# One Cohort at a Time: Young Workers' Outcomes and the Declining Gender Pay Gap*

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**Abstract**

This paper studies the interaction between the decrease in the gender pay gap and the stagnation in the careers of younger workers, analyzing data from Italy and the United States. Our findings highlight the importance of labor-market entry to understand the shrinking of the gender pay gap. The entire decline in the aggregate pay gap originates from (i) newer worker cohorts who enter the labor market with smaller-than-average gender pay gaps and (ii) older worker cohorts who exit with higher-than-average gender pay gaps. Among the factors driving convergence at labor-market entry, we document that younger men's positional losses in firms' hierarchies and the overall pay distribution have played an important role. We propose an explanation by which a larger supply of older workers can reduce opportunities for younger workers to move up firms' ranks. These negative career spillovers disproportionately affect younger men because they were more likely than younger women to benefit from promotion opportunities at baseline. Consistent with this aging-driven crowd-out interpretation, younger men experience the largest positional losses within the hierarchies of firms that are more exposed to workforce aging. These findings hold after controlling for other factors that have contributed to progressively closing the gender pay gap at labor-market entry. Finally, we document that the retirement of older cohorts has been the sole contributor to the decline in the gender pay gap after the mid-1990s, indicating that without structural breaks, the closure of the gender pay gap is unlikely in the foreseeable future.

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Keywords: gender gap, workforce aging, cohort turnover, wage growth, labor-market entry, entry wages, initial conditions, age pay gap.

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## 1 Introduction

The gender pay gap has been decreasing in many high-income economies since the mid-1970s (Blau and Kahn, 2017). Throughout the same period, younger workers have been faring progressively worse compared to older workers, experiencing a widening age pay gap (Rosolia and Torrini, 2007), lower likelihood of being promoted to higher-paying jobs (Bianchi et al., 2023), and lower employment rates in high-skill jobs (Mohnen, 2025). In this paper, we document how the worsening of the labor-market outcomes of younger workers is related to the narrowing gender pay gap observed in the employee population as a whole.

Using both US survey data and Italian administrative records, we show that cross-cohort generational turnover accounts for the entire decrease in the aggregate gender pay gap: newer cohorts with smaller-than-average gender pay gap levels gradually replaced older worker cohorts with larger-than-average gaps, closing the overall gender pay differential. Crucially, we document that cross-cohort gender convergence at labor-market entry was in large part driven by younger men falling closer to younger women in both firms' hierarchies and the market-wide pay distribution. Finally, in both the US and Italy, gender convergence at labor-market entry stopped in the mid-1990s, a period that coincided with a slowdown in the closure of the aggregate gender pay gap. Since then, the retirement of older worker cohorts with higher-than-average gender pay differentials can account for the entire decline in the gender pay gap, a result that has important consequences for projecting the closure of the pay gap.

We argue that the empirical facts are consistent with an explanation by which an increased supply of older workers reduces younger workers' promotion opportunities across different levels of firms' hierarchies. We formalize this logic by extending a model of the labor market with cross-cohort spillovers between younger and older workers (Bianchi and Paradisi, 2023) to include gender groups. Albeit stylized, this model generates several predictions that closely align with our empirical findings.

The aging-driven crowd-out explanation works as follows. Over the past four decades, the relative supply of older workers in high-income economies has increased as a result of population aging, declining fertility rates, and longer life expectancy (Scott, 2023). Older workers have remained in the labor market longer and have been more likely to advance within their firms, benefiting from factors such as backloaded wage schemes (Ke et al., 2018), knowledge spillovers (Sandvik et al., 2020), firm-specific human capital (Lazear, 2009), and employment protection laws (Bentolila and Bertola, 1990). As workforce aging intensified, firms, especially those most affected by it, have not always been able to expand their ranks to protect promotion paths for younger workers.

As a result, older workers have become more likely to advance into the upper-tier roles within their career paths, creating congestion at multiple points along the job ladder. This dynamic has constrained younger workers' upward mobility—not only into the highest echelons of firms' hierarchies but also into mid-level and senior roles. Crucially, before workforce aging began, younger men were substantially more likely than younger women to hold higher-ranked jobs within most career paths. Hence, workforce aging has displaced younger men from these positions at a higher rate than younger women, contributing to the shrinkage in gender pay differentials.

Our first empirical result illustrates how the closure of the aggregate gender pay gap over the past four decades has stemmed from reductions happening through labor-market entry and exit of worker cohorts,

rather than via changes in the within-cohort, life-cycle profile of the gender gap. This pattern aligns well with our model's prediction that workforce aging shrinks the gender pay gap among younger workers. Moreover, we show that the deceleration in the closing of the total gender pay gap in the economy, which started in the mid-1990s, coincided with a slowdown in the closing of the between-cohort gap.

We then quantify how much of the shrinkage in the gender pay gap stems from cross-cohort convergence between men and women. Specifically, we compute the between-cohort change in the gender pay gap, which excludes any variation in the gap taking place over the cohorts' life cycle. In the baseline analysis, we assign each worker in our data the mean earnings of workers of the same gender and birth year (a cohort) from the first year in which that cohort appears in our sample, but the results are robust to alternative parametrizations. In all countries, more than the entire decline in the aggregate gender pay gap in weekly earnings can be accounted for by a progressive decrease in this between-cohort component. Our analysis thus reveals that the trend in the aggregate gender pay gap can be entirely explained by the entry of younger cohorts with smaller earnings differentials and the exit of older cohorts with larger differentials.

Next, we show evidence consistent with our model's prediction that workforce aging narrows the gender pay gap across cohorts by disproportionately worsening the labor-market outcomes of younger men. First, we analyze the probability of reaching managerial jobs as a proxy for the likelihood of reaching the upper-tier roles within many career paths inside firms. We document that the share of higher-paying managerial jobs held by younger men plummeted between the mid-1970s and mid-1990s, while the share of these jobs held by younger women stayed relatively constant throughout. For example, in the US, the share of managerial jobs with pay in the top quartile of the earnings distribution held by men between 25 and 30 years old dropped from 12 percent in 1976 to 5 percent in 1995, converging to the 2-percent share of these jobs held by younger women.

Second, we examine how the position of 25-year-old men and women evolved over time in the overall pay distribution, rather than focusing exclusively on managerial jobs. The narrowing of the gender pay gap at labor-market entry, which lasted until the mid-1990s, was primarily driven by younger men falling closer to younger women in the pay distribution. In the US, the average rank of younger men at age 25 fell from the 50th percentile of the wage distribution in 1976 to the 39th percentile in 1995, while the mean position of women at age 25 remained fairly stable around the 30th percentile during the same period. After the mid-1990s, the positions of younger men and younger women followed the same flat trajectory. The results are robust to alternative choices for the age of labor-market entry and to considering the median rather than the mean entrant.

Third, we use the Italian administrative data with employer-employee matched records to show that younger men experienced larger positional losses than younger women within the pay distributions of both lower- and higher-paying firms. However, these losses were the largest within the latter group, where older workers have become especially overrepresented over time. Moreover, subsequent cohorts of younger men were progressively less likely to sort into higher-paying firms, eventually converging towards younger women in being underrepresented at higher-paying firms.

We continue to use the Italian administrative data to draw a more direct link between the firm-level exposure to workforce aging and the career outcomes of younger men and women. To this end, for a variety

of time windows between 1976 and 2016, we regress the firm-level change in the gender pay gap at ages 25-30 on the change in the firm-level share of workers aged 51-60, controlling for trends correlated with firm age, firm size, sector, and province.

To account for potential endogeneity, we instrument the change in the 51-60 share with the firm-level difference between the share of workers aged 41-50 and the share of workers aged 51-60 at baseline. This instrument leverages cross-firm variation in the exposure to workforce aging stemming from the age distribution of workers over 40 in the initial period. The high tenure of these workers indicates that cross-firm differences in this variable are likely to originate from hiring decisions that firms made decades earlier, rather than recent firms' actions or firm-level shocks. These IVs confirm that the gender pay gap among younger workers closed significantly faster within firms that experienced a larger increase in the share of older workers. Within these firms, younger men faced significantly more negative career outcomes and converged more dramatically toward younger women.

Finally, if we focus on the last twenty years of data, we show that the gender pay gap has been shrinking due almost exclusively to the exit of older cohorts from the labor market, as convergence at labor-market entry stopped in the mid-1990s.[1] Therefore, in contrast to forecasts based on trends in the aggregate gender pay gap (World Economic Forum, 2023), which usually predict that the mean earnings of men and women will match in a few decades, we project that the gender pay gap is not slated to disappear in the high-income countries in our sample in the absence of structural breaks.

We consider a variety of concurrent factors that may have contributed to close the gender pay gap at labor-market entry, such as time-varying selection into employment, an increase in part-time work, trends in educational attainment, variations in the child pay penalty borne by new parents, sectoral shifts, and the manufacturing decline. Even after accounting for these alternative channels, we find that the aging-driven crowd-out mechanism aligns well with the empirical findings.

A vast literature establishes the existence of persistent gender gaps in the labor market (Goldin et al., 2006; Niederle and Vesterlund, 2011; Fortin et al., 2017, Bertrand, 2020; Olivetti et al., 2024), as well as the recent convergence in the gender pay gap in most high-income economies (Olivetti and Petrongolo, 2016; Blau and Kahn, 2017). Prior work (for example, Black and Spitz-Oener (2010) and Hsieh et al. (2019)) has linked this decline to factors that have improved women's wages and occupational choices. We complement these findings by showing that part of the narrowing in the gender pay gap at labor-market entry was driven by the relative worsening of younger men's labor-market outcomes, a trend that we connect to the phenomenon of career spillovers between older and younger workers.

Moreover, prior studies have shown that the gender pay gap has become progressively smaller for younger cohorts while widening within each cohort (Goldin (2014) and Blundell et al. (2024) for the United States; Fortin (2019) for Canada). We build upon this evidence by zooming in on the determinants and consequences of cross-cohort convergence, using data covering a long period and different countries. Our main contribution is to show that labor-market entry and cohort-replacement effects can fully account for the dynamics of the gender pay gap over the past forty years (i) partially through the *inflows* of newer cohorts with

[1] Consistent with prior work (for example, Sloane et al., 2021), we show that in both Italy and the US, at least among college-educated workers, a large portion of the remaining gender pay gap at labor-market entry by the mid-1990s can be accounted for by differential sorting across higher- and lower-paying majors.

lower gaps for the first two decades, and (ii) exclusively through the *outflows* of older cohorts with higher gaps for the last two decades.

A related body of work has demonstrated that economic conditions at the time of labor-market entry have lasting effects on career trajectories. For example, Oyer (2006), Kahn (2010), and Oreopoulos et al. (2012) show that macroeconomic conditions at the time of graduation affect the careers of new entrants for several years after entry.[2] Bovini et al. (2024) and Foliano et al. (2024) have specifically analyzed the gender pay gap at labor-market entry and its evolution over time. We contribute to this body of work by quantifying the importance of conditions at labor-market entry in shaping the trajectory of the *aggregate* gender pay gap. We find that a greater gender balance in the earnings of new entrants not only was relevant for the gender pay gap of the directly affected cohorts, but was also a major driver of the closure of the economy-wide gender pay gap.

Finally, building on recent work on the worsening outcomes of younger workers (Guvenen et al., 2022; Dabla-Norris et al., 2023), the economic consequences of population aging (Jones, 2022; Maestas et al., 2023), and the interconnectedness of the careers of older and younger workers (Boeri et al., 2022; Bianchi et al., 2023; Bianchi and Paradisi, 2023; Mohnen, 2025), we show both empirically and theoretically that the aging-driven slowdown in the careers of younger workers can disproportionately worsen the labor-market outcomes of younger men, leading to a narrowing of the gender pay gap.

## 2 A Model of the Gender Gap with Cross-Cohort Spillovers

Bianchi et al. (2023) and Bianchi and Paradisi (2023) illustrate how an increase in the supply of older workers can limit access to higher-paying jobs for younger workers, thus widening the pay gap between the two age groups. Under the same conditions that lead to crowding out of younger workers from top jobs, the stylized framework in this section shows that workforce aging can contribute to shrinking the pay gap between men and women.

**Production.** An economy with a price-taking representative firm has a fixed supply of $l_y$ younger workers and $l_o$ older workers. Workers differ with respect to their gender so that the labor supply of each age group can be written as the sum of men and women ($l_a = m_a + f_a$). The firm employs these labor inputs to perform a top job $t$ and a bottom job $b$. These two jobs can be thought of as different levels within specific career paths inside firms, rather than strictly denoting top-level executive positions and entry-level jobs. For example, in a manufacturing firm, the model can capture a blue-collar career path, where an assembly line worker holds a lower-ranked job $b$ and a shift supervisor holds a higher-ranked job $t$.

Production occurs through the production function $AY(L_y, L_o)$, where $A$ is a productivity shifter, $Y_{L_a} > 0$, and $Y_{L_a,L_a} < 0 \ \forall a \in \{y,o\}$. Moreover, younger and older workers are complements in production such that $Y_{L_y,L_o} > 0$. The inputs $L_y$ and $L_o$ are efficiency units of younger and older labor, respectively: $L_a = \theta_{a,t}(m_{a,t} + f_{a,t}) + \theta_{a,b}(m_{a,b} + f_{a,b})$, where $\theta_{a,j}$ is the marginal productivity in job $j \in \{t,b\}$ of workers in the age group $a \in \{y,o\}$. We assume that $\theta_{a,t} > \theta_{a,b} \ \forall a$ to make all workers more productive in the top job.

[2] Further evidence on the importance of initial conditions includes Arellano-Bover (2022), which documents the effect of initial macroeconomic conditions on long-term skill accumulation, and Arellano-Bover (2024), which shows the relevance of first-employer quality for long-term earnings.

**Cross-cohort spillovers and gender pay gap.** In this model, we introduce key features to generate negative career spillovers and a gender pay gap.

We begin by incorporating two components that enable cross-cohort spillovers in employment levels and wages. First, we assume that older workers' wages and job allocations are stickier than those of younger workers. Theoretical and empirical evidence from labor and organizational economics supports this assumption. Older workers are often more sheltered from firm-level shocks due to factors such as backloaded wage schemes (Lazear, 1979; Ke et al., 2018), firm-specific human capital (Lazear, 2009), knowledge spillovers (Sandvik et al., 2020), and employment protection laws (Bentolila and Bertola, 1990).[3]

In this model, we capture this notion by assuming that the firm inherits a stock of older workers from period $-1$ and cannot change their job assignment and wages. Specifically, the number of *legacy workers* in job $j$ is $\rho_j l_{o,j}^{-1}$, where $\rho_j$ denotes the retention rate in job $j$ and $l_{o,j}^{-1}$ represents the number of older workers in job $j$ in period $-1$.

Second, we assume that the firm incurs a quadratic organizational cost proportional to the parameter $\kappa > 0$ to create and maintain $K$ slots at the top ($K = l_{o,t} + m_{y,t} + f_{y,t}$). This cost reflects the constraint the firm faces when expanding higher-ranked positions, even when it is financially capable of paying the associated wages.[4] In fact, top jobs often entail managerial responsibilities and decision-making authority. Therefore, creating a new top job requires slack in both the firm's organizational capacity (available high-level responsibilities) and its payroll budget. For instance, returning to the earlier example of a blue-collar career path, a firm may not be able to freely create additional shift-supervisor roles—even if it has the payroll budget to do so—unless there are shifts that require an additional supervisory position.

Next, we introduce a gender wedge in favor of men which leads to a gender pay gap. Specifically, although men and women are perfect substitutes in production, (i) the firm pays a quadratic cost proportional to $c_g$ for employing younger workers of gender $g$ in the top job, and (ii) this cost is higher for younger women ($c_f > c_m$).[5] These parameters, which make younger women less concentrated in top jobs, can be microfounded as either taste-based or statistical discrimination.[6]

**Wage formation and timing.** Following Acemoglu and Restrepo (2023), we assume that wages in the top job pay an exogenous rent over wages in the bottom job: $w_{a,t}^g = \mu_a w_{a,b}^g$, where $\mu_a > 1$ is the exogenous rent for age group $a$ and $w_{a,j}^g$ is the wage in job $j$ for workers in age group $a$ and gender group $g \in \{m, f\}$.

The timing is as follows. First, the firm is endowed with older workers from period $-1$. Then, given a set of wages for younger workers, the firm decides how many younger men and younger women to slot in the top and bottom jobs by equating their marginal revenue products in the two positions to their marginal costs. Based on these decisions, the firm allocates younger workers randomly between the top and bottom jobs until its labor demands in the two positions are satisfied. Finally, the production is realized, and the firm

[3] Bianchi and Paradisi (2023) uses Italian administrative data to show that older workers' wages respond significantly less than those of younger workers to firm-level negative value-added shocks.

[4] This idea of constrained slots aligns with models and findings discussed by Lazear et al. (2018), Bianchi et al. (2023), and Bianchi and Paradisi (2023).

[5] In principle, we could apply these costs also to older workers. However, they would be redundant because the firm does not choose older workers' employment in period 0.

[6] Alternatively, we could rewrite the production function assuming that (i) men and women are imperfect substitutes in the top job, and (ii) women are less productive than men in the top job.

pays all workers.

**The firm problem.** The firm problem is to choose the number of younger men and younger women (hereafter, shortened to *younger men and women* for ease of exposition) to employ in top and bottom jobs that maximizes its profits, as follows:

$$\max_{m_{y,t},f_{y,t},m_{y,b},f_{y,b}} AY\left(L_y,L_o\right) - \sum_{g\in\{m,f\}}\sum_{a\in\{y,o\}}\sum_{j\in\{t,b\}}\left(w^g_{a,j}g_{a,j}\right) - \frac{\kappa}{2}K^2 - \sum_{g\in\{m,f\}}\left(\frac{c_g}{2}g^2_{y,t}\right).$$

Appendix B discusses the full solution of the firm problem.

In equilibrium, there is a gender gap in employment in top jobs. Specifically, the marginal revenue product of labor of younger men and women in bottom jobs, and hence their wages in both bottom and top jobs, are the same. However, the number of younger women in top jobs is lower than the number of younger men in those jobs because the cost of employing the former is higher than the cost of employing the latter: $c_f > c_m$. In fact, it is optimal for the firm to keep a constant ratio between younger men and women in top jobs below 1: $f_{y,t}/m_{y,t} = c_m/c_f = \delta_f < 1$.

**Comparative statics.** In this labor market, cross-cohort spillovers are crucial drivers of the trend in the gender pay gap. By construction, the gender pay gap can change only if the pay gap between younger men and women differs from that found among older workers. To this end, we consider the effects of an increase in the number of legacy older workers in top jobs inherited by the firm in period 0 ($l^{-1}_{o,t}$) on the mean wages of younger men and women.[7] In doing so, we treat older workers as a single group rather than distinguishing by gender, as our model does not assume gender-specific promotion tracks. For example, in the United States, the mean age of the population increased from 32.5 years in 1976 to 38.7 years in 2019 (Figure A1, Panel A). The mean age of managers reversed trend at the beginning of our sample and increased from 39.3 years in 1981 to 44.3 in 2019 (Figure A1, Panel B).

The mean wage $\bar{w}_{y,g}$ of younger workers of gender $g$ changes as follows:

$$\frac{\partial \bar{w}_{y,g}}{\partial l^{-1}_{t,o}} = \underbrace{\frac{1}{g_y}\left(\mu_y - 1\right)w_{y,b}\frac{\partial g_{y,t}}{\partial l^{-1}_{o,t}}}_{\text{Career spillovers}} + \underbrace{\left(\frac{1}{g_y}\left(\mu_y g_{t,y} + g_{b,y}\right)\right)\frac{\partial w_{y,b}}{\partial l^{-1}_{o,t}}}_{\text{Wage level}}, \tag{1}$$

for each $g \in \{m,f\}$.

An increase in the number of older workers induces the firm to add slots at the top due to the complementarity in production between younger and older workers. However, there is a threshold $\bar{\kappa}$ for the cost parameter $\kappa$ above which this endogenous increase in top jobs $K$ does not compensate for the increased supply of older workers. Hence, when $\kappa > \bar{\kappa}$, the first component of Equation (1) describes negative career spillovers. An increased supply of older workers at the top restricts the career opportunities of younger workers by decreasing their chances of being assigned to higher-paying jobs ($\frac{\partial g_{y,t}}{\partial l^{-1}_{o,t}} < 0$). In contrast, the second component of Equation (1) is positive and refers to changes in the level of wages paid to younger

[7] The implicit assumption is that firms made past hiring decisions without considering future changes (i) in the relative size of cohorts, (ii) in the length of workers' careers, or (iii) in the economic growth rate. We capture this dynamic consideration within our static framework by studying an unforeseen increase in the number of older workers after period $-1$.

workers in both bottom and top jobs. Having more older workers increases the wages of younger workers (i) due to the complementarity of younger and older workers in the production function and (ii) due to the fact that younger workers become more likely to be in bottom jobs and, therefore, their marginal revenue product of labor increases.

**Asymmetric impacts for younger men and younger women.** The model predicts that these negative career spillovers are larger in magnitude among younger men as long as the latter are more concentrated in top jobs than younger women ($\frac{m_{y,t}}{m_y} > \frac{f_{y,t}}{f_y}$).[8] Therefore, by blocking younger workers from top positions, a larger supply of older workers can narrow the preexisting gender pay gap by compressing the earnings of younger men and women toward the bottom of the distribution.

In this framework, an increase in the retention rate of older workers and a decrease in the rate of economic growth each produce the same negative spillovers on the employment outcomes of younger workers. The data confirm that these two phenomena have coexisted with population aging: workers have progressively experienced a slower GDP growth rate (Figure A1, Panel C) and a lower degree of firm dynamism (Decker et al., 2014; Hummels and Yue, 2024).

**Extension: heterogeneous firms.** We replace the representative firm with $N$ heterogeneous firms to study how the gender pay gap varies within and between different firms. Consistent with the idea that the opportunity cost of retirement is increasing with wages, higher-paying firms (higher $A_n$) have a higher retention rate of older workers (higher $\rho_{t,n}$). On the labor-supply side, worker $i$ of age group $a$ and gender $g$ derives the following utility when working in job $j$ and firm $n$: $U_{i,a,j,n} = \log\left(w^g_{a,j,n}\right) + \xi_{i,a,j,n}$, where $\xi_{i,a,j,n}$ represents the idiosyncratic preference of worker $i$ over job $j$ of firm $n$. We assume that $\xi_{i,a,j,n}$ is unobserved by firms and follows a type-1 extreme distribution with a parameter $\sigma > 0$.

This extension (more details in Appendix B) produces two additional insights. First, an increase in the supply of older workers decreases the probability of younger men holding top jobs more than that of younger women within all firms, regardless of their productivity. However, these negative career spillovers are larger in magnitude for both younger men and women within higher-productivity and higher-paying firms because the number of older workers increases more in these firms.

Second, given that younger men are more likely to be displaced from the top jobs of higher-paying firms, they are also more likely than younger women to migrate toward the bottom jobs of other firms. Appendix B outlines under what conditions younger men move from higher-paying to lower-paying firms, a result that finds empirical support.

**Extension: introducing skills.** In this extension (more details in Appendix B), we discuss how our framework can accommodate the slower decline in the gender pay gap that started in the mid-1990s. A key prediction from the baseline model is that younger men are more concentrated in higher-ranked jobs than younger women and, therefore, suffer more harshly from these positions being progressively occupied by

[8] A model inspired by the one in Card and Lemieux (2001), in which older workers are perfect substitutes for younger men and imperfect substitutes for younger women, can produce this result without additional firm-level constraints on the creation of top jobs. However, for a fixed set of substitution patterns and given that the relative supply of older workers has increased throughout our sample period, such a model would not generate the change in trend in younger workers' outcomes in the mid-1990s/early 2000s that we illustrate in Section 5.

older workers. When younger men and women become equally concentrated in top jobs ($\frac{m_{y,t}}{m_y} \approx \frac{f_{y,t}}{f_y}$), further increases in the supply of older men can still harm the prospects of younger workers but cannot do so differentially across genders. After this point, factors other than the initial job assignment, such as gender imbalances that predate entry into the labor market, become the primary drivers of changes in the gender pay gap.

Here, we assume that each worker enters the labor market with either high ($h$) or low ($l$) skills, which represent cross-worker differences in college major choices among other pre-labor-market factors. Moreover, each job is divided into two different tasks, and there is a one-to-one correspondence between skills and tasks. The younger workers' vector of efficiency units of labor is $\mathbf{L_y} = \left(L_{y,h}, L_{y,l}\right)$, and workers with different skills are complements in the production function. The rest of the firm problem is unchanged.

We model a scenario in which younger men and women are concentrated equally in higher-ranked jobs by assuming that the number of older workers in top jobs is large enough that no higher-ranked positions remain available for younger workers in period 0. We then study what happens to the mean wages of younger workers when the number of older workers in top jobs increases even further. Whether the resulting wage change is larger for men or women crucially depends on their distribution across different skills/tasks. If the complementarity between younger and older workers is proportional to a task's marginal product, the change in mean wages of younger women is larger than that of younger men if women are overrepresented in high-skill tasks.

Given that prior research has established that men choose higher-return college majors (skill $h$ in the context of our framework) more than women do (for example, see Black et al. (2008) and Sloane et al. (2021)), an increased supply of older workers is unlikely to further shrink the gender pay gap.

**Summary.** In the rest of the paper, we document a set of empirical facts that are consistent with several predictions of this stylized framework:

1. Cross-cohort differences in the gender pay gap are the main source of decline in the aggregate gender pay gap (Section 4).

2. The gender pay gap narrows across cohorts because younger men lose more positions in the overall pay distribution and in firms' hierarchies, relative to younger women (Section 5).

3. These cross-cohort spillovers are more negative among younger men than among younger women within all firms. For all younger workers, they are larger in magnitude among higher-paying firms (Section 5).

4. Compared to younger women, younger men leave higher-paying firms at a higher rate (Section 5).

5. When the concentration of younger men and women in higher-ranked jobs becomes more balanced and predetermined education choices account for a large share of the gender pay gap, workforce aging stops shrinking the gender pay gap at labor-market entry (Section 8).

## 3 Data

This paper uses administrative and survey data with 375 million observations from the United States and Italy . The combination of Italian and US datasets allows us to exploit the relative strengths of administrative population data (employer-employee linkages) and large-scale survey data (detailed information on all persons regardless of labor force participation).

### 3.1 US: Labor Force Surveys

Most of our US analyses rely on forty-four years (1976-2019) of repeated cross-sections from the Annual Social and Economic March Supplement of the Current Population Survey (CPS), which we accessed through IPUMS. We impose similar sample restrictions across all the datasets available to us: we limit our sample to individuals between 25 and 64 years old, working in the private sector for at least 24 weeks during the past year, and with strictly positive earnings.[9]

The CPS data allow us to construct three compensation measures: (i) the annual wage and salary income, (ii) weekly earnings, obtained by dividing the annual wage and salary income by the number of weeks worked during the previous year, and (iii) hourly earnings, obtained by dividing weekly earnings by the usual number of hours worked per week. All compensation measures are expressed in 2015 USD, using the CPI provided by the Bureau of Labor Statistics. Moreover, they are winsorized yearly at the $99.9^{\text{th}}$ percentile from above.

