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

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Abstract

We investigate the effect of female leadership on gender-specific wage distributions and firm performance using a unique Italian matched employer-employee panel data set. We find that female executives increase the variance of women's wages within firms due to 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 the share of female workers employed at the firm has a positive impact on firm performance (sales per worker, value added per worker, and TFP). These results are robust to different measures of female leadership and to different estimation samples, as well as to including controls for unobservable heterogeneity at the firm, workforce, and executive level. 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 corporate hierarchies.

JEL Codes: M5, M12, J7, J16.

Keywords: gender gap, statistical discrimination

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1 Introduction

A growing literature shows that executives' characteristics such as management practices, style, and attitude towards risk make a difference for firm outcomes.[1] In this paper, we focus on two firm outcomes - workers' wage distributions and firms' performances - and we investigate how they are affected by one specific executive characteristics - gender - by using a unique matched employer-employee panel dataset representative of the Italian manufacturing sector.

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 Italian data show that around 26% of workers in the manufacturing sector are women compared with only 3% of the executives and 2% of CEOs. Toghether, these facts suggest that looking at gender as a potentially relevant executive characteristic is not only interesting but may also have important productivity and welfare implications.

We provide three contributions. First, we develop a theoretical model highlighting the channels of the interaction between female executives, female workers, wage policies, job assignment, and overall firm performance. 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

[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 thin: 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 on 2012 Current Population Survey and ExecuComp data.

the empirical predictions of the model on the relationship between female leadership and firm performance. Unlike previous literature, we do not look at measures of financial performance and we focus instead on sales per worker, value added per worker and Total Factor Productivity (TFP); these are measures of firm productivity that are less volatile and less likely to be affected by gender discrimination than financial indicators (Wolfers 2006).

We use a unique matched employer-employee panel dataset including all workers employed by firms with at least 50 employees in a "core" sample representative of the Italian manufacturing sector between 1982 and 1997. Because we observe all workers and their individual compensation in each firm, we can evaluate the impact of female leadership on the wage distribution at the firm level. The data set is rich in firm-level characteristics, including data on performance. The data set also contains the complete labor market trajectories of any worker who ever transited through any of the core firms in the sample period. This feature maximizes the number of transitions available to identify firm and worker 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 and allow us to control for unobservable heterogeneity at the workforce, firm and executive level.

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 productivity signal and the worker's gender, CEOs assign workers to jobs and wages. We assume that CEOs are better (more accurate) at reading signals from workers of their own gender.[5] We also assume that complex tasks require more skills to be completed successfully, and that if they are not completed successfully they may generate 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 female workers' productivity and job requirements. The model delivers two sharp, testable empirical implications:

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;

[5] We discuss this assumption in Subsection 2.3.

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

The intuition for the first implication is that a female CEO is better at processing information about female workers' skill, and therefore female wages become more sensitive to their individual-specific productivity. The second result follows because when signals are more precise female workers are better matched to job assignments. The more women are employed by the firm, the larger the effect because there are more women that can be potentially better matched.

There is a large literature studying 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 quite scarce. Bell (2005) looks at the impact of female leadership in US firms but only on *executives* wages. Cardoso and Winter-Ebmer (2010) consider 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 supervisors' gender on workers' wages in the U.S. but does not have a matched employer-employee panel data set. Gagliarducci and Paserman (2014) use German linked employer-employee data to study the effect of the gender composition of the first two layers of management on firm and worker outcomes. Thanks to the richness of our data, we can analyze the impact on the entire wage distribution within the firm allowing for heterogenous effects across workers. 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. Many contributions focus on financial performance looking at the impact on stock prices, stock returns and market values.[6] By conditioning on a wide range of firm-level controls and using less volatile measures of firm performance, 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.

Our empirical specifications exploit within-firm variation, i.e. they are obtained

[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). One rare exception is Matsa and Miller (2013) which looks at operating profits.

by conditioning on firm fixed-effects. Moreover, the results are robust to including controls for unobservable heterogeneity at the workforce level and at the executive level. Finally, 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.

The paper proceeds as follows. In Section 2 we present our theoretical model and derive its empirical implications. In Section 3 we describe the data, and in Section 4 we present our empirical strategy and the results. Section 5 discusses if and how alternative explanations may fit our findings, and Section 6 concludes.

2 Theoretical Framework

We present a simple theoretical model where inequalities are generated by employers' incomplete information about workers' productivity and where 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 their same gender. This may be the result of better communication and better aptitude at interpersonal relationships among individuals of the same gender, of more similar cultural background shared by individuals of the same gender, or other factors. From the model we derive a set of implications that we test in our empirical analysis.

2.1 Environment

We extend the standard statistical discrimination model in Phelps (1972) to include two types of employers (female and male), and two types of jobs (simple and complex). The two-jobs extension is needed to derive efficiency costs from discrimination, which is one focus of our empirical analysis.[7] Female (f) and male (m) workers have ability q which is distributed normally with mean μ and variance σ^2. Ability, productivity (and wages) are expressed in logarithms. CEOs 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 or f. The signal's variance can be interpreted as a measure of the signal's information quality. Employers assign workers to one of two jobs: one requiring complex (c) tasks to be performed and the other requiring simple tasks (e) to be performed. Crucially for our argument, mismatches are costlier in the complex

[7] 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.

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 $h > l \geq 0$.[8]

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[9] 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

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

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.[10] Competition ensures that wages w are equal to expected marginal

[8] The threshold rule for productivity is a strong assumption, which we adopted to simplify the derivation of the model's outcome, but it is not crucial. What is crucial is that productivity increases with ability, and that lower ability workers are more costly mismatched in the complex job.

