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

Luca Flabbi, Mario Macis, Andrea Moro, and Fabiano Schivardi

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Abstract

We investigate whether female executives make a difference on gender-specific wage distributions and firm performance using a unique matched employer - employee panel data set of Italian workers that allows us to control for firm and worker fixed effects. We find that female executives increase the variance of women's wages within firms because of a positive impact on wages at the top of the distribution, and a negative impact on wages at the bottom. Moreover, we find that the interaction between female leadership and share of female workers employed at the firm has a positive impact on firm performance. Differently from the previous literature, we focus on less volatile, more long-term measures of actual firm productivity: TFP, value added per worker and sales per worker. These results are robust to different measures of female leadership and to different estimation samples. This evidence is consistent with a model of statistical discrimination where female executives are better equipped at interpreting signals of productivity from female workers. Our interpretation suggests that there are costs associated with the underrepresentation of women at the top of the firm. JEL Codes: M5, M12, J7, J16.

*Flabbi: IDB, Georgetown University and IZA, lf74@georgetown.edu. Macis: Johns Hopkins University and IZA, mmacis@jhu.edu. Moro: Università Ca' Foscari di Venezia and Vanderbilt University, andrea@andreamoro.net. Schivardi: LUISS University, EIEF and CEPR, fschivardi@luiss.it. We thank seminar participants at the 2010 NBER Labor/Personnel Summer Institute, the 1st Fondazione Debenedetti Fellows Workshop, the University of Maryland Robert H. Smith School of Business, the University of Michigan Labor Lunch, the 2012 IZA Workshop on the Economics of Leadership, the 2013 Institute for Compensation Studies Emerging Scholars Conference for very useful comments and suggestions.

1 Introduction

A growing literature is showing that executives' characteristics such as management practices, style, and attitude towards risk make a difference for the firm's outcomes[1]. In this paper we investigate whether workers' gender gaps and firms' performance are affected by the executives' gender using a matched employer-employee panel data set containing the a representative sample of Italian manifacturing firms.

The labor economics literature has provided abundant evidence of systematic gender differentials in the labor market.[2] More recently, research on the economics of leadership has singled out an astounding empirical regularity: women are almost ten times less represented than men in top positions at the firm[3]. For example, recent U.S. data show that even though females are a little more than 50% of white collar workers, they represent only 4.6% of the executives[4]. Our own data Italian data 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. Toghether, these 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 relatively thin literature. First, we develop a theoretical model highlighting the channels of the interaction between female executives, wage policies, job assignments, and overall firm performance or productivity. Second, we investigate the empirical predictions of the model on the relationship between female leadership and the gender-specific wage distribution at the firm level. Differently from previous literature and consistently with our model, the main focus is not on impacts at the mean but on differential impacts over the wage distribution. Third, we investigate the empirical predictions of the model on the relationship be-

[1]Bloom and Van Reenen (2007) is of the first constribution emphasizing differences in management practices. See also a recent survey in Bloom and Van Reenen (2010). A growing literature showing the effects of CEOs characteristics follows the influntial Bertrand and Schoar (2003). Among recent contributions, see Bennedsen et al. (2012), Kaplan et al. (2012), or Lazear et al. (2012). For research on executives' overconfidence, see Malmendier and Tate (2005). For theoretical contributions, see for example Gabaix and Landier (2008) and Tervio (2008). For contributions focusing on both executives and firms characteristics, see Bandiera et al. (2011).

[2]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).

[3]Evidence from U.S. firms 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 et al. (2012), Dezsö and Ross (2012). The literature on other countries is extremely scarce: see Cardoso and Winter-Ebmer (2010) (Portugal), and Ahern and Dittmar (2012) and Matsa and Miller (2013) (Norway). A related literature is concerned with under-representation of women at the top of the wage distribution, see for example Albrecht et al. (2003). Both phenomena are often referred to as a *glass-ceiling* preventing women from reaching top positions in the labor market.

[4]Our elaboration of Current Population Survey and ExecuComp data sets.

tween female leadership and firm performance. Differently from previous literature we focus on less volatile, more long-term measures of actual firm productivity: sales per worker, value added per worker and Total Factor Productivity (TFP).

We use a unique matched employer-employee panel dataset including all workers employed by firms with more than 50 workers belonging to a sample representative of the Italian manufacturing sector between 1982 and 1997. Because we observe all workers and their total compensation in each firm, we can evaluate the impact on the wage distribution at the firm level. The data set is rich in firm-level characteristics, including performance information that have not been considered in this literature. Finally, the data set also contains the labor market trajectories of any worker who ever transited through the sample of firms in the sample period. This feature maximizes the number of transitions available to identify both firms' and workers' fixed effects in a joint two-way fixed effects regressions *à la* Abowd et al. (1999) and Abowd et al. (2002) These fixed effects help addressing the scarcity of worker-level characteristics in our data set.

In the theoretical model, we extend the standard statistical discrimination model of Phelps (1972)to include two types of jobs, one requiring complex tasks and the other simple tasks, and two types of CEOs, male and female. Based on a noisy signal and the worker's type, CEOs assign workers to jobs and wages. We assume that CEOs are better at reading signals from their own gender[5]. We also assume that complex tasks require more skills to be completed successfully and if they are not completed successfully may actually generates losses. After defining the equilibrium generated by this environment, we focus on the empirical implications of a female CEO taking charge of a male CEO-run firm. Thanks to the more precise signal they receive from female workers, female CEOs reverse statistical discrimination against women, adjusting their wages and reducing the mismatch between worker's productivity and job requirements. The two empirical implications of the model we focus on are:

1. The impact of a female CEO on the firm-level wage distribution is positive for women at the top of the wage distribution and negative for women at the bottom of the wage distribution

2. The impact of a female CEO on firm performance is increasing with the proportion of women employed by the firm.

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

The intuition for the first implication is that when the manager is female, female workers produce more precise signals of skill, therefore female wages become more sensitive to their individual-specific productivity. The second result follows because when signals are more precise, there is less mis-matching in the job assignment. The more women are employed by the firm, the larger the effect.

There is a large literature studiying gender differentials in the labor market, and a fairly developed literature studiying gender differentials using matched employer-employee data. However, the literature on the relationship between the gender of the firm's executives and gender-specific wages at the firm is very scarce. Bell (2005) looks at the impact of female leadership in US firms but only on *executives* wages. Cardoso and Winter-Ebmer (2010) look at the impact on all workers on a sample of Portuguese firms but without allowing for heterogeneous effects over the distribution. Fadlon (2010) looks at the impact of the gender of the supervisor on the wages of U.S. workers, but does not have a matched employer-employee panel data set. Thanks to our data, we can look at the impact on the entire wage distribution at the firm allowing for heterogenous effects. Our regressions by wage quantiles show that this heterogeneity is relevant and it is consistent with the predictions of our model: the impact of having a female CEO is positive on women at the top of the wage distribution but negative on women at the bottom of the wage distribution.

