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Gender, careers and peers' gender mix

Elena Ashtari Tafti
Mimosa Distefano
Tetyana Surovtseva

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Economic and Social Research Council

Abstract
We use Italian Social Security data to study how the gender composition of a worker's professional network influences their career development. By exploiting variation within firms, occupations, and labor market entry cohorts, we find that young women starting their careers alongside a higher share of female peers experience lower wage growth, fewer promotions and increased transitions into non-employment. In contrast, male workers appear unaffected. The analysis reveals that these gender-specific effects are largely driven by structural differences in the networks of men and women. Networks predominantly composed of women appear to be less effective in the labor market. Women, who experience higher attrition and lower promotion rates, have fewer connections to employment opportunities, and their connections tend to be less valuable. When accounting for these differences, we find that connections among female peers offer a crucial safety net during adverse employment shocks. Our findings highlight the critical role of early-career peers and provide a new perspective on the barriers to career advancement for women

Keywords: gender peer effects, networks, labor market entrants, career progression
JEL codes: J16; J1

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Elena Ashtari Tafti, Ludwig Maximilian University of Munich and IFS. Mimosa Distefano, Centre for Economic Performance at London School of Economics and CReAM. Tetyana Surovtseva New York University Abu Dhabi and CReAM.

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1 Introduction

The personal connections individuals establish with their peers in the workplace can be valuable assets in the labor market. People frequently learn about job opportunities via such network of relationships (Granovetter, 1973; Ioannides & Loury, 2004; Topa, 2011). Moreover, matches between employers and employees often occur through referrals, which provide both parties with valuable information that may not have been accessible otherwise (Dustmann et al., 2016; Essen & Smith, 2023; Glitz, 2017; Pallais & Sands, 2016).

The nature and scope of opportunities that arise from professional and social networks are, however, the result of those who are part of them (Ibarra, 1993). In this paper, we examine how the gender composition of a worker's network influences their career development. We focus on young workers when they enter the labor market, a pivotal stage in their careers (Arellano-Bover, 2022, 2024; von Wachter, 2020), and investigate whether the gender mix of their initial group of peers has an enduring effect on their future employment, wages, earnings, job-to-job transitions, and promotions.

It has long been hypothesized that gender disparities in access to effective professional networks may hinder women's ability to unlock essential resources for career advancement (Ibarra, 1993). Recent economic research has highlighted the significance of gender differences in network access for labor market outcomes (Ductor, Goyal, & Prummer, 2023; Lalanne & Seabright, 2022; Lindenlaub & Prummer, 2020). However, empirical evidence on how the gender mix of a worker's peer network influences their labor market outcomes remains limited.

The gender mix of peers may affect the career of female workers, as connections typically exhibit a degree of group-based homophily, i.e., the tendency of people to connect to others with similar characteristics (McPherson, Smith-Lovin, & Cook, 2001). On the one hand, if the probability of connections and effective communication increases as groups become more homogeneous, female workers exposed to same-gender peers may have better chances of forming effective labor market networks. On the other hand, social connections created with men may be beneficial for female workers. For example, men are generally found to be more likely to pursue promotions or assume leadership positions compared to their female counterparts (Haegele, 2022; Hospido, Laeven, &

Lamo, 2022). Exposure to a higher share of male colleagues may result in more opportunities for women if men have more connections or their contacts lead to better referrals (Essen & Smith, 2023). Whether one or the other effect prevails is primarily an empirical matter.

To investigate whether the gender mix of peers matters for the career of workers, we use the universe of employment records for all private non-agricultural firms provided by the Italian Social Security Institute (INPS). This data allows us to observe the employment trajectories of young male and female workers into ten years after labor market entry. The first ten years of a worker's career is when most job changes and wage growth occur and when lifelong outcomes take shape (Topel & Ward, 1992). We focus on labor market entrants as these are a blank slate regarding work experience. Selection concerns based on prior job or wage histories, which complicate many other empirical studies of the career impacts of workplace characteristics, are not present in our context (von Wachter, 2020).

The main challenge to identification is that women and men are not randomly allocated to jobs. In fact, the differential sorting of women and men across occupations and firms can partly explain the persistence of the gender wage gap (Blau & Kahn, 2017). Therefore, comparing the career outcomes of women in female-dominated jobs to those in male-dominated jobs would largely capture systematic differences in career prospects across professions rather than the effect of interest.

We argue that whereas differences in gender mix across firms and occupations are likely endogenous, variation in gender mix across adjacent cohorts within the same firm-occupation is likely not. Our identifying variation arises from changes in the gender mix of new hires in a firm and occupation that occur within three years. By focusing on variation in gender mix within firm-occupation, we account for the differential sorting of women and men across jobs (Blau & Kahn, 2017). To limit the influence of time-varying confounders that could impact future labor market outcomes of new entrants, our analysis directly controls for firm-level employment, average wages, employment and wage growth. Furthermore, focusing on a narrow time frame limits the impact of changes in firm-specific hiring practices that may correlate with worker outcomes. We only compare workers who joined the same firm and occupation at approximately the same time, so we keep fixed labor market conditions and firm-specific dynamics.

The results show that the initial peers' gender mix significantly affects the labor market progression of young female workers. The effect is particularly evident in female employment trajectories, with women exposed to a higher share of female peers in their first job being more likely to enter non-employment. Conditional on being employed, having more female peers also negatively impacts women's wages and promotions. This translates into substantial earnings losses for women. Specifically, a one-standard-deviation increase in exposure to female peers at entry leads to a 4 percent drop in earnings two to seven years post-entry. We also find evidence of higher job-to-job mobility among women exposed to more female peers in their initial jobs. We do not find any of these effects for young male workers.

To gain insight into the mechanisms behind these findings, we adopt a method similar to Cingano and Rosolia (2012), focusing on workers who experience job displacement due to firm closures. This approach allows us to explore how a worker's initial network affects their chances of reemployment, thereby highlighting the role these initial peers play in facilitating new job opportunities. By examining cases of exogenous unemployment spells, we effectively avoid the selection bias typically associated with endogenous job search. Moreover, as our analysis compares individuals displaced by the same firm at the same time, we can rule out the presence of common latent determinants induced by firm sorting. In this analysis, we also account for differences in network characteristics between men and women by directly controlling for the share of employed connections among the worker's initial peer group (*network size*) and the average wage of these connections (a proxy for *network quality*). This is not possible in our initial analysis because gender composition is measured at labor market entry, a point at which network characteristics have not yet developed.

Using this approach, which allows us to account for differences in network size and quality, we show that a higher share of female initial peers positively affects women's re-employment after job displacement. However, the jobs that women secure via their networks offer lower wages. We take this to suggest that in our baseline result the effect of gender mix masked two opposite forces: 1) the strength of women's networks and 2) the characteristics of women's networks—female networks are smaller and have fewer ties to individuals of higher status (Lalanne & Seabright, 2022; McDonald, 2011). In the job displacement analysis, we can separate these two opposite forces and show that women's ties to other women are strong and can offer an important safety net in moments of need.

Our paper contributes to several areas within the economics literature. Firstly, it expands the literature on gender gaps in the labor market. Economic research has long sought to understand the underlying causes of gender imbalances observed in the labor market (Andrew et al., 2021). Sorting across industries, occupations, and firms (Blau & Kahn, 2017; Card, Cardoso, & Kline, 2016), motherhood (Kleven, Landais, & Søgaard, 2019), and gender norms (Bertrand, 2019; Boelmann, Raute, & Schönberg, 2021; Farre et al., 2023; Kleven et al., 2019) have all been shown to be relevant factors in explaining why women and men still face diverging labor market realities. We propose a new mechanism—the gender composition of initial peers within firms—that may influence labor market gender dynamics. Given the significant gender-based sorting of workers across firms and occupations, this aspect of early-career experiences is particularly important. Our findings provide essential insights into the persistence of gender disparities in the labor market, highlighting the long-term effects of initial peer networks on career outcomes.

Some economic research has been conducted on the impact of gender composition in management on workers and firms. Exposure to female role models is essential for women to see themselves succeeding in a profession (Canaan & Mouganie, 2021; Porter & Serra, 2020). Additionally, having a female manager could improve female workers' outcomes and workplace climate through better mentoring and support (Alan et al., 2023; Athey, Avery, & Zemsky, 2000; Kunze & Miller, 2017), or because managers are better at assessing the productivity of workers of the same gender (Flabbi et al., 2019). To the best of our knowledge, this is the first work to focus on the gender composition of initial peers.[1] The impact of peers operates through fundamentally different mechanisms than those associated with the gender composition of managers, thereby addressing an inherently distinct and novel research question. This sheds new light on the dynamics of gender in the workplace.

[1] Kunze and Miller (2017) is the only study that investigates the effect of the share of female co-workers on women's outcomes. However, their focus is on *contemporaneous* peers, high-skilled women, and promotions. Our study examines *initial* peers—those co-workers who enter the labor market in the same firm and occupation as the focal worker. This distinction is crucial as it allows us to analyze the dynamic effects of the gender composition of initial peers over time. Furthermore, we focus on the average effects of peers' gender on all men and women and analyze these effects across various outcomes, most notably employment and wages. Most importantly, our study provides a comprehensive examination of the underlying mechanisms, which are critical to understanding the main estimates.

The second strand of literature our paper speaks to is the literature on networks and peer effects in the labor market. Previous studies in this field have identified significant positive impacts of social networks on several aspects of employment, such as job-finding (Dustmann et al., 2016; Kramarz & Skans, 2014), re-employment following displacement (Glitz, 2017; Saygin, Weber, & Weynandt, 2021), wages, and, to some extent, productivity (Amodio & Martinez-Carrasco, 2023; Jarosch, Oberfield, & Rossi-Hansberg, 2021). Notably, recent studies have highlighted gender differences in network effects. Lindenlaub and Prummer (2020) suggests that network structures may vary by gender, leading to labor market implications. Ductor, Goyal, and Prummer (2023) shows that gender differences in network structure can account for a considerable output gap between male and female economists. In this paper, we focus on the gender composition of the network of initial peers and analyze their dynamic impact on men and women separately. This emphasis on gender composition of peers adds a unique dimension to our study. Secondly, we estimate the impact of the gender share of the *initial* network on re-employment post-displacement while also accounting for the network size and quality. This comprehensive approach allows us to provide a deeper understanding of how the gender composition of early peer networks shapes the characteristics of male and female professional networks, thereby influencing long-term labor market outcomes for both genders.

