Do Female Executives Make a Difference? The Impact of Female Leadership on Firm Performance and Gender Gaps in Wages and Promotions.*

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Abstract

We study whether female executives make a difference by proposing three contributions. First, we examine the relationship between gender leadership at the firm (CEOs and top executives) and firm performance. Differently from the previous literature, we focus on less volatile, more long-term measure of actual firm productivity: TFP, value added per worker and sales per worker. Second, we investigate the mechanisms behind this relationship, focusing on the impact of firm leadership on wages and promotion policies. Finally, we propose a theoretical framework consistent with our results and able to evaluate the cost of the heavy underrepresentation of women at top positions within firms. In performing our empirical work, we use a unique matched employer-employee data set from Italy where we observe the entire labor force at each firm over 17 years. We find that female executives make a difference: The interaction between female leadership and female workers at the firm has a positive significant impact on firm performance. We suggest that an important mechanism behind this interaction is the wage policy at the firm: female leadership implies wage increases for women at the top of the wage distribution and wage decreases for women at the bottom. We conclude by interpreting this evidence as being consistent with a model of statistical discrimination where female executives correct discrimination generated by male executives. If our interpretation is correct, there are productivity costs associated with the underrepresentation of women at the top of the firm.

JEL Codes: M5, M12, J7, J16.

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1 Introduction

A growing literature is showing that executives make a difference at the firm.[1] From their management style to their attitude towards risk, executives' characteristics seems to be, together with management practices,[2] one of the main drivers of firms' success and productivity. In this paper, we ask whether one specific individual characteristic - gender - makes a difference.

The labour literature has provided abundant evidence of systematic gender differentials in the labor market.[3] More recently, the economics of leadership literature has singled out an astounding empirical regularity: women are almost ten times less represented than men in top positions at the firm.[4] For example, recent data on the US show that even though females are a little more than 50% of white collar workers, they represent only 4.6% of the executives. Our own data on Italy show that a little more than 20% of white collars workers in the manufacturing sector are women compared with only 2.5% of the executives.[5] Both sets of facts suggest that looking at gender as a relevant executive characteristics is not only interesting but may also have important productivity and welfare implications.

We provide three contributions to this extremely thin literature. First, we study the relationship between gender leadership at the firm (CEOs and top executives) and firm performance. Differently from the previous literature, we focus on less volatile, more long-term measures of actual firm productivity: sales per worker, value added per worker and TFP. Second, we investigate the mechanisms behind this relationship, focusing on the im-

[1] A growing literature is following the influntial Bertrand and Schoar (2003). Among recent contributions, see Kaplan, Klebanov, Sorensen (2012); Bennedsen, Perez-Gonzales, Wolfenzon (2012); Lazear, Shaw, Stanton (2012). For work on overconfidence, see Malmendier and Tate (2005). For theoretical contributions, see for example Gabaix and Landier (2008) and Tervio (2008) For contributions focusin on both executives and firms characteristics, see Bandiera, Guiso, Prat and Sadun (2012).

[2] See Bloom and Van Reenen (2007) for one of the first constribution enphasizing this point. A recent survey is Bloom and Van Reenen (2010).

[3] For an overview of the gender gap in the US labor market in the last twenty years, see Blau and Kahn (2004), Eckstein and Nagypal (2004) and Flabbi (2010).

[4] The literature on the US is based on the Standard and Poor's Execucomp dataset, which contains information on top executives in the S&P 500, S&P MidCap 400, S&P SmallCap 600. See for example, Bertrand and Hallock (2001); Wolfers (2006); Gayle, Golan, Miller (2011); Dezso and Ross (2012). The literature on other countries is extremely scarce: see Cardoso and Winter-Ebner (2010) on Portugal, and Ahern and Dittmar (2012) and Matsa and Miller (2012) on Norway (the latter papers however consider the gender composition of corporate boards). A related literature is concerned with underrapresentation of women at the top of the wage distribution, see for example Albrecht, Bjorklund and Vroman (2003). Both phenomena are often referred to as a *glass-ceiling* preventing women from reaching top positions in the labor market.

[5] Sources for the US are: Current Population Survey data for the white collars workers and ExecuComp data for the executives. Sources for Italy are our own raw data, a rapresentative sample of the Italian manufacturing sector. See the data section of the paper for details.

pact of firm leadership on wages and promotion policies. Finally, we propose a theoretical framework consistent with our results and able to evaluate the cost of the heavy underrepresentation of women at the top of the firm.

In performing our empirical work, we use a unique matched employer-employee dataset from Italy which includes information on the entire labor force of a large sample of firms representative of the manufacturing sector in the period 1982-1997. The data set is very rich in firm-level characteristics (including balance sheet information). Crucially, we observe the gender of all workers, including the top executives and the top earners. We use this information to measure the extent of the presence of women in executive positions at the firm and to infer the gender of the CEO. We consider three measures of female leadership in the firm: 1) the share of female executives, 2) an indicator for whether females represent more than 25% of executives, and 3) an indicator for whether the firm's CEO (defined as the highest-paid executive) is female.

Thanks to these data, we can study the effect of female leadership on firm performance by conditioning on a wider range of controls than the ones included in the few previous works in the literature. We can control not only for unobserved firm heterogeneity, but also for labor force and executives' observed and unobserved heterogeneity. Specifically, we use the large panel sample of matched employer-employee data to estimate a two-way fixed effects regression on individual wages (Abowd, Kramarz and Margolis, 1999), which gives us estimates of the value of individuals' (workers and executives) unobservable (to the econometrician) skills, independent of observables and of the characteristics of the particular firms where they are employed at a given point in time.[6] The data are particularly appropriate for this exercise because they include a large representative sample of firms observed over 17 years and *all* the workers hired by these firms or that have transited through them. This particular feature maximizes the number of transitions available to identify both firms' and workers' fixed effects. We then use the estimated individual fixed effects as controls for the composition of the unobserved ability of the labor force at the firms, and for the unobserved individual ability of the executives when estimating the impact of the female leadership on firm performance. We find that a systematic relationship between female leadership and firm performance does exist. The result is robust to three different definitions of firm performance (sales per employee, value added per employee, and TFP),

[6] The Abowd, Kramarz, Margolis (1999) wage decomposition rests on an assumption of exogenous worker mobility conditional on observables. Following Card, Heining and Kline (2013), we performed several tests and conclude that the assumption is roughly met in the data (see section 4.2 below and the Appendix for details).

two different samples (full sample and balanced panel), and to the different measures of female leadership described above. The relationship crucially depends on the gender composition of the labor force at the firm: if a sufficiently high share of the labor force is female, then female leadership is associated with higher firm performance; the opposite is true if females represent only a small proportion of the firm's workforce.

To analyze the mechanisms behind this relationship, we look at the effect of female leadership on wages and promotions at the firm. If a large literature exists that studies gender differentials in the labor market, and a fairly developed literature exists that studies gender differentials using matched employer-employee data, the literature on the relationship between the gender of the firm's executives and gender differentials at the firm is extremely scarce. Bell (2005) looks at the impact of female leadership in US firms but only on *executives* wages. Cardoso and Winter-Ebner (2010) look at the impact on all workers on a sample of Portuguese firms but without allowing for heterogeneous effects over the distribution. Thanks to our data, we can look at the impact on the entire labor force at the firms allowing for heterogenous effects over the wage distribution. Our quantile regression results show that this heterogeneity is relevant: the impact of female leadership is positive on women at the top of the wage distribution but negative on women at the bottom of the wage distribution. Preliminary descriptive evidence on promotion to executives shows a similar pattern: female leadership increases the probability of promotion for women only if women are in the top quartile of the wage distribution.

We propose a theoretical framework able to jointly take into account all our empirical results. We embed employer statistical discrimination in an assignment model with asymmetric information, labor market frictions, turn-over and learning. We further assume that employers are better at extracting information from workers of their same gender (Cornell and Welch, 1996). Starting with initial conditions where a higher proportion of employers are male, the equilibrium generates a misallocation of women to jobs, a gender gap in wages, and a glass-ceiling effect. Female CEOs and executives optimally counteract pre-existing statistical discrimination by improving the wage and promotion prospects of high-ability females. As a result, women's wages increase at the top of the wage distribution but decrease at the bottom when female leadership arises at the firm. The results on firm performance are consistent with this model because female leadership can improve firm performance only if there are enough mismatched women at the firm.

The remainder of the paper is structured as follows. The next section sketches the theoretical framework. Section 3 describes the data and the estimation samples. Section

4 presents our analysis of the effect of female leadership on firm performance. Section 5 presents evidence on the relationship between female executives and wage and promotion policies at the firm. Section 6 concludes.

2 Theoretical Framework [PRELIMINARY]

2.1 Environment

We extend the standard statistical discrimination model in Phelps (1972) to include two types of jobs. There are males (m) and female (f) workers with productivity q distributed normally with mean μ and standard deviation σ. Initially, firms are managed by male CEOs who observe a signal of productivity $s = q + \epsilon$, where ϵ is distributed normally with mean 0 and standard deviation $\sigma_{\epsilon g}$ that differ across genders m and f. The signal's standard deviation can be interpreted as a measure of the signal's informativeness. We assume $\sigma_{\epsilon m} < \sigma_{\epsilon f}$ to indicate that male CEOs have better ability to communicate and observe productivity of workers of their own gender.[7] Employers assign workers to two jobs, which require complex (c) and simple tasks (e). We normalize productivity of all workers in the simple task to zero, whereas productivity in the complex task is 1 only if workers have productivity $q > \overline{q}$, and -1 otherwise.[8] The idea is that the complex task requires more skills to be completed succesfully and if it is not completed succesfully may actually generates losses.

2.2 Only Male CEOs

Firms compete for workers and maximize production given wages. Workers care only about wages and not about job assignment, therefore in equilibrium each worker is paid its marginal product, therefore wages are zero in the simple task, and $E(q|s)$ in the complex task. The wage in the complex task is the same as the wage schedule in Phelps (1972).

Standard properties of the bivariate normal distribution imply that $E(q|s)$ follows a normal distribution, which we denote with $f_g(q|s)$, with mean $\alpha_g q + (1 -_g \alpha)s$, where $\alpha_g = \sigma^2_{\epsilon g}/(\sigma^2_{\epsilon g} + \sigma)$, and standard deviation $\sigma\alpha_g$, $g = \{m, f\}$. The conditional mean is increasing in both q and s. Hence, in equilibrium, employers assign workers to jobs using a cutoff rule: workers will be employed in job-task c if $s \geq \overline{s}$ computed as the unique solution

[7] See Fadlon (2010) for a brief survey of the medical, psychological and linguistics literature on demographic differences in communication quality. Cornell and Welch (1996) also make the same assumption in their model of screening discrimination.

[8] It may be helpful to think of all variables as expressed in logarithms, which leads to log normal productivity and wage distributions

to $E(q \geq \overline{q}|s) - E(q < \overline{q}|s) \geq 0$. We denote this solution with $\overline{s}(\sigma_{\epsilon g})$ to stress its dependence on the signal's noise. The worker with signal $\overline{s}$ has the same expected productivity (zero) in both jobs. Competition ensures that wages paid are equal to expected marginal products: $w_g(s) = E(q \geq \overline{q}|s) - E(q < \overline{q}|s) = 2E(q \geq \overline{q}|s) - 1$ in the complex job, and 0 in the simple job. It is possible to show that if $\overline{q} < (=, >)\mu$ then $\overline{s} < (=, >)\mu$. It is informative to stress the properties of this wage schedule as a function of the signal's noise $\sigma_{\epsilon g}$. Consider the case $\overline{q} < \mu$. In this case, $\overline{s} < \mu$. As the signal's informativeness decrease ($\sigma_{\epsilon g}$ increase), the mean of $f_g(q|s)$ decrease and its standard deviation increase. It can be shown that $E(q \geq \overline{q}|s)$ decreases for any s. Therefore, $\overline{s}$ decreases. Figure 1 displays the outcome for workers with two different value for the variance of the signal's noise, and two different values of $\overline{q}$. The darker lines display the equilibrium wages, whereas the lighter red and black lines display expected marginal product in the complex task conditional on the signal in ranges of the signal where it is optimal to employ workers in the simple task.

Assume that the noisier signal comes from female workers. Females have expected productivity that is more concentrated around the mean. The associated cdf of $f_g(s)$ is therefore flatter, which implies that females wages are higher in the complex task for low values of the signal, and lower for higher values of the signal. The threshold signal is lower for females in the first panel, where $\overline{q} < \mu$, and is higher in panel b, where $\overline{q} > \mu$.

To give a numerical example, with the parameters used to display panel (a), there are fewer females than males in the right tail of the quality distribution conditional on any given signal, fewer males are mismatched, and productivity for males is, on average, 0.478, whereas for females it is 0.408. If workers were perfectly assigned, productivity would be 0.691. With the parameters of panel (b), 28.6 percent of males and 18.6 percent of females are employed in the complex task and their average production is respectively 0.119 and 0.039, whereas output under perfect information would have been 0.34.

