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

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Abstract

Using data from multiple high-income countries, this paper shows that the growing gap in the wages of older and younger workers primarily stems from a change in their relative positions in the wage distribution. This finding is compatible with a growing gap in the accumulation of wage-enhancing factors between younger and older workers, not with an increase in the prices of these factors. Additional results corroborate the hypothesis that a larger supply of older workers with progressively longer working lives harmed the careers of younger workers. Unlike what other explanations predict, a large portion of the gap increase happened within firms with constraints in adding higher-ranked positions. Moreover, the rank loss experienced by younger workers stemmed from both an immediate loss at entry and lower post-entry growth. Finally, the gap increase did not depend on changes in the workforce composition.

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1 Introduction

The average age of the workforce has been increasing 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.

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 current aging of the workforce, we would expect the larger supply of older workers to have decreased their wage growth relative to the wage growth of younger workers. Instead, using extensive administrative and survey data, we establish that many high-income countries experienced the opposite trend: the *age wage gap* significantly widened in favor of older workers. For example, the wage gap increased by 0.12 log points in favor of older workers in the United States (1979-2020) and by 0.18 log points in Italy (1985-2019).[2]

After establishing that the age wage gap has been widening, this paper investigates what factors may drive this wage trend. The 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 information on 6.9 million workers from the Luxembourg Income Study for nineteen high-income countries 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 data sources. In the rest of the introduction, we will often 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.

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

[2] We define younger workers as those who were under 35 years old and older workers as those who were above 55 years old.

We first establish one key result. The widening of the age wage gap was primarily driven by a change in the relative positions of younger and older workers in the wage distribution. Specifically, we show that the change in the wage gap between older and younger workers can be divided into two separate parts: (i) a *rank-gap* 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 at baseline; and (ii) a *distributional-gap* component that computes the counterfactual change in the wage gap 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 baseline. We find that the rank gap was the primary driver of the widening of the wage gap in seventeen out of the nineteen high-income economies in our sample. For example, it accounted for 78 percent of the increase in the age wage gap in Italy and for 98 percent in the United States.

Thanks to this initial finding, we can start identifying what explanations are compatible with the widening of the age wage gap. For example, in theory, wage inequality could have caused the age wage gap to increase. At baseline, older workers were already more likely to have higher mean wages, compared with younger workers. Therefore, the widening of the age wage gap could have been a consequence of the increasing distance between higher and lower wages, that is, wage inequality. However, the distributional-gap component directly speaks about the importance of wage inequality because it describes shifts in mean wages in different parts of the distribution. Its small magnitude in most high-income countries indicates that wage inequality is at best a second-order driver of the age wage gap.

Moreover, the importance of the rank gap allows us to draw broader conclusions that extend beyond wage inequality. The remaining possible explanations for the widening of the age wage gap can be categorized in two groups. On the one hand, the prices of several wage-enhancing factors, which older workers possessed in greater quantity at baseline, may have increased over time. For example, prior work has documented that the returns to experience increased in some professions as a result of a higher "burden of knowledge" (Jones, 2009). Similarly, prior work on skill-biased technological change has shown that the introduction of new technology raised the prices of non-routine skills and decreased those of routine skills (Autor, Katz, and Kearney, 2006). Due to the fact that older workers on average have more experience and non-routine skills, an increase in the prices of these factors could have widened the age wage gap. On the other hand, the difference in the quantity of wage-enhancing factors possessed by older and younger workers may have increased over time, a trend that could have widened the age wage gap even without any price change.

Next, we employ a simple numerical framework to simulate changes in either the price of a wage-enhancing factor x or the distribution of x among younger and older workers. For each simulation, we compute the increase in the age wage gap and decompose it into the rank gap and the distributional gap. Under multiple scenarios and starting conditions, the simulated data indicate that a hike in the price of x widens the age wage gap almost exclusively through an increase in the distributional gap. In this case, the share of the overall wage-gap increase stemming from the distributional gap is never below 97 percent. The intuition behind this finding is that a higher price of x can increase the age wage gap only if there is already a positive difference in the quantity of x between older and younger workers at baseline. In contrast, increasing the difference in the mean quantity of x possessed by older and younger workers widens the age wage gap mainly through the rank gap. The share of the overall wage-gap increase coming from the rank gap ranges between 57 percent and 99 percent, depending on the starting conditions. In short, a price hike is only able to exacerbate preexisting wage differences, while a quantity change allows older workers to overcome younger workers in the wage distribution. The latter scenario represents a much better fit for the widening of the age wage gap observed in the data.

After ruling out explanations that revolve around price changes, such as increases in the returns to experience, higher prices for skills, and skill-biased technological change, we discuss four reasons why younger workers may have faced increasing challenges in accumulating wage-enhancing factors. First, Bianchi et al. (2022) has shown that the higher supply of older workers and the lengthening of their working lives can generate negative career spillovers among younger workers, preventing them from receiving wage increases and promotions. Second, Goldschmidt and Schmieder (2017) has documented that a growing number of large firms in Germany has started outsourcing entry-level jobs, which are more likely to be held by younger workers, to other domestic lower-paying business-service companies. Third, Deming (2021) has shown that the employment share in decision-intensive occupations, in which more experienced older workers are more productive than less experienced younger workers, has been increasing in the United States since the 1970s. Fourth, the selection of younger workers may have worsened over time, and vice versa for older workers. The rest of the analysis tests the fit of these four hypotheses to the data. Overall, our results point to the importance of negative career spillovers from older workers to younger workers.

We start by showing that a large portion of the increase in the rank gap happened within firms and within 3-digit sectors, even if the between-firm component grew in magnitude after 2001. In Italy, the within-firm component accounted on average for 61 percent of the rank gap between 1985 and 2019, while the within-sector component accounted for 90 percent. Overall, these findings are not fully compatible with the domestic-outsourcing hypothesis, according to which the increase in the rank gap should happen predominantly between sectors.

We further prove this point by dropping from the sample all sectors that Goldschmidt and Schmieder (2017) identified as primary receivers of domestically outsourced jobs. If domestic outsourcing was the main explanation for the widening of the age wage gap, we should expect to see a much smaller increase in the rank gap after excluding the sectors that gained most of the outsourced jobs. Instead, we find that the increase in the rank gap, the within-firm component, and the within-sector component remain large after dropping high-outsourcing 3-digit sectors. In contrast, these results are consistent with the hypothesis that older workers blocked the careers of younger workers. Bianchi et al. (2022) shows that negative career spillovers can be large both within firms, as exemplified by lower wage growth and fewer promotions, and between firms, in the form of higher turnover. Consistent with these predictions, we also find that younger workers became less likely to hold managerial positions and more likely to experience turnover events, while older workers faced the opposite trends.

Next, we decompose the change in wage rank experienced by younger workers over time into two parts: (i) the change in the wage rank at the time of entry in the labor market, and (ii) the change in rank growth in the years after labor-market entry. We find that both components contributed to decreasing the average rank of younger workers in the wage distribution, and the loss in the rank at labor-market entry had the largest negative magnitude. In Italy, the worsening in the entry rank accounted on average for 58 percent of the total rank loss for workers under 35 years old, while lower post-entry rank growth accounted for the remaining 42 percent. These results indicate that an increase in the demand for decision-making skills may not be the main factor behind the widening of the age wage gap. As shown by Deming (2021), an increase in the supply of decision-intensive jobs, in which the returns to experience are higher than in other types of occupations, is compatible with (i) lower mean wages for new entrants with no experience and (ii) faster wage growth in the post-entry years. However, our results indicate that these patterns in the *wage level* of younger workers do not apply to their *wage rank*, which is the main driver of the widening of the age wage gap. In the case of wage rank, both the entry rank and the post-entry growth substantially decreased over time. In contrast, negative career spillovers can simultaneously worsen the entry rank and the post-entry rank growth of younger workers because more higher-ranked positions are occupied by older workers.

Moreover, we test whether the magnitude of the results is associated with the characteristics of firms. We find that the widening of the age wage gap was significantly larger among firms with more limited opportunities to promote their younger workers, that is, among older and larger firms with lower employment growth. For example, in Italy, the age wage gap increased by 0.24 log points among firms with below-median employment growth and by 0.17 log points among firms with above-median employment growth. This difference is large in magnitude (38 percent of the average increase in the age wage gap) and statistically significant at the 1 percent. In a model of career spillovers, a key feature is that at least some firms need to face constraints in adding higher-ranked jobs to their organizational charts. The fact that firms in a more mature stage of their life cycle may be more likely to face such constraints is consistent with the empirical findings in Bianchi et al. (2022) and the theoretical model in Bennett and Levinthal (2017). In contrast, domestic outsourcing produces opposite predictions. More mature firms were more likely to outsource low-entry low-skill jobs and, therefore, to employ a progressively more positively selected younger workforce. Based on this positive selection, we can infer that the widening of the age wage gap should be smaller than average within these firms.

Finally, we directly test whether changes in the workforce composition over time can explain the widening of the age wage gap. First, using both the administrative and survey data, we regress log wages on individual controls for gender, nationality or race, contract length, education, and health. We then use the residuals from these regressions to compute the resulting age wage gap. Out of 71 total measurements with controls, the increase in the age wage gap is larger than the one obtained without controls in 30 cases and is smaller by at least 50 percent in only 5 cases. Second, we show that the results hold if we focus on older workers who were between 56 years old and 60 years old, rather than all workers over 55 years old. This subsample is less likely to have experienced changes in the selection into retirement, especially in countries with large-scale public-pension systems. Third, we estimate a standard AKM model to assess the influence of unobservable worker and firm fixed effects on the age wage gap. In Italy, differences in the appropriation of firm rents between younger and older workers explain 69 percent of the widening in the age wage gap, a much higher share relative to other forms of wage gap (for example, the gender wage gap). In short, our analysis suggests that changes in worker selection are not plausible explanations for the trends in the age wage gap.

The contribution of this paper is twofold. First, it contributes to the literature that studies changes in the labor outcomes of younger workers. Rosolia and Torrini (2007) and Naticchioni, Raitano, and Vittori (2014) use Italian survey data to show that early-career wages decreased during the 1990s. We complement their findings by further exploring the nature of the age wage gap in multiple countries, an analysis that often requires access to large-scale administrative data that match employers to employees. Moreover, our analysis clarifies how the age wage gap fits within the broader literature on labor economics by investigating its previously untested relationships with several wage trends. For example, we show that the importance of the rank gap rules out well-studied wage trends, such as wage inequality (Autor, Katz, and Kearney, 2008; Card, Heining, and Kline, 2013; Song et al., 2019), changes in the returns to experience (Jones, 2009; Azoulay et al., 2020), skill-biased technological chance (Acemoglu and Autor, 2011; Autor, Katz, and Kearney, 2006), as possible drivers. This finding is also compatible with Jeong, Kim, and Manovskii (2015), which has documented that an increase in the supply of older workers, if anything, decreases the price of experience. Moreover, we provide new results on whether four wage trends that are a priori compatible with the importance of the rank gap fit the data: career spillovers (Bianchi et al., 2022), domestic outsourcing (Goldschmidt and Schmieder, 2017), demand for non-routine skills (Deming, 2021), and selection.

Second, this paper contributes to the literature that studies the interconnectedness of the careers of coworkers. 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; Boeri, Garibaldi, and Moen, 2021; Bianchi et al., 2022; Mohnen, 2021). Our paper uses extensive worker-level administrative and survey 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

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 a full-time contract, had earned strictly positive wages, and had not retired. We impose these restrictions to weed out workers with very short-lived job spells within each year. This dataset allows us to 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.[3] Second, we compute weekly wages by dividing the yearly

[3] 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

labor earnings by the number of working weeks. This new variable may conflate variation in hours worked and pay rates only if workers differ in the number of days they work within a week. Although this is 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.[4] Moreover, they are winsorized at the 99.9th 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 A1, Panel A).

2.2 Data for Other Countries

In addition to the Italian data, we have access to confidential employer-employee Social Security data for Germany from 1996 to 2017 provided by the Institute for Employment Research (IAB). This dataset combines (i) information from a sample of establishments with at least one employee subject to Social Security taxation (the IAB Establishment Panel) 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 95th percentile. We select our sample applying the same restrictions described in Section 2.1 for the Italian Social Security data.[5]

Without access to administrative datasets, we can compute the age wage gap for other countries using survey data from the Luxembourg Income Survey (LIS) database. Out of all the available countries in the LIS database, we focus on nineteen high-income economies with sufficiently long time series: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom, and United States. For each country, we compute changes in the age wage gap using yearly labor earnings, after converting them to 2011 purchasing-power-parity US dollars. Moreover, whenever possible, we apply the same sample restrictions used on the

is a voluntary bonus usually paid during the summer.

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

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

administrative data from Italy and Germany.

Finally, it should be noted that both the German data and the LIS database have some limitations in comparison to the Italian INPS data. In light of these limitations, the German and LIS data can be used to replicate only a subset of all the empirical tests that we carry out with the Italian INPS data (Table A2 for an overview). However, this subset of tests shows that the various data sources produce similar results, indicating that Italy and most of the other high-income economies in the sample shared similar trends in the age wage gap.

3 The Widening of the Age Wage Gap

3.1 The Age Wage Gap in Italy

The Italian administrative data indicate that the mean worker age increased by 19 percent from 35.8 years in 1985 to 42.7 years in 2019 (Table 1, Panel A, columns 1 and 2). Three main post-World-War-II demographic trends can explain this stark aging of the workforce. First, the birth rate in Italy decreased from 18.1 births per 1,000 people in 1960 to 7.3 births per 1,000 people in 2018.[6] Second, life expectancy at birth increased by 21 percent from 1960 to 2018, moving from 69.1 years to 83.3 years.[7] 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.[8]

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 workers who were over 55 years old (thereafter, *O55 workers*) and workers who were under 35 years old (*U35 workers*) grew by 0.18 log points from 0.19 log points in 1985 to 0.37 log points in 2019 (Figure 1, Panel A). This large widening of the age wage gap did not happen only at the average, but rather at every point of the distribution of weekly wages (Table 1, Panel A, columns 6 to 10). For example, the age gap increased by 0.2 log points at the 10^{th} percentile, by 0.1 log points at the 25^{th} percentile, by 0.14 log points at the median, by 0.25 log points at the 75^{th} percentile, and by 0.18 log points at the 90^{th} percentile.

Moreover, we observe that 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

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

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

[8] 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.

1985 and 2019, while O55 workers experienced wage increases between 33 percent for 56-year-olds and 53 percent for 65-year-olds (Figure 1, Panel B). As a consequence, the age profile of wages became much steeper over time.

Finally, the increase is even larger if we compute the age gap using yearly labor earnings, rather than weekly wages (Figure 1, Panel C). In this case, we find that the gap in mean yearly earnings between O55 workers and U35 workers increased by 0.2 log points between 1985 and 2019. This larger increase indicates that differences in the number of working weeks contributed to widen the earning gap between older and younger workers.

3.2 The Age Wage Gap in Other High-Income Countries

The aging of the workforce and the growing gap in wages between older and younger workers did not affect only the Italian labor market.

In Germany, the other country for which we have extensive employer-employee administrative data, the mean worker age increased by 9 percent between 1996 and 2017, while the age wage gap between O55 workers and U35 workers increased by 0.1 log points over the same period (Table 1, Panel A). Unlike the Italian case, the widening of the age gap in Germany was concentrated around the 25^{th} percentile (+0.34 log points) and the median (+0.1 log points) of the distribution of daily wages.

The LIS survey data allow us to look at the same trends in many different countries (Table 1, Panel B). Out of nineteen countries in our sample, eighteen of them witnessed an increase in the mean age of the workforce in the past decades. Finland and Denmark experienced the largest growth (+19 percent and +17 percent, respectively), while Israel was the only country in which mean worker age decreased.

Moreover, as we observed in Italy and Germany, the labor earnings of O55 workers grew at a much faster pace than those of U35 workers. The age gap in mean yearly earnings increased in seventeen countries, while it decreased only in France and Ireland. For example, it increased by 0.12 log points in the United States (1979-2020), by 0.06 log points in the United Kingdom (1979-2018), by 0.09 log points in Canada (1991-2017), and by 0.23 log points in the Netherlands (1983-2018). Finland and Denmark are two other interesting case studies. These countries started at very low degrees of disparity between older and younger workers: in 1987, the age wage gap was equal to only 0.04 log points in Finland and to 0.16 log points in Denmark.[9] Then, their age gaps experienced a very steep increase, growing by 0.21 log points and 0.19 log points, respectively, by the end of 2016.