Since the CPS does not include information on college graduates' field of study, we complement some of our analyses with data from the 2009–2019 waves of the American Community Survey (ACS), also accessed through IPUMS.

### 3.2 Italian Social Security Data

We use confidential administrative data provided by the Italian Social Security Institute (INPS). This dataset comprises forty-four years (1976-2019) of matched employer–employee records for the whole population of private-sector, nonagricultural firms with at least one salaried employee. In each year, we focus on workers who were between 25 and 64 years old, had worked at least 24 weeks, had earned strictly positive earnings, and had not retired by December 31. Unlike the CPS data, the INPS dataset matches workers to firms, a feature that allows us to draw a closer link between firm-level exposure to workforce aging and the trends in the gender pay gap.

The Italian administrative data include two main compensation measures: (i) total annual earnings, which comprise all forms of gross labor compensation, and (ii) full-time-equivalent (FTE) weekly earnings, computed as the ratio between total annual earnings and FTE working weeks. Both variables are expressed in 2015 euros using the CPI provided by the OECD. Moreover, they are winsorized at the $99.9^{\text{th}}$ percentile from above.[10] We complement the administrative data with the Labor Force Survey for the years 2009-2019 to shed light on the changes in college graduates' fields of study.

[9] At baseline, we focus on private-sector workers for comparability with the Italian administrative records. However, we show that our results are robust to including US public-sector workers in the sample.

[10] Annual earnings are also winsorized at €3,000 from below to address a few instances in which yearly compensation is implausibly low.

## 4 The Cross-Cohort Decline in the Gender Pay Gap

### 4.1 Aggregate and Cohort-Specific Trends in the Gender Pay Gap

**Aggregate gap.** For at least the last four decades, the United States and Italy have been experiencing a decrease in the gender gap in weekly earnings (Figure 1). Between 1976 and 2019, the gender gap shrank by 0.47 log points or 59 percent (relative to the baseline level of 0.8 log points) in the US and by 0.19 log points or 57 percent (relative to the baseline level of 0.33 log points) in Italy.[11] If we replace yearly earnings for weekly earnings, the decrease in the gender gap remains large, at -59 percent in the US and -26 percent in Italy (Table A1).

**Gap between and within cohorts.** We now start to highlight the importance of cross-cohort dynamics in driving the aggregate trend in the gender pay gap (Figure 2, Panels A and B). Specifically, for various worker birth cohorts, we plot the trend in the gender gap from the year in which all workers in the cohort turned 25 years old to the year in which they turned 50 years old.[12] This graph shows three main results that will inform most of the further analysis in the rest of the paper.

First, consistent with Prediction 1, the aggregate downward trend in the gender gap stems entirely from the fact that younger worker cohorts entered the labor market with smaller initial differences in the log weekly earnings of men and women. In the US, the gender gap at age 25 decreased from 0.55 log points for the cohorts born between 1947 and 1951 to 0.19 log points for the cohorts born between 1967 and 1971. Similarly, in Italy the gender gap at age 25 declined from 0.21 log points for the cohort born in 1951 to 0.09 log points for the cohort born in 1971.[13]

Second, the gender gap almost always increases over the life-cycle of each cohort (Bertrand et al., 2010).[14] Moreover, this within-cohort increase becomes steeper across subsequent worker cohorts, a trend that works against closing the aggregate gender gap. If we consider the 1951 cohort, the gender gap increased between age 25 and age 30 by 0.07 log points in the US and 0.01 log points in Italy. The same increase for the 1971 cohort was equal to 0.17 log points in the US and 0.03 log points in Italy. These within-cohort dynamics are consistent with many prior findings in the literature. For example, the child penalty incurred by mothers in the labor market (Kleven et al., 2019) and women's propensity to move towards more flexible but lower-paying jobs (Goldin, 2014) are two factors that contributed to increasing the gender pay gap after labor-market entry, especially among more recent worker cohorts.

Third, convergence at labor-market entry across subsequent worker cohorts significantly slowed after 1995. As already discussed, the gender pay gap at age 25 dropped by 0.36 log points in the US and by 0.12 log points in Italy between the 1951 cohort and the 1971 cohort, but then declined by only 0.01 log points in the US and by 0.02 log points in Italy by the 1991 cohort. The end of this convergence coincided with a slowdown in the closure of the aggregate gender pay gap.

[11] In the United States, the aggregate gender pay gap was largely stable between 1955 and 1975 (Bailey et al., 2024).

[12] We stop at 50 years old to limit the influence coming from selection into retirement.

[13] In the CPS data, we create groups of five cohorts to increase precision. In this case, we start reporting the cohort-level gaps when all cohorts within a group turn 25 years old. In the remainder, we refer to these groups using their youngest cohort.

[14] The flattening toward the end of each cohort's career is consistent with more negative selection into early retirement among women (Goldin and Mitchell, 2017).

### 4.2 The Gender Pay Gap Within and Between Cohorts

We now introduce a more formal test of Prediction 1, which states that most of the decline in the gender pay gap has been taking place across worker cohorts. To this end, we propose a decomposition of the change in the gender pay gap within and between worker cohorts.

First, we write the average log earnings of birth-year cohort $c$ of gender $g$ at time $t$ ($w_{c,g,t}$) as the sum of two terms: $w_{c,g,t} = w^e_{c,g} + \Delta w_{c,g,t}$, where $w^e_{c,g}$ represents cohort $c$'s mean log earnings in the first year in which it appears in our sample ($e$ for entry into the sample), and $\Delta w_{c,g,t} = w_{c,g,t} - w^e_{c,g}$ is the growth of the average log earnings of cohort $c$ between year $t$ and the first in-sample year. In our baseline results, we compute $w^e_{c,g}$ as the cohort-gender mean earnings either (i) in 1976 for workers who were at least 25 years old in the first sample year or (ii) in the year in which workers who were younger than 25 years old in 1976 turned 25. In Section 6, we show that the results are robust if we choose different entry ages.

Let $w_{g,t}$ represent the average log earnings of all workers of gender $g$ in year $t$ and let $a(c,t)$ denote the age of cohort $c$ in year $t$. The change between year $t$ and year $t' > t$ in the average log earnings of gender group $g$ is:

$$
\begin{aligned}
w_{g,t'} - w_{g,t} \quad = \quad & \underbrace{\sum_{c:a(c,t')\in[25,64]} s_{c,g,t'} \cdot w^e_{c,g} - \sum_{c:a(c,t)\in[25,64]} s_{c,g,t} \cdot w^e_{c,g}}_{\text{Between-Cohort Change}} \\
& + \underbrace{\sum_{c:a(c,t')\in[25,64]} s_{c,g,t'} \cdot \Delta w_{c,g,t'} - \sum_{c:a(c,t)\in[25,64]} s_{c,g,t} \cdot \Delta w_{c,g,t}}_{\text{Within-Cohort Change}},
\end{aligned} \tag{2}
$$

where $s_{c,g,t}$ is the share of workers of gender $g$ from cohort $c$ in year $t$ over the total number of workers of the same gender. This share operates as a weight for a given cohort of active employees (between 25 and 64 years old) in a given year.

The first two terms in Equation (2) quantify the *between-cohort* change between $t$ and $t'$. This between-cohort component captures variation in the mean log earnings of gender group $g$ that stems from (i) cross-cohort differences in earnings at sample entry and (ii) changes in the distribution of workers across birth cohorts over time. In contrast, the last two terms of Equation (2) measure the *within-cohort* change between $t$ and $t'$, which isolates variation in the mean log earnings of gender group $g$ that originates from (i) changes in the life-cycle earnings growth for the average cohort active in the labor market between $t$ and $t'$, and (ii) changes in the relative size of cohorts over time. If we subtract Equation (2) for women from Equation (2) for men, we can quantify the contribution of the *between-cohort* and *within-cohort* components to the aggregate trend in the gender pay gap.

This decomposition between and within cohorts does not directly map into "cohort effects" in the canonical model of separate and unrestricted age, time, and cohort effects (see chapter 2.7 in Deaton, 1997). Instead, we define birth cohorts—and consequently, between-cohort effects—by the interaction of age (time of labor-market entry) and birth year. This decomposition serves as an initial test of whether the trends in the gender pay gap align with our broader hypothesis, rather than as a formal identification strategy. For this evidence to be a perfect test of our model, we would need to assume that there are no fundamental, unob-

served differences (for example, men's ability) across birth cohorts. Our subsequent analyses provide a more direct validation of our hypothesis by establishing a link between workforce aging and worker outcomes at the firm level and by accounting for several cohort-varying factors that have influenced the gender pay gap.

The data highlight the importance of cross-cohort effects in driving the trend in the overall gender pay gap (Figure 2, Panels C and D). In both the United States and Italy, the between-cohort decline in the gender pay gap is at least as large as the total decline. These findings hold for different earnings measures (Table A1). The fact that, in most sample years, the between-cohort component accounts for more than 100 percent of the total decline in the gender pay gap confirms that the gender gap has been increasing over the life cycle of the average worker cohort.

## 5 The Wage Ranks of Younger Workers

Section 5.1 and Section 5.2 below present the empirical evidence in support of Prediction 2, which states that the gender pay gap among younger workers has closed because younger men have fallen toward younger women in firms' hierarchies and in the pay distribution.

### 5.1 The Probability of Holding Higher-Ranked Positions

We first study trends in the probability of younger men and women holding relatively higher-ranked jobs within firms' hierarchies. Ideally, we would like to have access to detailed personnel data to analyze the probability of younger men and women accessing the higher ranks of specific career paths within firms. Using the administrative and survey data available to us, we focus on managerial jobs as a proxy for the type of higher-ranked positions that represent the culmination of at least some promotion paths. In Section 5.2, we show that our findings do not apply only to these jobs but more broadly to the overall labor market.

We classify higher-ranked positions as all management occupations with associated annual earnings in the top quartile of the year-specific distribution.[15] While this classification is not a necessary condition for our crowd-out mechanism to apply, it is likely a sufficient one

In both countries, higher-paying managerial jobs have become substantially less likely to be filled by younger workers (Figure A2). For example, in the US, the likelihood of a higher-ranked position being filled by a younger worker decreased from 13 percent in 1976 to 7 percent in 2019, even though these jobs accounted for a slightly increasing share of all jobs in the economy (from 6.5 percent in 1976 to 7 percent in 2019) during the same period.

Importantly, this crowding out of younger workers from these positions has affected younger men more than younger women, which aligns with Prediction 2 (Figure 3, Panels A and B). In the US, the share of higher-ranked jobs filled by men between the ages of 25 and 30 fell from 12 percent in 1976 to 5 percent in 1995, and then to 4 percent in 2019. Meanwhile, the corresponding share for women in the same age group and job category increased from 1 percent in 1976 to 2 percent in 1995, and to 3 percent in 2019.

In summary, younger men have progressively held a smaller share of higher-ranked positions, even as the overall prevalence of such roles in the labor market has slightly increased. Younger women were not subject

[15] In the CPS data, managerial occupations are identified using 2-digit Standard Occupational Classification (SOC) code 11. In the INPS data, we use the highest ranked position out of the four main job categories in the Italian labor system: in ascending order, these are apprenticeships, blue-collar jobs, white-collar jobs, and managerial jobs. The figures based on Italian data show a spurious trend discontinuity in the mid 1990s because the definition of managerial jobs in the INPS data changes from 1996.

to the same degree of crowd-out because they did not have these promotion opportunities at baseline. If anything, they have become more likely to progress further along firms' hierarchies.

## 5.2 The Pay Rank Gap at Labor-Market Entry

This section shows that the main takeaway of Section 5.1 holds if we investigate changes in the rank of new entrants within the wage distribution at the time of their labor market entry, rather than their probability of holding managerial jobs.

Let $F_t(w)$ represent the distribution of weekly earnings for all workers in year $t$.[16] For each new entrant $i$ with weekly earnings $w^E_{it}$, we compute where they rank in the overall distribution: $p_{it} \equiv F_t(w^E_{it})$. We then compute the average rank among all entrants of gender $g$ in year $t$ as follows: $\bar{p}_{gt} = \frac{1}{N_{gt}} \sum_{i \in \{g,t\}} p_{it}$, where $N_{gt}$ is the number of labor market entrants of gender $g$ in year $t$. As discussed in Section 4.2, we fix the time of labor-market entry in the data at age 25.

Building upon the analysis of the racial wage gap in Bayer and Charles (2018), we also consider an alternative metric focusing on the position of the *median* entrant to discount the influence of potential outliers in either tail of the pay distribution. Let $F_t(w)$ represent the distribution of weekly earnings for all workers in year $t$ and $F^E_{gt}(w)$ represent the distribution of weekly earnings at entry among gender $g$ in year $t$. The gender-specific quantile-$q$ entry pay is given by $w^E_{qgt}$, defined so that $F^E_{gt}(w^E_{qgt}) = q$. The rank of the median entrant in the overall distribution is given by $P_{qgt}$, where $P_{qgt} \equiv F_t(w^E_{qgt})$ and $q = 0.5$.

Consistent with Prediction 2, the gender pay gap at labor-market entry has shrunk because the mean position of younger men in the wage distribution has declined substantially more than that of younger women (Figure 3, Panels C and D). In 1976, the average rank of younger men at age 25 was equal to the 50th percentile of all weekly earnings in the United States and to the 47th percentile in Italy. By 1995, the position of younger men had fallen to the 39th percentile in the US and to the 36th percentile in Italy. During the same period, the mean position of women at age 25 remained fairly stable around the 30th percentile in both countries.

We reach the same conclusions if we consider the median position, rather than focusing on the mean rank (Figure A3, Panels A-B). Similarly, the results are robust to using hourly earnings for the US (Figure A4).

As prior work (for example, Black and Spitz-Oener (2010) and Hsieh et al. (2019)) has documented, women have experienced significant advancements in labor-market outcomes over this period. Thus, our findings should not be interpreted as evidence that younger women have seen no progress at labor market entry. Rather, their relatively stable position in the pay distribution can reflect the interplay of opposing forces. Workforce aging, which we argue has contributed to the decline in younger men's positions, could have also negatively affected younger women—albeit to a lesser extent. However, other factors, such as lower degrees of gender discrimination, may have simultaneously improved younger women's outcomes. The net effect of these forces appears to be a stable position around the 30th percentile, rather than a decline.

[16] Using the position in the population's pay distribution allows a close mapping between the model and the results. In fact, Prediction 2 concerns the *rank* of younger men and women in the pay distribution, rather than their average wage. In addition, by focusing on ranks, we avoid any potential confounders in the level of wages that stem from trends in wage inequality, among other factors.

Moreover, more significant improvements among older women may have kept younger women near the bottom of the pay distribution. To explore this possibility, we replicate our baseline analysis by recalculating the ranks of younger men and women within the earnings distribution of men aged over 55, therefore excluding older women from the benchmark group (Figure A6). At least in the United States, younger women gained some ground within this more restricted pay distribution between 1976 and 1995. Nonetheless, the main result remains: the gender pay gap at labor-market entry closed in large part because younger men fell closer to the bottom of the pay distribution.

Finally, one concern is that the positional loss younger men experienced may not reflect a true worsening of their labor-market outcomes if wages at the lower end of the pay distribution have converged to the median. However, prior research shows that low wages have grown more slowly than wages at or above the median in both the Unites States (Autor et al., 2008; Danieli, 2024) and Italy (Depalo and Lattanzio, 2025). To further address this concern, we calculate the distance between younger workers' mean log weekly earnings (separately for younger men and women) and the total mean log weekly earnings in the private sector. Even after accounting for changes in the earnings distribution over time, the data indicate that younger men shifted closer to the bottom of the distribution, converging toward younger women (Figure A5).

### 5.3 Younger Workers in Lower-Paying and Higher-Paying Firms

This section documents how the gender pay gap among new entrants has changed in lower- and higher-paying firms. For this analysis, we are limited to the Italian context because we must use administrative data matching workers to firms.

We start by dividing workers into one hundred percentiles based on their employer's mean wage in each sample year so that these firm groups have the same number of workers but varying wage levels. As expected, the data indicate that workforce aging is more severe among higher-paying firms, in which monetary returns of postponing retirements are higher (Figure A7). Between 1976 and 1995, the same period in which the careers of younger workers, especially men, substantially slowed down, the share of workers over 50 employed by firms with above-median mean pay increased by 6 percentage points and by firms in the top two deciles of mean pay by 5.2 percentage points.

Next, we analyze the outcomes of younger men and women across these firm groups. To this end, we compute the mean percentile of men and women at age 25 using the wage distribution within each percentile of mean firm pay. The empirical findings support Prediction 3, which states that younger men experience career spillovers that are more negative than younger women do in higher- and lower-paying firms, and that these losses are larger for younger workers of both genders in higher-paying firms, where workforce aging is more extreme. Compared to younger women, younger men have experienced larger declines in their mean percentile within ninety-three out of one hundred firm groups (Figure 4, Panel A). Moreover, the results indicate that the positional losses were more pronounced within higher-paying firms for all younger workers. Between 1976 and 1995, the mean positional change within above-median firm groups was equal to -10 percentiles for men and -6 percentiles for women, while the same change within below-median firm groups was -7 percentiles for men and +0.5 percentiles for women. As already discussed in Section 5.2, the gender pay gap among new entrants stopped closing after the mid-1990s. Consistent with this prior evidence, we find that younger men and women experienced similar rank losses between 1995 and 2019 in all firm

groups (Figure 4, Panel B).

Finally, consistent with Prediction 4, the share of younger men in higher-paying firms has declined more than that of younger women (Figure 4, Panel C): between 1976 and 1995, the probability of 25-year-old men working in the top decile of firm groups decreased on average by 6 percentage points (a 62 percent decline from the 1976 level), while the same probability for 25-year-old women fell by only 2 percentage points (a 28 percent decline from the 1976 level). At baseline, younger men were fairly equally distributed across lower-paying and higher-paying firms, while women were overrepresented among lower-paying firms.[17] Over time, the distribution of younger men across different firm groups moved closer to that of younger women. As expected, there are not remarkable differences across the two genders after 1995 (Figure 4, Panel D).

## 6 Alternative Explanations and Robustness Checks

### 6.1 Labor Force Participation

In this set of tests, we explore whether our prior results can stem exclusively from differential trends in the labor force participation of men and women, especially around labor-market entry. In the US, female labor force participation at age 25 increased by 8 percentage points between 1976 and 1986 and has remained stable ever since (Figure A8).[18]

To account for changes in selection into the labor market, we follow the procedure outlined in Blau et al. (2024). First, we expand the sample to include individuals who worked less than 24 weeks in the year (but at least 100 hours) and had positive labor earnings. Second, we impute the weekly earnings of nonparticipants based on their probability of falling into each decile of the pay distribution. We predict these probabilities via an ordered probit estimated separately by year and gender using the following observable characteristics: years of education, a dummy for college graduation, a dummy for advanced degrees, potential experience (age-years of education-6), potential experience squared, race (white, black, others) and ethnicity (hispanic) dummies, and fixed effects for Census divisions.

All our prior results hold when we replicate them on this selection-adjusted sample (Figure A9). The between-cohort component keeps explaining more than the entire decline in the aggregate gender pay gap. Moreover, the average rank of younger men at age 25 fell from the 57th percentile of the selection-adjusted distribution of weekly earnings in 1976 to the 42nd percentile in 1995, while the average rank of younger women at age 25 remained fairly stable around the 35th percentile during the same period. The relative positions of both genders showed little variation after the mid-1990s. These results alleviate the concern that the increase in the labor-force participation of younger women between 1976 and 1986 had direct negative effects on the career outcomes of younger men, a conclusion that is consistent with the findings in Fukui et al. (2023).

[17] Our result that younger women were always overrepresented in lower-paying firms is consistent with the findings in Card et al. (2016) and Casarico and Lattanzio (2024).

[18] This section focuses on the US for two reasons. First, the INPS data include only employees. Second, data from the Bank of Italy's Survey of Household and Income Wealth indicate that women's labor-force participation was fairly constant in the 1980s and the 1990s and only slightly declined in the 21st century.

### 6.2 Sectoral Shifts

We test whether the decline in the gender pay gap across cohorts is entirely accounted by variation in the sorting of men and women across sectors. To do so, we consider the between-cohort component in Equation (2) and further decompose it between and within sectors. Sectors are defined using 1-digit NACE Rev. 2 codes in the United States and 2-digit codes in Italy.[19]

In both countries, most of the between-cohort decline in the gender pay gap has taken place within sectors (Figure A10). Specifically, 18 percent of the total between-cohort change between 1976 and 2019 occurred across 1-digit sectors in the US, while none of the decline between 1976 and 2019 took place between 2-digit sectors in Italy. Therefore, the data suggest that a loss of employment in economic sectors where men historically received high wages, such as manufacturing (Charles et al., 2019), does not appear responsible for a meaningful portion of the cross-cohort decline in the gender pay gap.

Next, we directly address the progressive decline of the manufacturing sector. Using data from the first five sample years (1976-1981), we estimate a probit model for an indicator for working outside of manufacturing as a function of several worker-level characteristics.[20] Next, we use the estimated coefficients to predict the probability of working outside of manufacturing for the whole sample. Then, we retain in the sample only individuals with a predicted probability above the year-specific median (Figure A11). All prior results hold after either dropping every manufacturing worker or retaining only workers with a higher predicted probability of working outside of manufacturing.

### 6.3 Changes in Educational Attainment

We investigate whether an increase in the college graduation rate of women or a decline in that of men (Autor and Wasserman, 2013; Blau and Kahn, 2017) could fully account for the cross-cohort shrinkage of the gender pay gap.[21] Using an approach similar to the one described for studying sectoral shifts, we decompose the total decline in the gender pay gap as well as its between-cohort component within and between two education levels: workers with and without a college degree (Figure A12). In this decomposition, the between-college component quantifies how much of the gender pay gap's decline stems from the fact that women have become more likely to graduate from college over time (or men have become less likely to graduate). In the US, the between-college dimension accounts for only a minor share of the decline in both the total (14 percent) and between-cohort (14 percent) gender gap between 1976 and 2019.

Next, we show that the results in Section 4 and Section 5 hold for individuals with and without a college degree (Figure A13). For example, the finding that younger men have become less likely than younger women to hold higher-ranked positions is robust when analyzing only the jobs held by college graduates or workers without a college education.

While rising college graduation rates among younger women have undoubtedly expanded their career

[19] Although the information on 2-digit codes is available for the United States, we use 1-digit codes in order to have enough observations in each cohort-year-sector cell.

[20] We use the following regressors: US Census divisions or Italian regions fixed effects interacted with age, age squared, completed education (less than high school, high school, some college, four years of college or more; US only), gender, race (the same three categories used to address selection into the labor market; US only), ethnicity (US only), and a foreign born dummy (Italy only).

[21] Here, we focus on the US because the INPS data lack information on completed education for most workers in the sample.

opportunities, part of the gender convergence in pay at labor market entry stems from a worsening in the careers of younger men *regardless* of educational attainment. We argue that this pattern is consistent with workforce aging being a contributing factor to gender pay equity. Older workers with and without a college education have started occupying a larger share of the upper-tier jobs they can achieve within their education level. Even if not all these jobs are positioned at the very top of firms' hierarchies, workforce aging can still impede the career progression of younger workers (especially men) of similar educational backgrounds. In other words, older workers with a college education can crowd out younger men of similar education from top managerial jobs, while older workers without a college education can crowd out younger workers of similar education from middle-management and supervisory positions.

Finally, we test whether our choice of observing many outcomes at age 25 is problematic. For example, an increasing trend in college graduation rates over time could change the average work experience of 25-year-olds. First, we show that our findings are robust to alternative definitions of younger workers: individuals observed at ages 25 (the baseline), 28, 30, and ages 25 to 30 (Table A1, Columns 3 to 6). Second, the between-cohort component continues to account for the whole decline in the gender pay gap if we exploit the longitudinal dimension of the Italian data to define $w^e_{c,g}$ as the earnings observed during the first year in the labor market for each worker who started working after 1976 (Table A1, Columns 7 to 8). Third, the findings hold when we analyze younger workers by years of potential work experience rather than by age (for the US only; Figure A14).

### 6.4 Child Penalty

We test whether a decrease in the child penalty borne by mothers in the labor market could fully explain the importance of the between-cohort convergence in earnings. Since childbirth tends to happen in a woman's earlier career stages, a progressively lower child penalty could disproportionately benefit women in younger cohorts. We expect that accounting for this factor would reduce the contribution of the between-cohort component, albeit modestly, given that the overall wage effects of the child penalty estimated in the literature are relatively small.

For each year, we estimate how much of the between-cohort change in the gender pay gap is explained by disparities in the negative consequences of having children on the careers of new mothers and fathers. Following Kleven et al. (2019) and Casarico and Lattanzio (2023), we first calculate estimates of the child penalty in weekly earnings between mothers and fathers in the United States and between women with and without children in Italy, using a subset of data for which we have fertility information from maternity leave applications. We then create counterfactual weekly earnings by multiplying women's weekly earnings by the product of the child penalty and the fraction of mothers in each year and cohort. This variable is an estimate of women's earnings if we were to eliminate the adverse effects of parenthood on women's careers.

As expected, we find that accounting for the child penalty decreases the contribution of the between-cohort component to the overall decline in the gender gap, but this effect tends to be small in magnitude (Figure A15). Even after adjusting for the child penalty in the United States and Italy, the main takeaways of the prior two sections still holds: the decline in the gender pay gap stems entirely from differences across worker cohorts, and younger men lost more ground than younger women in the pay distribution.

### 6.5 Other Trends

**Full-time workers.** We then move to investigate whether a disproportionate increase in the proportion of full-time female workers could serve as an explanation for the between-cohort convergence in mean earnings. To this end, we replicate all the prior findings, limiting the sample to only full-time workers (Figure A16). In this more restricted sample, the main results hold.

**Public employees.** For comparability, we omit public-sector employees from our preferred sample as they are present in the CPS data but not in the Italian INPS data. Here, we show that all our prior findings hold if we include public-sector employees in the CPS data. We can also use this larger sample to replicate the procedure outlined in Section 6.1 to account for time-varying selection into both the private and public sector. The data clearly indicate that the results are robust if we (i) include public-sector employees in the sample (Figure A17, Panels A-C) and (ii) expand the sample to public employees while also accounting for time-varying and gender-specific selection into the labor market (Figure A17, Panels D and E).

**Residual earnings.** Finally, we control for multiple observable characteristics at once. We regress the log of weekly earnings on a dummy for part-time workers, a dummy for temporary workers (only in Italy), a dummy for domestic-born workers (only in Italy), dummies for race (only in the US), a dummy for college graduation (only in the US), and a dummy for workers with children (only in the US). For the US, we have a second version in which we control for even more variables: in addition to the previous regressors, we include a dummy for hispanic ethnicity, dummies for marital status, and fixed effects for Census divisions. We estimate these regressions separately by year and country to allow the coefficients to vary over time and across different datasets. Based on these coefficients, we compute residual earnings and use them to show that the main findings in Section 4 and Section 5 are all robust (Figure A18).

