v,t} \\
&= \sum_v s_{a,v,t'}\bar{w}_{v,t'} - \sum_v s_{a,v,t}\bar{w}_{v,t} + \sum_v s_{a,v,t'}\bar{w}_{v,t} - \sum_v s_{a,v,t'}\bar{w}_{v,t} \\
&= \sum_v \left(s_{a,v,t'} - s_{a,v,t}\right) \bar{w}_{v,t} + \sum_v s_{a,v,t'} \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&= \sum_v \left(s_{a,v,t'} - s_{a,v,t}\right) \bar{w}_{v,t} + \sum_v s_{a,v,t'} \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&\quad + \sum_v s_{a,v,t} \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) - \sum_v s_{a,v,t} \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&= \overbrace{\underbrace{\sum_v \left(s_{a,v,t'} - s_{a,v,t}\right) \bar{w}_{v,t}}_{\text{Ranking shift}} + \underbrace{\sum_v \left(s_{a,v,t'} - s_{a,v,t}\right) \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Ranking shift x Wage trend}}}^{\text{Total ranking shift}} \\
&\quad + \underbrace{\sum_v s_{a,v,t} \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Wage trend}}.
\end{aligned}$$

Proposition 2. 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:

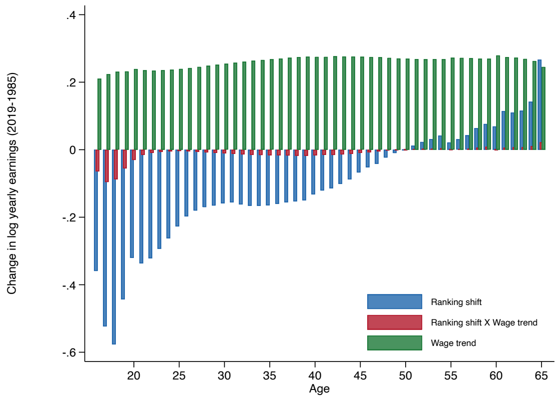
$$\Delta w_{O55}^{t,t'} - \Delta w_{U35}^{t,t'} = \overbrace{\underbrace{\sum_v \Delta s_{O55-U35,v,t'-t} \bar{w}_{v,t}}_{\text{Ranking shift}} + \underbrace{\sum_v \Delta s_{O55-U35,v,t'-t} \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Ranking shift x Wage trend}}}^{\text{Total ranking shift}} \\ + \underbrace{\sum_v \left(s_{O55,v,t} - s_{U35,v,t}\right) \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Wage trend}}. \tag{D.2}$$

In this equation, $\Delta s_{O55-U35,v,t'-t}$ 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'. It can be rewritten as: $\Delta s_{O55-U35,v,t'-t} = \left(s_{O55,v,t'} - s_{O55,v,t}\right) - \left(s_{U35,v,t'} - s_{U35,v,t}\right)$.

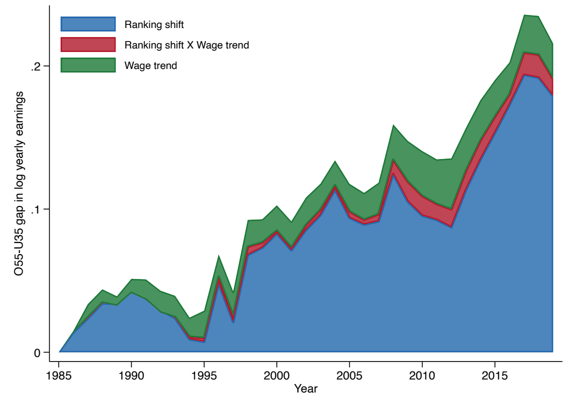
Proof of proposition 2. The last equation can be obtained by differencing the last row of Equation (D.1):

$$\begin{aligned}
\Delta w_{O55}^{t,t'} - \Delta w_{U35}^{t,t'} &= \sum_v \left(s_{O55,v,t'} - s_{O55,v,t}\right) \bar{w}_{v,t} + \sum_v \left(s_{O55,v,t'} - s_{O55,v,t}\right) \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&\quad + \sum_v s_{O55,v,t} \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) - \sum_v \left(s_{U35,v,t'} - s_{U35,v,t}\right) \bar{w}_{v,t} \\
&\quad - \sum_v \left(s_{U35,v,t'} - s_{U35,v,t}\right) \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) - \sum_v s_{U35,v,t} \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&= \sum_v \left(\left(s_{O55,v,t'} - s_{O55,v,t}\right) - \left(s_{U35,v,t'} - s_{U35,v,t}\right)\right) \bar{w}_{v,t} \\
&\quad + \sum_v \left(\left(s_{O55,v,t'} - s_{O55,v,t}\right) - \left(s_{U35,v,t'} - s_{U35,v,t}\right)\right) \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&\quad + \sum_v \left(s_{O55,v,t} - s_{U35,v,t}\right) \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right) \\
&= \overbrace{\underbrace{\sum_v \Delta s_{O55-U35,v,t'-t} \bar{w}_{v,t}}_{\text{Ranking shift}} + \underbrace{\sum_v \Delta s_{O55-U35,v,t'-t} \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Ranking shift x Wage trend}}}^{\text{Total ranking shift}} \\
&\quad + \underbrace{\sum_v \left(s_{O55,v,t} - s_{U35,v,t}\right) \left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Wage trend}}.
\end{aligned}$$

Figure D1: Decomposition of Change in Yearly Earnings



Panel A: 2019-1985 for all ages



Panel B: O55 workers - U35 workers over time

Notes: Panel A plots the change in mean log yearly earnings (decomposed into the three components of Equation (1)) between 1985 and 2019 for different age groups. Panel B plots the change in mean log yearly earnings between O55 workers and U35 workers, as well as between 1985 and year t. This double difference is further decomposed into three components, following Equation (2). *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

E Decomposition Between and Within Firms

Proposition 3. In year t, the difference in average log weekly wages between U35 workers and O55 workers can be written as follows:

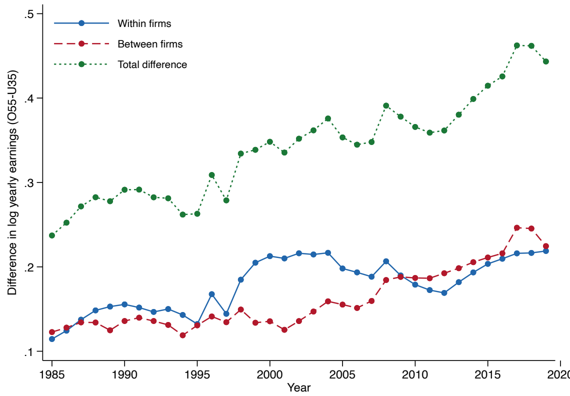
$$\bar{w}_{O55,t} - \bar{w}_{U35,t} = \overbrace{\frac{1}{N_{O55,t}} \sum_{i \in O55} \bar{w}_{j(i),t} - \frac{1}{N_{U35,t}} \sum_{i \in U35} \bar{w}_{j(i),t}}^{\text{Difference between firms}} + \overbrace{\frac{1}{N_{O55,t}} \sum_{i \in O55} \Delta w_{i,j(i),t} - \frac{1}{N_{U35,t}} \sum_{i \in U35} \Delta w_{i,j(i),t}}^{\text{Difference within firms}}. \tag{E.1}$$

On the left-hand side of this equation, $\bar{w}_{O55,t}$ is the average log weekly wage of O55 workers in year $t$and $\bar{w}_{U35,t}$ is the average log weekly wage of U35 workers in year t. On the right-hand side of the equation, $N_{O55,t}$ is the number of O55 workers in year t, $N_{U35,t}$ is the number of U35 workers in year t, $\bar{w}_{j(i),t}$ is the average log weekly wage in year t within firm $j(i)$, in which individual i works, and $\Delta w_{i,j(i),t}$ is the difference between the wage of worker i and the average log weekly wage in firm $j(i)$ in year t. The last term could be rewritten as $\Delta w_{i,j(i),t} = w_{i,j(i),t} - \bar{w}_{j(i),t}$.

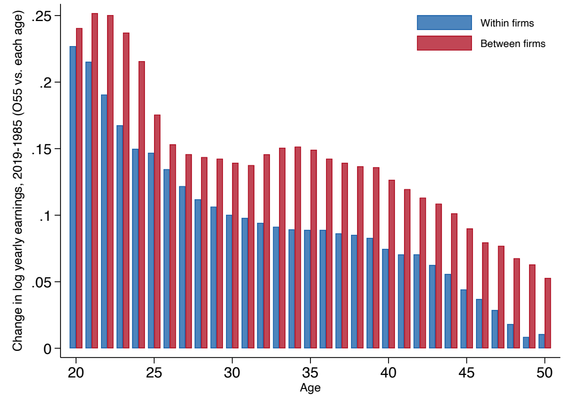
Proof of proposition 3. This decomposition of the difference in average log weekly wages between U35 workers and O55 workers in year t can be obtained as follows:

$$\begin{aligned}
\bar{w}_{O55,t} - \bar{w}_{U35,t} &= \frac{1}{N_{O55,t}} \sum_{i \in O55} w_{i,j(i),t} - \frac{1}{N_{U35,t}} \sum_{i \in U35} w_{i,j(i),t} \\
&= \frac{1}{N_{O55,t}} \sum_{i \in O55} \left(w_{i,j(i),t} + \bar{w}_{j(i),t} - \bar{w}_{j(i),t}\right) - \frac{1}{N_{U35,t}} \sum_{i \in U35} \left(w_{i,j(i),t} + \bar{w}_{j(i),t} - \bar{w}_{j(i),t}\right) \\
&= \frac{1}{N_{O55,t}} \sum_{i \in O55} \left(\overbrace{\bar{w}_{j(i),t}}^{\text{Firm Average}} + \overbrace{\Delta w_{i,j(i),t}}^{\text{Deviation from Firm Average}} \right) \\
&\quad - \frac{1}{N_{U35,t}} \sum_{i \in U35} \left(\bar{w}_{j(i),t} + \Delta w_{i,j(i),t}\right) \\
&= \overbrace{\frac{1}{N_{O55,t}} \sum_{i \in O55} \bar{w}_{j(i),t} - \frac{1}{N_{U35,t}} \sum_{i \in U35} \bar{w}_{j(i),t}}^{\text{Difference between firms}} \\
&\quad + \overbrace{\frac{1}{N_{O55,t}} \sum_{i \in O55} \Delta w_{i,j(i),t} - \frac{1}{N_{U35,t}} \sum_{i \in U35} \Delta w_{i,j(i),t}}^{\text{Difference within firms}}.
\end{aligned}$$

Figure E1: Difference in Yearly Earnings Between and Within Firms



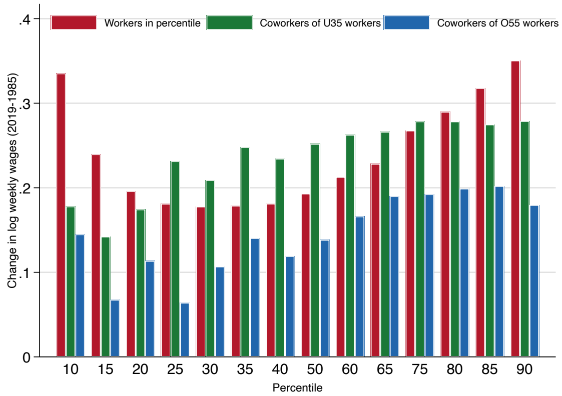
Panel A: O55 workers - U35 workers over time