Previous literature on the effect of female leadership on firm performance is scarce as well. Many contributions focus on the impact on stock prices, stock returns and market values.[6] The only exception is Matsa and Miller (2013), which looks at operating profit. By conditioning on a wide range of firm-level controls and using less volatile measures of firm performance (sales per employee, value added per employee, and TFP), we can run firm-level regressions closer to our model's implication that are also more relevant to assess the costs of the underrepresentation of women in top positions at the firm. We find that, as predicted by the model, the impact of female CEOs on firm performance is a positive function of the proportion of female workers employed by the firm.

The empirical results exploit within-firm variation, i.e. they are obtained by conditioning on firm fixed-effects. Moreover, all the results are robust to a different measure of female leadership (the proportion of the firm's female executives) and to the selection induced by entry and exit of firms, which we control for by estimating both on a balanced and on an unbalanced panel of firms.

[6]See for example, Wolfers (2006), Albanesi and Olivetti (2009), Ahern and Dittmar (2012); in the strategy literature, Dezsö and Ross (2012), Adams and Ferreira (2009), Farrell and Hersch (2005).

2 Theoretical Framework

We present a simple theoretical model capable of producing the implications we later present in our empirical analysis. In this model, group inequalities are generated by employers' incomplete information about workers productivity. Employers' gender matters. The essential ingredient of our argument is that female and male executives are better equipped at assessing the skills of employees of the same gender. This may be the result of better communication skills, better aptitude at interpersonal relationships, cultural background shared by individuals of the same gender, and so on.[7] Section 5 discusses how alternative explanations may fit our findings.

2.1 Environment

We extend the standard statistical discrimination model in Phelps (1972) to include two types of employers (male and female), and two types of jobs. The two-jobs extension is needed to derive efficiency costs from discrimination, which is one focus of our empirical analysis[8]. There are males (m) and female (f) workers with ability q, distributed normally with mean μ and variance σ^2. Ability, productivity (and wages) are expressed in logarithms. At this stage we consider only firms managed by male CEOs who observe a signal of ability $s = q + \epsilon$, where ϵ is distributed normally with mean 0 and variance $\sigma^2_{\epsilon g}$ where g is workers' gender m and f. The signal's variance can be interpreted as a measure of the signal's information quality. We assume $\sigma^2_{\epsilon m} < \sigma^2_{\epsilon f}$ to indicate that CEOs have better ability to communicate and observe productivity of workers of their own gender. Employers assign workers to two jobs, which require complex (c) and simple tasks (e) to be performed. Crucially for our argument, mismatches are costlier in the complex job, where workers with higher ability are more productive. One way to model this requirement is by assuming that the dollar value of productivity of workers in the complex (easy) job is h (l) if workers have ability $q > \overline{q}$, and $-h$ ($-l$) otherwise, with $h > l \geq 0$. [9]

[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. More recently, Bagues and Perez-Villadoniga (2013)'s model generates a similar-to-me-in-skills result where employers endogenously give higher valuations to candiates that excels in the same dimensions as them. The result may give some foundation to our assumptions if we assume that female workers are more likely to excel in the same dimensions as female executives.

[8] In the standard model of Phelps (1972) discrimination has a purely redistributive nature. If employers were not allowed to use race as a source of information, production would not increase, but this is due to the extreme simplicity of the model. See Fang and Moro (2011) for details.

[9] The threshold rule for productivity is a strong assumption, which we adopted to simplify the derivation of the model's outcome. What is crucial is that productivity increases with ability, and that lower ability workers are more costly mismatched in the complex job.

Firms compete for workers and maximize production given wages. Workers care only about wages and not about job assignment.

2.2 Homogenous CEOs

It is helpful to start the analysis by exploring the effect of the worker's signal precision on labor market outcomes when all CEOs are males; later on we will extend the environment to include female CEOs.

Firms' competition for workers implies that in equilibrium each worker is paid his or her expected marginal product, which depends on her expected ability $E(q|s)$. Standard properties of the bivariate normal distribution[10] imply that $E(q|s) = (1 - \alpha_g)\mu + \alpha_g s$, where $\alpha_g = \sigma^2/(\sigma_{\epsilon g}^2 + \sigma^2)$. The conditional distribution, which we denote with $\phi_g(q|s)$ is also normal, with mean equal to $E(q|s)$ and variance $\sigma^2(1 - \alpha_g)$, $g = \{m, f\}$. Denote the corresponding cumulative distributions with $\Phi_g(q|s)$. Expected ability is a weighted average of the population average skill and the signal, with weights equal to the relative variance of the two variables. When the signal is perfectly informative ($\sigma_{\epsilon g} = 0$), the population mean is ignored; when the signal is pure noise ($\sigma_{\epsilon g} = \infty$), expected ability is equal to the population average. With a partially informative signal, the conditional mean is increasing in both q and s.

It is optimal for employers to use a cutoff job assignment rule: workers will be employed in job c if $s \geq \overline{s}_g$. The cutoff $\overline{s}_g$ is computed by equating expected productivity in the two jobs, as the unique solution to

$$h\left(\Pr(q \geq \overline{q}|s, g) - \Pr(q < \overline{q}|s, g)\right) = l\left(\Pr(q \geq \overline{q}|s, g) - \Pr(q < \overline{q}|s, g)\right). \tag{2.1}$$

We denote this solution with $\overline{s}(\sigma_{\epsilon g})$ to stress its dependence on the signal's informativeness. The worker with signal $\overline{s}_g$ has the same expected productivity (zero) in both jobs[11]. Competition ensures that wages paid w are equal to expected marginal products, which are function of the signal received and the worker's gender:

$$w(s; \sigma_{\epsilon g}) = \begin{cases} l\left(1 - 2\Phi_g(\overline{q}|s)\right) & \text{if } s < \overline{s}_g \\ h\left(1 - 2\Phi_g(\overline{q}|s)\right) & \text{if } s \geq \overline{s}_g \end{cases}.$$

[10] See Eaton (1983)

[11] Equation 2.1 is satisfied where $\Pr(q \geq \overline{q}|s, g) = 1/2$ because of the extreme symmetry of the setup. This implies also that expected productivity is zero for workers with signal equal to the threshold. This can be relaxed: all that is needed to obtain our qualitative implications is that productivity increases with ability, and a comparative advantage to place higher ability workers in the complex job.