Finally, our paper contributes to recent literature on the characteristics of the first job on long-term labor market outcomes. Early studies in this area have focused on specialized workers such as PhD-level economists (Oyer, 2006), MBAs (Oyer, 2008), or CEOs (Schoar & Zuo, 2017). Few studies have focused on a broader category of workers (von Wachter and Bender, 2006, Müller and Neubaeumer, 2018, Arellano-Bover, 2024). To our knowledge, this study is the first to establish a direct link between young female workers' peers and long-term outcomes, tracing how early-career peer heterogeneity can have implications for long-term labor market outcomes.

The paper is organized as follows. Section 2 describes the data and sample, section 3 introduces the empirical strategy, section 4 presents our main results, section 5 discusses potential mechanisms, and section 6 concludes.

2 Data and Descriptive Statistics

2.1 Italian Social Security Data

We use data provided by the Italian Social Security Institute (INPS, *Istituto Nazionale di Previdenza Sociale*), which comprises all men and women employed in the non-agricultural private sector and covered by the Italian social security system, with self-employed workers, military personnel, and civil servants excluded.[2]

This is a linked employer-employee dataset. On the worker side, we observe essential demographic characteristics and a complete employment biography. For each job spell, we know the employer's identity, wage, type of contract (including permanent or fixed term and part- or full-time), broad occupational category (blue-collar, white-collar, managers and apprentices), and start and end job date. On the employer side, we have information on industrial classification[3], location, firm date of opening, and, if applicable, closing. We also aggregate the workers' data to create additional relevant firm-level characteristics, including firm size, average wages, and firm employment and wage growth.

We apply restrictions at the worker and firm level. First, we focus on Italian nationals who entered their first full-time employment between 2000 and 2011, aged 16 to 30. This is done to minimize the likelihood of prior labor market experience outside Italy, which we cannot observe, and sample attrition due to return migration. Second, we focus on firms with at least four workers and exclude firms that are fully segregated by gender.[4] We also examine only hiring cohorts where at least two workers are hired within the same occupation. These restrictions ensure that we have enough variation in the gender mix and that all relevant controls can be calculated for the year of observation.

[2]This data was provided as part of the 'VisitINPS scholars' program.

[3]This a 7-digit industry classification.

[4]Note that this does not necessarily mean that each hiring cohort cannot consist of individuals of a single gender. Our focus is on firms that, in the year before the focal worker joined, had at least one female and one male employee.

2.2 Labor Market Entrants

Our sample includes 1,816,582 individuals entering the labor market between 2000 and 2011, of which 42 percent are female. Table I summarizes the characteristics of these workers in their first year of full-time employment. The female workers in our sample (columns 1 and 2) start working about one year later than their male counterparts (columns 3 and 4), at an average age of 23 years. Approximately 37 percent of female workers enter their first full-time employment as blue-collar workers, 46 percent start as white-collar workers, and the remainder as apprentices. For male entrants, the distribution is 53 percent for blue-collar jobs, 27 percent for white-collar jobs, and 20 percent for apprentice positions. Despite the higher representation of male entrants in lower-skilled jobs, they appear to be more likely to hold open-ended contracts, and their average wages are 6 percent higher than those of female entrants. This is partly due to female entrants working in smaller firms and firms that pay lower wages, as shown in Figure I.

Differences between female and male labor market entrants persist and grow over time. From the second year after entering the labor market, earnings for male and female workers start to diverge, as depicted in panel (c) of Figure II. This earning gap can primarily be attributed to gender-based employment disparities, as women become increasingly more likely to become non-employed over time, as indicated in panel (a) of Figure II. Wage differences, on the other hand, remain relatively stable, increasing from 6 to 10 percent in the first ten years since labor market entry (see panel (b) of Figure II for details). Firm characteristics seem to account for a significant portion of the earnings gap observed in the raw data. In Figure III, we compare the differences in female and male earnings in every year post-entry in the labor market. Conditional on initial firm and initial occupation, women appear to have higher earnings than men at least six years after entry when this reverses.

2.3 Peers Gender Mix

For every worker in our sample, we calculate the gender mix of her initial peers. We use the term *peers* to refer to workers hired by the same firm, in the same occupation and calendar year, who entered the labor market within two years of each other. These are co-workers with similar labor market experience, hired together in a firm. The term *initial* is used to identify the peers in the first full-time job of a given worker in our sample. The gender composition of these initial peers, termed Gender Mix (GMX), is determined as follows:

$$\mathrm{GMX}_{ijo\tau} = \frac{\sum_{n \in \mathcal{N}_{ijo\tau}}^{|\mathcal{N}_{ijo\tau}|} \mathbb{1}[Female_n]}{|\mathcal{N}_{ijo\tau}|} \tag{1}$$

$\mathcal{N}_{ijo\tau}$ denotes the set of focal worker i's initial peers and $|\mathcal{N}_{ijo\tau}|$ denotes the number of elements in this set. It is to be noted that $\mathcal{N}_{ijo\tau}$ is different across focal workers, because focal workers themselves are excluded from the set, but $|\mathcal{N}_{ijo\tau}|$ is the same for all i's in initial firm j, occupation o, and year of entry τ. $\mathrm{GMX}_{ijo\tau}$ ranges from 0 to 1 and captures the share of women among initial peers of an individual i.

In Figure IV, we plot the distribution of the gender mix among peers for male and female labor market entrants. There is significant heterogeneity in the gender mix across and within genders. As illustrated in Table I, compared to men, women tend to be employed in firms with a more balanced gender mix. For female entrants, the average share of women among their peers is 56 percent, while for male entrants, it is approximately 30 percent. This pattern remains consistent when considering the overall gender mix within the firm (i.e., the share of women among all employees) and the share of women among more senior peers within the same occupation (i.e., 2 to 5 years of tenure within the firm). The share of women among managers also tends to be marginally higher in firms where female workers start their careers, although this difference is not statistically significant.

Figure V shows the correlation between workers' employment probability and initial peers' gender mix. There appears to be a negative correlation between gender mix and the employment status of female labor market entrants 2, 5, 7, and 10 years after entering the labor market. The situation is notably different for male entrants. For men, there appears to be no discernible relationship between the gender composition of their peers and their future employment status, except in cases where the share of women among peers exceeds 80 percent, as depicted in panel b of Figure V. The relationship depicted in Figure V captures variations in the gender composition of peers, both within and between firms. Hence, while it provides a valuable representation of the core relationship we are interested in, it does not fully represent the causal impact of the gender mix of peers on the employment of labor market entrants, which we identify exploiting variation in the gender mix of initial peers across three years within firm-occupation cell. The identification strategy is described in detail in the next section.

3 Empirical Approach

We start the analysis by providing evidence that the gender mix of initial peers matters for the career progression of young workers. Our empirical model is the following:

$$y_{ijo\tau}^{\tau+t} = \beta \mathrm{GMX}_{ijo\tau} + X_{ij\tau}\gamma + \eta_{jo\tilde{\tau}} + u_{ijo\tau}^{\tau+t} \tag{2}$$

$$u_{ijo\tau}^{\tau+t} = \epsilon_{ijo\tau}^{\tau+t} + e_{jo\tau}^{\tau+t} \tag{3}$$

The dependent variable $y_{ijo\tau}^{\tau+t}$ represents the labor market outcome of individual i joining firm j and occupation o in year τ. Outcomes are measured t years after the entry year τ, where $t \in \{2, 5, 7, 10\}$. We are mostly interested in employment outcomes, which are a key contributor to gender inequality, but conditional on employment, we also look at full-time employment, wages, and promotions. The focus of our analysis is on $\mathrm{GMX}_{ijo\tau}$ representing the gender mix of initial peers of worker i who joined firm j and occupation o in year τ, as defined in Equation 1. $X_{ij\tau}$ comprises a set of individual and firm characteristics. For individual factors, we control for age at entry and initial wage. On the firm side, we account for lagged firm size, average wages, and wage and employment growth over the previous year. The term $\eta_{jo\tilde{\tau}}$ represents firm-occupation-cohort fixed effects. We define four broad labor market entry cohorts, $\tilde{\tau}$, 2000-2002, 2003-2005, 2006-2008, and 2009-2011, which group individuals joining the labor market at similar times. Lastly, $u_{ijo\tau}^{\tau+t}$ is the residual component which can be decomposed into $\epsilon_{ijo\tau}^{\tau+t}$ and $e_{jo\tau}^{\tau+t}$, respectively all individual i and firm j specific factors that contribute to the outcome of the individual i, which are not observed and captured by the model.

3.1 Identification

The coefficient of interest in Equation 2 is denoted by β, which, if identified, captures the impact of the initial peers' gender mix on the career trajectory of labor market entrants. Identifying β in Equation 2 is challenging, as gender mix may correlate to individual and firm unobservable characteristics. We exploit variation in gender mix within narrow groups of workers to address this identification problem. Central to our strategy is the term $\eta_{jo\tilde{\tau}}$, i.e., the firm-occupation-cohort fixed effect. We assume that conditional on $\eta_{jo\tilde{\tau}}$ and $X_{ij\tau}$, there is no correlation between the gender mix an individual is exposed to in her first full-time job and any unobserved worker and firm characteristics likely to impact her labor market outcomes in the future. We discuss below why this assumption is satisfied in our context and the threats to identification it addresses. We present our argument separately for the worker's and the firm's unobserved characteristics, which may bias our results.

3.1.1 Worker Side

Worker sorting across industries, firms, and occupations is well known to explain an essential part of the gender pay gap (Card, Cardoso, & Kline, 2016; Sloane, Hurst, & Black, 2021). For example, if women tend to gravitate towards more flexible but lower-paying jobs, this would naturally lead to a negative correlation between their earnings and the gender mix of their initial peers. To account for this, our identification strategy relies exclusively on within firm and occupation variation in initial peers' gender mix. Effectively, we necessitate two things to estimate a causal effect in this scenario. First, we need variation over time in the gender mix of young workers joining a given firm and occupation. If firms hired women and men in the same proportion yearly, we could not estimate any effect, as this would dry out our source of identifying variation. Second, we require the decision of a worker to join a firm and occupation at a given time not to depend on the gender mix of her initial peers. In practice, this means that conditional on the occupation and firm, there is no strategic choice around the time of entry in the labor market based on peers' gender mix. As our focal workers are new labor market entrants, they have no visibility of the other workers who are hired at the same time, we find it unlikely that such strategic behavior is actually in place here.