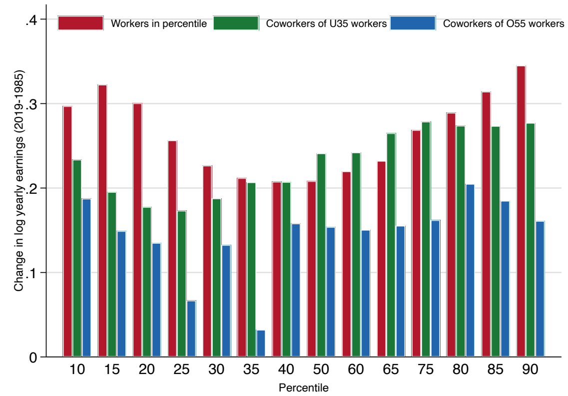
Panel B: O55 workers - each age, 2019-1985

Notes: Panel A plots the difference in log yearly earnings (decomposed into the two components of Equation (3)) between O55 workers and U35 workers for each year between 1985 and 2019. "Between firms" computes the difference in average log yearly earnings at the firm level. "Within firms" computes the difference in the average deviation of individual workers' yearly earnings from the firm averages. Panel B plots the difference in log yearly earnings between O55 workers and individual age groups and between 1985 and 2019. Again, this difference is decomposed into the same two components (Equation (3)). *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure E2: Descriptive Evidence on Within-Firm Effects



Panel A: Change in weekly wages for coworkers of U35 workers and O55 workers



Panel B: Change in yearly earnings for coworkers of U35 workers and O55 workers

Notes: Panel A shows the difference in log weekly wages between 1985 and 2019 for the coworkers of U35 workers and O55 workers in different percentiles of the distribution of weekly wages. Specifically, in each year, we assign each worker in the sample to a different percentile of the wage distribution. Then, for different percentiles, we compute the change in mean log weekly wages between 1985 and 2019 ("**Workers in percentile**"). Moreover, for U35 workers in percentile p and year t, we compute the average log weekly wage of their coworkers who were older than 35 years old. We repeat this procedure for several percentiles and years and, then, we plot the difference in mean log weekly wage of coworkers of U35 workers between 1985 and 2019 ("**Coworkers of U35 workers**"). Finally, for O55 workers in percentile p and year t, we compute the average log weekly wage of their coworkers who were younger than 55 years old. We repeat this procedure for several percentiles and years and, then, we plot the difference in mean log weekly wage of coworkers of O55 workers between 1985 and 2019 ("**Coworkers of O55 workers**"). For example, "0.24" for coworkers of U35 workers in percentile 10 means that the average weekly wage of the older coworkers of U35 workers in the 10^{th} percentile of the distribution of weekly wages increased by 0.24 log points between 1984 and 2015. Panel B repeats the same process using yearly earnings, rather than weekly wages. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

F Counterfactual Decomposition of Ranking Shift

The goal of the following analysis is to decompose the ranking-shift component of Equation (D.1) into a between-firm element and a within-firm element. To do so, we adapted a methodology previously used by Machado and Mata (2005), Autor, Katz, and Kearney (2005), and Song et al. (2019) to our specific empirical setting.

In each year, we compute the average log weekly wage within every firm. Then, we sort workers into 100 percentiles or firm-based groups using their firm's average log weekly wage. In most cases, this procedure ensures that all workers within a firm are assigned to the same firm-based group. There are exceptions to this rule for firms whose average log weekly wages are close to the border of the next percentile.

Next, within each firm-based group, we sort workers into 500 quantiles or worker-based groups using the deviation of each worker's log weekly wage from the average log weekly wage within the firm-based group.

The result of this exercise is a sorting of workers into 50,000 firm-worker groups that take into account both differences in average wages between firms (the 100 firm-based percentiles) and differences of individual wages from the average wage in each firm-based group (the 500 worker-based quantiles within each firm-based percentile). As a check on the validity of this process, we compare the shares of workers in different age groups and vigintiles of the distribution of weekly wages predicted by the sorting outcome (that is, the distribution of average log weekly wages computed in each firm-worker group) to the actual shares observed in the raw data. As expected, the predicted shares are close to the actual ones (Figure F1). Discrepancies arise only due to the forced binning of workers in 50,000 groups of equal dimension, as briefly discussed above. This test confirms that these discrepancies are not common.

We can use this sorting to rewrite the share of workers in age group a, firm-worker group (f, e), and year t, as follows:

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

Equation (F.1) rewrites the unconditional share of workers in age group a and firm-worker group (f, e) as the product of the share of workers in age group a and firm-group f and the share of workers in age group a and worker group e conditional on being in firm group f.

Next, we can use Equation (F.1) to rewrite the ranking-shift component of Equation (D.1) into a between-firm element and a within-firm element.

Proposition 4. The ranking-shift component of the change in log weekly wages for workers in age group a between t and t' can be written as follows:

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

On the left-hand side of this equation, we have the ranking-shift component of Equation (D.1). Specifically, 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 created by the sorting and $\bar{w}_{g,t}$ is the average wage in firm-worker group g and year t.

Proof of proposition 4. 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 using Equation (F.1), as follows:

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

This equation indicates that the change in the share of workers in age group a and firm-worker group $g = (f, e)$ between t and t' can be written to capture two interesting counterfactual scenarios. First, we have a between-firm counterfactual, defined as the change in the share of workers in age group a and firm group f between t and t', while keeping the distribution of workers within each firm-worker group g fixed in year t. In other words, we allow workers of age group a to change their sorting across firm groups, while keeping intra-firm distributions untouched. Second, there is a within-firm counterfactual, defined as the change in the share of workers in age group a and firm-worker group $(e|f)$, as well as between t and t', while keeping the sorting of workers across firm groups f fixed in year t. In other words, we allow workers in age group a to resort within firms as they did in the data, but we keep their allocation across firms fixed in year t. Third, there is a residual component that is the product of the two previous changes in the shares of workers.

Based on Equation (F.3), the ranking-shift component of the change in weekly wages for workers in age group a between t and t' can be written as follows:

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

Proposition 5. The interaction between the ranking-shift component and the wage-trend component of Equation (D.1) can be written as follows:

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

Proof of proposition 5. As seen under Proposition 4, this rewriting of the interaction between the ranking-shift component and the wage-trend component of Equation (D.1) stems directly from Equation (F.1).

Figure F2. In Panel A, Figure F2 decomposes the total-ranking-shift component of Equation (D.1) into a between-firm element, a within-firm element, and a residual. In other words, for U35 workers and O55 workers separately, it decomposes the average wage difference between 1985 and 2019 that stems from the total ranking shift, as follows:

$$\sum_{v}\left(s_{a,v,2019}-s_{a,v,1985}\right)\bar{w}_{v,1985}+\sum_{v}\left(s_{a,v,2019}-s_{a,v,1985}\right)\left(\bar{w}_{v,2019}-\bar{w}_{v,1985}\right). \qquad \text{(F.5)}$$

The between-firm component is as follows:

$$\begin{gathered}
\textstyle\sum_{g\in(f,e)}\left(s_{a,f,2019}-s_{a,f,1985}\right)\cdot s_{a,(e|f),1985}\cdot\bar{w}_{g,1985} \\
+\textstyle\sum_{g\in(f,e)}\left(s_{a,f,2019}-s_{a,f,1985}\right)\cdot s_{a,(e|f),1985}\cdot\left(\bar{w}_{g,2019}-\bar{w}_{g,1985}\right).
\end{gathered}$$

The within-firm component is as follows:

$$\textstyle\sum_{g\in(f,e)} s_{a,f,1985}\cdot\left(s_{a,(e|f),2019}-s_{a,(e|f),1985}\right)\cdot\bar{w}_{g,1985}$$
$$+\textstyle\sum_{g\in(f,e)} s_{a,f,1985}\cdot\left(s_{a,(e|f),2019}-s_{a,(e|f),1985}\right)\cdot\left(\bar{w}_{g,t}-\bar{w}_{g,1985}\right).$$

The residual is as follows:

$$\textstyle\sum_{g\in(f,e)} \left(s_{a,f,2019}-s_{a,f,1985}\right)\left(s_{a,(e|f),2019}-s_{a,(e|f),1985}\right)\bar{w}_{g,1985}$$
$$+\textstyle\sum_{g\in(f,e)} \left(s_{a,f,2019}-s_{a,f,1985}\right)\left(s_{a,(e|f),2019}-s_{a,(e|f),1985}\right)\left(\bar{w}_{g,t}-\bar{w}_{g,1985}\right).$$

In Panel B, Figure F2 shows the decomposition of the total-ranking-shift component of Equation (D.2) into a between-firm element, a within-firm element, and a residual. In other words, in each year $t\in[1986,2019]$, it computes the average wage difference between O55 workers and U35 workers, as well as between 1985 and t, that stems from the total ranking shift:

$$\overbrace{\underbrace{\sum_v \Delta s_{O55-U35,v,t-1985}\cdot\bar{w}_{v,1985}}_{\text{Ranking shift}}+\underbrace{\sum_v \Delta s_{O55-U35,v,t-1985}\cdot\left(\bar{w}_{v,t}-\bar{w}_{v,1985}\right)}_{\text{Ranking shift x Wage trend}}}^{\text{Total ranking shift}}. \tag{F.6}$$

The between-firm component is as follows:

$$\textstyle\sum_{g\in(f,e)} \Delta s_{O55-U35,f,t-1985}\cdot\Delta s_{O55-U35,(e|f),1985}\cdot\bar{w}_{g,1985}$$
$$+\textstyle\sum_{g\in(f,e)} \Delta s_{O55-U35,f,t-1985}\cdot\Delta s_{O55-U35,(e|f),1985}\cdot\left(\bar{w}_{g,t}-\bar{w}_{g,1985}\right),$$

where

- $\Delta s_{O55-U35,f,t-1985}$ is $\left(s_{O55,f,t}-s_{O55,f,1985}\right)-\left(s_{U35,f,t}-s_{U35,f,1985}\right)$;
- $\Delta s_{O55-U35,(e|f),1985}$ is $s_{O55,(e|f),1985}-s_{U35,(e|f),1985}$.

The within-firm component is as follows:

$$\textstyle\sum_{g\in(f,e)} \Delta s_{O55-U35,f,1985}\cdot\Delta s_{O55-U35,(e|f),t-1985}\cdot\bar{w}_{g,1985}$$
$$+\textstyle\sum_{g\in(f,e)} \Delta s_{O55-U35,f,1985}\cdot\Delta s_{O55-U35,(e|f),t-1985}\cdot\left(\bar{w}_{g,t}-\bar{w}_{g,1985}\right),$$

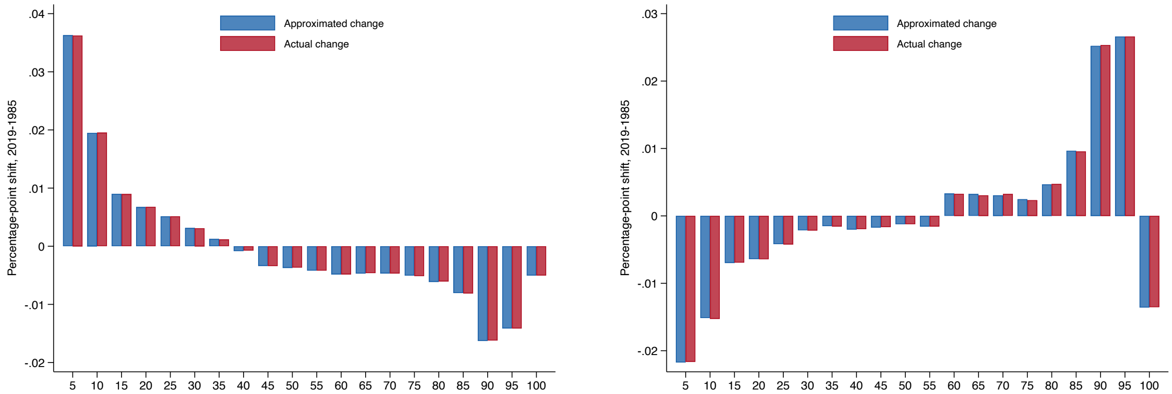
where

- $\Delta s_{O55-U35,f,1985}$ is $s_{O55,f,1985}-s_{U35,f,1985}$;
- $\Delta s_{O55-U35,(e|f),t-1985}$ is $\left(s_{O55,(e|f),t}-s_{O55,(e|f),1985}\right)-\left(s_{U35,(e|f),t}-s_{U35,(e|f),1985}\right)$.