2.3 Male CEOs and "few" Female CEOs

We now introduce female CEOs but we assume that there are "few" of them. By this we mean that the proportion of female CEOs is so small that the economy is characterized by the male CEOs equilibrium wages. As a result, when a female CEO enters a new firm, she assumes that the wages and the job assignment have been made by a male CEO. Given the actual very low proportion of female CEOs in the data, this assumption is quite reasonable: in the data, no female CEO becomes CEO in a firm previously managed by a woman.[9]

[9] However, we assume the number of female CEO's that enter is sufficient to drive wages of their workers to marginal products. In principle, two CEOs engaging in Bertrand competition are enough to generate this

Female CEOs are characterized by a better ability to assess the productivity of female workers. We model this intuition by assuming that female re-interpret the female workers' signal as being extracted from a more precise distribution, with $\sigma_{\epsilon F} < \sigma_{\epsilon f}$.[10] Female CEOs, when taking over a company managed by males, do not discard the previous CEOs assessment of male workers since they know it is more precise than their own. Therefore male workers are unaffected by the change of management.[11]

The outcome for female workers is now equivalent to the black line in the Figure 1. In equilibrium, in firms managed by female CEOs, female receive higher wages if they have high signal value, but wages decrease for values that are relatively lower. Wages remain constant in the simple task, but this is only because quality has no effect on the simple task's productivity. If quality had some effect on productivity, wages of low signal workers would decrease when their signal quality improves.

2.4 Empirical Implications

If we start with initial conditions characterized by a gender imbalance in the number of employers - the majority of employers are men - then the model would generate the following implications (without needing to assume higher productivity for men than women):

1. Women will receive lower wages than men and they will be "mismatched" to jobs more frequently than men because their signal is noisier for a larger proportion of employers.

2. Female CEOs and executives improve performance at firms with a significant proportions of female workers (i.e., where the initial misallocation is more severe) because they are able to correct the previous "wrong" wages and job assignments of the female workforce (put in place by the previous largely male CEOs).

3. Female CEOs and executives have limited scope in re-assigning male employees because they are already better assigned to job and wages than female employees.

4. Correction of previous "wrong" wages and job assignments means wage increases for women at top of the wage distribution and wage decreases at the bottom.

result.

[10] This assumption can be micro-founded assuming that female CEOs observa an additional signal for each workers, but that the female workers' signal is more precise than male workers'.

[11] We do this for simplicity. The crucial assumption for our purposes is that female CEO's have more precise information than males over the skills of female workers, and less precise information over the skills of male workers.

3 Data and Descriptives

The data used in this paper come from two sources, INVIND-INPS and Company Accounts Data Service (CADS). INVIND-INPS is a matched employer-employee data set which has the following structure. The starting point is the Bank of Italy's annual survey of manufacturing firms (INVIND), an open panel of around 1,000 firms per year, representative of manufacturing firms with at least 50 employees. The Italian Social Security Institute (INPS) provided the complete work histories of all workers who were ever employed at an INVIND firm in the period 1980-1997, including spells of employment in which they were employed in firms not listed in the INVIND survey. The information on workers contained in the INVIND-INPS data includes gender, age, tenure,[12] occupational status (production, non-production, manager), annual gross earnings (including irregular payments such as overtime, shift work and bonuses), number of weeks worked, and a firm identifier. All records with missing entries on either the firm or the worker identifier, those corresponding to workers younger than 15 and older than 65, and those corresponding to workers with less than four weeks worked in a given year have been deleted. For each individual-year, we kept only the observation corresponding to the main job (identified in terms of number of weeks worked). Overall, the INVIND-INPS data set includes information on about a million workers per year, more than half of whom are employed in INVIND firms in any given year. The remaining workers are employed in about 450,000 other firms of which we only know the firm identifier.[13] In Table 1 we report summary statistics on workers' characteristics for the entire sample. About 66% of observations pertain to production workers, 32% to non-production employees, and 2.1% are executives. Even though females represent about 21% of the workforce, only 2.5% of executives are women. On average, workers are 37 years old, with males being about 2.5 years older than females (37.1 vs. 34.5). Average gross weekly earnings at 1995 constant prices are around 391 euros, with female earning about 28% less than males (310 euros vs. 411 euros).

The CADS data includes balance-sheet information for a sample of about 40,000 firms (including most INVIND firms) in the period 1982-1997. The data include information on the industry, geographic location, sales revenues, value added at the firm-year level, and a firm identifier. Because the firm identifier in CADS and INVIND-INPS are the same, we are able to match the worker-level data with the firm-level data. The merged INVIND-INPS-CADS dataset includes 7,909 firm-year and 4,567,316 worker-year observations. In

[12] Our data on tenure is left-censored because we do not have information on workers prior to 1981.
[13] This is the same database used by Iranzo, Schivardi and Tosetti (2008) and Macis and Schivardi (2012).

Table 2 we report summary statistics on the entire, matched INVIND-INPS-CADS sample of firms as well as for a balanced panel, which we will use as our estimating sample in our main empirical analyses. A total of 822 unique firms are included in the INVIND-INPS-CADS sample. Of these, 234 form the balanced panel of firms continuously in the data set between 1987 and 1997. For the entire sample, average gross weekly earnings at 1995 constant prices are about 389 euros, and the average age of workers is 37.3 years. 68.6% of the observations are blue collars, 29% are white collars, and 2.4% are executives. The corresponding characteristics in the balanced sample are very similar.

We identify female leadership at the firm making heavy use of the classification "executive" present in the data. As already observed by Bandiera, Guiso, Prat and Sadun (2012), one advantage of using data from Italy is that this indicator is very reliable since the job title of executive is subject to a different type of labor contract and is registered is a separate account with the social security administration.[14] Within the executives, we identify the CEO as the executive with the highest earnings. Given our fairly complete measure of compensation and given the structure of the salary determination in the Italian manufacturing sector, this assumption should be quite accurate in capturing the top executive in charge of the firm.

In terms of aggregate descriptive statistics, females are 26.4% of the workforce at INVIND firms, but only 3.1% of the executives. Only 1.9% of CEOs are females. The descriptive statistics for the balanced panel are quite similar to those referring to the whole sample and confirm the underrepresentation of women in top positions at the firm found for other countries. In particular, the ratio between women in the labor force and women classified as executives is very similar to the ratio obtained from the Execucomp data for the U.S.

Figure 2 shows that the female representation in executive positions in Italy increased over time, but remains very small by the end of the period. In 1980, slightly above 10 percent of firms had at least one female executive, and females represented 2% of all executives and 1% of CEOs. In 1997, these figures were 20%, 4% and 2%, respectively. Table 3 presents the distribution of female executives across industries. Even though there is substantial variation across industries in the presence of females in the executive ranks, no obvious pattern emerges in terms of the relationship between female leadership and the presence of females in the non-executive workforce in the various industries.

Table 4A reports descriptive statistics for firms with no female executives and firms with at least one female executive. Firms with some female executives are larger, pay

[14] The original job description in Italian is *dirigente*, which roughly corresponds to a top manager in a US firm.

higher wages and appear to be more productive based on sales per employee, value added per employee, and TFP. The composition of the workforce differs in that firms with some female executives employ a larger share of non-production workers (39 percent vs. 27 percent). The raw average gender wage gap is larger in firms with some female executives (about 18 percent vs. 14 percent). In Table 4B we compare firms with a male CEO with those with a female CEO. Firms with a female CEO are smaller, both in terms of employment and in terms of revenues, pay lower wages, and employ a larger share of blue collars. Firms with a female CEO also employ a slightly larger share of female workers (35 vs. 31 percent). However, when one looks at measures of productivity (sales per employee, value added per employee, and TFP), the differences shrink considerably. For instance, total revenues are on average 6.47 times higher in firms with a male CEO than in firms with a female CEO, but revenues for employee, value added per employee and TFP are 1.33, 1.29 and 1.06 times higher, respectively.

4 Female Leadership and Firm Performance

As discussed in section 2 above, if female executives improve the allocation of female talents within the firm by counteracting pre-existing statistical discrimination, this would have efficiency consequences which could result in improved firm performance. The efficiency-enhancing effects of female executives should be stronger the larger the presence of female workers.

4.1 Econometric Model

We will be estimating the following econometric model:

$$y_{jt} = \mathbf{c}'_{jt}\beta_1 + \mathbf{z}'_{jt}\beta_2 + \mathbf{x}'_{jt}\beta_3 + \beta_4\gamma_{jt} + \boldsymbol{\alpha}'_{jt}\beta_5 + \boldsymbol{\lambda}_j + \eta_t + \varepsilon_{jt} \qquad (1)$$

where y_{jt} is a measure of firm performance, z_{jt} is a vector of firm-level observable characteristics, λ_j is a vector of unobservable firm effects; c_{jt} is a vector of observable firm executives' characteristics, including indicators of female leadership (our main object of interest), γ_{jt} is a measure of executives' unobservable ability, x_{jt} is a vector of workforce characteristics aggregated at the firm-year, and α_{jt} is unobservable workforce ability (mean and standard deviation of workers' ability in each firm-year); η_t are year dummies.

The main parameter of interest is the first element of the vector of coefficients β_1, i.e., the coefficient on the indicators of female leadership. We will use three measures of female leadership: 1) the share of female executives in a firm-year, 2) dummy variables for whether females represent 0%, between 0 and 25%, or more than 25% of executives in a given firm-year, and 3) a dummy variable equal to 1 if the firm's CEO is female in a firm-year.

If relevant unobserved heterogeneity at the worker- and firm-level were left out of the equation, three sources of bias would arise. First, the labor force composition at the firm may be different: firms with important female leadership representation may have systematically higher or lower ability workers. Second, on top of labor force composition, other unobservable firm effects may make one firm more productive than another and this unobserved firm-level component may not be randomly assigned between male- and female-led firms. Third, the selection on unobserved individual ability in the position of executive/CEO may not be the same by gender so that women executives/CEOs may be of systematically higher or lower ability than men executives/CEOs, and female leadership indicators might be capturing such difference rather than a "pure" gender effect.

We perform the estimation in two steps. In the *second* step, we estimate (1). In the *first* step, we jointly estimate the set of unobservables $\left(\gamma_{jt}, \lambda_j, \alpha_{jt}\right)$. We do so by estimating a two-way fixed effects regressions following the identification strategy outlined in Abowd, Kramarz and Margolis (1999) (AKM henceforth) and the estimation strategy proposed by Abowd, Creecy and Kramarz (2002).[15] Specifically, ther regression is the following:

$$w_{it} = \mathbf{s}'_{it}\beta + \eta_t + \alpha_i + \sum_{j=1}^{J} dj_{it}\Psi_j + \zeta_{it} \tag{2}$$

where w_{it} is the wage for individual i at time t, $\mathbf{s}'$ is a vector of observable individual characteristics, α_i is the individual fixed effect, dj_{it} is a dummy equal 1 if worker i is in firm j at time t and Ψ_j are the firms' fixed effects.

In the *second* step we plug the unobserved heterogeneity components thus estimated into (1). We perform the analysis in two steps because the gender of the executives is observed only for a subset of firms in our sample (those included in the INVIND survey) while we want to exploit the full set of transitions in the complete INPS sample to obtain a more robust identification of the unobserved heterogeneity at the worker and firm level. In fact, the identification of both the individual α_i and firm Ψ_j effects in equation (2) requires mobility of workers across firms in the sample. Prior to the actual estimation, we need to identify the groups of "connected" workers and firms. A connected group includes all the workers ever employed by any firm in the group, and all the firms that any worker in the group has ever worked for. It is only within connected groups that worker- and firm-effects

[15] We use the code developed by Ouazad (2008) for Stata.

can be identified (Abowd, Creecy and Kramarz 2002).[16]

Under the assumption of exogenous mobility of workers across firms conditional on observables, the estimated worker fixed effects can be interpreted as the component of wages due to the worker's pure ability, irrespective of the characteristics of the particular firm that employes the worker in a given year, and net of the personal, time-variant characteristics included in the controls. Likewise, the firm effect is interpreted as the component of wages specific to the firm where the employee works, and it might be due to particular compensation policies, such as efficiency wages or rent-sharing. However, as discussed at length in Card, Heining and Klein (2013, CHK henceforth), violations of the exogenous mobility assumption would change the interpretation of the estimated firm effects. Following CHK, we performed several tests to probe the validity of the exogenous mobility assumption. Specifically, a model including unrestricted match effects delivers only a very modest improved statistical fit compared to the AKM model, and the departures from the exogenous mobility assumption suggested by the AKM residuals are small in magnitude. Moreover, wage changes for job movers show patterns that suggest that worker-firm match effects are not a primary driver of mobility in the Italian manufacturing sector. Instead, the patterns that we uncover are consistent with the predictions of the AKM model for job movers. We conclude that in our context, similarly to what found by CHK in the case of Germany, the additively separable firm and worker effects obtained from the AKM model can be taken as reasonable measures of the unobservable worker and firm components of wages. The tests and results are described in detail in the Appendix.