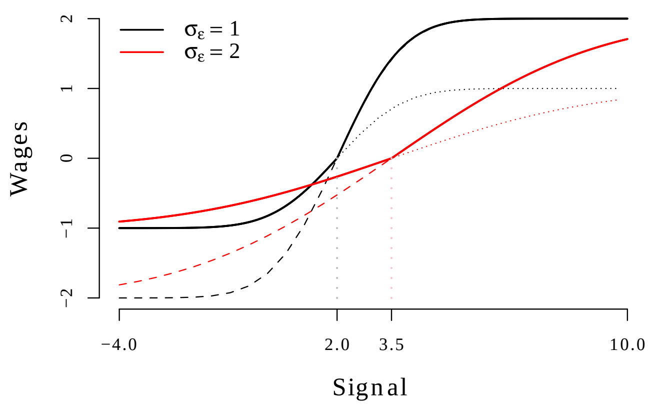

Figure 1: Simulation of the solution to the problem with parameters σ=1, $\overline{q} = 1.5$, $\mu = 1, h = 2$, $l = 1$.

We explore now the properties of the wage schedule as a function of the signal's noise variance $\sigma^2_{\epsilon g}$. Figure 1 displays the outcome for workers with two different value of $\sigma^2_{\epsilon g}$. The darker lines display the equilibrium wages. The dashed red and black lines display expected marginal product of a worker in the complex job in the range of signals where such workers are more productive in the easy job. The dotted red and black lines display the expected marginal product of workers in the simple job, in ranges of the signal where it is optimal to employ them in the complex job. The following proposition states that expected marginal product of a worker is higher when the signal is noisier if the signal is small enough. Conversely, for a high enough signal, the expected marginal product will be lower the noisier the signal. Formally,

Proposition 1. *Let $w(s;\sigma_{\epsilon g})$ be the equilibrium wage as a function of the workers' signal for group g, extracting a signal with noise standard deviation equal to $\sigma_{\epsilon g}$. If $\sigma_{\epsilon f} > \sigma_{\epsilon m}$ then there exists $\widehat{s}$ such that $w(s;\sigma_{\epsilon f}) > w(s;\sigma_{\epsilon m})$ for all $s < \widehat{s}$ and $w(s;\sigma_{\epsilon f}) < w(s;\sigma_{\epsilon m})$ for all $s > \widehat{s}$.*

Proof. The proof relies on a "single-crossing" property of the Normal distribution's cdf: for two normal distributions F, G with different variance ($\sigma_F > \sigma_G$), regardless their mean, there exists a unique $\overline{x} : F(x) > G(x)$ for all $x < \overline{x}$, and $F(x) < G(x)$ for all $x > \overline{x}$.[12] Consider first workers' productivity in the complex job, where the

[12] To prove this single crossing property, denote with f, g the densities of distributions F, G. Because f, g are symmetric around their respective means, and $\sigma_F > \sigma_G$, the two densities intersect at points x_1, x_2 with $f(x) > g(x)$ if $x < x_1$ or $x < x_2$, and $f(x) < g(x)$ for $x_1 < x < x_2$. But then $F(x) > G(x)$ for all $x < x_1$ and $1 - F(x) > 1 - G(x)$, or $F(x) < G(x)$ for $x > x_2$. Hence any

expected product a linear transformation of a Normal cdf: $h\left(1-2\Phi_g(\overline{q}|s)\right)$. The negative sign inside the parenthesis implies that male workers, having a signal with lower variance, have higher expected productivity when the signal is higher than some threshold s_c, and lower when the signal is below the same threshold (in Figure 1 this threshold occurs where the red and black dashed lines intersect). The same holds true for the expected products of male and female workers in the easy job, which cross at some threshold s_e. The thresholds for job assignment $\overline{s}_m, \overline{s}_f$ are generally different from s_c, s_e, and depend on the values of the other parameters of the model. Recall that $w(\overline{s}_f) = w(\overline{s}_m) = 0$ for both $g = m, f$. We need to consider two cases: either (i) $\overline{s}_m < \overline{s}_f$, or (ii) $\overline{s}_m \geq \overline{s}_f$. In case (i) $w(\overline{s}_f) = w(\overline{s}_m)$ and $\overline{s}_m < \overline{s}_f$ imply $\Phi_m(\overline{s}_m) < \Phi_f(\overline{s}_m)$. Hence, within a neighborhood of $\overline{s}_m$ the expected productivity of male workers must be higher than that of female workers both in the complex and in the simple task. But then it must also be the case that the two distribution have crossed to the left of $\overline{s}_m$: $s_c < \overline{s}_m$ and $s_e < \overline{s}_m$ (this is the case displayed in the figure). For all $s > \overline{s}_m$ we know $w(\overline{s}_f) < w(\overline{s}_m)$, while for all $s < \overline{s}_m$ wages are paid according to the simple task productivity, and the distributions cross once at $\hat{s} = s_e$ and the proposition follows. In case (ii) we must instead have $s_c > \overline{s}_m$ and therefore $s_e > \overline{s}_f$, and the result follows defining $\hat{s} = s_c$. $\square$

The next proposition states that productivity is higher when the signal is more precise.

Proposition 2. *Let $y_g(\sigma_{\epsilon g})$ the total production of workers from group g when their signal's noise has standard deviation $\sigma_{\epsilon g}$. Production y_g is decreasing in $\sigma_{\epsilon g}$.*

Proof. This follows observing that expected ability is closer to the workers' signal when $\sigma^2_{\epsilon g}$ is smaller, hence CEOs are less likely to misassign workers of their own gender. $\square$

With the parameters used in Figure 1, 13.2 percent of females and 24 percent of males are employed in the complex job. However, because there are fewer females than males in the right tail of the quality distribution conditional on any given signal, fewer males are mismatched; males' total value of production is equal to -0.29, whereas females' production is -0.35. To assess the inefficiency cost arising from incomplete information, consider that if workers were perfectly assigned, the value of production would be 1.31 for each group.

intersection between F and G must occur between x_1 and x_2, but in this range $f(x) > g(x)$, that is, $F(x)$ has derivative greater than the derivative of $G(x)$, therefore there can be only one intersection.

2.3 Male and Female CEOs

Consider now an environment in which some firms are managed by female CEOs.[13] Female CEOs are characterized by a better ability to assess the productivity of female workers, that is, female workers' signal is extracted from a more precise distribution, with noise variance $\sigma^2_{\epsilon F} < \sigma^2_{\epsilon f}$. Symmetrically, female CEOs evaluate male workers' with lower precision than male CEOs: $\sigma^2_{\epsilon M} > \sigma^2_{\epsilon m}$. We are interested in comparing the equilibrium wages in the two types of firms.