[9] See Eaton (1983)

[10] Equation 2.1 is satisfied when $\Pr(q \geq \overline{q}|s, g) = 1/2$ 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.

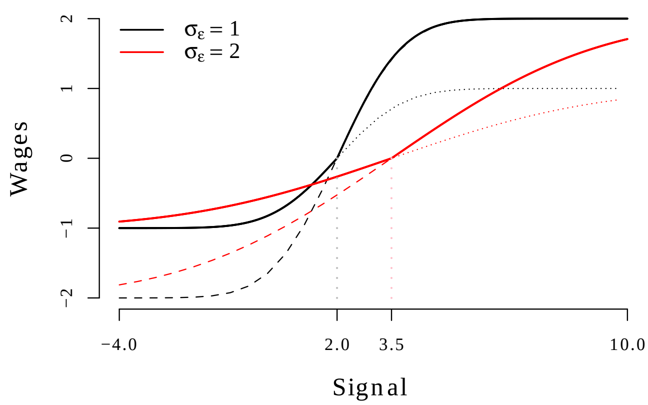


Figure 1: Simulation of the solution to the problem with parameters σ=1, $\overline{q} = 1.5$, $\mu = 1, h = 2$, $l = 1$.

products, which are function of the signal received and the worker's gender:

$$w(s;\sigma_{\epsilon g}) = \begin{cases} l\left(1 - 2\Phi_g(\overline{q}|s)\right) & \text{if } s < \overline{s}_g \\ h\left(1 - 2\Phi_g(\overline{q}|s)\right) & \text{if } s \geq \overline{s}_g \end{cases}. \tag{2.2}$$

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 values of $\sigma^2_{\epsilon g}$. The continuous 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 the 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 $s > \widehat{s}$.*

The proof is in the appendix. This "single-crossing" property of the wage functions of signals of different precision rely to some extent on the assumptions of symmetry of the production function and of the signaling technology distributions. However the result that a more precise signal implies higher wages at the top of the distribution, and lower wages at the bottom, is more general, and will hold even if the wages cross more than once.

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

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 $\sigma_{\epsilon g}$.*

With the parameters used in Figure 1, and assuming that female workers are those with the larger signal noise variance ($\sigma_{\epsilon m}=1$ and $\sigma_{\epsilon f}=2$), 24 percent of males and 13.2 percent of females are employed in the complex job. Moreover, since there are fewer females than males in the right tail of the quality distribution conditional on any given signal, more females 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.

2.3 Heterogenous CEOs: Female and Male

Consider now an environment in which some firms are managed by female CEOs and some by male CEOs.[11] 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 $\sigma^2_{\epsilon F} < \sigma^2_{\epsilon f}$ (where the capital F denotes female workers when assessed by a female CEO, and lowercase f when assessed by a male CEO). Symmetrically, female CEOs evaluate male workers' with lower precision than male CEOs: $\sigma^2_{\epsilon M} > \sigma^2_{\epsilon m}$.

This assumption may be motivated by any difference in language, verbal and non-verbal communication styles and perceptions that may make it easier to generate between people of the same gender a better understanding of personal skills and attitudes, improve conflict resolutions, assignment to job-tasks, etc... The socio-linguistic literature has studied differences in verbal and non-verbal communication

[11] We do not model the change in CEO gender at this stage or how the CEO is selected as we are interested in comparing differences in gender-specific wage distributions between firms where the top management has different gender.

styles between groups defined by race or gender that may affect economic and social outcomes (see Dindia and Canary (2006)).[12] In the economics literature, Lang (1986) develops a theory of discrimination based on language barriers between "speech communities" defined by race or gender. To motivate this assumption, which may be interpreted to produce effects similar to those of the assumption we make, Lang surveys the socio-linguistic literature demonstrating the existence of such communication barriers. Cornell and Welch (1996) adopt the same assumption in a 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 candidates who excel in the same dimensions as them. This result provides foundation to our assumptions if we assume that female workers are more likely to excel on the same dimensions as female executives.

We are interested in comparing the equilibrium wages and firm performance in firms with CEOs of different gender. Figure 2 displays the wage distributions of female workers employed at firms with female or male CEOs. The distribution displayed by the dashed black line was computed using a signal with noise variance $\sigma^2_{\epsilon m} = 3$, representing draws from the (less precise) signals received by male CEOs; the distribution displayed by the solid red line was computed using a signal with noise variance $\sigma^2_{\epsilon f} = 2$, representing draws from the (more precise) signals received by female CEOs. Note that the wage distribution of female workers employed at female CEOs firms has thicker tails[13].

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

Empirical implication 1. *Wages of female workers in firms with female CEOs are higher at the top of the wage distribution, and lower at the bottom of the wage distribution relative to wages of female workers employed by male CEOs. Symmetrically, wages of male workers in firms with female CEOs are higher at the bottom and lower at the top of the wage distribution relative to wages of male workers employed by male CEOs.*

To test this implication, in Section 4 we subdivide the female and male firm-level wage distributions by quantiles, and use the average wage in each quantile as a dependent variable. For results to be consistent with Empirical Implication 1, the coefficient on a female CEO dummy (or other measures of female leadership) should be positive in the regressions on the top quantiles of the female wage distribution,

[12] There exists also an extensive medical literature showing how physician-patient interactions are affected by the gender of both the physician and the patient (see Cooper-Patrick et al. (1999) Rathore et al. (2001), and Schmid Mast et al. (2007)).

[13] 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.