It is not realistic, however, to assume any absence of correlation between unobserved worker's characteristics, $\epsilon_{ijo\tau}^{\tau+t}$, and the gender mix of entrants in a profession over a long period. Our data includes young workers entering the Italian labor market from 2000 to 2011. Over these ten years, men and women educational attainment has changed substantially. In particular, the share of women in Italy with tertiary education grew from 12 percent in the early 2000s to 25 percent in 2011. Simultaneously, the share of women working increased from 39 to 46 percent.[5] As we have no information on workers' education in our sample, we cannot directly control for these differences. To make sure, however, to compare only the outcomes of workers with similar characteristics (including educational attainment), we categorize the individuals in our sample into four broad labor market entry cohorts and only rely on within-firm, occupation, and cohort variation in the gender mix of initial peers to estimate our effect of interest. Further, we directly control for age at the time of entry (a proxy for educational level) and initial wage (a proxy of ability). On the worker side, therefore, the identifying assumption required for estimating a causal effect is:

$$Corr(\epsilon_{ijo\tau}^{\tau+t}, GMX_{ijo\tau}|X_{ij\tau}, \eta_{jo\tilde{\tau}}) = 0 \tag{4}$$

In Equation 4, $\epsilon_{ijo\tau}^{\tau+t}$ represents all individual specific factors that we do not observe but that can influence the career progression of worker i which entered the labor market in year τ, firm j, occupation o. $GMX_{ijo\tau}$ is the gender mix of i's initial peers in firm j and occupation o. The assumption states that conditional on $\eta_{jo\tilde{\tau}}$—the firm, occupation, and broad cohort—and $X_{ij\tau}$—the set of individual and time-varying firm characteristics we control for—there is no correlation between unobserved individual factor affecting the career of i and the gender mix of her initial peers.

3.1.2 Firm Side

The longitudinal character of our data allows us to control, through fixed effects, for firm unobserved attributes that may correlate with their propensity to hire female workers and the outcomes of their employees. In fact, our results may be biased if, for example, firms that hire more women (e.g.,

[5]Source: EUROSTAT Education and Employment Statistics. Respectively, 'Tertiary educational attainment by sex' and 'Employment rates by sex, age, and citizenship'

female-friendly firms) are also more likely to promote them. If these factors are fixed for our sample period, we should be free of such biases. The hiring of women, however, may also correlate to the state of the business cycle (Stephens, 2002), which can have persistent impacts on the careers of young workers (von Wachter, 2020). Firm and cohort of entry fixed effects can effectively capture this correlation. By restricting the identifying variation to changes in gender mix that occur within three years, we focus our comparison on workers who entered the labor market under similar economic conditions. The same argument applies to any other time-varying firm-level factor that can be realistically assumed to change at a pace that can be ignored for this short time interval (Mundlak, 1978). To further strengthen the validity of our approach, we include in $X_{ij\tau}$ lagged firm size, average wages, and firm wage and employment growth. On the firm side, therefore, the identifying assumption required for estimating a causal effect is:

$$Corr(e^{\tau+t}_{jo\tau}, GMX_{ijo\tau}|X_{ij\tau}, \eta_{jo\tilde{\tau}}) = 0 \tag{5}$$

In Equation 5, $e^{\tau+t}_{jo\tau}$ represents all firm-specific factors that we do not observe, but that can influence the career progression of worker i which entered the labor market in year τ, firm j, occupation o. $GMX_{ijo\tau}$ is the gender mix of i's initial peers in firm j and occupation o. The assumption states then that conditional on $\eta^{\tau+t}_{jo\tilde{\tau}}$—the firm, occupation, and broad cohort—and $X_{ij\tau}$—the set of individual and time-varying firm characteristics—there is no correlation between unobserved factors affecting the career of i and the gender mix of her initial peers in the firm. Assumption 5 may be violated if some unobserved firm characteristics, not fixed within a cohort and not included in $X_{ij\tau}$, jointly affect the outcome of workers and the gender mix of new hires in a given year, for example, the firm's management style. To test whether this is the case, we look at the correlation between peers' gender mix over time. In Figure VI Panel (a), we plot the share of women among new hires in a firm in year t versus $t-1$. This closely follows a 45-degree line, indicating persistence in the gender mix. This suggests that firms hiring more women in one year tend to do the same in the next, signifying persistence in firms' gender composition. In Panel (b), we show the residual variation of this variable after accounting for firm-specific effects. Here, the data points align horizontally around zero, indicating no systematic correlation between the proportion of women among new hires in year t and $t-1$. Once we control for the fact that some firms have a higher propensity to hire women, year-to-year changes in gender composition of new hires appear to be as good as random. We take this as evidence that once we control for the firm the worker is employed by, there are no time-varying characteristics that make firms more likely to hire female workers in a given year.

4 Gender Mix and Career Outcomes

4.1 Employment

We begin our analysis by examining the impact of an individual initial peers' gender mix on her future employment status. The results are presented in Table II, where Panel A and B display the estimates for women and men, respectively. In columns 1 through 4, the dependent variable is employment 2, 5, 7, and 10 years after an individual's first full-time job. The dependent variable in columns 5 to 8 is full-time employment 2, 5, 7, and 10 years after entry, conditional on employment. In all specifications, we control for worker age, initial wage, year of entry, lagged firm size and average wage, as well as firm wage and employment growth between $\tau-1$ and τ.

The initial peers' gender mix has a negative and statistically significant effect on future female employment. Increasing the proportion of women among a female entrant's initial peers by 22 percentage points (1 standard deviation among female entrants, see Table I) reduces her probability of remaining in employment two years later by nearly 0.29 percentage points. In the 5th year since labor market entry, this effect is 0.40 percentage points; by seven years after, it is estimated to be 0.31 percentage points. We find no effect on the probability of employment ten years in the future. The magnitude of the estimated effects relative to the labor market attrition rate of women two years after entry is 4 percent, it is 4.6 percent at the 5-year mark, and 3.3 percent at the 7-year point.[6] These findings sharply contrast with those for male entrants, whose estimates are close to zero and are not statistically significant throughout. While women commencing their careers in the

[6] These magnitudes are calculated as follows $\frac{\hat{\beta}}{(1-\bar{y}^t)} \times 100$, where $\hat{\beta}$ is the estimated effect of GMX on employment, and $\bar{y}^t$ is the share of women employed t years post entry.

same workplace as other women experience a significant reduction in their employment prospects later on, the same pattern does not hold for men. These results are robust to alternative model specifications, which we present and discuss in detail in the Appendix.

We also find that the probability of having a full-time job decreases as the share of female initial peers increases. However, the estimates are only statistically significant two years after entry into the labor market.

4.2 Wages and Earnings

Our second labor market outcome of interest is individual wage growth with respect to the initial wage. That is, conditional on remaining employed, we analyse how the initial peers' gender mix affects an individual's wage growth 2, 5, 7 and 10 years after the entry. The estimated effects are presented in columns 1 to 4 of Table III. The initial peers' gender mix has a consistently negative and persistent effect on wage growth for young female workers. One-standard-deviation increase in the share of women among initial peers reduces wage growth by 0.5 percent two years after entry and by approximately 0.2-0.3 percent at 5, 7, and 10 years after entry among female workers. The coefficient is, however, not statistically significant at the 7-year mark. We find no effect for male workers. The estimated impact consistently hovers around zero and is not statistically significant.

In columns 5 to 8 of Table III, the wage and employment effects are combined and summarized as earnings effects. The outcome variable is log annual labor earnings, which are set to zero for non-employed individuals. An increase in the share of women among entrants' peers by one standard deviation (22 percentage points) results in a 3.4 percent reduction in earnings two years after entry for female entrants. The most significant impact is seen at the 5-year mark, with a 4.1 percent reduction in earnings for women. This effect decreases to 3.3 percent after 7 years and becomes essentially zero after 10 years, although it is not statistically significant. To put these estimates in perspective, the gender-based earnings gap after two years in the labor market is 4 percent, 41 percent 5 years in, and 68 percent after 7 years. This means that the effects of a one-standard-deviation increase in GMX relative to the gender earnings gap are 100 percent, 10 percent, and 5 percent at the 2-year, 5-year, and 7-year marks, respectively. For men, the effects are never statistically different from zero.

4.3 Job Transitions and Promotions

Lastly, we analyze how, conditional on employment, having more women among initial peers affects individual job-to-job transitions, the quality of such transitions, and promotions.

In Table IV, columns 1 to 4 report our estimates for job-to-job transitions, while columns 5 to 8 look at whether these transitions deliver a higher wage. We find that female labor market entrants exposed to a higher share of female initial peers are more likely to change jobs, conditional on employment, but there are no discernible effects on wages in the new firm.

Table V shows the estimated effects on promotions. Results for female entrants are reported in Panel A, and male entrants are in panel B. In columns 1 to 4, we present the findings regarding promotions to managerial positions. For female entrants, there is a significant adverse effect on promotions five years after entry. This effect is approximately 40 percent of the baseline probability of promotion into a managerial role. We find no such effect on male entrants. In columns 5 to 8, we present the findings concerning occupational upgrading, such as transitions from apprenticeship to blue- or white-collar roles, blue-collar to white-collar positions, or any of the aforementioned to managerial occupations. We find a significant negative impact of gender mix on women seven years after entry. The estimated effect size relative to the proportion of women promoted at the seven-year mark is substantial, at 4 percent. Once again, we find no such effect on male entrants.

5 Gender Mix and Job Opportunities

Our findings suggest that a higher share of female initial peers negatively affects the career progression of young female workers, but has no impact on male workers. Various mechanisms could explain this negative effect.

A worker exposed to more women in their network may have access to less information about jobs and job openings. As Figure II.a and Table II show, women tend to enter non-employment at higher rates than men, potentially reducing the overall information about employment opportunities available within the network.[7] Given the higher labor market attrition rates among women, individuals whose initial network is predominantly composed of women are likely to have a network of smaller size and less information about job openings. We refer to this channel as the *network size*: the larger the network—the share of employed workers—the higher the probability of finding a new job.

A worker exposed to more women in their network may also have less information about high-quality jobs and less leverage to be considered for one. As depicted in Figures I and II.b and supported by the data in Table V, women are often employed in lower-paid jobs and less likely than men to hold managerial roles. We refer to this channel as *network quality*: the better the quality of the network, the higher the wage (quality) of the new job conditional on re-employment. As networks with a higher proportion of women might not provide the same level of access to high-paid jobs as those with more men, workers with a higher share of women among initial peers tend to have a network of worse quality.