The fact that the LIS data cover different time periods in each country makes it difficult

[9] In comparison, the age gap between O55 workers and U35 workers in 1987 was equal to 0.27 log points in Italy (INPS data), 0.33 log points in the Netherlands, and 0.25 log points in the United States.

to directly compare the magnitude of these trends across different economies. However, this analysis clearly indicates 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, the United Kingdom, and Canada), in Northern European countries with more developed welfare states (like Germany, Denmark, Finland), as well as in other Southern European countries (like Greece and Spain).

4 The Age-Based Rank Gap in Wages

Up to this point, we have established that the age wage gap has been widening in Italy, as well as in most other high-income economies, for at least the last three decades. In this section, we propose a decomposition of this wage trend that allows us to start analyzing its drivers.

4.1 Distributional Wage Gap and Rank Wage Gap

The widening of the age wage gap can be expressed as the sum of two forces. On the one hand, 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. On the other hand, U35 workers may have shifted toward the bottom of the wage distribution, while O55 workers may have risen to the top. This shift along the wage distribution did not necessarily require changes to the support of the distribution. In this section, we decompose the age wage gap into these two components.

Proposition 1. *The change in the average log wage w between U35 workers and O55 workers, as well as between years t and t', can be written as follows:*

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

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

Equation (1) indicates that the widening of the age wage gap can be written as the sum of three components. A first portion stems from variation over time in the average wages earned in different vigintiles v of the distribution, keeping the share of workers in all age groups and vigintiles fixed at baseline year t. This component represents a pure *distributional gap*. In fact, it measures how much the progressive change in the support of the wage distribution affected the wage gap between younger and older workers, while preventing individuals in both age groups from moving along the wage distribution over time. Next, a second portion comes from variation over time in the difference between the shares of younger and older workers in each vigintile v of the wage distribution, keeping the overall shape of the wage distribution fixed at baseline. This component is a pure *rank gap* that stems entirely from shifts in the relative positions of younger and older workers along the wage distribution, while the support of the distribution is kept untouched. Finally, a third portion is a *residual* that comes from the interaction between changes in shares s and mean wages $\bar{w}$.

Using the Italian administrative data and Equation (1), we decompose the age wage gap in log weekly wages between 1985 and 2019 to establish three main results. First, by 2019, the rank gap accounted for 78 percent of the total increase in the wage gap between U35 workers and O55 workers (Figure 2, Panel A). Second, the rank gap has been the major driver of the widening of the age wage gap throughout the period under consideration, contributing between 53 percent in 1987 and 81 percent in 2004. Third, if we replace weekly wages with yearly earnings, the rank gap accounted for an even larger share of the age gap (83 percent in 2019) (Figure B1).

We can further investigate the differences between the distributional gap and the rank gap by decomposing the change in mean wages over time separately for each age group (Figure 2, Panel B). These results indicate that the distributional gap increased the wages of both age groups, albeit the increase was larger among O55 workers (+0.27 log points vs. +0.24 log points). Moreover, the rank gap contributed to decreasing the wages of younger workers (-0.09 log points) and to increasing the wages of older workers (+0.06 log points). This finding indicates that the movement of U35 workers between vigintiles of the wage distribution over time caused a decrease in their weekly wages, while the opposite is true for O55 workers.

The fact that younger and older workers moved in opposite directions along the wage distribution is apparent in the data beyond the decomposition in Equation (1). Between 1985 and 2019, the probability of U35 workers being in the top quartile of the distribution of weekly wages decreased by 34 percent, while their probability of being in the bottom quartile increased by 23 percent (Figure 3, Panel A). In contrast, O55 workers experienced the opposite trend, becoming more likely to be at the top of the wage distribution and less likely to be at the bottom (Figure 3, Panel B). This finding holds if we move from quartiles to vigintiles (Figure 3, Panels C and D).

Finally, we repeat the decomposition in Equation (1) using the LIS survey data. Out of the seventeen countries in which the age wage gap widened in the last decades, the rank gap accounts for the absolute majority of the increase in twelve countries and for its relative majority in fourteen countries (Table 1, Panel B, Columns 4 and 5). For example, it accounted for 98 percent of the increase in the age wage gap in the United States.

4.2 What Can and Cannot Explain the Widening of the Age Wage Gap

Several phenomena could a priori explain why the age wage gap has been increasing in favor of older workers, in spite of a concurrent and stark increase in their relative supply. Here, we discuss what explanations are compatible with the main takeaway of Section 4.1, that is, the fact that a change in the relative rank of younger and older workers in the wage distribution accounts for most of the widening in the age wage gap.

We start from wage inequality because it has a direct connection to Equation (1). Many prior papers have documented a substantial increase in wage inequality in high-income economies (for example, Piketty and Saez (2003) and Autor, Katz, and Kearney (2008)). In theory, this phenomenon could have widened the age wage gap. In fact, O55 workers were always more likely to hold higher-paying jobs, which experienced higher increases in mean wages, while U35 workers were always more likely to hold lower-paying jobs, which experienced much smaller or no increases in mean wages. In Equation (1), the distributional gap directly captures the influence of wage inequality; it measures how shifts in mean wages in different parts of the distribution contributed to the widening of the age wage gap, while keeping the relative rank of younger and older workers fixed at baseline. As documented in Section 4.1, the distributional gap, and therefore wage inequality, can account for only a minor portion of the widening in the age wage gap in most high-income countries.

Next, we address other phenomena that are a priori consistent with the trends in the age wage gap. However, unlike wage inequality, these explanations do not have a one-to-one correspondence with a single component of Equation (1). Therefore, it is not yet clear whether they operate through the distributional gap or the rank gap. In what follows, we propose a simple numerical framework that allows us to (i) divide the remaining explanations in two macro-groups and (ii) assess through what component of Equation (1) these two macro-groups influence the age wage gap.

Consider a simple setting in which wages are a function of a single wage-enhancing factor: $w^t_{i,a} = \beta_0 + \beta^t_1 x^t_{i,a}$. In this equation, $w^t_{i,a}$ measures the wage of worker i of age group $a \in \{\text{Younger}, \text{Older}\}$ in period t, $x^t_{i,a}$ captures the quantity of the wage-enhancing factor possessed by worker i in period t, and β_1^t is the unitary price of factor x in period t. The variable x represents any worker characteristic that is associated with higher wages, such as experience, skills, education, job level, and other features of the labor contracts. Moreover, it is not equally distributed between younger and older workers; we assume that older workers posses on average a higher quantity of x. This assumption implies that the age wage gap is positive in favor of older workers in the baseline period t, a fact that is consistent with all the data sources explored in Section 3.

Even in its extreme simplicity, this framework allows us to isolate two groups of plausible mechanisms for the increase in the age wage gap. First, some explanations involve an increase over time in the price of the wage-enhancing factor x. Since older workers possess on average a higher quantity of x, an increase in its price translates into an increase in the age wage gap. Second, other explanations involve a growing gap in the quantity of x owned by older and younger workers, which in turn widens the age wage gap. In order to assess the importance of these two forces, we calibrate a change in either the coefficient β_1 or the distribution of x among younger and older workers. In each of these scenarios, we compute the increase in the age wage gap and use Equation (1) to decompose it into the rank gap and the distributional gap. In order to match the empirical evidence in Section 4.1, the changes in the price and quantity of x need to operate on the age wage gap mostly via the rank gap.

To start, we test the consequences of an increase in the price of factor x (Table 2, Panel A). Under the baseline scenario, we calibrate the wage equation to match five moments in the first available year of the Italian administrative data: the mean (5.6) and standard deviation (0.5) of the log weekly wages of U35 workers, the mean (5.7) and standard deviation (0.7) of the log weekly wages of O55 workers, and the ratio between O55 workers and U35 workers (0.08). Therefore, we set $\beta_0 = 1$, $\beta_1^t = 1$, $x_{\mathrm{Y}}^t \sim N(4.6, 0.25)$ for younger workers, $x_{\mathrm{O}}^t \sim N(4.7, 0.49)$ for older workers, and the share of older workers to 8 percent. When β_1 increases from 1 in period t to 2 in period t', the age wage gap increases by 0.09 log points (columns 1 to 3). Out of this total increase, 99 percent stems from the distributional gap. The intuition behind this finding is that a higher price of x can increase the age wage gap only if there is already a positive difference in the quantity of x between older and younger workers at baseline. In this case, a higher price of x modifies the overall shape of the wage distribution by pushing older workers farer apart from younger workers.

This result holds if we allow the share of older workers to grow in period t' to either 20 percent or 35 percent, an increase that matches the actual growth observed in Italy by 2019. Moreover, the results are robust if the coefficient β_1 increases to 4, instead of 2. Finally, we find that the distributional gap accounts for at least 97 percent of the increase in the age wage gap even after different assumptions for the distribution of x in the baseline period t.

Specifically, we test cases in which there is either a smaller or bigger distance in the mean of x between younger and older workers (columns 4 to 9), as well as scenarios in which the distributions of x at baseline have either lower or higher variance (columns 10 to 15).

In short, the first implication of this numerical exercise is that an increase in the price of a wage-enhancing factor that older workers posses in greater quantity *cannot* generate a large increase in the rank gap between younger and older workers. Two main phenomena fall within this category. First, several papers have shown that the returns to experience increased over time. For example, Jones (2009) shows that many academic and scientific tasks became more complex and started requiring more skills. This increased "burden of knowledge" induced many inventors to lengthen their investment in education, thereby pushing the peak in their labor earnings later in their life cycle. Azoulay et al. (2020) finds similar results for entrepreneurs. Second, within the rich literature on skill-biased technological change (for an overview, see Acemoglu and Autor (2011)), Autor, Katz, and Kearney (2006) formulates a model in which new technology complements the non-routine tasks of high-wage jobs, which increases the prices of these tasks. Compared with younger workers, older workers are more likely to hold higher-paying jobs and perform non-routine tasks, due to their higher experience and tenure. In an adjacent strand of the literature, prior work has shown that the demand for skills changed over time in ways that may have favored older workers (for example, Deming (2021) for decision-making skills). This mechanism tends to have two parts: a change in the share of occupations requiring certain skills, and a change in the market returns of these skills. Our framework indicates that the latter component cannot be a first-order factor behind the widening of the age wage gap. Beyond our numerical exercise, Jeong, Kim, and Manovskii (2015) shows that the progressive increase in the supply of older workers was responsible for a decrease in the price of experience, which in turn would have reduced the age wage gap. The fact that we observe a large widening of the age wage gap, together with an increase in the supply of older workers, confirms that the underlying mechanism does not involve an increase in the returns to experience.

Next, we test the consequence of an increase in the mean of x for older workers (Table 2, Panel B). Under the baseline scenario, when the mean of x increases from 4.7 in period t to 4.8 in period t', the age wage gap increases by 0.09 log points (columns 1 to 3). Using Equation (1), we establish that 97 percent of the total increase comes from the rank gap, while only 2 percent stems from the distributional gap. The rank gap drives the majority of the increase in the age wage gap even if we allow the share of older workers to grow in period t' or if the mean of x for older workers increases to 5, instead of 4.8. Moreover, this finding holds under different assumptions for the distributions of x at baseline (columns 4 to 15). Here, we show that, even if the rank gap is always accounting for the majority of the increase in the age wage gap, its contribution tends to be larger when the distributions of x among younger and older workers are more overlapping in period t. The intuition is that more overlap at baseline allows older workers to overcome more younger workers in the overall wage ranking when the two distributions move farther apart in period t'.

In short, a progressively larger gap in the quantity of a wage-enhancing factor possessed by younger and older workers *can* generate a large increase in the rank gap.

4.3 Hypotheses Compatible with the Increase in the Rank Gap

In this section, we describe four phenomena that may have increased the preexisting age gap in the quantity of various wage-enhancing factors, therefore widening the age rank gap in wages.

The first mechanism revolves around the interconnectedness of the careers of younger and older workers. Specifically, prior work has shown that the increased supply of older workers and the lengthening of their working lives negatively affected the career prospects of younger workers, especially within firms that had more difficulty in adding higher-ranked positions. For example, Bertoni and Brunello (2020), Boeri, Garibaldi, and Moen (2021), and Bianchi et al. (2022) show that an unexpected increase in the minimum retirement age in Italy led to fewer promotions, lower wage growth, more layoffs, and less hiring among younger workers. In the United States, Mohnen (2021) documents that fewer retirees in a commuting zone are associated with higher youth unemployment in low skill jobs in the same area.

Bianchi et al. (2022) shows both theoretically and empirically that two types of labor-market frictions are needed to generate these negative career spillovers. First, firm separations need to be costly for the worker and/or the firm, so that workers receive a premium for staying longer at the firm. 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). 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). Second, at least some firms need to face constraints in adding higher-level positions to their organizations.

Within our simple framework, the increasing supply of older workers and the lengthening of their working lives implies that older workers started filling more higher-ranked jobs for more years. This demographic shift, combined with the inability of many firms to add slots at the top, allowed older workers to accumulate a larger quantity of many wage-enhancing factors x (experience, skills, higher job titles), while younger workers experienced the opposite trend.

The second mechanism is domestic outsourcing. Goldschmidt and Schmieder (2017) shows that a growing number of large firms in Germany has started outsourcing low-skill jobs to external lower-paying business-service firms. Since younger workers are more likely to hold the low-skill jobs that have been progressively outsourced (Figure B2), domestic outsourcing could have widened the age wage gap.

The third mechanism is a shift in the demand of job skills. Deming (2021) shows that the employment share in decision-intensive occupations has been increasing since the 1970s. These same occupations offer a competitive advantage to older workers, due to the fact that experience is more valuable for decision-making non-routine tasks than for other types of jobs. Therefore, an increase in the availability of occupations in which older workers are more productive may have improved their employment opportunities, allowing older workers to widen their wage gap over younger workers.

Finally, the selection of younger and older workers may have changed over time in ways that moved the distributions of several wage-enhancing factors x farther apart. For example, the progressive increase in youth employment may have induced more low-skill younger workers in the labor market, widening the age wage gap. In the data, this mechanism implies that the share of workers with characteristics that are more often associated with lower wages should have grown more quickly among younger workers.

5 Characteristics of the Age-Based Rank Gap in Wages

In Section 4, we identified four main mechanisms that are compatible with the primary role played by the rank gap in widening the age wage gap: career spillovers, domestic outsourcing, demand for skills, and selection. In this section, we propose four sets of tests to further analyze the nature of the increase in the rank gap: (i) a decomposition between and within firms or sectors, (ii) a decomposition between the rank gap at the time of labor-market entry and its subsequent post-entry growth, (iii) an heterogeneity analysis across different types of firms, and (iv) controls for changes in the workforce composition. Out of the four hypotheses, career spillovers are the only one compatible with all sets of results.

5.1 Gap Between and Within Firms or Sectors

In this section, we measure how much of the increase in the rank gap happened either between or within firms. We then repeat the same analysis for 3-digit sectors. In order to further decompose the rank gap in Equation (1), 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).