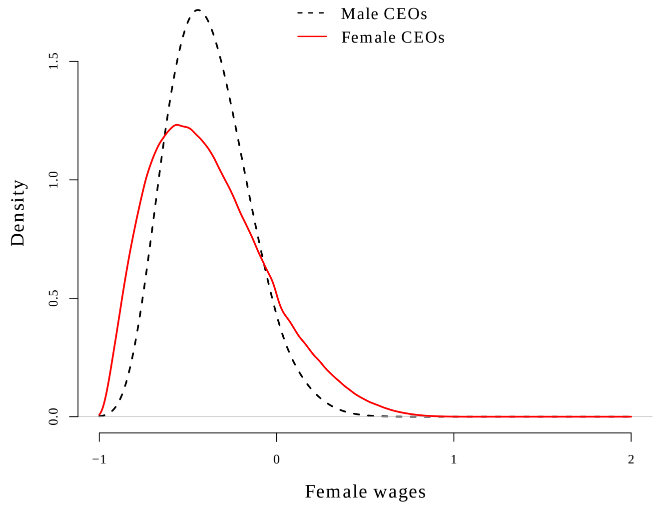


Figure 2: Wage distributions of female workers

and negative in the regressions on the bottom quantiles. The opposite should hold in regressions using as a dependent variable quantiles of the male wage distribution: the model predicts the coefficient of a female CEO dummy to be negative at the top quantiles, and positive at the bottom quantiles.

For an additional confirmation, we check whether the variance of the wage distribution of female workers employed by female CEOs is higher than the variance of the wage distribution of female workers employed by male CEOs. Our model also predicts the opposite to be true on the variance of male wages: the wage distribution of male workers employed by female CEOs should have a lower variance than that of workers employed by male CEOs.

In terms of firm performance, the following implication follows directly from Proposition 2:

Empirical implication 2. *The productivity of firms with female CEOs increases with the share of female workers.*

To test this implication, we regress various measures of firm performance on a female CEO dummy interacted with the fraction of female workers. The model predicts the coefficient on this interaction to be positive.

We derived Propositions 1 and 2 using specific distributional assumptions, but the empirical implications are robust to alternative distributions of the signal's noise and of the underlying productivity. A higher signal precision always implies less mismatching of workers to jobs, and a higher correlation of signals with productivity always implies lower wages when the signal is small and higher wages when the signal is high. These 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. Assuming all firm initially have male CEOs, firms acquiring female CEOs update the expected productivity of female workers with higher precision. The result follows because female CEOs will rely on a larger number of more precise signals from female workers than male CEOs.

3 Data and Descriptive Statistics

3.1 Data Sources and Estimation Samples

We use data from three sources that we label INVIND, INPS and CADS. From these three sources of data, we build a matched employer-employee panel data set and from this matched data set we extract our final estimation samples.

INVIND stands for the *Bank of Italy's annual survey of manufacturing firms*, an open panel of about 1,000 firms per year, representative of Italian manufacturing firms with at least 50 employees. INPS stands for the *Italian Social Security Institute* which 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. We match the INVIND firms with the INPS work histories thanks to unique worker and firms identifiers to create what we call the INVIND-INPS data set. This data set includes for each worker: gender, age, tenure[14], occupational status (production workers, non-production workers, executives), annual gross earnings (including 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

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

INVIND-INPS data set. 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).

CADS, the third data source we use, stands for *Company Accounts Data* and includes balance-sheet information for a sample of about 40,000 firms between 1982 and 1997, including almost all INVIND firms. The data include information on industry, location, sales, revenues, value added at the firm-year level, and a firm identifier. Again thanks to a unique and common firm identifier, we can match CADS with INVIND-INPS.

We will focus most of our empirical analysis on the balanced panel sample consisting of firms continuously observed in the period 1987-1997. In Table 1 we report summary statistics both on this sample and on the entire, unbalanced INVIND-INPS-CADS sample for the same period. The unbalanced INPS-INVIND-CADS panel includes 5,029 firm-year observations from a total of 795 unique firms. Of these, 234 compose the balanced panel. In the unbalanced sample, average gross weekly earnings at 1995 constant prices are equal to about 400 euros. On average, workers are 37.2 years old and have 8 years of tenure in the firm. About 68% of the workers are blue collars, 30% white collars, and 2% are executives. The corresponding characteristics in the balanced sample are very similar.

3.2 Female Leadership

We identify female leadership from the job classification *executive*[15] 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) with respect to workers that are not executives. We identify the CEO as the executive with the highest compensation in the firm. This procedure is supported by the following: i) Salary determination in the Italian manufacturing sector is such that the compensation ordering follows very closely the hierarchical ranking within each of the three broad categories we observe (executives, non-production workers, production workers); ii) There is no doubt that the firm's CEO (the top executive in charge of the firm) is classified

[15]The original job description in Italian is *dirigente*, which corresponds to an executive in a US firm.