## 7 Firm-Level Exposure to Workforce Aging

This section tests the core idea behind the stylized framework in Section 2 by drawing a direct link between workforce aging and changes in the gender pay gap of younger workers. Using the Italian employer–employee matched data, we exploit variation across firms in the degree of aging they experience. Consider the following firm-level regression equation:

$$\Delta y_f^{(25-30)} = \alpha + \beta \Delta s_f^{(51-60)} + X_f' \gamma + \varepsilon_f, \tag{3}$$

where $\Delta$ represents changes in firm-level variables between 1976 and 1986, the period of fastest pay convergence between younger men and women. The dependent variable $y_f^{(25-30)}$ measures either the gender pay gap or the mean outcomes of men and women in firm $f$, computed for workers aged 25-30. The key independent variable $s_f^{(51-60)}$ denotes the share of firm $f$'s workers who are between 51 and 60 years old. The vector $X_f'$ includes province fixed effects, firm age, firm size, and sector, all observed at baseline. Due to its first-difference setup, this specification implicitly controls for any time-invariant firm-level factors, while $\gamma$ controls for differential trends as a function of covariates included in $X_f'$. Standard errors are clustered at

the province level.[22]

The parameter of interest is $\beta$, which measures how changes in the share of older workers in firm $f$ affect the evolution of the gender pay gap or mean pay rank of younger employees. However, OLS estimates of $\beta$ may be biased if unobserved firm-level labor-demand shocks influence both workforce aging and changes in younger workers' outcomes.

### 7.1 Instrumental Variable: Firms' Age Structure at Baseline

To address this concern, we propose an instrument that exploits variation in the age distribution of firms' workforce at baseline. In particular, we instrument $\Delta s_f^{(51-60)}$ with the ten-year change in the share of firm $f$'s workforce over 50 that is projected on the basis of the age distribution of workers just younger than 50 in 1976. Denoting the projected $\Delta s_f^{(51-60)}$ by $\widetilde{\Delta} s_f^{(51-60)}$, our instrument is defined as:

$$\widetilde{\Delta} s_f^{(51-60)} = \left( s_{f,1976}^{(41-50)} - s_{f,1976}^{(51-60)} \right),$$

where $s_{f,1976}^{(41-50)}$ is the share of firm $f$'s workers between 41 and 50 years old in 1976.[23] This instrument captures changes in the firm-level share of workers over 50 between 1976 and 1986 driven by the natural aging of employees who were *already* working at firm $f$ in 1976. This strategy mirrors the approach used by Mohnen (2025) to study the effects of differences in retirement rates across US commuting zones on youth employment.

**IV Relevance.** The variable $\widetilde{\Delta} s_f^{(51-60)}$ has two characteristics that make it a suitable instrument. First, it is highly, but not perfectly, correlated with the endogenous regressor $\Delta s_f^{(51-60)}$ (Table A2, Panel A). A 1-percentage-point increase in $\widetilde{\Delta} s_f^{(51-60)}$ is associated with a 0.58-percentage-point increase in $\Delta s_f^{(51-60)}$, an effect that is statistically significant at the 1 percent level. The fact that this coefficient is less than one suggests some degree of turnover among older workers. The first stage is strong, with F-statistics that range between 2,000 and 11,000 depending on the sample and specification (Table 1).

**IV Exclusion.** Second, the exogeneity of the instrument relies on the assumption that the projected change in workers over 50 in 1976 ($\widetilde{\Delta} s_f^{(51-60)}$) affects changes in younger workers' outcomes between 1976 and 1986 ($\Delta y_f^{(25-30)}$) only through its influence on the actual change in the share of workers over 50 during the same period ($\Delta s_f^{(51-60)}$). Although this exclusion restriction is not directly testable, we argue that, unlike $\Delta s_f^{(51-60)}$, differences in $\widetilde{\Delta} s_f^{(51-60)}$ mostly reflect cross-firm variation in hiring decisions made many years before 1976. Consequently, they are unlikely (or at the minimum, much less likely than cross-firm differences in $\Delta s_f^{(51-60)}$) to be directly related to unobserved shocks or firms' decisions affecting the change in

[22] When the dependent variable is the outcomes of younger men and women, rather than the gender pay gap, we estimate stacked regressions in which the outcomes of men and women are treated as separate observations in each year. The modified regression is $\Delta y_{g,f}^{(25-30)} = \alpha + \beta \Delta s_f^{(51-60)} + \gamma \Delta s_f^{(51-60)} \cdot m_g + \delta m_g + X_f' \theta + \varepsilon_{g,f}$, where the subscript $g$ denotes gender, and $m_g$ is a dummy variable equal to 1 for men's labor-market outcomes.

[23] The sample for this analysis consists of all firms with more than five total employees in 1976, at least one man and one woman under 30 years old in both 1976 and 1986, and at least one worker over 40 in 1976. These restrictions ensure that we consider non-micro firms employing younger men, younger women, and older workers. To limit noise, we compute firm-level values for year $x$ (for example, 1976) as three-year averages from $x$ to $x+2$. In spite of these restrictions, our sample still captures a large share of the total workforce (46 percent of all workers in the Italian data).

the gender pay gap of younger workers between 1976 and 1986.[24] To support this claim, we show that 59 percent of workers between 41 and 50 years old in 1986 were hired at their employer ten or more years earlier (Figure A19).[25]

### 7.2 Main Results

We first show the reduced-form estimates by plotting the relationship between the IV and younger workers' outcomes using binned scatter plots (Figure 5). There is a negative and linear relationship between the projected firm-level workforce aging and the change in the gender pay gap among younger workers (Panel A). The gender pay differential among younger workers narrows more dramatically within firms more exposed to workforce aging because younger men's career outcomes worsen significantly more than those of younger women (Panel D).

We next show OLS and 2SLS regressions (Table 1, Panel A). Here, the actual change in the share of older workers is the regressor of interest, and the outcome variable is the change in young workers' gender pay gap. According to the OLS estimates, a 1-percentage-point increase in the share of workers aged 51-60 between 1976 and 1986 is associated with a 3.1-percentile additional reduction in the gender gap in pay rank among younger coworkers at the firm. This effect is 77 percent larger than the average decline in the gender pay gap during this period. The 2SLS estimates corroborate this conclusion, confirming that firms experiencing more pronounced workforce aging saw a sharper convergence in the mean pay rank between younger men and women. Here, a 1-percentage-point rise in the share of older workers is associated with a 4.7-percentile faster closure in the gender pay rank gap.[26]

Consistent with our findings in Section 5, the gender gap in pay rank closes faster in firms with more workforce aging because younger men fall closer to younger women in the pay distribution (Table 2, Panel A). According to the 2SLS regressions, a 1-percentage point increase in the share of workers aged 51-60 correlates with a 3.8-percentile positional loss for younger men and with a 1.1-percentile positional gain for younger women. The former effect is statistically significant at the 1-percent level, while the latter is insignificant at the 10 percent level.

### 7.3 Robustness and additional results

These results hold if we estimate the effects of workforce aging over the entire twenty-year period between 1976 and 1996, during which the pay differentials between younger men and women narrowed substantially (Table 1, Panel B). For these regressions, the instrument for $\Delta s_f^{(51-60)}$ becomes $\widetilde{\Delta} s_f^{(51-60)} = \left(s_{f,1976}^{(31-40)} - s_{f,1976}^{(51-60)}\right)$, where $s_{f,1976}^{(31-40)}$, the share of firm's $f$ workers aged 31-40 in 1976, replaces $s_{f,1976}^{(41-50)}$.[27]

[24] For example, a negative demand or productivity firm-level shock could relate to (i) $\varepsilon_f$ if it induces the firm to pay new entrants lower wages, and (ii) $\Delta s_f^{(51-60)}$ if experienced workers are less likely to leave the firm following the negative shock. However, since the IV $\widetilde{\Delta} s_f^{(51-60)}$ is predetermined in 1976, it is unlikely to correlate with such shocks once $X_f$ is controlled for.

[25] We compute the tenure distribution for 1986, the first year with complete data on at least ten years of tenure (due to the dataset's 1976 start date).

[26] The larger magnitude of 2SLS relative to OLS could be driven by a combination of IV correcting for confounders and giving greater weight to "complier" firms—those for whom projected aging better predicts actual aging. These firms could have a more immobile set of experienced workers, more stringent slot constraints, and thus stronger aging-driven career spillovers.

[27] Similar to workers aged 41-50, these slightly younger workers had a high mean tenure in 1986 (Figure A19, Panel C). Specifically, 51 percent of them were hired at their current firm eight or more years earlier.

This analysis is more taxing on the data, as it requires observing the same firm twenty years apart, rather than only ten. Consequently, the number of firms included in the estimating sample decreases from 25,279 in the baseline analysis to 13,993 in this extension. Despite this reduction, the results remain consistent with the baseline findings. For example, a 1-percentage-point increase in the share of firm $f$'s older workers between 1976 and 1996 is associated with an additional reduction in the pay rank gap between younger men and women of 4.9 percentiles in the OLS estimates and 6.2 percentiles in the 2SLS estimates. The magnitudes of these effects are slightly smaller than those estimated over the 1976-1986 period, relative to the larger mean decline in the gender pay gap between 1976 and 1996.

We can replicate this analysis over the subsequent twenty-year period, 1996-2016, when convergence in the gender pay gap at labor-market entry stalled (Table 1, Panel C).[28] Based on our earlier findings, we expect more muted effects of workforce aging on younger workers' outcomes during this period. Consistent with this expectation, a 1-percentage-point increase in the share of older workers between 1996 and 2016 is associated with an additional decline in the pay rank gap between younger men and women of 0.2 percentiles in the OLS estimates and 0.9 percentiles in the 2SLS estimates, two effects that are statistically insignificant.

Finally, rather than highlighting a few key periods, we estimate Equation (3) on all ten-year periods with ending year between 1986 and 2016 (Figure A20). The analysis using this extended rolling ten-year window confirms our prior findings. The instrument remains a strong predictor of the endogenous variable. Moreover, more severe firm-level workforce aging is correlated with a larger decline in the gender pay gap (Panels A and B) and more negative outcomes for younger men until the mid-1990s (Panels C and D), while the association wanes afterwards.

## 8 Two Phases of Convergence in the Gender Pay Gap

Prior sections have shown that the gender pay gap of new entrants into the labor market rapidly shrank until the mid-1990s and then stabilized until 2019. Section 8.1 quantifies the contribution of the convergence in entry earnings to the overall between-cohort change. Section 8.2 then studies the implications of the post-mid-1990s stagnation in the convergence at labor-market entry for the future of the aggregate gender pay gap. Finally, Section 8.3 connects the stop in the convergence at entry with gender differences in college majors (Prediction 5).

### 8.1 Convergence from Inflows and Outflows of Worker Cohorts

We quantify to what extent the decline in the between-cohort gender pay gap has stemmed from the fact that men and women have been entering the labor market with progressively more similar mean earnings (*convergence at entry*), or, instead, from the fact that older worker cohorts, who had higher-than-average gender disparity in earnings, have naturally retired over time (*convergence through exit*).

To this end, starting from the between-cohort component in Equation (2), we further neutralize any cross-cohort convergence in the mean earnings of men and women that happened at the time of labor market entry. Specifically, considering a baseline year $t_b$, our new counterfactual fixes the earnings at labor-market entry (at age 25) of all cohorts who enter in that year *or later* to the average earnings at entry computed between $t_b$ and the following two years. Hence, this new between-cohort component measures what would

[28] In this case, the instrument becomes $\widetilde{\Delta} s_f^{(51-60)} = \left( s_{f,1996}^{(31-40)} - s_{f,1996}^{(51-60)} \right)$.

have happened if the convergence in the early-career earnings of men and women had stopped at $t_b$ and if only the natural turnover of older cohorts had affected the overall level of the gender pay gap.

Under this counterfactual scenario, in which we freeze convergence at entry in the first sample year, the data indicate that both sources of convergence (at entry and through exit) are important drivers of the decline in the gender gap that took place between 1976 and 2019 (Figure A21, Panels A and B). In 2019, convergence at entry accounted for 36 percent of the total between-cohort shrinkage in the gender gap in the US and 43 percent in Italy.

Consistent with our prior findings, we observe that the importance of the convergence at labor-market entry wanes as $t_b$ increases, while the opposite is true for convergence through labor-market exit (Figure A21, Panel C). The latter begins to consistently explain at least 100 percent of the total decline in the between-cohort gap when the benchmark year $t_b$ is equal to 2001 in the US and 2003 in Italy.

## 8.2 Consequences for Future Convergence

The ongoing importance of convergence through exit carries relevant implications for the future of the gender pay gap. Since retirees with higher-than-average gaps are currently the only source of convergence, the gender pay gap is *not* projected to close.

Strikingly, if we were to predict future convergence by looking at the recent trends in the *aggregate* gender pay gap computed on the whole workforce, we would reach different conclusions. Since the aggregate gender pay gap has been decreasing, any projection would predict full convergence in a few decades in most high-income countries. For example, in its 2023 Global Gender Gap Report, the World Economic Forum predicts that Europe will reach gender parity in 67 years, while North America in 95 years (World Economic Forum, 2023).

To better appreciate the differences between the two predictions, we estimate the rate of earnings convergence at early career stages across subsequent worker cohorts and over time. Denote with $g_s^e$ the gender pay gap at age 25 of the cohort who entered the labor market in year $s$. Assuming that the convergence rate is linear, we model the gender pay gap at entry in year $t$ as follows:

$$g_s^e = \alpha_t - \beta_t (s - \underline{s}_t), \tag{4}$$

where $\underline{s}_t$ is the entry year of the cohort with the maximum age used to estimate convergence in year $t$ (age 45 in the baseline analysis), $s \in [\underline{s}_t, t]$, $\alpha_t$ is the gender gap at age 25 for the cohort $\underline{s}_t$, and the coefficient $\beta_t$ measures the rate of convergence in the gender pay gap at age 25 observed between year $\underline{s}_t$ and $t$. Starting from a given year $t$, if the convergence continued at the same rate in the following cohorts and the demographic composition of men and women remained the same, the gender pay gap would close for the first time for the cohort who entered the labor market in year $s^* = \frac{\alpha_t}{\beta_t} + \underline{s}_t$.[29] In addition to estimating Equation (4), we can estimate the linear trend in the aggregate gender pay gap for each year $t$ using the prior twenty years of data. We can then use the estimated coefficients from these regressions to predict the first year in which the total gap would close if its linear path continued without modifications.

[29] If older cohorts have larger gender pay gaps than younger cohorts, $s^*$ underestimates the year in which the gender pay gap would close for the labor market as a whole.

As expected, the between-cohort gender pay gap at age 25 is not bound to converge. We first show the estimated linear function in Equation (4) in the US and Italy for two years: the year 2000 and the last sample year (Figure 6, Panels A and D). Both countries' convergence rate $\beta_t$ dramatically decreased from 2000 to 2019. In addition to highlighting two different years, we show the evolution of $\beta_t$ across all years in the sample (Figure 6, Panels B and E): at least from 1995, the convergence rate rapidly decreased until it reached zero in the second half of the 2010s.

Next, we show how the projected year of closure of the gender pay gap at age 25 changed over time (Figure 6, Panels C and F). Specifically, we plot the predicted $s^*$, or year of entry into the labor market for the first cohort with zero gap at age 25, for all years $t$ in our sample. The first year with no gender gap at age 25 has been following the opposite trend of the convergence rate $\beta_t$. In 1995, the projected first worker cohort without a positive gender pay gap at age 25 was slated to enter the market in 2022 in the United States and 2028 in Italy. By 2019, the entry year of this same cohort had slipped after year 2300 in the US, while no cohort was projected to have a zero gap in Italy. In contrast, simply extrapolating the current negative trend in the total gender gap suggests that convergence should be attainable in 2073 in the US and 2062 in Italy.

### 8.3 Why Did Convergence at Labor-Market Entry Stop?

This section examines why the convergence at entry stopped after the mid-1990s. Our framework predicts that when younger men and women are fairly equally concentrated in higher-paying jobs, a larger supply of older workers cannot shrink the gender pay gap by pushing more younger men toward lower-ranked positions. Consistent with the theory, we have shown that the differences between younger men and women in the share of relatively higher-ranked jobs (Section 5.1) and in mean pay rank (Section 5.2) were small by 1995 and remained constant afterwards.

After the mid-1990s, the effects of a further increase in the number of older workers on the gender pay gap depend on the sources of the remaining earning differential between younger men and women. If (i) the outstanding gap depends primarily on education outcomes that predate their labor-market entry, such as their choice of a college major (Black et al., 2008; Bertrand, 2020; Huneeus et al., 2021; Sloane et al., 2021; Bovini et al., 2024; Humphries et al., 2024) and (ii) older workers are not closer complements of younger workers in low-skill jobs, Prediction 5 states that further workforce aging will not close the gender pay gap.

This section documents that gender differences in college majors have accounted for a substantial share of the gender pay gap at labor-market entry since the mid-1990s, a finding that is in line with the model's prediction. For this analysis, we focus on college graduates and assess the portion of the remaining entry gender pay gap explained by their college major choices. We use the American Community Survey for the United States and the Italian Quarterly Labor Force Survey for Italy. Building upon Bertrand (2018), we start from full-time native-born male employees and compute average residual weekly earnings for each college major from regressions that net out year fixed effects and a quadratic polynomial of age. We then quantify the share of individuals in each cohort and gender group that graduated in a specific major. By interacting average residual weekly earnings with the shares of graduates in each college major, we compute

the major-predicted average weekly earnings of each cohort-gender combination at labor-market entry.[30]

In both countries, the gender pay gap at entry predicted by younger workers' major choices slightly declined until the mid 1980s (Figure A23).[31] After this period, it has remained stable for nearly three decades. Notably, the major-predicted gap has been stable since the convergence at entry stopped, constituting approximately 63 percent of the entry gap for college graduates in the United States and 51 percent in Italy.[32] These two large shares are likely a lower bound of the importance of pre-labor-market choices for the gender pay gap at entry, given that we are considering only a single predetermined factor (major choice).

## 9 Conclusion

In this paper, we argue that workforce aging can be added to the list of factors that have contributed to the narrowing of the gender pay gap.

Over the past four decades, older workers have become more numerous and have extended their participation in the labor force, increasing their likelihood of holding higher-ranked and higher-paying positions for longer periods. At the same time, many firms, facing this positive employment shock and dwindling growth prospects, have struggled to expand the number of available slots, limiting the career progression of younger workers. Our hypothesis is that, as a group and relative to baseline, younger men have been more exposed to these negative consequences because they were more likely than younger women to hold the positions that have been increasingly occupied by older workers.

We report several findings that support this crowd-out mechanism. First, the reduction in the gender pay gap originates primarily from cohort turnover, with newer worker cohorts entering the labor market with smaller gender pay gaps than those of older cohorts. Second, younger men have experienced greater career stagnation and positional losses within firms' hierarchies, leading to a relative convergence with younger women. Third, these effects are especially pronounced in firms that have faced more binding constraints in expanding their top positions, such as those experiencing a larger increase in their older workers' supply. Fourth, in the absence of structural breaks, the labor markets in high-income countries are unlikely to reach full gender pay convergence, as the ongoing reduction in the gap stems mainly from the exit of older workers with large pay disparities.

Overall, this paper offers two key takeaways for public policy. First, within-cohort factors have not meaningfully contributed to the narrowing of the aggregate gender pay gap and remain a persistent source of gender disparities. Second, our results suggest that future efforts to reduce the gender pay gap should view new cohorts' early years in the labor market as a critical period to influence gender pay differentials for each cohort's entire life cycle. Moreover, they should consider the importance of protecting younger workers' job opportunities and career progression to more effectively shield them from the potentially neg-

[30] Given that we observe the combination of wages and college majors only in more recent years, the major-predicted earnings for older cohorts implicitly assume that the relative wages between majors have been stable over time. In support of this assumption, we show that college major choices have been stable after 1995 in both countries (Figure A22). In addition, our results show a stable major-predicted gender pay gap, which is unlikely to be driven by changes in average wages that perfectly offset each other.

[31] This effect is quantitatively small relative to the observed convergence at entry in average wages (for the US, -0.04 log points compared to -0.25 log points).

[32] Our results based on Italian survey data are slightly smaller than estimates based on Italian administrative data (60 percent from Bovini et al. (2024)).

ative consequences of low-growth forecasts, declining dynamism, and an aging workforce.

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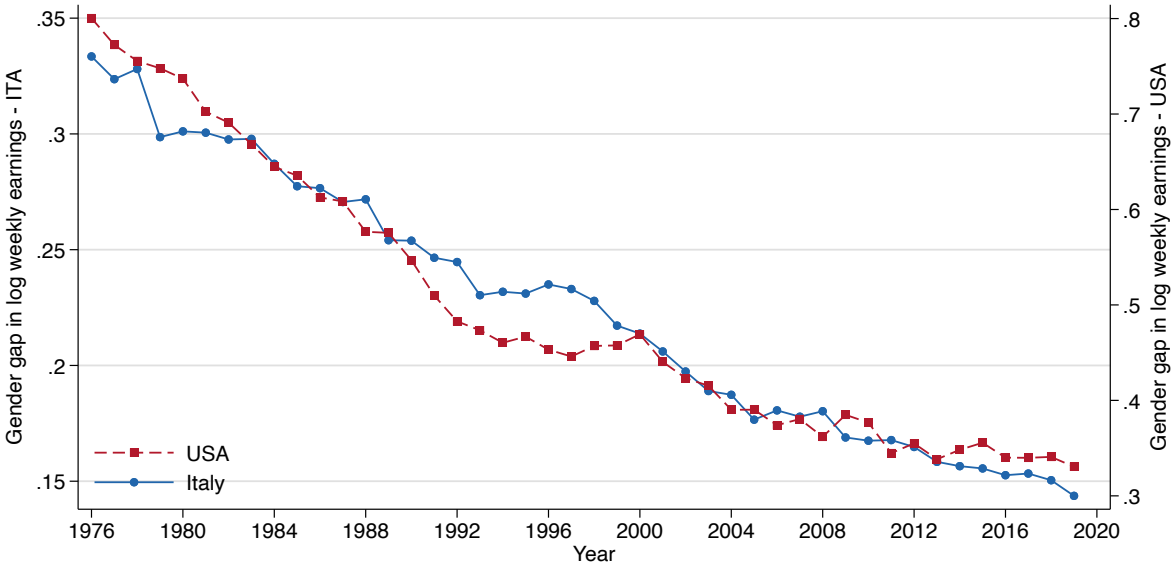
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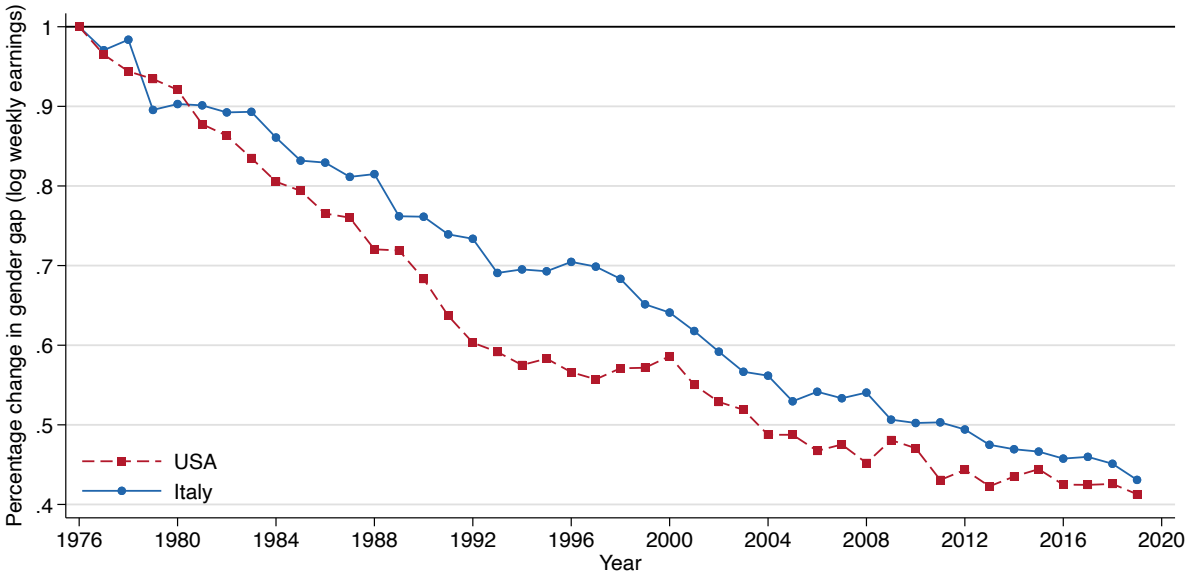
## Figures and Tables