The following empirical implications follow directly from Propositions 1 and 2:

Empirical implication 1. *Wages of female (male) workers in firms with female CEOs display higher variance than wages of female (male) workers employed by firms with male CEOs. This is the because wages of female (male) workers employed by firms with female CEO(s) have higher (lower) wages at the top of the wage distribution, and lower (higher) wages at the bottom of the wage distribution.*

Empirical implication 2. *The productivity of firms with female CEOs is higher, the higher the share of female workers.*

Figure 2 displays the wage distributions of female workers with male and female CEOs; the distribution displayed by the dashed black line was computed using a signal with noise variance $\sigma^2_{\epsilon m} = 3$, representing a draw from a (relatively imprecise) signal from a Male CEOs; the distribution displayed by the solid red line, labeled "Female CEOs", was computed using a signal with variance 2, representing a more precise signal from a female CEO. Note that the distribution of the wages of female workers has thicker tails[14], which is implied by the statement of Empirical implication **??**. We will compare this theoretical prediction with the results of our empirical analysis in Section 4.2.

While Propositions 1 and 2 rely on parametric assumptions, the empirical implications are robust to alternative distribution of the signal's noise and of the underlying productivity. A higher signal precision allows less mis-matching of workers to jobs, and a higher correlation of signals with actual productivity, which implies lower expected when the signal is small, and higher wages when the signal is large. The implications are also robust to alternative specifications of the signal extraction technology. In the online appendix, for example, we derive the same empirical implications assuming a dynamic model where signals are extracted every period.

[13] We do not model the change in CEO gender at this stage; in the data, female CEOs, and female management in general is generally scarce. We are only interested in comparing the wage distribution as the gender of the top management changes.

[14] Other parameters used in this simulation: $\sigma = 1, \overline{q} = 1, \mu = .5, h = 1.1, l = 1$. We picked these parameters to produce a graph that could show the qualitative features of the proposition.

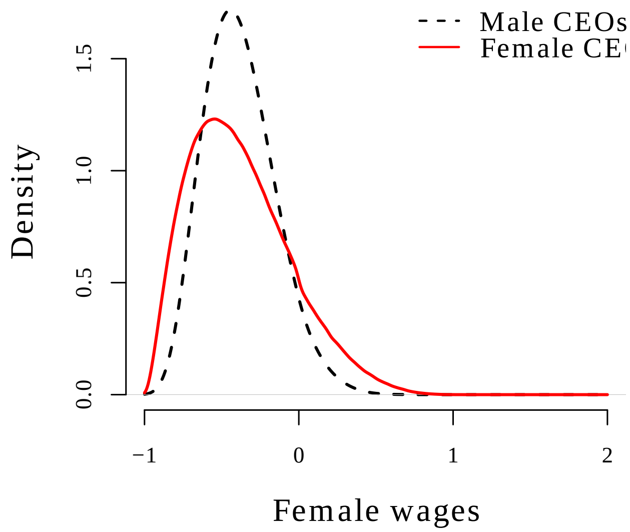

Figure 2: Wage distributions of female workers

Assuming all firm initially have male CEOs, firms acquiring female CEOs update the expected productivity of female workers with higher precision, and the results follow.

3 Data and Descriptive Statistics

We use data from two sources, INVIND-INPS and Company Accounts Data Service (CADS)[15]. INVIND-INPS is a matched employer-employee data set with the following structure. The starting point is the Bank of Italy's annual survey of manufacturing firms (INVIND), an open panel of about 1,000 firms per year, representative of Italian manufacturing firms with at least 50 employees. The Italian Social Security Institute (INPS) provided the work histories of all workers ever employed at an INVIND firm in the period 1980-1997, including spells of employment in firms not included in the INVIND survey. The information contained in the INVIND-INPS data includes for each worker: gender, age, tenure[16], occupational status (production workers, non-production workers, executives), annual gross earnings (including

[15]For other papers using this data, see Iranzo et al. (2008) and Macis and Schivardi (2012).

[16]Tenure information is left-censored because we do not have information on workers prior to 1981.

Table 1: Descriptive statistics: Full INVIND-INPS sample

	Mean	Std. 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	

overtime pay, shift work pay and bonuses), number of weeks worked, and a firm identifier. We exclude 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. For each worker-year, we kept only the observation corresponding to the main job (the job with the highest 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. 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% to 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 second data set we use, CADS, includes balance-sheet information for a sample of about 40,000 firms (including most INVIND firms) between 1982 and 1997. The data include information on industry, geographic location, sales revenues, value added at the firm-year level, and a firm identifier. Because the firm identifier in

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)
% non-prod. workers	29.0		30.4	
% executives	2.4		2.6	
% females	26.4		25.0	
Female executives (% 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]	

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 Table 2 we report summary statistics on the matched INVIND-INPS-CADS sample of firms as well as for a balanced panel sample constructed including only firms continuously observed in the period 1987-1997. In our empirical analyses we will use both of these samples. A total of 822 unique firms are included in the full sample. Of these, 234 form the balanced panel. In the entire sample, average gross weekly earnings at 1995 constant prices are equal to 389 euros, the average workers' age 37.3 years. 68.6% of the observations are from blue collar workers, 29% are white collars, and 2.4% are executives. The corresponding characteristics in the balanced sample are very similar.

We identify female leadership from the job classification "executive" in the data. As already observed by Bandiera et al. (2011), one advantage of using data from Italy is that this indicator is very reliable because the job title of executive is subject to a different type of labor contract and is registered in a separate account with the social security administration agency (INPS)[17]. We identify the CEO as the

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

executive with the highest earnings. Given our detailed 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.

Using these definitions, we find that while females are 26.4% of the workforce in INVIND firms, they are only 3.1% of the executives, and only 1.9% of CEOs. 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.

Female representation in executive positions in Italy has somewhat increased over time but remains very small: 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. There is substantial variation across industries in the presence of females in the executive ranks, but no obvious pattern emerges about the relationship between female leadership and the presence of females in the non-executive workforce in the various industries[18].

Table 3 reports descriptive statistics for firms with and without female executives. Firms with some female executives are larger, pay 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 unconditionl gender wage gap is larger in firms with some female executives (about 18 percent vs. 14 percent).

In Table 4 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.

