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The Gender Gap in Career Trajectories: Do Firms Matter?*

David Card† Francesco Devicienti‡ Mariacristina Rossi§ Andrea Weber¶

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Abstract

The gender wage gap rises with experience. To what extent do firm policies mediate this rise? We use administrative data from Italy to identify workers' first jobs and compute wage growth over the next 5 years. We then decompose the contribution of first employers to the rise in the gender wage gap, taking account of maternity events affecting a third of female entrants. We find that idiosyncratic firm effects explain 20% of the variation in early career wage growth, and that the sorting of women to slower-growth firms accounts for a fifth of the gender growth gap. Women who have a child within 5 years of entering work have particularly slow wage growth, reflecting a maternity effect that is magnified by the excess sorting of mothers-to-be to slower-growth firms. Many entrants change jobs within their first 5 years and we find that the male-female difference in early career wage growth arises from gaps for both movers and stayers. The firm components in wage growth for stayers and movers are highly correlated, and contribute similar sorting penalties for women who stay or leave.

JEL Codes: J00, J23, J24, J31, J38, J58, L13.

Keywords: Gender gaps; Firm effects; Maternity; Matched Employer-Employee Data

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1 Introduction

Average wages rise rapidly in the first few years after labor market entry, reflecting skill accumulation (Becker, 1964; Ben-Porath, 1967; Adda and Dustmann, 2023), enhanced matching (Jovanovic, 1979), and progress up the job ladder (Manning, 2003). At the same time, the gender wage gap widens steadily, even for women with no children (e.g., Manning and Swaffield, 2008; Bronson and Thoursie, 2021). Recent research has emphasized the importance of initial conditions at labor market entry (Guvenen et al., 2022) and the availability of jobs at higher-paying firms (Oreopoulos et al., 2012) or larger firms (Arellano-Bover, 2024) for career success. Other work shows that firms' hiring and wage setting policies have a substantial effect on the average *wage gap* between women and men (Card et al., 2016; Cruz and Rau, 2022; Li et al., 2023; Casarico and Lattanzio, 2024). To date, however, the role of firms in explaining individual heterogeneity in *wage growth* and the differences in wage growth between women and men has remained relatively unstudied.

In this paper we make a start at filling this gap using detailed records from the Istituto Nazionale della Previdenza Sociale (INPS) in Italy. We identify a cohort of workers entering their first substantial job in the period from 2010 to 2012 and follow them over the next 5 years, constructing a measure of wage growth for the roughly 70% who are working 5 years after initial entry.[1] We find that average wages grow by about 18% in the first 5 years of work, with substantial variation across workers.[2] Crucially, we also find that the pace of wage growth varies systematically across first employers, consistent with evidence in Arellano-Bover and Saltiel (forthcoming) that there is heterogeneity in the returns to experience. Knowing the firm that someone started at explains about 20% of the variance of individual growth rates, suggesting that some employers invest more in the training of new recruits or facilitate more learning-by-doing.

Our second key finding is that women have slower average wage growth than men (14% on average for women versus 24% for men among workers who start at firms that hire both men and women). Consistent with a growing body of work on the career costs of children (e.g., Kunze, 2015; Kleven et al. 2019) we also find that earnings growth is slower for women who have a child in their first 5 years.[3] While mothers-to-be start off with slightly *higher* mean wages than non-mothers, childless women experience an average growth rate of 16% while wages for women who have a child grow by only 10%.

[1] We start our analysis in 2010 because information on workers' education is only available after that date. As discussed below the fractions of men and women with a job 5 years later are similar (70% versus 67%).

[2] Early studies of variation in the growth rate of earnings at the start of the career include Lillard and Weiss (1979) and Hause (1980). Guvenen (2009) presents evidence of heterogeneity in the growth rate of earnings for a wider population of workers.

[3] Some of this slowdown is arguably driven by taking time off work after a child is born, though in our sample the interruptions are relatively short. In a structural model of career interruptions Adda et al. (2017) estimate that work interruptions have relatively small causal effects for women at the beginning of their careers – less than a 1% loss in skills per year of interuption.

Our third finding is that about 20% of the widening in the gender gap in the first 5 years of work arises because women are less likely than men to start their careers at "high growth" firms. This sorting effect is even larger for women who will have a child, and the estimated maternity gap falls in magnitude by about 11% when we add firm effects to our models of wage growth. In other words, women who will have a child early in their careers are *even less likely* to start at high-growth firms than those who delay childbirth (or end up childless), and this extra degree of sorting contributes to the child penalty effect.

Finally, we compare the wage growth of the roughly 50% of workers who remain at the same firm over their first 5 years (stayers) versus those who change jobs (movers). Stayers of both genders experience faster wage growth than movers: the gap is particularly large for childless women. When we estimate separate wage growth models for movers and stayers we find that sorting to high growth firms explains about the same share of the gender gap for both groups, and about the same shares of the gaps for mothers and childless women. Moreover, the estimated firm effects from two models are very highly correlated: firms that offer faster wage for stayers also improve the wage growth for workers who leave within 5 years, suggesting that the growth effect may be driven by accumulation of general skills rather than firm-specific skills.

2 Conceptual framework

2.1 Sources of early career job growth

The fact that workers' wages tend to rise very quickly in their first few years of work has been known to economists for at least a century.[4] Two leading explanations for this rise are on-the-job investments in human capital (Becker, 1964; Ben-Porath 1967) and learning-by-doing (Arrow, 1962), both of which suggest an important role for firm-specific policies in determining the pace of wage growth.[5] Two other explanations – dynamic sorting based on the quality of the worker-firm match (Jovanovic, 1979; Topel and Ward, 1992), and search-based rises up the job ladder (Burdett and Mortensen, 1998; Manning, 2003) – also highlight the role of firms, though in these models it is movements *between* employers that drive wage growth.[6]

Similar theories have been used to interpret the generally slower growth of women's wages than men's in the early stages of their career. For example,

[4]For example, Walsh (1935) presented data drawn from a survey in the mid-1920s by Lord (1928) on mean wages by age for various education groups. Among male high school graduates in this survey (the largest group in this analysis), mean earnings grew by about 70 log points between ages 19 and 24.

[5]A large body of existing work explores a third explanation for idiosyncratic wage growth: employer learning about the abilities of workers (e.g., Altonji and Pierret, 2001). As noted by Farber and Gibbons (1996), however, standard "market learning" models imply that individual wages evolve as a Martingale, with no average trend.

[6]More complex learning models in which information about worker's skills can be used to better allocate their time to different tasks (e.g., Gibbons and Waldman, 1999) potentially lead to within-employer wage increases.