The residual is as follows:

$$\textstyle\sum_{g\in(f,e)} \Delta s_{O55-U35,f,t-1985}\cdot\Delta s_{O55-U35,(e|f),t-1985}\cdot\bar{w}_{g,1985}$$
$$+\textstyle\sum_{g\in(f,e)} \Delta s_{O55-U35,f,t-1985}\cdot\Delta s_{O55-U35,(e|f),t-1985}\cdot\left(\bar{w}_{g,t}-\bar{w}_{g,1985}\right).$$

Figure F1: Actual Vs. Approximated Shares

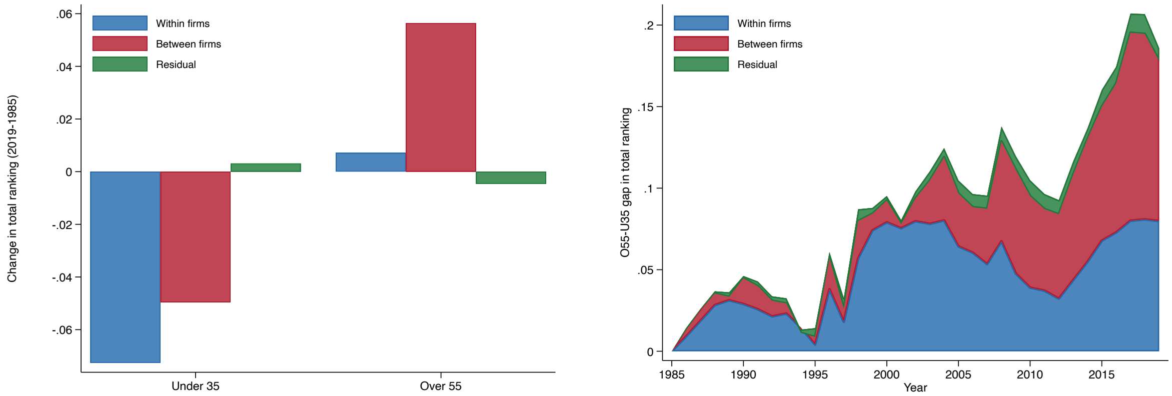


Panel A: U35 workers

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 F. Specifically, workers are first sorted in 100 percentiles (firm-based groups) based on their firm's average weekly wages. Within each percentile, workers are then sorted in 500 quantiles (firm-worker groups) based on the difference between their weekly wage and the average weekly wage in their firm group. Then, the percentage-point difference is computed starting from the distribution of the average weekly wages of each firm-worker group. 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 over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure F2: Decomposition of Total Ranking Shift

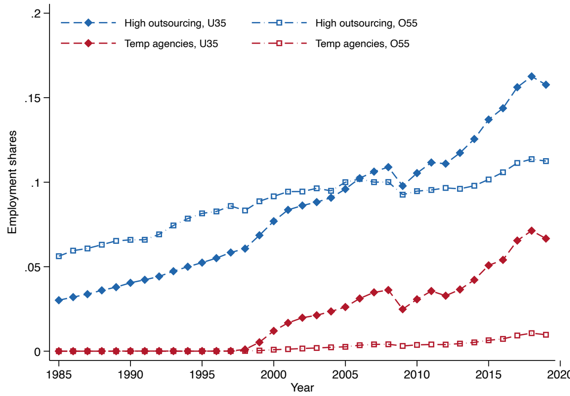


Panel A: Yearly earnings
2019-1985 for U35 workers & O55 workers

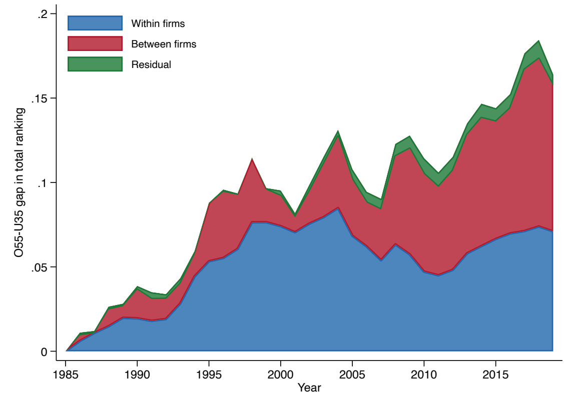
Panel B: Yearly earnings
O55 workers - U35 workers over time

Notes: Panel A decomposes the total-ranking-shift change in log yearly earnings (Equation (1)) between 1985 and 2019 for U35 workers and O55 workers, separately. Panel B decomposes the total-ranking-shift change in log yearly earnings between O55 workers and U35 workers and between year t and 1985. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure F3: Decomposition of Total Ranking Shift, Low-Outsourcing Sectors



Panel A: Employment shares
in high-outsourcing 3-digit sectors



Panel B: Weekly wages
O55 workers - U35 workers over time

Notes: Panel A shows the employment shares of U35 and O55 workers in 3-digit sectors that included many outsourced jobs, following the classification by Goldschmidt and Schmieder (2017). "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) sectors 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 only sectors 78.1, 78.2, and 78.3. Panel B decomposes the total-ranking-shift change in log weekly wages between O55 workers and U35 workers and between year t and 1985, **using only sectors that are not classified as high outsourcing**. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

G More Details on the AKM Model

In this section, we provide more details about the econometric model of wages introduced in Section 5:

$$w_{i,t} = \theta_i + \psi^{a(i)}_{j(i,t),p} + \beta^{a(i)} X_{i,t} + \varepsilon_{i,t}. \tag{G.1}$$

Deviations from basic AKM model. The log of the weekly wage of individual i in year t ($w_{i,t}$) is written as the sum of worker-level fixed effects ($\theta_{i,p}$), fixed effects for firm $j(i,t)$ that employs worker i in year t ($\psi^{a(i)}_{j(i,t),p}$), time-varying worker-level characteristics ($X_{i,t}$), and time-varying unobservable factors ($\varepsilon_{i,t}$). The worker-level characteristics include a quadratic function of age and experience.

Our framework makes two main deviations from the most basic form of the AKM model. First, we estimate the model separately for workers in age group $a \in \{U35, O55\}$ in order to obtain separate sets of firm fixed effects. So, for each firm j in the sample, we will estimate one set of fixed effect for U35 workers and one set of fixed effect for O55 workers. This strategy is in the same vein as the estimation of gender-specific firm rents in Card, Cardoso, and Kline (2016) and of age-specific firm rents in Kline, Saggio, and Sølvsten (2020).

Second, the basic AKM model has time-invariant firm fixed effects, an assumption that can be acceptable when the analysis focuses on a short time period. However, we study 35 years of labor-market data: in this case, assuming that firm-level rents do not vary over time is too restrictive. Therefore, in Equation (G.1), we interact the time-invariant firm rents with twelve dummies that identify consecutive three-year periods $p \in$\{85-87, 88-90, 91-93, 94-96, 97-99, 00-02, 03-05, 06-08, 09-11, 12-14, 15-17, 18-19\}. So, for each firm j and age group a, we obtain up to twelve fixed effects that allow us to measure variations in firm rents over time. Several prior works have estimated a similar time-varying AKM model when studying long periods of time (for example, Lachowska et al. (2019) and Engbom and Moser (2020)).

Therefore, average firm rents estimated with Equation (G.1) can change over time for three reasons. First, the individual firm fixed effects can change from period p to period p' because Equation (G.1) allows them to vary every three years. Second, the averages may change every year because the number of firms can change from year to year. Third, the average firm rents may change over time because the share of U35 workers and O55 workers in each firm can vary every year.

The construction of the sample. As already discussed in Appendix B.1, the initial Social Security dataset has a row for each worker-firm pair. In other words, in each year, a worker who moves across two firms appears twice: one row has information about the contract with the old firm, while the other row has information about the contract with the new firm. In order to estimate Equation (G.1), we need to transform this extensive dataset into a panel with a single worker-level observation per year. Therefore, in case of multiple worker-level observations per year, we simplify the dataset by keeping the working spell with the highest wage.

This data management implies three things. First. we miss a firm-to-firm move only when the following conditions are met: (i) worker i moves from firm j to firm $j+1$ in year t and the wages earned at firm j in year t are lower than the wages earned at firm $j+1$ in year t, and (ii) worker i moves from firm $j+1$ to firm $j+2$ in year $t+1$ and the wages earned at firm $j+1$ in year $t+1$ are lower than the wages earned at firm $j+2$ in year $t+1$. In this specific case, the final dataset shows that worker i moved from firm j in year t to firm $j+2$ in year $t+1$. These cases are rare and thus unlikely to bias our findings: out of 29,622,176 firm-to-firm transitions between 1985 and 2019, only 536,123 or 1.8 percent are lost when we simplify the panel to have a single observation per worker and year.

Second, the final dataset might postpone firm-to-firm transitions by a few months. For example, if worker i moves from firm j to firm $j+1$ in the third quarter of year t and the wages earned at firm j are lower than the wages earned at firm $j+1$, the final dataset shows that worker i moved from firm j in year t to firm $j+1$ at the beginning of year $t+1$, rather than in the third quarter of year t.

These two problems are common to all studies that measure worker turnover with yearly data. In fact, yearly data cannot capture a turnover event that happens on a specific day without some degree of measurement error. If anything, the Italian dataset has more advantageous characteristics with respect to many other employer-employee datasets. For example, the German Social Security data distributed by the Institute for Employment Research (IAB) are a static snapshot of the labor market on the 30^{th} of June of every year. This structure implies that all firm-to-firm transitions that happen in the second semester and do not persist until the 30^{th} of June of the following year cannot be observed in the data. Using the Italian Social Security dataset, we can see all firm-to-firm transitions and thus study the impact that omitting some of them may have on the final results.

Third, it should be noted that the weekly wages are always a correct measure of earnings even when we drop a working spell. In fact, this variable is measured using information for the working spell that was retained in the dataset. For example, if worker i has working spells A and B in year t and we drop spell B, the weekly wage for year t is computed as the total earnings in spell A divided by the weeks worked in spell A. Again, this is an advantage of the Italian Social Security data over the employer-employee datasets that provide a single cross-section on a specific day of each year.

Finally, Equation (G.1) is estimated for both U35 workers and O55 workers on the largest dual connected set. This is the largest set of firms connected by direct firm-to-firm transitions of both younger and older workers (Table G1).

Decomposition of firm rents. We decompose the overall difference in firm rents between U35 workers and O55 workers into two components: (i) sorting between higher-rent and lower-rent firms and (ii) wage setting within firms. Specifically, we adapt to our empirical context a decomposition of firm fixed effects proposed by Card, Cardoso, and Kline (2016), as follows:

$$E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} \mid a(i) = \text{O55}\right) - E\left(\Delta_{t-1985}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{U35}\right) \tag{G.2}$$

$$= \underbrace{E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} - \Delta_{t-1985}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{O55}\right)}_{\text{Wage setting}} \tag{G.3}$$

$$+ \underbrace{E\left(\Delta_{t-1985}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{O55}\right) - E\left(\Delta_{t-1985}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{U35}\right)}_{\text{Sorting}}$$

$$= \underbrace{E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} - \Delta_{t-1985}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{U35}\right)}_{\text{Wage setting}} \tag{G.4}$$

$$+ \underbrace{E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} \mid a(i) = \text{O55}\right) - E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} \mid a(i) = \text{U35}\right)}_{\text{Sorting}}.$$

For sake of brevity, this equation simplifies the notation of the expected values. For example, the first term $E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} \mid a(i) = \text{O55}\right)$ can be rewritten as follows:

$$E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} \mid a(i) = \text{O55}\right)$$
$$= E\left(\psi^{O55}_{j(i,t),p} \mid a(i) = \text{O55}, T = t\right) - E\left(\psi^{O55}_{j(i,1985),p} \mid a(i) = \text{O55}, T = 1985\right).$$

In other words, it is the difference between the average firm rents of O55 workers in year t, conditional on the O55 workers present in year t, and the average firm rents of O55 workers in year 1985, conditional on the O55 workers present in year 1985.