Table 1: Descriptive statistics: INVIND-INPS-CADS sample

	INVIND-INPS		INVIND-INPS-CADS			
			Unbalanced panel		Balanced panel	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
% Prod. workers	66.5		67.6	(18.7)	67.4	(18.3)
% Non-prod. wrk	31.3		29.8	(17.7)	30.0	(17.3)
% Executives	2.2		2.5	(1.7)	2.6	(1.8)
% Females	21.1		26.2	(20.9)	25.8	(20.1)
% Fem. execs.	2.49		3.3	(10.3)	3.4	(10.1)
% Female CEO			2.1		1.8	
Firm size (empl.)			675.0	(2,628.6)	704.2	(1,306.9)
Age	37.0	10.1	37.2	(3.6)	37.4	(3.4)
Tenure	5.1	4.1	8.1	(2.6)	8.7	(2.3)
Wage (weekly)	387.2	253.8	400.3	(86.0)	404.5	(88.7)
Wage (males)	408.1	271.8	343.3	(67.0)	433.9	(97.5)
Wage (females)	309.5	146.6	429.3	(92.7)	346.4	(68.5)
Sales ('000 euros)			110,880	(397,461)	118,475	(231,208)
Sales/worker (ln)			4.93	(0.62)	4.95	(0.57)
Val. add./wkr (ln)			3.77	(0.43)	3.79	(0.41)
TFP			2.49	(0.50)	2.49	(0.49)
N. Observations	18,664,304		5,029		2,340	
N. Firms	448,284		795		234	
N. Workers	1,724,609					

within the executive category; iii) We have a very detailed and precise measure of compensation because we have direct access to the administrative data that each firm is required by law to report and that each worker has the incentive to verify it is correctly reported; iv) We have access to all the workers employed by a given firm in a given year.[16]

Using these definitions, we find that while females are 26.2% of the workforce in INVIND firms, they are only 3.3% of the executives, and only 2.1% of CEOs. The descriptive statistics for the balanced panel are quite similar to those referring to the unbalanced sample and confirm the underrepresentation of women in top positions

[16]We have the complete set of workers only for the INVIND firms and as a result we can only assign CEO's gender to INVIND firms. However, this is irrelevent for our final estimation sample at the firm level since for other reasons explained below we limit our main empiricial analysis to a subset of INVIND firms.

in firms 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[17] 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]

In Table 2 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 larger share of female workers (37 vs. 26 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 about 3 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 only about 21 percent, 19 percent and 4 percent higher, respectively.

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 firm performance.

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 the fraction of female executives; $FIRM_{jt}$ is a vector of observable time-varying firm characteristics (dummies for size,

[17] Execucomp is compiled by Standard and Poor and contains information on 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).

[18] See Table B1 in the Web Appendix for details

Table 2: Descriptive statistics: Firms with Male and Female CEO

	Male CEO		Female CEO	
	Mean	St.Dev.	Mean	St.Dev.
CEO's age	49.5	(7.1)	46.6	(7.1)
CEO's tenure	4.4	(3.7)	4.0	(2.8)
CEO's pay	165,238	(130,560)	115,936	(54,030)
% Production workers	67.5	(18.7)	75.4	(13.5)
% Non-prod. workers	30.0	(17.8)	22.2	(13.1)
% Executives	2.5	(1.7)	2.4	(1.4)
% Females	25.9	(20.7)	37.2	(27.0)
% Female executives	2.4	(6.9)	46.8	(29.5)
Firm size (employment)	683.7	(2,655.4)	270.3	(409.9)
Age	37.2	(3.6)	35.9	(3.5)
Tenure	8.1	(2.6)	8.6	(2.2)
Wage (earnings/week)	401.6	(86.0)	341.3	(61.7)
Wage (males)	430.6	(92.8)	369.4	(64.2)
Wage (females)	343.3	(66.2)	345.4	(97.1)
Sales (thousand euros)	112,467	(401,486)	37,185	(55,982)
Sales per worker (ln)	4.9	(0.6)	4.7	(0.6)
Value added per worker (ln)	3.8	(0.4)	3.6	(0.4)
TFP	2.5	(0.5)	2.4	(0.5)
N. Observations	4,923		106	
N. Firms	788		33	

industry, and region); $WORK_{jt}$ is a vector of observable workforce characteristics aggregated at the firm-year level (age, tenure, occupation distribution, fraction female) plus worker fixed effects aggregated at the firm-year level and estimated in a "first stage" regression described in detail below; $EXEC_{jt}$ is a vector of observable characteristics of the firm leadership (age, tenure as executive or CEO) plus executives' fixed effects estimated in the first stage regression; λ_j are firm fixed effects; η_t are year dummies and $\tau_{t(j)}$ are industry-specific time trends.

Our approach in specifying equation (4.1) is to control for firm characteristics, female leadership characteristics, workforce characteristics and time effects. Given our observables and the possibility of running firm fixed effects regressions, we believe that our set of firm characteristics provides controls capable of accounting for substantial firm-level heterogeneity even if our data do not include a rich set of controls for executives and workers characteristics.[19] Our specifications cannot directly control for the nonrandom assignments of female CEOs to firms. However, this selection problem is alleviated because we control for firm fixed effects and time-varying firm characteristics, including changes in the workforce, and for female leadership characteristics.

In particular, to construct controls for unobservable heterogeneity at teh workforce and executive level, we exploit the fact that our data set includes the entire work history of all of the workers who ever transited through one of the INVIND firms, including any and all transitions through non-INVIND firms. This large matched employer-employee sample (about 19 million worker-year observations) contains a large number of transitions of workers across firms and is thus 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 ever worked for, and can therefore capture some scale effects in workers productivity which would be typically captured by education, other time-invariant 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 female and male workers, which our data possesses. Consistency at the firm level requires a large number of workers in each firm. This is also true in our data, as by construction the minimum employment level to be included in the INVIND survey is 50 employees, and the average number of workers in INVIND firms is around 700 see Table 1). Consistency of a given individual worker fixed effect requires 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 two-way fixed effects regression equation we estimate is as follows:

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

[19] For example, we have no measure of education or other proxies of individual ability. This is because, as common in other administrative data sources, the data set contains only a limited set of variables at the individual worker level.

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

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.