4.2 Estimation Results

4.2.1 Estimating worker and firm effects

In Table 5, we present the first stage results, i.e., the results from estimation of Equation (2). The dependent variable is the natural logarithm of weekly wages. The vector of observable individual characteristics, $\mathbf{s}'$, includes age, age squared, tenure, tenure squared, a dummy variable for non-production workers and a dummy for executives (occupational status changes over time for a considerable number of workers), as well as a full set of interactions of these variables with a female dummy (to allow the returns to age, tenure and occupation to vary by gender), and a set of year dummies. As we mentioned when we discussed the identification issues, the first step in implementing the Abowd, Creecy and Kramarz (2002) methodology is the identification of connected groups of workers and

[16] The Abowd, Creecy and Kramarz (2002) estimation algorithm sets the average of worker effects to zero, and one of the firm-year effects to zero. Therefore, the absolute size of the estimated effects is meaningless.

firms. As it turns out, our sample consists of essentially one large connected group, with 99% of the sample forming a single connected group. Thus, in our estimation we focus on the largest connected group and disregard the remaining observations. The identification of firm effects and worker effects is guaranteed by the relatively high mobility of workers in the sample: about 70% have more than one employer during the 1980-1997 period, and between 8 and 15 percent of workers change employer from one year to the next. The estimated coefficients on the workers' observable characteristics are shown in Table 5. Results are as expected: wages appear to exhibit concave age and tenure profiles, and there is a substantial wage premium associated with white collar jobs and, especially, with executive positions.

4.2.2 Female Leadership and Firm Performance

Table 6 presents our first set of results on firm performance, i.e. coefficients from estimating model (1). We present results for our three measures of female leadership at the firm and three measures of firm performance. We focus our analysis on the balanced panel (firms that were continuously observed from 1987 through 1997) to avoid the selection of firms entering and exiting the sample. In Table 8 we present robustness checks where we use the full INVIND-INPS-CADS sample.[17]

The results from Table 6 broadly confirm what found in the previous literature [Wolfers (2006) and Albanesi and Olivetti (2008)][18]: female leadership does not appear to have a significant impact on firm performance.[19] However, a change in the specification leads to different results. Previous literature on the impact of female leadership has shown that one important channel of this interaction are policies related to the work force at the firm. The labor literature on gender differential has shown the importance of segregation, i.e. concentration of minority workers in given occupations, industries or firms. Finally, our own theoretical framework implies an important interaction between female leadership and gender composition of the workforce at the firm. This all indicates that empirical specifications should take these interactions into account.

[17] Tables A3-1, A3-2 and A3-3 in the Appendix present the full results.

[18] Recent works on the impact of gender quota for firms' boards have found a negative impact on short-term profits (Ahern and Dittmar (2012); Matsa and Miller (2012)). However, first, these papers consider the composition of boards, not executive bodies; second, it is not clear whether the impact is due to imposing a constraint on the composition of the board or to the fact that the added members of the boards are female.

[19] The only exception is represented by the proportion of female executives, for which we estimate a negative, large and significant coefficient when the dependent variable is value added for employee and TFP (columns 6 and 9 of Table 6). However, the interpretation of the coefficient is the partial effect on firm performance of a one-unit change in the explanatory variable, i.e. a jump from 0% to 100% in the proportion of female exexutives. Evaluated at reasonable values of the share of female executives, the magnitude of this effect is quite small.

The results are shown in Table 7. On all three measures of female leadership and three measures of firm performance, we find the same result: the interaction between female leadership and the proportion of non-executive female workers at the firm is positive and significant. In term of magnitude, the positive interaction term together with the negative intercept generates a non-significant impact at the mean of the proportion of women at the firm (about 20%). The result indicates that the non-significant impact we found in Table 6 was therefore entirely due to composition effects. If the proportion of women at the firm is about one standard deviation higher than the mean we obtain a positive significant impact, if it is about one standard deviation lower than the mean we obtain a negative significant impact. We want to emphasize that, contrary to previous literature, we obtain this result on measures of firm performance that are less affected by the perceptions of financial market operators on female leadership. In fact, our dependent variables are closer to actual measures of firm productivity. In particular, TFP is a measure of the efficiency with which the factors of production (labor, capital, materials) are combined to obtain a firm's output, and, according to Lucas (1978), TFP is directly determined by the ability of the firm's top executive(s). We computed TFP using the Olley and Pakes (1996) procedure.[20]

Our result of a positive effect of female leadership provided that a sufficient fraction of the workforce is female holds on the larger unbalanced sample. In Table 8 we replicate all of our main analyses using the full INVIND sample and we find that our results broadly hold qualitatively and, with a few exceptions, also quantitatively.

5 Female Leadership and Wages at the Firm

5.1 Econometric Model

We will be estimating by Quantile Regression the following econometric model:

$$w_{ijt}|g = FLead'_{ijt}\boldsymbol{\beta}^g + Work'_{ijt}\boldsymbol{\delta}^g + Firm'_{ijt}\boldsymbol{\gamma}^g + Exec'_{ijt}\boldsymbol{\chi}^g + \eta_t^g + \varepsilon_{ijt} \quad (3)$$

where w_{ijt} are the log weekly gross earnings of worker i at firm j in year t of gender g. $FLead_{ijt}$ are the same measures of female leadership we have used in the performance regressions: female CEO (dummy); proportion of female executives > 25% (dummy); and the proportion of female executives in the firm. We control for firm heterogeneity through two sets of variables. The vector $Firm_{ijt}$, which includes the following variables: 2-digit industry dummies, region dummies, employment dummies (100-250, 250-500, 500+), share

[20] See Iranzo et al. (2008) for the details.

females in non-executive workforce, average age of workforce, share blue collars, firm fixed-effect from the 2-way F.E. regression reported in Table 5. And the vector $Exec_{ijt}$, which includes the following Executive/CEO characteristics averaged at firm-year level: age, experience, tenure, executive fixed-effect from the 2-way F.E. regression reported in Table 5. We control for worker heterogeneity through the vector $Work'_{ijt} =$, wich includes: age, age squared, production worker dummy, average and SD of worker fixed-effect from the 2-way F.E. regression reported in Table 5. Finally, we control for time effects with the year dummies η_t.

5.2 Estimation Results

We run the quantile regressions separately on female workers and male workers. In Figures 3A-3C, we report the coefficients on the female leadership indicators for the 10th, 25th, 50th, 75th and 90th percentile regressions.[21] We begin, in Figure 3A, with reporting the coefficients on the share of female executives. Our results indicate that the share of female executives at the firm is associated with lower wages for female workers at the bottom decile of the conditional wage distribution, with zero or slightly positive effects at the 25th and 50th percentiles, and with positive and effects at the 75th and especially at the 90th percentile of the female wage distribution. As for males, the estimated coefficients are negative at the bottom, and very small and not statistically significant at the top of the male wage distribution. Thus, the male-female wage gap is reduced especially at the top of the wage distribution. In Figure 3B we show the coefficients on the dummy variable equal to 1 if the share of female executives is at least 25% , and we obtain a very similar pattern: this measure of female leadership is associated with higher wages for females at the top quantiles of the female wage distribution, and it does not have a significant effect on the wages of men. Finally, in Figure 3C we look at the coefficient on the female CEO dummy. Here we obtain that a female CEO substantially reduces wages for females at the bottom and increases them at the top.

These results are consistent with female CEOs raising wages and therefore reducing the gender wage gap for female workers at the top of the ability distribution, as predicted by a model where female executives counteract pre-existing statistical discrimination. In contrast, if female executives were simply favoring female workers, we would have observed a more uniform increase of female wages across the whole wage distribution.

[21] Tables A4-1, A4-2 and A4-3 in the Appendix present the full results.

6 Female Leadership and Promotions at the Firm [PRELIMINARY]

The INVIND-INPS data include an indicator for workers' occupation: production worker, non-production worker and executives. This enables us to observe promotions of workers to the executive rank.

In Table 9, we present a descriptive exploration of whether female executives have any impact on this gap. We limit the sample to white collars, which is the group of workers from which the vast majority of new executives comes from. The descriptive evidence presented in the table indicates a positive correlation between female leadership at the firm and the probability that a female white collar in year t is promoted to executive in year t+1 only if the female worker is in the top 25% of the (firm-gender-year-specific) wage distribution. This preliminary unconditional correlation points to a similar behavior to the one observed on wage determination: female leadership favors only top women at the firm.

Of course, this descriptive evidence does not account for possible individual and firm-level heterogeneity. In fact, it is possible that "female friendly" firms have both an important representation of females in leadership positions and higher promotion rates for female employees for some common, unobserved reason. Also, it is possible that high-ability females, who therefore have a higher probability to be promoted to executives, disproportionately join firms with female CEOs. Both factors might generate a spurious positive association between female leadership and promotion rates of female employees.

Econometric analysis: TO BE COMPLETED

7 Conclusion

We use a unique matched employer-employee dataset from Italy - which includes information on the entire labor force of a large sample of firms - to study whether female leadership at the firm makes a difference. Our empirical analysis suggests that it does: 1) The interaction between female leadership and the proportion of women at the firm has a positive impact on firm performance; 2) The impact of female leadership on women's wages is heterogenous: positive at the top and negative at the bottom of the wage distribution; 3) the unconditional correlation between female leadership at the firm and the proportion of women promoted to executive positions is also heterogenous: it is positive only for women in the top 25% of the white collar wage distribution.

Our proposed theoretical framework can account for all of these results. We start with a standard Statistical Discrimination model where workers' productivity is observed through a noisy signal and executives decides wages and job assignments based on the signal and the worker's type (gender). We assume, following Cornell and Welch (1996), that executives are better at extracting information from workers of their same type (gender). If most of the executives are male, then most of high productivity women are underpaid and misallocated in relatively low productivity jobs. Low productivity women, instead, are overpaid but also matched to the wrong jobs. When female leadership takes over a firm, this statistical discrimination is corrected. As a result, wages of high productivity women increase and wages of low productivity women decrease, as our second empirical result shows. At the same time, women are reallocated to jobs better matching their productivity, generating an increase in firm performance directly proportional to the fraction of women at the firm. This implication matches our first empirical result. By the same mechanism, only high wage / high ability women will see their chance of promotion to executive increase, as our third empirical evidence suggests.

We conclude that if our model correctly describes the mechanism behind our empirical results, then the observed strong underrepresentation of women in top positions at the firm may have high costs in terms of firm productivity and efficient allocation of resources.

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Table 1 - Descriptive statistics: Full INVIND-INPS sample

INVIND-INPS Data, 1980-1997		
	mean	(st.dev.)
% Production workers	65.7%	
% Non-prod. workers	32.2%	
% Executives	2.1%	
% Females	20.9%	
% Female execs.	2.5%	
Age	37.1	(10.1)
Age (Males)	34.5	(9.6)
Age (Females)	37.7	(10.1)
Wage (earnings/weeks)	390.6	(255.7)
Wage (Males)	411.8	(273.3)
Wage (Females)	310.3	(148.1)
Number of worker-year observations	18,938,837	
N. of unique workers	1,726,836	
N. of unique firms	453,000	

Table 2 - Descriptive statistics: INVIND-INPS-CADS sample

	Full sample		Balanced panel	
	Mean	(Std. Dev.)	Mean	Std. Dev.
Average employment	698.6	(3,269.3)	706.7	(1,309.1)
Average age of employees	37.3	(3.5)	37.6	(3.4)
Average wage (weekly)	389.1	(83.6)	406.9	(89.3)
Share non-prod. workers	29.0%		30.4%	
Share executives	2.4%		2.6%	
Share females	26.4%		25.0%	
Female executives (share of execs)	3.1%		3.8%	
Female CEO	1.9%		2.3%	
Sales (thousand euros)	92,770	(370,428)	118,890	(231,614)
Sales per worker	146.2	(147.6)	167.72	(110.76)
Value added per worker	43.9	(21.4)	48.23	(20.20)
TFP	2.42	(0.51)	2.50	(0.48)
Firm-Year Obs. (firms) [years]	7,909 (822) [16]		2,340 (234) [10]	

Notes: INVIND-INPS-CAD data. The balanced panel includes firms continuously observed in the period 1987-1997.

Table 3 - Females in the Workforce and Executive Positions, by Industry

	INVIND firms, 1982-1997		
Industry	Non-exec % females	Executives % female	CEOs % female
Wood and cork, except furniture.	26.1%	7.6%	7.0%
Wearing apparel; dressing and dyeing of fur	73.0%	6.5%	3.9%
Leather; luggage, handbags, saddlery, harness and footwear	46.8%	6.3%	0.5%
Chemicals, Coke, refined petroleum and nuclear fuel	24.4%	5.0%	2.3%
Motor vehicles, trailers and semi-trailers	17.7%	4.0%	2.9%
Other transport equipment	6.3%	3.2%	1.5%
Basic metals	7.7%	3.2%	4.2%
Textiles	45.8%	3.1%	3.2%
Fabricated metal products, except machinery and equipment	22.5%	1.6%	1.1%
Furniture; manufacturing.	21.1%	1.4%	0.0%
Pulp, paper and paper products	18.4%	1.4%	0.0%
Radio, television and communication equipment and apparatus	33.2%	0.6%	0.6%
Office machinery and computers	33.4%	0.5%	0.0%
Medical, precision and optical instruments, watches and clocks	37.6%	0.3%	0.0%

Notes: INVIND-INPS-CAD data, 1982-1997.