Both the network size and quality mechanisms result from fundamental structural differences in the careers of male and female workers. If there were no gender disparities in employment or advancement opportunities at any career stage, the size of the network and the quality of its connections would not depend on the gender composition of the initial peer group. Nevertheless, gender composition may still matter if workers exhibit gender-based *homophily* (McPherson, Smith-Lovin, & Cook, 2001). If within-gender connections were more effective at conveying information about job opportunities and support within the network, then we might expect the gender composition of initial peers to influence outcomes even in the absence of the aforementioned size and quality mechanisms.

Our baseline specification does not allow us to distinguish between the effects of network size and quality—both evolving as careers progress—and the potential effect of forming same-gender

[7] For simplicity, we assume all initial peers are part of the labor market entrant's network. In practice, workers might form relationships only with a subset of these peers. The extent of overlap between a worker's initial peers and their network largely depends on the firm size and the entry cohort size. We note that this assumption is made for simplicity of exposition and is not required to validate our results.

connections at labor market entry. In our baseline specification, we measure the gender composition of a worker's peers at entry. We find that networks with a higher share of women evolve to have fewer employed connections and of lower quality; however, we cannot identify the network size and quality at the time of labor market entry, as those are not yet formed.

In this section, we adopt a complementary strategy that enables us to control for network size and quality. This approach, inspired by Cingano and Rosolia (2012), mitigates potential selection bias that arises from endogenous job transitions and estimates network effects by comparing individuals displaced from the same firm when they simultaneously begin their job search. Assuming that workers are sorted with the same criteria over time, former and current colleagues will likely share the same unobserved traits. Comparisons within the same closing firm thus control for differences across networks that correlate with employment outcomes. Here we estimate the effect of the gender composition of initial peers at the time of entry, while directly controlling for the share of employed connections (network size) and the average wage of employed peers (a proxy for the network quality). Thus, we provide evidence on whether female networks are more or less conducive to job opportunities, above and beyond the network characteristics. Furthermore, we estimate the same effect on wages conditional on employment to examine the direct impact on the quality of jobs after re-employment.

For our sample of workers displaced by a firm closure, we estimate the following empirical model, separately for men and women:

$$y_{ig} = \lambda GMX_{i(jo\tau)} + \mu EMP_{i(jo\tau)} + \gamma \log(\overline{W}_{i(jo\tau)}) + \theta \log(|\mathcal{N}_{i(jo\tau)}|) + Z'_{ig}\zeta + \phi_g + \psi_t + \nu_{o'} + \upsilon_{ig} \quad (6)$$

Our main regressor remains $GMX_{i(jo\tau)}$, which represents the gender mix of the initial peers, as defined in Section 3. $EMP_{i(jo\tau)}$ measures the share of worker i's initial peers who are employed (network size) at the time i is displaced by the firm closure. $\overline{W}_{i(jo\tau)}$ is the average weekly wage of i's initial peers (network quality) in the year of firm closure. Average wages are set to zero if none of the initial peers is employed in the year of firm closure. $(|\mathcal{N}_{i(jo\tau)}|)$ is the number of peers in the initial network. $\nu_{o'}$, ψ_t, and ϕ_g, represent respectively occupation, year of closure, and closing firm fixed effects. Lastly, Z_{ig} includes individual controls: wage level at firm closure, age, labor market experience, and initial wage.

Approximately 14 percent of our initial sample of workers experienced a firm closure between the second and ninth year post-entry. The incidence of firm closures is not significantly different between genders. In total, 59,093 women and 83,872 men affected by a firm closure had at least one coworker from a different initial firm, allowing us to estimate an effect. Table VI presents the descriptive statistics for this subsample. On average, both male and female entrants were impacted by closures around their fifth year in the labor market. Nearly 30 percent of their initial peers were also affected by the same event, yet 70 percent of the initial peer network remained employed in the year of the closure. The year after job displacement, 75 percent of women and 80 percent of men secured employment. Those affected by closures differed from our primary sample in several respects: individuals in the closure sample were older at labor market entry and more likely to be white-collar workers, with fewer blue-collar workers among both genders. Additionally, wages and the prevalence of open-ended contracts were higher in this group. Lastly, the proportion of female peers was smaller for female entrants but larger for male entrants.

5.1 Job-finding Probabilities and Wages

Table VII presents the estimated effect of the gender mix of initial peers on post-closure re-employment (in columns 1 and 2) and wages (in columns 3 and 4) where we control for the peers' employment rate $EMP_{i(jo\tau)}$ (network size) and the peers' average wages $\overline{W}_{i(jo\tau)}$ (network quality) at the time of firm closure.

Having a higher share of employed initial peers (network size) positively affects the re-employment of both men and women in the year following the closure. The estimated coefficient in column 1 indicates an increase of about 1.2 percentage points in re-employment probability for women and 0.9 percentage points for men per one standard deviation increase in the share of employmed workers among initial peers. We find no impact of network size on wages conditional on re-employment (columns 3 and 4).

The effect of average wages within the initial network on re-employment is negative. A one-standard-deviation wage increase within the network reduces the probability of re-employment by one percentage point for women and 0.6 percentage points for men. This negative effect could be attributed to high-wage peers having access to fewer job openings due to increased competition following the firm closure (Chiplunkar, Kelley, & Lane, 2024), or it may reflect the workers' higher wage expectations that make it more difficult for them to find suitable employment quickly.[8] Conditional on employment, average network quality positively affects men's wages (as shown in Panel B of columns 3 and 4). There is no impact on women's wages.[9]

Controlling for network size and quality results in a distinctive positive effect associated with the gender mix of initial peers (GMX) on the re-employment post-closure for female workers. A one-standard-deviation increase in the share of women among initial peers (22 percentage points) raises the probability of re-employment by approximately 0.7 percentage points. This suggests network homophily for women. Homophily can result in strong ties between network members. Strong ties are based on deep trust, knowledge, and more significant emotional investment with people of similar backgrounds or life experiences (Krackhardt, Nohria, & Eccles, 2003). Strong ties are more important for individuals of minorities or in disadvantaged positions, as they can mitigate the effects of interpersonal dissimilarity and the attribution biases prevalent in superficial relationships (Ibarra, 1997). However, employment secured through these connections tends to be of lower quality, as evidenced by the negative estimates of GMX on female wages in columns 3 and 4 of Table VII. This appears to suggest that although female peers assist their female colleagues in looking for a job, the quality of this employment is lower.

The gender composition of initial peers has no discernible impact on re-employment probability or wages for men. This finding is consistent with our primary analysis, which indicates that the gender mix of peers does not affect the career trajectories of male labor market entrants. The absence

[8] Specifically, higher wages among a displaced worker's initial peers can put upward pressure on focal workers' reservation wage levels. This mechanism aligns with Caldwell and Harmon (2019) which shows that a worker's network can impact wage negotiations and job mobility by affecting their outside options.

[9] The positive effect of average wages for men may indicate a reservation wage mechanism. A high wage level within the network may create high wage expectations among workers, who would only accept a job offer if that expectation is met. Women may be less likely recipients of such job offers, and for this reason, we do not observe an effect on their wages.

of an effect for men may suggest that men exhibit less homophily,[10] or it might indicate that they are more incline to form connections outside their initial peer group upon which our analysis focuses, thus relying less on initial connections. Economic literature suggests that male and female networks might differ in aspects such as connectedness and density. For example, Lindenlaub and Prummer (2020) and Ductor, Goyal, and Prummer (2023) show that male networks generally have more connections, whereas female networks tend to be denser, with higher levels of clustering. These findings imply that in the presence of homophily and a peer group with a high share of female peers, male labor market entrants would form connections outside this group, leading to a negligible impact of the gender composition of peers on their career outcomes.

6 Conclusion

This paper investigates the impact of the gender composition of peers at the time of labor market entry on the long-term career outcomes of workers in Italy, focusing on differences between men and women. Our results show that women with a higher share of female peers are more likely to enter non-employment, have lower wage growth, and receive fewer promotions. By contrast, the gender composition of initial peers has no significant impact on male labor market outcomes.

We suggest that a potential mechanism behind this negative effect is the nature of networks composed predominantly of women. Specifically, the gender composition of a worker's initial peers may affect their network's size and quality. A network with a higher proportion of female peers offers fewer connections to job opportunities (network size effect), as women tend to enter non-employment at higher rates than men. Moreover, a network with a higher proportion of female peers is associated with lower job quality conditional on employment (network quality effect), as women are often employed in lower-paid jobs and less likely than men to hold managerial roles.

Exploiting firm closures as an exogenous employment shock, we separately assess the contributions of network size and quality from the strength of women's networks. Our findings indicate that, once network characteristics are accounted for, connections to a higher share of women among

[10] The degree of homophily across genders remains a topic of debate (see Mengel (2020)).

initial peers lead to higher employment among displaced women. Thus, when network structure is accounted for, we find that connections to other women positively impact women's employment. However, the impact of these female connections on wages, conditional on re-employment, is negative, indicating lower job quality of these connections. We interpret this as evidence of homophily among female peers.

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Tables

Table I: DESCRIPTIVE STATISTICS OF ITALIAN LABOR MARKET ENTRANTS

Sample	Female Entrants		Male entrants	
Summary statistic	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)
Age	22.79	[3.67]	21.87	[3.72]
Blue-collar (%)	36.76	[48.21]	53.26	[49.89]
White-collar (%)	45.72	[49.82]	26.86	[44.32]
Apprentices (%)	17.73	[38.19]	20.06	[40.05]
Log weekly wage	5.62	[0.58]	5.68	[0.52]
Indefinite contract (%)	38.23	[48.60]	39.47	[48.88]
Gender mix peers (GMX)	56.18	[21.65]	30.52	[23.97]
Gender mix 2-3 tenure	58.09	[30.48]	33.00	[28.97]
Gender mix 4-5 tenure	44.18	[37.83]	26.09	[31.42]
Overall GMX	53.93	[20.55]	31.64	[18.81]
Managers GMX	9.94	[15.58]	8.83	[13.88]
Log size of the initial peer group	3.77	[2.44]	3.83	[2.68]
Log firm size in τ-1	5.44	[2.56]	5.61	[2.69]
Log average wage in a firm in τ-1	5.89	[0.44]	5.95	[0.40]
Number of observations	785,394		1,031,188	

Notes: Standard deviations in brackets. Source INPS data. The sample includes Italian nationals who entered their first full-time employment between 2000 and 2011, aged 16 to 30, employed in non-agricultural private sector firms. We exclude those employed in firms with less than five workers and employing workers of only one gender. Gender mix among peers is a share of women among workers within the same firm, occupation, and with the same firm tenure. Gender mix among other levels of firm hierarchy refers to the share of women among workers at that specific level.