Starting from the decomposition between and within firms, we sort workers into 100 percentiles or *firm groups* using their firm's average log weekly wage, separately for each year in the sample. Next, within each of these 100 initial groups, we sort workers into 500 quantiles based on the difference between their weekly wage and the average weekly wage in their firm group. The end product of this two-step process is the sorting of all workers into 50,000 equal-sized bins, which we call *firm-worker groups*.[10] 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:

$$s_{a,(f,e),t} = \underbrace{s_{a,f,t}}_{\text{Share of } a \text{ in } f} \cdot \underbrace{s_{a,(e|f),t}}_{\text{Share of } a \text{ in } e \text{ conditional on } f} . \tag{2}$$

The unconditional share of workers in age group a and firm-worker group (f, e) is the product of (i) the share of workers in age group a and firm-group f ($s_{a,f,t}$) and (ii) the share of workers in age group a and worker group e conditional on being in firm group f ($s_{a,(e|f),t}$). Using Equation (2), we can rewrite the rank gap in Equation (1) as follows:[11]

$$\begin{aligned}\underbrace{\sum_v \Delta s_{O55-U35,v,t'-t}\bar{w}_{v,t}}_{\text{Rank gap}} &= \underbrace{\sum_{g\in(f,e)} \Delta s_{O55-U35,f,t'-t} \cdot \Delta s_{O55-U35,(e|f),t} \cdot \bar{w}_{g,t}}_{\text{Between firms}} \\ &+ \underbrace{\sum_{g\in(f,e)} \Delta s_{O55-U35,f,t} \cdot \Delta s_{O55-U35,(e|f),t'-t} \cdot \bar{w}_{g,t}}_{\text{Within firms}} + \underbrace{\varepsilon^{t,t'}_{\text{O55-U35}}}_{\text{Residual}} .\end{aligned} \tag{3}$$

This equation indicates that the rank gap can be written as the sum of two main counterfactual scenarios. First, a between-firm component identifies a change in the share of workers in age group a and firm group f between t and t', while keeping both (i) the distribution of workers within each firm-worker group g and (ii) the mean wages in each firm-worker group g fixed in year t. Under this scenario, workers of age group a can move over time across firm groups, but the intra-firm-group distributions are kept untouched. Second, a within-firm component isolates a change over time in the share of workers in age group a and firm-worker group $(e|f)$, while keeping both (i) the distribution of workers across firm groups f and (ii) the mean wages in each firm-worker group fixed in year t. In other words, workers in age group a can move over time within firm groups, but their allocation across firm groups stays fixed in year t. Finally, there is a residual component that is the product

[10] In most cases, this procedure ensures that all workers within a firm are assigned to the same firm-based group. 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 to the actual shares observed in the raw data. As expected, the predicted shares are close to the actual ones (Figure C1).

[11] Appendix C.1 provides more details on this decomposition.

of the two previous changes in the shares of workers.

Using the Italian administrative data, we measure the magnitudes of the components in Equation (3) (Figure 4, Panel A). The within-firm component was the main driver of the widening in the rank gap until 2008, and its magnitude remained large until 2019. On average, it accounted for 61 percent of the rank-gap increase between 1985 and 2019. After 2001, the between-firm component became responsible for most of the increase in the rank gap. While its average contribution was 43 percent, it accounted for 62 percent of the rank-gap increase in 2019.

Next, we further analyze the between-firm component by decomposing the increase in the rank gap between and within 3-digit sectors (Figure 4, Panel B). There are two minor differences in this procedure. First, instead of creating 100 initial groups, we consider each 3-digit sector as a separate *sector group*. Second, we create 200 worker groups within each 3-digit sector for a total of 54,000 *sector-worker groups*.[12] The results indicate that a significant portion of the between-firm component remained within 3-digit sectors. The within-sector component was by far the main driver of the rank gap throughout sample, accounting on average for 90 percent of the total increase.

These tests allow us to assess the fit of two hypotheses to the data: domestic outsourcing and career spillovers. Domestic outsourcing requires that most of the increase in the rank gap should happen between firms and, more importantly, between sectors. One of the key takeaway in Goldschmidt and Schmieder (2017) is that outsourced jobs progressively moved from large and established firms operating in many different fields to smaller business-service firms concentrated in just a few sectors. Therefore, domestic outsourcing is broadly consistent with the fact that the magnitude of the between-firm component increased from 2007. However, the more general takeaway from the data is that the within-sector portion accounted for the vast majority of the increase in the rank gap, a fact that is incompatible with domestic outsourcing.

There is another piece of evidence that clashes with the predictions of domestic outsourcing. We can repeat this analysis dropping from the sample the few sectors identified by Goldschmidt and Schmieder (2017) as primary receivers of domestically outsourced jobs (Figure 4, Panels C and D).[13] If domestic outsourcing was the main driver of the increase in the age wage gap, this subsample would show a much smaller increase in the rank gap and different results from the decomposition in Equation (3). Instead, we observe that the increase in the rank gap remains large.

[12] We create 200, rather than 500, worker groups within each sector in order to have enough observations in each worker-sector group.

[13] In the NACE Rev. 2 classification, these 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.

In contrast, career spillovers offer different implications for the decomposition between and within firms. Surely, a model of career spillovers does not predict that these negative effects should be concentrated in the few sectors exposed to domestic outsourcing. Moreover, Bianchi et al. (2022) shows that negative career spillovers can exist both within and between firms. Within firms, older workers who stay longer in their positions can harm the career prospects of their own younger coworkers. Between firms, blocked career opportunities can induce younger workers to find other jobs, leading to losses in their accrued firm-specific benefits and subsequent wage penalties. If firms use seniority for promotion decisions, the theoretical model in Bianchi et al. (2022) points out that negative career spillovers should increase voluntary turnover especially among U35 workers, who tend to have the lowest tenure and therefore less to lose from leaving. Moreover, we can infer that younger workers who decide to switch firms for better career prospects, may decide to stay within the same 3-digit sector in order to take advantage of the sector-specific human capital they accrued in their previous job. In short, according to the career-spillover hypothesis, we should expect to see a combination of within-firm and between-firm effects, and the within-sector component should be predominant. Moreover, there should be little heterogeneity across high-outsourcing and low-outsourcing sectors. The data match these predictions well.

Beyond the decomposition in Equation (3), our data offer additional evidence on the existence of these negative spillovers both within and between firms. Within firms, we observe an increasing age gap in the probability of holding higher-ranked job titles.[14] 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 percent to 3 percent over the same period (Figure C2, Panel A).[15] Between firms, U35 workers became increasingly more likely to have fragmented careers, while O55 workers experienced the opposite trend (Figure C3, Panel A). Moreover, unlike O55 workers, U35 workers became increasingly more likely to work for firms with high turnover rate (Figure C3, Panels B and C).

5.2 Entry Rank and Rank Growth

In this section, we test whether the loss in wage rank experienced by younger workers happened at the time of labor-market entry or during the post-entry years. To do so, we decompose the rank change of U35 workers between year t and t' as follows:

[14] The INPS 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.

[15] Due to the fact that O55 workers were more likely to be managers at baseline, the progressive aging of the population could mechanically increase the share of O55 managers. However, the results hold if we divide the number of O55 (U35) managers by the total number of O55 (U35) workers, rather than by the total number of managers (Figure C2, Panel B).

$$
\underbrace{\sum_{v}\left(s_{a(b,t'),v,t'} - s_{a(b,t),v,t}\right)\bar{w}_{v,t}}_{\text{Rank change}} = \underbrace{\sum_{a(b,t')\in[16,34]} s_{a(b,t),t}\cdot\sum_{v}\left[\left(s^{E}_{a(b,t'),v} - s^{E}_{a(b,t),v}\right)\cdot\bar{w}_{v,t}\right]}_{\text{Change in entry rank}} + \underbrace{\sum_{a(b,t')\in[16,34]} s_{a(b,t),t}\cdot\sum_{v}\left[\left(\Delta s^{t'-E}_{a(b,t'),v} - \Delta s^{t-E}_{a(b,t),v}\right)\cdot\bar{w}_{v,t}\right]}_{\text{Change in rank growth}}, \tag{4}
$$

where $a(b,t)$ is age $a \in [16,34]$ of birth cohort b in year t, v indicates a vigintile of the distribution of weekly wages, $s_{a(b,t),v,t}$ is the share of U35 workers of age a in vigintile v and year t, $\bar{w}_{v,t}$ is the mean wage in vigintile v and year t, $s_{a(b,t),t}$ is the share of U35 workers of age a in year t, $s^{E}_{a(b,t),v}$ is the share of U35 workers of age a in vigintile v *at the time of entry in the labor market* (E), and $\Delta s^{t-E}_{a(b,t),v}$ is the change in the share of U35 workers of age a in vigintile v between labor-market entry E and current year t. The last component can be rewritten as $\Delta s^{t-E}_{a(b,t),v} = s_{a(b,t),v,t} - s^{E}_{a(b,t),v}$.[16]

Equation (4) indicates that the left-hand side can be expressed as the sum of two terms. The first component revolves around the difference in the wage rank at the time of labor-market entry between U35 workers at time t and U35 workers at time t'. The second component measures how much the growth in wage rank of U35 workers between the year of labor-market entry and the current year changed between t and t'. If we plotted the wage rank over the life cycle, the first term would isolate changes over time in the intercept of the curve, while the second term would describe changes over time in the slope during the first years after labor-market entry.

We measure Equation (4) using the Italian administrative data, which is the only dataset under our control with information about the year of labor-market entry. Since the INPS data become first available in 1974, we start this analysis in 1995, one of the first years with information on the entry wage for all U35 workers. Moreover, in order to reduce noise, we compute the wage distribution at labor-market entry using the first three years of work, rather than just the first one. Between 1995 and 2019, changes in the wage rank of U35 workers reduced weekly wages by 0.07 log points (Figure 5, Panel A). During the first years of the sample, most of this decrease stemmed from a decline in the post-entry rank growth, which accounted for 79 percent of the total rank loss in 2002. Starting in 2003, the worsening in the entry rank became the primary driver of the total loss in wage rank. By 2019, the entry rank represented 86 percent of the overall decline in wage rank. The role of the entry

[16]In Equation (4), we keep the share of U35 workers of age a fixed at baseline. Appendix C.2 shows that the results hold we adopt different assumptions.

rank is even more important if we decompose the rank change for U30 workers, rather than U35 workers. Focusing on a younger group of workers with shorter careers allows us to push the start of the analysis back to 1990 (Figure 5, Panel B). In this case, the loss in wage rank was equal to 0.1 log points in 2019, and 87 percent of it stemmed from a worsening in the entry rank.

These results allow us to further assess the fit of all four hypotheses outlined in Section 4.3 to the data. If a change in the demand for skills caused the loss in the wage rank experienced by younger workers, we would expect starkly different patterns in the decomposition from Equation (4). Focusing on the level of wages over the life cycle, Deming (2021) shows that an increase in the supply of decision-intensive jobs is compatible with a decrease in the intercept of the wage curve and an increase in its slope. In other words, the average level of wages for new entrants in the labor market has progressively lowered in part because because the share of decision-intensive jobs, which offer larger rewards for experience, has expanded. By the same token, the growth rate in the level of wages during the post-entry years has increased because the labor market has more positions with higher returns to experience. However, the data indicated that these patterns in the wage *level* of younger workers do not apply to their wage *rank*. In this case, we observe that both the entry rank (the intercept) and the post-entry rank growth (the slope) substantially decreased over time.

In contrast, the other three explanations in Section 4.3 are compatible with the results from Equation (4). Negative career spillovers can simultaneously worsen the entry rank and the post-entry rank growth of younger workers because more higher-ranked positions are occupied by older workers. According to domestic outsourcing, the younger workers who join the lower-paying outsourcing firms are more likely to have lower entry wages and worse career prospects. Finally, a more negative selection of younger workers over time would explain both their worse entry rank and lower rank growth.

5.3 Heterogeneities Across Firms

In this section, we test whether some firm characteristics are correlated with the widening of the age wage gap. Specifically, we use the Italian administrative data to first categorize firms based on their rate of employment growth (below and above median), their age (at most or above ten years old), and their size (thresholds at 50, 100, and 500 employees). Then, we compute the trend in the age wage gap separately across these firm groups.

The data confirm some results that we already discussed in previous sections (Table 3). For example, the widening of the age wage gap was large within all types of firms, ranging from 0.16 log points to 0.24 log points. Moreover, regardless of firm characteristics, the age-based rank gap was by far the primary driver of the increase in the age wage gap. Finally, the role of the distributional gap tended to be larger in firms with less overlapping in the wage distribution of younger and older workers at baseline, that is, larger and older firms.

Moreover, we also find that the magnitude of the age-wage-gap increase significantly differed across different types of firms. Specifically, the age gap in weekly wages increased by 0.24 log points within firms with below-median employment growth, while it increased by only 0.17 log points within firms with above-median employment growth (Table 3, Panel A). This difference is both economically and statistically significant: it is equal to 37 percent of the mean increase in the age wage gap (0.18) and is significant at the 1 percent level. Moreover, the age wage gap increased significantly more in firms that were more than ten years old (Table 3, Panel B) and employed more workers (Table 3, Panel C).

These tests allow us to assess the fit of two hypotheses: career spillovers and domestic outsourcing. A model of career spillovers has clear implications about the firm characteristics that are associated with larger effects. As outlined in Section 4.3, one of the key components of career spillovers is the difficulty of firms in adding higher-ranked positions to their organizational charts. When this constraint applies, the increased supply of older workers and the lengthening of their careers can negatively affect younger workers because firms do not have enough available higher-ranked positions for all younger workers who deserve a promotion. Therefore, if career spillovers fit the data, the widening of the age wage gap should be more prominent among firms in a more mature stage of their life cycle, that is, firms that are more likely to face constraints in adding higher-ranked slots. This prediction fits the data well. Consistent with the empirical and theoretical results in Bianchi et al. (2022) and Bennett and Levinthal (2017), the widening of the age wage gap was larger among firms that had lower employment growth, were older, and had more employees.

There are two additional pieces of evidence that speak about the importance of these firm-level constraints. First, older firms have become more common over time; the mean firm age increased by 35 percent from 11.9 years in 1985 to 16.1 years in 2019 (Figure C5).[17] Second, most high-income countries have been experiencing a stark decrease in GDP growth (Figure C6) over the last decades. In short, the fact that Italy, like most of the other high-income economies, experienced (i) an overall slowdown in economic growth and (ii) an increase in the share of firms in a mature stage of their life cycle indicates that constraints in adding higher-ranked jobs, and therefore negative career spillovers, may have become more severe over time.

In contrast, the domestic-outsourcing hypothesis offers different implications for the heterogeneities across firms. As discussed by Goldschmidt and Schmieder (2017), the domestic

[17] 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.

outsourcing of jobs (i) primarily happened within large and established firms and (ii) affected low-pay entry-level positions, which were always more likely to be held by younger workers. We then infer that the younger workforce who remained within these larger and older firms was more likely to work in relatively higher paying positions. Therefore, we should expect to find a lower increase in the age wage gap among older and larger firms, in which outsourcing may have caused a progressive positive selection in the composition of the younger workforce. As we already observed, this prediction does not fit the empirical evidence.

5.4 Changes in Workforce Composition

In this section, we directly tackle the hypothesis that the selection of younger and older workers changed over time in ways that may have contributed to widen the age wage gap. 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 various characteristics.

To start, we focus on socio-demographic and labor variables. For example, the increasing labor-force participation of women could have driven at least part of the increase in the age wage gap if (i) women have on average worse labor-market outcomes than men, and (ii) the increase in their labor-force participation was more prevalent among younger generations. While there is a difference in mean wages between men and women in most high-income economies (Table C1, column 1), the data do not support the hypothesis that the labor-force participation of U35 full-time female workers grew more quickly than the one of O55 full-time female workers (Table C1, column 2). As another example, the share of workers who (i) were born abroad or (ii) had temporary contracts, two features that are associated with lower-than-average wages, may have increased more rapidly among U35 workers.[18] For example, in Italy, the share of temporary workers, who on average earn 0.45 log points less than permanent workers (Table C1, column 5), increased by 15 percentage points more among U35 workers than among O55 workers between 1985 and 2019 (Table C1, column 6). Alternatively, at least in some countries, the increased age wage gap could have been the result of a brain drain that progressively deprived the sending economies of their most talented and educated younger workers (Anelli et al., 2021). Instead of stemming exclusively from more negative selection of younger workers, the widening of the age wage gap could also be driven by positive selection among older workers. For example, health improvements could have allowed older workers to retain high levels of productivity for longer.

Using both administrative data from Italy and Germany and LIS survey data from nineteen high-income countries, we control for the influence of gender, nationality, contract

[18] A change in the incidence of part-time contracts cannot explain our results because the sample already includes only full-time workers.

length, education, and health. Whenever the information is available in a country, we regress log wages on the following variables: a male dummy, a dummy for nonimmigrant workers (a dummy for white workers in the United States to control for race, rather than nationality), a dummy for temporary contracts, a dummy for college education, and a dummy for disability status. We run separate 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 and perform the decomposition in Equation (1).