Mincer and Polachek (1974) argued that women invest less time in on-the-job training than men, in part because they expect to leave the labor force after their children are born. As noted by Blau and Kahn (2017), the pattern of labor force withdrawal after child birth was more pronounced for mothers in pre-baby-boom cohorts than in recent cohorts, though an important body of recent research has focused on the slowdown in wage growth that occurs after childbirth, even for mothers who return to work quickly (e.g., Manning and Swaffield, 2008; Fitzenberger and Kunze, 2005; Bertrand et al., 2010; Kunze, 2015;Kleven et al., 2019). Again, these mechanisms suggest a important role for employers in determining, for example, the job duties and training opportunities for mothers who return to work.

Several strands of related research on the gender gap also propose mechanisms that are wholly or partly mediated by employers. Studies by Blau and Devaro (2007), Bronson and Thoursie (2021) and Bensen et al. (2022) find that women are less likely to receive promotions than men, while Hospido et al. (2022) show that an explicit change in policies at the European Central Bank was able to close the promotion gap for professional economists. Card et al. (2016) (hereafter CCK) show that women in Portugal are less likely to work at firms that offer higher pay premiums to their male workers, and that women gain less from moves between firms than men. Parallel findings are reported by Casarico and Lattanzio (2024) for Italy, by Cruz and Rau (2022) for Chile, and by Li et al. (2023) for Canada.

2.2 Econometric model

a. Basic model

We start with a simple model of wage growth of the form:

$$y_i = \beta_0 + \beta_1 F_i + \beta_x X_i + \sum_k \gamma_k D_{ik} + \epsilon_i \tag{1}$$

where y_i is the change in the logarithm of the daily wage for individual i between her or his first substantial job (defined below) and the highest paying job they hold 5 years later, F_i is an indicator for female gender, X_i is a set of characteristics (education, year of initial labor market entry, and age at entry), and D_{ik} is a dummy variable indicating that individual $i's$ first job was at firm k. Our main coefficient of interest is β_1 – the female wage growth effect – which measures the widening of the gender gap between initial entry and year 5. In our baseline specification, this estimate is obtained after controlling for differences in the characteristics of male and female workers, and for potential differences in the average growth rate of wages for workers who start at different firms.

Our specification differs from that of Arellano-Bover and Saltiel (forthcoming), which models the level of wages at different points in the career and includes firm-specific coefficients associated with years of work experience at each previous employer.[7] In contrast, we only include an effect for the initial em-

[7] A related model is developed by De La Roca and Puga (2017), who include terms that

ployer – though we focus on first jobs that last at least two years – and we model wage growth. In principle it might be possible to distinguish the initial employer effect from heterogeneous returns to experience, but we leave that to future work.

To quantify the mediating role of firms in the differential wage growth of women and men, let π_k^F represent the fraction of all newly entering female workers who begin at firm k, and let π_k^M represent the parallel fraction of all entering males who begin their careers at firm k. The sorting effect of initial job assignment of women and men to different firms can then be defined as:

$$G = \sum_k \gamma_k (\pi_k^F - \pi_k^M).$$

This measures the difference in wage growth between men and women that arises because some firms have faster wage growth for workers of both genders (measured by the relative size of γ_k), *and* women have a different distribution across firms than men. In particular, if women tend to start their careers at firms that have slower average wage growth for all workers, then $G < 0$. Given estimates $\widehat{\gamma}_k$ of the firm effects in (1), we can estimate $\widehat{G} = \sum_k \widehat{\gamma}_k (\pi_k^F - \pi_k^M)$.

An alternative way to assess the magnitude of G starts from a simplified specification for wage growth:

$$y_i = b_0 + b_1 F_i + b_x X_i + v_i \tag{2}$$

that excludes the firm effects. In this model b_1 is the gender gap in mean wage growth, controlling only for the $X's$. Assuming that the coefficients for models (1) and (2) are defined as choices that minimize the expected mean squared errors of the models (i.e., the population equivalent of OLS), both models will fit the means of earnings growth for women and men exactly. As a result:

$$b_1 - \beta_1 = G - (b_x - \beta_x)(\mu_x^F - \mu_x^M)$$

where μ_x^F and μ_x^M are the means of the covariates for women and men, respectively. In the case where the coefficients b_x and β_x are approximately the same, we will then have:

$$G \approx b_1 - \beta_1.$$

In other words, if the coefficients of the other controls are invariant to the addition of the firms effects, the sorting effect can be approximated by the change in the estimated gender gap when we add firm effects. In our analysis below we estimate G directly and compare this to the difference in the estimated gender coefficients from models with and without firm effects. They are typically close in magnitude.[8]

reflect the years that an individual has worked in bigger and smaller cities, allowing heterogeneous returns to experience in different labor markets.

[8]The main reason why they are not the same is that adding the firm effects to the wage growth model typically leads to a reduction in the size of the coefficient associated with worker education. We discuss this further below.

b. Distinguishing between mothers and non-mothers

Next, consider an extension of model (1) in which we add two female effects: one for women with no children (F_i^n), and one for women who have a child in their first 5 years of work (F_i^c) :

$$y_i = \beta_0 + \beta_1 F_i^n + \beta_2 F_i^c + \beta_x X_i + \sum_k \gamma_k D_{ik} + \epsilon_i. \tag{3}$$

In this setting we can define two sorting effects:

$$\begin{aligned} G^n &= \sum_k \gamma_k(\pi_k^n - \pi_k^M) \\ G^c &= \sum_k \gamma_k(\pi_k^c - \pi_k^M) \end{aligned}$$

where π_k^n and π_k^c are the shares of women with no children and women with children whose first job is at firm k, respectively. Again, we can also compare the estimated female effects in equation (3) to the effects from a simplified model without firm effects:

$$y_i = b_0 + b_1 F_i^n + b_2 F_i^c + b_x X_i + \upsilon_i \tag{4}$$

It is straightforward to show that if the effects of the covariates are the same in specifications (3) and (4) then the estimated sorting effects will be equal to the differences between the estimated female effects in these two specifications:

$$\begin{aligned} G^n &\approx b_1 - \beta_1 \\ G^c &\approx b_2 - \beta_2. \end{aligned}$$

More generally, the two sorting effects differ from the changes in the coefficients by a factor that depends on how the effects of $X's$ differ with and without firm effects.