Table II: DYNAMIC IMPACT OF INITIAL PEERS' GENDER MIX ON EMPLOYMENT

Dep. var.	Employment indicator				Full-time employment indicator			
Time since entry	$\tau + 2$	$\tau + 5$	$\tau + 7$	$\tau + 10$	$\tau + 2$	$\tau + 5$	$\tau + 7$	$\tau + 10$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Females								
GMX	-0.0127**	-0.0180***	-0.0140**	0.0006	-0.0122**	-0.0054	-0.0059	-0.0030
	(0.0060)	(0.0061)	(0.0062)	(0.0063)	(0.0055)	(0.0069)	(0.0076)	(0.0086)
Observations	785,394	785,394	785,394	785,394	508,091	451,217	423,075	383,088
Mean Dep. Var.	0.68	0.61	0.58	0.53	0.57	0.47	0.42	0.36
Panel B: Males								
GMX	0.0064	0.0054	0.0026	0.0045	0.0013	0.0001	-0.0074	-0.0104**
	(0.0058)	(0.0058)	(0.0058)	(0.0059)	(0.0040)	(0.0048)	(0.0050)	(0.0052)
Observations	1,031,188	1,031,188	1,031,188	1,031,188	666,867	628,643	620,148	604,225
Mean Dep. Var.	0.68	0.65	0.64	0.63	0.63	0.58	0.57	0.55
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: GMX is a share of women among the entrant's peers. Controls include individual and time-varying firm controls. Individual controls are worker age at entry and initial full-time wage. Firm controls include lagged firm size, average wage, and wage and employment growth between $\tau - 1$ and τ. Fixed effects include firm-occupation-(broad) entry cohort fixed effects and yea ofentry fixed effects. Standard errors clustered on firm-level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table III: DYNAMIC IMPACT OF INITIAL PEERS' GENDER MIX ON WAGES AND EARNINGS

Dep. var.	Log weekly wage growth (WRT initial)				Log annual labor earnings			
Time since entry	$\tau+2$	$\tau+5$	$\tau+7$	$\tau+10$	$\tau+2$	$\tau+5$	$\tau+7$	$\tau+10$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Females								
GMX	-0.0211***	-0.0112*	-0.0098	-0.0131*	-0.1530***	-0.1860***	-0.1490**	-0.0072
	(0.0057)	(0.0062)	(0.0067)	(0.0069)	(0.0551)	(0.0577)	(0.0593)	(0.0603)
Observations	508,091	451,217	423,075	383,088	785,390	785,394	785,394	785,394
Mean Dep. Var.	0.14	0.27	0.33	0.39	6.22	5.76	5.50	5.10
Panel B: Males								
GMX	-0.0038	0.0010	-0.0003	0.0082	0.0553	0.0504	0.0291	0.0512
	(0.0052)	(0.0056)	(0.0058)	(0.0063)	(0.0521)	(0.0552)	(0.0556)	(0.0572)
Observations	666,867	628,643	620,148	604,225	1,031,187	1,031,188	1,031,188	1,031,188
Mean Dep. Var.	0.14	0.30	0.37	0.46	6.26	6.17	6.18	6.13
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: GMX is a share of women among the entrant's peers. Controls include individual and time-varying firm controls. Individual controls are worker age at entry and initial full-time wage. Firm controls include lagged firm size, average wage, and wage and employment growth between $\tau-1$ and τ. Fixed effects include firm-occupation-(broad) entry cohort fixed effects and year of entry fixed effects. Labor earnings are unconditional on employment and set to zero for non-employed individuals. Standard errors clustered on firm-level in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table IV: DYNAMIC IMPACT OF INITIAL PEERS' GENDER MIX ON JOB MOBILITY

Dep. var.	Moved into different firm				Wage change in the new firm			
Time since entry	$\tau+2$	$\tau+5$	$\tau+7$	$\tau+10$	$\tau+2$	$\tau+5$	$\tau+7$	$\tau+10$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Females								
GMX	0.0205**	0.0181**	0.0216***	0.0135*	-0.0076*	0.0007	-0.0010	-0.0051
	(0.0086)	(0.0077)	(0.0073)	(0.0069)	(0.0044)	(0.0053)	(0.0057)	(0.0061)
Observations	508,091	451,217	423,075	383,088	508,091	451,217	423,075	383,088
Mean Dep.Var.	0.53	0.75	0.81	0.85	0.05	0.12	0.16	0.19
Panel B: Males								
GMX	0.0041	-0.0014	0.0000	-0.0021	0.0007	0.0030	0.0000	0.0046
	(0.0085)	(0.0071)	(0.0071)	(0.0058)	(0.0040)	(0.0047)	(0.0049)	(0.0052)
Observations	666,867	628,643	620,148	604,225	666,867	628,643	620,148	604,225
Mean Dep.Var.	0.53	0.73	0.78	0.83	0.06	0.13	0.17	0.21
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: GMX is a share of women among the entrant's peers. Controls include individual and time-varying firm controls. Individual controls are worker age at entry and initial full-time wage. Firm controls include lagged firm size, average wage, and wage and employment growth between $\tau-1$ and τ. Fixed effects include firm-occupation-(broad) entry cohort fixed effects and year of entry fixed effects. In columns 1 to 4, the outcome variable is an indicator that an individual changed firm from the initial one. In columns 5 to 8, the outcome variable is the average wage differential in the new firm versus the initial one. Both outcomes in this table are conditional on employment. Standard errors are clustered on firm level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table V: DYNAMIC IMPACT OF INITIAL PEERS' GENDER MIX ON PROMOTIONS

Dep. Var.	Promotion to Manager				Promotion (WRT initial)			
Time since entry	$\tau+2$	$\tau+5$	$\tau+7$	$\tau+10$	$\tau+2$	$\tau+5$	$\tau+7$	$\tau+10$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Females								
GMX	-0.0005	-0.0039**	-0.0040	0.0003	-0.0043	-0.0059	-0.0124**	0.0009
	(0.0006)	(0.0017)	(0.0025)	(0.0036)	(0.0048)	(0.0060)	(0.0062)	(0.0066)
Observations	508,091	451,217	423,075	383,088	508,091	451,217	423,075	383,088
Mean Dep.Var.	0.00	0.01	0.02	0.04	0.11	0.25	0.31	0.35
Panel B: Males								
GMX	-0.0005	0.0000	-0.0018	0.0026	0.0028	0.0026	0.0031	0.0049
	(0.0008)	(0.0024)	(0.0031)	(0.0040)	(0.0046)	(0.0056)	(0.0059)	(0.0063)
Observations	666,867	628,643	620,148	604,225	666,867	628,643	620,148	604,225
Mean Dep.Var.	0.00	0.02	0.04	0.06	0.11	0.26	0.32	0.38
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: GMX is a share of women among the entrant's peers. Controls include individual and time-varying firm controls. Individual controls are worker age at entry and initial full-time wage. Firm controls include lagged firm size, average wage, and wage and employment growth between $\tau-1$ and τ. Fixed effects include firm-occupation-(broad) entry cohort fixed effects and year of entry fixed effects. In columns 1 to 4, the dependent variable is an indicator that takes on value one if an individual changed from his or her initial occupation into a managerial one. In columns 5 to 8, the dependent variable is an indicator that takes on value one if an individual changed from his or her initial occupation into a higher occupational category than the one they started in. Standard errors are clustered on firm-level in parentheses. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table VI: DESCRIPTIVE STATISTICS OF LABOR MARKET ENTRANTS AFFECTED BY FIRM CLOSURES IN THE FIRST 9 YEARS POST-ENTRY

Sample	Female Entrants		Male entrants	
Summary statistic	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)
Age at entry	23.03	[3.65]	22.33	[3.76]
Blue-collar (%)	32.24	[46.74]	50.12	[50.00]
White-collar (%)	49.70	[50.00]	32.09	[46.68]
Apprentices (%)	18.28	[38.65]	18.04	[38.45]
Log weekly wage	5.70	[0.52]	5.74	[0.48]
Indefinite contract (%)	41.71	[49.31]	41.61	[49.29]
Gender mix peers (GMX)	54.49	[21.85]	31.74	[23.73]
Overall GMX	51.65	[20.38]	31.82	[18.31]
Managers GMX	10.74	[15.58]	9.18	[14.07]
Log size of the initial peer group	3.88	[2.52]	3.87	[2.69]
Log firm size in $\tau - 1$	5.60	[2.66]	5.65	[2.68]
Log average wage in a firm in $\tau - 1$	5.95	[0.46]	5.97	[0.42]
Time of firm's closure	4.77	[2.29]	4.87	[2.30]
Share of initial peers affected by closure	29.53	[24.21]	29.39	[24.30]
Employed in the year post closure	75.69	[42.90]	80.97	[39.25]
Peers' employment rate in the year of closure (EMP)	68.96	[25.17]	69.66	[25.55]
Log of peer's average wage in the year of closure (AVGW)	5.33	[1.37]	5.33	[1.38]
Number of observations	59,093		83,872	

Notes: Sample includes a subsample of the main sample of 2000 to 2011 Italian labor market entrants affected by firm closures between 2 and 9 years after labor market entry. Gender mix among peers is a share of women among workers within the same firm, occupation, and with the same firm tenure. EMP and AVGW are the initial peers' employment rate and log average wages in the year of the firm's closure. Standard deviations in brackets.