The results indicate that controlling for several observable characteristics cannot account for a large share of the increase in the age wage gap (Table 4). For example, in Italy, the administrative data allow us to include gender, nationality, and contract length. Simultaneously controlling for all these variables leads to an increase in the age wage gap of 0.17 log points, a 1.6 percent reduction from the baseline gap without controls. If we use the LIS survey data from Italy, we can control for gender, education, and disability status. In this case, the increase in the age wage gap with controls is 0.11 log points, instead of 0.14 log points without controls. These findings apply more generally to the other countries in the sample. Out of 71 total measurements with controls, the increase in the age wage gap declines by at least 50 percent in only 5 cases.

Next, we address another possible change in the selection of older workers. In many countries with large-scale public pension systems, the progressive increase in the eligibility threshold for public pensions may have induced more high-wage older individuals to stay in the workforce for longer. Although prior work on retirement choices has found that this form of selection is likely to be negative (Munnell, Sanzenbacher, and Rutledge, 2018; Kolsrud et al., 2021), we can further engage with this issue 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 4, column 15). The rationale for this test is that the minimum retirement age for most men was likely to be at least 60 years old even at the beginning of the sample in most high-income countries (for example, Italy). Focusing on this group of older workers, whose selection should not have changed as a result of higher eligibility requirements for a public pension, does not substantially affect the magnitude of the increases in the age wage gap.

Finally, we focus on unobservable time-invariant characteristics. We start from a model of wage formation that allows us to identify worker fixed effects separately from firm fixed effects. 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 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 ($X_{i,t}$), and time-varying unobserved factors ($\varepsilon_{i,t}$).

Equation (5) shares many commonalities with AKM models estimated by prior papers. Similar to what Kline, Saggio, and Sølvsten (2020) does, it is estimated separately for workers in age group $a \in \{U35, O55\}$. Moreover, instead of computing a single time-invariant fixed effect for each firm, we allow firm rents to vary every three years, following the examples of Lachowska et al. (2019) and Engbom and Moser (2020). All other features are common to all AKM models. For example, Equation (5) is estimated on the largest dual connected set, that is, the largest set of firms connected by firm-to-firm transitions of both younger and older workers. The firm rents are identified up to a normalization, which in our case is represented by the fixed effect of the largest firm in the dual connected set. Moreover, firm and worker fixed effects are separately identified in the data using firm-to-firm transitions. We discuss all these aspects in greater details in Appendix C.5.

From the estimation of Equation (5) with the Italian administrative data, we obtain 617,024 firm effects associated with 7,411,175 fixed effects for U35 workers as well as 551,146 firm effects associated with 2,511,677 fixed effects for O55 workers (Table C3). We use these two sets of fixed effects to compute the increase in age wage gap in both worker and firm rents. This 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 (Figure 6). On average, the gap in firm fixed effects between U35 workers and O55 workers explains 69 percent of the total widening of the age wage gap. The importance of firm premiums followed an inverted U-shape: it started low, reached a peak between 1997 and 2005, and then decreased until the end of the sample.

These findings differ from those of prior work on other types of 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.[19] 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.

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

In short, our analysis indicates that changes over time in worker characteristics were not a primary driver of the widening of the age wage gap.

6 Conclusions

This paper uses extensive administrative data on 38 million workers and 3.7 million firms in Italy and Germany, as well as survey data on 6.9 million workers from nineteen high-income countries, 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. For example, the wage gap between workers who were at least 55 years old and workers who were less than 35 years old increased by 0.18 log points in Italy between 1985 and 2019 and by 0.12 log points in the United States between 1979 and 2020.

Our analysis reveals one initial key finding about the widening of the age wage gap. Most of the increase stemmed from the growing difficulty experienced by younger workers in reaching the top of the wage distribution (rank gap), rather than from changes in the mean wages paid for different jobs (distributional gap). This result, together with a simple numerical exercise, allows us to rule out several hypotheses. Wage inequality, as well as all explanations that revolve around changes in the *prices* of various wage-enhancing factors, such as an increase in the returns to experience or skill-bias technological change, cannot account for the primary role played by the rank gap in widening the age wage gap. In contrast, the data are consistent with mechanisms that primarily involve a growing gap in the *quantity* of wage-enhancing factors possessed by younger and older workers.

Next, we propose four additional sets of analyses to assess how well the explanations that are compatible with the importance of the rank gap fit the data. First, the majority of the increase in the rank gap happened within firms and within 3-digit sectors. Second, the loss in the wage rank experienced by younger workers over time stemmed from both a loss in the rank at the time of labor-market entry and a lower rank growth in the post-entry years. Third, the widening of the age wage gap was more prominent within older and larger firms with low employment growth. Fourth, changes in worker characteristics were not major drivers of the age wage gap.

Taken together, these results point to the importance of negative career spillovers from older workers to younger workers. In a frictional labor market in which separations are costly and firms cannot always add higher-ranked jobs to their ranks, an increase in the supply of older workers and a lengthening of their careers allowed older workers to hold top jobs for longer and to slow down the careers of their younger coworkers, who experienced lower wage growth, fewer promotions, 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 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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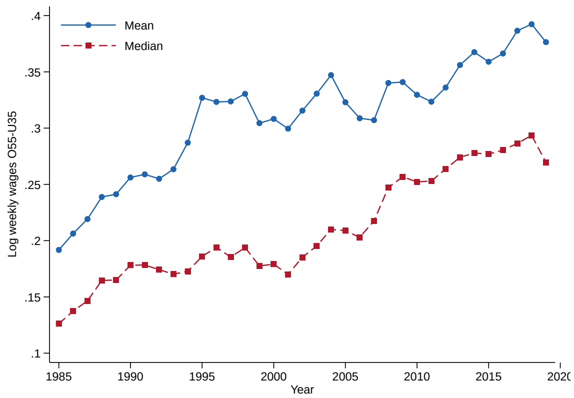
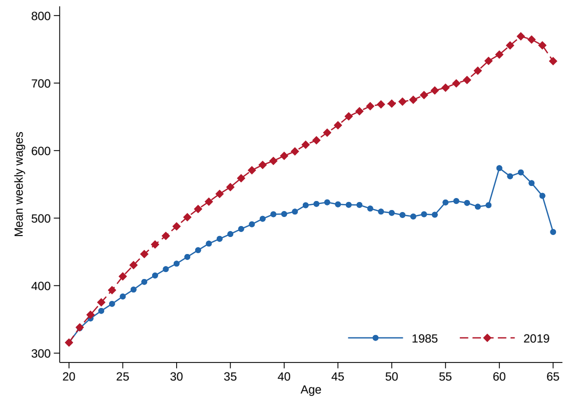
Figures and Tables

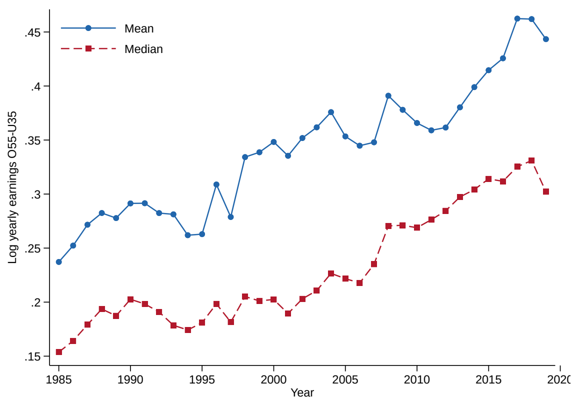
Figure 1: The Age Gap in Weekly Wages and Yearly Labor Earnings



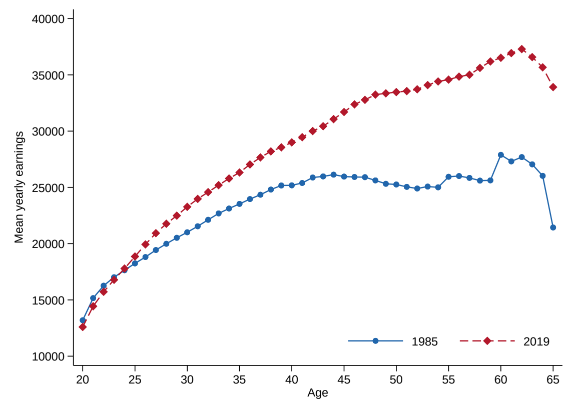
Panel A: Gap in log mean and median weekly wages



Panel B: Age profiles for mean weekly wages



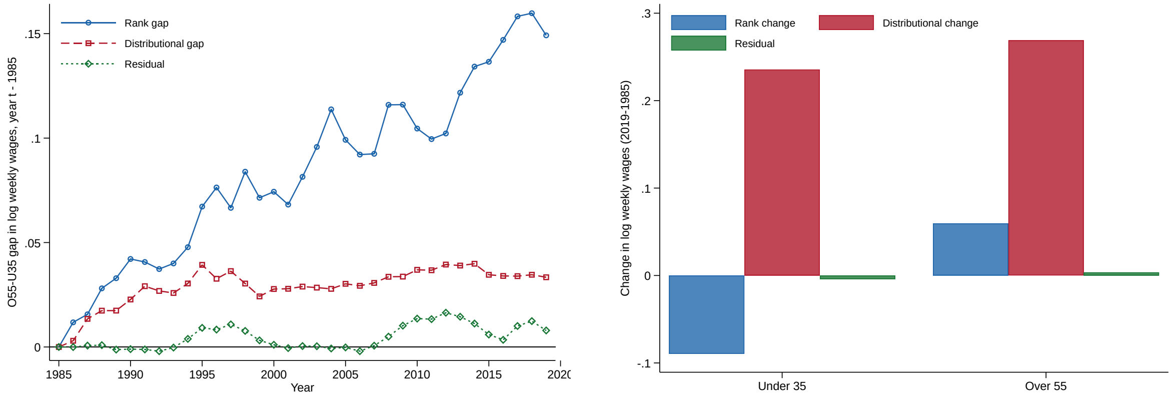
Panel C: Gap in log mean and median yearly earnings



Panel D: Age profiles for mean yearly earnings

Notes: Panel A plots the gap between the log weekly wages of O55 workers and the log weekly wages of U35 workers 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. Panels C and D repeat this analysis for yearly labor earnings, rather than for weekly wages. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure 2: Decomposition of Change in Weekly Wages

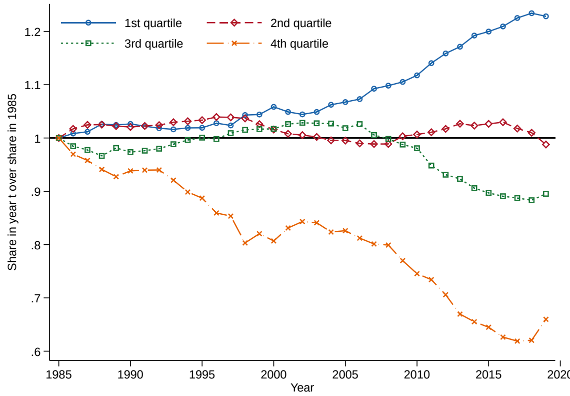


Panel A: $t \in [1986, 2019] - 1985$, O55 workers - U35 workers

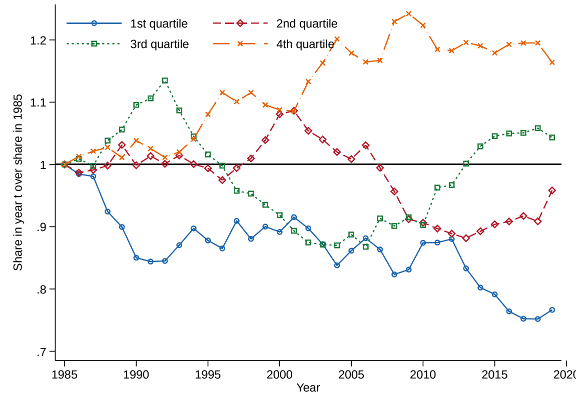
Panel B: 2019-1985, separate age groups

Notes: Panel A decomposes the change in mean log weekly wages between O55 workers and U35 workers, as well as between 1985 and year $t \in [1986, 2019]$, into three components (Equation (1)). Panel B plots the change in mean log weekly wages (decomposed into the same three components) between 1985 and 2019 separately for the two 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 strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

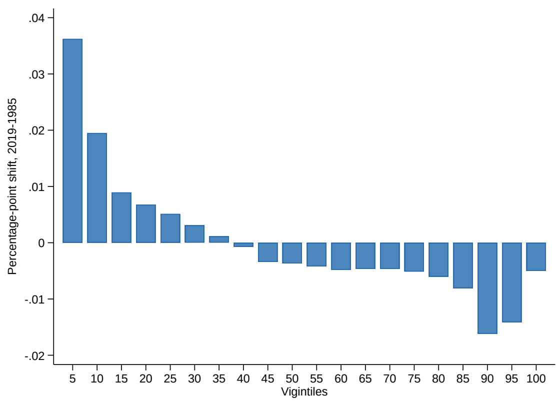
Figure 3: Worker Shares in Distribution of Weekly Wages



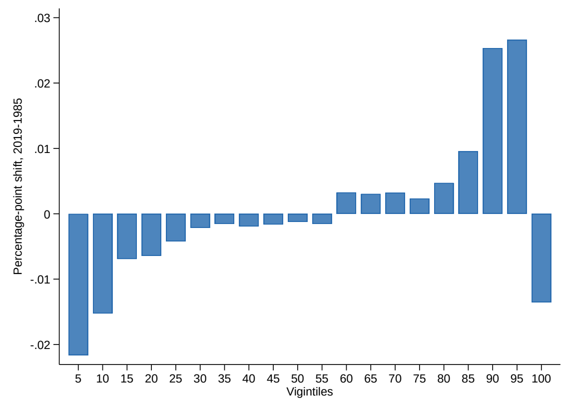
Panel A: U35 workers
Yearly change in quartiles



Panel B: O55 workers
Yearly change in quartiles



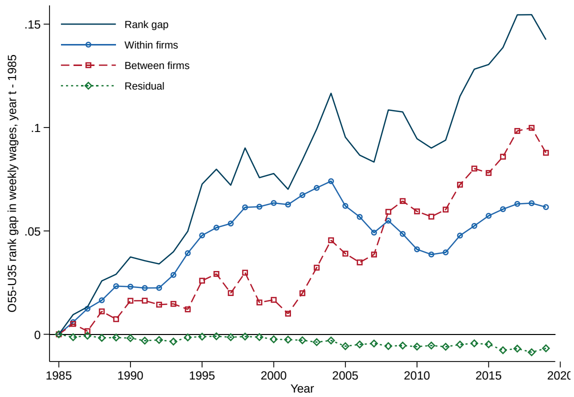
Panel C: U35 workers
$\Delta_{2019-1985}$ in vigintiles



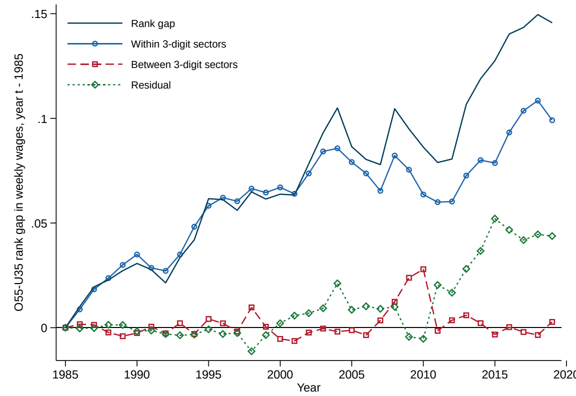
Panel D: O55 workers
$\Delta_{2019-1985}$ in vigintiles

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

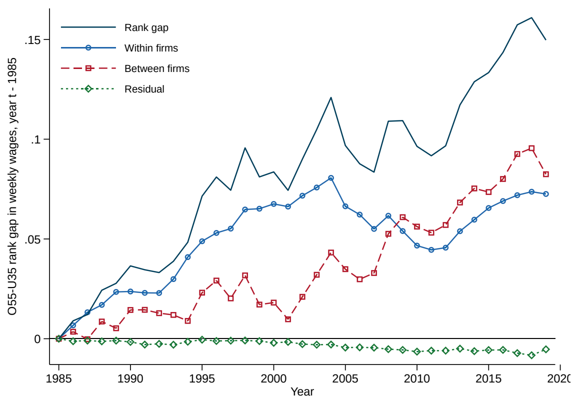
Figure 4: Increase in Rank Gap Between and Within Firms/Sectors