Following the popular Blinder-Oaxaca decomposition, Equation (G.3) decomposes the double difference of firm premiums between 1985 and year t and between U35 workers and O55 workers into two components: wage setting and sorting. The first component is the double difference in firm rents (i) between 1985 and year t and (ii) between younger and older workers, conditional on the set of jobs held by O55 workers. This element measures differences in internal wage-setting policies between U35 workers and O55 workers, that is, differences in their ability to appropriate firm rents in the same set of jobs. The second component measures the double difference of firm-specific rents among U35 workers (i) between 1985 and year t and (ii) between the the set of jobs held by O55 workers and the set of jobs held by U35 workers. It measures the effect that the sorting of U35 workers across different jobs had on the time trends of their firm rents.

It is possible to compute an alternative decomposition. In Equation (G.4), wage setting is the double difference in firm rents (i) between 1985 and year t and (ii) between younger and older workers, conditional on the set of jobs held by U35 workers. Sorting is the double difference of firm-specific rents among O55 workers (i) between 1985 and year t and (ii) between the the set of jobs held by O55 workers and the set of jobs held by U35 workers.

In practice,

- $E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} - \Delta_{t-1985}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{O55}\right)$ is the average difference between the change over time in firm rents for O55 workers and the change over time in firm rents for U35 workers within each firm, weighting each firm rent by the share of O55 workers employed by the firm in the relevant year.

- $E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} - \Delta_{t-1985}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{U35}\right)$ is the same average difference in firm rents, but it weights each firm rent by the share of U35 workers employed by the firm in the relevant year.

- $E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} \mid a(i) = \text{O55}\right)$ is the average change between 1985 and year t in the firm rents received by O55 workers.

- $E\left(\Delta_{t-1985}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{U35}\right)$ is the average change in the rents received by U35 workers.

- $E\left(\Delta_{t-1985,}\psi^{O55}_{j(i,t),p} \mid a(i) = \text{U35}\right)$ is the average change in the firm rents received by O55 workers weighting each firm fixed effects by the share of U35 workers at the firm.

- $E\left(\Delta_{t-1985,}\psi^{U35}_{j(i,t),p} \mid a(i) = \text{O55}\right)$ is the average change in the firm rents received by U35 workers weighting each firm fixed effects by the share of O55 workers at the firm.

Normalization. In a standard AKM model, the level of the firm fixed effects is not identified without a normalization. Moreover, it is well know that the choice of the normalization could affect the final results. For example, Card, Cardoso, and Kline (2016) measures the level of firm rents for men and women with Portuguese employer-employee data. It normalizes the firm rents for both genders using the average premium of firms with a value added below a certain threshold. However, it also notes that the normalized fixed effects correctly measure the level of firm rents only if the rents of firms below the value-added threshold are zero.

In our empirical context, the choice of the normalization does not bear any consequence on the analysis. The main reason is that Equation (G.2) measures a difference in the time trends of the firm rents of U35 workers and O55 workers, rather than a difference in their levels at a specific point in time. Specifically, in our estimation, we normalize all firm rents for both U35 workers and O55 workers by subtracting the fixed effect of the largest firm in the whole dual connected sample. In other words, we subtract the same constant from the firm rents estimated in every period and for both age groups. Therefore, when we consider a change over time in firm rents, the normalization constant always drops from the computation.

Identification. As it is well known from prior works, the AKM model estimates the firm fixed effects using movers, that is, workers who move between firms in the dual connected sample. Therefore, the nature of firm transitions in the data is crucial to ensure that the estimation of Equation (G.1) captures the true value of firm rents. Specifically, the firm fixed effects are unbiased if they are not correlated with the residual $\varepsilon_{i,t}$, conditional on worker fixed effects. In this framework, there three main threats to identification.

First, firm-to-firm switches should not be correlated with unobserved temporary firm shocks. If this condition is not met, workers may leave a firm in response to a negative short-term shock or may join a firm in expectation of a positive short-term shock. The result is that the firm fixed effects would not be able to isolate more permanent firm-level differences in wage premia. In event studies centered around firm transitions, this violations may coincide with dips or spikes in wages just before or after a job transition.

Second, firm-to-firm transitions should not be correlated with firm-worker match effects. If this condition is violated, workers may move to firms that have a more positive match component. In practice, if this type of violation makes up a large share of firm-to-firm switches, transitions to higher-rent and lower-rent firms do not generate symmetric and opposite wage changes. Moving to higher-rent firms may coincide with a wage change that is larger than the average change in wage premia between the old and new firm, because movers choose a new firm with a more positive match effect. For the same reason, moving to lower-rent firms may coincide with a wage change that is smaller than the average change in wage premia between the old and new firm.

Third, firm-to-firm transitions should not be correlated with short-term worker-level shocks. If this condition is not met, workers who received a positive wage shock and are on an increasing wage trend may be more likely to move to higher-rent firms, and vice versa. In practice, if this form of violation is a major driver of job transitions, we should observe increasing or decreasing trends in average wages in the periods just before a move.

The estimation of Equation (G.1) deviates from the standard AKM model in the definition of a job move. In the basic model, the firm rents are time invariant. Each firm in the connected set receives a single firm effect, which is identified by workers leaving and joining the firm throughout the time period covered by the data. In a time-varying AKM model like the one described by Equation (G.1), a firm is defined by a combination of a physical firm in the data and a period dummy. In our empirical context, in which we divided the time period into three-year periods, each physical firm becomes twelve firm-period pairs. In this model, job moves are defined based on the firm-period pairs, rather than the physical firms. This framework implies that the firm rents are estimated also using observations from stayers, that is, workers who stay in a firm across time periods. Using both movers and stayers (although, only across three-year periods) is advantageous for the purpose of the estimation because it substantially widens the pool of workers who contribute to identifying the firm effects, reducing the concerns related to small sample bias and selection into firm-to-firm transitions.

Residuals. A violation of the separability assumption between the worker effects and the firm rents is likely to produce large residuals in Equation (G.1) for some type of matches (as discussed, for example, by Card, Heining, and Kline (2013) and Card, Cardoso, and Kline (2016)). Therefore, a standard test for the goodness of fit of the model is to plot average residuals for different levels of worker and firm effects. Specifically, we divide the distributions of firm rents and worker effects in deciles and plot the mean residuals for their 100 combinations, separately for U35 workers and O55 workers (Figure G2).

There are at least two main results that corroborate the good fit of the model. First, there are not strong and recognizable patterns in the data. For example, we do not find that the mean residuals are always larger when high-effect workers are matched to low-effect firms. Second, the magnitudes of nearly all mean residuals are small and not economically significant. Out of 200 averages, only one is slightly larger than 0.02, five have an absolute value between 0.01 and 0.02, while all the others are even closer to zero.

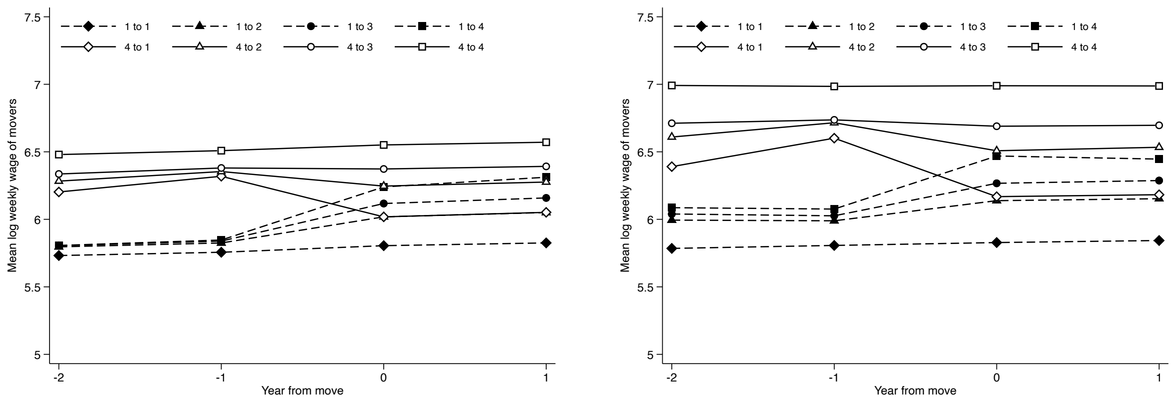
Firm-worker match effects. As it is standard in this literature, we also estimate a variation of the wage model in Equation (5) with firm-worker fixed effects in place of separate firm and worker dummies. The inclusion of job-match effects improves the fit of the model, but only slightly. The R^2 of the model for U35 workers increases by 4.6 percentage points, while the R^2 of the model for U55 workers increases by only 1.4 percentage points. Moreover, the standard deviation of the firm-worker fixed effects is substantially smaller than the one of the firm effects in the baseline model. These findings are common to many prior works in this field (for example, Card, Cardoso, and Kline (2016) and Song et al. (2019)) and suggest that the influence of firm-worker match effects is not significant.

The event studies in Section 5.4. To perform this analysis, we adapt to our specific needs an empirical process described by Lamadon, Mogstad, and Setzler (2019). In each year t between 1998 and 2016, we compute the value-added shock from $t-1$ to t for each firm in the sample.[47] Specifically, the value-added shock for firm j is the year-to-year change in value added for firm j minus the average year-to-year change in value added in the province and two-digit sector in which firm j operates. We then divide firms in tertiles based on their value-added shock in year t. On average, firms in the top tertile experienced a positive 0.18-log-point value-added shock between $t-1$ and t, while firms in the bottom tertile experienced a negative 0.13-log-point shock. In the next step, we create event-study panels for each year t by (i) appending data between $t-2$ and $t+3$, (ii) keeping observations only from U35 workers and O55 workers who stayed at the firm for the entire time window $[t-2, t+3]$, and (iii) computing the average log weekly wage and log value-added shock at the level of firms, age groups, and event periods. At this point, we append all these newly created datasets and compute the average log weekly wage and value-added shock by tertiles of the distribution of value-added shocks in period 0, age groups, and event periods, weighting each firm-level data point by the firm's number of either U35 workers or O55 workers.

[47] We restrict this analysis between 1998 and 2016 because (i) balance-sheet data with information about value added are available only between 1996 and 2019 and (ii) we need two years before and three years after each event period to study pre-event and post-event trends.