**Figure 1:** Gender Gap in Weekly Earnings

**Panel A:** Raw gap

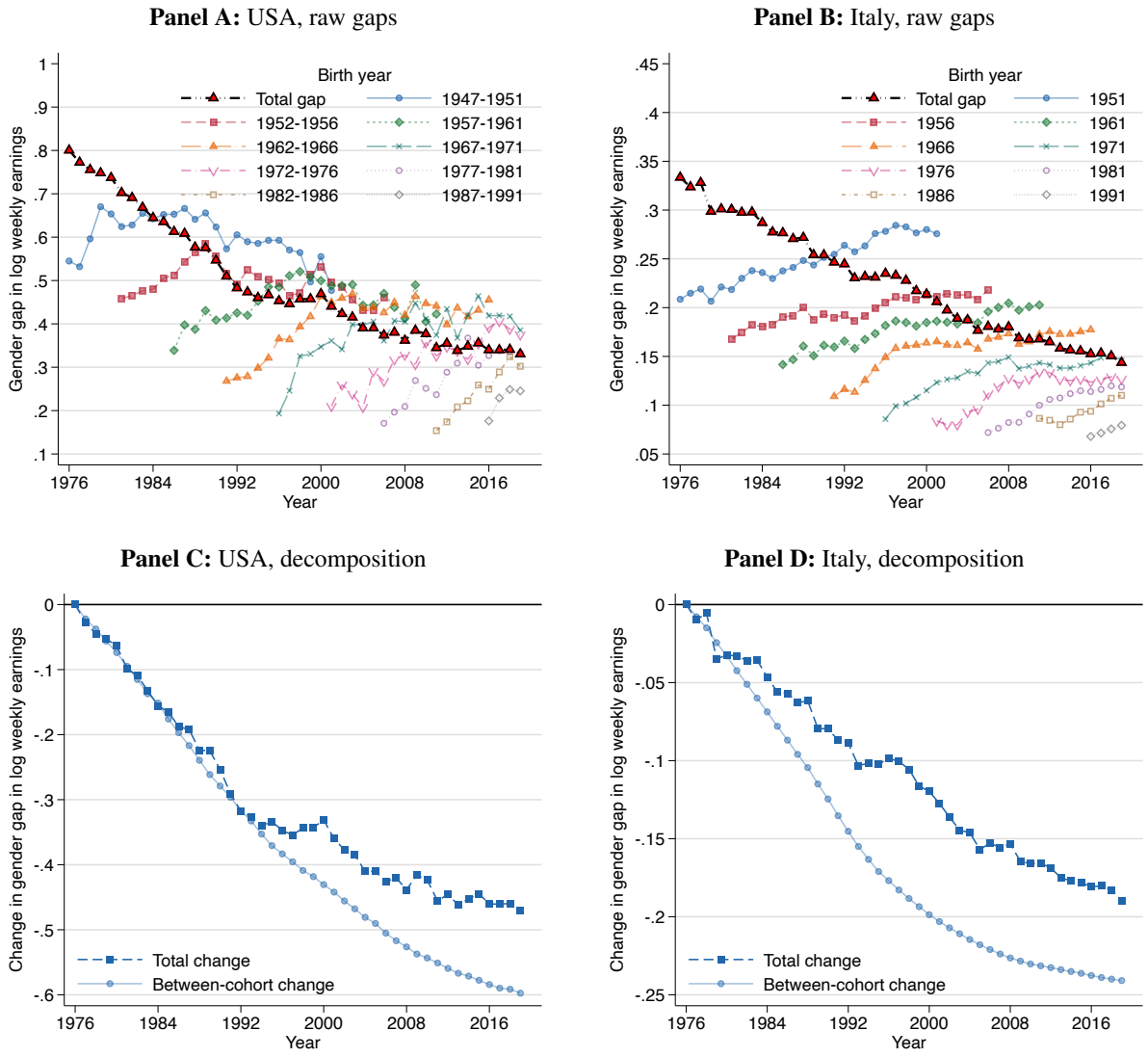



**Panel B:** Percentage deviation from first year



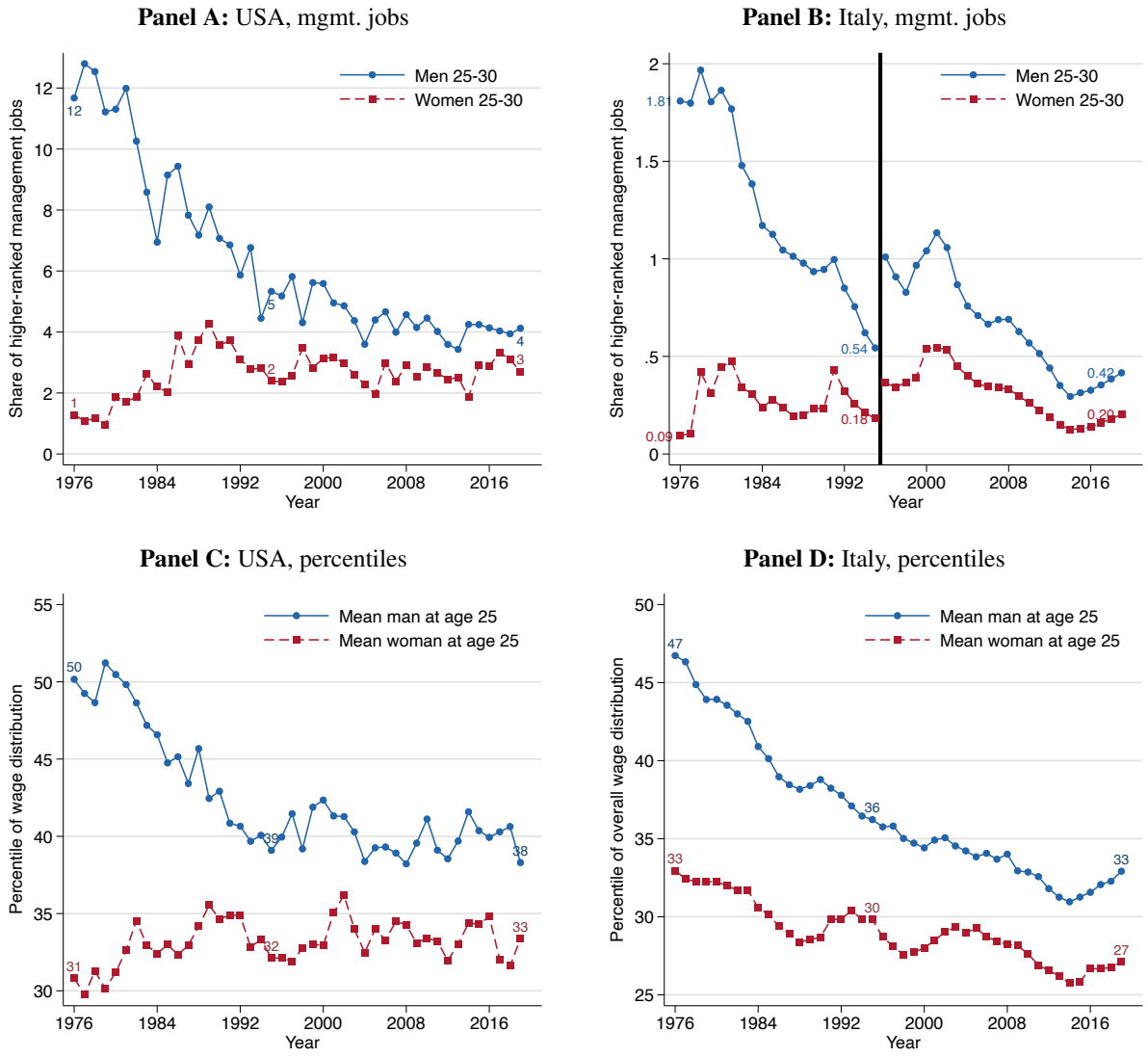

*Notes:* Panel A plots the trend in the raw mean gender pay gap (log weekly earnings of men - log weekly earnings of women) in Italy and the United States. Panel B shows the percentage deviation from the first year (1976). In each year, the data encompass information about all workers who were between 25 and 64 years old, had worked in the private sector for at least 24 weeks, had earned strictly positive earnings, and (only in Italy) had not retired by December 31.
*Source for Italy:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States*. Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure 2:** Gender Pay Gap Between and Within Cohorts




*Notes:* Panels A and B depict the trend in the mean gender pay gap (log weekly earnings) across different birth cohorts in the United States and Italy, respectively. The red triangles trace the trend in the mean gender pay gap across all cohorts active in the labor market in each year. This analysis includes only workers aged 50 or younger to limit the influence of cross-cohort changes in selection into retirement. Panels C and D show the change in the total gender pay gap and its between-cohort component in the United States and Italy, respectively, for log weekly earnings. To compute the between-cohort component, we assign each cohort (defined as a combination of birth year and gender) its mean log weekly earnings in the first year it appears in the sample (Equation (2)). In the baseline analysis, entry into the sample corresponds to the year in which workers in each cohort turn 25 years old (for workers younger than 25 in 1976, the first sample year). We assign cohorts who were older than 25 at the start of the sample their mean weekly earnings in the first sample year.
*Source for Italy:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States*. Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

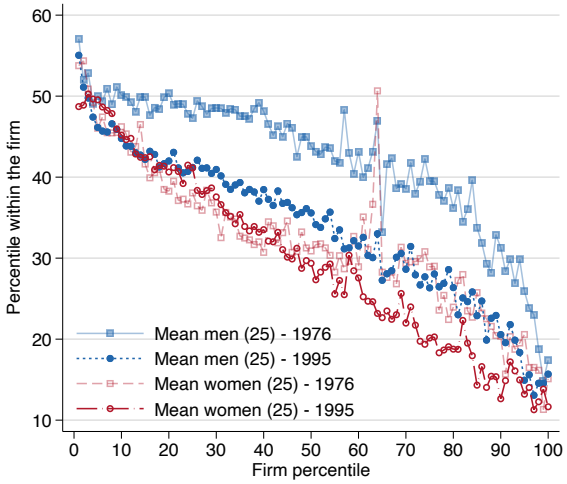
**Figure 3:** Younger Workers' Positions in Firms' Hierarchies and Pay Distribution



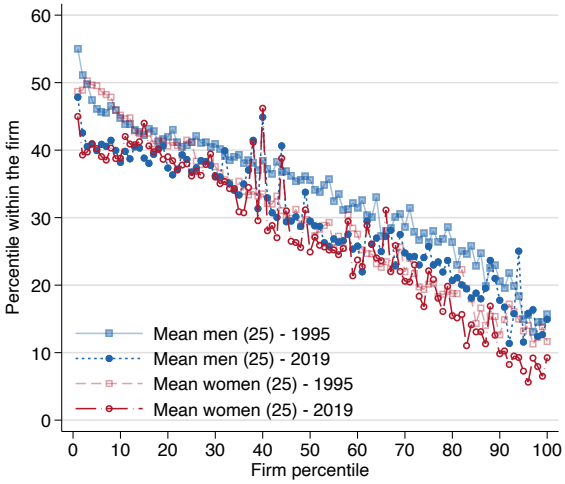

*Notes:* Panels A and B show the share of high-ranked managerial jobs held by men and women between 25 and 30 years old in the United States and Italy, respectively. We define as higher-ranked managerial jobs all managerial occupations with annual earnings in the top quartile of the year-specific distribution of annual earnings. In the CPS data, managerial occupations are identified using 2-digit Standard Occupational Classification (SOC) code 11. In the INPS data, we use the highest ranked position out of the four main job categories in the Italian labor system: in ascending order, these are apprenticeships, blue-collar jobs, white-collar jobs, and managerial jobs. The figures based on Italian data show a spurious trend discontinuity in the mid 1990s because the definition of managerial jobs in the INPS data changes from 1996. Panels C and D show the average earning percentile of men and women at 25 years old in the United States and Italy, respectively. In each year, the data encompass information about all workers who were between 25 and 64 years old, had worked in the private sector for at least 24 weeks, had earned strictly positive earnings, and (only in Italy) had not retired by December 31.
*Source for Italy:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States*. Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure 4:** Distribution Within and Between Firms for Workers Age 25—Italy

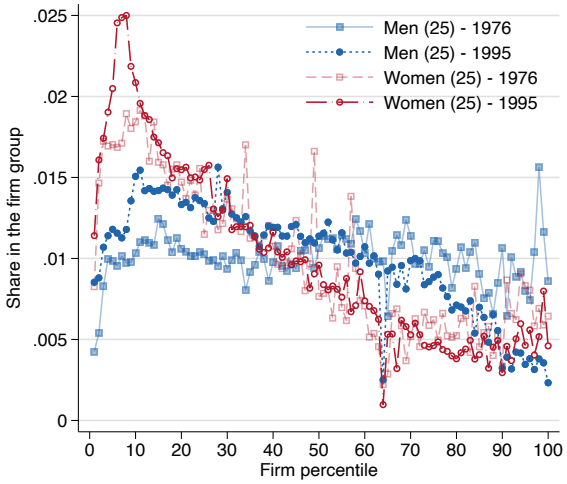
**Panel A:** Rank within firm, 1976 and 1995



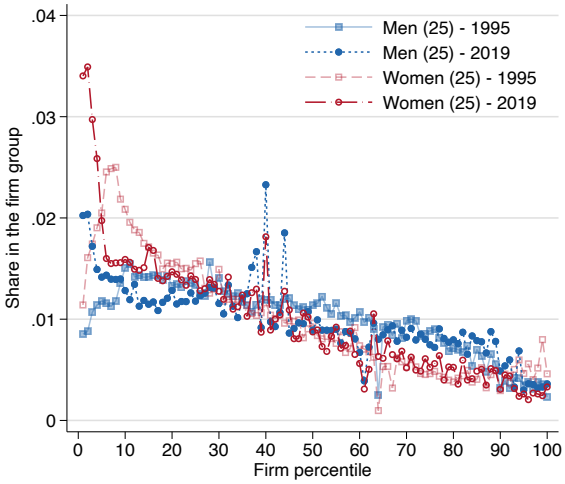

**Panel B:** Rank within firm, 1995 and 2019




**Panel C:** Share in firm percentile, 1976 and 1995

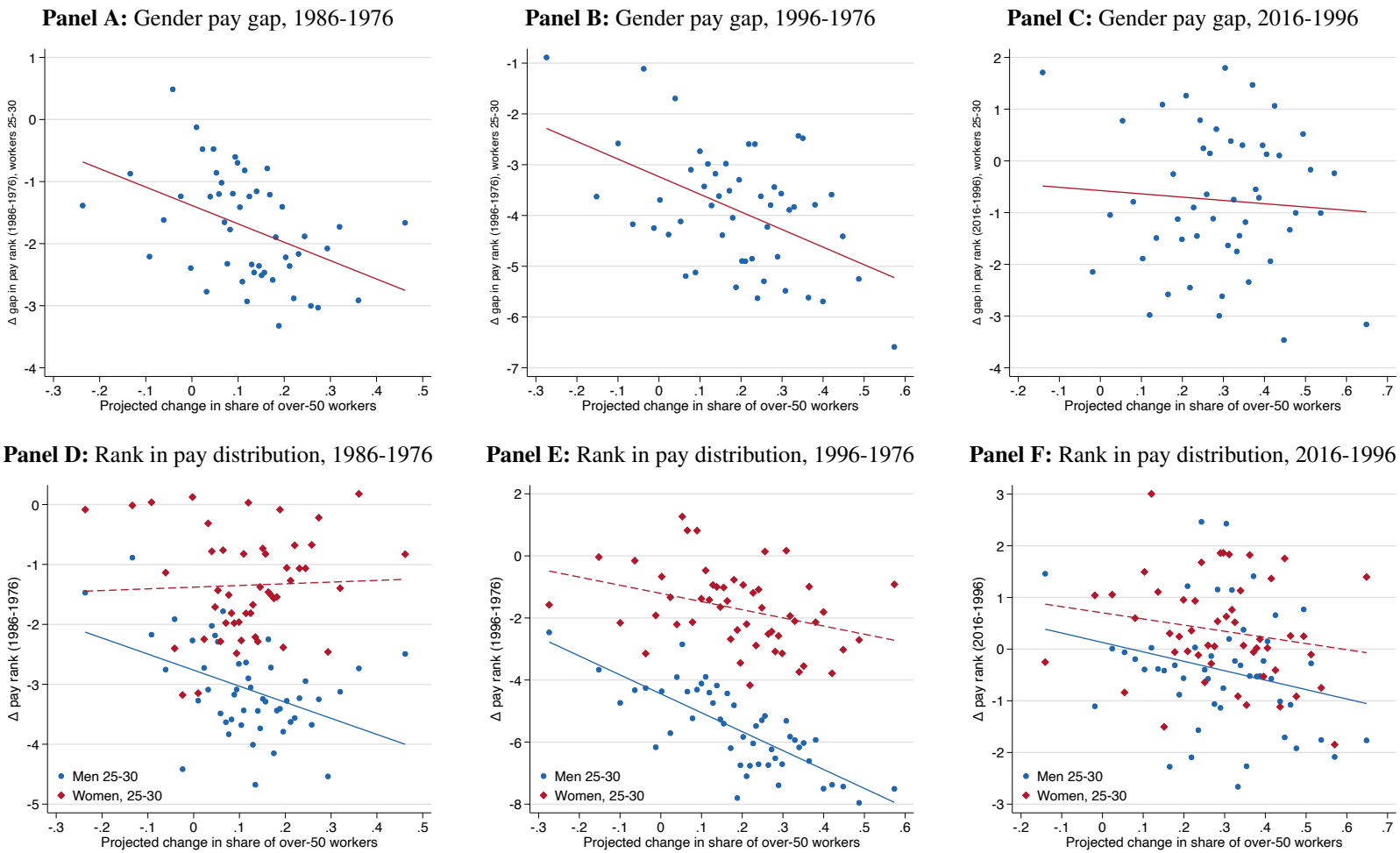



**Panel D:** Share in firm percentile, 1995 and 2019




Notes: Panels A and B show the average percentile, in the distribution of weekly earnings, of men and women at age 25 across percentiles of firm mean pay in 1976, 1995, and 2019. Panels C and D show the share of men and women at age 25 across percentiles of firm average pay in 1976, 1995, and 2019. In each year, the data encompass information about all workers who were between 25 and 64 years old, had worked in the private sector for at least 24 weeks, had earned strictly positive earnings, and had not retired by December 31. Source: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

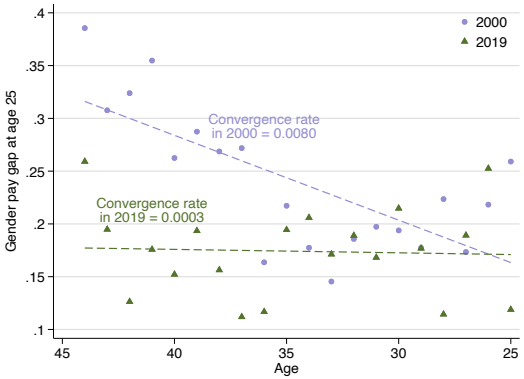
**Figure 5:** Firm-Level Workforce Aging and the Gender Pay Gap—Italy



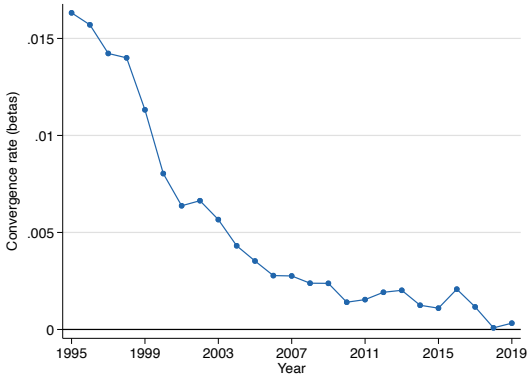

*Notes:* These figures show binned scatterplots that correlate firm-level changes in the gender pay gap of younger workers to firm-level projected changes in the share of workers over 50. Panel A: firm-level change in the gender gap in the pay rank among younger workers (25-30) from 1976 to 1986 on the y-axis and firm-level difference between the share of workers aged 41-50 and the share of workers aged 51-60 in 1976 on the x-axis. Panels B and C replicate the same analysis on the periods 1976-1996 and 1996-2016, respectively. Given that they cover 20-year periods, the projected change in the share of over-50 workers becomes the firm-level difference between the share of workers aged 31-40 and the share of workers aged 51-60 at baseline. Panel D: firm-level change in the pay rank (mean perc. in firm pay distribution) of younger men and women (25-30 years old) from 1976 to 1986 on the y-axis and the same variable used in Panel A on the x-axis. Panels E and F replicate the same analysis on the periods 1976-1996 and 1996-2016, respectively (changing the projected change in the share of over-50 workers accordingly). Firm-level values for year $x$ are computed as three-year averages over $x$ and $x+2$. In each panel, the sample of firms include all firms that had more than five total employees at baseline, at least one man and one woman under 30 years old in both the initial and final period, and at least one worker over 40 in the initial period. *Source:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

**Figure 6:** Projected Convergence in the Gender Pay Gap

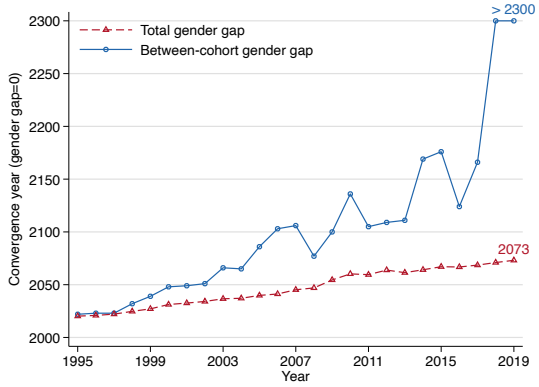
**Panel A:** Between-cohort trends (USA, log weekly earnings)



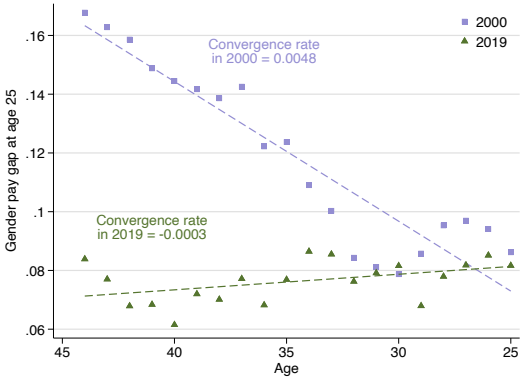

**Panel B:** Between-cohort convergence rate (USA, log weekly earnings)



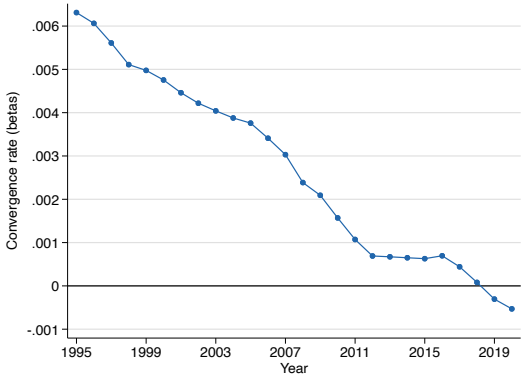

**Panel C:** Between-cohort convergence year (USA, log weekly earnings)



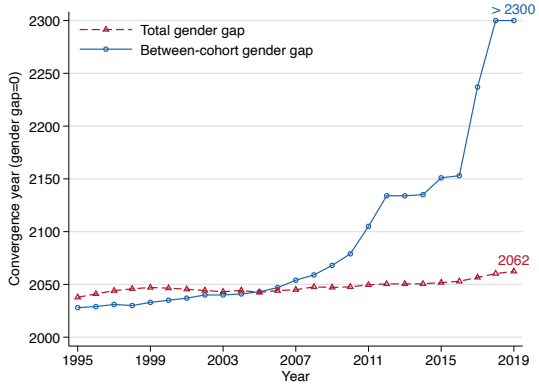

**Panel D:** Between-cohort trends (Italy, log weekly earnings)




**Panel E:** Between-cohort convergence rate (Italy, log weekly earnings)




**Panel F:** Between-cohort convergence year (Italy, log weekly earnings)




*Notes*: In each year $t$, we compute the gender gap at an early career stage for workers in age group $a$ using their earnings at age 25. Then, we estimate the linear relationship between the mean gender gap at labor-market entry and age (Equation (4)). Panels A and D show the best fit line in 2000 and 2019 for the United States and Italy, respectively. Panels B and E show the coefficients of age ($\beta_t$) for each year $t$. Panels C and F show the first year of convergence in the gender gap (first cohort with gap at most equal to zero at age 25) predicted by Equation (4) for each year between 1976 and 2019. In each year, the data encompass information about all workers who were between 25 and 64 years old, had worked in the private sector for at least 24 weeks, had earned strictly positive earnings, and (only in Italy) had not retired by December 31.
*Source for Italy:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States:* Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Table 1:** Firm-Level Workforce Aging and the Gender Pay Gap

| | Gap in pay rank between men and women at age 25-30 | | | | | |
|---|---|---|---|---|---|---|
| | OLS | | Reduced form | | 2SLS | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A: 1976-1986 | | | | | | |
| △ share older workers | -2.78** | -3.08*** | -2.83*** | -2.73*** | -4.88*** | -4.65*** |
| | (1.06) | (1.08) | (0.97) | (0.98) | (1.67) | (1.68) |
| KP F-stat | | | | | 7,168 | 11,259 |
| Mean dep. var. | -1.75 | -1.75 | -1.75 | -1.75 | -1.75 | -1.75 |
| SD dep. var. | 19.94 | 19.94 | 19.94 | 19.94 | 19.94 | 19.94 |
| Obs. | 25,279 | 25,279 | 25,279 | 25,279 | 25,279 | 25,279 |
| Panel B: 1976-1996 | | | | | | |
| △ share older workers | -5.02*** | -4.88*** | -3.50*** | -2.86** | -7.74*** | -6.24** |
| | (1.77) | (1.81) | (1.27) | (1.19) | (2.78) | (2.57) |
| KP F-stat | | | | | 4,389 | 4,734 |
| Mean dep. var. | -3.89 | -3.89 | -3.89 | -3.89 | -3.89 | -3.89 |
| SD dep. var. | 20.41 | 20.41 | 20.41 | 20.41 | 20.41 | 20.41 |
| Obs. | 13,993 | 13,993 | 13,993 | 13,993 | 13,993 | 13,993 |
| Panel C: 1996-2016 | | | | | | |
| △ share older workers | -0.42 | -0.24 | -0.43 | -0.37 | -1.11 | -0.93 |
| | (1.43) | (1.42) | (1.23) | (1.28) | (3.18) | (3.19) |
| KP F-stat | | | | | 2,286 | 4,364 |
| Mean dep. var. | -0.76 | -0.76 | -0.76 | -0.76 | -0.76 | -0.76 |
| SD dep. var. | 20.20 | 20.20 | 20.20 | 20.20 | 20.20 | 20.20 |
| Obs. | 14,644 | 14,644 | 14,644 | 14,644 | 14,644 | 14,644 |
| Controls | No | Yes | No | Yes | No | Yes |

Notes: This table shows results of OLS and IV firm-level regressions in which changes in the gender pay gap among younger workers (difference in mean pay rank between men and women between 25 and 30 years old) are regressed on changes in workforce aging. The "OLS" columns regress Δ gender gap in pay rank on Δ share of workers 51-60, both observed at the firm level. The "Reduced form" columns regress Δ gender pay rank gap on the difference between the share of workers aged 41-50 (Panel A) or 31-40 (Panels B and C) and the share of workers 51-60 at baseline. The "2SLS" columns regress Δ gender pay rank gap on Δ share of workers 51-60, instrumenting the latter with the difference between the share of workers aged 41-50 (Panel A) or 31-40 (Panels B and C) and the share of workers 51-60 at baseline. Controls include firm age, firm size, sector, and province fixed effects, all observed at baseline. Firm-level values for year $x$ are computed as three-year averages over $x$ and $x+2$. In each panel, the sample of firms include all firms that had more than five total employees at baseline, at least one man and one woman under 30 years old in both the initial and final period, as well as at least one worker over 40 in the initial period. Standard errors are clustered at the province level. Source: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