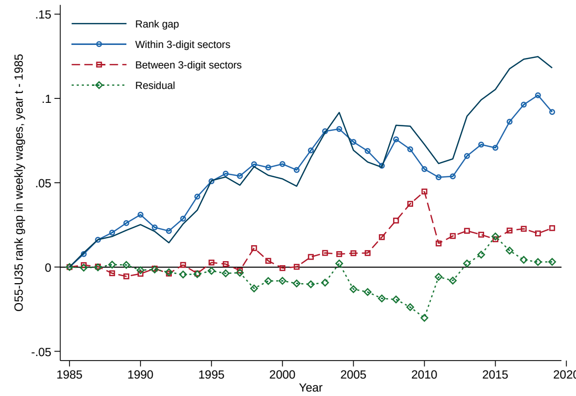
Panel A: firms,
all sectors



Panel B: 3-digit sectors
all sectors



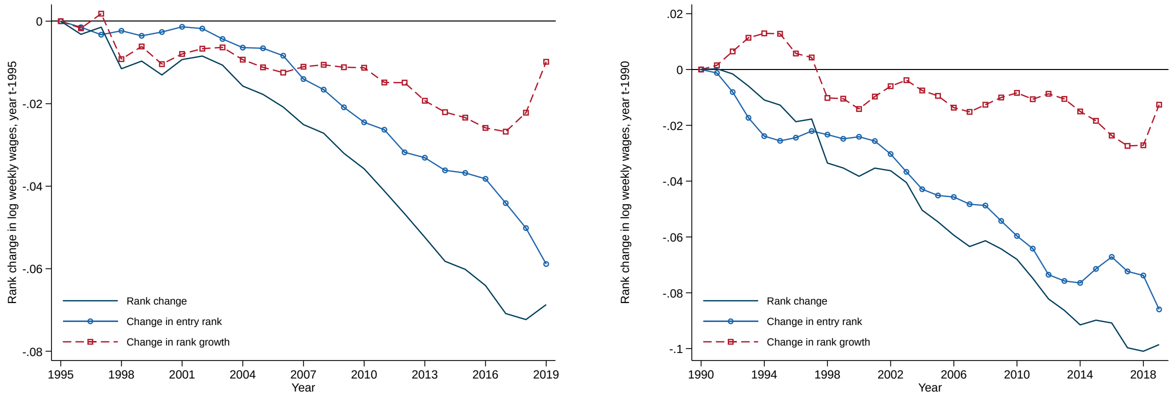
Panel C: firms,
no high-outsourcing sectors



Panel D: 3-digit sectors
no high-outsourcing sectors

Notes: In Panel A, the increase in rank gap in log weekly wages between O55 workers and U35 workers and between year t and 1985 is decomposed into three components: within firm groups, between firm groups, and a residual (Equation (3)). Panel B replaces firms with 3-digit sectors (NACE Rev. 2). Panels C and D drop from the sample all sectors identified by Goldschmidt and Schmieder (2017) as primary receivers of most domestically outsourced jobs: 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 (NACE Rev. 2). *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

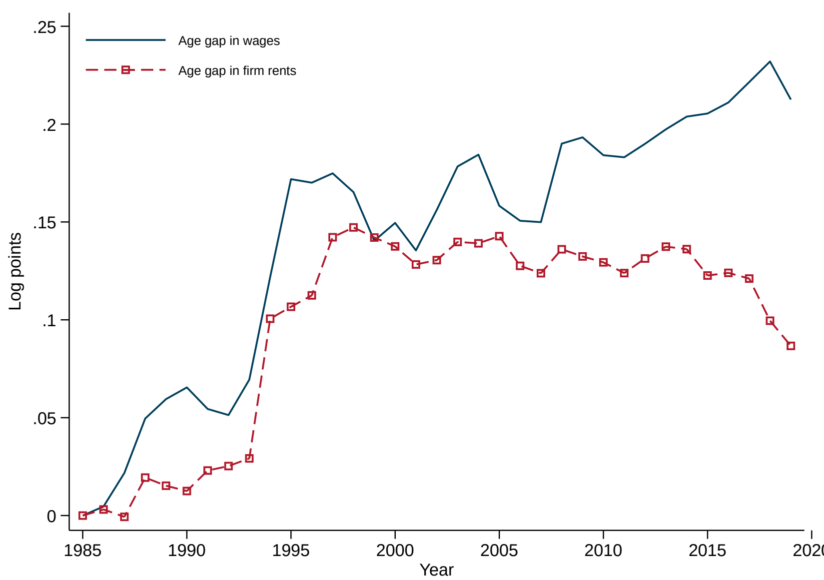
Figure 5: Entry Rank and Rank Growth



Panel A: U35, 1995-2019 Panel B: U30, 1990-2019

Notes: In Panel A, the increase in rank gap in log weekly wages for U35 worker between year t and 1995 is decomposed into two components: (i) the change in the wage rank at the time of entry in the labor market and (ii) the change in the rank growth between labor-market entry and year t (Equation (4)). Panel B repeats the same analysis for U30 workers. In this case, the starting year is 1990. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1974-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure 6: Firm and Worker Fixed effects



Notes: This figure shows the contribution of differences between U35 workers and O55 workers in mean worker and fixed effects to the overall increase in the age wage gap. It is based on Equation (5). *Sources:* Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table 1: Workforce Aging and Age Wage Gap

	Change in mean worker age		Change in age wage gap (O55-U35) at the mean			Change in age wage gap (O55-U35) at various percentiles				
	Δ years	Δ %	Δ wage gap (log)	Rank gap (%)	Distr. gap (%)	Perc. 10 (log)	Perc. 25 (log)	Median (log)	Perc. 75 (log)	Perc. 90 (log)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Employer-employee administrative data										
Italy (1985-2019)	6.87	19.21	0.180	78.32	17.52	0.200	0.100	0.140	0.250	0.180
Germany (1996-2017)	3.44	8.67	0.100	55.83	28.04	0.010	0.340	0.100	-0.010	-0.020
Panel B: Survey data from the Luxembourg Income Study (LIS) Database										
Australia (1981-2018)	2.40	6.21	0.036	-4.03	5.84	-0.317	0.012	0.187	0.216	0.210
Austria (1994-2019)	4.60	12.77	0.077	71.19	37.26	0.043	0.088	-0.029	0.032	0.055
Belgium (1985-2017)	4.62	12.58	0.228	72.39	15.62	0.410	0.217	0.176	0.150	0.189
Canada (1991-2017)	1.53	4.01	0.087	63.05	33.72	0.122	0.088	0.056	0.105	0.168
Denmark (1987-2016)	6.45	17.33	0.185	136.71	-9.54	0.300	0.226	0.131	0.135	0.146
Finland (1987-2016)	6.81	19.00	0.214	102.73	5.87	0.455	0.239	0.130	0.121	0.136
France (1996-2018)	1.83	4.65	-0.087	113.64	-16.71	0.015	-0.031	-0.047	-0.075	-0.151
Germany (1994-2019)	3.86	10.08	0.120	58.68	38.14	0.163	0.228	0.145	-0.016	-0.003
Greece (1995-2016)	2.95	7.51	0.180	100.75	3.40	0.130	0.202	0.202	0.206	0.206
Ireland (1994-2018)	5.42	15.00	-0.083	107.26	-31.90	-0.257	-0.056	0.069	-0.052	-0.161
Israel (1979-2018)	-2.92	-7.16	0.412	53.53	16.99	0.439	0.370	0.323	0.459	0.522
Italy (1987-2016)	6.21	16.24	0.139	82.40	11.67	0.007	0.115	0.083	0.178	0.309
Netherlands (1983-2018)	3.40	9.09	0.226	7.69	73.48	0.555	0.259	0.077	-0.022	-0.009
Norway (1979-2019)	1.82	4.40	0.096	250.85	-77.79	-0.351	0.024	0.115	0.202	0.271
Spain (1980-2016)	0.09	0.21	0.814	62.04	-18.98	1.136	0.885	0.711	0.608	0.487
Sweden (1981-2005)	3.04	7.68	0.083	-0.39	91.57	0.215	0.164	0.067	0.000	0.004
Switzerland (1982-2018)	2.44	6.20	0.481	49.61	7.03	1.415	0.342	0.169	0.184	0.167
United Kingdom (1979-2018)	3.53	9.58	0.057	47.69	21.00	-0.139	-0.093	0.020	0.166	0.314
United States (1979-2020)	4.74	12.51	0.121	97.67	18.37	0.201	0.087	0.135	0.126	0.132

Notes: The age wage gap measures the change in mean log wages between O55 workers and U35 workers, as well as between the first and last available year for each country. Appendix Table A1 provides more information about the wage variable and the sample restrictions in each country. The percentages in columns 4 and 5 refer to the decomposition of the age wage gap in Equation (1). *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. Details on the construction of these samples are in Appendix A.2. *Sources for survey data:* The survey data in Panel B come from the Luxembourg Income Study (LIS) Database, which can be accessed at https://www.lisdatacenter.org/. More details on these samples are in Appendix A.3.

Table 2: Simulating an Increase in the Age Wage Gap

	Baseline scenario at t $x^t_{\mathrm{Y}} \sim N(4.6, 0.25)$, $x^t_{\mathrm{O}} \sim N(4.7, 0.49)$, $\beta^t_1 = 1$, $\beta_0 = 1$, $s^t_O = 0.08$			Smaller distance in mean x at t $x^t_{\mathrm{Y}} \sim N(4.65, 0.25)$, $x^t_{\mathrm{O}} \sim N(4.7, 0.49)$, $\beta^t_1 = 1$, $\beta_0 = 1$, $s^t_O = 0.08$			Bigger distance in mean x at t $x^t_{\mathrm{Y}} \sim N(4.55, 0.25)$, $x^t_{\mathrm{O}} \sim N(4.7, 0.49)$, $\beta^t_1 = 1$, $\beta_0 = 1$, $s^t_O = 0.08$			Higher variance in x at t $x^t_{\mathrm{Y}} \sim N(4.6, 0.49)$, $x^t_{\mathrm{O}} \sim N(4.7, 0.81)$, $\beta^t_1 = 1$, $\beta_0 = 1$, $s^t_O = 0.08$			Lower variance in x at t $x^t_{\mathrm{Y}} \sim N(4.6, 0.09)$, $x^t_{\mathrm{O}} \sim N(4.7, 0.25)$, $\beta^t_1 = 1$, $\beta_0 = 1$, $s^t_O = 0.08$		
	Δ age wage gap (log)	Rank gap (%)	Distr. gap (%)	Δ age wage gap (log)	Rank gap (%)	Distr. gap (%)	Δ age wage gap (log)	Rank gap (%)	Distr. gap (%)	Δ age wage gap (log)	Rank gap (%)	Distr. gap (%)	Δ age wage gap (log)	Rank gap (%)	Distr. gap (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: Change in price of x at t'															
$\beta^{t'}_1 = 2$	0.093	0.56	98.87	0.047	0.33	99.33	0.139	0.15	99.70	0.095	0.44	99.12	0.090	-0.22	100.45
$\beta^{t'}_1 = 2$, $s^{t'}_O = 0.2$	0.103	-1.48	103.50	0.052	-1.33	103.16	0.153	-1.85	104.37	0.101	-0.94	102.12	0.107	-3.36	108.71
$\beta^{t'}_1 = 2$, $s^{t'}_O = 0.35$	0.106	-5.20	112.85	0.053	-5.42	113.25	0.159	-5.30	113.30	0.103	-4.07	109.36	0.113	-8.17	123.19
$\beta^{t'}_1 = 4$	0.280	0.42	98.30	0.142	0.74	97.02	0.417	0.20	99.18	0.287	0.64	97.44	0.269	0.13	99.49
Panel B: Change in distribution of x at t'															
$\mathbb{E}\left[x^{t'}_{\mathrm{O}}\right] = 4.8$	0.090	97.06	2.43	0.090	97.61	2.08	0.090	96.33	2.97	0.091	98.53	1.25	0.089	92.31	6.22
$\mathbb{E}\left[x^{t'}_{\mathrm{O}}\right] = 4.8$, $s^{t'}_O = 0.2$	0.102	83.14	11.66	0.099	87.13	7.68	0.105	78.87	15.99	0.101	88.79	7.38	0.107	69.92	22.63
$\mathbb{E}\left[x^{t'}_{\mathrm{O}}\right] = 4.8$, $s^{t'}_O = 0.35$	0.106	73.04	18.91	0.102	79.17	12.00	0.110	66.80	26.07	0.102	80.84	12.62	0.112	56.99	33.92
$\mathbb{E}\left[x^{t'}_{\mathrm{O}}\right] = 5$	0.280	93.84	3.06	0.280	95.00	2.46	0.281	92.50	3.83	0.286	96.72	1.63	0.278	84.94	7.52

Notes: Wage in period t is computed using the following equation: $w^t_{i,a} = 1 + 1 \cdot x^t_{i,a}$. Under the baseline scenario (columns 1 to 3), the variable x is distributed across younger (Y) and older (O) workers as follows: $x^t_{\mathrm{Y}} \sim N(4.6, 0.25)$ and $x^t_{\mathrm{O}} \sim N(4.7, 0.49)$. Finally, the share of older workers at t is 8 percent ($s^t_O = 0.08$). We chose this calibration to match five moments in the first available year of the Italian administrative data: the mean (5.6) and standard deviation (0.5) of the log weekly wages of U35 workers, the mean (5.7) and standard deviation (0.7) of the log weekly wages of O55 workers, and the ratio between O55 workers and U35 workers (0.08). Under a second scenario (columns 4 to 6), the difference in the means of x between younger (Y) and older (O) is smaller: $x^t_{\mathrm{Y}} \sim N(4.65, 0.25)$. Under a third scenario (columns 7 to 9), the difference in the means of x between younger (Y) and older (O) is bigger: $x^t_{\mathrm{Y}} \sim N(4.55, 0.25)$. Under a fourth scenario (columns 10 to 12), the distributions of x have higher variance. Under a fifth scenario (columns 13 to 15), the distributions of x have lower variance. For each scenario, Panel A simulates an increase in the coefficient of x in period t', calculates the increase in the age wage gap, and decomposes it using Equation (1). In two cases, it also assumes that the share of older people increases to either 20 percent or 35 percent. The second increase matched the growth in the share of O55 workers observed in Italy by 2019. Panel B simulates an increase in the mean of x for older workers in period t', calculates the resulting increase in the age wage gap, and decomposes it using Equation (1). All components that are not explicitly listed under Panels A and B stay constant at their value in period t.