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

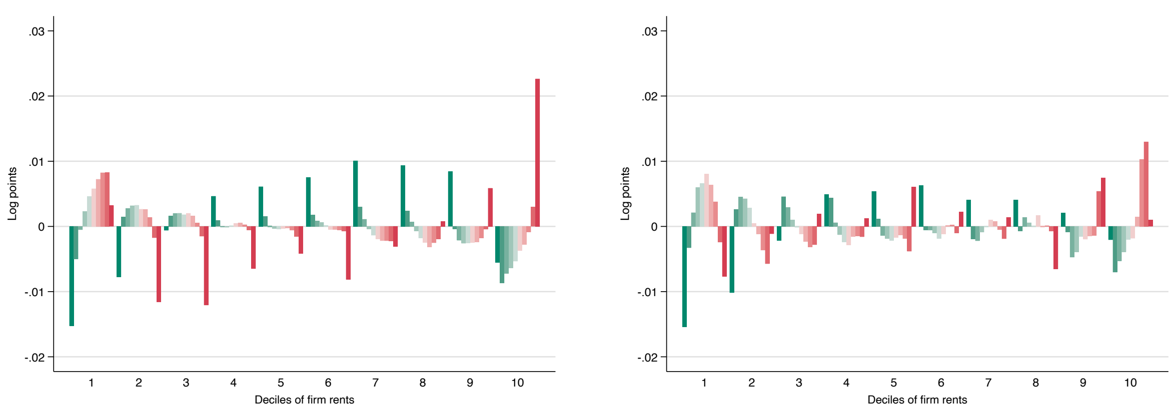
Figure G1: Event Studies Around Firm-to-Firm Transitions



Panel A: U35 workers   Panel B: O55 workers

Notes: These figures compute the mean log weekly wage associated with firm-to-firm job moves. Firms are divided into quartiles based on their average weekly wage in the last year before a job move and in the first year after a job move. The sample includes workers who were at the same firm in periods -2 and -1, moved to a new firm in period 0, and then stayed in the new firm until period 1. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

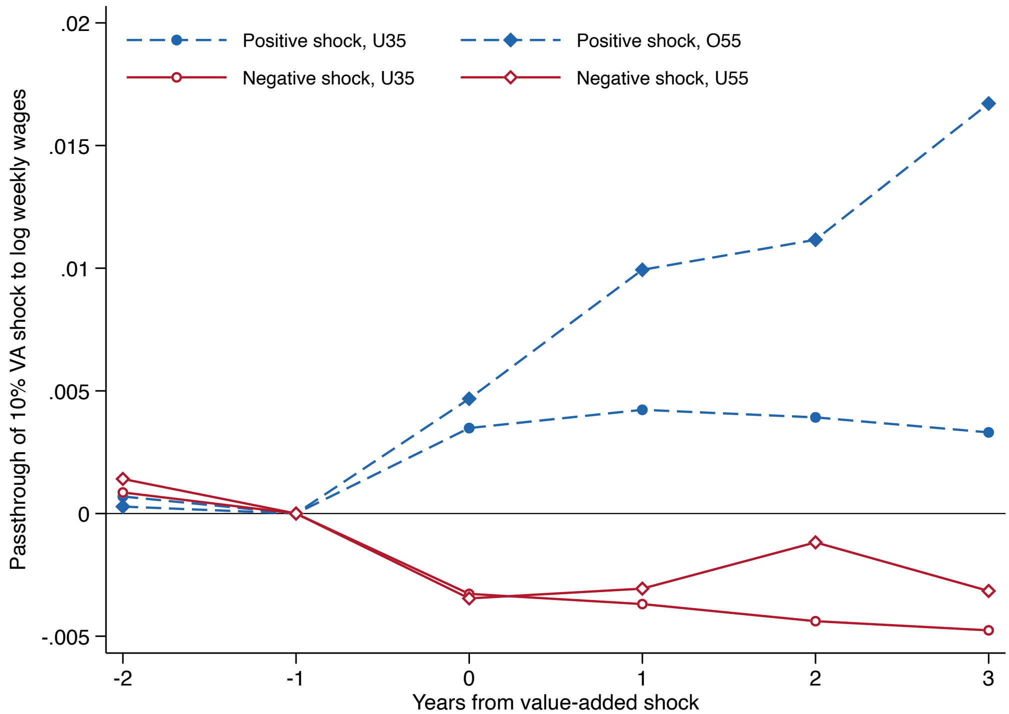
Figure G2: Residuals by Deciles of Worker and Firm Effects



Panel A: U35 workers   Panel B: O55 workers

Notes: These figures compute the mean residuals from Equation (5) by deciles of worker effects and firm rents. Specifically, for each decile of firm rents on the x axis, the figures show ten mean residuals, one for each decile of worker effects. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure G3: Wage Passthrough of Value-Added Shocks



Notes: Each line shows the average effect on wages of either U35 workers or O55 workers of either a positive 10-percent value-added shock or a negative 10-percent value-added shock. The dataset for the event study is created as follows. In each year t between 1998 and 2016, we compute the value-added shock from $t-1$ to t for each firm in the sample. The value added shock in the year-to-year change in value added minus the average year-to-year change in value added in a province and two-digit sector. We then divide firms in tertiles based on their value-added shock in year t. In the next step, we create event-study panels for each year t by (i) appending data between $t-2$ and $t+3$, (ii) keeping observations only from U35 workers and O55 workers, and (iii) computing the average log weekly wage and log value-added shock at the level of firms, age groups, and event periods. At this point, we append all these newly created datasets and compute the average log weekly wage and value-added shock by tertiles of the distribution of value-added shocks in period 0, age groups, and event periods, weighting each firm-level data point by the firm's number of either U35 workers or O55 workers. In the final step, we compute the change in log wages for U35 workers and O55 workers that stems from a positive shock, defined as the difference in value-added shock between the top tertile and the mid tertile. Similarly, we measure the wage change stemming for a negative value-added shock, leveraging the difference between the bottom tertile and the mid tertile. Country: Italy. Time period: 1996-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table G1: Panel AKM

	Full set			Single connected U35	Single connected O55	Dual connected set		
	All	U35 workers	O55 workers	All	All	All	U35 workers	O55 workers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	31.50	27.30	58.94	31.37	35.07	34.85	28.48	58.78
U35 workers	0.87	-	-	0.87	0.78	0.79	-	-
O55 workers	0.13	-	-	0.13	0.22	0.21	-	-
Male	0.65	0.63	0.78	0.66	0.71	0.71	0.68	0.8
Years in labor market	11.35	7.64	35.61	11.28	14.21	14.02	8.21	35.85
Temporary contract	0.08	0.09	0.05	0.09	0.12	0.12	0.14	0.05
Foreign-born	0.07	0.08	0.04	0.07	0.07	0.07	0.08	0.03
Manufacturing	0.36	0.37	0.29	0.38	0.35	0.35	0.36	0.28
Services	0.34	0.35	0.28	0.33	0.31	0.31	0.32	0.26
Construction	0.09	0.09	0.10	0.08	0.07	0.07	0.07	0.09
Log weekly wage	6.04	6.00	6.33	6.07	6.22	6.22	6.16	6.47
Log yearly earnings	9.86	9.81	10.18	9.89	10.05	10.05	9.98	10.32
Gap log weekly wage	0.33	-	-	0.37	0.30	0.31	-	-
N. of observations	149,399,136	129,564,212	19,834,924	135,368,861	58,874,922	58,244,384	46,005,610	12,238,774
N. of firms	9,414,361	8,515,068	899,293	4,894,368	391,549	334,028	240,666	93,362
N. of workers	24,059,933	19,915,864	4,144,069	21,001,557	9,337,485	9,219,767	6,788,884	2,430,883

Notes: Columns 1 to 3 describe the characteristics of the full sample of U35 workers and O55 workers. Columns 4 and 5 describe the characteristics of the single connected sets. Specifically, column 4 describes the characteristics of the set of firms that are directly connected by moves of U35 workers, while column 5 describes the characteristics of the set of firms that are directly connected by moves of O55 workers. Columns 6 to 8 describe the characteristics of the dual connected set, which is the sample used for the estimation of Equation(5). The dual connected set is a restricted set of firms that are connected by firm-to-firm transitions of *both* U35 workers and O55 workers. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table G2: Estimates of the AKM Model

	All periods	
	U35 workers	O55 workers
	(1)	(2)
Std. dev. of log weekly wages	0.389	0.626
Parameter estimates for baseline model		
Number of worker effects	7,411,175	2,511,677
Number of firm effects	617,024	551,146
Std. dev. of worker effects	0.245	0.564
Std. dev. of firm effects	0.214	0.424
Std. dev. of worker characteristics	0.102	0.026
Correlation worker/firm effects	0.003	-0.065
Adjusted R^2	0.771	0.911
Parameter estimates for job-match variant		
Number of job-match effects	20,726,984	6,746,212
Adjusted R^2	0.817	0.925
Std. dev. of job-match effects	0.127	0.125

Notes: The baseline model is described in Equation (G.1). The job-match variant replaces separate worker and firm effects with joint worker-firm fixed effects in order to capture worker-specific benefits for matching with different firms. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table G3: Wage Changes Associated with Job Moves

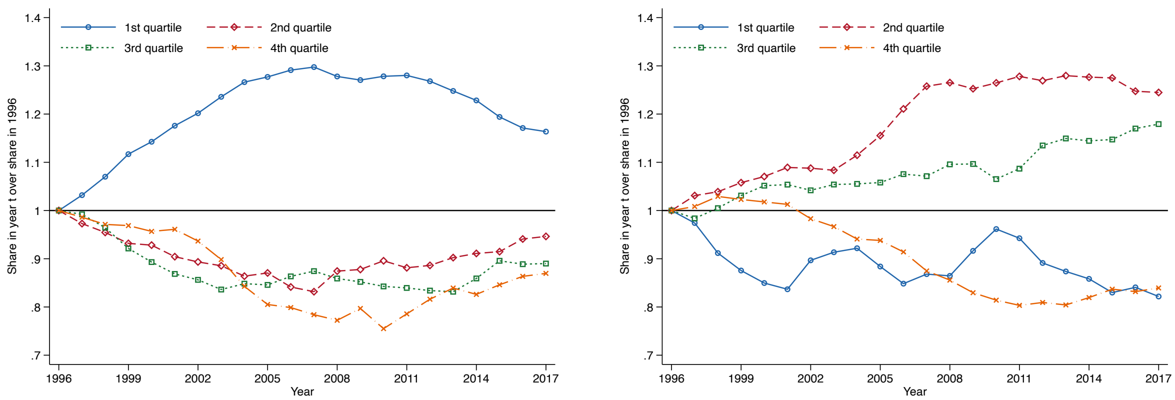
			Mean log weekly wages				% change	
	Number of job changes	Percent of job changes	2 years before	1 year before	Year of job move	1 year after	Raw	Adjusted
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: U35 workers								
1 to 1	362497	13.13	5.73	5.76	5.80	5.83	0.008	-0.010
1 to 2	156207	5.67	5.80	5.82	6.02	6.05	0.033	0.014
1 to 3	89440	3.25	5.80	5.84	6.12	6.16	0.048	0.028
1 to 4	33590	1.22	5.81	5.85	6.24	6.31	0.067	0.046
2 to 1	224841	8.14	5.98	6.02	5.95	5.97	-0.013	-0.031
2 to 2	296537	10.73	6.03	6.06	6.09	6.11	0.004	-0.014
2 to 3	160309	5.81	6.05	6.09	6.17	6.20	0.013	-0.006
2 to 4	79819	2.89	6.11	6.18	6.30	6.36	0.019	0.000
3 to 1	71292	2.58	6.08	6.14	5.97	6.00	-0.029	-0.047
3 to 2	229838	8.31	6.15	6.18	6.16	6.18	-0.003	-0.022
3 to 3	289287	10.45	6.20	6.22	6.26	6.28	0.006	-0.013
3 to 4	98412	3.56	6.23	6.28	6.39	6.43	0.017	-0.003
4 to 1	21003	0.76	6.20	6.32	6.02	6.05	-0.048	-0.065
4 to 2	51738	1.87	6.28	6.35	6.25	6.28	-0.017	-0.036
4 to 3	170620	6.16	6.34	6.38	6.37	6.39	-0.001	-0.020
4 to 4	429334	15.47	6.48	6.51	6.55	6.57	0.007	-0.013
Panel B: O55 workers								
1 to 1	60174	17.25	5.78	5.81	5.83	5.84	0.004	0.000
1 to 2	9120	2.59	5.99	5.99	6.14	6.15	0.025	0.021
1 to 3	2416	0.68	6.04	6.03	6.27	6.29	0.040	0.037
1 to 4	729	0.21	6.09	6.08	6.47	6.45	0.065	0.061
2 to 1	36944	10.49	6.09	6.12	6.03	6.05	-0.013	-0.017
2 to 2	32256	9.12	6.21	6.21	6.23	6.24	0.002	-0.001
2 to 3	7025	1.96	6.30	6.31	6.36	6.36	0.009	0.006
2 to 4	1538	0.43	6.43	6.46	6.58	6.58	0.020	0.016
3 to 1	9766	2.74	6.23	6.29	6.10	6.13	-0.031	-0.035
3 to 2	29931	8.39	6.33	6.36	6.31	6.33	-0.007	-0.010
3 to 3	33483	9.30	6.48	6.48	6.49	6.48	0.001	-0.002
3 to 4	5070	1.41	6.69	6.70	6.74	6.77	0.007	0.004
4 to 1	3105	0.87	6.39	6.60	6.17	6.18	-0.066	-0.069
4 to 2	5606	1.56	6.61	6.72	6.51	6.53	-0.031	-0.034
4 to 3	23922	6.65	6.71	6.74	6.69	6.70	-0.007	-0.010
4 to 4	94118	26.34	6.99	6.98	6.99	6.99	0.001	-0.002