Using the estimates from equations (3) and (4) we can also define the implied maternity costs with and without controlling for firm effects:

$$\begin{aligned} \tau &= \beta_2 - \beta_1 \\ T &= b_2 - b_1. \end{aligned}$$

If women who have a child tend to experience slower wage growth than non-mothers (as has been found in virtually all previous studies and is also true in our data), then $\beta_2 < \beta_1$ and $b_2 < b_1$. Moreover, abstracting from differences in the effects of the covariates in models (3) and (4), the relationship between the estimated maternity costs in models that exclude or include firm effects will have the simple form:

$$T - \tau \approx G^c - G^n = \sum_k \gamma_k(\pi_k^c - \pi_k^n).$$

If, for example, women who will have a child in their first 5 years tend to start at slower-growth firms than women who will delay fertility, then the motherhood gap in wage growth will be smaller when we control for initial firm by an amount that represents the difference in sorting effects for mothers and non-mothers.

c) Gender-specific firm effects?

In their analysis of the effect of firms on the gender gap in wages, CCK estimate separate wage models for men and women and implement a simple Oaxaca-style decomposition that isolates both a differential sorting effect and a differential pay-setting effect for men versus women. At first glance one might think that such an approach would also work for studying the gender gap in wage growth. Specifically, one might be tempted to estimate a wage growth model separately by gender and then decompose the difference in the weighted sums of the estimated firm effects for men and women (i.e., decompose $\sum_k \gamma_k^F \pi_k^F - \sum_k \gamma_k^M \pi_k^M$,where γ_k^F and γ_k^M are the firm effects in separate models for women and men). As discussed by Oaxaca and Ransom (1999), however, such a decomposition cannot separately identify the main effect of female gender (i.e., the coefficient β_1 in equation 1) and the gender gap in growth rates at whatever firm is taken as a reference group in defining the firm fixed effects. To illustrate, consider the generalized gap $\widehat{G}' = \sum_k \widehat{\gamma}_k^F \pi_k^F - \sum_k \widehat{\gamma}_k^M \pi_k^M$. If one were to normalize the firm effects of each gender group by setting their weighted average across all firms to 0, then $\widehat{G}' = 0$. But alternative normalizations could give a wide range of values for $\widehat{G}'$. CCK normalize the firm effects in models for *wage levels* by assuming that low-productivity firms pay a zero wage premium to both genders. Unfortunately, there does not appear to be a similarly appealing normalization for *wage growth* effects.

d) Job turnover: stayers versus leavers

Young workers switch jobs relatively often (see e.g., Farber (1999)). As discussed below, using our definition of a first substantial job, about one-half of recent Italian labor market entrants are working at a different job 5 years after starting their first job. Job transitions are a critical driver of wage growth in models of learning about match quality (Jovanovic, 1979) and in posted-wage job search models (Manning, 2003). But job stability can also promote wage growth in models with firm-specific investments (see Topel, 1991; Altonji and Williams, 2005).

With respect to gender, many studies suggest that women change jobs about as often as men, but gain less from a job change (Loprest, 1992; Hospido, 2009; Del Bono and Vuri, 2011). A natural question is how differences in job retention rates, wage growth for job stayers, and wage growth for job movers vary across firms, and whether the gender gap in wage growth is attributable in part to women's under-representation at firms that are "good places to come from."

To investigate the role of turnover in the gender gap in early career growth, and quantify the impact of firms, note that for any group, the mean rate of wage growth ($\overline{y}$) is just a weighted average of the growth rates for stayers and leavers:

$$\overline{y} = s\overline{y}^s + (1-s)\overline{y}^\ell$$

where s is the share of the group that stay with the same employer, $\overline{y}^s$ is the mean wage change for stayers, and $\overline{y}^\ell$ is the mean wage change for workers who leave the firm. Using this expression, the difference in mean wage growth between men and women can be decomposed as:

$$\begin{aligned}\overline{y}^M - \overline{y}^F &= s^M\overline{y}^{sM} + (1-s^M)\overline{y}^{\ell M} - s^F\overline{y}^{sF} - (1-s^F)\overline{y}^{\ell F} \\ &= \underbrace{s^M(\overline{y}^{sM} - \overline{y}^{sF})}_{stayers} + \underbrace{(1-s^M)(\overline{y}^{\ell M} - \overline{y}^{\ell F})}_{leavers} \\ &\quad + \underbrace{(s^M - s^F)(\overline{y}^{sF} - \overline{y}^{\ell F})}_{interaction} \qquad (5)\end{aligned}$$

This equation has 3 terms: (1) a term attributable to the gender gap in mean wage wage growth of stayers; (2) a term attributable to the gender gap in wage growth of leavers; (3) an interaction term, which depends the gender gap in retention rates ($s^M - s^F$) and on the difference in mean wage growth between female stayers and leavers. Notice that equation (5) can be applied to differences in wage growth between men and women as a whole, or between males and a *subgroup* of females (e.g., those who do or do not have a child in their early careers). It can also be used to decompose the difference in average wage growth between mothers and non-mothers.

Finally, we can estimate models like (1) and (3) separately for workers who remain at the same firm and those who leave. Using analogues of the sorting effects G, G^n and G^c we can then calculate the share of each of the three terms in equation (5) that can be attributed to differential sorting of women and men to firms with faster or slower wage growth. For example, if we estimate (1) separately for stayers and leavers we can calculate G^s and G^ℓ – the estimated effects of differential sorting across firms on the gender gap in wage growth for stayers and leavers, respectively. Using these estimates we can then calculate the contributions of differential sorting to the wage growth of stayers and leavers. Building on equation (5) we can also summarize the effect of differential sorting to the overall gender gap in wage growth:

$$\underbrace{s^M G^s}_{stayers} + \underbrace{(1-s^M)G^\ell}_{leavers} + \Delta, \qquad (6)$$

where Δ represents the part of the overall sorting effect attributable to interaction effects.[9]

3 Empirical results

i) Derivation of analysis sample

Our empirical analysis is based on the population of private-sector employees registered with the Italian Social Security Agency (INPS). INPS collects information on job spells and earnings and makes available a merged longitudinal

[9]Specifically, a variant of equation (5) implies that we can decompose $G = s^M G^s + (1 - s^M)G^\ell + \Delta$, where the interaction effect Δ represents the difference in average firm effects for female stayers versus leavers. We construct an estimate of the interaction effect as $\widehat{\Delta} = \widehat{G} - s^M\widehat{G}^s - (1-s^M)\widehat{G}^\ell$.

data set that includes basic demographic information, contract type (fixed-term versus open-ended), full or part time status, and total pay and days worked for all job spells. Beginning in 2010 there is also information on education for workers who start a new job. Since we want to control for education, in this paper we use data from 2010 to 2017 (the last year for which INPS data were available to us).

A key feature of our setting is that we can observe all maternity events for women whose employment spells are recorded by INPS. Specifically, Italian law specifies a *mandatory* maternity leave of 5 months starting (roughly) 2 months before childbirth and paid by INPS at 80% of the pre-birth wage.[10] In addition, new parents are entitled to a voluntary leave of up to 11 months, 6 of which are paid at 30% of the pre-birth wage. Voluntary leave payments can in principle be split between mothers and fathers.