[18]See table B1 in the external appendix for details

Table 3: Descriptive statistics: Firms with No Female Executives and with some Female Executives

	No Female Execs		Some Female Execs	
	Mean	Std .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]	

Table 4: 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]	

4 Empirical Analysis

4.1 Specification and Identification

The unit of observation of our analysis is a given firm j observed in a given year t. We are interested in the impact of female leadership on the workers' wage distribution and on the performance of a firm. While we cannot control for the nonrandom assignments of female CEOs to firms, this selection problem is alleviated because we estimate regressions with firm fixed effects where we add controls for time-varying firm characteristics, including changes in the workforce, and for female leadership characteristics.

We will estimate regressions of the following form:

$$y_{jt} = FLEAD'_{jt}\beta + FIRM'_{jt}\gamma + WORK'_{jt}\delta + EXEC'_{jt}\chi + \lambda_j + \eta_t + \tau_{t(j)}t + \varepsilon_{jt} \quad (4.1)$$

where: y_{jt} is the dependent variable of interest: either moments of the workers wage distribution or firm performance measures; $FLEAD_{jt}$ is a vector of measures of female leadership: either a female CEO dummy or dummies for different proportions of female executives; $FIRM_{jt}$ is a vector of observable time-varying firm characteristics (dummies for size, industry, and region); $WORK_{jt}$ is a vector of observable workforce characteristics aggregated at the firm level (age, tenure, occupation distribution, fraction female) plus workers fixed effects aggregated at the firm level and estimated in the "first stage" regression we describe below; $EXEC_{jt}$ is a vector of observable characteristics of the female leadership (age, tenure as executive or CEO) plus executives fixed effects estimated in the first stage regression; λ_j are the firm fixed effects; η_t are year dummies and $\tau_{t(j)}$ are industry-specific time trends.

Our approach in specifying equation (4.1) has been to control for firm characteristics, female leadership characteristics, workforce characteristics and time trends. Given our observables and the possibility of running firm fixed effects regressions, we think that our set of firm characteristics provide controls capable of accounting for substantial firm-level heterogeneity as adopted by the current literature. However, our data do not have good controls for executives and workers characteristics. This is because, as common in other administrative data sources, the data set contains only limited set of controls at the individual worker level.[19]

To alleviate this problem, we exploit a useful feature of our data. Our data contain a large set of workers and executives that we do not use in the estimation of the firm fixed effects regressions. This is because workers and executives are followed

[19]For example, we have no measure of education or other proxies of individual ability.

when they leave the set of firms included in the INVIND data set; moreover, not all of the INVID firms are included in the CADS database. The overall matched employer-employee sample is very large (about 19 millions worker-years observations) and contains a lot of transitions of workers across firms well suited to estimate two-way fixed effects as in Abowd et al. (1999)(henceforth, AKM). A worker fixed effect estimated from such a regression has the advantage of controlling for the firms the workers has been working for, and can therefore capture some scale effects in workers productivity which would be typically captured by education, other human capital characteristics or other proxies for "ability" that our data do not contain. Notice that in our statistical discrimination framework, these individual fixed effects can be consistently estimated because in the absence of group differences in average underlying skills, there is no wage discrimination on average, but only in variance.

Consistency at the group level just requires a large number of femal and male workers, which our data possesses. Consistency at the firm level requires a large number of workers in each firm which we frequently have (the sample of INVIND firms only include firms with 50 employees or more). Consistency of a given individual worker fixed effects require many transitions for that worker, which is much less common. However, we need consistency of this latest individual fixed effect only to control for the CEOs fixed effect and CEOs are in fact on average more mobile than average workers.

We perform the two-way fixed effect estimation using the estimation strategy proposed by Abowd et al. (2002).[20] The method hinges crucially on the assumptions of exogenous mobility of workers across firms conditional on observables. We follow Card et al. (2013) (CHK henceforth), in performing several tests to probe the validity of the 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 external appendix.

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

The two-way fixed effects regression equation we estimate is as follows:

$$w_{it} = \mathbf{s}'_{it}\beta + \eta_t + \alpha_i + \sum_{j=1}^{J} dj_{it}\Psi_j + \zeta_{it}. \tag{4.2}$$

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, 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. Our sample consists of essentially one large connected group (99% of the sample belongs to a single connected group). Thus, in our estimation we focus on this connected group and disregard the remaining observations. The identification of firm effects and worker effects is delivered by the relatively high mobility of workers in the sample over the period under consideration: 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 results, reported in Appendix table A.1 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 Female Leadership and Firm-Level Workers Wages Distributions

As discussed in Section 2, female executives extract more precise signals of productivity from female workers. A more precise signal implies that women at the top of the wage distribution should see higher wages than females at the top of the distribution employed by male executives. Women at the bottom of the wage distribution should see lower wages when employed by female executives. As a result, the overall wage dispersion of female workers in each firm should be higher if in firms managed by female CEOs.

We directly investigate these empirical implications by estimating model (4.1) where the dependent variable y_{jt} is a set of firm-level and gender-specific statistics of the workers wages distribution: standard deviation, average wages below the 10th and 25th percentile and average wages above the 75th and 90th percentile. The main set of results are reported in Tables 5 (effects on female workers' wages) and 6 (effects on male workers' wages). They are performed using the most direct measure

Table 5: Impacts on Firm-Level Female Wages Distributions

	Standard	Average Wages Below		Average Wages Above	
	Deviation	10th Pctile	25th Pctile	75th Pctile	90th Pctile
Female Leadership measure:					
Female CEO	0.295***	-0.027	-0.038*	0.083***	0.091***
	(0.064)	(0.036)	(0.022)	(0.019)	(0.026)
CEO characteristics:					
Age/10	0.0004	0.0001	0.0009	0.0003	0.0003
	(0.002)	(0.001)	(0.0007)	(0.0007)	(0.0008)
Tenure as CEO	0.003	0.002	-0.000	0.000	0.001
	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
First Stage Fixed Effect	0.048	0.003	0.016	0.014	0.015
	(0.037)	(0.021)	(0.012)	(0.011)	(0.015)
Non-executive workforce:					
Fraction female	-0.328	-0.698***	-0.670***	-0.771***	-0.648***
	(0.244)	(0.138)	(0.082)	(0.071)	(0.098)
Mean age	0.098***	0.050***	0.046***	0.066***	0.070***
	(0.013)	(0.007)	(0.004)	(0.004)	(0.005)
Mean First Stage F. E.	2.348***	1.245***	1.139***	1.681***	1.752***
	(0.317)	(0.179)	(0.107)	(0.092)	(0.127)
SD First Stage F. E.	1.576***	-0.037	-0.002	0.418***	0.522***
	(0.282)	(0.158)	(0.094)	(0.081)	(0.112)
(see note for the full list of other included controls)					
R^2:					
Within	0.121	0.053	0.109	0.268	0.210
Between	0.131	0.090	0.336	0.448	0.316
Overall	0.119	0.068	0.279	0.427	0.301
N. Observations: 2340 (234 Firms, 10 years)					