Notes: This table describes the number and variation in weekly wages of firm-to-firm changes between firms in different quartiles of the average wage distribution. Firms are assigned to quantiles of weekly wage based on their average weekly wage in period -1 and period 0. The sample includes workers who were at the same firm in periods -2 and -1, moved to a new firm in period 0, and then stayed in the new firm until period 1. Column 7 shows the percentage change between period -1 and period 0. Column 8 shows the percentage change between period -1 and period 0 in the adjusted weekly wages. We first regress the wages of workers who stayed for at least 4 years within the same firm on a quadratic function of age and year fixed effects. We then use these coefficients to predict wages of movers. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

H Evidence from Germany and the United States

H.1 Germany

Figure H1: Shifts in Distribution of Daily Wages (Germany)

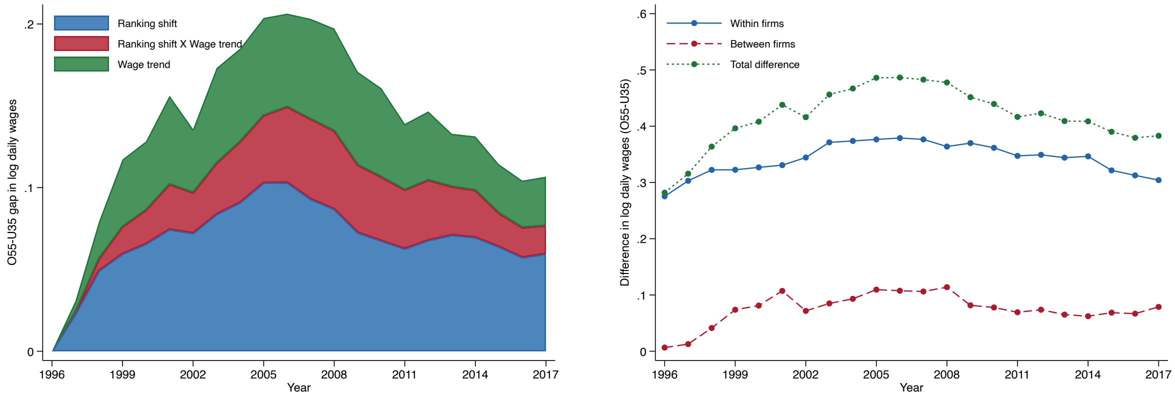


Panel A: U35 workers
Yearly change in quartiles

Panel B: O55 workers
Yearly change in quartiles

Notes: These graphs show the changes in the shares of U35 and O55 workers in different parts of the distribution of daily wages. Specifically, Panel A shows the ratio between the share of U35 workers in each quartile and year $t \in [1997, 2017]$ and the share of U35 in the same quartile in 1996. Panel B plots the same information for O55 workers. *Sources:* In each year, the data pools information about all workers who were over 16 years old, had a full-time contract, and earned positive wages. Country: Germany. Time period: 1996-2017. Database: LIAB Cross-Sectional Model 2, Institute for Employment Research (IAB).

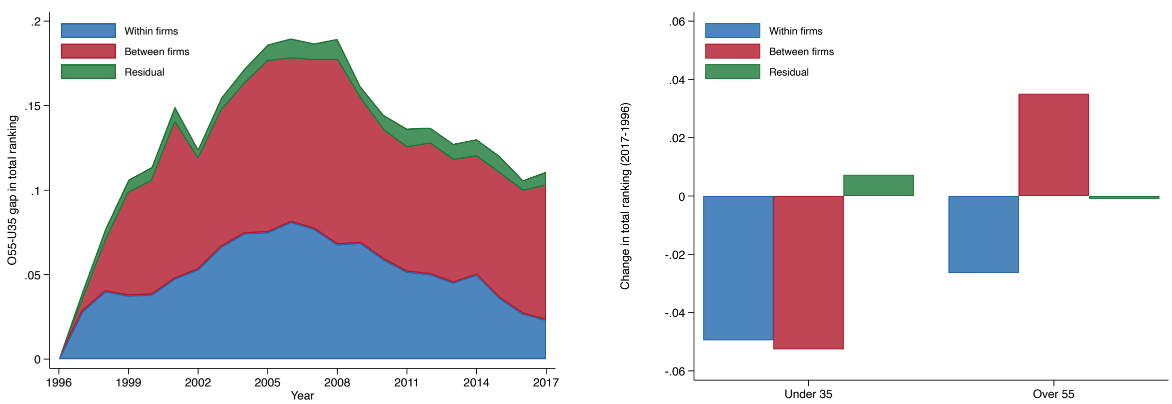
Figure H2: Decomposition of Change in Daily Wages (Germany)



Panel A: Job ranking vs. wage trend | Panel B: Between vs. within firms

Notes: Panel A plots the change in mean log daily wages between O55 workers and U35 workers, as well as between 1996 and year $t \in [1997, 2017]$. This double difference is further decomposed into three components, following Equation (2). Panel B plots the difference in log daily wages between O55 workers and U35 workers for each year between 1996 and 2017, decomposing it into a between-firm and a within-firm component (Equation (3)). *Sources:* In each year, the data pools information about all workers who were over 16 years old, had a full-time contract, and earned positive wages. Country: Germany (1996-2017). Database: LIAB, Institute for Employment Research (IAB).

Figure H3: Decomposition of Total Ranking Shift (Germany)



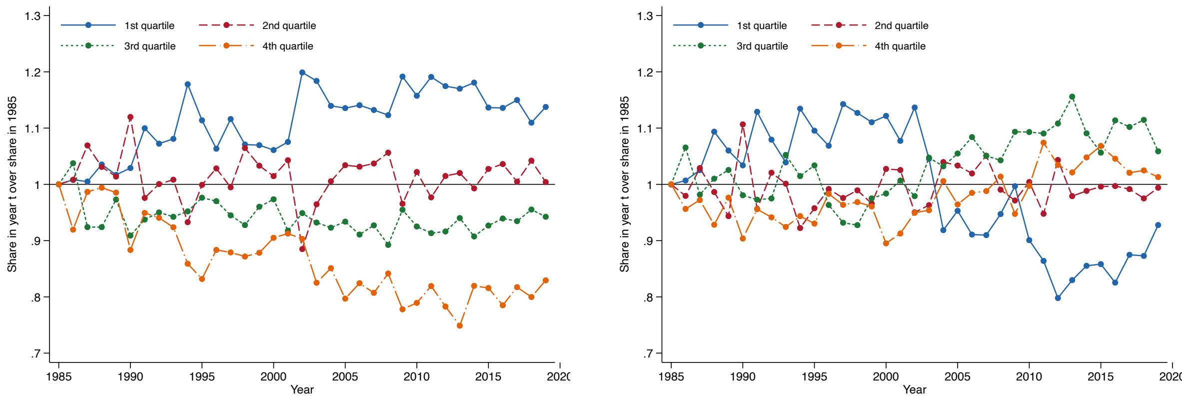
Panel A: Daily wages
O55 workers - U35 workers over time

Panel B: Daily wages
2017-1996 for U35 workers & O55 workers

Notes: Panel A decomposes into a between-firm and a within-firm component the total-ranking-shift change (Equation (2)) in log daily wages between O55 workers and U35 workers and between 1996 and year $t \in [1997, 2017]$. Panel B decomposes the total-ranking-shift change in log daily wages between 1996 and 2017 for U35 workers and O55 workers, separately. *Sources:* In each year, the data pools information about all workers who were over 16 years old, had a full-time contract, and earned positive wages. Country: Germany (1996-2017). Database: LIAB, Institute for Employment Research (IAB).

H.2 United States

Figure H4: Shifts in Distribution of Weekly Wages (USA)

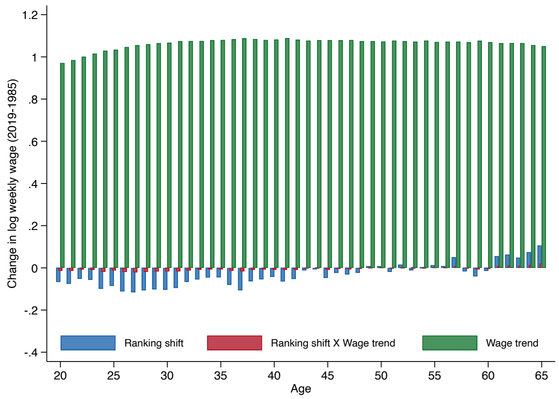


Panel A: U35 workers
Yearly change in quartiles

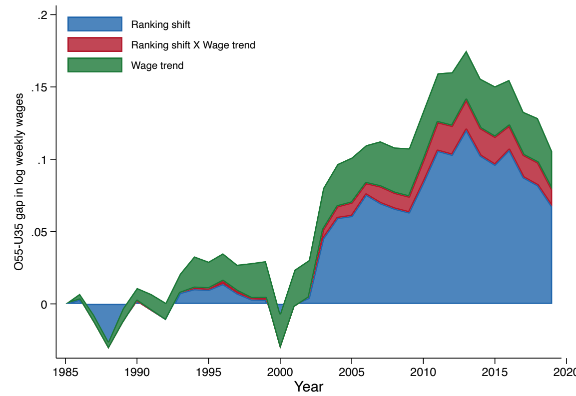
Panel B: O55 workers
Yearly change in quartiles

Notes: These graphs show the changes in the shares of U35 and O55 workers in different parts of the distribution of weekly wages. Specifically, Panel A shows the ratio between the share of U35 workers in each quartile and year $t \in [1986, 2019]$ and the share of U35 in the same quartile in 1985. Panel B plots the same information for O55 workers. *Sources:* In each year, the data is a representative sample of workers who were over 16 years old, had a full-time contract, and earned positive wages. Country: United States. Time period: 1985-2019. Database: Merged Outgoing Rotation Groups (MORG) of the CPS, https://data.nber.org/morg/annual/.