To allow at least a 5 year followup for new job entrants, we focus on people who started their first INPS-recorded job of at least 2 years duration in 2010-2012. We define the starting year of that job as their year of labor market entry. We exclude workers who do not have a job lasting at least 2 years that starts within the first 3 years they are observed in the INPS file. (This eliminates people who cycle between many shorter jobs in their first years of work). We assign each worker their main job in every calendar year (the one at which they received the highest total earnings over the year), and calculate their average daily wage on their main job in their year of entry and 5 years later. For most of our analysis we exclude people who did not have a job in their 5th year. This eliminates people who had no (full time) job in that year, as well as others who may have moved to the public sector or to self employment, or emigrated out of Italy.

Table 1 illustrates the derivation of our analysis sample. We begin with around 423,000 new entrants to the Italian labor market in 2010-2012 who meet our definition of starting a "first substantial job". As shown in columns 1 and 2, 240,000 (57%) of these are men and 183,000 (43%) are women. Columns 3 and 4 present information on the 70% of the newly entering men and 67% of the newly entering women have a wage 5 years later.[11] These are people for whom we can potentially measure our main outcome of interest, wage growth over the first 5 years since entry. The 3 percentage point smaller share of women who are observed working in year 5 suggests that there may be slightly more selection bias in the observed wage changes for women than men. Assuming that people with higher wage growth are more likely to remain employed, this differential bias may slightly raise the observed growth rate of women relative to men.[12]

[10] Some workers receive the extra 20% under terms of their collective bargaining agreement. See Carta et al. (2024).

[11] The relatively small gender gap in employment rates in year 5 is interesting, since new mothers are potentially eligible to receive unemployment (UI) benefits if they quit after their child is born – see Carta et al. (2024) for an analysis of a change in the duration of such benefits that was introduced in 2015 and would have affected some of the mothers in our sample. They show that the rate of new mothers quitting and moving into UI rose from around 16% to 21% after the reform.

[12] For example, if one was willing to assume that the lower bound on wage growth is 0, then

Since our main focus is on the question of how firms affect the relative wage growth of women versus men, we make one additional restriction for our main analysis sample: we narrow attention to people who start working at firm that hired at least two new entrants of each gender in the 2010-2012 period. This is similar to the restriction to men and women in the "dual connected set" of firms in CCK and related studies, and ensures that our sample has newly entering men and women at every firm in the sample. Columns 5 and 6 of Table 1 shows that this restriction keeps about 24% of the men and 33% of the women who had a job 5 years after entry, narrowing our main analysis sample to about 16% of the men and 22% of the women in our entering cohorts.[13] Finally, columns 7 and 8 focus on the subset of workers in our main analysis sample with a higher degree (i.e., a bachelor's degree or higher). These workers account for 6% of all entering men and 9% of entering women.

ii) Sample characteristics

Rows 2-8 of Table 1 show the characteristics of workers in the various samples. A typical labor market entrant (as defined by starting a job that lasts at least 2 years) is around 24 years of age; those with a higher degree are about 2 years older. About 15% of male entrants and 23% of female entrants have a bachelor's degree or more; this rate is a little higher among those who also have a job 5 years later, and is around twice as high among those who start at a firm with 2+ entrants of each gender. Around 60% of entry jobs of men have an open-ended contract compared with around 54% of entry job of women. Interestingly, these rates are not too different among the subset of entrants who are working in year 5, but they are about 15 percentage points (ppt) lower among those who start at firms with 2+ entrants of each gender, reflecting the greater use of temporary contracts by larger firms.

Mean daily wages of entrants are around 63 Euros per day for males and 59 Euros per day for females, implying a gender gap in entry wages of about 7 percent. Mean starting wages are only slightly higher among the subset of entrants with a job 5 years later, but are around 18% higher for men and women in our main analysis sample, which focuses on those who start at firms with at least 2 entrants of each gender. Mean starting wages for the subsets of both gender groups with a higher degree are about 13% higher still. Interestingly, then, the gender gaps in starting wages are very similar across all four samples in Table 1.

Among entrants who have a job 5 years later, nominal wages have grown about 20 ppt for men and 13 ppt for women. Narrowing attention to workers in our main analysis sample (columns 5 and 6) leads to a somewhat faster pace of wage growth for men, but little change in the wage growth for women. Thus

adding in 3 percentage points more women with observed wage growth of 0 would lower the average rate of wage growth for women by about 4% or 0.006, and *widen* the gender gap in wage growth slightly.

[13] These workers were employed at some 4,500 firms which on average are substantially larger than a typical employer in INPS.

among entrants whose first job is at a firm with at least 2 entrants of each gender, the gender gap in early career wage growth is about 10 ppt – somewhat *bigger* than the gap for all entrants. As shown in columns 7 and 8, early career wage growth is faster for both men and women with a higher degree but the gender gap in wage growth is even wider (around 14 ppt).

Only about 32 percent of male entrants and 30 percent of female entrants are still employed at their entry firm 5 years later. These rates are substantially higher conditional on having any job in the 5th year (close to 45 percent for bother genders), and higher still focusing on entrants who have a job and started at a firm with at least two entrants of each gender (about 50% for men and 48% for women). Finally, among the subset of workers in our main analysis sample with a higher degree about 65% of each gender group were still employed at the same firm after 5 years.

In the second last row of Table 1 we show the fractions of females in each sample who had a child in the first 5 years of their career. Perhaps surprisingly, the rates rise as we go from all entrants (23%) to those with a job in their 5th year (28%), to those in our main analysis sample (31%), and to the subset in our main analysis sample with a higher degree (36%). Across the 4 samples of women in Table 1, the early fertility rate is therefore *positively* correlated with average starting wages ($\rho = 0.9$).

Table 2 presents some comparisons between female entrants in our main analysis sample who had no maternity leave in their first 5 years and those who had a child. The subset of mothers is slightly older and better educated. Interestingly, their average entry wage is also a little higher than the average among the non-mothers, as is the share with an open-ended contract in their first job. They were also more likely to remain with their entry firm (57%) than non-mothers (43%). Consistent with the literature on the career costs of children, however, women with a child had slower wage growth over their first 5 years (9.5 ppt versus 15.7 ppt).

iii) Wage growth models

With this background, we turn to estimates of the simple models of wage growth described by equations (1)-(4). Table 3, columns 1 and 2 present estimates of equations (2) and (1), respectively, in panel A of the table, and estimates of equations (4) and (3), respectively, in panel B. Columns 4 and 5 repeat this analysis focusing on the subset of workers with a higher degree.