**Table 2:** Firm-Level Workforce Aging and Younger Workers' Rank

| | Men, 25-30 | | | | Women, 25-30 | | | |
|---|---|---|---|---|---|---|---|---|
| | Reduced form | | 2SLS | | Reduced form | | 2SLS | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: 1976-1986 | | | | | | | | |
| △ share older workers | -2.67*** | -2.20*** | -4.60*** | -3.77*** | 0.16 | 0.63 | 0.28 | 1.11 |
| | (0.80) | (0.72) | (1.37) | (1.24) | (0.85) | (0.81) | (1.46) | (1.39) |
| KP F-stat | | | 3,584 | 3,584 | | | 3,584 | 3,584 |
| Mean dep. var. | -2.19 | -2.19 | -2.19 | -2.19 | -2.19 | -2.19 | -2.19 | -2.19 |
| SD dep. var. | 16.50 | 16.50 | 16.50 | 16.50 | 16.50 | 16.50 | 16.50 | 16.50 |
| Obs. | 50,558 | 50,558 | 50,558 | 50,558 | 50,558 | 50,558 | 50,558 | 50,558 |
| Panel B: 1976-1996 | | | | | | | | |
| △ share older workers | -6.07*** | -5.74*** | -13.42*** | -12.58*** | -2.57* | -2.24* | -5.68* | -4.84* |
| | (1.10) | (0.85) | (2.53) | (1.86) | (1.49) | (1.23) | (3.33) | (2.72) |
| KP F-stat | | | 2,194 | 2,194 | | | 2,194 | 2,194 |
| Mean dep. var. | -3.65 | -3.65 | -3.65 | -3.65 | -3.65 | -3.65 | -3.65 | -3.65 |
| SD dep. var. | 18.25 | 18.25 | 18.25 | 18.25 | 18.25 | 18.25 | 18.25 | 18.25 |
| Obs. | 27,986 | 27,986 | 27,986 | 27,986 | 27,986 | 27,986 | 27,986 | 27,986 |
| Panel C: 1996-2016 | | | | | | | | |
| △ share older workers | -1.77 | -1.09 | -4.57 | -2.75 | -1.34 | -0.67 | -3.47 | -1.64 |
| | (1.07) | (0.89) | (2.83) | (2.27) | (1.18) | (1.00) | (3.09) | (2.54) |
| KP F-stat | | | 1,143 | 1,143 | | | 1,143 | 1,143 |
| Mean dep. var. | -0.03 | -0.03 | -0.03 | -0.03 | -0.03 | -0.03 | -0.03 | -0.03 |
| SD dep. var. | 17.92 | 17.92 | 17.92 | 17.92 | 17.92 | 17.92 | 17.92 | 17.92 |
| Obs. | 29,288 | 29,288 | 29,288 | 29,288 | 29,288 | 29,288 | 29,288 | 29,288 |
| Controls | No | Yes | No | Yes | No | Yes | No | Yes |

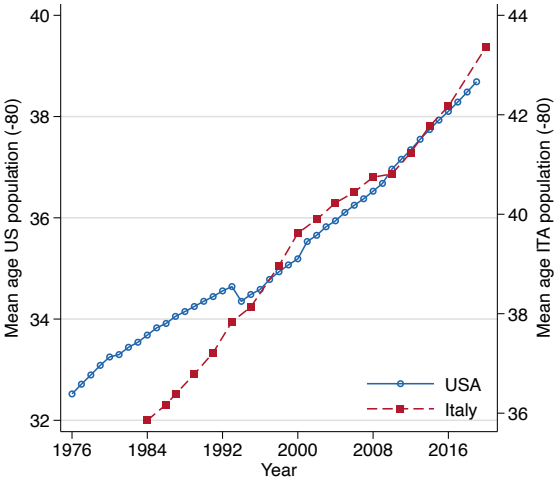
*Notes:* This table shows results of OLS and IV firm-level regressions in which changes in the mean percentile of younger men and women (aged 25-30) in their firms' pay distributions are regressed on changes in workforce aging. The "Reduced form" columns regress Δ mean pay rank of younger men and women on firm-level differences between the share of workers aged 41-50 (Panel A) or 31-40 (Panels B and C) and the share of workers 51-60 at baseline. The "2SLS" columns regress firm-level Δ mean pay rank of younger men and women on firm-level Δ share of workers 51-60, instrumenting the latter with differences between the share of workers aged 41-50 (Panel A) or 31-40 (Panels B and C) and the share of workers 51-60 at baseline. Controls include firm age, firm size, sector, and province fixed effects, all observed at baseline. Firm-level values for year $x$ are computed as three-year averages over $x$ and $x+2$. In each panel, the sample of firms include all firms that had more than five total employees at baseline, at least one man and one woman under 30 years old in both the initial and final period, as well as at least one worker over 40 in the initial period. Standard errors are clustered at the province level. *Source:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

# Online Appendix

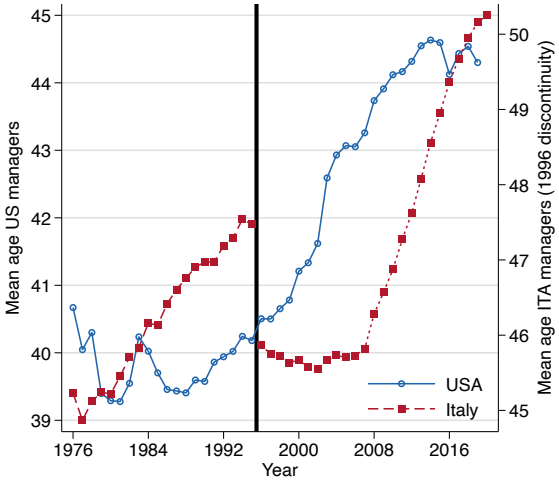
## A Additional Figures and Tables

**Figure A1:** Workforce Aging and GDP Growth

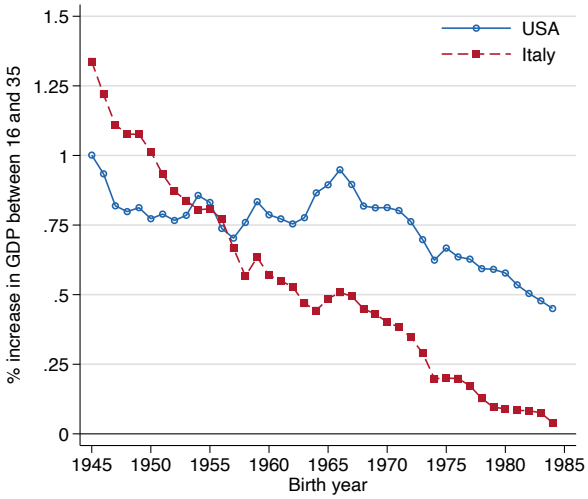
**Panel A:** Population




**Panel B:** Managers



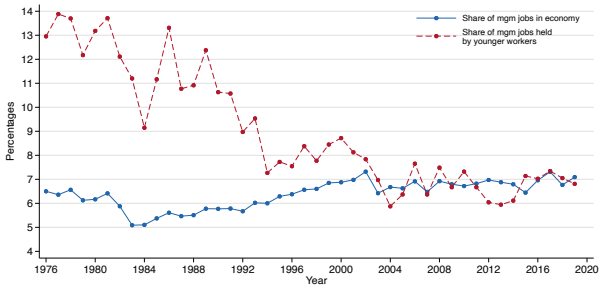

**Panel C:** GDP growth



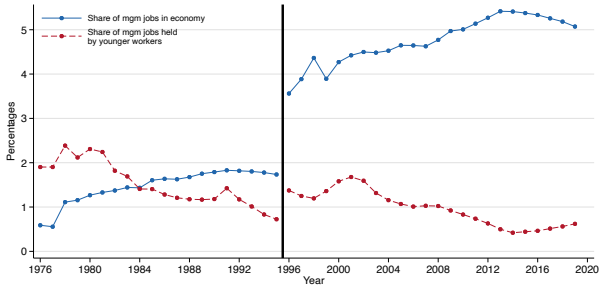

Notes: Panels A shows the mean age of the population. Panel B shows the mean age of managers in the private sector. Managerial positions are identified using (i) 2-digit Standard Occupational Classification (SOC) code 11 in the United States and (ii) the highest ranked position in the Italian labor system in Italy. The figures based on Italian data show a spurious trend discontinuity in the mid 1990s because the definition of managerial jobs in the INPS data changes from 1996. All age variables are winsorized at age 80. Panel C computes the cumulative percentage change in GDP (in 2010 USD) over the first years in the labor market for individuals born in different years. For example, the data point for the birth year "1945" computes the percentage growth in GDP between 1961 (when individuals born in 1945 were 16 years old) and 1980 (when individuals born in 1945 were 35 years old). *Sources for Italy*: Survey of Household Income and Wealth, Bank of Italy (Panel A). UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS) (Panel B). *Source for the United States*: Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.*Source for GDP data*: World Development Indicators by the World Bank, last accessed on 04/21/2023 at https://databank.worldbank.org/reports.aspx?source=2&series=NY.GDP.MKTP.CD&country=.

**Figure A2:** Share of Higher-Ranked Managerial Positions in Economy

**Panel A:** USA



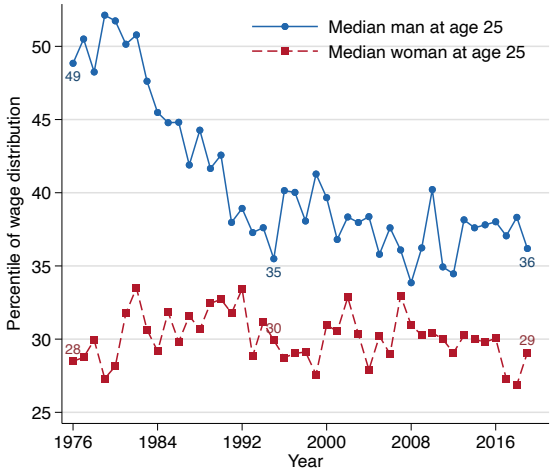

**Panel B:** Italy



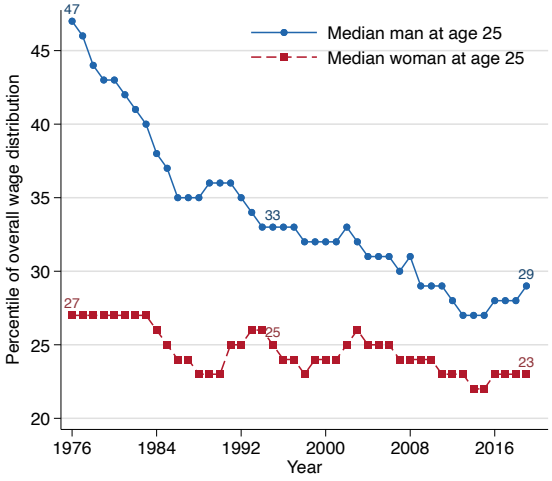

*Notes:* Panels A and B show the share of high-ranked managerial jobs out of all jobs in the economy and the share of high-ranked managerial jobs held by workers between 25 and 30 years old in the United States and Italy, respectively. We define as higher-ranked managerial jobs managerial occupations with annual earnings in the top quartile of the year-specific distribution of annual earnings. In the CPS data, managerial occupations are identified using 2-digit SOC code 11. In the INPS data, we use the highest ranked position out of the four main job categories in the Italian labor system: these are apprenticeships, blue-collar jobs, white-collar jobs, and managerial jobs. The Italian data shows a spurious trend discontinuity in the mid 1990s because the definition of managerial jobs in the INPS data changes from 1996. *Source for the United States*. Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A3:** Rank at Labor-Market Entry; Median

**Panel A:** USA, median worker
Log weekly earnings

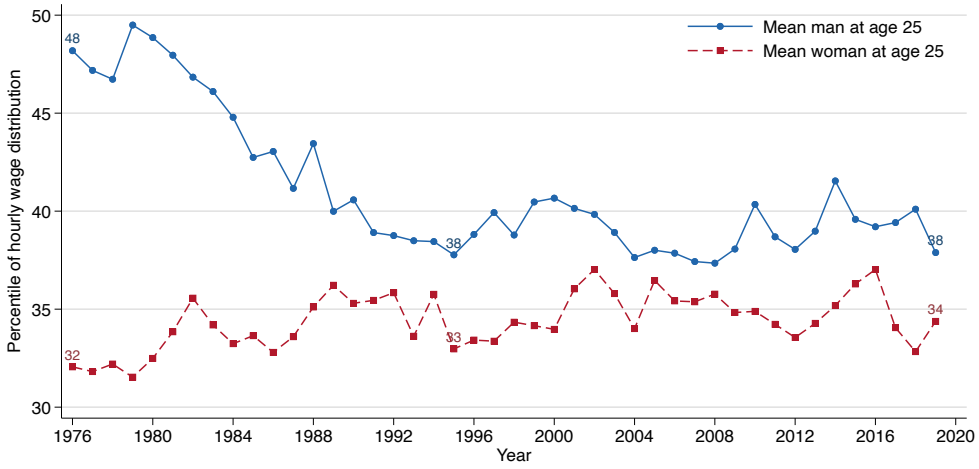



**Panel B:** Italy, median worker
Log weekly earnings




*Notes:* Panels A and B show the median earning percentile of men and women at age 25 in the United States and Italy, respectively. In each year, the data encompass information about all workers who were 25 years old, had worked in the private sector for at least 24 weeks, had earned strictly positive earnings, and (only in Italy) had not retired by December 31. *Source for Italy:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States*. Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

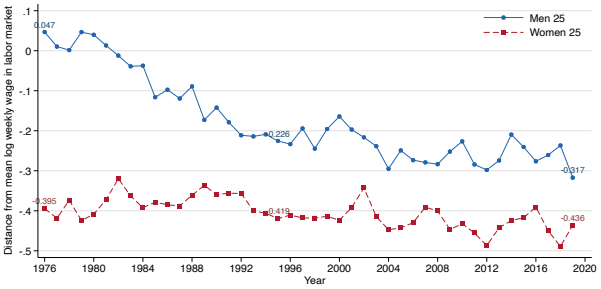
**Figure A4:** Rank in Distribution of Hourly Earnings (US)



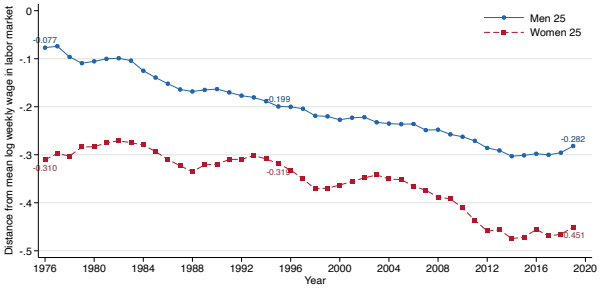

*Notes:* The figure shows the average percentile of men and women at age 25 in the distribution of hourly earnings in the United States. In each year, the data encompass information about all workers who were between 25 and 64 years old, had worked in the private sector for at least 24 weeks, had earned strictly positive earnings.
*Source:* Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A5:** Younger Workers' Distance from Mean Earnings

**Panel A:** USA

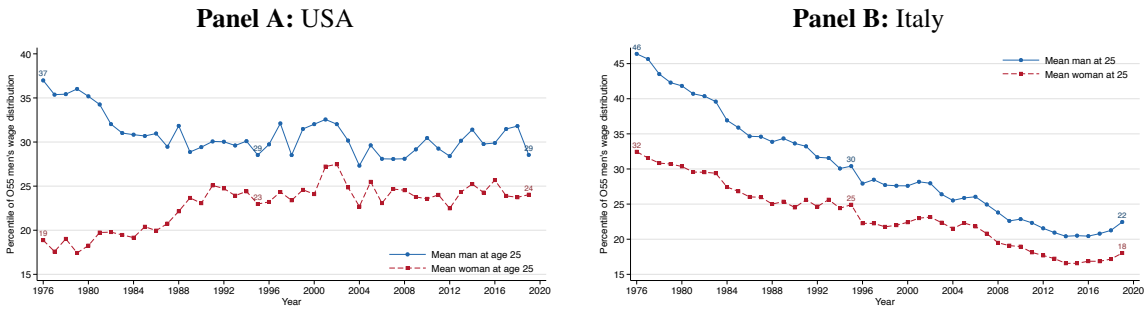



**Panel B:** Italy



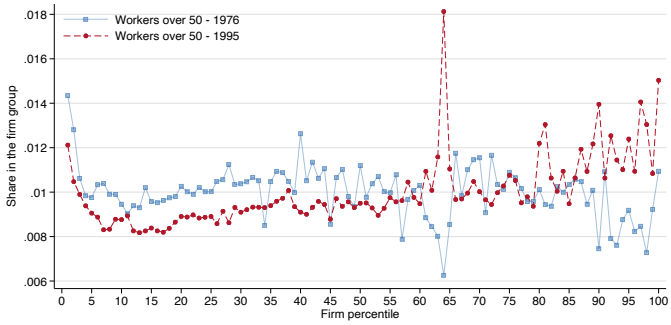

*Notes:* Panels A and B show the difference between the mean log weekly earnings of men and women at age 25 and the mean log weekly earnings computed using all private-sector workers in the labor market in the United States and Italy, respectively. In each year, the data encompass information about all workers who were between 25 and 64 years old, had worked in the private sector for at least 24 weeks, had earned strictly positive earnings, and (only in Italy) had not retired by December 31.
*Source for Italy:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States*. Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A6:** Rank in Pay Distribution of Over-55 Men



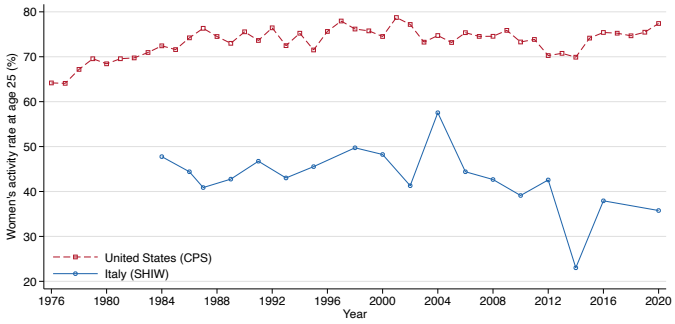

*Notes:* Panels A and B show the average earning percentile of men and women at 25 years old in the distribution of weekly earnings of over-55 male workers in the United States and Italy, respectively.
*Source for Italy:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States*. Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A7:** Share of Workers Over 50 in Lower-Paying and Higher-Paying Firms




*Notes:* Figure shows the distribution of workers over 50 across percentiles of firms' mean pay in 1976 and 1995 in Italy. In each year, the data encompass information about all workers who were between 25 and 64 years old, had worked in the private sector for at least 24 weeks, had earned strictly positive earnings, and had not retired by December 31.
*Source:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

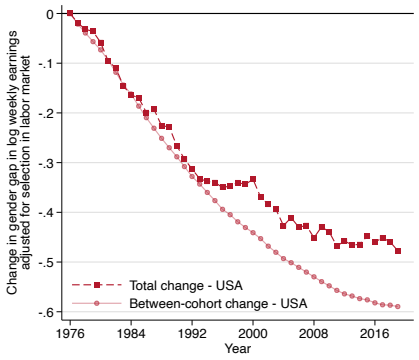
**Figure A8:** Participation Rates at Age 25



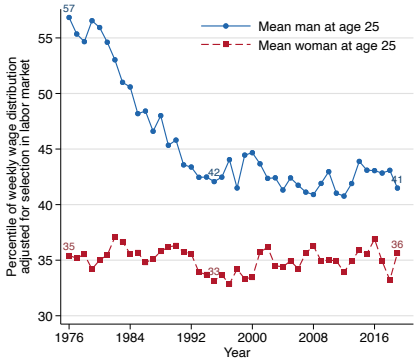

*Notes*: The figure shows participation rates of women at age 25 in the United States and Italy. *Source for Italy*: Survey of Household Income and Wealth, Bank of Italy. *Source for the United States*: Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A9:** Results Adjusted for Selection into Labor Market, Weekly Earnings

**Panel A:** Between-cohort change



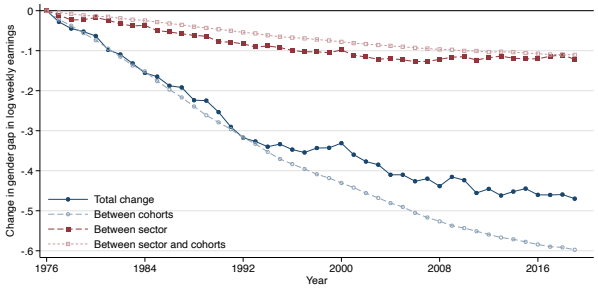

**Panel B:** Rank in pay distribution



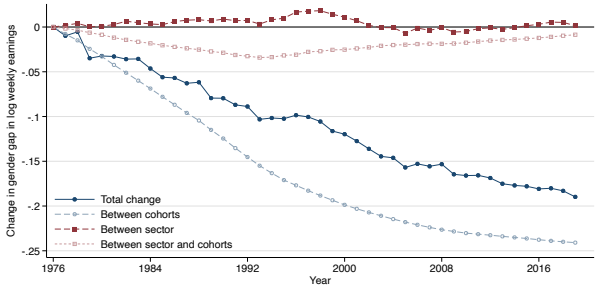

*Notes:* These figures replicate the main findings of the paper using a larger sample in which nonparticipants in the labor market are included with imputed weekly earnings. To account for changes in selection into the labor market, we follow the procedure outlined in Blau et al. (2024). First, we expand the sample to include individuals who worked less than 24 weeks in the year (but at least 100 hours) and had positive labor earnings. Second, we impute the weekly earnings of nonparticipants based on their probability of falling into each decile of the pay distribution. We predict these probabilities via an ordered probit estimated separately by year and gender using the following observable characteristics: years of education, a dummy for college graduation, a dummy for advanced degrees, potential experience (age-years of education-6), potential experience squared, race (white, black, others) and ethnicity (hispanic) dummies, and fixed effects for Census divisions. Each nonparticipant is then included in the sample ten times, one per decile, and assigned the decile-specific median weekly earnings, while the predicted probabilities of falling in each decile are used to adjust the sampling weights. This procedure is repeated until the earning distributions at the start and end of the imputation process become sufficiently similar.
*Source:* Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A10:** Between-Cohort Decline in Gender Pay Gap, Between and Within Sectors

**Panel A:** USA

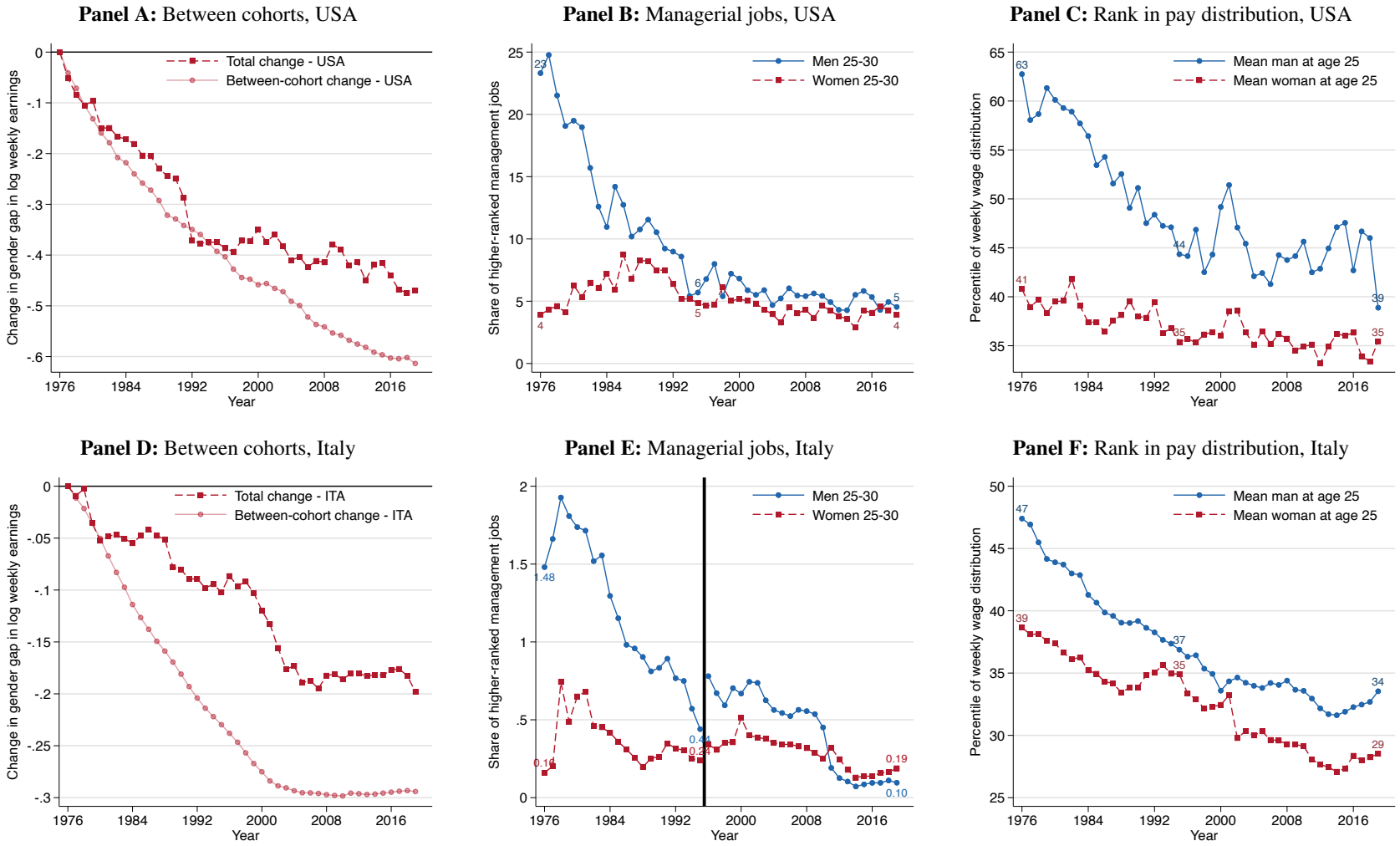



**Panel B:** Italy



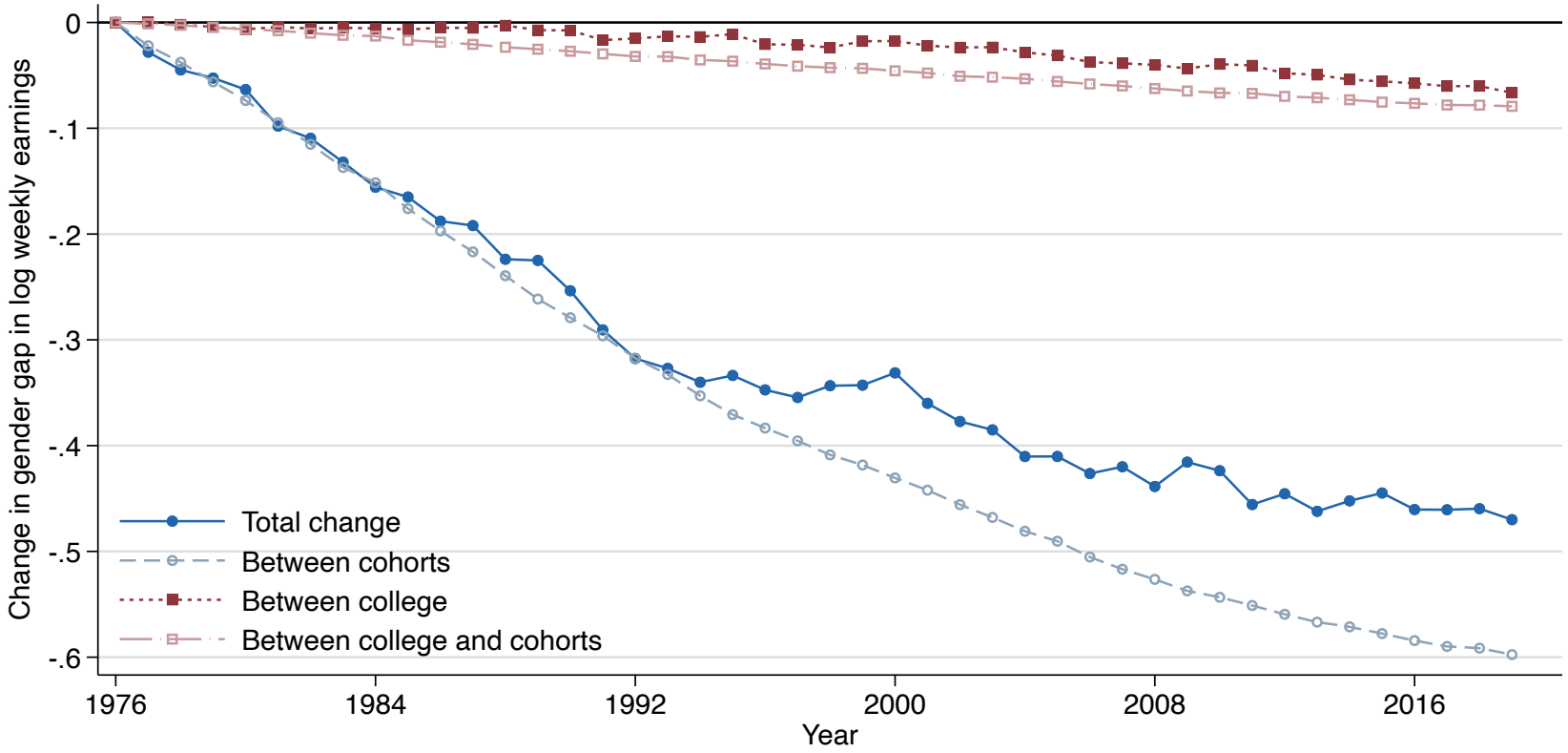

*Notes*: Panels A and B decompose both the total change in gender pay gap and just its between-cohort component between and within sector (1- and 2-digit NACE Rev. 2 in the United States and Italy, respectively).
*Source for Italy*: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States*: Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A11:** Workers With High Probability of Working Outside Manufacturing