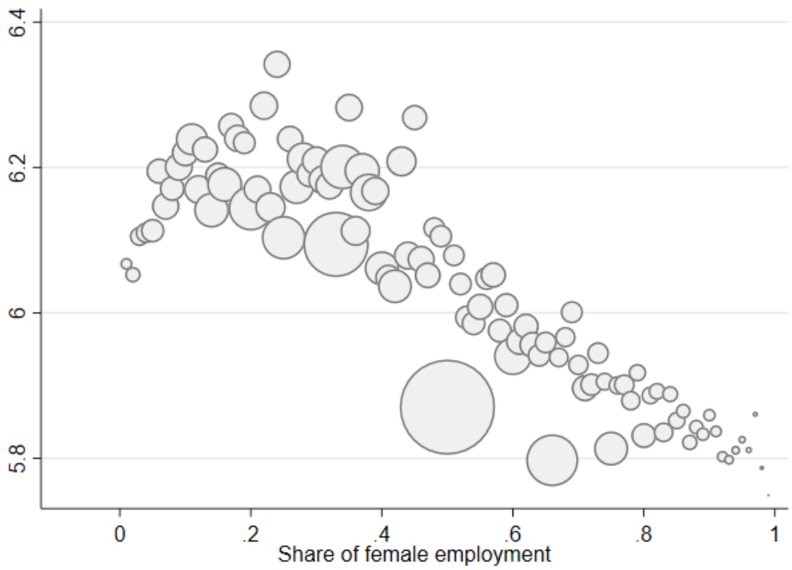
Table VII: EFFECT OF INITIAL NETWORKS ON RE-EMPLOYMENT AND WAGES AFTER FIRM CLOSURE

Dep. var.	Re-employment indicator		Log Weekly Wage	
	(1)	(2)	(3)	(4)
Panel A: Females				
GMX	0.0290***	0.0302***	-0.0286***	-0.0201**
	(0.0097)	(0.0098)	(0.0098)	(0.0100)
EMP	0.0460***	0.0443***	0.0218	0.0099
	(0.0156)	(0.0154)	(0.0191)	(0.0178)
AVGW	-0.0075***	-0.0075***	0.0007	0.0010
	(0.0028)	(0.0028)	(0.0033)	(0.0032)
Observations	59,093	59,093	42,284	42,284
Panel B: Males				
GMX	0.0058	0.0084	-0.0012	0.0055
	(0.0068)	(0.0068)	(0.0068)	(0.0071)
EMP	0.0376***	0.0359***	0.0034	-0.0017
	(0.0132)	(0.0131)	(0.0112)	(0.0111)
AVGW	-0.0047**	-0.0047**	0.0039**	0.0039**
	(0.0021)	(0.0021)	(0.0019)	(0.0019)
Observations	83,872	83,872	64,933	64,933
Controls	Yes	Yes	Yes	Yes
Closure fixed effects	Yes	Yes	Yes	Yes
Entry wage		Yes		Yes

Notes: Sample includes a subsample of the main sample of 2000 to 2011 Italian labor market entrants affected by firm closures between 2 and 9 years after labor market entry. EMP and AVGW are the initial peers' employment rate and log average wages in the year of the firm's closure. GMX is a share of women among the entrant's peers. Controls include log peer group size, age, labor market experience at the moment of closure, and wage level in the year of closure. Closure fixed effects include year of closure fixed effects, and closing firm fixed effects, occupation fixed effects. In columns 1 and 2, the dependent variable is the employment indicator in the year after firm closure. In columns 3 and 4, the dependent variable is the log weekly wage in the year after firm closure conditional on employment. Standard errors are clustered on firm-level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

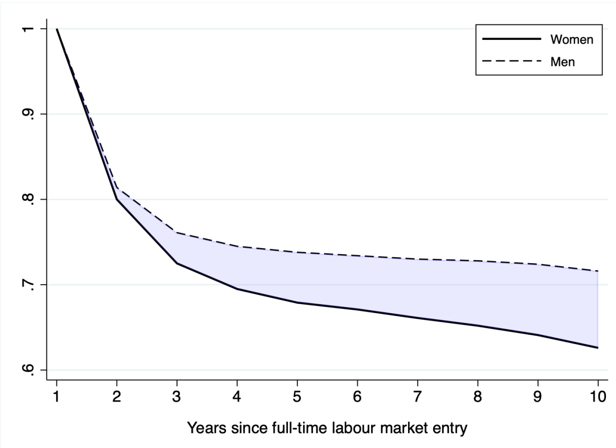
Figures

Figure I: AVERAGE WAGE VS SHARE OF FEMALE EMPLOYMENT IN A FIRM

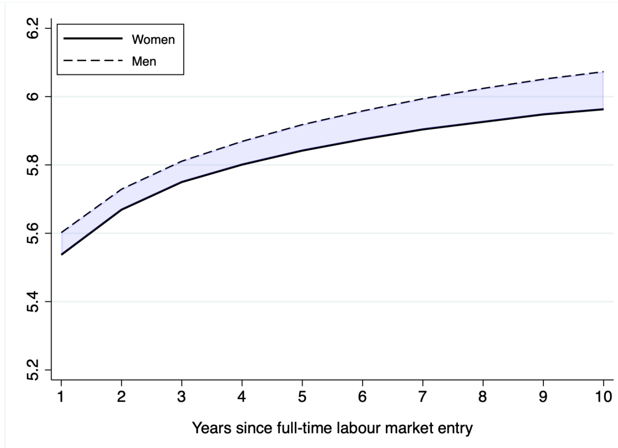


Notes: Sample of Italian workers in 2010. The figure is a binned scatter plot depicting the relationship between average wages and the share of female employment in firms in the year 2010 within the Italian labor market. The size of each circle is proportional to the number of workers in each bin. The vertical axis represents average log weekly wages.

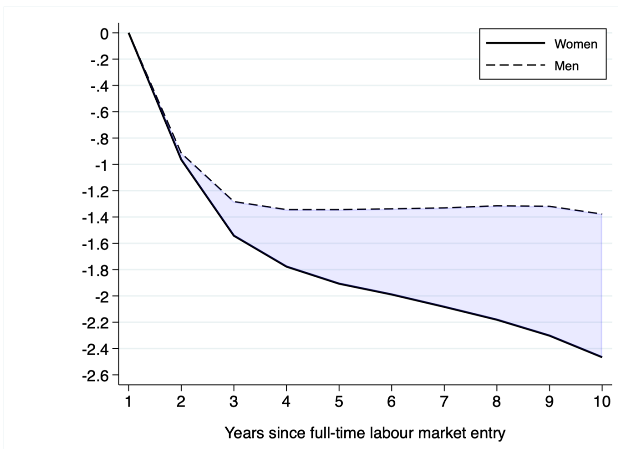
Figure II: PROFILES OF ITALIAN LABOR MARKET ENTRANTS, 2000-2011



(a) Employment by gender



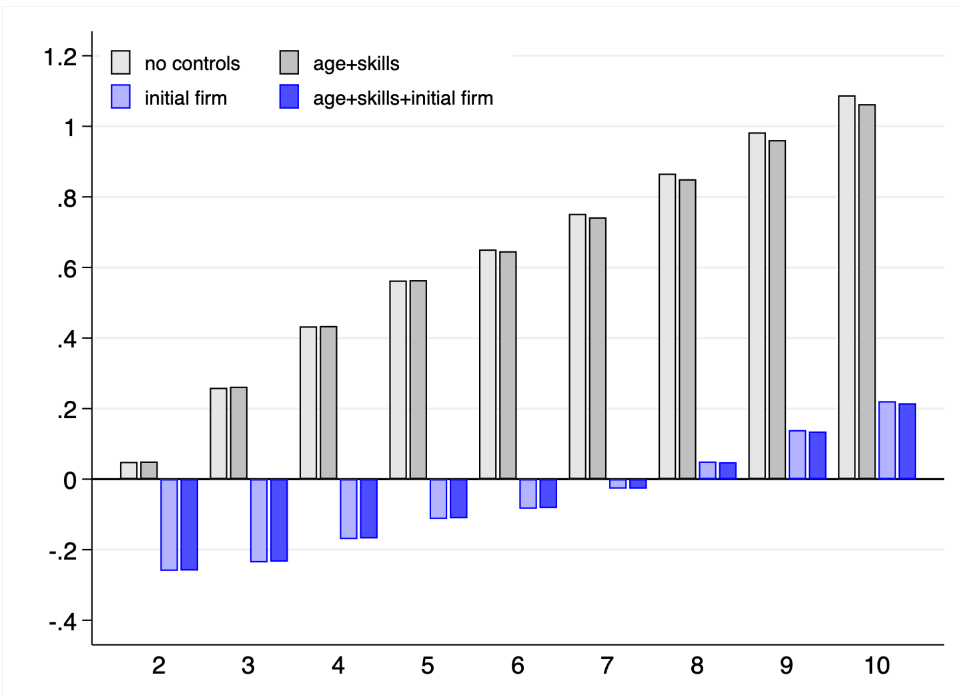
(b) Log wages by gender



(c) Earnings by gender

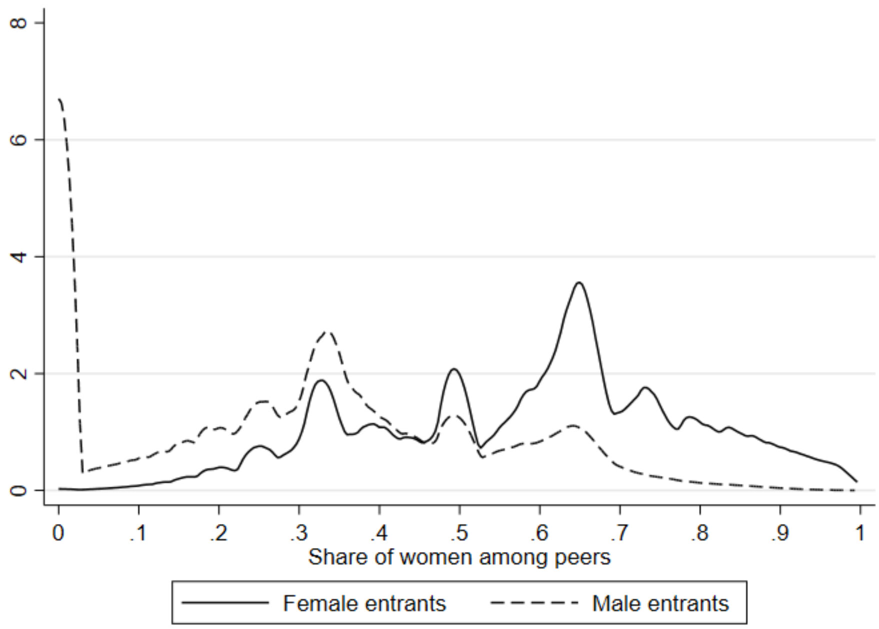
Notes: In this Panel a, we present employment profiles of men and women who entered their first full-time employment between the years 2000 and 2011, up to 10 years after their initial entry. These raw profiles reflect the overall share of women and men who remained employed every year post-entry, without any additional controls. In Panel b, we display wage profiles (log weekly wages) of men and women who started their first full-time employment between 2000 and 2011, up to 10 years post-entry. This includes the estimated constant, thus showing the initial gender wage gap as well as its evolution over time. In Panel c, we showcase the labor earnings, unconditional on employment, for men and women who entered full-time employment between 2000 and 2011 for the first time. These profiles are displayed with respect to the initial year of employment, up until year ten post-entry. When estimating earnings profiles in panel c, no controls were included, and earnings were set to zero for non-employed individuals.