Table 4A - Descriptive statistics

Firms with No Female Executives and with some Female Executives

	No Female Execs		Some Female Execs	
	Mean	(St.Dev.)	Mean	(St.Dev.)
CEO's age	48.64	(7.0)	49.78	(7.1)
CEO's tenure	4.15	(3.3)	3.64	(2.9)
CEO's pay	147,506	(108,628)	234,372	(178,054)
Female Execs. age			44.70	(7.1)
Male Execs. age	46.49	(4.8)	46.63	(3.9)
Female Execs mean pay			99,033	(42,695)
Male Execs mean pay	103,855	(45,834)	118,076	(46,574)
Average employment	490.99	(1,971.4)	1563.64	(6,173.05)
Average age of employees	37.20	(3.5)	37.84	(3.15)
Average wage (weekly)	378.54	(75.5)	432.67	(99.7)
Average wage (Females)	324.38	(58.6)	352.21	(68.8)
Average wage (Males)	374.83	(67.8)	422.49	(89.2)
Share females	0.25	(0.21)	0.31	(0.21)
Share non-prod. workers	0.27	(0.16)	0.39	(0.21)
Share Executives	0.02	(0.02)	0.03	(0.02)
Female executives			0.16	(0.19)
Sales (thousand euros)	64,903	(298,668)	181,535	(301,686)
Sales per worker	140.27	(150.5)	171.13	(132.29)
Value added per worker	42.70	(20.8)	49.41	(23.16)
TFP	2.38	(0.49)	2.56	(0.56)
Firm-Year Obs. (firms) [years]	6,378 (746) [16]		1,531 (229) [16]	

Notes: INVIND-INPS-CAD data, 1982-1997.

Table 4B - Descriptive statistics

Firms with Male and Female CEO

	Male CEO		Female CEO	
	Mean	St.Dev.	Mean	St.Dev.
CEO's age	48.91	(7.0)	45.92	(7.6)
CEO's tenure	4.05	(3.3)	4.04	(2.7)
CEO's pay	165,238	(130,560)	115,936	(54,030)
Female Execs. age	44.70	(7.11)	44.66	(6.55)
Male Execs. age	46.54	(4.54)	45.23	(7.81)
Female Execs mean pay	97,938	(42,134)	109,348	(46,564)
Male Execs mean pay	106,773	(46,443)	90,659	(31,719)
Average employment	707.42	(3,299.1)	234.92	(360.78)
Average age of employees	37.35	(3.5)	35.91	(3.3)
Average wage (weekly)	389.85	(83.7)	345.15	(61.7)
Average wage (Females)	330.32	(61.5)	300.53	(66.7)
Average wage (Males)	384.67	(75.1)	351.78	(54.9)
Share females	0.31	(0.20)	0.35	(0.28)
Share non-prod. workers	0.41	(0.21)	0.23	(0.14)
Share Executives	0.04	(0.02)	0.02	(0.01)
Female executives	0.12	(0.11)	0.54	(0.32)
Sales (thousand euros)	93,949	(373,760)	30,525	(48,827)
Sales per worker	146.45	(148.4)	131.87	(92.60)
Value added per worker	44.08	(21.5)	39.24	(14.13)
TFP	2.42	(0.51)	2.40	(0.43)
Firm-Year Obs. (firms) [years]	7,762 (815) [16]		147 (40) [16]	

Notes: INVIND-INPS-CAD data, 1982-1997.

Table 5: Worker and Firm Unobserved Heterogeneity: Two-Way Fixed Effects ("AKM") Regression

Number of Observations	18,938,837
Number of Individual FEs	1,726,836
Number of Firm FEs	453,000
F	39.68
Prob > F	0.000
R-squared	0.838
Adj. R-squared	0.817
Root MSE	0.166
Coeffs. on worker characteristics:	
Age	0.0619
Age squared	-0.0002
Age * Female	-0.0194
Age squared * Female	0.0002
Tenure	0.0051
Tenure squared	-0.0004
Tenure * Female	-0.0031
Tenure squared * Female	0.0001
White collar	0.0704
Executive	0.5734
White collar * Female	0.0007
Executives * Female	0.0328
Year effects	(not reported)
SD of worker effects	0.510
SD of firm effects	0.153
Correlation	-0.087

Notes: The sample includes all firms and all workers in the largest connected group, years 1980-1997. The estimation was performed using the conjugate gradient algorithm introduced by Abowd, Creecy and Kramarz (2002) and implemented by the Stata code “a2reg” written by Ouazad (2008). See Section 2.2 for details.

Table 6: Impact of Female Leadership on Firm Performance

- Balanced Panel Sample -

Female Leadership Measures:	Firm Performance Measures: Sales per Employee (Log)			Value Added per Employee (Log)			TFP		
Fem CEO	0.034			-0.078			-0.084*		
	(0.040)			(0.049)			(0.048)		
FemEx>25%		0.036			-0.063			-0.070	
		(0.045)			(0.055)			(0.054)	
FemEx			-0.078			-0.263***			-0.231***
			(0.077)			(0.094)			(0.092)
R-sq	0.59	0.59	0.59	0.22	0.22	0.22	0.17	0.17	0.18
NT	2,340	2,340	2,340	2,340	2,340	2,340	2,340	2,340	2,340
N	234	234	234	234	234	234	234	234	234
T	10	10	10	10	10	10	10	10	10

Notes: The sample includes a balanced panel of INVIND firms, years 1987-1997. Each observation is a firm-year. The dependent variables are the log of sales per employee (columns 1-3), the log of value added per employee (columns 4-6) and TFP (columns 7-9). FemEx is the share of female executives at the firm-year, FemEx>25% is a dummy equal to 1 if females represent more than 25% of executives at the firm-year (0% female executives is the omitted category; 0-25% dummy is included in the regression but coefficient is not reported), and Fem CEO is a dummy variable equal to 1 if the CEO is a female in a given firm-year. All regressions include firm fixed effects, year effects, 2-digit industry dummies, industry-specific time trends, region dummies, time-varying firm characteristics (employment dummies (100-250, 250-500, 500+), share non-production workers, average employee age, average worker unobserved heterogenity, standard deviation of worker unobserved heterogenity), executives/CEO observable characteristics (age, tenure), and executives/CEO unobserved heterogeneity. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent confidence levels, respectively.

Table 7: Impact of Female Leadership on Firm Performance with Interaction Effects

- Balanced Panel Sample -

Female Leadership Measures:	Firm Performance Measures: Sales per Employee (Log)			Value Added per Employee (Log)			TFP		
Fem CEO	-0.12*			-0.27***			-0.23***		
	(0.06)			(0.08)			(0.08)		
Fem CEO *FemNonEx	0.62***			0.78***			0.59**		
	(0.20)			(0.24)			(0.24)		
FemEx>25%		-0.15*			-0.27***			-0.27***	
		(0.08)			(0.10)			(0.09)	
FemEx>25% *FemNonEx		0.53***			0.65***			0.62***	
		(0.19)			(0.23)			(0.23)	
FemEx			-0.49***			-0.50***			-0.44**
			(0.13)			(0.16)			(0.15)
FemEx *FemNonEx			1.29***			0.76*			0.66*
			(0.32)			(0.39)			(0.39)
R-sq	0.60	0.59	0.60	0.22	0.22	0.22	0.18	0.18	0.18
NT	2,340	2,340	2,340	2,340	2,340	2,340	2,340	2,340	2,340
N	234	234	234	234	234	234	234	234	234
T	10	10	10	10	10	10	10	10	10

Notes: The sample includes a balanced panel of INVIND firms, years 1987-1997. Each observation is a firm-year. The dependent variables are the log of sales per employee (columns 1-3), the log of value added per employee (columns 4-6) and TFP (columns 7-9). FemEx is the share of female executives at the firm-year, FemNonEx is the share of females in the non-executive workforce at the firm-year, FemEx<25% (FemEx>25%) is a dummy equal to 1 if females represent less than (more than) 25% of executives at the firm-year (0% female executives is the omitted category), and Fem CEO is a dummy variable equal to 1 if the CEO is a female in a given firm-year. All regressions include firm fixed effects, year effects, 2-digit industry dummies, industry-specific time trends, region dummies, time-varying firm characteristics (employment dummies (100-250, 250-500, 500+), share non-production workers, average employee age, average worker unobserved heterogenity, standard deviation of worker unobserved heterogenity), executives/CEO observable characteristics (age, tenure), and executives/CEO unobserved heterogeneity. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent confidence levels, respectively.

Table 8: Impact of Female Leadership on Firm Performance with Interaction Effects
- All INVIND Firms Sample -

Female Leadership Measures:	Firm Performance Measures:								
	Sales per Employee (Log)			Value Added per Employee (Log)			TFP		
Fem CEO	-0.02			-0.11**			-0.09*		
	(0.04)			(0.05)			(0.05)		
Fem CEO *FemNonEx	0.15*			0.11			-0.03		
	(0.09)			(0.11)			(0.11)		
FemEx>25%		-0.04			-0.23***			-0.22***	
		(0.04)			(0.05)			(0.05)	
FemEx>25% *FemNonEx		0.21**			0.31***			0.25**	
		(0.09)			(0.11)			(0.11)	
FemEx			-0.21***			-0.32***			-0.29***
			(0.08)			(0.09)			(0.09)
FemEx *FemNonEx			0.56***			0.40**			0.26
			(0.15)			(0.18)			(0.17)
R-sq	0.75	0.75	0.75	0.30	0.30	0.30	0.24	0.24	0.24
NT	7,909	7,909	7,909	7,909	7,909	7,909	7,909	7,909	7,909
N	822	822	822	822	822	822	822	822	822
T	15	15	15	15	15	15	15	15	15

Notes: The sample includes all INVIND firms, years 1982-1997. Each observation is a firm-year. The dependent variables are the log of sales per employee (columns 1-3), the log of value added per employee (columns 4-6) and TFP (columns 7-9). FemEx is the share of female executives at the firm-year, FemNonEx is the share of females in the non-executive workforce at the firm-year, FemEx<25% (FemEx>25%) is a dummy equal to 1 if females represent less than (more than) 25% of executives at the firm-year (0% female executives is the omitted category), and Fem CEO is a dummy variable equal to 1 if the CEO is a female in a given firm-year. All regressions include firm fixed effects, year effects, 2-digit industry dummies, industry-specific time trends, region dummies, time-varying firm characteristics (employment dummies (100-250, 250-500, 500+), share non-production workers, average employee age, average worker unobserved heterogenity, standard deviation of worker unobserved heterogenity), executives/CEO observable characteristics (age, tenure), and executives/CEO unobserved heterogeneity. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent confidence levels, respectively.

Table 9: Female Leadership and Promotion to Executive

Promotion Probabilities of Female White Collar Employees (% Year to Year)

Wage Quartile	Female Leadership		Male Leadership
	Female CEO	Prop Fem Exec. > 25%	
1st	0.000	0.000	0.017
2nd	0.000	0.000	0.005
3rd	0.000	0.000	0.009
4th	0.726	0.844	0.210
N worker-year obs.	1,787	3,475	166,992

Notes: The sample includes the longest uninterrupted job spell of all female white collar workers employed at INVIND firms in the years 1982-1997. Wage quartiles are by firm-gender-year.

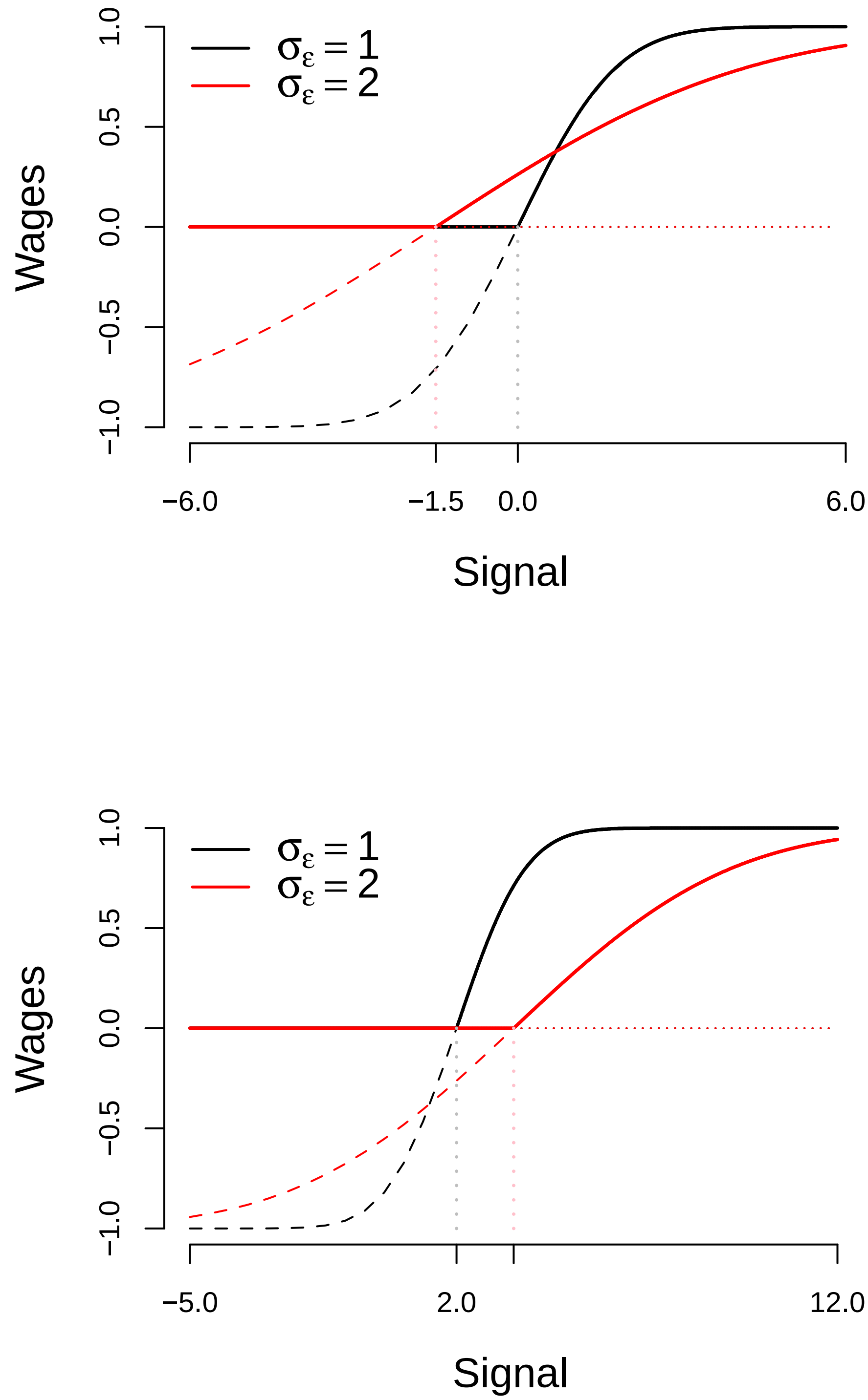

Figure 2: Model's Figures: Panel (a) top; Panel (b) bottom.