Notes: Firms Fixed-Effects regressions reported. We included as controls also 15 region dummies, 20 industry dummies, 4 firm size dummies, 10 year dummies, and industry-specific trends. Dependent variables are in logs. Standard Errors in parentheses. Balanced Panel sample. CEO fixed effects and Workforce fixed effects are estimated in a separate first stage 2-way fixed effect regression on the entire INVIND sample as described in Section 4.1

Table 6: Impacts on Firm-Level Male Wages Distributions

	Standard Deviation	Average Wages Below 10th Pctile	Average Wages Below 25th Pctile	Average Wages Above 75th Pctile	Average Wages Above 90th Pctile
Female Leadership measure:					
Female CEO	-0.275***	-0.028*	-0.016	-0.088***	-0.135***
	(0.037)	(0.014)	(0.010)	(0.015)	(0.020)
Controls CEO characteristics:					
Age/10	0.001***	0.0003	0.000	0.003***	0.005***
	(0.000)	-0.0004	(0.000)	-0.0004	-0.0006
Tenure as CEO	-0.001	-0.001	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.0005)	(0.001)	(0.001)
First Stage Fixed Effect	0.254***	0.017**	0.009	0.056***	0.096***
	(0.022)	(0.008)	(0.006)	(0.009)	(0.011)
Non-executive workforce:					
Fraction female	0.100	-0.191***	-0.169***	0.036	0.059
	(0.143)	(0.054)	(0.040)	(0.056)	(0.076)
Mean age	0.090***	0.040***	0.039***	0.081***	0.081***
	(0.008)	(0.003)	(0.002)	(0.003)	(0.004)
Mean First Stage F. E.	2.325***	0.846***	0.834***	1.987***	1.989***
	(0.185)	(0.070)	(0.052)	(0.073)	(0.099)
SD First Stage F. E.	0.148	-0.202***	-0.108**	0.195***	0.228***
	(0.164)	(0.061)	(0.046)	(0.065)	(0.087)
(see note for the full list of other included controls)					
R^2:					
Within	0.2306	0.1955	0.2759	0.4072	0.323
Between	0.3136	0.2282	0.253	0.3625	0.3041
Overall	0.2934	0.2207	0.2555	0.3633	0.3011

N. Obs: 2340 (234 firms, 10 years)

Notes: Firms Fixed-Effects regressions reported. We included as controls also 15 region dummies, 20 industry dummies, 4 firm size dummies, firm fixed effects, 10 year dummies, and industry-specific trends. Dependent variables are in logs. Standard Errors in parentheses. Balanced Panel sample. CEO fixed effects and Workforce fixed effects are estimated in a separate first stage 2-way fixed effect regression on the entire INVIND sample as described in Section 4.1

of female leadership: female CEO. They are run employing the balanced sample[21] to avoid the selection of firms entering and exiting the sample. Robustness with respect to both the measure of female leadership and the estimation sample are reported in the Appendix in Tables A.2 and A.3.

The first row of Table 5 shows that female CEOs have a strong, positive impact on female wages variance, which stems from a positive effect on wages at the top of the distribution, and a statistically significant, negative effect on wages below the 25th percentile of the wage distribution. This is exactly the main implication of our theoretical framework, as expressed in Proposition 2. The corresponding row of Table 5 shows that this result is reversed on male workers: firms with a female CEOs have a negative effects on male's wage standard deviation, and a negative effect over the whole range of the wage distribution. This result may be consistent with our theoretical framework in the presence of a high enough turnover of male workers.

The main impact of the controls we add to the specification is through the fixed effect (which we do not report in the Tables): on top of the firms fixed effects, we have industry, region, year and size fixed effects. Other controls for the firm workforce have significant impacts and we report them in the Tables. Control for CEO characteristics are never significant in the female wages regressions while they play a more important role in the male wages regressions.

The main results on the female wage distributions (increase in variance and increase at the top and decrease at the bottom) are robust to using the unbalanced panel and to changing the measure of female leadership. The second panel in Table A.2 reports results on the unbalanced panel and shows a positive effect of the female CEO dummy on the wage variance of female workers, with positive effects at the top of the wage distribution and negative (but imprecisely estimated) effects at the bottom. The bottom panel in Table A.2 reports results using dummies for the proportion of female executives as measure of female leadership. Again we find strong positive effect on wage variance when the firm has a strictly positive share of female leadership. Wages at the top of the distribution are higher when the firm has some executives, with a stronger effects if there are more than 25% of female executives. Impact on wages at the bottom are, instead, always insignificant.

Generally speaking, these results are reversed for male workers: we find strong, negative effects on the wage variations, and generally negative effects on the overall wage distribution of male workers.

[21] Firms that were continuously observed from 1987 through 1997.

4.3 Female Leadership and Firm-Level Performance

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

Table 7 presents our first set of results on firm performance, i.e. coefficients from estimating model (4.1) where the dependent variable y_{jt} is one of the three measures of firm performance (Sales per employee; Value Added per employee and TFP[22]) and the female leadership is a dummy =1 if the firm's CEO is a woman. 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 A.4 we present robustness with respect to other measures of firm performance and to using the unbalanced sample of firms.

The first column of each firm performance measure presents a specification similar to the one used in the previous literature and broadly confirm previous results: just as found by Wolfers (2006) and Albanesi and Olivetti (2008)[23] female CEOs do not appear to have a significant impact on firm performance.[24] However, a change in the specification motivated by our model leads to different results. To test if the reassignment of women is an important channel of the impact of female CEO on firm performance, we estimated a specification where the female CEO dummy is interacted with the proportion of non-executive female workers at the firm.[25] If the firm employs female workers, then the female CEO can reassign them and generate gains in firm productivity. Moreover, the more women are present at the firm, the larger the effect. The empirical prediction is that the interaction term should have a strong positive significant effect. This is the result we find in all three specifications. The magnitude of the impact is substantial: for example, a female CEO taking over a firm where half of the workers are women would increase sales per employee by about 19%.

[22]We computed TFP using the Olley and Pakes (1996) procedure: see Iranzo et al. (2008) for the details.

[23]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 (2013)). 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.

[24]The only exception is TFP reporting a marginally significant negative impact.

[25]We focus only on non-executive because the proportion of executive at the firms depends on having a female CEO.