Table 3: Firm Heterogeneity

	Age wage gap	Rank gap		Distributional gap	
	Logs	Logs	%	Logs	%
	(1)	(2)	(3)	(4)	(5)
Panel A: Heterogeneity by employment growth					
Firms with high emp. growth	0.168	0.125	74.26	0.035	20.93
Firms with low emp. growth	0.236	0.193	81.83	0.035	14.90
Low-high	0.067***				
Panel B: Heterogeneity by firm age					
Younger firms ($\leq$ 10 y.)	0.155	0.135	87.27	0.020	12.73
Older firms ($>$ 10 y.)	0.215	0.167	77.71	0.037	16.98
Older-younger	0.060***				
Panel C: Heterogeneity by firm size					
Smaller firms ($\leq$ 50 emp.)	0.177	0.166	93.46	0.014	8.12
Larger firms ($>$ 50 emp.)	0.210	0.149	70.87	0.047	22.18
Larger-smaller	0.033***				
Smaller firms ($\leq$ 100 emp.)	0.175	0.159	90.71	0.017	9.97
Larger firms ($>$ 100 emp.)	0.203	0.138	68.09	0.050	24.52
Larger-smaller	0.028***				
Smaller firms ($\leq$ 500 emp.)	0.168	0.143	84.95	0.024	14.46
Larger firms ($>$ 500 emp.)	0.196	0.123	62.86	0.058	29.55
Larger-smaller	0.028***				

Notes: In Panel A, we first compute the mean yearly employment growth within a three-year window (from $t-3$ to t) for each firm and year in the sample. Then, firms with low employment growth had below-median mean employment growth between 1985 and 2019, while firms with high employment growth had above-median mean 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table 4: Age Wage Gap and Workforce Composition

	Baseline		Gender		Nationality		Contract length		Education		Disability		All		U35 vs. 56-60	
	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)	Δ wage gap (log)	Rank gap (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Panel A: Employer-employee administrative data																
Italy (1985-2019)	0.180	78.32	0.243	79.15	0.168	79.77	0.124	81.70	-	-	-	-	0.177	83.88	0.172	76.93
Germany (1996-2017)	0.100	55.83														
Panel B: Survey data from the Luxembourg Income Study (LIS) Database																
Australia (1981-2018)	0.036	-4.03	0.080	35.60	-	-	-	-	-	-	0.047	51.27	0.119	41.20	0.055	8.98
Austria (1994-2019)	0.077	71.19	0.101	62.77	0.060	72.82	-	-	0.096	78.78	-	-	0.010	84.52	0.063	72.12
Belgium (1985-2017)	0.228	72.39	0.280	53.74	0.330	62.05	0.182	67.07	0.189	41.71	0.236	70.13	0.213	65.47	0.230	71.49
Canada (1991-2017)	0.087	63.05	0.126	71.91	0.168	-398.12	-	-	0.081	50.14	-	-	0.211	-118.66	0.065	51.34
Denmark (1987-2016)	0.185	136.71	0.195	126.48	0.175	138.77	-	-	0.180	136.16	-	-	0.169	127.38	0.187	136.98
Finland (1987-2016)	0.214	102.73	0.200	99.74	-	-	-	-	0.214	100.88	0.209	86.93	0.131	99.61	0.195	103.23
France (1996-2018)	-0.087	113.64	-0.082	113.34	-0.079	114.37	-0.129	108.90	-0.046	143.58	-	-	-0.089	118.70	-0.094	108.01
Germany (1994-2019)	0.120	58.68	0.149	63.77	0.101	44.10	0.019	-65.90	0.156	77.33	0.135	70.29	0.091	71.32	0.177	65.91
Greece (1995-2016)	0.180	100.75	0.248	93.33	0.179	105.25	-	-	0.201	100.91	-	-	0.177	97.43	0.190	101.76
Ireland (1994-2018)	-0.083	107.26	-0.014	162.78	-0.094	103.09	-	-	0.008	-100.97	-	-	0.037	48.41	-0.079	118.14
Israel (1979-2018)	0.412	53.53	0.451	55.72	-	-	-	-	0.351	56.40	-	-	0.371	59.13	0.574	53.52
Italy (1987-2016)	0.139	82.40	0.182	64.39	-	-	-	-	0.163	64.34	0.138	90.35	0.106	69.16	0.147	131.36
Netherlands (1983-2018)	0.226	7.69	0.277	24.17	-	-	-	-	0.312	25.84	0.179	-127.60	0.221	-53.53	0.237	13.21
Norway (1979-2019)	0.096	250.85	0.182	164.20	-	-	-	-	-	-	-	-	0.229	164.20	0.121	245.03
Spain (1980-2016)	0.814	62.04	0.813	60.74	-	-	-	-	0.861	61.13	-	-	0.535	61.27	0.831	60.26
Sweden (1981-2005)	0.083	-0.39	0.133	28.76	-	-	-	-	-	-	-	-	0.142	28.76	0.119	15.17
Switzerland (1982-2018)	0.481	49.61	0.472	53.87	0.442	53.61	-	-	-	-	-	-	0.304	54.68	0.355	28.05
United Kingdom (1979-2018)	0.057	47.69	0.110	64.45	-	-	-	-	-	-	-	-	0.165	64.45	0.040	35.36
United States (1979-2020)	0.121	97.67	0.148	81.85	0.105	101.64	-	-	0.097	111.40	-	-	0.119	86.88	0.077	95.21

Notes: "Gender" regresses log wages on a male dummy and computes the age wage gap using the residuals from these regressions. "Nationality" uses a dummy for nonimmigrant workers as a regressor (white in the United States to control for race). "Contract length" controls for temporary contracts. "Education" controls for college education. "Disability" controls for disability status. "All" simultaneously controls for all the worker characteristics available in each country. "U35 vs. 56-60" computes the age wage gap between workers who are between 56 and 60 years old and U35 workers. *Sources for Italy:* Database UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Sources for Germany:* The German data come from the LIAB Linked Employer-Employee Dataset provided by the Institute for Employment Research. *Sources for survey data:* The survey data in Panel B come from the Luxembourg Income Study (LIS) Database, which can be accessed at https://www.lisdatacenter.org/.

Online Appendix

A Data Appendix

A.1 Italian Data

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

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 strictly 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.

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 are expressed in 2015 euros using the conversion tables prepared by the OECD.[20] 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.

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

A.2 German Data

The data on the German labor market are available between 1996 and 2017 and are provided by the Research Data Centre (FDZ) of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

We employ the Linked Employer-Employee Data from the *LIAB Cross-Sectional Model 2* (LIAB).[21] This dataset combines information from the IAB Establishment Panel with information from the Integrated Employment Biographies (IEB).[22] 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.[23]

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

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

To create a dataset that is as close as possible to the Italian one, we select employees who (i) were between 16 years old and 75 years old, (ii) had a full-time contract, and (iii) earned strictly positive wages.[24] These restrictions reduce the sample from 12,451,266 workers to 8,865,294 workers.

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

A.3 Data from Other Countries

In this section, we provide more information about the survey data that we used to measure the age wage gap in all other countries. The data source is the Luxembourg Income Study (LIS) database, which can be accessed at https://www.lisdatacenter.org/. The LIS database aggregates and harmonizes heterogeneous survey data coming from many different countries. A full list of the original data sources is in the notes of Table A1. Out of all the available countries in the LIS

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

[22] 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.

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

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

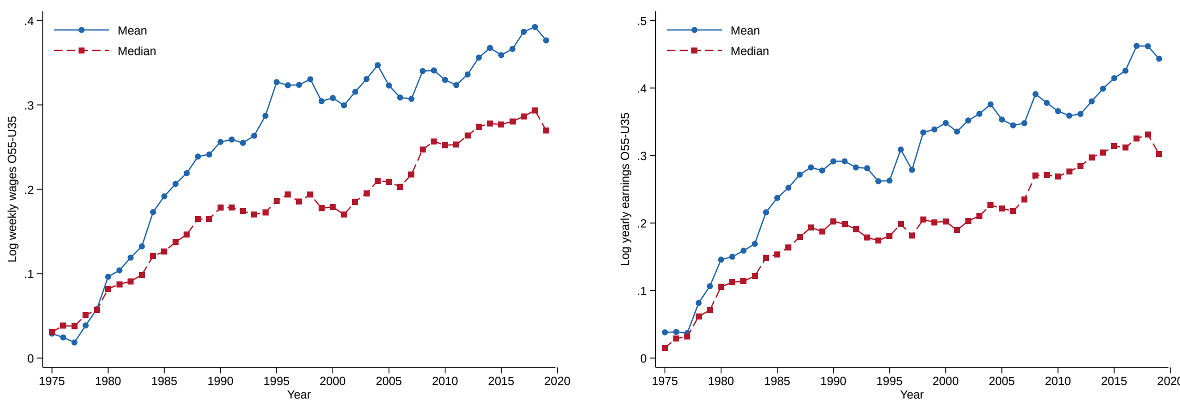
database, we focus on 19 high-income economies with sufficiently long time series: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom, and United States.

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

Whenever possible, we apply the same sample restrictions used on the administrative data from Italy and Germany. Specifically, we restrict each year of data to workers who (i) were over 16 years old, (ii) earned strictly positive wages, (iii) were employees, (iv) had a full-time contract, and (v) worked at least 20 weeks during the year. Restrictions (i) and (ii) can be imposed in every country and year, while restrictions (iii) to (v) require variables that are not available in every country. Table A1 lists all cross-country differences in the construction of the sample.

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

Figure A1: The Age Gap in Italy from 1975



Panel A: Gap in log mean and median weekly wages

Panel B: Gap in log mean and median yearly earnings

Notes: Panel A plots the gap between the log weekly wages of O55 workers and the log weekly wages of U35 workers between 1985 and 2019 for both mean and median wages. Panel B repeats this analysis for yearly labor earnings, rather than for weekly wages. The main difference from Figure 1 is that the sample starts in 1975, rather than 1985. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1975-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Table A1: Characteristics of Data Sources

	# available years	# observations	# workers	# firms	Wage definition	Restrict to employees	Restrict to full time	Restrict working weeks
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Employer-employee administrative data								
Italy (1985-2019)	35	312,065,728	28,911,242	3,532,905	Weekly	Yes	Yes	Yes
Germany (1996-2017)	22	35,092,712	8,865,294	127,782	Daily	Yes	Yes	No
Panel B: Survey data from the Luxembourg Income Study (LIS) Database								
Australia (1981-2018)	12	108,794	-	-	Yearly	No	Yes	No
Austria (1994-2019)	20	70,509	-	-	Yearly	Yes	Yes	Yes
Belgium (1985-2017)	21	68,656	-	-	Yearly	Yes	Yes	No
Canada (1991-2017)	24	587,130	-	-	Yearly	Yes	Yes	Yes
Denmark (1987-2016)	9	540,889	-	-	Yearly	Yes	No	No
Finland (1987-2016)	9	79,119	-	-	Yearly	Yes	No	Yes
France (1996-2018)	23	718,217	-	-	Yearly	Yes	Yes	No
Germany (1994-2019)	26	208,481	-	-	Yearly	Yes	Yes	Yes
Greece (1995-2016)	7	25,887	-	-	Yearly	Yes	No	No
Ireland (1994-2018)	21	53,090	-	-	Yearly	Yes	Yes	Yes
Israel (1979-2018)	22	162,407	-	-	Yearly	Yes	Yes	No
Italy (1987-2016)	12	62,067	-	-	Yearly	Yes	Yes	Yes
Netherlands (1983-2018)	13	64,589	-	-	Yearly	Yes	Yes	No
Norway (1979-2019)	11	1,131,639	-	-	Yearly	Yes	No	No
Spain (1980-2016)	9	88,285	-	-	Yearly	Yes	No	No
Sweden (1981-2005)	6	56,942	-	-	Yearly	Yes	No	No
Switzerland (1982-2018)	15	74,382	-	-	Yearly	Yes	Yes	No
United Kingdom (1979-2018)	28	403,865	-	-	Yearly	Yes	Yes	No
United States (1979-2020)	42	2,370,654	-	-	Yearly	Yes	Yes	Yes

Sources for Italy: Database UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Sources for Germany:* The German data come from the LIAB Linked Employer-Employee Dataset provided by the Institute for Employment Research. *Sources for Australia:* Income and Housing Survey (1981); Income Distribution Survey (1985); Survey of Income and Housing Costs and Amenities (1989); Survey of Income and Housing, Household Expenditure Survey (2004); Survey of Income and Housing (all other years). *Sources for Austria:* Micro-census (1987, 1995); European Community Household Panel (ECHP; 1994, 1997, 2000); Survey on Income and Living Conditions (SILC; all other years). *Sources for Belgium:* Socio-Economic Panel (1992 and earlier; 1997); Panel Study on Belgian Households, ECHP (1995, 2000); SILC (all other years). *Sources for Canada:* Survey of Consumer Finances (1991, 1994); Survey of Labour and Income Dynamics (1996-2011); Canadian Income Survey (2012 and later). *Sources for Denmark:* sample based on administrative records; The Danish National Centre for Social Research, Statistics Denmark, Ministry of Finance, Ministry of Economic Affairs and the Interior, Ministry of Taxation. *Sources for Finland:* Income Distribution Survey (before 2004); SILC (2004 onwards). *Sources for France:* Tax and Social Incomes Survey. *Sources for Germany (LIS):* German Socio-Economic Panel. *Sources for Greece:* ECHP (1995, 2000); SILC (all other years). *Sources for Ireland:* Survey of Income Distribution Poverty and Usage of State Services (1987); Living in Ireland Survey, ECHP (1994, 1995, 1996, 2000); SILC (all other years). *Sources for Israel:* Household Expenditure Survey. *Sources for Italy (LIS):* Survey of Household Income and Wealth. *Sources for Netherlands:* Amenities and Services Utilization Survey (1983, 1987, 1990); Socio-Economic Panel Survey (1993, 1999); SILC (all other years). *Sources for Norway:* Income Distribution Survey (2004 and before); Household Income Statistics (2007 and after). *Sources for Spain:* Household Budget Survey (1980, 1990); Household Budget Continuous Survey (1985); ECHP (2000); SILC (all other years). *Sources for Sweden:* Household Income Survey. *Sources for Switzerland:* Swiss Income and Wealth Survey (1982); National Poverty Study (1992); Income and Expenditure Survey (2000, 2002, 2004); SILC (all other years). *Sources for United Kingdom:* Family Expenditure Survey (1991 and earlier); Family Resources Survey (1994 and later). *Sources for United States:* CPS March Supplement (2001 and before); CPS Annual Social and Economic Supplement (2002 and later).

Table A2: Empirical Analysis and Data Sources

	Δ wage gap	Rank gap vs. distributional gap	Between/within firms and sectors	Entry rank vs. Rank growth	Firm Heterogeneity	Workforce composition	AKM model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Employer-employee administrative data							
Italy (1985-2019)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Germany (1996-2017)	Yes	Yes	Yes	No (no info on entry wage)	Yes	Yes	No (subsample of firms)
Panel B: Survey data from the Luxembourg Income Study (LIS) Database							
Australia (1981-2018)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Austria (1994-2019)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Belgium (1985-2017)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Canada (1991-2017)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Denmark (1987-2016)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Finland (1987-2016)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
France (1996-2018)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Germany (1994-2019)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Greece (1995-2016)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Ireland (1994-2018)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Israel (1979-2018)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Italy (1987-2016)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Netherlands (1983-2018)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Norway (1979-2019)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Spain (1980-2016)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Sweden (1981-2005)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
Switzerland (1982-2018)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
United Kingdom (1979-2018)	Yes	Yes	No (no firm info)	No (no info on entry wage)	No (no firm info)	Yes	No (no firm info)
United States (1979-2020)	Yes	Yes	No (no firm info)	No (no info on entry wage)-	No (no firm info)	Yes	No (no firm info)

Notes: "No (no firm info)" means that the data source does not match workers to firms. "No (no info on entry wage)" means that the data source does not include any information on the entry year of each worker. This missing information prevents us from assigning to workers their initial wage. "No (subsample of firms)" means that the data source includes only a random subsample of establishments, preventing us from observing the full careers and all firm-to-firm movements of the workers in the sample.