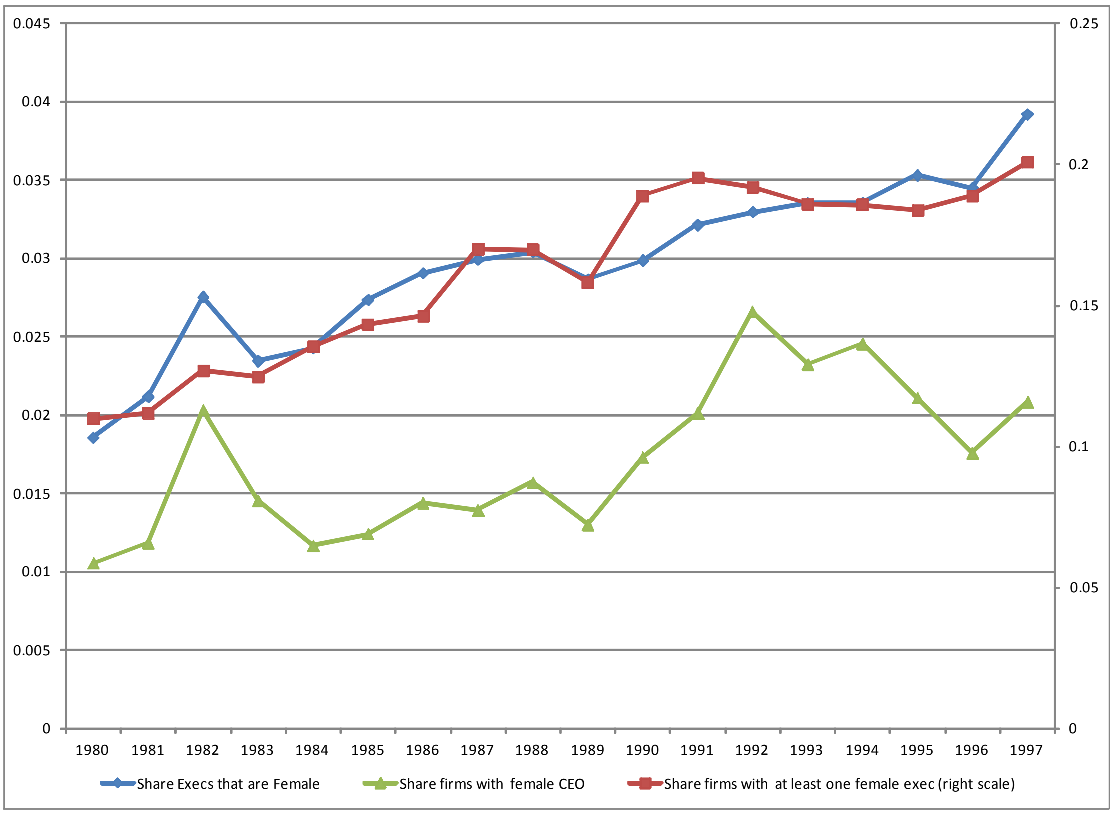

Figure 3: **Female Leadership in Italian Manufacturing Firms.**

Note: INVIND-INPS data, 1980-1997.

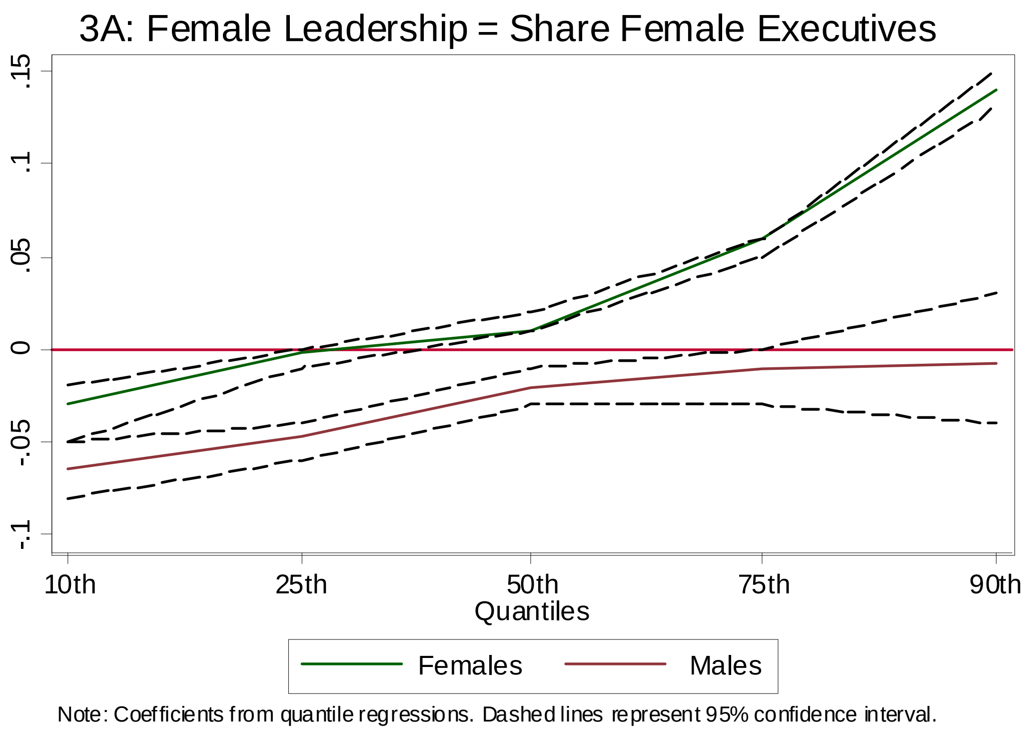
3A: Female Leadership = Share Female Executives
.15
.1
.05
0
-.05
-.1
10th
25th
50th
75th
90th
Quantiles
Females
Males
Note: Coefficients from quantile regressions. Dashed lines represent 95% confidence interval.

Figure 4:

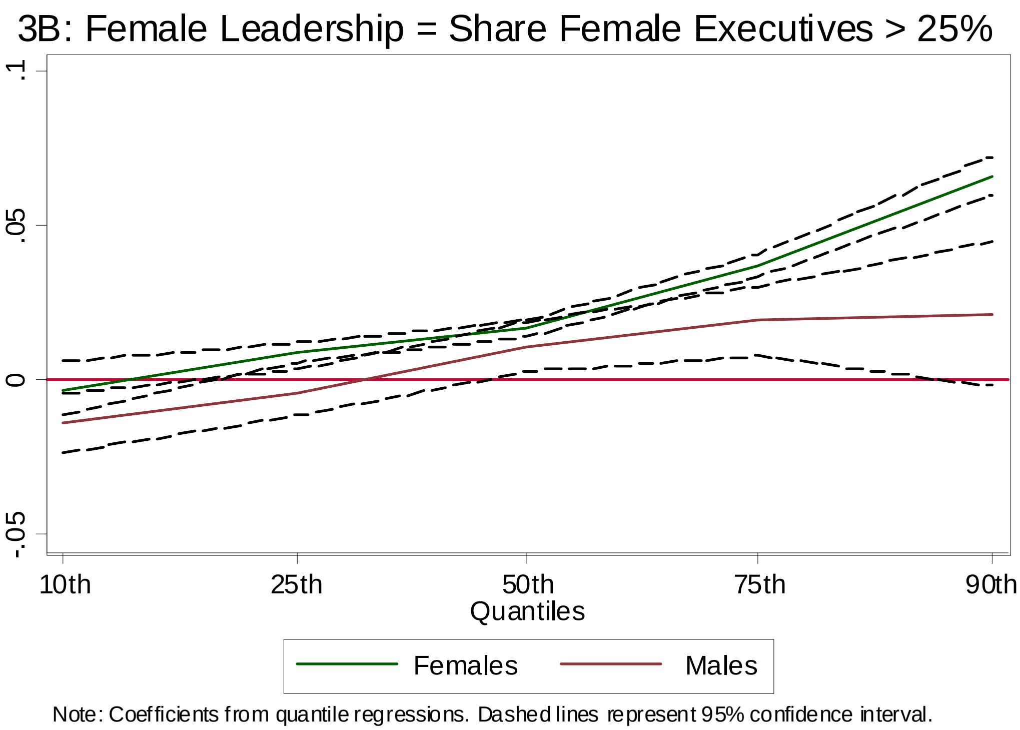
3B: Female Leadership = Share Female Executives > 25%
.1
.05
0
-.05
10th
25th
50th
75th
90th
Quantiles
Females
Males
Note: Coefficients from quantile regressions. Dashed lines represent 95% confidence interval.

Figure 5:

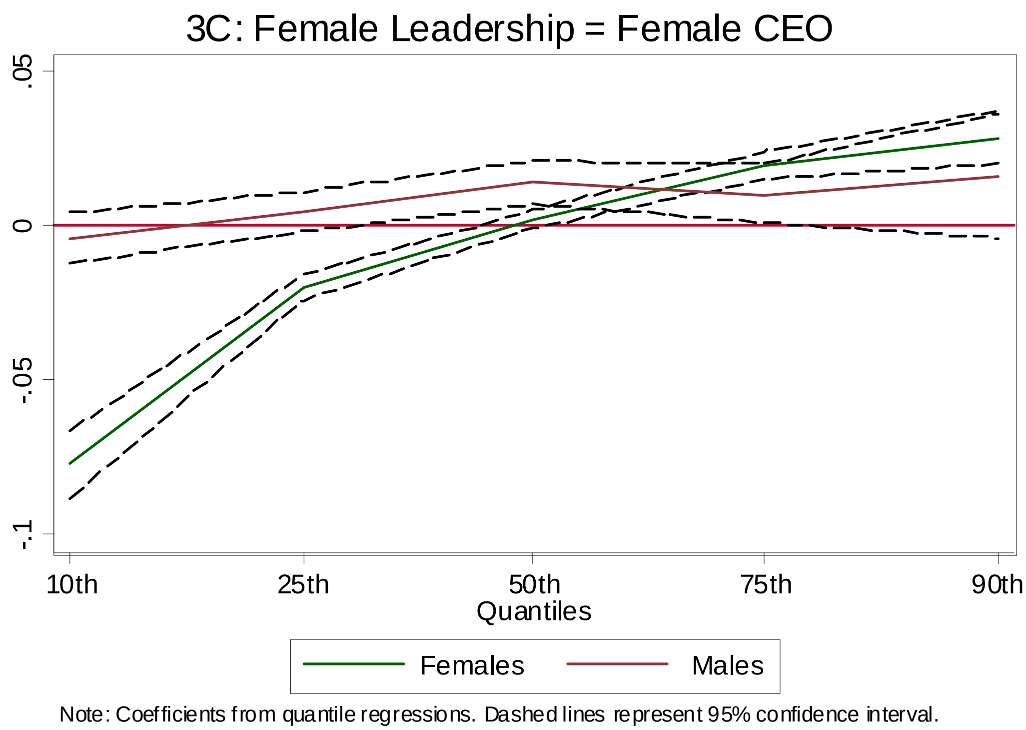
3C: Female Leadership = Female CEO
.05
0
-.05
-.1
10th
25th
50th
75th
90th
Quantiles
Females
Males
Note: Coefficients from quantile regressions. Dashed lines represent 95% confidence interval.

Figure 6:

Do Female Executives Make a Difference?
The Impact of Female Leadership on Firm Performance and Gender Gaps in Wages and Promotions

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Web Appendix

1. Tests of the AKM exogenous mobility assumption.

The Abowd-Kramarz-Margolis (AKM henceforth) method rests on an assumption of "exogenous mobility" conditional on observables. As discussed at length in Card, Heining and Klein (2013, CHK henceforth), violations of this assumption would change the interpretation of the estimated firm effects. Following CHK, we have considered various possible violations of the exogenous mobility assumptions and performed the associated checks with our data. We describe our analyses below.