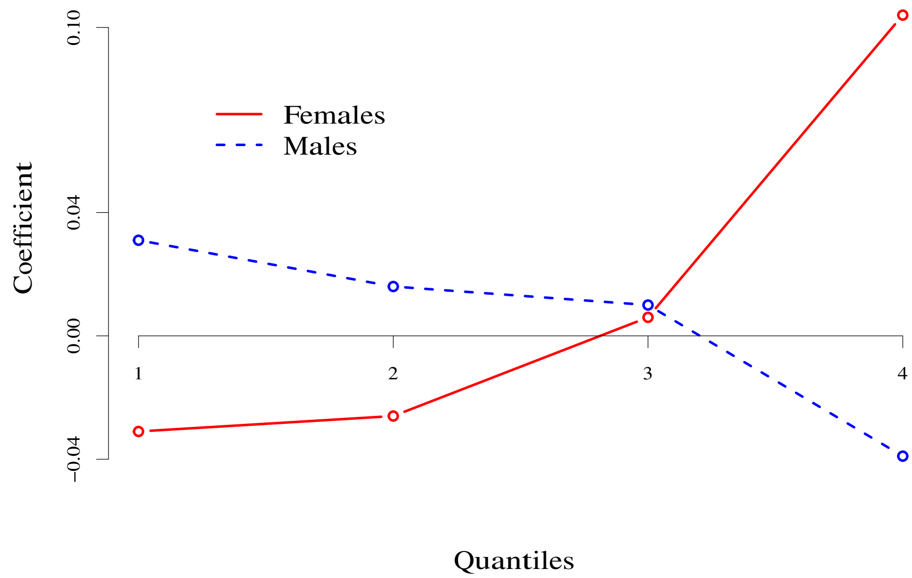
The AKM method hinges crucially on the assumptions of exogenous mobility of workers across firms conditional on observables. We follow Card et al. (2013) (CHK henceforth) in performing several tests to probe the validity of the assumption. Specifically, a model including unrestricted match effects delivers 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 online appendix.

The results from this regression, 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

In the model we presented 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

Figure 3: Coefficients of female CEO dummy on average wages by quantile of the female and male wage distributions



the distribution employed by male executives. Women at the bottom of the wage distribution, on the other hand, 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 outlined in Section 2 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 and above the median, below the 10th and above the 90th percentile, and average wages within each quartile of the wage distribution. In these regressions, our main regressor of interest is a measure of female leadership (a female CEO dummy or the share of female executives), and controls include CEO age, tenure as CEO, CEO fixed effects computed in the 2-way fixed-effects regression described above, the fraction of non-executive female workers, the fraction of non-production workers, the mean age of the workforce, the average of workers' fixed effects computed in the 2-way fixed-effects regression, and a set of 15 region dummies, 20 industry dummies, 4 firm-size dummies, year dummies, industry-specific trends, and firm fixed effects.

Figure 3 summarizes our main results by reporting the estimated coefficients on the female CEO dummy on the four quartiles of the wage distribution using our benchmark specification. The red continuous line shows that female leadership has a positive effect on female wages at the top of distribution and a negative effect at the bottom of the distribution. The effect on the male wage distribution is symmetric and of the opposite sign, as illustrated by the blue dashed line. These effects are consistently increasing moving from the bottom to the top of the female wage distribution, whereas they are decreasing moving from the bottom to the top the male distribution. These results conform to Empirical prediction 1 derived in Section 2.

To provide more details on the precision and robustness of these results, we report the estimated effects of the variable indicating female leadership on various moments of the female wage distribution in Table 3 and of the male wage distribution in Table 4, according to six different specifications (panels (a) through (f)).[21] Coefficient estimates for the more relevant controls are reported for the benchmark specification in the Appendix.

Panel (a) reports the results of our benchmark specification, where the measure of female leadership is a dummy variable indicating whether the firm is managed by a female CEO. This specification is estimated using the balanced sample[22] to avoid the selection of firms entering and exiting the sample. To avoid possible confounding effects induced by workers hired after the appointment of the female CEO, this specification uses only observations from workers employed at the firm before the female CEOs entered the firm. The other specifications are reported to inform the reader on how this sample selection and choice of variables is affecting our results. The specification in panel (b) includes all workers, including those hired by the female CEO. The specification in panel (c) includes an additional control for whether the CEO was recently appointed; this is done to account for the concern that the female CEO dummy might just be capturing the effect of a CEO change. Panel (d) reports the results from the benchmark specification run on the full (unbalanced) panel to check whether firm selection into the sample plays a relevant role. Panel (e) reports results using a different measure of female leadership: the proportion of female executives.[23] Finally, results in panel (f) are obtained from regressions that do not include the controls for unobserved workforce heterogeneity and CEO ability from the 2-way fixed-effects regression.

[21] Dependent variables in columns (4)-(9) are defined as follows: Decile 1 (column 4): average wage of earners below the 10th percentile of the wage distribution. Decile 10 (column 5): average wage of earners above the 90th percentile. Quantile 1: average wages below the 25th percentile; Quantile 2: average wages between the 25th and 50th percentile; Quantile 3: average wages between the 50th and the 75th percentile; Quantile 4: average wages above the 75th percentile of the wage distribution.

[22] 234 Firms that were continuously observed from 1987 through 1997.

[23] With this specification a larger number of firms provide a source of variation in female leadership than with the other specifications.