B Appendix of Section 4

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

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

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

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

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

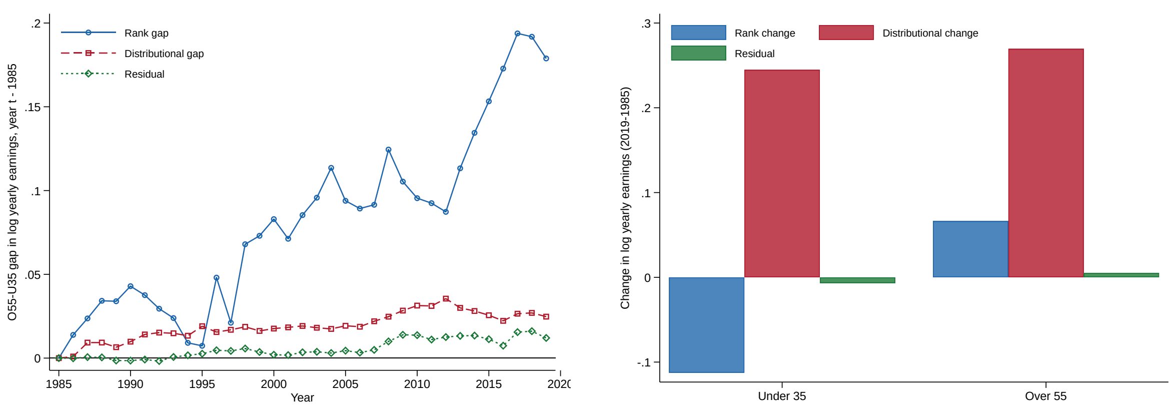
$$\Delta w_{O55}^{t,t'} - \Delta w_{U35}^{t,t'} = \underbrace{\sum_v \left(s_{O55,v,t} - s_{U35,v,t}\right)\left(\bar{w}_{v,t'} - \bar{w}_{v,t}\right)}_{\text{Distributional gap}} + \underbrace{\sum_v \Delta s_{O55-U35,v,t'-t}\bar{w}_{v,t}}_{\text{Rank gap}} + \underbrace{\sum_v \Delta s_{O55-U35,v,t'-t}\left(\bar{w}_{v,t'}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

In this equation, $\Delta s_{O55-U35,v,t'-t}$ 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:

$\Delta s_{O55-U35,v,t'-t} = \left(s_{O55,v,t'} - s_{O55,v,t}\right) - \left(s_{U35,v,t'} - s_{U35,v,t}\right)$. This decomposition can be obtained from the last two rows of Equation (B.1) by taking the difference for two age groups:

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

Figure B1: Decomposition of Change in Yearly Earnings

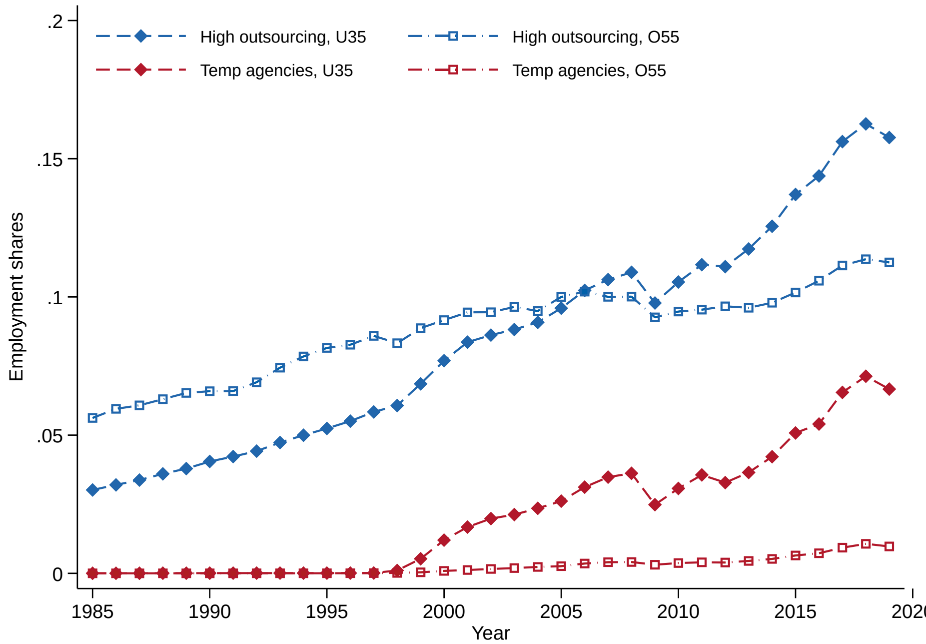


Panel A: $t \in [1986, 2019] - 1985$, O55 workers - U35 workers

Panel B: 2019-1985, separate age groups

Notes: Panel A decomposes the change in mean log yearly earnings between O55 workers and U35 workers, as well as between 1985 and year $t \in [1986, 2019]$, into three components (Equation (1)). Panel B plots the change in mean log yearly earnings (decomposed into the same three components) between 1985 and 2019 separately for the two 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 strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure B2: Employment Shares in High-Outsourcing Sectors



Notes: The figure 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 sectors 78.1, 78.2, and 78.3. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

C Appendix of Section 5

C.1 More Results on Between/Within Decomposition

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

$$
\begin{aligned}
\sum_{v}\left(s_{a,v,t'}-s_{a,v,t}\right)\bar{w}_{v,t} \;=\;& \underbrace{\sum_{g\in(f,e)}\left(s_{a,f,t'}-s_{a,f,t}\right)s_{a,(e|f),t}\bar{w}_{g,t}}_{\text{Between firms}} \\
&+\underbrace{\sum_{g\in(f,e)}s_{a,f,t}\left(s_{a,(e|f),t'}-s_{a,(e|f),t}\right)\bar{w}_{g,t}}_{\text{Within firms}} \\
&+\underbrace{\sum_{g\in(f,e)}\left[\left(s_{a,f,t'}-s_{a,f,t}\right)\left(s_{a,(e|f),t'}-s_{a,(e|f),t}\right)\right]\bar{w}_{g,t}}_{\text{Residual}}\,.
\end{aligned}
\tag{C.1}
$$

On the left-hand side of this equation, the average wage in vigintile of the distribution of weekly wages v and year t ($\bar{w}_{v,t}$) is multiplied by the change between t and t' in the share of workers in age group a and vigintile v. On the right-hand side, g identifies one of the 50,000 firm-worker groups and $\bar{w}_{g,t}$ is the average wage in firm-worker group g and year t.

This decomposition can be obtained using the multiplication in Equation (2). A change in the share of workers in age group a and firm-worker group $g=(f,e)$ between t and t' can be rewritten as follows:

$$
\begin{aligned}
s_{a,(f,e),t'}-s_{a,(f,e),t} &= s_{a,f,t'}\cdot s_{a,(e|f),t'}-s_{a,f,t}\cdot s_{a,(e|f),t} \\
&= s_{a,f,t'}\cdot s_{a,(e|f),t'}-s_{a,f,t}\cdot s_{a,(e|f),t}+\left(s_{a,f,t'}\cdot s_{a,(e|f),t}-s_{a,f,t'}\cdot s_{a,(e|f),t}\right) \\
&\quad+\left(s_{a,f,t}\cdot s_{a,(e|f),t'}-s_{a,f,t}\cdot s_{a,(e|f),t'}\right)+\left(s_{a,f,t}\cdot s_{a,(e|f),t}-s_{a,f,t}\cdot s_{a,(e|f),t}\right) \\
&= \underbrace{\left(s_{a,f,t'}-s_{a,f,t}\right)s_{a,(e|f),t}}_{\text{Between firms}}+\underbrace{s_{a,f,t}\left(s_{a,(e|f),t'}-s_{a,(e|f),t}\right)}_{\text{Within firms}} \\
&\quad+\underbrace{\left(s_{a,f,t'}-s_{a,f,t}\right)\left(s_{a,(e|f),t'}-s_{a,(e|f),t}\right)}_{\text{Residual}}.
\end{aligned}
\tag{C.2}
$$

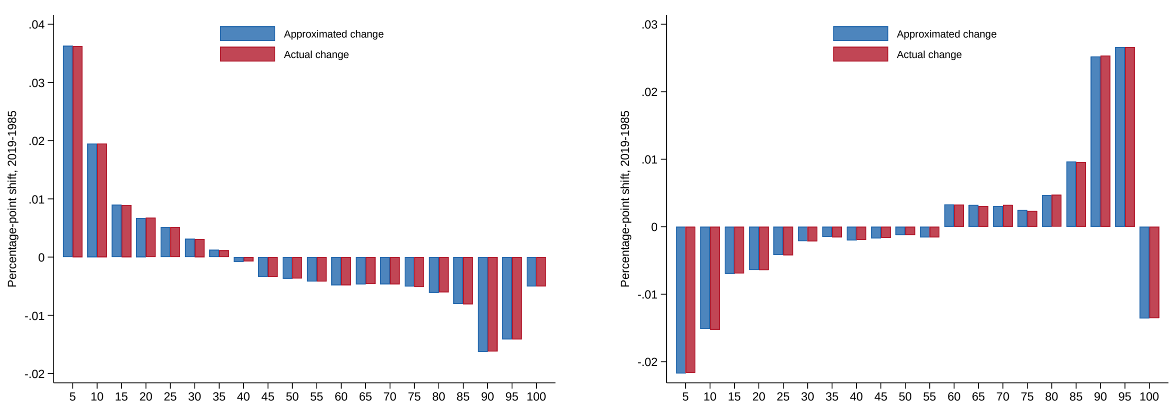
Then, the decomposition in Equation (C.1) can be obtained by multiplying all the three components in Equation (C.2) by $\bar{w}_{g,t}$ and by summing over the firm-worker groups g.

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

$$\underbrace{\sum_{v} \Delta s_{O55-U35,v,t'-t} \bar{w}_{v,t}}_{\text{Rank gap}} = \underbrace{\sum_{g \in (f,e)} \Delta s_{O55-U35,f,t'-t} \cdot \Delta s_{O55-U35,(e|f),t} \cdot \bar{w}_{g,t}}_{\text{Between firms}} + \underbrace{\sum_{g \in (f,e)} \Delta s_{O55-U35,f,t} \cdot \Delta s_{O55-U35,(e|f),t'-t} \cdot \bar{w}_{g,t}}_{\text{Within firms}} + \underbrace{\sum_{g \in (f,e)} \Delta s_{O55-U35,f,t'-t} \cdot \Delta s_{O55-U35,(e|f),t'-t} \cdot \bar{w}_{g,t}}_{\text{Residual}}, \tag{C.3}$$

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

Figure C1: Actual Vs. Approximated Shares

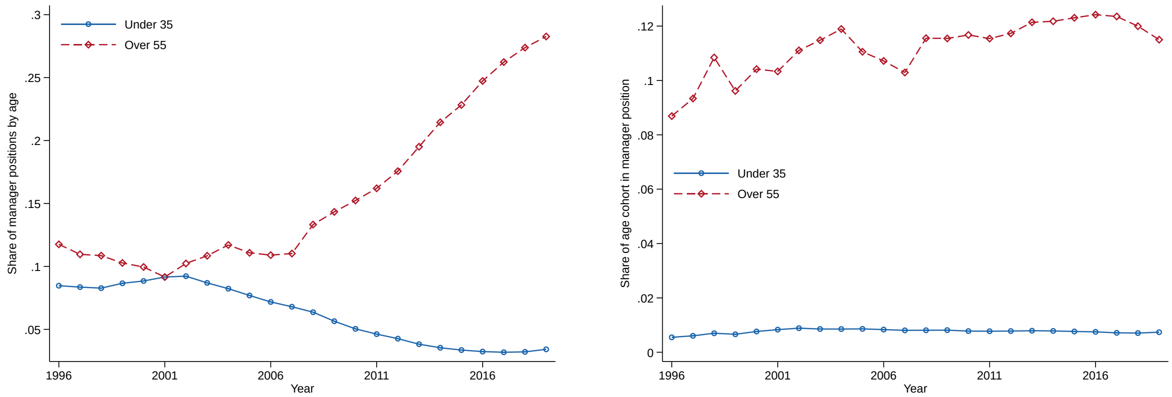


Panel A: U35 workers

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 C.1. Specifically, workers are first sorted in 100 percentiles (firm groups) based on their firm's average weekly wages. Within each percentile, workers are then sorted in 500 quantiles (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 strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

Figure C2: Probability of Holding Managerial Positions

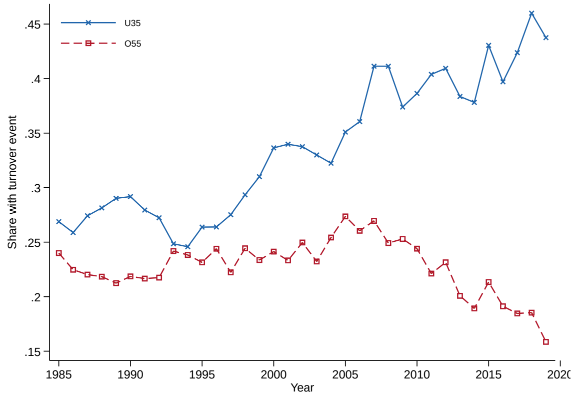


Panel A: Share of manager jobs by age group

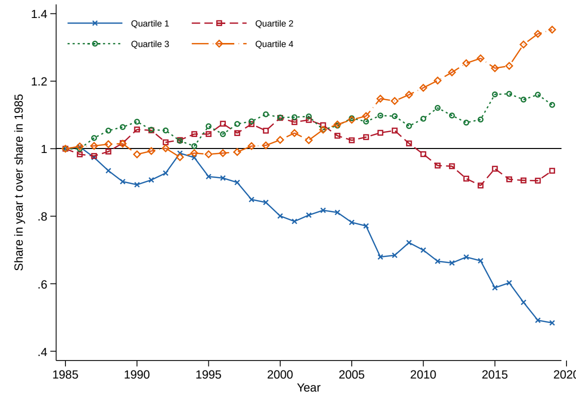
Panel B: Share of age group in manager jobs

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

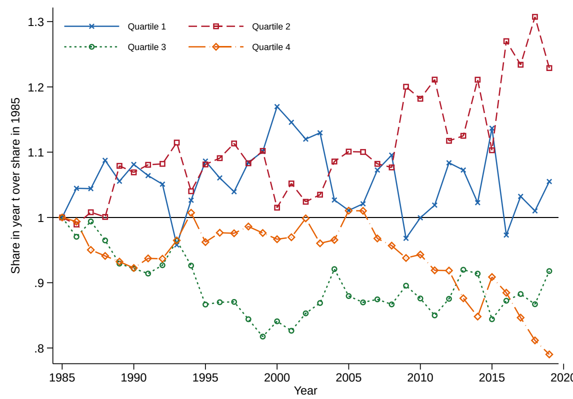
Figure C3: Turnover



Panel A: Share of workers
with turnover events



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



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

Notes: Panel A plots the share of workers with a turnover event (voluntary or involuntary) by year for U35 workers and O55 workers, separately. Panels B and C plot the distribution of younger and older workers across firms with different turnover level. 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 B shows the ratio between the share of U35 workers in each quartile and the share of U35 in the same quartile in 1985. Panel C 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 strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1985-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

C.2 More Results on Entry Rank and Rank Growth

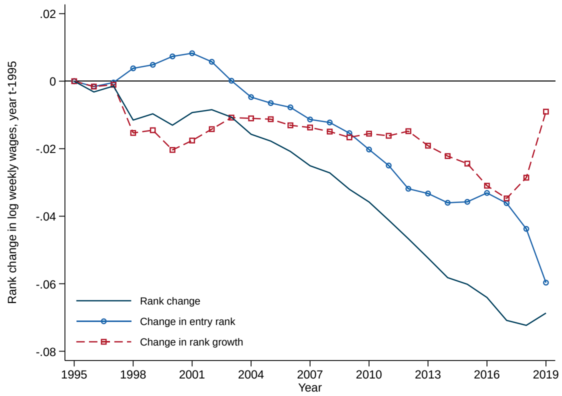
The rank change in Equation (B.1) can be rewritten by simply adding and subtracting the distribution of U35 workers of age a in vigintile v at labor-market entry E:

$$\underbrace{\sum_v \left(s_{a(b,t'),v,t'} - s_{a(b,t),v,t}\right) \bar{w}_{v,t}}_{\text{Rank change}} = \underbrace{\sum_{a(b,t')\in[16,34]} s_{a(b,t'),t'} \cdot \sum_v \left[s^E_{a(b,t'),v} \cdot \bar{w}_{v,t}\right]}_{\text{Change in entry rank—part 1}}$$
$$- \underbrace{\sum_{a(b,t)\in[16,34]} s_{a(b,t),t} \cdot \sum_v \left[s^E_{a(b,t),v} \cdot \bar{w}_{v,t}\right]}_{\text{Change in entry rank—part 2}}$$
$$+ \underbrace{\sum_{a(b,t')\in[16,34]} s_{a(b,t'),t'} \cdot \sum_v \left[\left(s_{a(b,t'),v,t'} - s^E_{a(b,t'),v}\right) \cdot \bar{w}_{v,t}\right]}_{\text{Change in rank growth—part 1}}$$
$$- \underbrace{\sum_{a(b,t)\in[16,34]} s_{a(b,t),t} \cdot \sum_v \left[\left(s_{a(b,t),v,t} - s^E_{a(b,t),v}\right) \cdot \bar{w}_{v,t}\right]}_{\text{Change in rank growth—part 2}}. \tag{C.4}$$

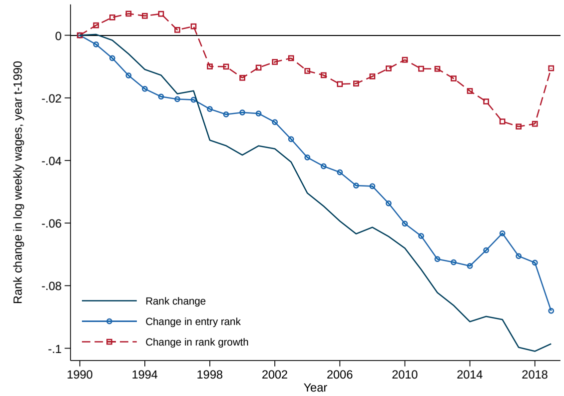
There is one key difference between Equation (C.4) and Equation (4) in Section 5.2. In the full decomposition in Equation (C.4), the share of U35 workers of age a is allowed to change from year t ($s_{a(b,t),t}$) to year t' ($s_{a(b,t'),t'}$). Therefore, the two key terms of the decomposition can confound two types of changes: (i) variation in entry rank and rank growth or (ii) variation in the age distribution of U35 workers. For example, the change in entry rank can stem from the fact that the wage distribution at labor-market entry of workers who were below 35 years old in year t' was different from the wage distribution at labor-market entry of workers who were below 35 years old in year t'. Or, it can stem from the fact that U35 workers became either younger or older between t and t'.