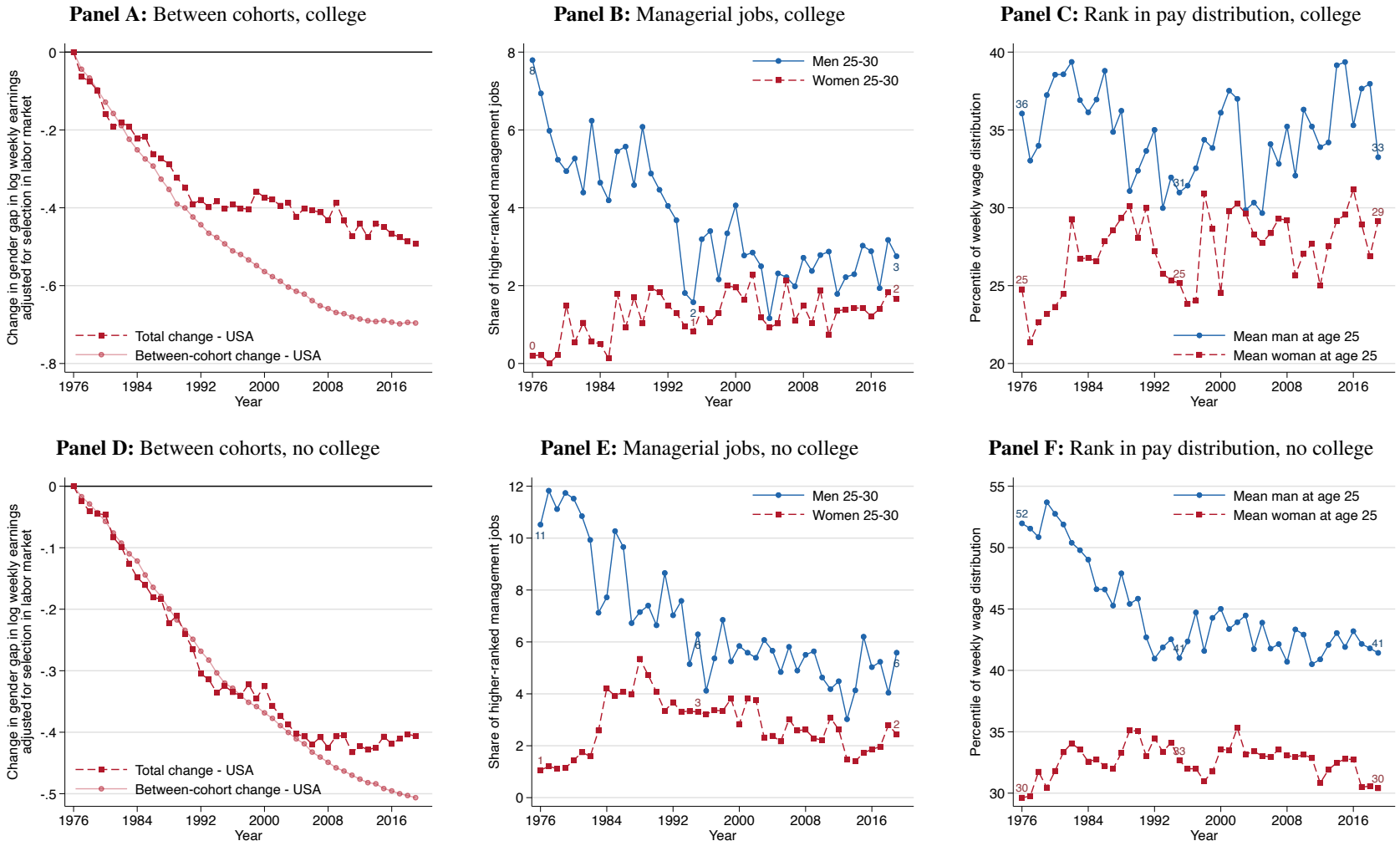

*Notes*: These figures replicate the main findings after keeping in the sample only workers with high predicted probability of working outside manufacturing. We predict the probability of working outside of manufacturing using the first five sample years (1976-1981) and the following observable characteristics: Census divisions (US) or region (IT) FEs interacted with age, age squared, completed education (less than high school, high school, some college, four years of college or more; US), gender, race (the same three categories used to address selection into the labor market; US), ethnicity (US), and a foreign-born dummy (IT). Next, we use the coefficients to predict the probability of working outside of manufacturing for the whole sample. Then, we retain in the sample only individuals with predicted probability above the year-by-year median. *Source for Italy*: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States*: Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A12:** Between-Cohort Decline in Gender Pay Gap, Between and Within College Education



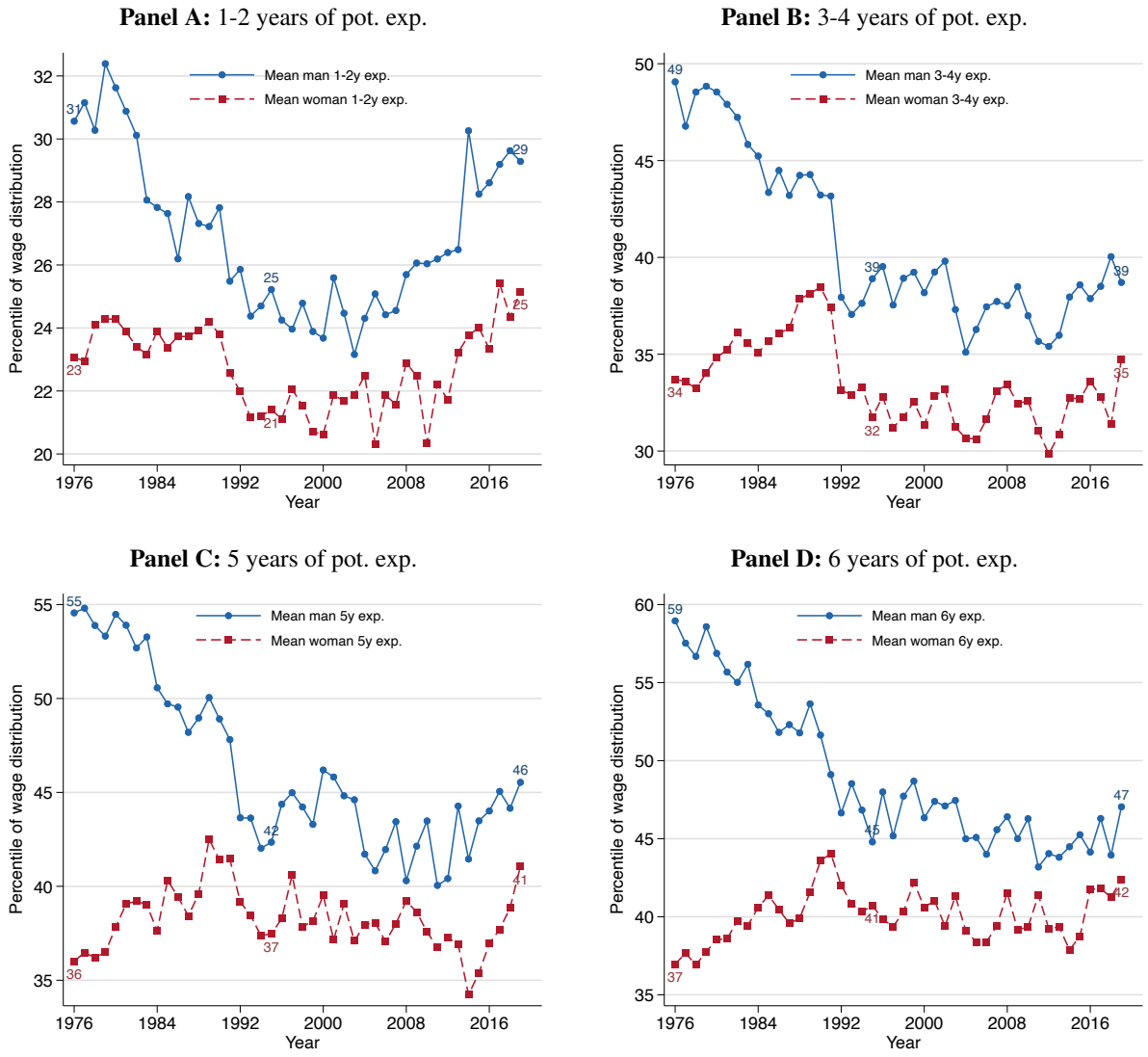

*Notes*: The figure decomposes both the total change in gender pay gap and just its between-cohort component between and within college graduation in the United States.
*Source*: Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A13:** Results for Workers With and Without College Education




*Notes*: These figures replicate the main findings separately for workers with (Panels A-C) and without (Panels D-F) a college education in the United States.
*Source*: Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A14:** Rank in Pay Distribution Based on Potential Experience

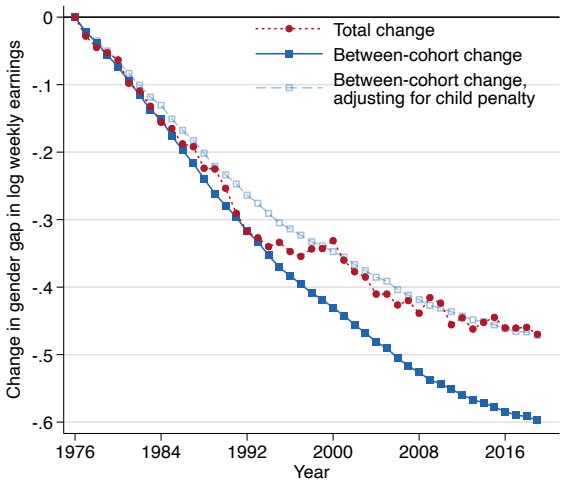



*Notes:* Panels A to D show the average earning percentile of men and women at different years of potential experience in the United States. Potential experience is calculated as age – years of education – 6. In each year, the data encompass information about all workers who were between 25 and 64 years old, had worked in the private sector for at least 24 weeks, had earned strictly positive earnings.

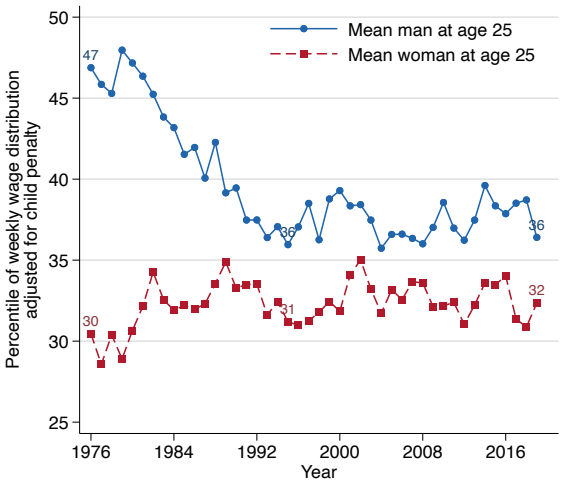
*Source*: Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A15:** Controlling for Child Penalty

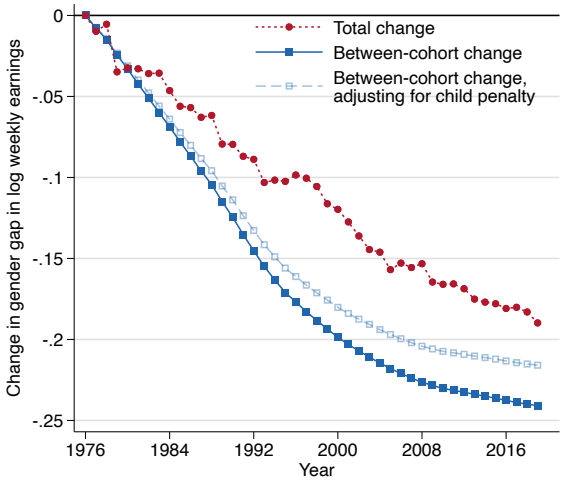
**Panel A:** USA, between-cohort change



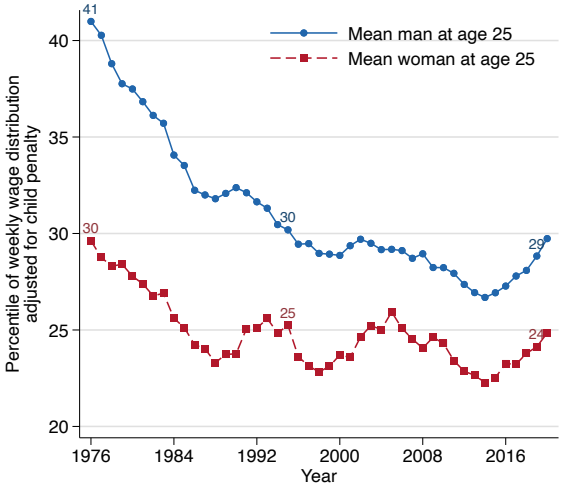

**Panel B:** USA, rank in pay distribution




**Panel C:** Italy, between-cohort change

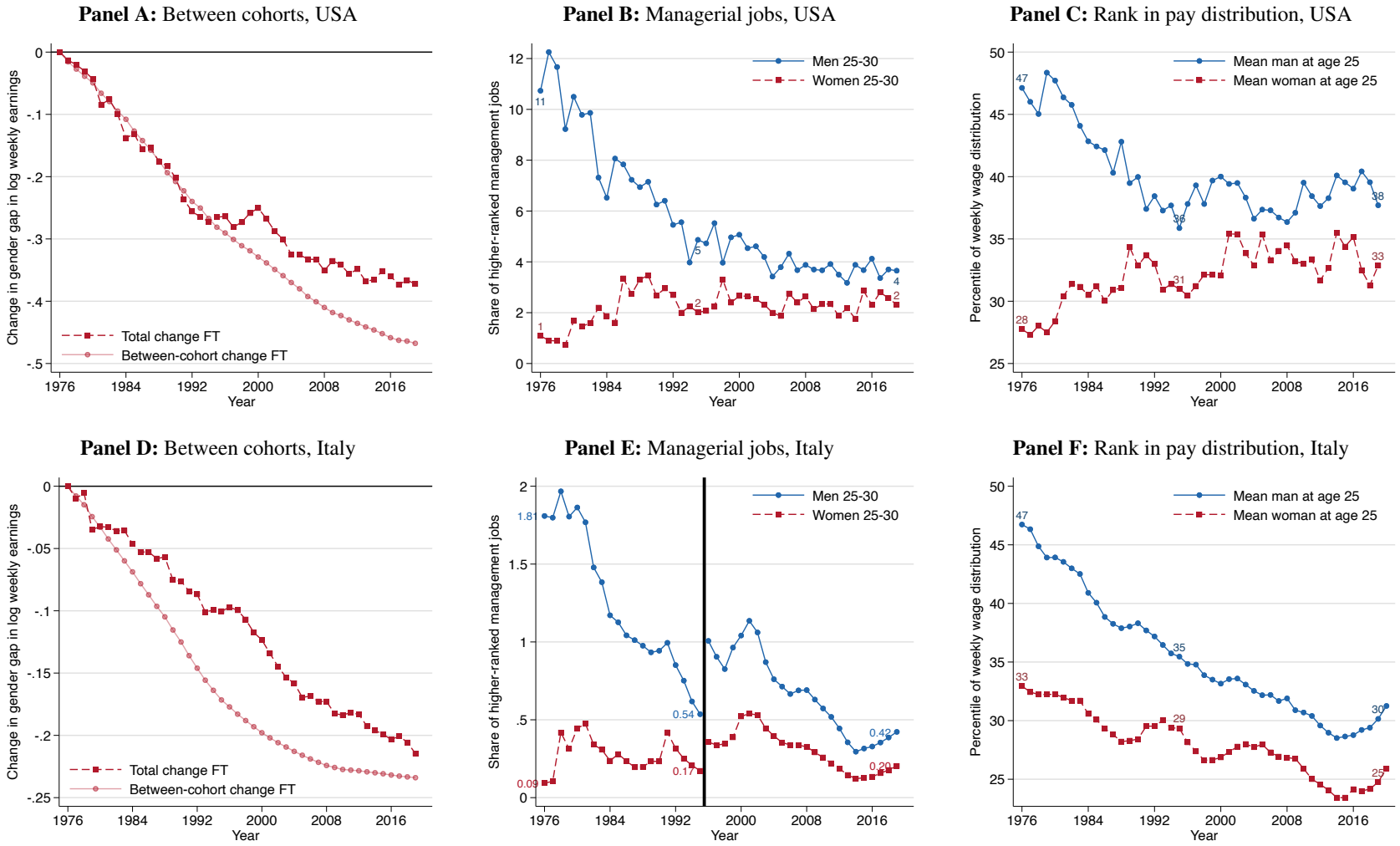



**Panel D:** Italy, rank in pay distribution




*Notes:* These figures use weekly earnings that include the child penalty borne by women in the labor market (Kleven et al., 2019). *Source for Italy:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States*. Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

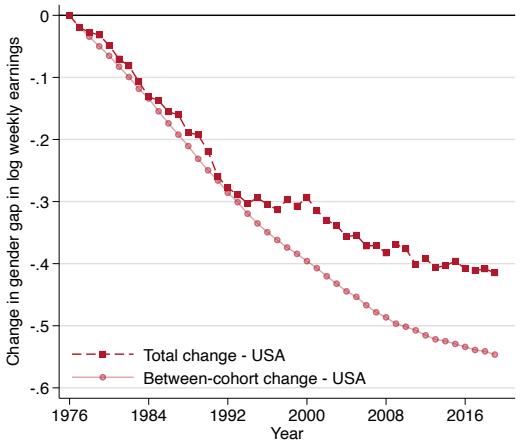
**Figure A16:** Full-Time Workers



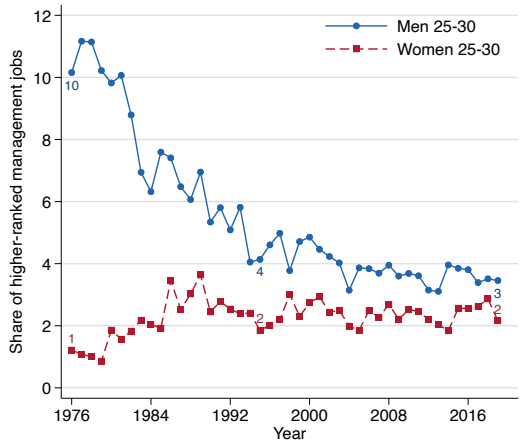

*Notes*: These figures replicate the main findings after keeping in the sample only workers with full-time contracts.
*Source for Italy*: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States*: Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A17:** Private-Sector and Public-Sector Employees

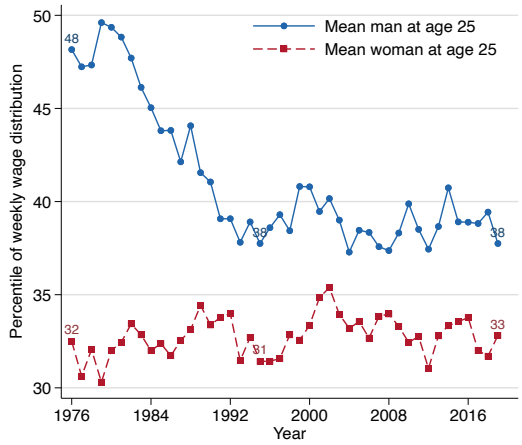
**Panel A:** Between cohorts



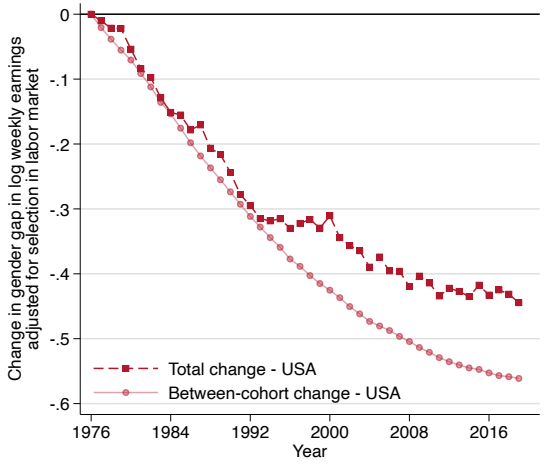

**Panel B:** Managerial jobs



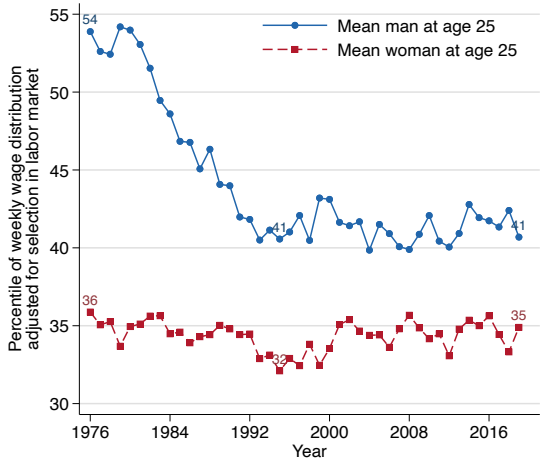

**Panel C:** Rank in pay distribution




**Panel D:** Between cohorts, adjusted for selection into labor force



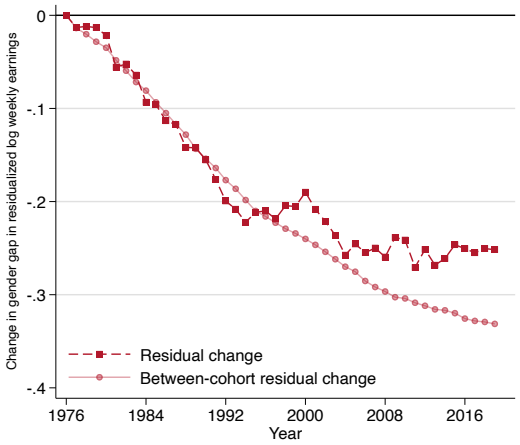

**Panel E:** Rank in pay distribution adjusted for selection into labor force



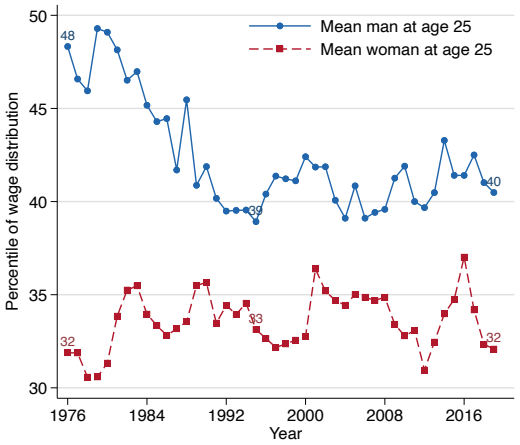

*Notes*: These figures replicate the main findings including in the sample also public-sector employees in the United States. Panels A-C expand the sample, including public-sector employees. Panels D and E expand the sample with public-sector employees and impute weekly earnings to nonparticipants using the process outlined in Blau et al. (2024). *Source*: Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A18:** Residual Earnings