1. **Mobility based on the value of worker-firm match.** In AKM, the firm effects are wage premia paid to all workers in a given firm, irrespective of the characteristics of the specific workers. However, if the exogenous mobility assumption is violated due to sorting based on the value of a worker-firm match component, and workers change jobs to join firms to which they are better matched, then the wage premium would include a match component that would be specific to each worker-firm pair, and no longer common across all workers in the firm. To test for such sorting, we follow CHK and perform two analyses: first, we look at wage changes for job movers, and second, we compare the AKM regression with a regression including match (worker-firm) fixed effects.
    a. Wage changes for job movers. Specifically, we considered all job changers in the years 1980-1997 with at least two consecutive years in the old and new firm. We then classified the origin and destination jobs based on the quartiles of the estimated firm effects;[1] we formed sixteen cells based on quartiles of origin and destination, and computed average wages of movers in each cell in the two years before the change and the two years after the change.[2] Under the exogenous mobility assumption, workers who move from a "low firm-effect" firm to a "high firm-effect" firm should experience a wage increase and workers who move in the opposite direction a wage reduction. Moreover, the wage gain for the former group and the wage loss for the latter should be roughly symmetrical – the "firm effect" gained by one group should be roughly equal to that gained by the other group. Also, workers who transition between firms that pay similar wages should not experience any wage change. If, instead, the exogenous mobility assumption is violated because workers change firms based on the value of the idiosyncratic match component, then job changes will be

[1] The quartiles were computed on a yearly basis. Therefore, because the composition of the firms' sample can change from year to year due to some firms exiting and new firms joining the sample, it is possible that a given firm belongs to a different quartile in different years.
[2] Firms with less than three workers in a given firm-year were dropped from the sample; we also excluded workers who experienced multiple transitions in the sample period, and workers with gaps in the data between the old job and the new one.

associated with wage increases even for moves between firms with similar estimated firm effects, and possibly (if the match component is sufficiently important) even for moves from high- to low-estimated-firm-effect firms. We report the results of our exercise in Appendix Table A1, together with the number of movers in each of the sixteen cells, and a trend-adjusted wage change, again for each job change cell. The table delivers two main results: First, workers who move from a low-firm-effect quartile to a high-firm-effect quartile experience wage increases that are monotonically increasing with the gap between origin and destination quartiles, and workers who move in the opposite direction experience similar wage declines; Appendix Figure A1 shows the wage profiles for workers leaving the first and fourth quartiles, and illustrates the approximate symmetry of the wage gains and losses of those who move from the first quartile up and from the fourth quartile down, respectively. Second, the wages of job changers who stay within the same quartile group are essentially flat between the two years before and the two years after the move (also see Appendix Figure A2). The lack of a mobility premium for the job changers who stay in the same firm-effect quartile suggests that idiosyncratic worker-firm match effects are not the primary driver of job mobility, and the symmetry between wage increases for movers from low to high quartiles and the wage decreases for movers in the opposite direction are as predicted by the AKM model.

   b. <u>Comparison of AKM and match fixed effects regression.</u> If match effects are important, a model with worker-firm fixed effects should out-perform the AKM model in terms of statistical fit. We run a regression with match fixed effects (the results are reported in Appendix Table A2 below), and compare it with the AKM regression. We find that the match effects model has an adjusted R2 that is only slightly higher (0.85 vs. 0.82), and a Root MSE only slightly lower (0.159 vs. 0.166) than those from the AKM regression. Thus, although these results indicate that a match component in wages is present, the improvement in fit relatively to the AKM model is only modest.

2. **Drift in worker-specific ability or fluctuations in the transitory component of wages predicting firm-to-firm transitions.** As illustrated in CHK (2013), if workers' ability is revealed slowly over time and certain talents are valued differently at different firms, then workers who turn out to be more productive than expected will receive wage increases at their original employer, and will also be more likely to move to a firm where their talents will receive higher compensation. This too would be a violation of the exogenous mobility assumption and bias the estimates of the firm effects. Similarly, if the idiosyncratic component of wages is systematically associated with transitions between high-wage and low-wage firms, that would also

violate the exogenous mobility assumption. If that is the case, the wages of movers will show an upward trend in the years before the move.

a. Trends in wages of movers prior to the move. Inspection of columns (2) and (3) in Appendix Table A1 reveals that wages of movers show no systematic trend in the years prior to their move. In other words, similar to CHK, we find no evidence that transitory wage fluctuations predict mobility patterns.
b. Examination of residuals from AKM. We have also examined the residuals from the AKM regression. Specifically, we again followed CHK and formed deciles based on the estimated worker effects and firm effects, and computed average residuals in each of the 100 worker x firm decile cell, to explore whether there are any notable systematic patterns in the distribution of residuals for particular types of matches. The mean residuals by cell are shown in Appendix Figure A3. The mean residuals are generally small. In 84 cases out of 100, the mean residual is smaller than 1% in magnitude. In only 5 cases the mean residual is larger than 1.5%, with the largest deviation being 4.4%. The largest deviations appear among the lowest-decile workers and the lowest-decile firms (similar to what found by CHK in Germany), and some deviations from the AKM assumption are also found among the lowest-decile workers employed at the highest-decile firms. However, as noted above, the deviations are only a few, and they are small in magnitude.

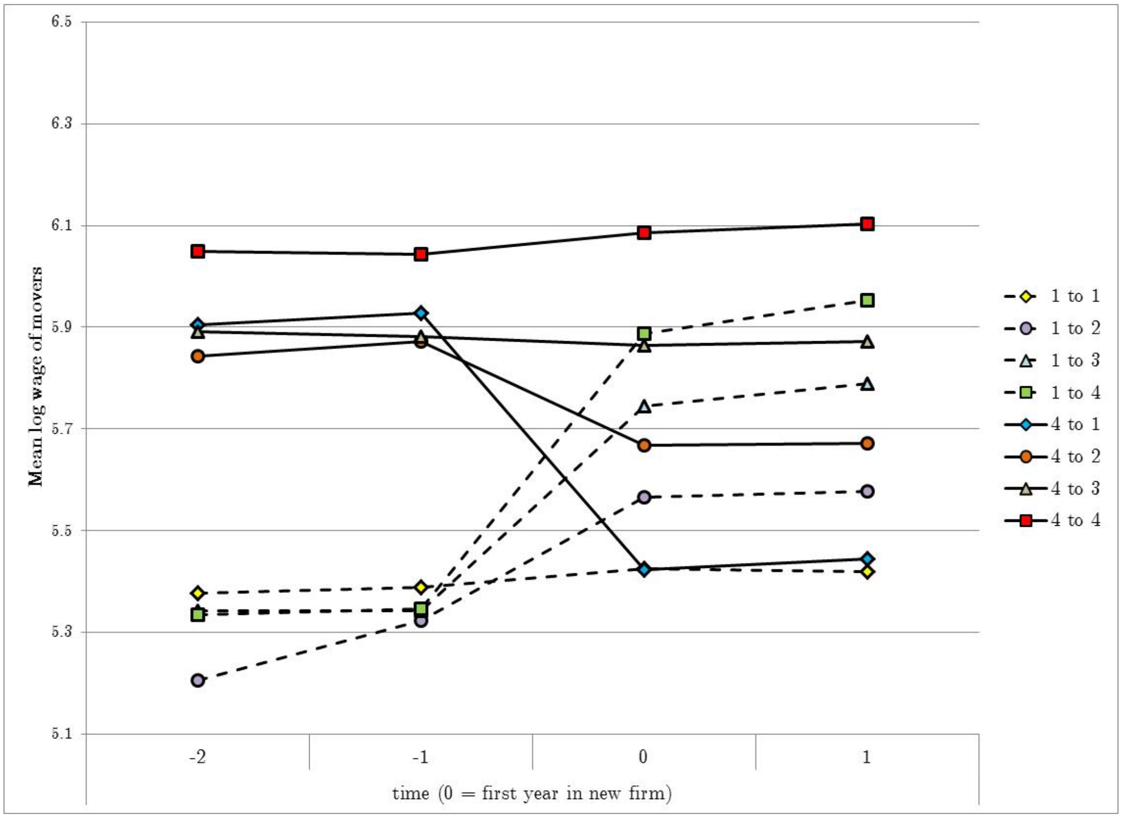
The tests that we performed indicate that the exogenous mobility assumption is roughly met in our data. There is some evidence that worker-firm match effects are present, but a model including unrestricted match effects delivers only a very modest improved statistical fit compared to the AKM model, and the departures from the exogenous mobility assumption suggested by the AKM residuals are small in magnitude. On the other hand, the symmetry of wage gains upon moving from a low-firm-effect to a high-firm-effect firm and the wage losses from moving in the opposite direction, and the absence of wage gains for workers who move between firms with similar estimated firm effects suggest that match effects are not a primary driver of mobility. We conclude that in the Italian, manufacturing sector context, the additively separable firm and worker effects obtained from the AKM model can be taken as reasonable measures of the unobservable worker and firm components of wages.

Table A1: Mean Log Wages Before and After Job Change, by Quartile of AKM Firm Effect at Origin and Destination Firms

Origin/destination quartile(*)	N. of observations (1)	Mean log wage of movers: 2 years before (2)	1 year before (3)	1 year after (4)	2 years after (5)	Change from 2 years befor to 2 years after: Raw (6)	Adjusted(**) (7)
1 to 1	1,204	5.38	5.39	5.43	5.42	0.041	0.000
1 to 2	1,597	5.21	5.32	5.57	5.58	0.371	0.330
1 to 3	3,253	5.34	5.34	5.74	5.79	0.446	0.405
1 to 4	2,851	5.34	5.35	5.89	5.95	0.617	0.576
2 to 1	1,644	5.59	5.59	5.47	5.46	-0.135	-0.146
2 to 2	29,913	5.88	5.87	5.87	5.89	0.011	0.000
2 to 3	11,192	5.64	5.64	5.77	5.79	0.150	0.285
2 to 4	5,130	5.63	5.64	5.89	5.94	0.311	0.446
3 to 1	3,298	5.73	5.71	5.43	5.23	-0.500	-0.552
3 to 2	8,562	5.71	5.71	5.68	5.71	-0.001	-0.053
3 to 3	49,559	5.79	5.79	5.84	5.84	0.052	0.000
3 to 4	22,071	5.87	5.87	6.00	6.02	0.141	0.089
4 to 1	1,424	5.91	5.93	5.42	5.45	-0.460	-0.515
4 to 2	2,878	5.84	5.87	5.67	5.67	-0.172	-0.226
4 to 3	27,566	5.89	5.88	5.86	5.87	-0.019	-0.073
4 to 4	72,555	6.05	6.04	6.09	6.10	0.055	0.000

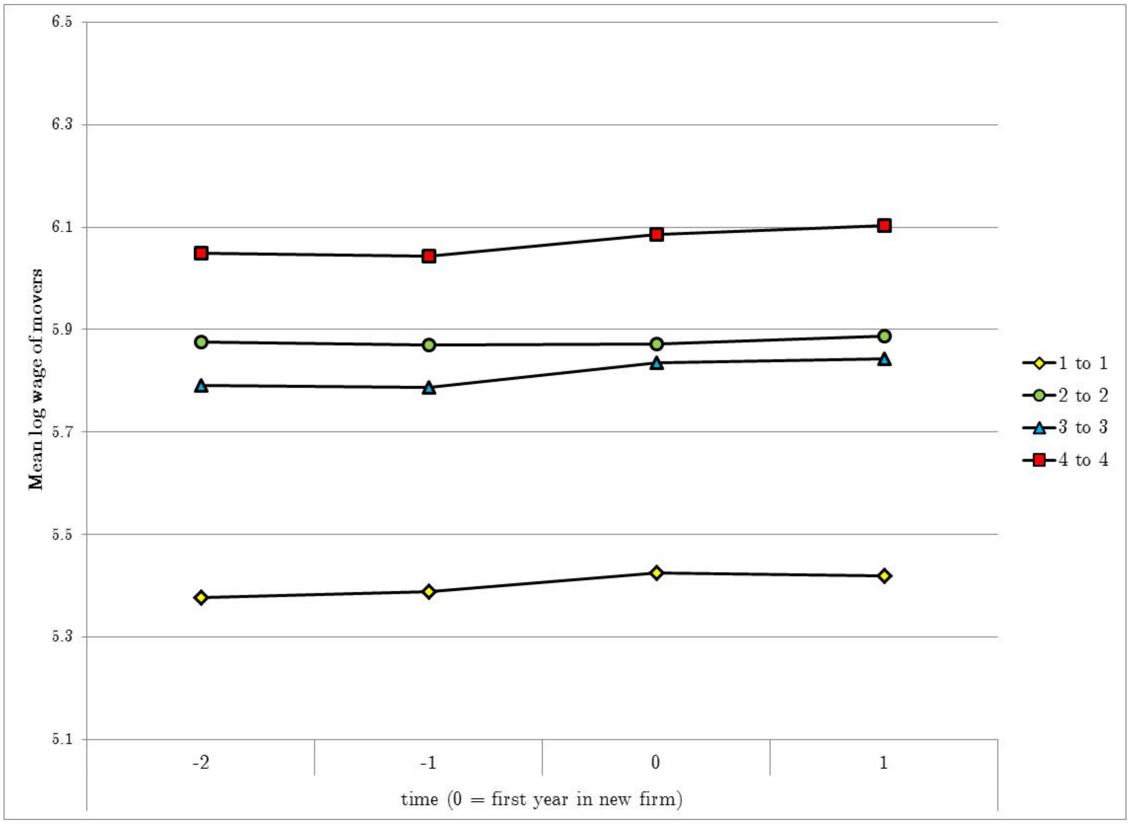
Notes: Entries are average log real weekly earnings for all job changers observed for at least 2 years of prior to a job change, and two years after. (*) Quartiles are based on firm effects estimated with the Abowd-Kramarz-Margolis method. (**) Computed as the mean wage change for the origin-destination group, minus the mean change for job movers from the same origin quartile who remain in the same quartile at destination.