Focusing first on the simple models that make no distinction between mothers and non-mothers, we see in column 1 that the gender gap in wage growth, adjusting for age and year of entry and presence of a higher degree is 10.7 ppt – very close to the unadjusted gap of 10.1 ppt. Adding fixed effects for the initial firm lowers this gap to 8.2 ppt – a reduction of 23.4 percent, as shown in column 3. It is also interesting that the adjusted R-squared of the model rises from 5.8 percent to 26.7 percent. Comparing these model fits it is clear that the identity of one's initial firm explains a relatively large share of the variation in early career wage growth, even accounting for worker demographics.

Using the estimated firm effects from the model in column 2 we can construct an estimate of the sorting term G. This has a value of -2.3 ppt, only slightly smaller than the change in the estimated gender gap (-2.5 ppt), implying that initial sorting to slower-wage growth firms explains 21.5 percent of the gender gap from the model in column 1.

Turning to the results in panel B, we see that with basic controls the gap in wage growth between men and non-mothers is 8.2 ppt (the same as the corresponding unadjusted difference in wage growth) while the gap for women who have a child in their first 5 years is 16.3 ppt – somewhat larger than the unadjusted gap of 14.4 ppt. The main explanation for the *rise* in the gap with the adjustment is the relatively high level of education among mothers (49 percent of whom have a higher degree, versus 38 percent of men and of women with no child), and the fact that higher education is associated with faster wage growth.[14] Adding firm effects to the wage growth model reduces the estimated growth penalty for childless women by 2 ppt and the estimated penalty for mothers by 3.5 ppt, suggesting that differential sorting to slower-wage growth firms is more important for women who will have a child, though the size of this effect relative to the overall wage growth gap for mothers is a little smaller than the relative effect for non-mothers (21.5% versus 24.4% in column 3). Using the estimated firm effects to construct the sorting terms G^n and G^c we get a comparable estimate of the effect of sorting on childless women, but a somewhat smaller estimate of the effect on mothers (17.8% versus 24.9% for non-mothers). Again, the discrepancy between the direct estimate of G^c and the change in the estimated wage growth effect for mothers when firm effects are added to the model arises mainly because of the higher education of mothers and the fact that adding firm effects shrinks the estimated effect of higher education on early career wage growth.

Finally, in panel C we show how the addition of controls for the starting firm affects the size of the maternity gap in wage growth. With only basic controls this is 8.1 ppt; adding firm effects lowers the effect to 6.6 ppt. Again we can calculate directly the difference in the sorting effects for the two groups of women, obtaining an estimate of $\widehat{G}^c - \widehat{G}^n = -0.009$ – an effect that explains about 11 percent of the overall maternity gap in wage growth.

Looking at the results for highly educated workers in columns 4-6 we see an interesting pattern relative to the results for all entrants. On average the gender wage gaps are larger among higher-educated workers (e.g., 14.3 ppt in a model without firm effects versus 10.7 ppt for all workers). The size of the estimated sorting effects G,G^c,and G^n are about the same for better-educated workers, however, so the *share* of the gender gaps explained by sorting is smaller.

iv) Movers versus stayers

As noted earlier, many young workers change jobs relatively frequently – though our definition of a "first job" eliminates the short jobs that account for a lot of

[14] Mothers are also somewhat older, and on average older entrants have faster wage growth.

turnover among young workers documented by Farber (1994).[15] Table 4 presents some descriptive comparisons of workers in our main analysis sample who are still employed by their initial firm 5 years later ("stayers") or are employed elsewhere ("movers"). Stayers tend to be better educated, are more likely to have a permanent contract on their first job, and have higher wages on their first job. They also have faster wage growth in their first 5 years. For men the wage growth premium for stayers is 8.1 ppt, while for women the premium is 9.7 ppt. Interestingly, the stayer premium is larger for the subset of women who do not have a child (12.9 ppt) than for those who do (5.8 ppt).

The fact that stayers have faster wage growth than movers is the opposite of the pattern identified in a well known paper by Topel and Ward (1992), which looked at relatively high frequency moves among young men in the U.S. labor market, and concluded that firm mobility was an important driver of wage growth. We suspect the difference is largely due to our focus on "first substantial jobs", and perhaps also to institutional differences between the U.S. labor market in the 1980s and the Italian labor market in the last decade.

Table 5 presents estimates of equations (1) and (3) separately for movers and stayers, as well as estimates of the sorting terms G, G^n, and G^c. An examination of the models in Panel A points to two main conclusions. First, as we found in Table 3, adding firm effects leads to a large increase in the adjusted R-squareds of the wage growth models for movers and stayers. Second, adding firm effects leads to a reduction in the magnitude of the female wage growth effect for stayers (-0.030) and movers (-0.016). Direct estimates of G for the two groups are very similar in magnitude and suggest that sorting reduces the wage growth of women by 15-18%.

An interesting question for the interpretation of the wage growth patterns in our data is whether a given firm tends to have similar effects on the wage growth of movers and stayers. Figure 1 shows a bin scatter of the firm effects from the model for movers (on the y-axis) against the firm effects for stayers (on the x-axis).[16] For reference, we also show a line with an intercept of 0 and slope of 1, along which the points would lie if jobs at a given firm had *the same effect on wage growth* for movers and stayers, and if the firm effects from our models were measured without error. Remarkably, the points for deciles 3-8 lie very close to the 45 degree line. We believe that the explanation for the departures from the line for the lowest 2 and highest 2 deciles is measurement error. Since many firms have small numbers of movers, the firm effects in the model for movers are estimated with error. Among firms assigned to the lowest deciles this measurement error is likely to be systematically negative, whereas for firms assigned to the highest deciles it is likely to be systematically positive. Taking into account the effect of measurement error in the assignment of deciles, we interpret the pattern in Figure 1 as suggesting that the firm effects for movers

[15] Farber (1994) uses high frequency data on job spells from the NLSY and shows that about one half of jobs taken by young workers in the US in the 1980s ended within a year.

[16] To construct this we first stratified firms into 10 equal sized groups based on the estimated firm effect in wage growth of stayers. We then constructed the mean of the firm effects for stayers and movers who started at firms in each of these decile groups.

and stayers are remarkably similar.

Panel B of Table 5 shows the estimates of equation (3) for movers and stayers, and the estimated values of the sorting effects G^n and G^c. We note that for both movers and stayers the estimates of the sorting effects for mothers are larger than the estimates for non-mothers. This implies that 10-15% of the maternity gap in wage growth for both stayers and movers is attributable to the excess sorting of mothers (relative to non-mothers) to firms where all stayers or all movers have relatively slow wage growth.