Table 7: Impacts on Firm-Level Performance

	Sales per Employee		Value Added per Employee		TFP	
Female Leadership measure:						
Female CEO	0.033	-0.123*	-0.079	-0.274***	-0.084*	-0.232***
	(0.040)	(0.064)	(0.049)	(0.078)	(0.048)	(0.077)
(Female CEO)*		0.628***		0.781***		0.592**
(Fraction Female)		(0.199)		(0.243)		(0.240)
CEO characteristics:						
Age/10	0.0006	0.0001	0.0022	0.0001	0.0017	0.0001
	(0.0013)	(0.000)	(0.0016)	(0.000)	(0.0016)	(0.000)
Tenure as CEO	-0.003	-0.003	-0.001	-0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
First Stage Fixed Effect	-0.018	-0.018	0.034	0.035	0.030	0.030
	(0.023)	(0.023)	(0.029)	(0.028)	(0.028)	(0.028)
Non-executive workforce:						
Fraction female	-0.409**	-0.490***	-0.605***	-0.707***	-0.596***	-0.673***
	(0.159)	(0.161)	(0.195)	(0.197)	(0.192)	(0.194)
Mean age	0.003***	0.003***	0.003***	0.004***	0.002**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Mean First Stage F. E.	1.324***	1.374***	1.394***	1.456***	1.053***	1.100***
	(0.238)	(0.238)	(0.291)	(0.291)	(0.287)	(0.287)
SD First Stage F. E.	0.382**	0.378**	0.613***	0.608***	0.751***	0.747***
	(0.183)	(0.183)	(0.224)	(0.224)	(0.220)	(0.220)
(see note to Table 5 for the full list of other included controls)						
R^2:						
Within	0.593	0.595	0.218	0.222	0.174	0.176
Between	0.007	0.011	0.017	0.027	0.264	0.262
Overall	0.090	0.097	0.048	0.060	0.243	0.242
N. obs: 2340 (234 Firms, 10 years)						

Notes: Firms Fixed-Effects regressions reported. Standard Errors in parentheses. Balanced Panel sample. Interaction term in second row refers to fraction of female workers (non-excutive).

The result is confirmed when using other measures of female leadership. Details are reported in Table A.4 in the Appendix. If we use as measure of female leadership the presence of a substantial proportion of female executive at the firm (more than 25%) then we obtain the same strong, positive and significant interaction term. Results on the unbalanced sample are, instead, more mixed. Using sales per employee and value added per employee, we obtain again a positive coefficient on the interaction term but it is very imprecisely estimated and not significantly different from zero. Using TFP, the coefficient is small and negative but again not significantly different from zero.

4.4 Potential efficiency gain from gender quotas

In order to provide an order of magnitude of the potential efficiency gains generated by gender quotas, we performed a partial-equilibrium exercise using as a benchmark the parameters reported in Table 7. We performed two counterfactuals. In the first, we computed the predicted value of the dependent variable assuming that the female CEOs increase to 30 percent of the total number of CEOs, allocating randomly female CEOs among firms that have a male CEO. In the second counterfactual, we allocated a female CEO to all firm that have a male CEO and where female employees are at least 40 percent. Thus results in 15% firms with a female CEO.

Results are reported in Table 8. When Female CEOs are allocated randomly, the average percent change is generally small, and its sign depends on the measure of performance. Because our baseline regression implies large, positive interaction effects between female leadership and share of female workers, in the second counterfactual we see large, positive effects in firms that acquire a female CEO, and positive effects on average, which are more limited in size because the treated firms are only about 12 percent.

While there are are general equilibrium and other types of effects that may affect these figures, these results confirm that the order of magnitude of the efficiency gains for having a higher female representation in firm leadership is large.

The effect on the average gender wage gap, not shown in the table, is small because the higher wages of female workers in firms that acquire femal leadership is compensated by the lower wages at the low end of the wage distribution.

5 Other explanations

Table 8: Impact of gender quotas

Counterfactual	Average percent gain			Percent gain for treated		
	Sales	Value added	TFP	Sales	Value added	TFP
30% random	1.1	-2.0	-2.2	3.7	-7.4	-8.8
>40% female share	3.7	3.1	2.0	28.9	24.0	15.8

Note: average percent gains relative to fitted data. "Treated" firms are firms that acquire a female CEO.

5.1 Not an effect of gender preferences

It is difficult to explain the evidence we uncovered by assuming that female CEOs give preferential treatment to female workers. One could argue that female leaders have special preferences for skilled female workers. However, the effect of female leadership on female wages is increasing with skill in our main specification, but has no clear pattern on male wages. This asymmetry make it difficult to justify our results without ad-hoc assumptions on preferences.

Moreover, preferential treatment is inconsistent with our results on firm performance illustrated in Subsection 4.3. If female CEOs had preferential treatment for female workers, they would be prone to hire and promote workers without considering their expected skill level, therefore it would be unlikely to observe a positive impact on performance of the interaction between female leadership and share of female workers at the firm.

5.2 Not an effect of complementarities between female managers and skilled workers

Our explanation provides predictions similar to assuming that female leadership is complementary to skilled labor input from female workers. Statistical discrimination provides a source for such complementarities. Arguably, similar effects could be derived from a complete information model where complementarities arise from technology. For example, one could assume that communication is more efficient between workers and executives of the same gender. Such communication skills provide a possible micro-foundation of the crucial assumption of our statistical discrimination framework: the difference in the quality of signals from workers of different gender. However, it is possible to think of an environment with complete information where communication skills enter directly into the production function, or where complementarities are generated because of peer-group effects or where female managers are role model for skilled female workers. These explanations can generate both the wage effects and the productivity effects we found in our results. However, it would be hard to explain the negative effects on low-skilled female wages, which we believe are unique to the statistical discrimination assumptions.

6 Conclusion

Motivated by the recent literature showing the importance of executives at the firm and by the traditional literature on gender differential in the labor market, we investigate whether female executives make a difference on gender-specific wage distributions and firm performance using a unique matched employer-employee panel data set of Italian workers that allows us to control for firm and worker fixed effects. We find that female executives increase the variance of women's wages at the firm because they have a positive impact on wages at the top of the distribution, and a smaller, negative impact on wages at the bottom. Moreover, we find that the interaction between female leadership and share of female workers employed at the firm has a positive impact on 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. These results are robust to different measures of female leadership and to different estimation samples.

This evidence is consistent with a model of statistical discrimination where female executives are better equipped at interpreting signals of productivity from female workers. As a result, when a female CEO takes charge of a previously male-led firm, she will reverse statistical discrimination, paying women wages that are closer to their actual productivity and matching them to job that are more in line with their skills. Our interpretation suggests that there are costs - potentially very high, given the increasing supply of highly skilled women in the market - associated with the underrepresentation of women at the top of the firm.