Figure A1: Mean wages of job changers classified by quartile of the AKM firm effect – Workers leaving quartile 1 and quartile 4 firms.



Notes: the sample includes all job changers in the years 1980-1997 with at least two observations prior to the move and two observations after the move and only one transition in the period considered.

Figure A2: Mean wages of job changers classified by quartile of the AKM firm effect - Workers moving to a firm in the same quartile.



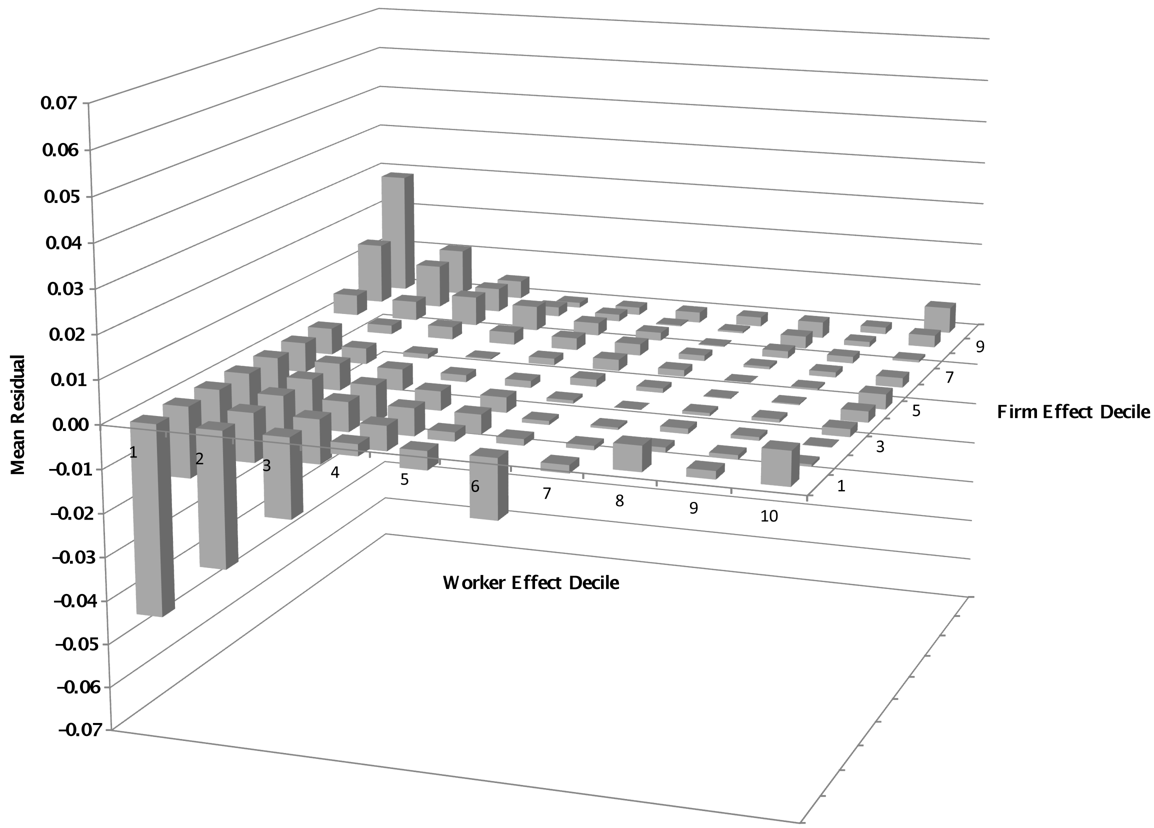
Notes: the sample includes all job changers in the years 1980-1997 with at least two observations prior to the move and two observations after the move and only one transition in the period considered.

Table A2: Worker-Firm Match Fixed Effects Regression

Number of Observations	18,938,837	
Number of Match FEs	3,949,483	
F	79741.1	
Prob > F	0.000	
R-squared	0.882	
Adj. R-squared	0.851	
Root MSE	0.159	
Coeffs. (std. err.) on worker characteristics:		
Age	0.0324	(0.0001)
Age squared	-0.0001	(0.0000)
Age * Female	-0.0221	(0.0002)
Age squared * Female	0.0002	(0.0000)
White collar	0.0430	(0.000)
Executive	0.4329	(0.001)
White collar * Female	-0.0033	(0.001)
Executives * Female	0.0293	(0.007)
Year effects	(not reported)	

Notes: The sample includes all firms and all workers in the largest connected group, years 1980-1997. The regression includes worker-firm match fixed effects.

Figure A3: Mean Residual by Estimated Worker/Firm Effects Deciles, 1980-1997



Notes: The figure shows mean residuals from the AKM regression (Table 5 in the text) by cells defined by decile of the estimated worker effect x decile of the estimated firm effect.

2. Firm Performance Regressions: Full results.

A3-1: Impact of Female Leadership on Firm Performance.

Sample	Balanced Panel								
Dependent variable	Sales per Employee			Value Added per Employee			TFP		
Fem CEO	0.034			-0.078			-0.084*		
	(0.040)			(0.049)			(0.048)		
0 < FemEx < 25%		-0.003			-0.059***			-0.035	
		(0.019)			(0.023)			(0.022)	
FemEx > 25%		0.036			-0.063			-0.070	
		(0.045)			(0.055)			(0.054)	
FemEx			-0.078			-0.263***			-0.231**
			(0.077)			(0.094)			(0.092)
Exec Ability	-0.021	0.019	0.055	0.031	-0.000	0.038	0.027	-0.083	-0.052
	(0.023)	(0.067)	(0.068)	(0.029)	(0.082)	(0.083)	(0.028)	(0.081)	(0.082)
Exec Tenure	-0.003	-0.003	-0.002	-0.001	0.000	0.001	-0.001	-0.000	0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Exec Age	0.000	0.000	0.000	0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FemNonEx	-0.383**	-0.397**	-0.366**	-0.575***	-0.517***	-0.508***	-0.570***	-0.518***	-0.504***
	(0.158)	(0.160)	(0.160)	(0.194)	(0.196)	(0.195)	(0.191)	(0.192)	(0.192)
Mean Age Workforce	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.002**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share White Collars	0.275**	0.269**	0.266**	-0.008	-0.022	-0.011	0.037	0.032	0.044
	(0.132)	(0.132)	(0.132)	(0.162)	(0.162)	(0.161)	(0.159)	(0.159)	(0.159)
Mean AKM Worker Effect	1.297***	1.279***	1.284***	1.350***	1.389***	1.362***	1.008***	1.033***	1.011***
	(0.237)	(0.237)	(0.237)	(0.290)	(0.289)	(0.289)	(0.286)	(0.285)	(0.284)
SD of AKM Worker Effect	0.359**	0.376**	0.391**	0.585***	0.639***	0.646***	0.724***	0.746***	0.762***
	(0.179)	(0.179)	(0.179)	(0.219)	(0.219)	(0.219)	(0.215)	(0.215)	(0.215)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm size dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	0.593	0.592	0.592	0.217	0.218	0.219	0.173	0.174	0.175
Firm-Year Observations	2,340	2,340	2,340	2,340	2,340	2,340	2,340	2,340	2,340
N. of firms	234	234	234	234	234	234	234	234	234
N. of years	10	10	10	10	10	10	10	10	10

Notes: The sample includes a balanced panel of INVIND firms, years 1987-1997. Each observation is a firm-year. FemEx is the share of female executives at the firm-year, FemNonEx is the share of females in the non-executive workforce at the firm-year, 0<FemEx<25% is a dummy equal to 1 if females represent more than zero but less that 25% of executives at the firm-year, and FemEx>25% is a dummy equal to 1 if females represent more than 25% of executives (0% female executives is the omitted category). Fem CEO is a dummy variable equal to 1 if the CEO is a female in a given firm-year. Firm size dummies are for less than 100, between 100 and 250, between 250 and 500, and more than 500 employees. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent confidence levels, respectively.

A3-2: Impact of Female Leadership on Firm Performance with Interaction Effects.

Sample	Balanced Panel								
Dependent variable	Sales per Employee			Value Added per Employee			TFP		
Fem CEO	-0.122*			-0.272***			-0.231***		
	(0.064)			(0.078)			(0.077)		
Fem CEO	0.623***			0.775***			0.588**		
* FemNonEx	(0.199)			(0.244)			(0.240)		
0 < FemEx < 25%		-0.036			-0.033			-0.010	
		(0.032)			(0.039)			(0.039)	
0 < FemEx < 25%		0.091			-0.120			-0.112	
* FemNonEx		(0.090)			(0.110)			(0.108)	
FemEx > 25%		-0.146*			-0.273***			-0.270***	
		(0.079)			(0.096)			(0.095)	
FemEx > 25%		0.529***			0.649***			0.618***	
*FemNonEx		(0.191)			(0.233)			(0.230)	
FemEx			-0.484***			-0.501***			-0.439***
			(0.127)			(0.155)			(0.153)
FemEx			1.292***			0.760*			0.663*
*FemNonEx			(0.321)			(0.394)			(0.388)
Exec Ability	-0.020	0.027	0.075	0.031	0.007	0.050	0.027	-0.076	-0.042
	(0.023)	(0.067)	(0.068)	(0.029)	(0.082)	(0.084)	(0.028)	(0.081)	(0.082)
Exec Tenure	-0.003	-0.002	-0.001	-0.001	0.001	0.002	-0.000	-0.000	0.001
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Exec Age	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FemNonEx	-0.463***	-0.498***	-0.518***	-0.675***	-0.566***	-0.597***	-0.646***	-0.565***	-0.582***
	(0.160)	(0.165)	(0.164)	(0.196)	(0.202)	(0.200)	(0.193)	(0.199)	(0.197)
Mean Age Workforce	0.003***	0.003***	0.003***	0.004***	0.003***	0.003***	0.003**	0.002**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share White Collars	0.262**	0.275**	0.269**	-0.023	-0.021	-0.009	0.025	0.033	0.046
	(0.132)	(0.132)	(0.132)	(0.161)	(0.161)	(0.161)	(0.159)	(0.159)	(0.159)
Mean AKM Worker Effect	1.344***	1.257***	1.295***	1.409***	1.342***	1.369***	1.052***	0.988***	1.017***
	(0.237)	(0.237)	(0.236)	(0.290)	(0.289)	(0.289)	(0.286)	(0.285)	(0.284)
SD of AKM Worker Effect	0.356**	0.398**	0.440**	0.582***	0.640***	0.674***	0.721***	0.747***	0.787***
	(0.179)	(0.179)	(0.179)	(0.218)	(0.219)	(0.219)	(0.215)	(0.215)	(0.216)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm size dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	0.595	0.594	0.595	0.221	0.222	0.220	0.175	0.178	0.176
Firm-Year Observations	2,340	2,340	2,340	2,340	2,340	2,340	2,340	2,340	2,340
N. of firms	234	234	234	234	234	234	234	234	234
N. of years	10	10	10	10	10	10	10	10	10

Notes: The sample includes a balanced panel of INVIND firms, years 1987-1997. Each observation is a firm-year. FemEx is the share of female executives at the firm-year, FemNonEx is the share of females in the non-executive workforce at the firm-year, 0<FemEx<25% is a dummy equal to 1 if females represent more than zero but less that 25% of executives at the firm-year, and FemEx>25% is a dummy equal to 1 if females represent more than 25% of executives (0% female executives is the omitted category). Fem CEO is a dummy variable equal to 1 if the CEO is a female in a given firm-year. Firm size dummies are for less than 100, between 100 and 250, between 250 and 500, and more than 500 employees. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent confidence levels, respectively.

A3-3: Impact of Female Leadership on Firm Performance with Interaction Effects. Full Sample.