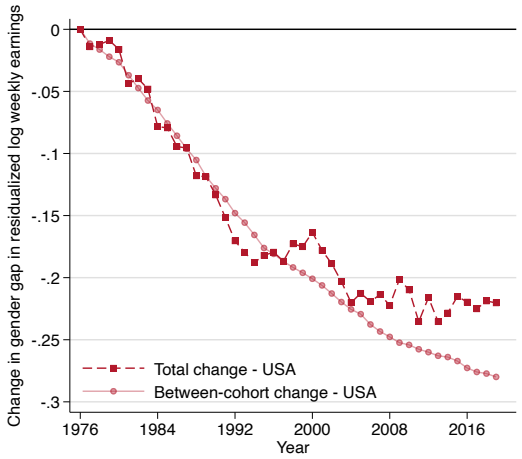
**Panel A:** Between cohorts, USA



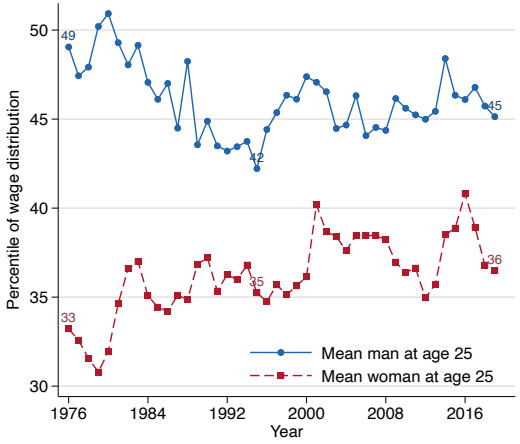

**Panel B:** Rank in pay distribution, USA



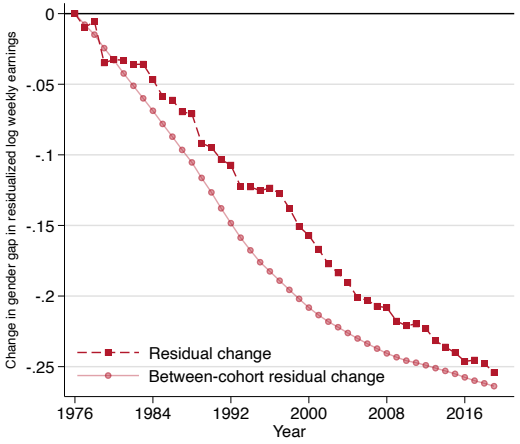

**Panel C:** Between cohorts, USA



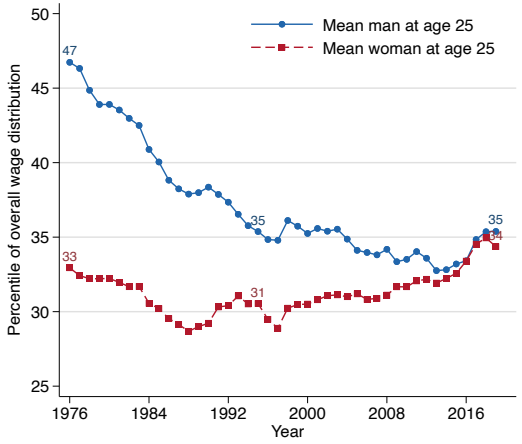

**Panel D:** Rank in pay distribution, USA




**Panel E:** Between cohorts, Italy



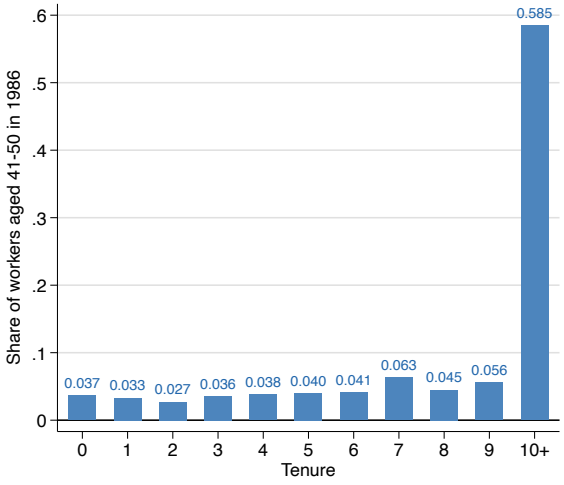

**Panel F:** Rank in pay distribution, Italy



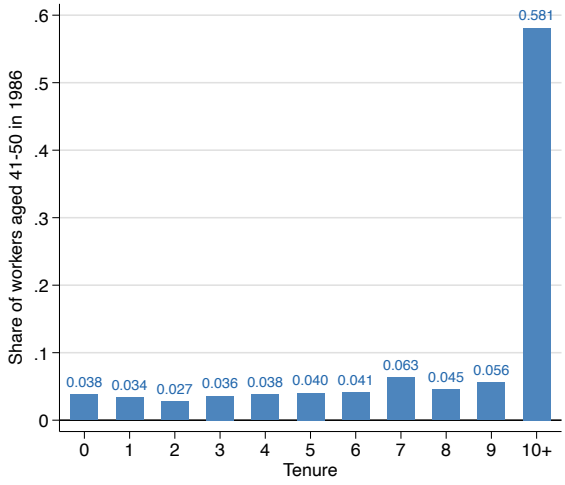

*Notes*: We regress the log of weekly earnings on a dummy for part-time workers, a dummy for temporary workers (only in Italy), a dummy for domestic-born workers (only in Italy), dummies for race (only in the US), a dummy for college graduation (only in the US), and a dummy for workers with children (only in the US). For the US, we have a second version in which in addition to the previous regressors, we also include a dummy for hispanic ethnicity, dummies for marital status, and fixed effects for Census divisions (Panels C and D). We estimate these regressions separately by year and country. *Source for Italy*: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States*: Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Figure A19:** Tenure of Workers Aged 41-50 and 31-40 in 1986

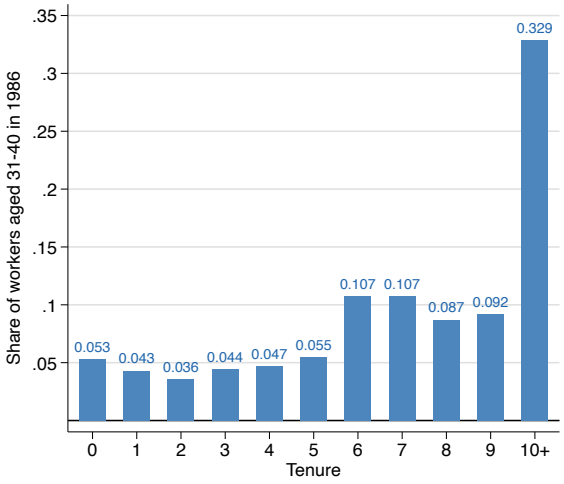
**Panel A:** Workers 41-50 in larger firms that existed in 1976



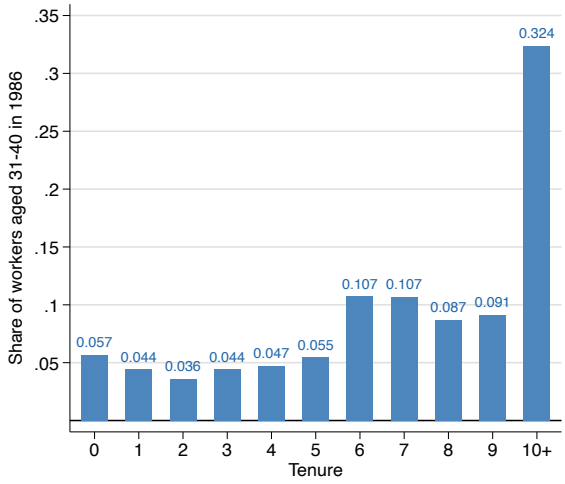

**Panel B:** Workers 41-50 in firms that existed in 1976




**Panel C:** Workers 31-40 in larger firms that existed in 1976

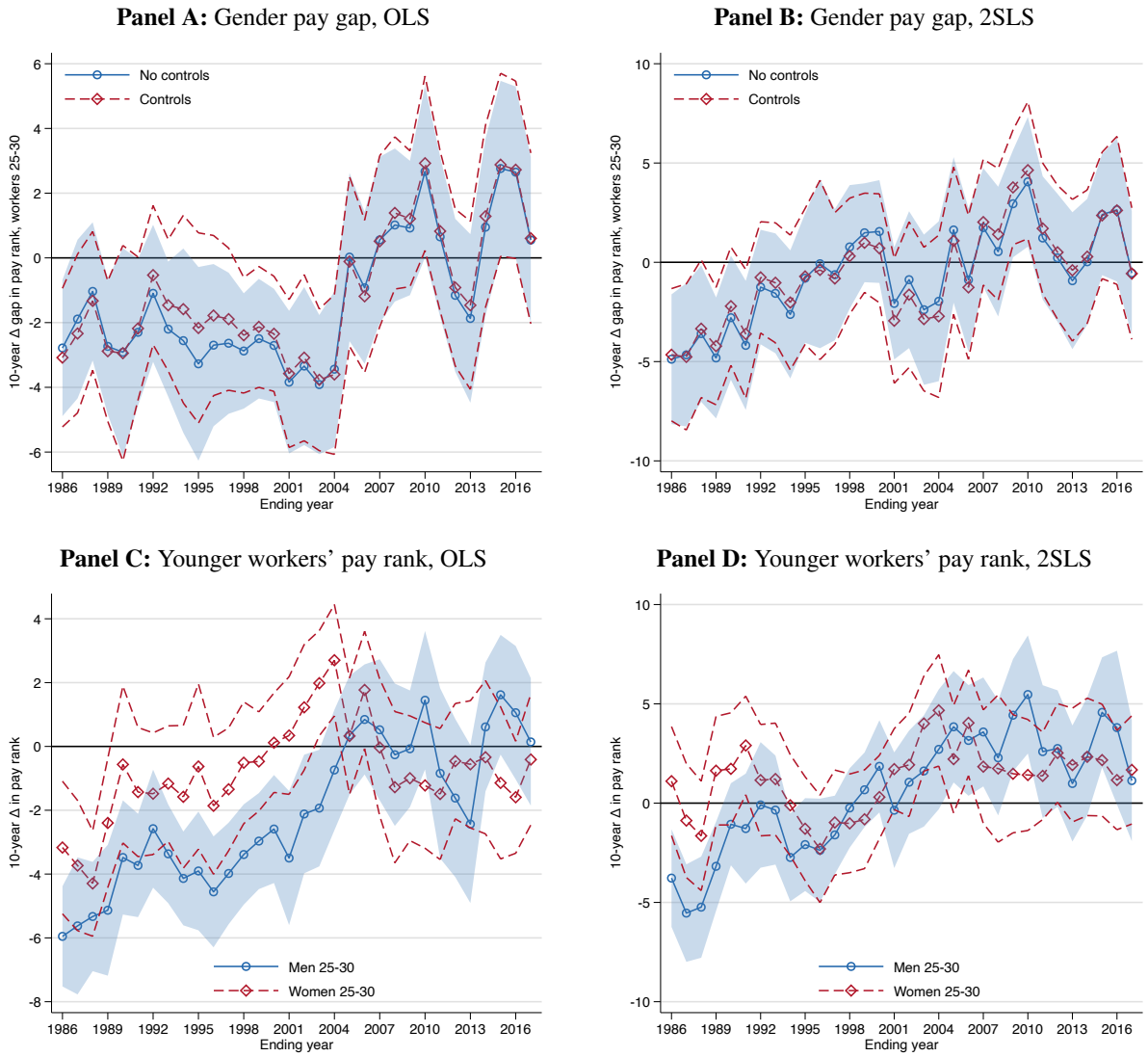



**Panel D:** Workers 31-40 in firms that existed in 1976



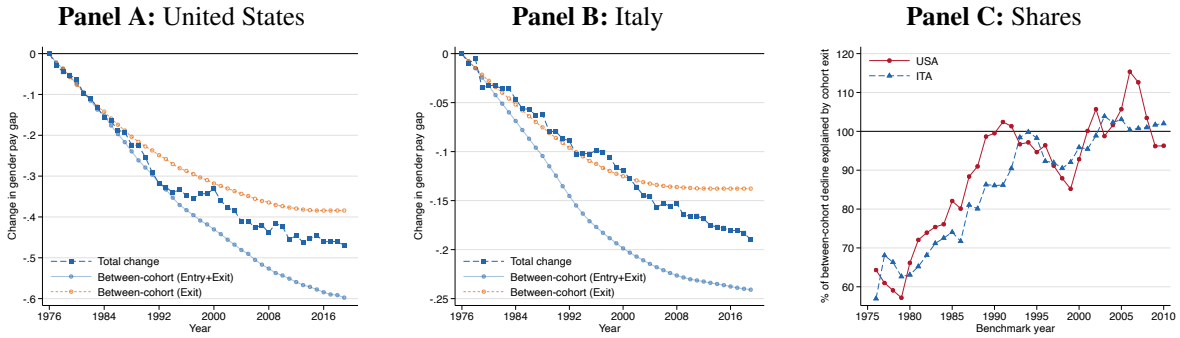

*Notes*: Panels A and B show the tenure distribution of workers who were between 41 and 50 years old in 1986 in Italy. The distribution of tenure is censored at 10 years because the database starts in 1976. In each year, the data encompass information about all workers who were between 41 and 50 years old, had worked in the private sector for at least 24 weeks, had earned strictly positive earnings, and had not retired by December 31. Moreover, Panel A further restricts the sample to workers who were employed by firms that (i) had more than five total employees in the period 1976-78, (ii) at least one man and one woman under 30 years old in both the periods 1976-78 and 1986-88, and (iii) at least one worker over 40 in the period 1976-78. Panel B drops the requirement for firms to have more than five employees. Panel C and D show the same distributions of tenure for workers who were between 31 and 40 years old in 1986 in Italy.
*Source:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

**Figure A20:** Firm-Level Workforce Aging and the Gender Pay Gap, Rolling 10-Year Changes



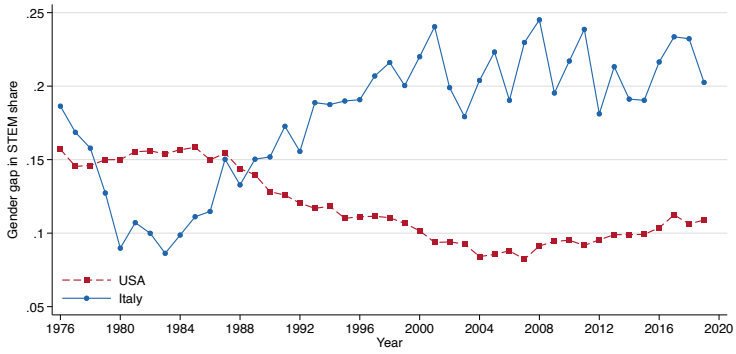

*Notes:* Each point on the x-axis represents the end year of a ten-year rolling window used to estimate the correlation between changes in the gender pay gap and workforce aging at the firm level. For example, the point labeled 1986 corresponds to regressions on the change from 1976 to 1986, the point labeled 1987 corresponds to regressions from 1977 to 1987, and so forth. Panel A regresses Δ gender pay rank gap on Δ share of workers 51-60. Panel B regresses Δ gender pay rank gap on Δ share of workers 51-60, instrumenting the latter with the difference between the share of workers aged 41-50 and the share of workers 51-60 at baseline. Panel C regresses Δ in the mean pay rank of younger men and women on Δ share of workers 51-60. Panel D regresses Δ in the mean pay rank of younger men and women on Δ share of workers 51-60, instrumenting the latter with differences between the share of workers aged 41-50 and the share of workers 51-60 at baseline. Controls include firm age, firm size, sector, and province fixed effects, all observed at baseline. Firm-level values for year $x$ are computed as three-year averages over $x$ and $x+2$. In each panel, the sample of firms include all firms that had more than five total employees at baseline, at least one man and one woman under 30 years old in both the initial and final period, as well as at least one worker over 40 in the initial period. Standard errors are clustered at the province level. *Source:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

**Figure A21:** Between-Cohort Change Without Convergence in Entry Earnings




*Notes:* Panels A and B compute for the United States and Italy, respectively, what would have happened to the gender pay gap if the cross-cohort convergence in the earnings of men and women at age 25 had stopped in benchmark year $t_b = 1976$. In this counterfactual exercise, the weekly earnings of cohorts who entered the labor market after 1976 are set equal to the average weekly earnings of cohorts who entered the labor market between 1976 and the following two years. Panel C shows the ratio between the change (last year - first year) in the wage gap predicted by this new counterfactual scenario and the change in the gender gap predicted by the total between-cohort component from Equation (2) when the benchmark year $t_b$ moves between 1976 and 2010. The ratio is such that 100 implies that the decline in the gender pay gap predicted by the new counterfactual scenario accounts for the entire between-cohort change. In each year, the data encompass information about all workers who were between 25 and 64 years old, had worked in the private sector for at least 24 weeks, had earned strictly positive earnings, and (only in Italy) had not retired by December 31.
*Source for Italy:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States*. Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

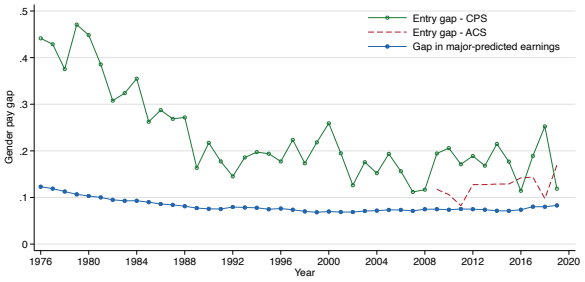
**Figure A22:** Gender Gap in the Share of STEM Graduates



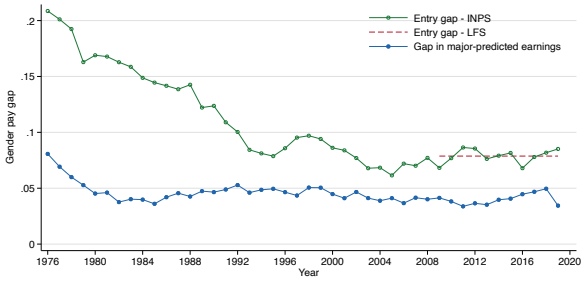

*Notes*: The figure shows the gender gap (men − women) in the share of graduates in STEM subjects at age 25 in the United States and Italy. STEM subject areas are: Natural Sciences, Physics, Mathematics, Statistics, Computer Science, Information Engineering, Industrial Engineering, Architecture and Civil Engineering. *Source for Italy:* Quarterly Labour Force Survey, Istituto Nazionale di Statistica (ISTAT). *Source for the United States*: Integrated Public Use Microdata Series, American Community Survey. Minneapolis, MN: IPUMS.

## **Figure A23:** Major-Predicted Gender Pay Gap

**Panel A:** USA




**Panel B:** Italy




*Notes:* The figure shows the gender gap in major-predicted residual weekly earnings computed from the American Community Survey in the United States (Panel A) and from the Labor Force Survey in Italy (Panel B). Predicted residual weekly earnings are computed by averaging across college majors the residual weekly earnings of native-born male employees working full-time in the private sector. Residual weekly earnings are obtained from OLS log wage regressions that control for a quadratic polynomial in age and time fixed effects over the period 2009-2019 in both countries. Then, we multiply these major-specific residuals by cohort-gender shares in each major. There are 32 college majors in the data for Italy and 176 for the United States. The gender gap at entry (age 25) is measured with both CPS and ACS (for college graduates) data in the United States and with both INPS and LFS (for college graduates) data in Italy. In the last case, we report the average between 2009 and 2019 because yearly averages are too noisy.
*Sources for Italy:* Quarterly Labour Force Survey, Istituto Nazionale di Statistica (ISTAT); UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Sources for the United States*: Integrated Public Use Microdata Series, American Community Survey; Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

## **Table A1:** Alternative Definitions of Labor-Market Entry

| | Total change in gender gap (last year - first year) | | Between-cohort change in gender gap (last year - first year) | | | | Between-cohort change in gender gap (Shorter time series) | |
|---|---|---|---|---|---|---|---|---|
| | First year | Change | Earnings at age 25 | Earnings at age 28 | Earnings at age 30 | Earnings b/w age 25 and age 30 | Total change (last y. - 1980) | True entry earnings |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Log weekly earnings | | | | | | | | |
| United States (1976-2019) | 0.800 | -0.470 | -0.598 | -0.606 | -0.615 | -0.575 | - | - |
| Italy (1976-2019) | 0.333 | -0.190 | -0.241 | -0.218 | -0.197 | -0.218 | -0.157 | -0.280 |
| Panel B: Log yearly earnings | | | | | | | | |
| United States (1976-2019) | 0.835 | -0.495 | -0.621 | -0.645 | -0.657 | -0.598 | - | - |
| Italy (1976-2019) | 0.350 | -0.092 | -0.204 | -0.165 | -0.127 | -0.166 | -0.061 | -0.270 |
| Panel C: Log hourly earnings | | | | | | | | |
| United States (1976-2019) | 0.568 | -0.361 | -0.452 | -0.464 | -0.458 | -0.441 | - | - |

Notes: Columns 1 and 2 show the change in gender gap between the first and last available years for each country. Columns 3 to 6 show the between-cohort component of the change in the gender gap between the first and last available years (Equation (2)). These columns differ in the definition of entry into the sample: mean earnings at age 25 (Col. 3), at age 28 (Col. 4), at age 30 (Col. 5), and between age 25 and age 30 (Col. 6). Cohorts who are above these age thresholds in the first sample year receive their mean earnings in the first sample year. In Column 8, we assign to each cohort its true earnings at labor-market entry, rather than its mean earnings at age 25. This analysis is available only for Italy and only from 1980. *Source for Italy*: UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS). *Source for the United States:* Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [dataset]. Minneapolis, MN: IPUMS.

**Table A2:** First Stage of Firm-Level IV Regressions

| | △ share over-50 workers | |
|---|---|---|
| | (1) | (2) |
| Panel A: 1976-1986 | | |
| Share workers 41-50 − share workers 51-60 in 1976 | 0.58*** | 0.59*** |
| | (0.01) | (0.01) |
| Mean dep. var. | 0.01 | 0.01 |
| SD dep. var. | 0.11 | 0.11 |
| Obs. | 25,279 | 25,279 |
| Panel B: 1976-1996 | | |
| Share workers 31-40 − share workers 51-60 in 1976 | 0.45*** | 0.46*** |
| | (0.01) | (0.01) |
| Mean dep. var. | -0.00 | -0.00 |
| SD dep. var. | 0.11 | 0.11 |
| Obs. | 13,993 | 13,993 |
| Panel C: 1996-2016 | | |
| Share workers 31-40 − share workers 51-60 in 1996 | 0.39*** | 0.40*** |
| | (0.01) | (0.01) |
| Mean dep. var. | 0.16 | 0.16 |
| SD dep. var. | 0.12 | 0.12 |
| Obs. | 14,644 | 14,644 |
| Controls | No | Yes |

*Notes:* This table shows the results of OLS firm-level regressions in which changes in workforce aging are regressed on the firm-level age distribution at baseline. Specifically, Δ share of workers 51-60 is regressed on the difference between the share of workers aged 41-50 (Panel A) or 31-40 (Panels B and C) and the share of workers 51-60 at baseline, all observed at the firm level. As such, these regressions measure the portion of firm-level workforce aging that stems from the age distribution of a firm's workforce at baseline, rather than from firms' or workers' choices during the period under consideration. Controls include firm age, firm size, sector, and province fixed effects, all observed at baseline. Firm-level values for year $x$ are computed as three-year averages over $x$ and $x+2$. In each panel, the sample of firms include all firms that had more than five total employees at baseline, at least one man and one woman under 30 years old in both the initial and final period, as well as at least one worker over 40 in the initial period. Standard errors are clustered at the province level. *Source:* UNIEMENS, Istituto Nazionale della Previdenza Sociale (INPS).

# B A Model of Career Spillovers

**Solving the firm problem.** The firm problem is

$$\max_{m_{y,t},f_{y,t},m_{y,b},f_{y,b}} AY\left(L_y,L_o\right)-\sum_{g\in\{m,f\}}\sum_{a\in\{y,o\}}\sum_{j\in\{t,b\}}\left(w^g_{a,j}g_{a,j}\right)-\frac{\kappa}{2}K^2-\sum_{g\in\{m,f\}}\left(\frac{c_g}{2}g^2_{y,t}\right).$$

The FOCs are

$$\begin{aligned}
\left\{f_{y,t}\right\}: &\quad AY_{L_y}\theta_{y,t}-w^f_{y,t}-\kappa K-c_f f_{y,t} &&=0;\\
\left\{m_{y,t}\right\}: &\quad AY_{L_y}\theta_{y,t}-w^m_{y,t}-\kappa K-c_m m_{y,t} &&=0;\\
\left\{f_{y,b}\right\}: &\quad AY_{L_y}\theta_{y,b}-w^f_{y,b} &&=0;\\
\left\{m_{y,b}\right\}: &\quad AY_{L_y}\theta_{y,b}-w^m_{y,b} &&=0.
\end{aligned}$$

The last two first order conditions indicate that the marginal revenue products of labor of younger men and women in the bottom job $b$ are the same, hence their wages in the bottom job are also the same:

$$w^f_{y,b} = w^m_{y,b} = w_{y,b} = AY_{L_y}\theta_{y,b}.$$

Given that the wage in the top job pays a constant wedge over the wage in the bottom job, it follows that the wages of younger men and women in the top job $t$ are also the same:

$$w^f_{y,t} = w^m_{y,t} = w_{y,t} = \mu_y w_{y,b}.$$

From the two initial first order conditions, we can pin down the optimal employment of younger men and women in the top job:

$$f^*_{y,t} = \frac{AY_{L_y}\left(\theta_{y,t} - \mu_y\theta_{y,b}\right) - \kappa K}{c_f}; m^*_{y,t} = \frac{AY_{L_y}\left(\theta_{y,t} - \mu_y\theta_{y,b}\right) - \kappa K}{c_m}.$$

Given that $c_f > c_m$, we can conclude that the optimal number of younger women in top jobs is lower than the optimal number of men in top jobs: $f_{t,y} < m_{t,y}$. Furthermore, in equilibrium, the firm keeps the ratio of younger women and men in the top job constant:

$$\frac{f_{y,t}}{m_{y,t}} = \frac{c_m}{c_f} = \delta_f < 1.$$

Next, we consider an increase in the number of older workers in top jobs from period $-1$. The bottom wage of younger workers (for both gender groups) responds as follows:

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

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

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

We can rewrite the change in the bottom wage as follows:

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

An increase in the supply of older workers causes negative career spillovers (or crowding out of younger workers from top spots) if $\frac{\partial l_{y,t}}{\partial l^{-1}_{o,t}} = \frac{\partial m_{y,t}}{\partial l^{-1}_{o,t}} + \frac{\partial f_{y,t}}{\partial l^{-1}_{o,t}} = \frac{\partial K}{\partial l^{-1}_{o,t}} - \rho_t < 0$, which implies that the total number of top jobs grows less that the number of older workers at the top. The key driver for the sign of this derivative is the change in the number of top jobs. The number of top slots is:

$$K = \frac{AY_{L_y}\left(\theta_{y,t} - \mu_y\theta_{y,b}\right) - c_m m_{y,t}}{\kappa}.$$

Next, we write the derivative of $K$ with respect to $l^{-1}_{o,t}$:

$$\frac{\partial K}{\partial l^{-1}_{o,t}} = \frac{A\left(\theta_{y,t} - \mu_y\theta_{y,b}\right)}{\kappa}\left[Y_{L_yL_y}\left(\theta_{y,t} - \theta_{y,b}\right)\left(\frac{\partial K}{\partial l^{-1}_{o,t}} - \rho_t\right) + Y_{L_yL_o}\theta_{o,t}\rho_t\right] - \frac{c_m}{\kappa}\frac{\partial m_{y,t}}{\partial l^{-1}_{o,t}}.$$

We use the fact that the ratio of younger men and women in top jobs is constant in equilibrium to rewrite the derivative of $m_{y,t}$ as a function of the derivative of $K$:

$$\text{[Step 1]} \quad \frac{\partial f_{y,t}}{\partial l^{-1}_{o,t}} = \frac{c_m}{c_f}\frac{\partial m_{y,t}}{\partial l^{-1}_{o,t}}.$$

$$\text{[Step 2]} \quad \frac{\partial m_{y,t}}{\partial l^{-1}_{o,t}} = \frac{\partial K}{\partial l^{-1}_{o,t}} - \frac{\partial f_{y,t}}{\partial l^{-1}_{o,t}} - \rho_t = \frac{\partial K}{\partial l^{-1}_{o,t}} - \frac{c_m}{c_f}\frac{\partial m_{y,t}}{\partial l^{-1}_{o,t}} - \rho_t = \frac{c_f}{c_f + c_m}\left(\frac{\partial K}{\partial l^{-1}_{o,t}} - \rho_t\right).$$

Going back to the derivative of $K$, we can rewrite it as follows:

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

We simplify the notation:

$$B \quad = \quad A\left(\theta_{y,t}-\mu_y\theta_{y,b}\right)>0;\ D=\left(\theta_{y,t}-\theta_{y,b}\right)>0;\ E=\frac{c_m c_f}{c_f+c_m}>0.$$

Then, we can further simplify the derivative of K as follows:

$$\frac{\partial K}{\partial l_{o,t}^{-1}} = \frac{1}{\kappa}\left\{B\left[Y_{L_yL_y}D\left(\frac{\partial K}{\partial l_{o,t}^{-1}}-\rho_t\right)+Y_{L_yL_o}\theta_{o,t}\rho_t\right]-E\left(\frac{\partial K}{\partial l_{o,t}^{-1}}-\rho_t\right)\right\} = \underbrace{\frac{1}{\kappa-Y_{L_yL_y}BD-E}\left\{B\left[Y_{L_yL_o}\theta_{o,t}-Y_{L_yL_y}D\right]-E\right\}\rho_t}_{\text{Negative career spillovers if }<1}.$$

If the term multiplying $\rho_t$ is less than 1, an increase in the number of older workers in top jobs decreases the number of top slots available to younger workers. This scenario happens when the following condition holds:

$$1>\frac{1}{\kappa-Y_{L_yL_y}BD-E}\left\{B\left[Y_{L_yL_o}\theta_{o,t}-Y_{L_yL_y}D\right]-E\right\}$$
$$\kappa>\bar{\kappa}=BY_{L_yL_o}\theta_{o,t}=A\left(\theta_{y,t}-\mu_y\theta_{y,b}\right)Y_{L_yL_o}\theta_{o,t}>0.$$

This inequality indicates that the cost parameter $\kappa$ needs to be higher than the productivity gains that younger workers experience from their complementarity with older workers. The term on the right-hand side is greater than zero because $\left(\theta_{y,t}-\mu_y\theta_{y,b}\right)>0$. The latter follows from the condition that guarantees a positive $K$ (see the formula of the equilibrium $K$) and from the fact that $f_{y,t}=K-m_{y,t}-l_{t,o}$.