Table 6 summarizes the implications of the decomposition based on equation (5) for the wage growth gap between all women and men (first row); between childless women and men (second row); between women who have a child and men (third row); and between mothers and women without children (bottom row). We show the average wage growth of the target and reference groups (columns 1 and 2), the shares of movers (columns 3 and 4), the wage growth of movers of each group (columns 5 and 6), the wage growth of stayers of each group (columns 7 and 8), and the gap in overall wage growth between the target and reference groups (column 9). Columns 10-12 show the three terms of equation (5) as well as the share that each term represents of the overall gap, and the part of each term that is attributable to differential sorting of the target group relative to the reference group (i.e, the three terms in equation (6) and their respective shares of the three terms in equation (5)).[17]

Starting with the first row, we see that there is an 10.1 ppt gap in wage growth between the target group of interest (all women) and the reference group (men). As noted above, there is not much difference in the overall share of movers between these groups, but for both movers and stayers the target group has lower wage growth than the reference group. The entries in columns 10-12 show that the gender gap in wage growth of movers accounts for 53% of the overall gender gap in wage growth, while the gap for stayers accounts for 45% of the overall gap and the interaction term accounts for a relatively small share. The sorting components of the mover and stayer terms in equation (5) account for just under 20% of each term.

Looking at the data in row 2 for the comparison between childless women and men, we see a substantially larger gap in the wage growth of movers ($-0.098 = 0.101 - 0.199$) than in the wage growth of stayers ($-0.050 = 0.230 - 0.280$), and this is reflected in the somewhat larger share of the overall gap in wage growth between childless women and men that is attributable to the shortfall in wage growth of movers (see the entry in column 10). Again the sorting components of the mover and stayer terms are approximately equal, but as a share of the stayer-related component in equation (5) the sorting component is larger. The relative sizes of the mover and stayer components of equation (5) is reversed for women with children (see row 3), but as in rows 1 and 2 the sorting components of the mover and stayer terms are approximately equal.

Finally, in the comparison between mothers and non-mothers in row 4, we

[17]Since the interaction effects in equation (5) are very close to zero we do not show the percent of these effects attributable to the interaction component of the sorting effect.

see a relatively small maternity gap in the wage growth of movers ($-0.039 = 0.062 - 0.101$) but a relatively large maternity gap in the wage growth of stayers ($-0.110 = 0.120 - 0.230$). Consequently, our decomposition attributes a relatively large share of the overall maternity gap to the slower wage growth of mothers who remain at the same firm relative to non-mothers who remain with their initial firm. Here, the sorting component of the gap between mothers and non-mothers is relatively small: mothers are not much less likely to begin their careers at firms with faster wage growth *for stayers* than non-mothers.

4 Conclusions

A stylized fact is that women's wages grow more slowly over their careers than men's. This paper presents a descriptive analysis aimed at better understanding the role of firms in this gender growth gap. We have asked whether some firms offer their workers better career opportunities, and thus higher wage growth than others, and whether women and men start their careers in systematically different firms. To answer these questions, we have relied on rich matched employer-employee data from Italy to identify a worker's first-job firm. We have computed the worker's wage growth over the next 5 years, restricting attention to workers entering into firms that hire at least 2 female and 2 male entrants. Our focus has been on the impact of this first-job firm on gender differences in future career trajectories and wage growth.

Our results can be summarized as follows. First, we have found that the average rate of wage growth of newly entering workers is relatively high but varies substantially across firms – even among the firms in our main analysis sample that hire relatively frequently. This basic finding confirms that firm policies have an important mediating role in workers' wage growth, as is implicitly spelled out in standard models of on the job training, and is documented in the recent study by Arellano-Bover and Saltiel (forthcoming).

Second, we confirm the finding in several recent studies that the gender gap in wages is relatively modest at initial entry to the labor market (about 7%), but widens with experience, reflecting slower average wage growth for women than men. In our sample of entrants who start off with jobs lasting at least 2 years, the gender gap in wage levels reaches about 13 ppt after 5 years for all entrants, and 17 ppt for those who start at frequently-hiring firms. Moreover, as has been noted in the recent literature on the career costs of children, women who have a child in their first 5 years experience even slower wage growth than other women.

Third, we find that differences in the sorting of women to different entry firms can account for about 20% of the slower growth in wages of women as a whole, and 25% of the slower growth in wages of childless women relative to men. Importantly, differential sorting also explains about 10% of the relatively slower wage growth for women with children, even among higher-educated women.

Fourth, we find that there are similar gender gaps in the wage growth of people who remain at the same firm in the first 5 years of their career and those who switch jobs. The differential sorting of women to their first jobs accounts for 15-20% of the gender gap in wage growth for both movers and stayers. Indeed, our analysis suggests that the *same* firm-specific component of wage growth is shared by movers and stayers. This suggests that the main difference across firms is in the provision of training or on-the-job learning that is valued by the market as a whole, rather than firm-specific knowledge.

Finally, a comparison between movers and stayers sheds some new light on the motherhood-related gap in wage growth. In particular, we find that the gap between mothers and non-mothers is especially large for workers who stay at the same firm, and is smaller for job movers. Contrary to our initial expectations, having a stable employer does not seem to lessen the career costs associated with the arrival of a child.

While our analysis has brought some new insights into the role of firms in generating a gender wage gap over the life cycle, much remains to be done in future research. We have not explored the connections between the initial level of wages and the rate of wage growth. This relationship is central to the traditional theory of on-the-job training (e.g., Hause 1980 and Lillard and Weiss, 1979) which assumes that workers accept lower initial wages to work in jobs that provide more training. The recent analysis by Arellano-Bover and Saltiel (forthcoming), however, finds no evidence of such a trade off.

Another limitation of our analysis is that many smaller firms are excluded by our requirement that firms hire at least 4 entrants over 3 years. We suspect it may be possible to sidestep this limitation using the clustering approach of Bonhomme and Manresa (2015), which effectively pools similar firms.[18] Finally, our analysis focuses on early career wage growth, and only looks at the effect of the first employer. Using additional data it would be possible to examine outcomes over the longer term and assess the persistence in wage growth differences originating from an entrant's first job versus later jobs. It also would be interesting to know how the size of the slowdown in wage growth for mothers who have children varies by the timing of childbirth, and whether there is more or less heterogeneity across employers in the relative slowdown for later births.

[18] Arellano-Bover and Saltiel (forthcoming) use this approach to estimate returns to experience for classes of firms.