Figure III: GENDER EARNINGS GAP OF ITALIAN LABOR MARKET ENTRANTS



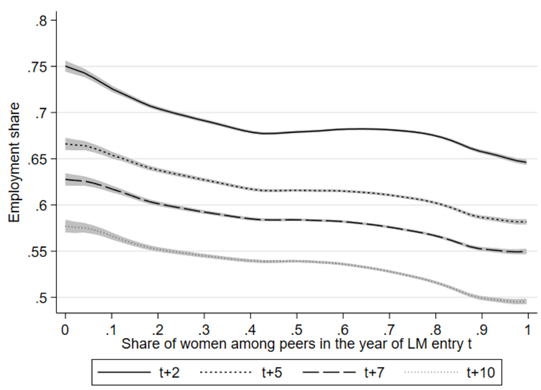
Notes: Sample of men and women who entered their first full-time employment between the years 2000 and 2011. This figure presents the earnings differentials between men and women, as shown in panel c of Figure II, in a "no control" specification. Subsequently, it depicts similar differentials using alternative specifications. These alternatives include controls for age and skills (proxied by broad occupational category), referred to as "age+skill", or controlling for initial firm fixed effects, referred to as "initial firm", and in the final case, both "age+skill+initial firm" are controlled for.

Figure IV: GENDER MIX AMONG PEERS (GMX) DISTRIBUTION

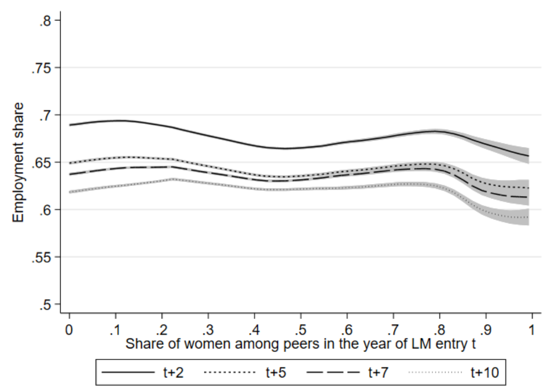


Notes: Sample of men and women who entered their first full-time employment between the years 2000 and 2011 observed in the year of entry. The figure plots the distribution of gender mix among peers of female and male labor market entrants. Peers' gender mix is a share of women among workers within the same firm, occupation and entry cohort.

Figure V: FUTURE EMPLOYMENT VS SHARE OF WOMEN AMONG INITIAL PEERS



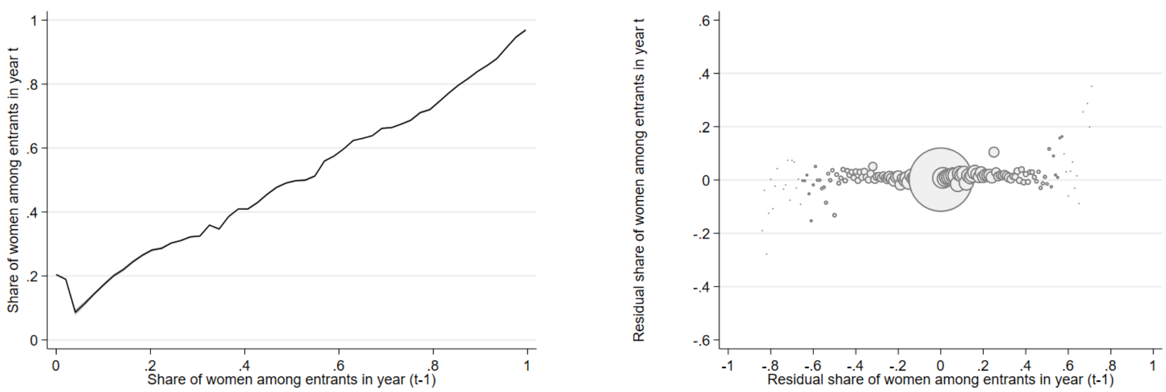
(a) Female entrants



(b) Male entrants

Notes: Sample of men and women who entered their first full-time employment between the years 2000 and 2011. Panels a and b plot the relationship between the employment shares of female and male labor market entrants 2, 5, 7 and 10 years post-entry and the share of women among their initial peers. This relationship is unconditional to any controls. The shaded area represents 95 percent confidence bands. The non-parametric regression uses the bandwidth of 0.10

Figure VI: FIRM GMX BETWEEN t AND t-1



(a) Raw relationship

(b) Residual relationship

Notes: Sample of men and women who entered their first full-time employment between the years 2000 and 2011. In panel a and panel b we plot respectively the raw and residual relationships between the share of women among new workers in years t and year t-1. The residual is obtained after controlling for the firm and year fixed effects. In panel b, the residuals are then binned by the value in t-1.The size of the circle is proportional of the number of labor market entrants in each bin.

Appendices

A.1 Robustness analysis of employment effects

We assess the robustness of our main results across various dimensions. In panel A of Figure A.1, we investigate the robustness of our findings by considering the gender composition of firms at different levels of hierarchy. Entrant's choice of a particular firm could potentially be influenced by the dynamic gender composition of the firm's workforce at a given moment. To account for this, subpanels i and ii of Figure A.1 include the gender mix of coworkers with 2 to 3 and 4 to 5 years of firm tenure, respectively. In essence, we aim to isolate the primary impact of peers' gender composition while also considering those within the same firm and occupation but with slightly higher seniority.

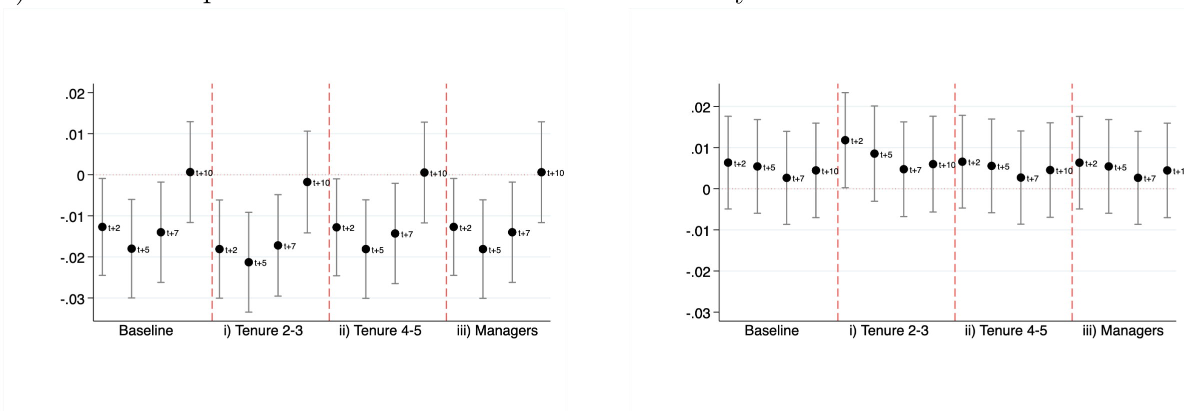
Another potential identification concern is that female labor market entrants might prefer firms with female managers, or conversely, from the firm's perspective, female managers might select a specific type of female labor market entrants. In model iii, we address this concern by incorporating the proportion of women among the firm's management at the time the entrant joined. Including the gender composition of more senior co-workers or managers does not alter the estimated impact of peers' gender composition. This reinforces our assertion that the baseline effects reflect a causal impact of peers' gender mix on employment. Overall, given firm, occupation, and broad entry cohort conditions, it appears that labor market entrants are not actively sorting across firms and occupations based on the evolving gender composition of a firm's workforce.

In panel B of Figure A.1, we test the sensitivity of our results to alternative sets of cohorts. Our main sample includes labor market entrants who joined full-time employment between year 2000 and 2011. This of course includes the period of important economic turmoil in Italy and worldwide. Starting one's labor market career during periods of recession may have long lasting consequences which could potentially differ by gender. In subpanel iv, we re-estimate the baseline model excluding cohorts 2008 and 2009, the recession years in Italy, while in panel v we only focus on pre-financial crisis cohorts, i.e. 2000 to 2007. The results remain largely unchanged.

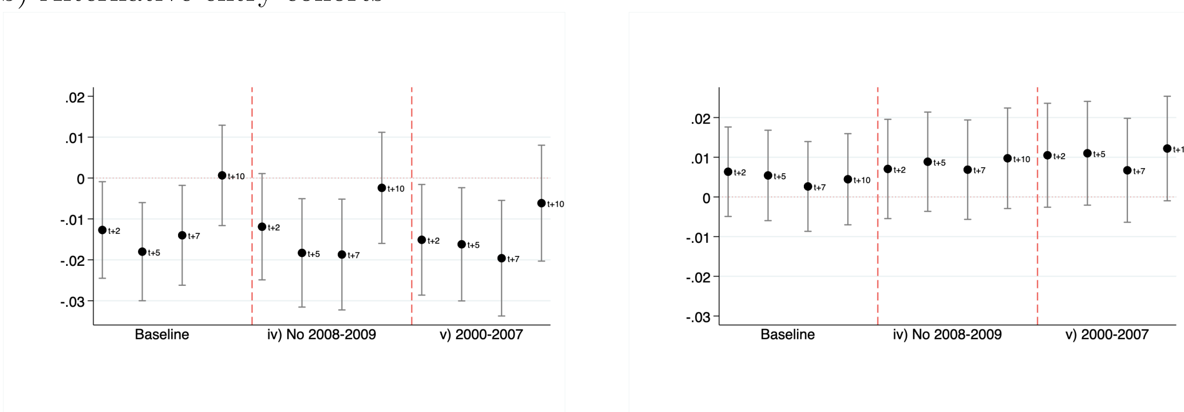
Overall, the baseline results exhibit robustness across various dimensions and sample variations. This robustness provides substantial supporting evidence for the validity of the baseline estimates.

Figure A.1: ROBUSTNESS CHECKS

(a) Gender composition at other levels of firm hierarchy



(b) Alternative entry cohorts



Female Entrants **Male entrants**

Notes: The figure displays the coefficient estimates from columns 1 to 4 in Table II which are compared to five alternative models in subpanels i-v. The coefficient estimates are plotted with the corresponding 95% confidence bands. The coefficient estimates displayed are those for GMX among peers, i.e. $\hat{\beta}$ from Eq. 2. In panel (a), Models i to iii in addition to peers' GMX, we include gender mix at other levels of firm hierarchy. Model i controls for the share of women within the same firm and occupation with 2 to 3 years of tenure. Model ii controls for the share of women within the same firm and occupation with 4 to 5 years of tenure. Model iii controls for the share of women among the firm's managers. In panel (b), we exclude the Great-Recession cohorts, i.e., the 2008-2009 cohorts, in model iv, and in model v we only focus on the pre-recession cohorts, 2000-2007. Panels on the left show the results for female entrants, and panels on the right show the results for male entrants.