Sample	Full Sample								
Dependent variable	Sales per Employee			Value Added per Employee			TFP		
Fem CEO	-0.018			-0.114**			-0.085*		
	(0.039)			(0.047)			(0.047)		
Fem CEO	0.150			0.109			-0.031		
* FemNonEx	(0.092)			(0.111)			(0.110)		
0 < FemEx < 25%		-0.082***			-0.050**			-0.034	
		(0.019)			(0.023)			(0.023)	
0 < FemEx < 25%		0.244***			0.075			0.033	
* FemNonEx		(0.050)			(0.061)			(0.060)	
FemEx > 25%		-0.038			-0.231***			-0.218***	
		(0.044)			(0.053)			(0.052)	
FemEx > 25%		0.206**			0.310***			0.248**	
*FemNonEx		(0.088)			(0.106)			(0.105)	
FemEx			-0.209***			-0.320***			-0.292***
			(0.075)			(0.090)			(0.089)
FemEx			0.557***			0.401**			0.263
*FemNonEx			(0.146)			(0.176)			(0.174)
Exec Ability	0.015	0.030	0.036	0.074***	0.107***	0.110***	0.079***	0.115***	0.121***
	(0.014)	(0.030)	(0.030)	(0.017)	(0.036)	(0.037)	(0.017)	(0.036)	(0.036)
Exec Tenure	-0.002	0.001	0.001	-0.001	0.002	0.002	-0.000	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Exec Age	0.000	-0.000	-0.000	0.000***	0.000**	0.000**	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FemNonEx	-0.937***	-0.995***	-0.963***	-0.972***	-0.974***	-0.976***	-0.785***	-0.777***	-0.783***
	(0.080)	(0.081)	(0.080)	(0.096)	(0.098)	(0.097)	(0.095)	(0.097)	(0.096)
Mean Age Workforce	0.006***	0.006***	0.006***	0.004***	0.004***	0.004***	0.003***	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Share White Collars	0.326***	0.343***	0.326***	-0.000	0.002	0.008	0.059	0.054	0.065
	(0.062)	(0.062)	(0.062)	(0.075)	(0.075)	(0.075)	(0.074)	(0.074)	(0.074)
Mean AKM Worker Effect	1.791***	1.781***	1.794***	1.381***	1.379***	1.377***	1.055***	1.059***	1.053***
	(0.116)	(0.116)	(0.116)	(0.140)	(0.140)	(0.140)	(0.138)	(0.138)	(0.138)
SD of AKM Worker Effect	0.656***	0.674***	0.662***	0.785***	0.787***	0.790***	0.935***	0.927***	0.933***
	(0.086)	(0.086)	(0.086)	(0.104)	(0.103)	(0.103)	(0.102)	(0.102)	(0.102)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm size dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	0.748	0.749	0.749	0.303	0.303	0.302	0.237	0.237	0.236
Firm-Year Observations	7,906	7,906	7,906	7,906	7,906	7,906	7,906	7,906	7,906
N. of firms	822	822	822	822	822	822	822	822	822
N. of years	16	16	16	16	16	16	16	16	16

Notes: The sample includes the full sample of INVIND firms, years 1987-1997. Each observation is a firm-year. FemEx is the share of female executives at the firm-year, FemNonEx is the share of females in the non-executive workforce at the firm-year, 0<FemEx<25% is a dummy equal to 1 if females represent more than zero but less that 25% of executives at the firm-year, and FemEx>25% is a dummy equal to 1 if females represent more than 25% of executives (0% female executives is the omitted category). Fem CEO is a dummy variable equal to 1 if the CEO is a female in a given firm-year. Firm size dummies are for less than 100, between 100 and 250, between 250 and 500, and more than 500 employees. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent confidence levels, respectively.

3. Wage Quantile Regressions: Full results.

A4-1: Quantile regressions. Female leadership = Share of female executives.

Sample			Females					Males		
Dependent variable			ln wage					ln wage		
Quantile	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
FemEx	-0.033***	-0.002	0.013***	0.055***	0.141***	-0.058***	-0.045***	-0.022***	-0.017***	-0.003
	(0.007)	(0.003)	(0.002)	(0.003)	(0.005)	(0.003)	(0.002)	(0.002)	(0.003)	(0.007)
Mean Exec Ability	-0.020***	-0.007***	0.001	0.003**	-0.001	0.022***	0.010***	0.003***	0.016***	0.026***
	(0.004)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Mean Exec Experience	-0.002**	0.002***	0.003***	0.003***	-0.002***	0.002***	0.001***	0.002***	0.003***	0.001**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Mean Exec Tenure	0.000	0.000	-0.001***	-0.001***	-0.001***	0.001***	0.001***	0.001***	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean Exec Age	-0.006***	-0.005***	-0.004***	-0.005***	-0.013***	-0.003***	-0.006***	-0.008***	-0.002***	-0.008***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
FemNonEx	-0.344***	-0.264***	-0.235***	-0.226***	-0.225***	-0.227***	-0.240***	-0.236***	-0.211***	-0.170***
	(0.005)	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)	(0.001)	(0.001)	(0.002)	(0.004)
Mean Age Workforce	0.203***	0.135***	0.114***	0.117***	0.128***	0.168***	0.181***	0.201***	0.199***	0.190***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Age	0.199***	0.181***	0.145***	0.089***	0.056***	0.333***	0.297***	0.262***	0.234***	0.158***
	(0.004)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
Age Squared	-0.019***	-0.018***	-0.014***	-0.006***	-0.001**	-0.037***	-0.032***	-0.026***	-0.021***	-0.007***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share prod. workers	-0.179***	-0.166***	-0.185***	-0.245***	-0.353***	-0.192***	-0.224***	-0.306***	-0.440***	-0.645***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Firm Effect from AKM	0.678***	0.570***	0.562***	0.605***	0.653***	0.746***	0.804***	0.884***	0.926***	0.936***
	(0.007)	(0.003)	(0.002)	(0.003)	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)
Mean AKM Worker Effect	0.702***	0.477***	0.420***	0.441***	0.484***	0.428***	0.468***	0.554***	0.596***	0.608***
	(0.008)	(0.003)	(0.002)	(0.003)	(0.006)	(0.003)	(0.002)	(0.002)	(0.003)	(0.006)
SD of AKM Worker Effect	-0.150***	0.081***	0.131***	0.147***	0.144***	0.014***	-0.016***	-0.047***	-0.045***	-0.055***
	(0.012)	(0.004)	(0.003)	(0.005)	(0.009)	(0.003)	(0.003)	(0.003)	(0.004)	(0.008)
< 100 Employees	-0.029***	-0.020***	-0.016***	-0.013***	-0.009***	-0.013***	-0.008***	-0.007***	-0.007***	0.003
	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
250-500 Employees	0.017***	0.009***	0.007***	0.008***	0.006***	-0.003***	-0.001	-0.001	-0.004***	-0.007***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
> 500 Employees	0.032***	0.020***	0.016***	0.018***	0.020***	0.010***	0.007***	0.005***	-0.001	-0.011***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.002)
Constant	2.802***	3.467***	3.696***	3.788***	3.948***	2.971***	3.009***	3.059***	3.195***	3.546***
	(0.039)	(0.014)	(0.012)	(0.016)	(0.029)	(0.035)	(0.027)	(0.030)	(0.041)	(0.087)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,060,714	1,060,714	1,060,714	1,060,714	1,060,714	3,507,148	3,507,148	3,507,148	3,507,148	3,507,148

Notes: Quantile log wage regressions, separately by gender. The sample includes workers employed at INVIND firms, 1982-1997. Each observation is a worker-year. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent confidence levels, respectively.

A4-2: Quantile regressions. Female leadership = Share of female executives > 25%.

Sample			Females					Males		
Dependent variable			ln wage					ln wage		
Quantile	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
0 < FemEx < 25%	0.003***	0.003***	-0.001**	-0.003***	0.002**	-0.019***	-0.018***	-0.018***	-0.019***	-0.019***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
FemEx>25%	-0.003	0.009***	0.017***	0.037***	0.066***	-0.010***	-0.005***	0.008***	0.018***	0.043***
	(0.004)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Mean Exec Ability	-0.024***	-0.009***	-0.000	0.005***	0.001	0.023***	0.012***	0.006***	0.019***	0.030***
	(0.004)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Mean Exec Experience	-0.001**	0.002***	0.003***	0.003***	-0.003***	0.001***	0.000	0.001***	0.002***	0.001**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean Exec Tenure	0.000	0.000	-0.001***	-0.001***	-0.001***	0.001***	0.001***	0.001***	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean Exec Age	-0.007***	-0.006***	-0.004***	-0.005***	-0.011***	-0.004***	-0.006***	-0.008***	-0.003***	-0.009***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
FemNonEx	-0.346***	-0.264***	-0.236***	-0.228***	-0.221***	-0.231***	-0.245***	-0.239***	-0.213***	-0.174***
	(0.005)	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
Mean Age Workforce	0.203***	0.134***	0.115***	0.119***	0.127***	0.176***	0.189***	0.208***	0.205***	0.196***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Age	0.198***	0.181***	0.145***	0.089***	0.055***	0.333***	0.298***	0.263***	0.235***	0.158***
	(0.004)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Age Squared	-0.019***	-0.018***	-0.014***	-0.006***	-0.001**	-0.037***	-0.032***	-0.026***	-0.021***	-0.007***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share prod. workers	-0.179***	-0.166***	-0.185***	-0.245***	-0.354***	-0.192***	-0.224***	-0.306***	-0.441***	-0.646***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Effect from AKM	0.673***	0.568***	0.564***	0.611***	0.657***	0.747***	0.803***	0.885***	0.930***	0.938***
	(0.007)	(0.003)	(0.002)	(0.003)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Mean AKM Worker Effect	0.701***	0.475***	0.422***	0.446***	0.485***	0.441***	0.486***	0.569***	0.609***	0.623***
	(0.008)	(0.003)	(0.002)	(0.003)	(0.006)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
SD of AKM Worker Effect	-0.156***	0.077***	0.133***	0.153***	0.148***	0.020***	-0.007***	-0.035***	-0.033***	-0.046***
	(0.012)	(0.004)	(0.003)	(0.005)	(0.009)	(0.003)	(0.002)	(0.002)	(0.003)	(0.005)
100-250 Employees	0.029***	0.020***	0.016***	0.013***	0.010***	0.014***	0.009***	0.008***	0.008***	-0.003*
	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
250-500 Employees	0.017***	0.009***	0.008***	0.009***	0.007***	0.012***	0.009***	0.008***	0.005***	-0.008***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
> 500 Employees	0.032***	0.020***	0.017***	0.020***	0.021***	0.029***	0.021***	0.018***	0.012***	-0.008***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	2.825***	3.478***	3.687***	3.763***	3.952***	2.935***	2.973***	3.024***	3.157***	3.522***
	(0.039)	(0.015)	(0.012)	(0.016)	(0.029)	(0.033)	(0.025)	(0.024)	(0.030)	(0.050)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,060,714	1,060,714	1,060,714	1,060,714	1,060,714	3,507,148	3,507,148	3,507,148	3,507,148	3,507,148

Notes: Quantile log wage regressions, separately by gender. The sample includes workers employed at INVIND firms, 1982-1997. Each observation is a worker-year. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent confidence levels, respectively.

A4-3: Quantile Regressions. Female leadership = Female CEO.

Sample			Females					Males		
Dependent variable			ln wage					ln wage		
Quantile	10th	25th	50th	75th	90th	10th	25th	50th	75th	90th
Female CEO	-0.077***	-0.020***	0.002	0.019***	0.028***	-0.003	-0.004**	0.010***	0.015***	0.011***
	(0.006)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Mean Exec Ability	-0.005***	-0.006***	-0.010***	-0.014***	-0.018***	-0.001***	-0.005***	-0.008***	-0.009***	-0.008***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean Exec Experience	-0.000	-0.000***	-0.001***	-0.001***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean Exec Tenure	0.001***	0.001***	0.002***	0.002***	0.001***	-0.000	0.001***	0.001***	0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean Exec Age	0.001	-0.003***	-0.005***	-0.007***	-0.006***	0.014***	-0.001**	-0.005***	-0.004***	-0.002***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
FemNonEx	-0.341***	-0.267***	-0.240***	-0.226***	-0.216***	-0.166***	-0.232***	-0.247***	-0.241***	-0.214***
	(0.005)	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Mean Age Workforce	0.202***	0.138***	0.118***	0.119***	0.122***	0.160***	0.174***	0.189***	0.207***	0.204***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.199***	0.181***	0.145***	0.089***	0.056***	0.270***	0.333***	0.298***	0.263***	0.235***
	(0.004)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age Squared	-0.019***	-0.018***	-0.014***	-0.006***	-0.001**	-0.023***	-0.037***	-0.032***	-0.026***	-0.021***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Share prod. workers	-0.179***	-0.166***	-0.185***	-0.247***	-0.356***	-0.388***	-0.192***	-0.224***	-0.306***	-0.440***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm Effect from AKM	0.676***	0.572***	0.569***	0.617***	0.673***	0.901***	0.746***	0.806***	0.886***	0.931***
	(0.007)	(0.003)	(0.002)	(0.003)	(0.005)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Mean AKM Worker Effect	0.685***	0.477***	0.426***	0.445***	0.485***	0.532***	0.441***	0.486***	0.569***	0.608***
	(0.008)	(0.003)	(0.002)	(0.003)	(0.006)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
SD of AKM Worker Effect	-0.151***	0.079***	0.127***	0.144***	0.142***	0.029***	0.014***	-0.016***	-0.048***	-0.046***
	(0.012)	(0.004)	(0.003)	(0.005)	(0.009)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
< 100 Employees	-0.029***	-0.020***	-0.016***	-0.014***	-0.014***	-0.002*	-0.015***	-0.009***	-0.008***	-0.008***
	(0.004)	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
250-500 Employees	0.013***	0.009***	0.009***	0.010***	0.006***	-0.005***	-0.001*	0.001***	0.001	-0.002***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
> 500 Employees	0.028***	0.022***	0.021***	0.025***	0.025***	-0.003***	0.013***	0.012***	0.008***	0.002***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Constant	2.760***	3.443***	3.683***	3.798***	3.874***	3.074***	2.804***	2.830***	2.848***	2.987***
	(0.037)	(0.014)	(0.011)	(0.015)	(0.027)	(0.008)	(0.035)	(0.027)	(0.030)	(0.041)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,060,714	1,060,714	1,060,714	1,060,714	1,060,714	3,507,148	3,507,148	3,507,148	3,507,148	3,507,148

Notes: Quantile log wage regressions, separately by gender. The sample includes workers employed at INVIND firms, 1982-1997. Each observation is a worker-year. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent confidence levels, respectively.