Figure H5: Decomposition of Change in Weekly Wages (USA)



Panel A: By age

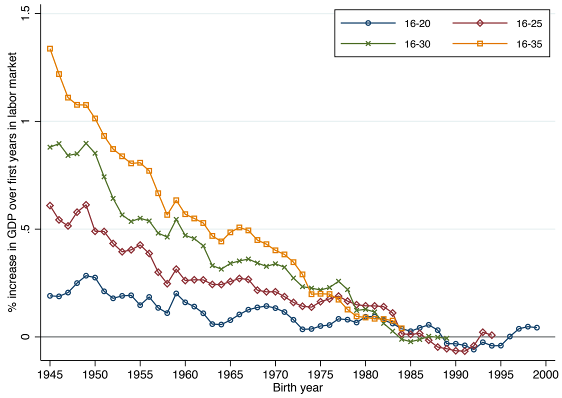


Panel B: By year

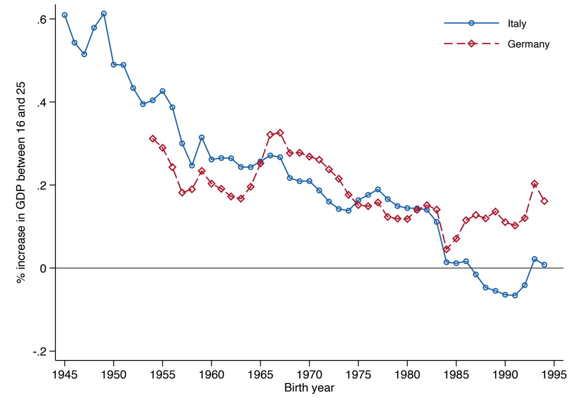
Notes: Panel A decomposes the change in log weekly wages between 1985 and 2019 into three components (Equation (1)) for each individual age. Panel B plots the change in mean log weekly wages between O55 workers and U35 workers, as well as between 1985 and year $t \in [1986, 2019]$. This double difference is further decomposed into three components, following Equation (2). *Sources:* In each year, the data is a representative sample of workers who were over 16 years old, had a full-time contract, and earned positive wages. Country: United States. Time period: 1985-2019. Database: Merged Outgoing Rotation Groups (MORG) of the CPS, https://data.nber.org/morg/annual/.

I Evidence on Forces Behind Age Wage Gap

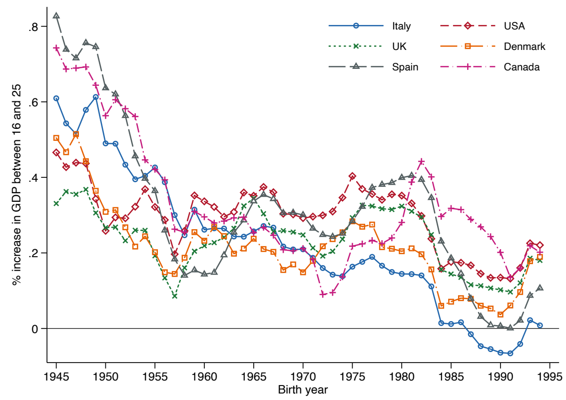
Figure I1: GDP Growth at Entry in Labor Market



Panel A: Italy



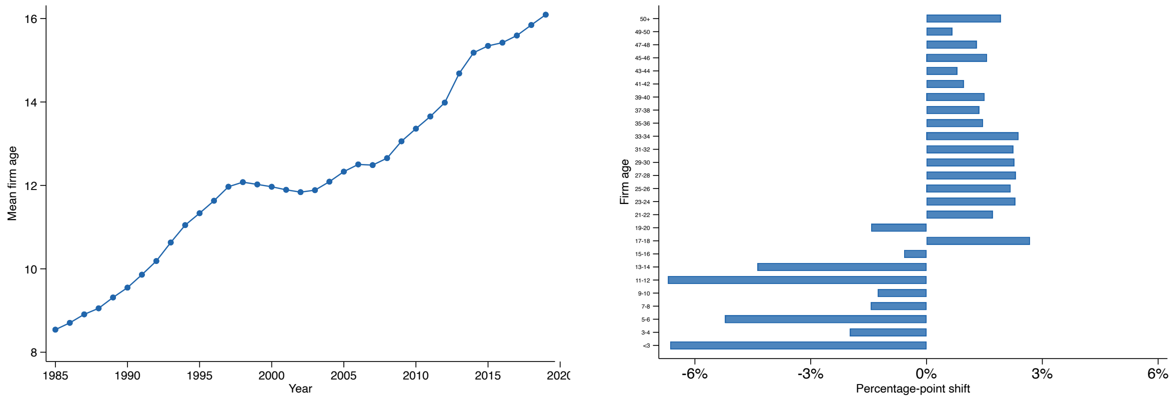
Panel B: Germany



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=.

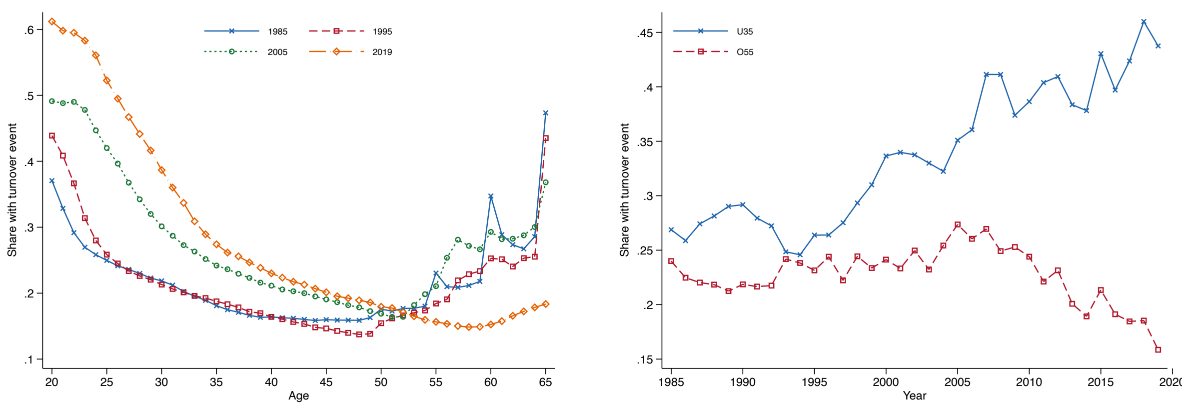
Figure I2: Aging of Firms



Panel A: Mean firm age   Panel B: Change between 1985 and 2019

Notes: Panel A plots the mean age of Italian firms by year. Panel B plots the percentage-point difference in the share of firms in each age bin between 1985 and 2019. For example, "+5%" indicates that the share of firms in that age bin increased by 5 percentage points between 1985 and 2019. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

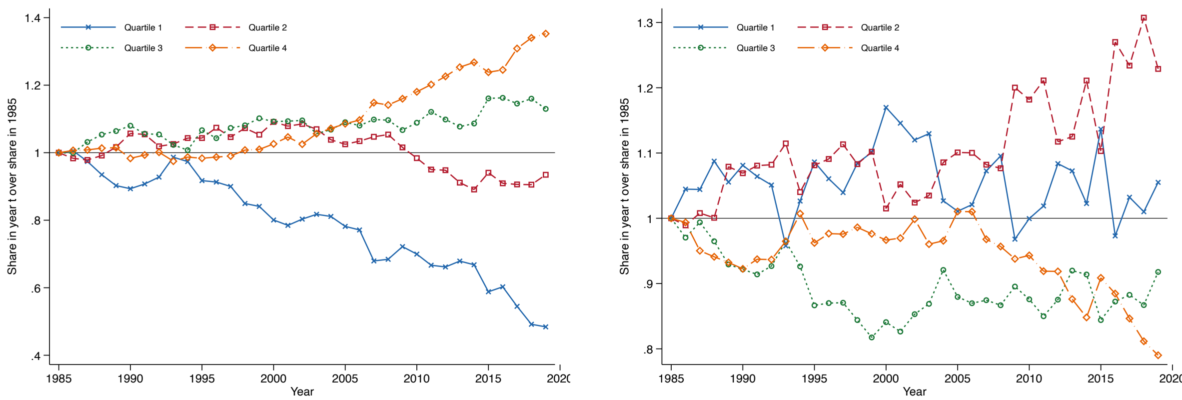
Figure I3: Share of Workers with Turnover Event



Panel A: By age   Panel B: By year

Notes: Panel A plots the share of workers with a turnover event (voluntary or involuntary) by age in four different calendar years. Panel B plots the share of workers with a turnover event (voluntary or involuntary) by year for U35 workers and O55 workers. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure I4: Employment by Quartiles of Firm-Level Turnover

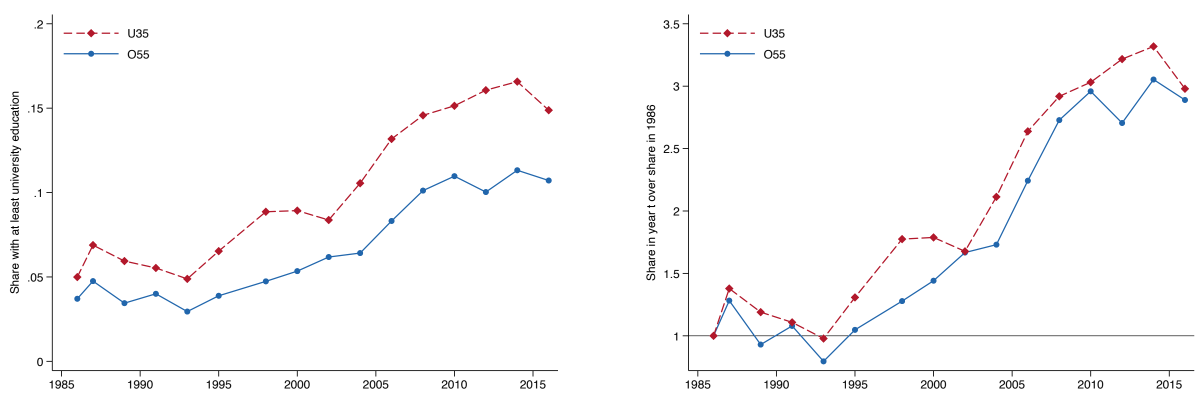


Panel A: U35 workers

Panel B: O55 workers

Notes: In each year, we divide the firms in the sample into quartiles based on the share of their employees who experienced a turnover event (voluntary or involuntary). Then, Panel A shows the ratio between the share of U35 workers in each quartile and the share of U35 in the same quartile in 1985. Panel B plots the same information for O55 workers. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure I5: Shares with at Least University Education

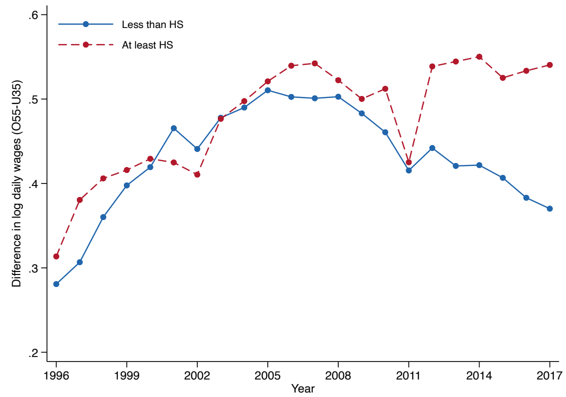


Panel A: Share with at least university education

Panel B: Deviations from 1986

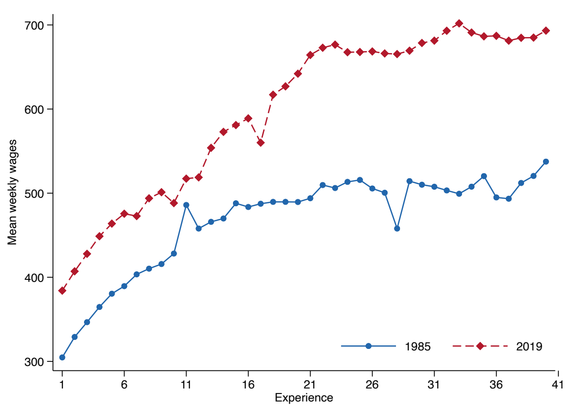
Notes: Due to the unavailability of education information for most workers in the Social Security data, these figures use observations from the Survey of Household Income and Wealth by the Bank of Italy. Panel A plots the share of respondents with at least a university education for U35 workers and O55 workers. Panel B plots the ratio between the share in year t and the share in 1986. *Sources:* Survey of Household and Income Wealth, Bank of Italy, available online at https://www.bancaditalia.it/statistiche/tematiche/indagini-famiglie-imprese/bilanci-famiglie/index.html?com.dotmarketing.htmlpage.language=1.