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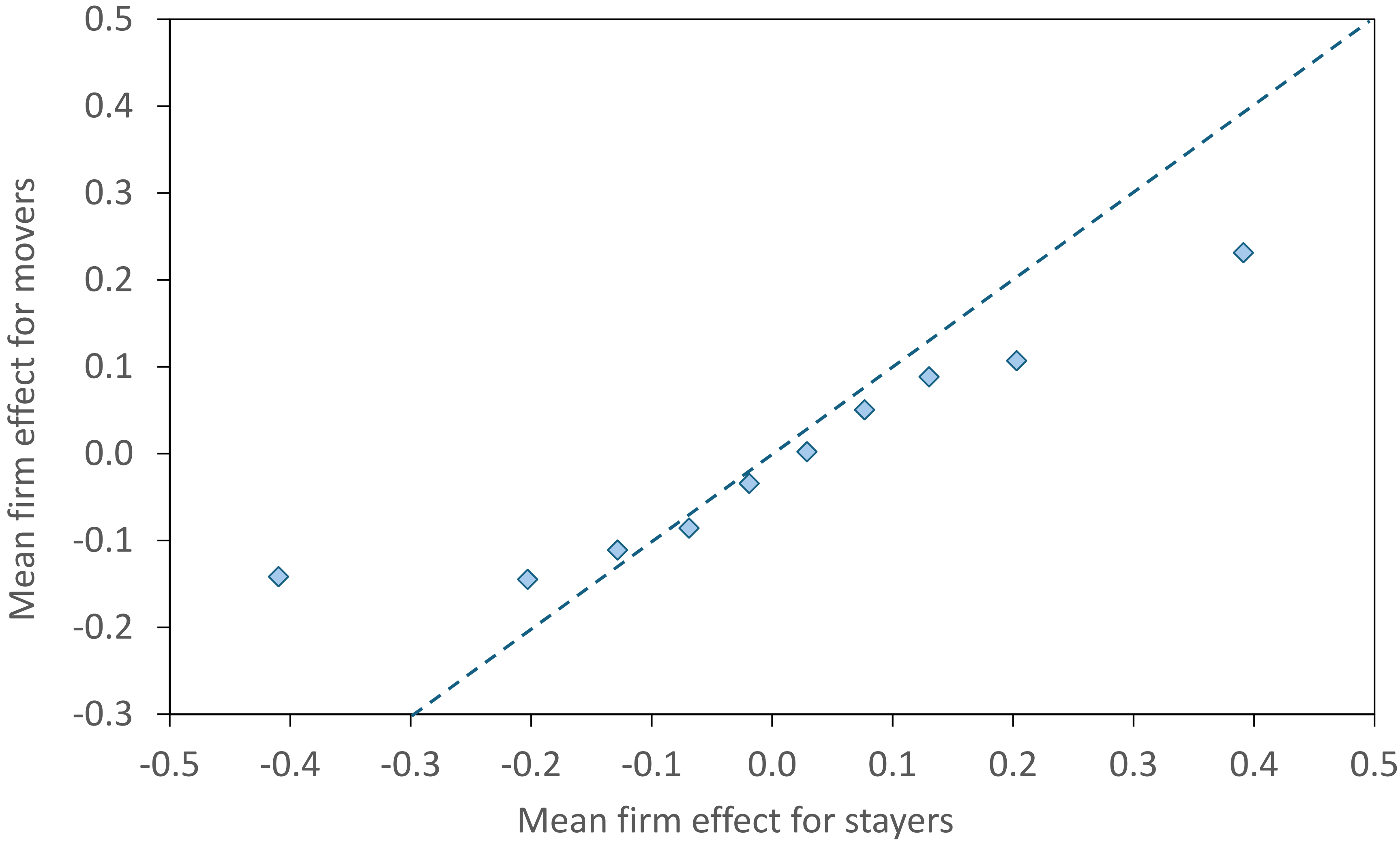
Figure 1: Bin-scatter of firm effects in models for movers vs. stayers



Note: X-axis shows mean estimated firm effects in model for wage growth of stayers; Y axis show mean estimated firm effects in model for wage growth of movers. Each point represents 10% of firms, binned by their firm effects for wage growth of stayers. Dashed line represents 45 degree line.

Table 1: Characteristics of First Job Entrants (2010-2012)

	All first job entrants 2010-2012		Entrants with a job 5 years later		Entrants with a job 5 years later, firm has 2+ entrants of each gender		Entrants with higher degree and job 5 years later, firm has 2+ entrants of each gender	
	Men (1)	Women (2)	Men (3)	Women (4)	Men (5)	Women (6)	Men (7)	Women (8)
Share of all first job entrants	1	1	0.700	0.665	0.160	0.221	0.062	0.093
Age at start of first job	23.68	23.87	23.62	23.83	24.40	24.48	26.45	26.18
Share with higher degree	0.149	0.229	0.171	0.263	0.391	0.418	1.000	1.000
Mean daily wage of first job	62.81	58.67	63.19	60.05	75.03	70.35	84.81	79.98
Share permanent first jobs	0.616	0.537	0.624	0.553	0.451	0.400	0.537	0.434
Has a job 5 years later	0.713	0.682	1.000	1.000	1.000	1.000	1.000	1.000
Mean log wage growth (first 5 years of career)	--	--	0.197	0.132	0.239	0.138	0.361	0.216
Share stayers (at initial firm)	0.322	0.302	0.455	0.445	0.497	0.476	0.565	0.557
Share has a child in first 5 years	--	0.225	--	0.280	--	0.306	--	0.357
Number of workers	240,442	182,990	168,280	121,712	38,353	40,501	15,009	16,935

Note: Based on authors' tabulations of INPS data. Wages refer to nominal wages. First time jobs of entrants are restricted to full time jobs with a daily wage of at least 10 euros, and information on the worker's education. To be classified as having a job 5 years later the entrant must have a job with a daily wage of at least 10 euros. Higher degree in columns 7 and 8 refers to a bachelor's degree or higher.

Table 2: Characteristics of Female First Job Entrants with and without a Child

	Entrants with job 5 years later		
	All	No Child	Has Child
	(1)	(2)	(3)
Share of group	1	0.694	0.306
Age at start of first job	24.48	24.16	25.19
Share with higher degree	0.418	0.388	0.487
Mean daily wage of first job	70.35	69.39	72.53
Share permanent first jobs	0.400	0.380	0.445
Mean log wage growth (first 5 years of career)	0.138	0.157	0.095
Share stayers (at initial firm)	0.476	0.434	0.573
Share has a child in first 5 years	0.306	0	1
Number of workers	40,501	28,092	12,409

Note: See note to Table 1.