Table 3: Impact of female leadership on moments of the firm-level female wage distributions

Dependent Variable	Standard Deviation	Average Wages							
		Median		Deciles		Quantiles			
		Below	Above	1st	10th	1	2	3	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(a) Benchmark									
Coefficient	0.475	-0.030	0.078	-0.043	0.167	-0.031	-0.026	0.006	0.104
St. Error	(0.131)	(0.025)	(0.032)	(0.043)	(0.069)	(0.033	(0.024	(0.033	(0.039
1-tail P-value	0.000	0.125	0.000	0.140	0.010	0.160	0.135	0.460	0.000
(b) All workers									
Coefficient	0.418	-0.032	0.049	-0.038	0.121	-0.036	-0.027	-0.020	0.072
St. Error	(0.130)	(0.020)	(0.034)	(0.041)	(0.056)	(0.032)	(0.018)	(0.024)	(0.041)
1-tail P-value	0.000	0.080	0.040	0.155	0.005	0.130	0.110	0.685	0.020
(c) With control for "New CEO"									
Coefficient	0.477	-0.030	0.079	-0.043	0.168	-0.030	-0.026	0.007	0.105
St. Error	(0.133)	(0.024)	(0.032)	(0.042)	(0.069)	(0.032)	(0.023)	(0.032)	(0.039)
1-tail P-value	0.000	0.120	0.000	0.140	0.010	0.160	0.135	0.440	0.000
(d) Full panel									
Coefficient	0.403	-0.016	0.073	-0.004	0.170	-0.007	-0.022	0.006	0.096
St. Error	(0.083)	(0.021)	(0.021)	(0.033)	(0.046)	(0.029)	(0.020)	(0.018)	(0.027)
1-tail P-value	0.000	0.195	0.000	0.400	0.000	0.370	0.120	0.425	0.000
(e) Different measure of female leadership: fraction of female managers									
Coefficient	2.108	-0.036	0.310	-0.114	0.789	-0.053	-0.022	-0.007	0.421
St. Error	(0.409)	(0.044)	(0.068)	(0.106)	(0.185)	(0.063)	(0.040)	(0.037)	(0.095)
1-tail P-value	0.000	0.205	0.000	0.115	0.000	0.175	0.275	0.570	0.000
(f) Without controls for unobservable workforce and CEO ability									
Coefficient	0.460	-0.035	0.072	-0.045	0.159	-0.035	-0.032	0.001	0.097
St. Error	(0.123)	(0.020)	(0.030)	(0.033)	(0.065)	(0.026)	(0.020)	(0.029)	(0.036)
1-tail P-value	0.000	0.040	0.008	0.086	0.007	0.089	0.055	0.486	0.004

Dependent variables are in logs. Dependent variables in columns (4-9) are defined in Footnote 21. Coefficients for a larger set of explanatory variables are reported in the Appendix. Number of observations: 2,340 (234 Firms, 10 years), all specification except (d); specification (d): 5,029 observations (795 firms). Details on the computation of standard errors are provided in Footnote 24.

Table 4: Impact of female leadership on moments of the firm-level male wage distributions

Dependent Variable	Standard Deviation	Average Wages							
		Median		Deciles		Quantiles			
		Below	Above	1st	10th	1	2	3	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(a) Benchmark									
Coefficient	-0.107	0.021	-0.027	0.029	-0.069	0.031	0.016	0.01	-0.039
St. Error	(0.109)	(0.019)	(0.035)	(0.023)	(0.066)	(0.019)	(0.019)	(0.025)	(0.043)
1-tail P-value	0.275	0.035	0.330	0.040	0.215	0.015	0.080	0.835	0.280
(b) All workers									
Coefficient	-0.113	-0.016	-0.037	-0.023	-0.071	-0.016	-0.015	-0.014	-0.047
St. Error	(0.098)	(0.015)	(0.029)	(0.018)	(0.055)	(0.014)	(0.015)	(0.018)	(0.036)
1-tail P-value	0.205	0.755	0.175	0.845	0.155	0.785	0.72	0.320	0.165
(c) With control for "New CEO"									
Coefficient	-0.105	0.022	-0.027	0.029	-0.067	0.031	0.016	0.01	-0.039
St. Error	(0.108)	(0.019)	(0.035)	(0.023)	(0.066)	(0.019)	(0.019)	(0.025)	(0.043)
1-tail P-value	0.285	0.035	0.345	0.04	0.225	0.015	0.09	0.835	0.285
(d) Full panel									
Coefficient	-0.152	0.030	-0.038	0.058	-0.092	0.049	0.019	0.005	-0.054
St. Error	(0.079)	(0.010)	(0.027)	(0.016)	(0.056)	(0.012)	(0.010)	(0.014)	(0.036)
1-tail P-value	0.060	0.000	0.145	0.000	0.090	0.000	0.005	0.725	0.115
(e) Different measure of female leadership: fraction of female managers									
Coefficient	-0.232	0.008	-0.091	-0.024	-0.203	-0.004	0.016	0.004	-0.128
St. Error	(0.234)	(0.036)	(0.071)	(0.062)	(0.135)	(0.045)	(0.033)	(0.035)	(0.091)
1-tail P-value	0.255	0.275	0.155	0.610	0.130	0.435	0.170	0.720	0.135
(f) Without controls for unobservable workforce and CEO ability									
Coefficient	-0.187	0.018	-0.043	0.023	-0.104	0.026	0.013	0.007	-0.060
St. Error	(0.084)	(0.017)	(0.027)	(0.022)	(0.054)	(0.018)	(0.017)	(0.021)	(0.034)
1-tail P-value	0.013	0.145	0.056	0.148	0.027	0.074	0.222	0.631	0.039

Dependent variables are in logs. Dependent variables in columns (4-9) are defined in Footnote 21. Coefficients for a larger set of explanatory variables are reported in the Appendix. Number of observations: 2,340 (234 Firms, 10 years), all specification except (d); specification (d): 5,029 observations (795 firms). Details on the computation of standard errors are provided in Footnote 24.