Figure I6: Age Wage Gap by Education Level (Germany)

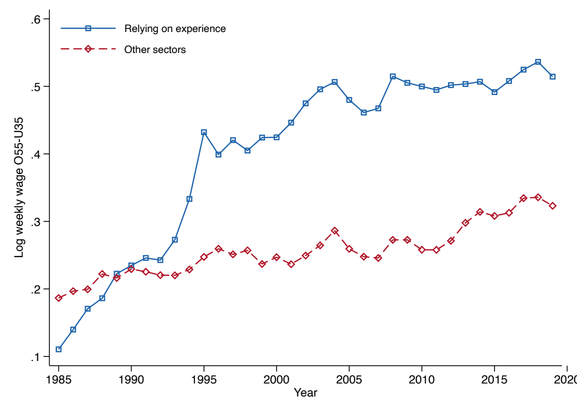


Notes: This graph plots the gap between the mean log daily wages of O55 workers and the mean log daily wages of U35 workers between 1996 and 2017 for workers who did not complete high school and workers who completed high school. The German data allow us to distinguish only between individuals with and without a high-school diploma. *Sources:* In each year, the data pools information about all workers who were over 16 years old, had a full-time contract, and earned positive wages. Country: Germany (1996-2017). Database: LIAB, Institute for Employment Research (IAB).

Figure I7: Influence of Job Experience



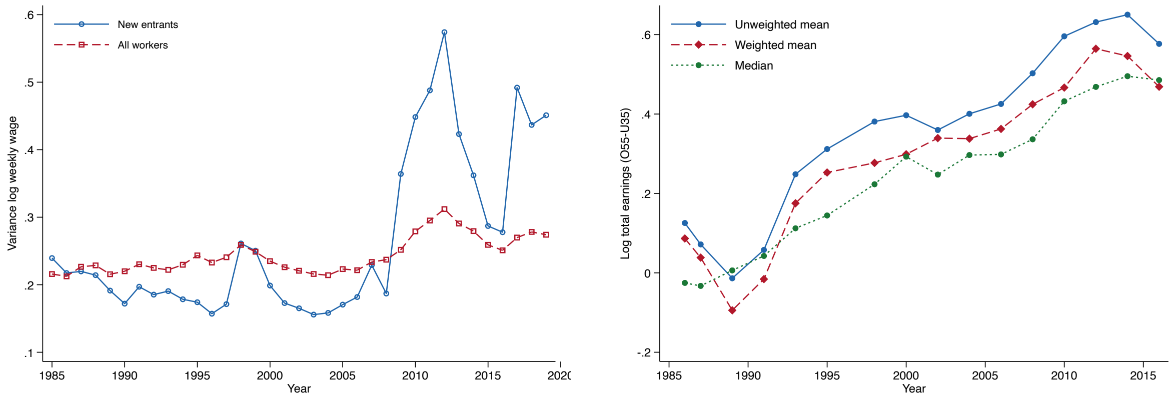
Panel A: Experience profiles (mean weekly wages)



Panel B: Wage gap by reliance on experience at baseline

Notes: Panel A plots the mean weekly wage by years of experience in 1985 and 2019. Panel B plots the age gap in mean log weekly wages between O55 workers and U35 workers distinguishing between two sets of sectors. "Relying on experience" are sectors in the bottom quartile of the share of workers (i) with at most five years of experience and (ii) with a weekly wage in the top decile of the within-sector wage distribution. The share of high-wage and low-experience workers is computed at baseline between 1985 and 1989. "Other sectors" are all the other 3-digit sectors in the economy. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure I8: Selection of Younger Workers

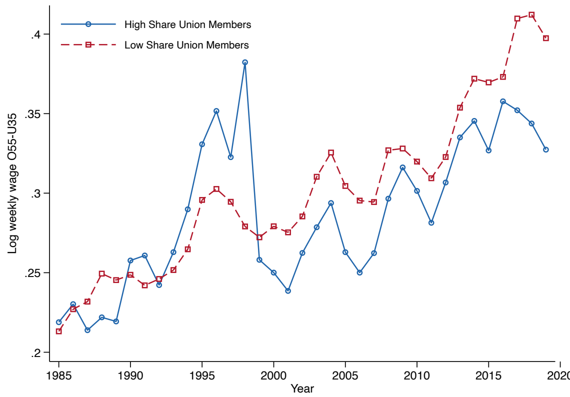


Panel A: Wage variance of younger workers

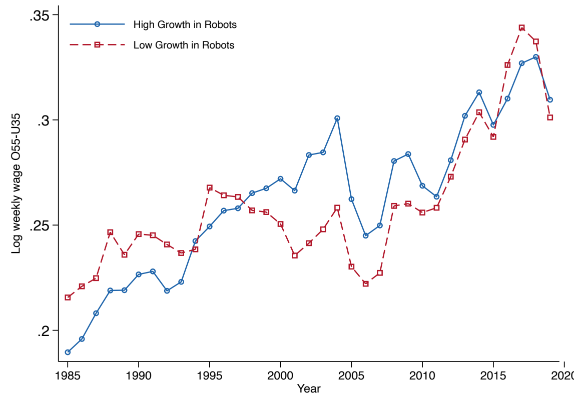
Panel B: Wage gap with all workers (SHIW)

Notes: Panel A plots the variance of log weekly wages of new entrants and all workers for each year. Panel B uses survey data from the Bank of Italy's Survey of Household Income and Wealth (SHIW). Unlike the Social Security data, this representative survey contains information about all types of workers in the labor market, including public servants and self-employed. In this sample, U35 workers were between 16 years old and 34 years old, while O55 workers were between 56 years old and 65 years old. "Weighted mean" weights each observation by the population weights provided with the survey. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Databases: UNIEMENS, Istituto Nazionale della Previdenza Sociale (Panel A); Bank of Italy's Survey of Household Income and Wealth (Panel B).

Figure I9: Influence of Unions and Automation



Panel A: Wage gap by unionization



Panel B: Wage gap by automation

Notes: Panel A plots the age gap in mean weekly wage distinguishing between sectors with low and high unionization at baseline. Data on unionization come from CGIL, the largest and most important Italian trade union: http://sirio2016.cgil.it/tesseramento/analisi.aspx?AspxAutoDetectCookieSupport=1. Using the membership data in 1990, the first available year, we computed the share of the workforce that was affiliated to CGIL in each 3-digit sector and Italian region. "High Share Union Members" identifies sector-region pairs with above-median share of CGIL members in 1990, while "Low Share Union Members" identifies sectors with below-median share of CGIL members. Out of all 271 3-digit sectors, this sample includes only the 133 sectors for which data on CGIL membership are available. Panel B plots the age gap in mean weekly wage distinguishing between sectors with low and high growth in the stock of robots between 1993 and 2019. Data on robots come from the International Federation of Robotics (IFR): https://ifr.org/worldrobotics/. For each 2-digit sector, which is the level of aggregation available in the data, we computed the difference in the per-worker number of robots between 1993, the first available year, and 2019, the last available year. "High Growth in Robots" identifies sectors with above-median growth in the stock of robots, while "Low Growth in Robots" identifies sectors with below-median growth. Out of all 88 2-digit sectors, this sample includes only the 38 sectors for which data on the stock of robots are available.

Table I1: Heterogeneity of Age Wage Gap

	Age wage gap	Ranking shift		Ranking shift x wage trend		Wage trend	
		Logs	Percentage	Logs	Percentage	Logs	Percentage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Heterogeneity by employment growth							
Firms with high emp. growth	0.168	0.125	0.743	0.008	0.048	0.035	0.209
Firms with low emp. growth	0.236	0.193	0.818	0.008	0.033	0.035	0.149
Low-high	0.067***	0.068	1.007	0.000	-0.006	0.000	-0.001
Panel B: Heterogeneity by firm age							
Younger firms ($\leq$ 10 y.)	0.155	0.135	0.873	0.000	0.000	0.020	0.127
Older firms (> 10 y.)	0.215	0.167	0.777	0.011	0.053	0.037	0.170
Older-younger	0.060***	0.032	0.532	0.011	0.189	0.017	0.279
Panel C: Heterogeneity by firm size							
Smaller firms ($\leq$ 50 emp.)	0.177	0.166	0.935	-0.003	-0.016	0.014	0.081
Larger firms (> 50 emp.)	0.210	0.149	0.709	0.015	0.069	0.047	0.222
Larger-smaller	0.033***	-0.017	-0.517	0.017	0.532	0.032	0.985
Smaller firms ($\leq$ 100 emp.)	0.175	0.159	0.907	-0.001	-0.007	0.017	0.100
Larger firms (> 100 emp.)	0.203	0.138	0.681	0.015	0.074	0.050	0.245
Larger-smaller	0.028***	-0.021	-0.757	0.016	0.587	0.032	1.170
Smaller firms ($\leq$ 500 emp.)	0.168	0.143	0.849	0.001	0.006	0.024	0.145
Larger firms (> 500 emp.)	0.196	0.123	0.629	0.015	0.076	0.058	0.295
Larger-smaller	0.028***	-0.019	-0.688	0.014	0.493	0.034	1.195
Panel D: Heterogeneity by labor-market experience of U35 workers							
O55 vs. U35 with 1 y. of exp.	0.137	0.094	0.686	0.019	0.138	0.024	0.176
O55 vs. U35 with 2 y. of exp.	0.149	0.106	0.714	0.010	0.069	0.032	0.217
O55 vs. U35 with 3 y. of exp.	0.142	0.101	0.708	0.006	0.042	0.036	0.250
O55 vs. U35 with 4 y. of exp.	0.149	0.107	0.720	0.004	0.026	0.038	0.254
O55 vs. U35 with 5 y. of exp.	0.153	0.112	0.734	0.000	-0.003	0.041	0.269
O55 vs. U35 with 6 y. of exp.	0.171	0.131	0.768	-0.002	-0.011	0.041	0.243
O55 vs. U35 with 7 y. of exp.	0.187	0.147	0.788	0.001	0.004	0.039	0.208
O55 vs. U35 with 8 y. of exp.	0.190	0.150	0.789	0.004	0.020	0.036	0.191
O55 vs. U35 with 9 y. of exp.	0.194	0.152	0.787	0.006	0.030	0.035	0.183
O55 vs. U35 with 10 y. of exp.	0.217	0.175	0.807	0.010	0.044	0.032	0.149
O55 vs. U35 with 11 y. of exp.	0.224	0.181	0.811	0.014	0.062	0.029	0.127
O55 vs. U35 with 12 y. of exp.	0.218	0.176	0.806	0.015	0.068	0.028	0.126
O55 vs. U35 with 13 y. of exp.	0.191	0.150	0.785	0.012	0.061	0.029	0.154
O55 vs. U35 with 14 y. of exp.	0.173	0.133	0.769	0.011	0.062	0.029	0.170
O55 vs. U35 with 15 y. of exp.	0.178	0.138	0.777	0.011	0.064	0.028	0.158
Panel E: Restricting O55 workers to 55-60							
56-60 vs. U35	0.172	0.133	0.769	0.008	0.046	0.032	0.185
56-60 vs. U35, men only	0.181	0.134	0.741	0.016	0.088	0.031	0.170
O55 vs. U35	0.190	0.149	0.784	0.008	0.041	0.033	0.175

Notes: In Panel A, firms with low employment growth had below-median employment growth between 1985 and 2019, while firms with high employment growth had above-median employment growth over the same period. In Panel B, younger firms were at most ten years old, while older firms were more than ten years old. In Panel C, firms are divided in two categories based on their number of employees. In Panel D, we compare O55 workers to U35 workers with different years of experience in the labor market. In Panel E, we compute the age wage gap including either only individuals between 56 years old and 60 years old among the older workers or all workers who were older than 55 years old (the baseline specification). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned positive wages, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).