In the main draft, we intended to isolate the first channel. Therefore, we fixed the age distribution at baseline in year t (1995 for U35 workers and 1990 for U30 workers). This assumption allowed us to rewrite Equation (C.4) as Equation (4) in Section 5.2. Alternatively, we could have fixed the age distribution in its final year t' (2019), or we could have allowed the age distribution to vary over time like in Equation (C.4). Figure C4 shows that the results are qualitatively similar under these different scenarios.

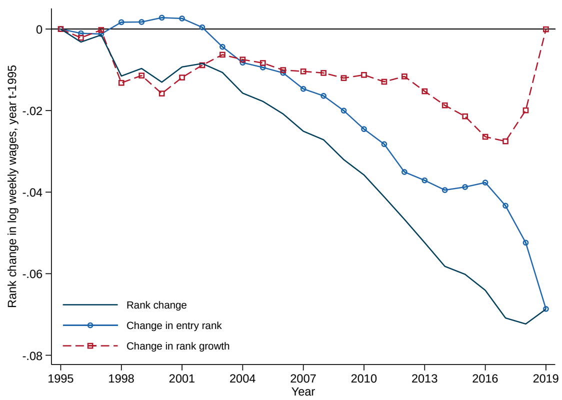
Figure C4: Entry Rank and Rank Growth, Robustness Checks



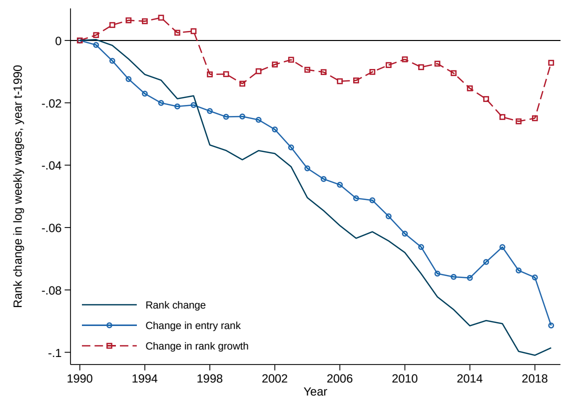
Panel A: U35, 1995-2019
Age distribution fixed in 2019



Panel B: U30, 1990-2019
Age distribution fixed in 2019



Panel C: U35, 1995-2019
Age distribution varies

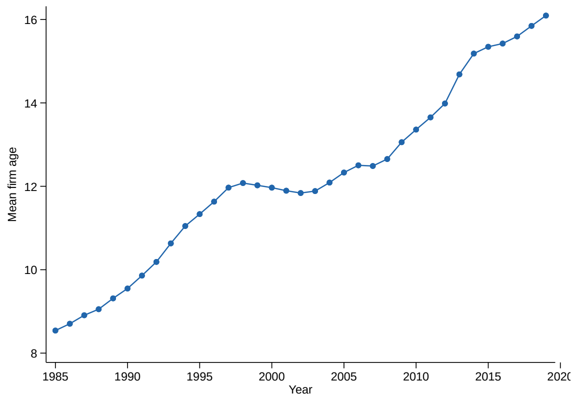


Panel D: U30, 1990-2019
Age distribution varies

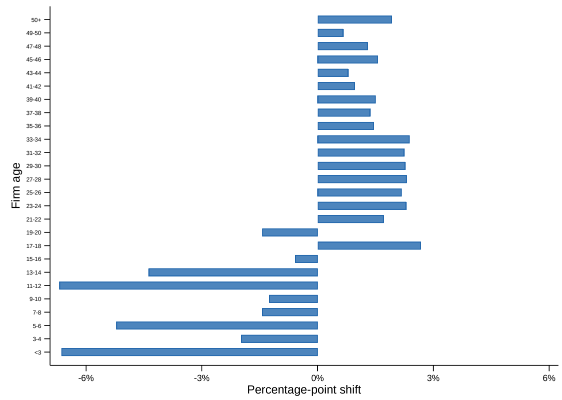
Notes: In Panel A, the increase in rank gap in log weekly wages for U35 worker between year t and 1995 is decomposed into two components: (i) the change in the wage rank at the time of entry in the labor market and (ii) the change in the rank growth between labor-market entry and year t (Equation (4)). Panel B repeats the same analysis for U30 workers. In this case, the starting year is 1990. *Sources:* In each year, the data pools information about all workers who were over 16 years old, worked at least six months, earned strictly positive wages, had full-time contracts, and did not retire. Country: Italy. Time period: 1974-2019. Database: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

C.3 More Results on Firm Heterogeneity

Figure C5: Aging of Firms



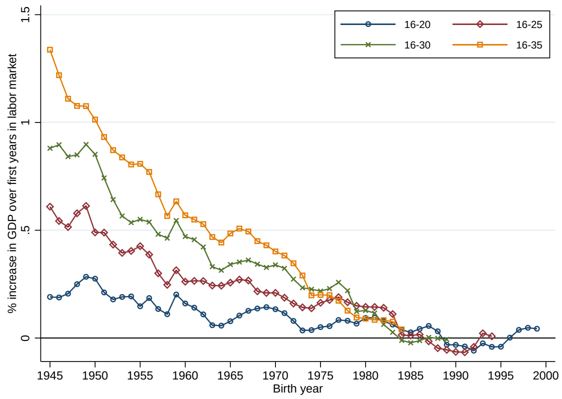
Panel A: Mean firm age



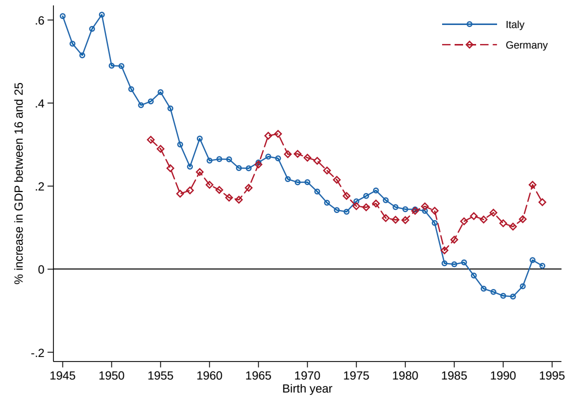
Panel B: Change between 1985 and 2019

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).

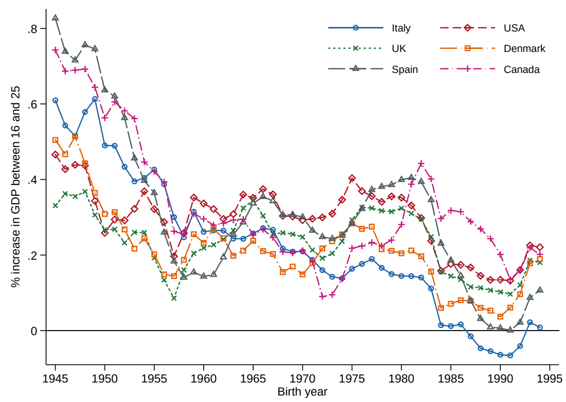
Figure C6: GDP Growth at Entry in Labor Market



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=.

C.4 More Results on the Composition of the Workforce

Table C1: Changes in Workforce Composition

	Gender		Nationality		Contract length		Education		Disability	
	Wage gap (log)	Δ share gap (%)	Wage gap (log)	Δ share gap (%)	Wage gap (log)	Δ share gap (%)	Wage gap (log)	Δ share gap (%)	Wage gap (log)	Δ share gap (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Employer-employee administrative data										
Italy (1985-2019)	0.277	-14.40	0.013	8.58	-0.448	-15.11	-	-	-	-
Germany (1996-2017)										
Panel B: Survey data from the Luxembourg Income Study (LIS) Database										
Australia (1981-2018)	0.361	-9.08	-	-	-	-	-	-	-1.569	8.35
Austria (1994-2019)	0.322	-2.73	0.183	8.21	-	-	0.273	-5.20	-	-
Belgium (1985-2017)	0.260	-16.23	0.073	-7.58	-0.204	9.71	0.240	14.51	-	-
Canada (1991-2017)	0.374	-8.72	0.067	-4.51	-	-	0.289	4.18	-	-
Denmark (1987-2016)	0.354	-3.20	0.211	6.97	-	-	0.318	-6.88	-	-
Finland (1987-2016)	0.306	0.59	-	-	-	-	0.513	2.60	-0.053	-10.90
France (1996-2018)	0.165	-2.43	0.016	4.65	-0.736	-5.40	0.441	-10.48	-	-
Germany (1994-2019)	0.326	-5.70	0.149	2.76	-1.017	-8.42	0.445	-7.44	0.166	-8.08
Greece (1995-2016)	0.278	-21.00	0.147	-2.04	-	-	0.378	-1.61	-	-
Ireland (1994-2018)	0.285	-18.46	-0.100	5.83	-	-	0.380	-12.29	-	-
Israel (1979-2018)	0.510	-6.33	-	-	-	-	0.428	10.00	-	-
Italy (1987-2016)	0.201	-20.14	-	-	-	-	0.414	-5.56	0.030	-1.15
Netherlands (1983-2018)	0.329	-8.80	-	-	-	-	0.500	-21.62	-	-
Norway (1979-2019)	1.029	-7.54	-	-	-	-	-	-	-	-
Spain (1980-2016)	0.315	0.16	-	-	-	-	0.710	-8.91	-	-
Sweden (1981-2005)	0.263	-13.73	-	-	-	-	-	-	-	-
Switzerland (1982-2018)	0.349	-6.69	0.079	0.37	-	-	-	-	-	-
United Kingdom (1979-2018)	0.471	-9.01	-	-	-	-	-	-	-	-
United States (1979-2020)	0.568	-5.64	0.274	6.70	-	-	0.377	6.77	-	-

Notes: The columns titled "Wage gap" show the difference in mean log wages when the dummy is equal to 1 and when it is equal to 0 in the first available year. The columns titled "Δ share gap" show the change in the share of workers for whom the dummy is equal to 1 between O55 workers and U35 workers, as well as between the first and last year in the sample. The dummies are the following: male for "Gender", nonimmigrant worker for "Nationality" (white in the United States to control for race), temp contract for "Contract length", college education for "Education", and disability status for "Disability." *Sources for Italy:* Database UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Sources for Germany:* The German data come from the LIAB Linked Employer-Employee Dataset provided by the Institute for Employment Research. *Sources for survey data:* The survey data in Panel B come from the Luxembourg Income Study (LIS) Database, which can be accessed at https://www.lisdatacenter.org/.

C.5 More Results on the AKM Model

Normalization. In a standard AKM model, the level of the firm and worker 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, by studying the increase in the age wage gap over time, we use the estimates of the AKM model to measure a difference in the *time trends* of the firm and the worker 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 is able to separate the firm fixed effects from the worker fixed effects using movers, that is, workers who move between firms. Therefore, the nature of firm transitions in the data is crucial to ensure that the estimation of Equation (5) 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.

As discussed, each of these three 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 all "movers" in the data, separately for U35 workers and O55 workers. The analysis of these event studies reveals four main results (Figure C7 and Table C4).

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

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.

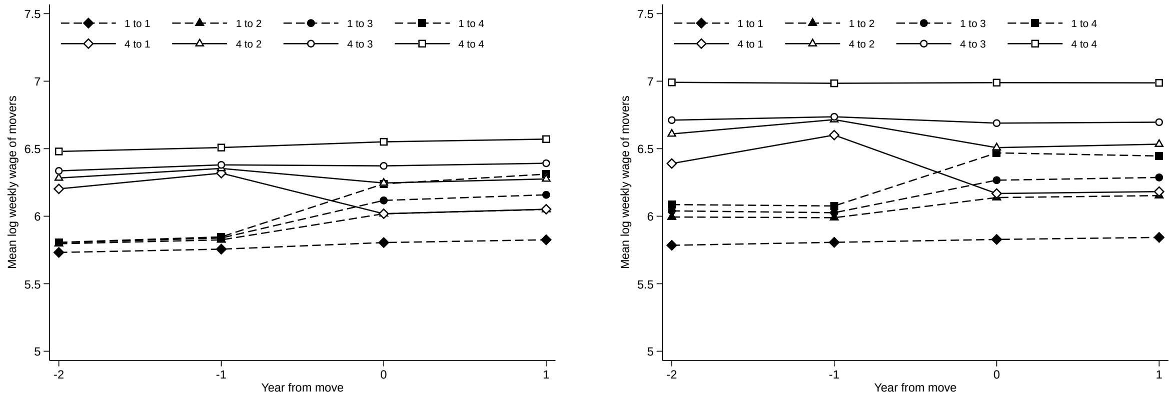
Fourth, there are not significant trends in mean wages during the periods that precede a firm-to-firm transition. Three quarters of the mean wage changes between period -2 and period -1 were less than 0.04 log points.

Residuals. A violation of the separability assumption between the worker effects and the firm rents is likely to produce large residuals in Equation (5) for some type of matches. 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 and worker premiums in deciles and plot the mean residuals for their 100 combinations, separately for U35 workers and O55 workers (Figure C8).

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 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.

Figure C7: Event Studies Around Firm-to-Firm Transitions

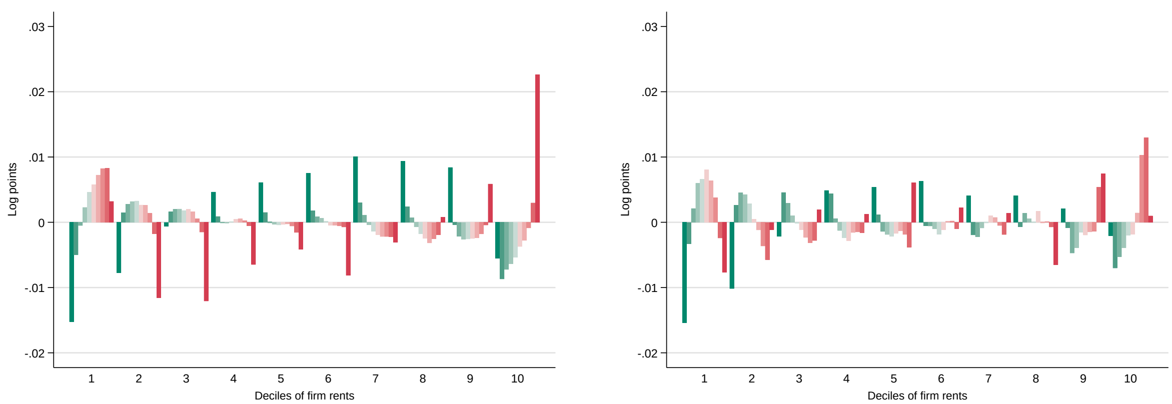


Panel A: U35 workers

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 C8: 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).

Table C2: 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 C3: 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 (5). 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 C4: Wage Changes Associated with Job Moves

	Number of job changes	Percent of job changes	Mean log weekly wages: 2 years before	Mean log weekly wages: 1 year before	Mean log weekly wages: Year of job move	Mean log weekly wages: 1 year after	% change: Raw	% change: 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).