For each specification, the tables report the coefficient on the measure of female leadership, and clustered standard errors. [24] In addition, because our model makes specific predictions on the effects of female leadership on the wage variance, and on wages at the top and bottom of the gender-specific wage distributions, we also report the p-values of 1-tailed tests of the model's predictions. Specifically, we test the null hypothesis that female leadership has zero impact on each of the dependent variables against different alternatives specified according to the predictions of the model. That is, we test against the alternative hypothesis that female leadership has a positive impact on the variance of female wages, a positive impact on female wages above the median, and a negative impact on wages below the median. On the corresponding moments of the male wage distribution, the alternative hypothesis is that the impact of female leadership has the opposite sign.

The results can be summarized as follows.

(i) Female leadership has a strong, economically and statistically significant positive effect on female wage variance that is robust to all specifications, as predicted by our theory (see column 1). The standard deviation of female wages is almost 50% larger when the firm is managed by a female CEO in our benchmark specification, and over 40% larger in the other specifications using this measure of female leadership. The effect on the male wage variance is also strong (between 10 and 15 percent) and, as predicted by theory, consistently of the opposite sign, but less precisely estimated in most specifications. The null hypothesis that the effect is zero against the alternative that it is negative is rejected only in specifications (d) and (f) with a p-value below 6%.

(ii) The effect of female leadership on wages at top of the female wage distribution (columns 3, 5, and 9) is strongly positive and statistically significant, with p-values of less than 1%. For example, in our benchmark specification females working for a female CEO with wages above the median earn average wages 7.8% higher than those of females employed by male CEOs above the median (Table 3 panel (a), column (3)). The effect of female leadershisp is stonger at the right end of the wage distribution: the (highly significant) positive impact of female leadership is 10.4% for females with wages above the 25th percentile (column 9) and 16.7% for those earning above the 10th percentile. These results are consistent across specifications.

Symmetrically, the effect of female leadership on wages at the *bottom* of the *male*

[24] Because specifications (a)-(e) use generated regressors, we bootstrap standard errors and p-values by resampling firms, with separate resampling for firms that never had a female CEO and firms that had a female CEO at least once. This procedure is meant to produce standard errors that are "clustered" at firm level and "stratified" by female CEO dummy. In specification (f) standard errors are clustered at the firm level.

wage distribution (Table 4, columns 2, 4, 6, and 7) are positive and significant in most specification.

(iii) The effect of female leadership is monotonically increasing moving from the bottom to the top of the female wage distribution (compare the point estimates of columns 2 and 3, 4 and 5, and of columns 6 through 9). The opposite holds true for the effect on male wages. For our benchmark specification, this is illustrated in Figure 3.

(iv) The effect of female leadership at the bottom of the female wage distribution (columns (2), (4), and (6)) is consistently negative and economically large across all specifications, although they are less precisely estimated than the effects at the top of the wage distribution. For example, most specifications reject the null hypothesis that the coefficient is zero against the alternative that it is negative with less than 15% confidence. Specifications (b) and (f) reject the null with a p-value below 10%. Symmetrically, the estimated effects on male wages at the top of the male distribution are consistently negative, but in this case they are estimated with lower precision.

(v) The estimates on the third quantile of the wage distribution (column 8 in both tables) generally do not reject the hypothesis that the coefficients are zero. This is not inconsistent with the theory, which predicts that the effects of female leadership should be zero somewhere in the interior of the wage distribution, but does not predict nonparametrically where the change of sign should occur.

To summarize, the sign of our point estimates of the effects of female leadership corresponds to the prediction of our theoretical model. These effects are strong and robust across specifications. Where these effects are predicted to be negative, the estimates that we obtaine are close but do not reach the conventional levels of statistical significance. However, there are several factors that we believe work in favor of not rejecting the theory. First, the sign of the point estimates is remarkably consistent across specifications. In particular, the point estimates are robust to extending the data to include the full panel, and to including all workers (not just those that were employed at the time the female CEO entered the firm). They are also not affected by excluding the generated regressors computed in the two-way fixed-effects regression. In this case, the point estimates are more precisely estimated even thought the reported standard errors are clustered at the firm level. The second factor that works in favor of not rejecting the model is that the effects are generally stronger at the extremes of the distribution, as one can observe comparing the extreme deciles to the first and forth quartiles. Finally, downward wage rigidity works against finding large negative effects, especiallyat the bottom of the wage distribution. Overall, we find it remarkable that we find negative effects at the bottom of the female wage distribution and the top of the male distribution so consistently in our results.

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 5 presents a 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[25]) and the female leadership is either a dummy =1 if the firm's CEO is a woman, or the fraction of female executives. As in the previous subsection, our benchmark specification focuses on the balanced panel (firms that were continuously observed from 1987 through 1997). In Table 5 we report the coefficients only on the variables of interest for our results, and relegate to the Appendix a complete set of estimated coefficients for the main explanatory variables.

Columns 1, 3, and 5 present specifications without interacting the female leadership dummy with the share of females in the firm's workforce, and broadly confirm previous results: just as found by Wolfers (2006) and Albanesi and Olivetti (2009)[26] female CEOs do not appear to have a significant impact on firm performance.[27] 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 specifications where the measure of female leadership is interacted with the proportion of non-executive female workers in the firm.[28] Results are reported in columns 2, 4, and 6 of Table 5. The logic from our model was that if a firm employs female workers, then a female CEO can reassign them thereby generating gains in firm productivity. Moreover, the more

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

[26] 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.