A Appendix

Table A.1: Two-Way Fixed Effects Regression Results

Variable	Coefficient
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 fixed effects	(not reported)
SD of worker effects	0.510
SD of firm effects	0.153
Correlation	-0.087
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

Table A.2: Impacts on Firm-Level Female Wages Distributions: Robustness

	Standard Deviation	Average Wages Below 10th Pctile	Average Wages Below 25th Pctile	Average Wages Above 75th Pctile	Average Wages Above 90th Pctile
Benchmark Specification					
Female CEO	0.295***	-0.027	-0.038*	0.083***	0.091***
	(0.064)	(0.036)	(0.022)	(0.019)	(0.026)
R^2:					
Within	0.121	0.053	0.109	0.268	0.210
Between	0.131	0.090	0.336	0.448	0.316
Overall	0.119	0.068	0.279	0.427	0.301
N. Obs. = 2340 (234 firms, 10 years)					
Robustness 1: Unbalanced Panel Sample					
Female CEO	0.403***	-0.007	-0.013	0.112***	0.173***
	(0.040)	(0.026)	(0.017)	(0.012)	(0.016)
R^2:					
Within	0.161	0.159	0.212	0.408	0.352
Between	0.040	0.270	0.383	0.324	0.218
Overall	0.054	0.173	0.297	0.333	0.229
N. Obs = 7904 (817 firms, 9.6 years on average)					
Robustness 2: Other Measures of Female Leadership					
Prop. Female Execs:					
Between 0 and 25%	0.401***	-0.004	0.001	0.086***	0.150***
	(0.028)	(0.017)	(0.010)	(0.008)	(0.011)
Over 25%	0.590***	0.030	0.015	0.221***	0.244***
	(0.066)	(0.039)	(0.024)	(0.019)	(0.026)
R^2:					
Within	0.219	0.052	0.107	0.336	0.2928
Between	0.269	0.224	0.432	0.521	0.4144
Overall	0.256	0.157	0.353	0.499	0.3956
N. Obs. = 2340 (234 firms, 10 years)					

Notes: Firms Fixed-Effects regressions reported. Dependent variables are in logs. Standard Errors in parentheses. All the specifications include all the controls reported in Table 5. Robustness 1: Full INVIND-INPS-CADS sample over 1980-1997. Robustness 2: Balanced Panel sample; Category omitted is No female executives.

Table A.3: Impacts on Firm-Level Male Wages Distributions: Robustness

	Standard Deviation	Average Wages Below 10th Pctile	Average Wages Below 25th Pctile	Average Wages Above 75th Pctile	Average Wages Above 90th Pctile
Benchmark Specification					
Female CEO	-0.275***	-0.028*	-0.016	-0.088***	-0.135***
	(0.037)	(0.014)	(0.010)	(0.015)	(0.020)
R^2:					
Within	0.2306	0.1955	0.2759	0.4072	0.323
Between	0.3136	0.2282	0.253	0.3625	0.3041
Overall	0.2934	0.2207	0.2555	0.3633	0.3011
N. Obs. = 2340 (234 firms, 10 years)					
Robustness 1: Unbalanced Panel Sample					
Female CEO	-0.351***	-0.038***	-0.020***	-0.142***	-0.200***
	(0.025)	(0.011)	(0.007)	(0.010)	(0.014)
R^2:					
Within	0.466	0.202	0.314	0.607	0.555
Between	0.363	0.268	0.315	0.432	0.390
Overall	0.422	0.228	0.309	0.493	0.455
N. Obs = 7904 (817 firms, 9.6 years on average)					
Robustness 2: Other Measures of Female Leadership					
Proportion Female Executives:					
Between 0 and 25%	-0.034*	0.003	0.005	0.003	-0.001
	(0.017)	(0.007)	(0.005)	(0.007)	(0.009)
Over 25%	-0.242***	-0.007	0.000	-0.100***	-0.150***
	(0.040)	(0.015)	(0.011)	(0.016)	(0.021)
R^2:					
Within	0.246	0.197	0.280	0.422	0.341
Between	0.307	0.219	0.386	0.405	0.333
Overall	0.288	0.214	0.372	0.403	0.329
N. Obs = 2340 (234 firms, 10 years)					

Notes: Firms Fixed-Effects regressions reported. Dependent variables are in logs. Standard Errors in parentheses. All the specifications include all the controls reported in Table 5. Robustness 1: Full INVIND-INPS-CADS sample over 1980-1997. Robustness 2: Balanced Panel sample; Category omitted is No female executives

Table A.4: Impacts on Firm-Level Performance: Robustness

	Sales per Employee	Value Added per Employee	TFP
Benchmark Specification			
Female CEO	-0.123*	-0.274***	-0.232***
	(0.064)	(0.078)	(0.077)
(Female CEO)*	0.628***	0.781***	0.592**
(Fraction Female)	(0.199)	(0.243)	(0.240)
R^2:			
Within	0.595	0.222	0.176
Between	0.011	0.027	0.262
Overall	0.097	0.060	0.242
Robustness 1: Unbalanced Panel Sample			
Female CEO	-0.017	-0.114**	-0.085*
	(0.039)	(0.047)	(0.047)
(Female CEO)*	0.148	0.108	-0.032
(Fraction Female)	(0.092)	(0.111)	(0.110)
R^2:			
Within	0.748	0.303	0.237
Between	0.128	0.100	0.413
Overall	0.269	0.161	0.405
Robustness 2: Other Measures of Female Leadership			
Proportion Female Executives:			
Between 0 and 25%	-0.039	-0.034	-0.011
	(0.032)	(0.040)	(0.039)
Over 25%	-0.147*	-0.272***	-0.270***
	(0.079)	(0.096)	(0.095)
Between 0 and 25%*	0.102	-0.118	-0.111
(Fraction Female)	(0.090)	(0.110)	(0.109)
Over 25%*	0.533***	0.648***	0.617***
(Fraction Female)	(0.191)	(0.233)	(0.230)
R^2:			
Within	0.594	0.223	0.178
Between	0.011	0.006	0.246
Overall	0.096	0.033	0.229

Notes: Firm fixed effects regressions reported. Dependent variables are in logs. Standard Errors in parentheses. Interaction term refers to fraction female workers non-excutive. All the specifications include all the controls reported in Table 7. Number of observations as in Table A.2. Robustness 1: Full INVIND-INPS-CADS sample over 1980-1997. Robustness 2: Balanced Panel sample; Category omitted is No female executives.

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