Table 3: Models for wage growth in first 5 years of career

	All workers			Workers with higher degree		
	Regression models for change in log wage in first 5 years		Percent of gender gap(s) explained by initial firm	Regression models for change in log wage in first 5 years		Percent of gender gap(s) explained by initial firm
	(1)	(2)	(3)	(4)	(5)	(6)
A. Combining mothers and non-mothers						
Female	-0.107	-0.082	23.36	-0.143	-0.107	25.17
	(0.003)	(0.003)		(0.004)	(0.004)	
Firm fixed effects	no	yes		no	yes	
Adjusted R-squared	0.058	0.267		0.057	0.291	
Direct estimate of G	-0.023		21.47	-0.021		14.34
B. Separating mothers and non-mothers						
Female with maternity leave	-0.163	-0.128	21.47	-0.220	-0.173	21.36
	(0.004)	(0.004)		(0.006)	(0.005)	
Female with no maternity leave	-0.082	-0.062	24.39	-0.100	-0.070	30.00
	(0.003)	(0.003)		(0.005)	(0.004)	
Firm fixed effects	no	yes		no	yes	
Adjusted R-squared	0.061	0.269		0.070	0.300	
Direct estimate of G^c	-0.029		17.98	-0.030		13.68
Direct estimate of G^n	-0.020		24.88	-0.016		15.60
C. Differences between mothers and non-mothers			Percent explained by sorting			Percent explained by sorting
Maternity penalty	-0.081	-0.066	18.52	-0.120	-0.103	14.17
Difference in G^c versus G^n	-0.009		11.11	-0.014		11.67

Notes: Estimated standard errors in parentheses. Sample size for models in columns 1 and 2 is 78,854 (see columns 5 and 6 of Table 1). Sample size for models in columns 3 and 4 is 31,944 (see columns 7 and 8 of Table 1).

Table 4: Characteristics of Job Stayers and Job Movers (Workers with initial job at firm with 2+ of each gender who have job 5 years later)

	Men			Women			Women without children			Women with children		
	All	Stayers	Movers	All	Stayers	Movers	All	Stayers	Movers	All	Stayers	Movers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age at start of first job	24.40	24.69	24.12	24.48	24.91	24.09	24.16	24.57	23.85	25.20	25.49	24.81
Share with higher degree	0.391	0.440	0.343	0.418	0.490	0.353	0.388	0.450	0.340	0.487	0.550	0.402
Mean daily wage of first job	75.03	78.83	71.28	70.35	74.05	66.99	69.39	73.23	66.45	72.53	75.46	68.59
Share permanent first jobs	0.451	0.520	0.383	0.400	0.460	0.345	0.380	0.440	0.334	0.445	0.490	0.383
Mean log wage growth (first 5 years of career)	0.239	0.280	0.199	0.138	0.189	0.092	0.157	0.230	0.101	0.095	0.120	0.062
Share stayers (at initial firm)	0.497	1	0	0.476	1	0	0.434	1	0	0.573	1	0
Number of workers	38,353	19,060	19,293	40,501	19,297	21,204	28,092	12,184	15,908	12,409	7,113	5,296

Notes: See note to Table 1.

Table 5: Models for wage growth in first 5 years of career, movers versus stayers

	Stayers			Movers		
	Regression models for change in log wage in first 5 years		Percent of gender gap(s) explained by initial firm	Regression models for change in log wage in first 5 years		Percent of gender gap(s) explained by initial firm
	(1)	(2)	(3)	(4)	(5)	(6)
A. Combining mothers and non-mothers						
Female	-0.096	-0.069	28.13	-0.111	-0.095	14.41
	(0.003)	(0.003)		(0.005)	(0.005)	
Firm fixed effects	no	yes		no	yes	
Adjusted R-squared	0.047	0.303		0.064	0.294	
Direct estimate of G	-0.018		18.24	-0.017		15.32
B. Separating mothers and non-mothers						
Female with maternity leave	-0.169	-0.133	21.30	-0.157	-0.134	14.65
	(0.005)	(0.004)		(0.007)	(0.007)	
Female with no maternity leave	-0.054	-0.032	40.74	-0.096	-0.082	14.58
	(0.004)	(0.004)		(0.005)	(0.005)	
Firm fixed effects	no	yes		no	yes	
Adjusted R-squared	0.061	0.313		0.066	0.295	
Direct estimate of G^c	-0.023		13.49	-0.024		15.29
Direct estimate of G^n	-0.015		27.96	-0.013		13.54
C. Difference between mothers and non-mothers			Percent explained by sorting			Percent explained by sorting
Maternity penalty	-0.115	-0.101	12.17	-0.061	-0.052	14.75
Difference in G^c versus G^n	-0.008		11.11	-0.011		11.67

Notes: Estimated standard errors in parentheses. Sample size for models in columns 1 and 2 is 38,357 (see columns 2 and 5 of Table 4). Sample size for models in columns 3 and 4 is 40,497 (see columns 3 and 6 of Table 4).

Table 6: Decomposition of Wage Growth Gaps into Components Attributable to Movers and Stayers

	Wage growth in first 5 years		Share movers		Wage growth movers		Wage growth stayers		Wage growth gap	Decomposition		
	Target	Reference	Target	Reference	Target	Reference	Target	Reference		Movers	Stayers	Interaction
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Comparison:												
1. Women (all) versus men	0.138	0.239	0.524	0.503	0.092	0.199	0.189	0.280	-0.101	-0.054	-0.045	-0.002
									Share of gap (%)	53.3%	44.8%	2.0%
									Sorting component	-0.009	-0.009	-0.005
									Sorting share (%)	15.9%	19.8%	--
2. Childless women versus men	0.157	0.239	0.566	0.503	0.101	0.199	0.230	0.280	-0.082	-0.049	-0.025	-0.008
									Share of gap (%)	60.1%	30.3%	9.9%
									Sorting component	-0.007	-0.007	-0.006
									Sorting share (%)	13.3%	30.0%	--
3. Women with child versus men	0.095	0.239	0.427	0.503	0.062	0.199	0.120	0.280	-0.144	-0.069	-0.080	0.004
									Share of gap (%)	47.9%	55.2%	-3.1%
									Sorting component	-0.012	-0.011	-0.006
									Sorting share (%)	17.5%	14.4%	--
4. Women with child versus childless women	0.095	0.157	0.427	0.566	0.062	0.101	0.120	0.230	-0.062	-0.022	-0.048	0.008
									Share of gap (%)	35.6%	77.0%	-13.0%
									Sorting component	-0.006	-0.003	0.002
									Sorting share (%)	28.2%	7.3%	--

Note: This table implements the decomposition described by equation (5) in the text. The sorting components shown in columns 10, 11, and 12 are based on estimates of G, G^n, and G^c shown in Tables 3 and 5, using equation (6). See text for explanation.