So, when $\kappa>\bar{\kappa}$, we can draw several conclusions. First, as already pointed out, there is crowding out of younger workers in top jobs: $\frac{\partial K}{\partial l_{o,t}^{-1}}-\rho_t<0$. Second, all younger workers become less likely to hold top jobs, but younger men lose more top spots than younger women because they are more likely to hold top jobs at baseline: $\left|\frac{\partial f_{t,y}}{\partial l_{o,t}^{-1}}\right|=\delta_f\left|\frac{\partial m_{t,y}}{\partial l_{o,t}^{-1}}\right|<\left|\frac{\partial m_{t,y}}{\partial l_{o,t}^{-1}}\right|$ because $\delta_f<1$. Third, a larger supply of older workers at the top raises the bottom wage of younger workers:

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

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

Next, we address a change in the mean wage of younger men and women. The mean wages of younger men and women are:

$$\overline{w}_{y,f}=\frac{f_{y,t}\cdot w_{y,t}^f+f_{y,b}\cdot w_{y,b}^f}{f_y};\ \overline{w}_{y,m}=\frac{m_{y,t}\cdot w_{y,t}^m+m_{y,b}\cdot w_{y,b}^m}{m_y},$$

where $w_{y,b}^f=w_{y,b}^m=w_{y,b}$, $w_{y,t}^f=w_{y,t}^m=w_{y,t}=\mu_y w_{y,b}$, and $g_y=g_{y,t}+g_{y,b}$ for each $g\in\{m,f\}$. Therefore, we can rewrite them as follows:

$$\left\{f_y\right\} \quad \overline{w}_{y,f}= \quad \frac{f_{y,t}\cdot\mu_y w_{y,b}+\left(f_y-f_{y,t}\right)\cdot w_{y,b}}{f_y}=\frac{1}{f_y}\left(\mu_y-1\right)f_{y,t}w_{y,b}+w_{y,b};$$
$$\left\{m_y\right\} \quad \overline{w}_{y,m}= \quad \frac{1}{m_y}\left(\mu_y-1\right)m_{y,t}w_{y,b}+w_{y,b}.$$

Starting from younger men, we consider the change in the mean wage that stems from a marginal increase in the number of older workers who held top jobs in period $-1$ ($l_{t,o}^{-1}$). Under the empirically relevant scenario of $\kappa>\bar{\kappa}$, we find that:

$$\frac{\partial \bar{w}_{y,m}}{\partial l_{o,t}^{-1}}=\underbrace{\frac{1}{m_y}\left(\mu_y-1\right)\frac{\partial m_{y,t}}{\partial l_{o,t}^{-1}}w_{y,b}}_{\text{career spillovers }<0}+\underbrace{\left(\frac{1}{m_y}\left(\mu_y-1\right)m_{y,t}+1\right)\frac{\partial w_{y,b}}{\partial l_{o,t}^{-1}}}_{\text{wage level }>0}.$$

The first component is negative because $\frac{\partial m_{y,t}}{\partial l_{o,t}^{-1}}<0$ and $\mu_y-1>0$. In contrast, the second component is positive because $\frac{\partial w_{b,y}}{\partial l_{t,o}^{-1}}>0$. Due to the complementarity between the two age groups, a larger number of older workers makes younger men more productive,

contributing to raise their mean wage. The same decomposition applies to the mean wage of younger women. Next, we compare the magnitude of the negative career spillovers between younger men and women. As long as the share of women in the top job is smaller than the equivalent share of men, the career spillovers have a more negative effect on the mean wage of younger men:

$$\begin{aligned}
\frac{1}{m_y}\left(\mu_y-1\right)\frac{\partial m_{y,t}}{\partial l_{o,t}^{-1}}w_{y,b} &< \frac{1}{f_y}\left(\mu_y-1\right)\frac{\partial f_{y,t}}{\partial l_{o,t}^{-1}}w_{y,b}\\
\frac{1}{m_y}\left(\mu_y-1\right)\frac{\partial m_{y,t}}{\partial l_{o,t}^{-1}}w_{y,b} &< \frac{1}{f_y}\left(\mu_y-1\right)\delta_f\frac{\partial m_{y,t}}{\partial l_{o,t}^{-1}}w_{y,b}\\
\frac{1}{m_y} &> \frac{1}{f_y}\delta_f \Rightarrow {}^{\frac{m_{y,t}}{m_y}}\!/_{\frac{f_{y,t}}{f_y}}>1.
\end{aligned}$$

**Introducing skills.** When all top jobs are already occupied by older workers, an increase in the supply of older workers has the following effect on the mean wage of younger men:

$$\begin{aligned}
\frac{\partial \bar{w}_{y,m}}{\partial l_{o,t}^{-1}} &= \sum_{s\in\{h,l\}}\left(\frac{1}{m_y}\left(\mu_y-1\right)m_{y,t,s}+1\right)\frac{\partial w_{y,b,s}}{\partial l_{o,t}^{-1}}\\
&= \sum_{s\in\{h,l\}}\left(\frac{m_{y,s}}{m_y}\right)A\theta_{y,b,s}Y_{L_{y,s}L_o}\theta_{o,t,s}\rho_t,
\end{aligned}$$

where $\frac{1}{m_y}\left(\mu_y-1\right)m_{y,t,s}+1=\frac{\mu m_{y,t,s}+m_{y,b,s}}{m_y}=\frac{m_{y,s}}{m_y}$ because all top jobs are occupied by older workers and, therefore, $m_{y,t,s}=0$, and $m_{y,b,s}=m_{y,s}$. Moreover, $\frac{\partial w_{y,b,s}}{\partial l_{o,t}^{-1}}=A\theta_{y,b,s}\cdot\left(Y_{L_{y,s}L_{y,s}}\frac{\partial L_{y,s}}{\partial l_{t,o}^{-1}}+Y_{L_{y,s}L_o}\frac{\partial L_{o,s}}{\partial l_{t,o}^{-1}}\right)=A\theta_{y,b,s}Y_{L_{y,s}L_o}\theta_{o,t,s}\rho_t$ because $\frac{\partial L_{y,s}}{\partial l_{o,t}^{-1}}=0$ for all skills/tasks $s$. Moreover, we assume that the retention rate of older workers in top jobs ($\rho_t$) is the same across all tasks.

We repeat the same computation for younger women:

$$\frac{\partial \bar{w}_{y,f}}{\partial l_{o,t}^{-1}}=\sum_{s\in\{h,l\}}\left(\frac{f_{y,s}}{f_y}\right)A\theta_{y,b,s}Y_{L_{y,s}L_o}\theta_{o,t,s}\rho_t.$$

For both younger men and women, the change in mean wages is positive. If we compare the two derivatives, we find that an increase in the number of older workers in top jobs shrinks the gender pay gap if the wage increase in larger for younger women:

$$\sum_{s\in\{h,l\}}\left(\frac{f_{y,s}}{f_y}\right)A\theta_{y,b,s}Y_{L_{y,s}L_o}\theta_{o,t,s}\rho_t>\sum_{s\in\{h,l\}}\left(\frac{m_{y,s}}{m_y}\right)A\theta_{y,b,s}Y_{L_{y,s}L_o}\theta_{o,t,s}\rho_t.$$

This inequality crucially depends on the distribution of younger men and women across different skills/tasks. We can further show this point by assuming that the cross-complementarity between younger and older workers is proportional to a task's marginal product: $Y_{L_{y,s}L_o}=Y_{L_{y,s}}\cdot C\left(\mathbf{L_y},L_o\right)$, where $C\left(\cdot,\cdot\right)$ is the same across tasks.[33] In this case, the change in mean wages for younger women is larger than that for younger men if:

$$\frac{f_{y,h}}{f_y}Y_{L_{y,h}}\theta_{y,b,h}\theta_{o,t,h}+\frac{f_{y,l}}{f_y}Y_{L_{y,l}}\theta_{y,b,l}\theta_{o,t,l}>\frac{m_{y,h}}{m_y}Y_{L_{y,h}}\theta_{y,b,h}\theta_{o,t,h}+\frac{m_{y,l}}{f_y}Y_{L_{y,l}}\theta_{y,b,l}\theta_{o,t,l}$$

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[33] This is true if the production function is a Cobb-Douglas or a nested CES. Indeed, for the Cobb-Douglas we have $Y=L_o^{\alpha_o}\cdot\prod_{s\in\{h,l\}}L_{a,s}^{\alpha_{a,s}}$ and

$$Y_{L_{y,s}L_o}=\alpha_{y,s}\alpha_o\frac{Y}{L_{y,s}L_o}=Y_{L_{y,s}}\cdot\frac{\alpha_o}{L_o},$$

where $\frac{\alpha_o}{L_o}$ is the same across all skills. In the nested CES case $Y=\left[\beta_y\left(L_{y,h}^{\rho_y}+L_{y,l}^{\rho_y}\right)^{\frac{\rho}{\rho_y}}+\beta_o L_o^{\rho}\right]^{\frac{1}{\rho}}$ and

$$\begin{aligned}
Y_{L_{y,s}L_o} &= \beta_y L_{y,s}^{\rho_y-1}\left(L_{y,h}^{\rho_y}+L_{y,l}^{\rho_y}\right)^{\frac{\rho}{\rho_y}-1}\left[\beta_y\left(L_{y,h}^{\rho_y}+L_{y,l}^{\rho_y}\right)^{\frac{\rho}{\rho_y}}+\beta_o L_o^{\rho}\right]^{\frac{1}{\rho}-2}\left(\frac{1}{\rho}-1\right)\beta_o\rho L_o^{\rho-1}\\
&= \underbrace{\beta_y L_{y,s}^{\rho_y-1}\left(L_{y,h}^{\rho_y}+L_{y,l}^{\rho_y}\right)^{\frac{\rho}{\rho_y}-1}\left[\beta_y\left(L_{y,h}^{\rho_y}+L_{y,l}^{\rho_y}\right)^{\frac{\rho}{\rho_y}}+\beta_o L_o^{\rho}\right]^{\frac{1}{\rho}-1}}_{=Y_{L_{y,s}}}\underbrace{\left(\frac{1}{\rho}-1\right)\beta_o\rho L_o^{\rho-1}\left[\beta_y\left(L_{y,h}^{\rho_y}+L_{y,l}^{\rho_y}\right)^{\frac{\rho}{\rho_y}}+\beta_o L_o^{\rho}\right]^{-1}}_{=C\left(\mathbf{L_y},L_o\right)}.
\end{aligned}$$

$$\left(\frac{f_{y,h}}{f_y}-\frac{m_{y,h}}{m_y}\right)\left(Y_{L_{y,h}}\theta_{y,b,h}\theta_{o,t,h}-Y_{L_{y,l}}\theta_{y,b,l}\theta_{o,t,l}\right)>0.$$

Assuming that high-skill tasks have higher marginal product than low-skill tasks ($Y_{L_{y,h}}\theta_{y,b,h}\theta_{o,t,h}-Y_{L_{y,l}}\theta_{y,b,l}\theta_{o,t,l}>0$), the inequality holds if women are overrepresented in high-skill tasks: $\frac{f_{y,h}}{f_y}>\frac{m_{y,h}}{m_y}$.

**Heterogeneous firms.** First, we replace the representative firm with $N$ firms, but each firm is small and does not internalize the consequences of its actions on other firms. We further assume that $\rho_{j,n}$ increases with firm-level productivity $A_n$ of firm $n$. Second, firms set wages for the bottom and top jobs, instead of taking them as given. Third, the ratio of top and bottom wages is not equal to a fixed rent and is not necessarily constant across firms. Fourth, we assume that $\kappa(K_n)$ is 0 up to a threshold level $\overline{K}_n$ and then is $\infty$ beyond $\overline{K}_n$. In practice, this is equivalent to a binding constraint on the number of top jobs: $l_{o,t,n}+m_{y,t,n}+f_{y,t,n}=\bar{K}_n$. Fifth, to make the computations more tractable, we assume that the cost of hiring younger workers in the top job is linear, instead of quadratic.

The timing of the model is as follows. First, each firm receives legacy older workers from period $-1$. Then, each firm posts wage offers for its bottom and top jobs, and each younger worker joins the firm and job that maximizes her utility. Finally, the production is realized, and the firm makes payments to all workers. In this scenario, the firm problem is to choose the wages of younger men and women in the top and bottom job that maximize its profits,

$$\max_{w^m_{y,t,n},w^f_{y,t,n},w^m_{y,b,n},w^f_{y,b,n}} A_nY\left(L_{y,n},L_{o,n}\right)-\sum_{g\in\{m,f\}}\sum_{a\in\{y,o\}}\sum_{j\in\{t,b\}}\left(w^g_{a,j,n}g_{a,j,n}\right)-\sum_{g\in\{m,f\}}c_gg_{y,t,n},$$

subject to the constraint: $l_{o,t,n}+m_{y,t,n}+f_{y,t,n}\leq\bar{K}_n$.

On the worker side, we assume that a worker $i$ of age group $a(i)$ and gender $g(i)$ derives the following utility when working in job $j$ and firm $n$:

$$U_{i,a,j,n}=\log\left(w^g_{a,j,n}\right)+\xi_{i,a,j,n},$$

where $\xi_{i,a,j,n}$ represents the idiosyncratic preference of worker $i$ over job $j$ of firm $n$. We assume that $\xi_{i,a,j,n}$, which is unobserved by firms, follows a type-1 extreme distribution with a parameter $\sigma$ that captures the degree of substitutability across jobs and firms in workers' preferences. In this context, firm $n$ faces the following labor supply function for its job $j$ from younger workers of gender $g$:

$$g_{y,j,n}=\frac{\left(w^g_{y,j,n}\right)^{\frac{1}{\sigma}}}{\sum_{n=1}^{N}\sum_{j\in\{t,b\}}\left(w^g_{y,j,n}\right)^{\frac{1}{\sigma}}}g_y.$$

The marginal change in the wage of job $j$ and firm $n$ has the following effect on the labor supply of younger workers of gender $g$ anticipated by the firm:

$$\frac{\partial g_{y,j,n}}{\partial w^g_{y,j,n}}=\frac{1}{\sigma}\frac{\left(w^g_{y,j,n}\right)^{\frac{1}{\sigma}-1}}{\sum_{n=1}^{N}\sum_{j\in\{t,b\}}\left(w^g_{y,j,n}\right)^{\frac{1}{\sigma}}}g_y=\frac{1}{\sigma}\frac{g_{y,j,n}}{w^g_{y,j,n}}.$$

In the first row, the denominator is left unchanged due to the assumption that firms do not anticipate the effect of a change in their wage on the other wages in the economy ( Card et al., 2018; Lamadon et al., 2022).

Firms choose optimal wages as follows:

$$\left\{w^g_{y,b,n}\right\}:A_nY_{L_{y,n}}\theta_{y,b,n}\frac{\partial g_{y,b,n}}{\partial w^g_{y,b,n}}-w^g_{y,b,n}\frac{\partial g_{y,b,n}}{\partial w^g_{y,b,n}}-g_{y,b,n}=0$$

$$\left\{w^g_{y,t,n}\right\}:A_nY_{L_{y,n}}\theta_{y,t,n}\frac{\partial g_{y,t,n}}{\partial w^g_{y,t,n}}-w^g_{y,t,n}\frac{\partial g_{y,t,n}}{\partial w^g_{y,t,n}}-g_{y,t,n}-c_g\frac{\partial g_{y,t,n}}{\partial w^g_{y,t,n}}-\lambda_n\frac{\partial g_{y,t,n}}{\partial w^g_{y,t,n}}=0,$$

where $\lambda_n$ is the multiplier on the constraint on the quantity of top jobs. Therefore, wages in the bottom job are equal to:

$$w^g_{y,b,n}=\underbrace{\frac{1}{1+\sigma}}_{\text{Markdown}}A_nY_{L_{y,n}}\theta_{y,b,n},$$

so that bottom wages pay a markdown below the marginal product of labor, and $w^f_{y,b,n}=w^m_{y,b,n}$ for all firms.

Instead, wages in the top job are equal to:

$$w^g_{y,t,n} = \underbrace{\frac{1}{1+\sigma}}_{\text{Markdown}} \left(A_n Y_{L_{y,n}} \theta_{y,t,n} - c_g - \lambda_n\right).$$

As we discussed in the version with a representative firm, younger men are paid more than younger women in top jobs ($c_m < c_f$) and, therefore, are more likely to hold these positions. Finally, all firms have $\overline{K_n}$ top jobs.

Next, we study a marginal increase in $l^{-1}_{o,t}$, the total number of older workers in top jobs in period $-1$. We assume that this increase affects all firms proportionately to the share of the total number of older workers they employ in top jobs.

Wages at the bottom change as follows (by the same amount for both genders):

$$\begin{aligned}
\frac{\partial w_{y,b,n}}{\partial l^{-1}_{o,t}} &= \frac{1}{1+\sigma} A_n \theta_{y,b,n} \left( Y_{L_{y,n}L_{o,n}} \theta_{o,t,n} \rho_{t,n} \frac{l^{-1}_{o,t,n}}{l^{-1}_{o,t}} \right. \\
&\quad \left. + Y_{L_{y,n}L_{y,n}} \left( \frac{1}{\sigma} \frac{(m_{y,b,n}+f_{y,b,n})}{w_{y,b,n}} \frac{\partial w_{y,b,n}}{\partial l^{-1}_{o,t}} \theta_{y,b,n} + \left( \frac{\partial m_{y,t,n}}{\partial l^{-1}_{o,t}} + \frac{\partial f_{y,t,n}}{\partial l^{-1}_{o,t}} \right) \theta_{y,t,n} \right) \right) \\
&= \frac{\frac{1}{1+\sigma} A_n \theta_{y,b,n} \left( Y_{L_{y,n}L_{o,n}} \theta_{o,t,n} - Y_{L_{y,n}L_{y,n}} \theta_{y,t,n} \right)}{1 - \frac{1}{1+\sigma} \frac{1}{\sigma} A_n \theta^2_{y,b,n} Y_{L_{y,n}L_{y,n}} \frac{(m_{y,b,n}+f_{y,b,n})}{w_{y,b,n}}} \rho_{t,n} \frac{l^{-1}_{o,t,n}}{l^{-1}_{o,t}} > 0,
\end{aligned}$$

Wages at the top change as follows (again, by the same amount for both genders):

$$\frac{\partial w_{y,t,n}}{\partial l^{-1}_{o,t}} = \frac{\partial w_{y,b,n}}{\partial l^{-1}_{o,t}} \frac{\theta_{y,t,n}}{\theta_{y,b,n}} - \frac{1}{1+\sigma} \frac{\partial \lambda_n}{\partial l^{-1}_{o,t}}.$$

If the marginal productivities of younger workers in top and bottom jobs are not too dissimilar, an increase in the number of older workers increases wages in the top job less than wages in the bottom job. This is due to the fact that $\frac{\partial \lambda_n}{\partial l^{-1}_{o,t}} > 0$ because the shadow value of relaxing the quantity constraint increases with the number of older workers in the economy.

Next, we show that the restricted access to top jobs leads to larger limitations in the number of younger men who hold these positions. We start by considering the ratio of younger workers of gender $g$ between the top and bottom job in firm $n$ : $\frac{g_{y,t,n}}{g_{y,b,n}} = \left( \frac{w^g_{y,t,n}}{w^g_{y,b,n}} \right)^{\frac{1}{\sigma}}$. The derivative of this ratio with respect to the number of older workers is as follows:

$$\frac{\partial \frac{g_{y,t,n}}{g_{y,b,n}}}{\partial l^{-1}_{o,t}} = \frac{1}{\sigma} \left( \frac{w^g_{y,t,n}}{w^g_{y,b,n}} \right)^{\frac{1}{\sigma}-1} \frac{\frac{\partial w^g_{y,t,n}}{\partial l^{-1}_{o,t}} w^g_{y,b,n} - \frac{\partial w^g_{y,b,n}}{\partial l^{-1}_{o,t}} w^g_{y,t,n}}{\left( w^g_{y,b,j} \right)^2} = \frac{1}{\sigma} \frac{g_{y,t,n}}{g_{y,b,n}} \left( \frac{\partial w^g_{y,t,n}}{\partial l^{-1}_{o,t}} \frac{1}{w^g_{y,t,n}} - \frac{\partial w^g_{y,b,n}}{\partial l^{-1}_{o,t}} \frac{1}{w^g_{y,b,n}} \right).$$

When $\frac{\partial \lambda_n}{\partial l^{-1}_{o,t}}$ is between $\frac{\theta_{y,t,f}-\theta_{y,b,f}}{\theta_{y,b,f}} (1+\sigma) \frac{\partial w_{y,b,f}}{\partial l^{-1}_{o,t}}$ and $\frac{\theta_{y,t,f}}{\theta_{y,b,f}} (1+\sigma) \frac{\partial w_{y,b,f}}{\partial l^{-1}_{o,t}}$, the change in the top wage is positive but lower than the change in the bottom wage. Hence, the difference within the parentheses is negative and the employment of younger workers in the top job decreases relative to their employment in the bottom job.

Moreover, it is possible to compare $\partial \frac{m_{y,t,n}}{m_{y,b,n}} / \partial l^{-1}_{o,t}$ to $\partial \frac{f_{y,t,n}}{f_{y,b,n}} / \partial l^{-1}_{o,t}$. The wage change at the top $\frac{\partial w^g_{y,t,n}}{\partial l^{-1}_{o,t}}$ is the same for both genders, but younger men are paid more in top jobs. Therefore, $\frac{\partial w^m_{y,t,n}}{\partial l^{-1}_{o,t}} \frac{1}{w^m_{y,t,n}}$ is smaller than $\frac{\partial w^f_{y,t,n}}{\partial l^{-1}_{o,t}} \frac{1}{w^f_{y,t,n}}$. In contrast, the percentage change at the bottom is the same for both younger men and women. Therefore, the difference in parentheses is more negative for younger men. In addition, it is also true that $\frac{m_{y,t,n}}{m_{y,b,n}} > \frac{f_{y,t,n}}{f_{y,b,n}}$ at baseline because the wages in top jobs are higher for younger men (due to the higher cost of hiring women in top jobs). Therefore, it follows that, if top wages increase in response to a larger supply of older workers (due to positive relative supply effects), then the share of younger men in top jobs decline more than the share of women in the same positions.

Finally, we consider whether more older workers can change the distribution of younger workers across different types of firms. Under the assumption that the retention rates are higher in higher-productivity firms, an increase in the total number of older workers in the economy leads to larger increases in the number of older workers in the top jobs of higher-productivity firms. The fact that younger workers (both men and women) experience more negative career spillovers in higher-productivity firms does not necessarily mean that they find employment in the bottom jobs of the same set of firms. Bianchi and Paradisi (2023) shows that an increase in the number of older workers induces younger workers to move toward firms with higher percentage increases in the

bottom wages (the increase is again a result of complementarity with older workers):

$$\frac{\partial \frac{g_{y,b,n}}{g_{y,b,n'}}}{\partial l_{o,t}^{-1}} = \frac{1}{\sigma} \frac{g_{y,b,n}}{g_{y,b,n'}} \left( \frac{\partial w_{y,b,n}^{g}}{\partial l_{o,t}^{-1}} \frac{1}{w_{y,b,n}^{g}} - \frac{\partial w_{y,b,n'}^{g}}{\partial l_{o,t}^{-1}} \frac{1}{w_{y,b,n'}^{g}} \right).$$

The derivative is positive if $\frac{\partial w_{y,b,n}^{g}}{\partial l_{o,t}^{-1}} \frac{1}{w_{y,b,n}^{g}} > \frac{\partial w_{y,b,n'}^{g}}{\partial l_{o,t}^{-1}} \frac{1}{w_{y,b,n'}^{g}}$. Bianchi and Paradisi (2023) also derives under what conditions a larger supply of older workers in top jobs coincides with younger workers moving toward lower-productivity firms, a fact that finds empirical support.

However, to better understand the consequences of this migration toward lower-productivity firms for the gender pay gap, we need to compare the formula above for younger men and women. The two derivatives $\partial \frac{m_{y,b,n}}{m_{y,b,n'}} / \partial l_{o,t}^{-1}$ and $\partial \frac{f_{y,b,n}}{f_{y,b,n'}} / \partial l_{o,t}^{-1}$ are the same because all their components are the same between younger men and women. Thus, the number of younger workers who migrate across firms is entirely driven by how many younger workers are blocked from accessing top jobs. Given that (i) younger men are always more negatively impacted than younger women, and (ii) there is more congestion within higher-productivity firms, there are more younger men who move from higher-productivity to lower-productivity firms.