A.2 Heterogeneity of Employment Effects

We assess heterogeneity in the main estimates across various dimensions. First, we explore heterogeneity by occupation and, subsequently, age at the first full-time job. The estimates from panel a of Figure A.2 reveal two critical insights. Primarily, the effect primarily manifests among white-collar workers, being statistically insignificant and essentially zero among blue-collar workers and apprentices.[11] Second, we observe marginally significant negative effects among male white-collar entrants.

In Panel b of Figure A.2, we delve into the heterogeneity of the main results concerning the age at which individuals entered the labor market. For women, the heterogeneity by age seems to align with the heterogeneity by occupation. This alignment is not surprising, as the later entry often stems from attending school and is therefore directly related to the occupation in which the entrant begins their labor market career. Conversely, for male entrants, there appears to be no discernible heterogeneity by age at entry.

Next, we examine potential heterogeneity in employment effects based on the proportion of women in the sector of initial employment. We categorize 2-digit sectors as male or female-dominated, depending on whether the overall share of female employment in the sector is above or below 50 percent. We then estimate the employment effects separately for men and women in both male- and female-dominated sectors. The results are presented in panel a of Figure A.3. Our findings indicate that male entrants are not influenced by the gender composition of their peers, regardless of the total share of women in their initial firm. In contrast, female entrants experience a negative impact when there is a higher share of women among their peers, regardless of whether the firm is male- or female-dominated. Interestingly, the effect appears to be somewhat stronger and more precisely estimated in female-dominated sectors.

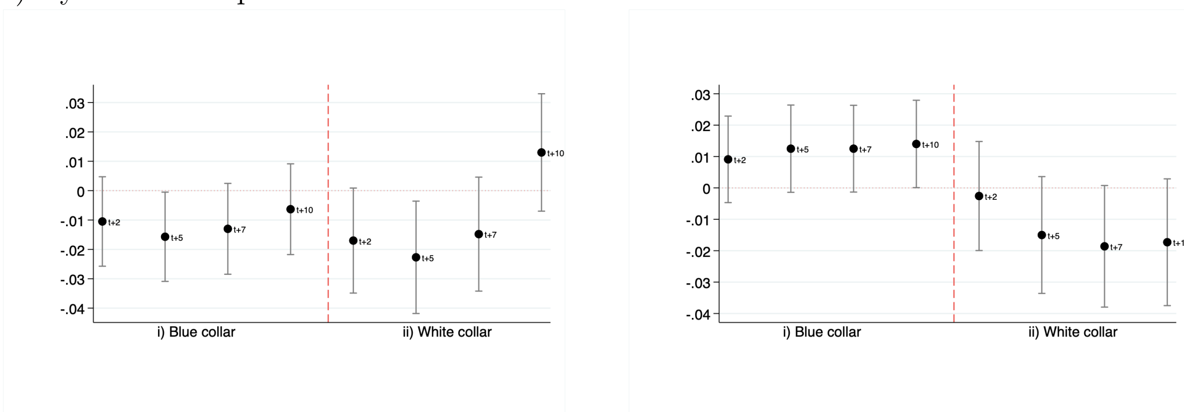
Regarding heterogeneity by firm size, the results in panel b of Figure A.3 indicate that the observed baseline employment effects for female entrants are primarily driven by dynamics in firms with fewer than 50 employees. In these smaller firms, the impact is negative, with a magnitude of 2percentage

[11] It's important to note that, for the purposes of this analysis, blue-collar workers and apprentices are grouped together.

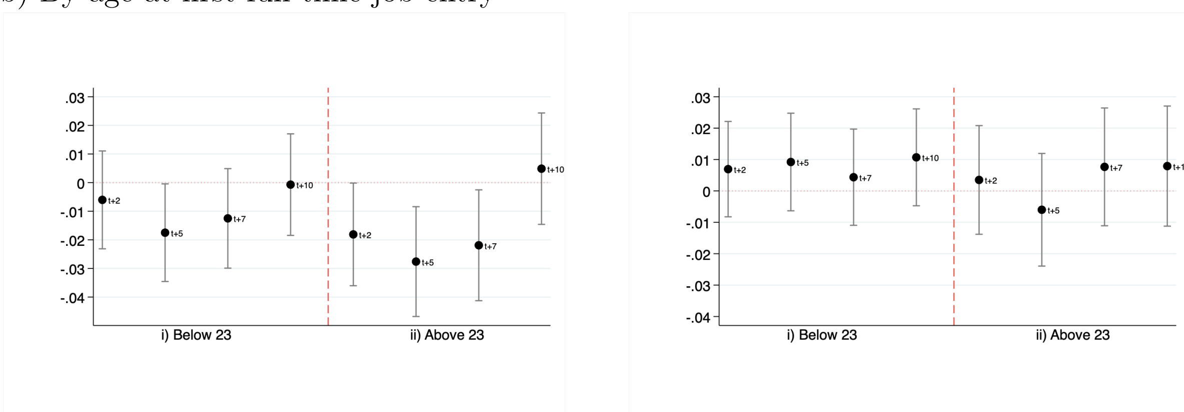
points at 2 years, 2.8percentage points after 5 years, and 1.7percentage points at 7 years, ultimately reducing to zero after 10 years. These effects are notably larger than the baseline estimates that average across all firm sizes. Interestingly, these effects are absent in larger firms and for male entrants.

Figure A.2: HETEROGENEITY OF THE EMPLOYMENT EFFECT BY BROAD OCCUPATION AND BY AGE AT ENTRY

(a) By broad occupation



(b) By age at first full-time job entry

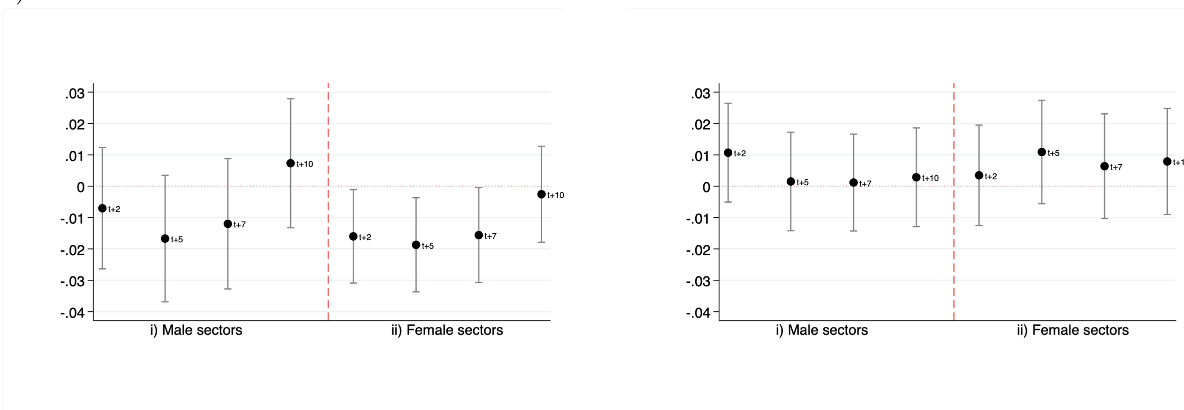


Female Entrants **Male entrants**

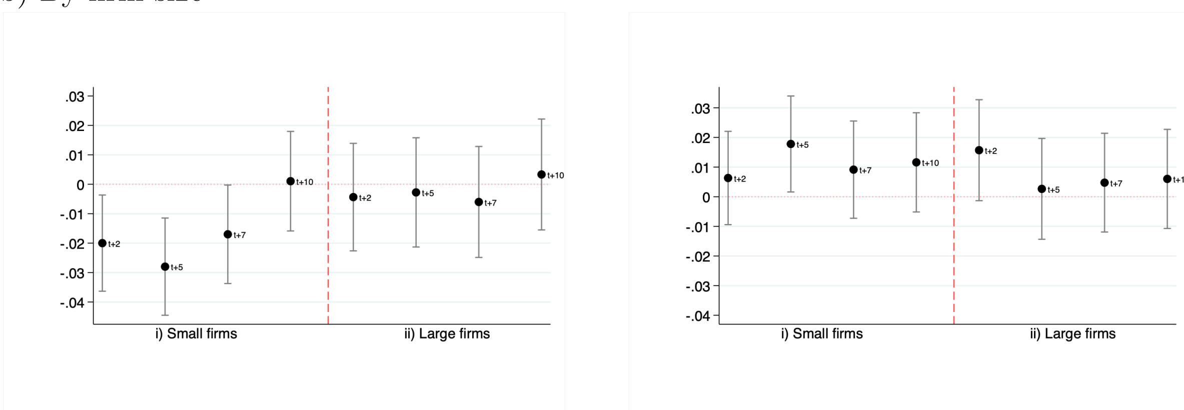
Notes: The coefficient estimates displayed are those for GMX among peers, i.e. $\hat{\beta}$ from Eq. 2 and the corresponding 95% confidence bands. Panels on the left show the results for female entrants, and panels on the right show the results for male entrants. In panel (a), the results are the estimates for blue- and white-collar workers separately. Blue collar category also includes apprenticeships in this case. In panel (b), the effects are estimated separately for individuals who started their first employment before and after turning 23.

Figure A.3: EMPLOYMENT EFFECT IN THE MALE VERSUS FEMALE-DOMINATED SECTORS AND BY FIRM SIZE

(a) Male versus female-dominated sectors



(b) By firm size



Female entrants **Male entrants**

Notes: The coefficient estimates displayed are those for GMX among peers, i.e. $\hat{\beta}$ from Eq. 2 and the corresponding 95% confidence bands. Panels on the left show the results for female entrants, and panels on the right show the results for male entrants. Industries at the 2-digit level are categorized as either male or female-dominated based on the proportion of female employment. If the female employment share is above 50 percent, the industry is labeled as female-dominated or *female*; otherwise, it is categorized as male-dominated or *male*. Firms with fewer than 50 employees are categorized as *small*, the rest are classified as *large*. In panel (a), the effects are estimated separately in male- and female-dominated sectors. In panel (b), the effects are estimated separately across firms with fewer and more than 50 employees.

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