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

[28] We focus only on non-executive because the proportion of executive at the firms is correlated with

having a female CEO.

Table 5: Impacts of female leadership on firm-level performance

Dependent Variable	Sales per Employee		Value Added per Employee		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
Expl. Variable:						
			(a) Benchmark			
Female CEO	0.033	-0.120	-0.046	-0.245	0.059	-0.213
	(0.074)	(0.092)	(0.069)	(0.087)	(-0.054)	(0.082)
Fem. CEO * Fraction of females		0.610		0.795		0.616
		(0.280)		(0.343)		(0.360)
1-tail p-value		0.015		0.010		0.043
			(b) Full panel			
Female CEO	0.029	-0.009	-0.049	-0.093	-0.061	-0.096
	(0.044)	(0.063)	(0.048)	(0.064)	(0.046)	(0.063)
Fem. CEO * Fraction of females		0.123		0.144		0.115
		(0.140)		(0.132)		(0.125)
1-tail p-value		0.189		0.138		0.181
			(c) Alternative meas. of leadership			
Frac. fem. managers	0.025	-0.322	-0.208	-0.429	-0.236	-0.413
	(0.103)	(0.220)	(0.113)	(0.223)	(0.122)	(0.244)
Frac. fem. man. * Fraction of females		1.098		0.697		0.559
		(0.463)		(0.516)		(0.556)
1-tail p-value		0.009		0.088		0.157
			(d) Without controls for unobservable worker and CEO ability			
Frac. fem. managers	0.027	-0.104	-0.064	-0.234	-0.072	-0.200
	(0.061)	(0.071)	(0.058)	(0.057)	(0.045)	(0.051)
Frac. fem. man. * Fraction of females		0.523		0.677		0.513
		(0.169)		(0.168)		(0.175)
1-tail p-value		0.001		0.000		0.002

Interaction term with "fraction of females" in second row of each panel refers to the fraction of female workers (non-excutive). Details on the computation of standard errors are provided in Footnote 24.

women are present at the firm, the larger the effect. The empirical prediction is thus that the interaction term should be positive. This is the result we find in all of our specifications. The magnitude of the impact is substantial: for example, based on our benchmark estimates (column (2) in panel (a) of Table5), a female CEO taking over a firm where half of the workers are women would increase sales per employee by about 19%.

The result are robust to adopting an alternative measure of female leadership: the fraction of female executives (panel (c)). Results on the unbalanced sample (panel (b)) are, instead, more mixed. Using sales per employee, value added per employee and TFP, we obtain again a positive coefficient on the interaction term but the precision of the estimates is not as good as in the other specifications.

Overall, these results confirm Empirical prediction 2 derived from the theory.

4.4 Potential efficiency gains 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 5. 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 firms that have a male CEO and where female employees are at least 40 percent. Thus results in 15% firms with a female CEO.

Table 6: 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.

Results are reported in Table 6. 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, based on our estimates, 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

In this section, we discuss the plausibility of possible alternative explanations for the results we obtain.

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. This asymmetry make it difficult to justify our results without ad-hoc assumptions on preferences.

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

5.2 Not an effect of complementarities between female managers asnd 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 models for skilled female workers. These explanations can generate the productivity effects we find in our results. However, they are inconsistent with some of the results from the wage regressions. In particular, this theory is hard to reconcile with the negative effects of the presence of female leadership on female wages at the bottom of the distribution, and with the positive effects of female leadership at the bottom of the male wage distribution, which we believe are unique to the statistical discrimination assumptions. It would also be difficult to reconcile this alternative hypothesis with any positive or negative effects on the male wage distribution.

6 Conclusion

Motivated by the recent literature showing the importance of executives in determining firm policies and outcomes, and by the traditional literature on gender differentials 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-level, worker-level and executive-level heterogeneity. 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 the share of female workers employed at the firm has a positive impact on firm performance. Our results are robust to different measures of firm productivity, different measures of female leadership, and to different specifications and 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 jobs 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 modern labor markets - associated with the underrepresentation of women at the top of corporate hierarchies.

A Appendix: proof of Proposition 1

Proof. Define $\widehat{s}$ as the signal satisfying $\Psi_m(\overline{q}|\widehat{s}) = \Psi_f(\overline{q}|\widehat{s})$, which exists and is unique because of a "single-crossing" property of the Normal distribution's cdf.[29] Note that the schedules defining productivity of male and female workers in the complex job (top equation in 2.2) cross at the same signal, $\widehat{s}$, than the schedules defining marginal product in the simple job (bottom equation in 2.2). In particular, we must have

$$\begin{aligned} 1 - 2\Phi_m(\overline{q}|s) &< 1 - 2\Phi_f(\overline{q}|s) \quad \text{for all} \quad s < \widehat{s} \\ 1 - 2\Phi_f(\overline{q}|s) &< 1 - 2\Phi_m(\overline{q}|s) \quad \text{for all} \quad s > \widehat{s} \end{aligned} \tag{A.1}$$

because under the assumption on the signals' noise $\sigma_{\epsilon f} > \sigma_{\epsilon m}$, Ψ_m has thinner tails than Ψ_f.

Observe also from the wage equation that either $\overline{s} \leq \min\{\overline{s}_m, \overline{s}_f\}$, or $\overline{s} \geq \max\{\overline{s}_m, \overline{s}_f\}$. To prove it, note that by definition of $\overline{s}_g$, $\Psi_m(\overline{q}|\overline{s}_m) = (\overline{q}|\overline{s}_f) = 1/2$, therefore $\Psi_m(\overline{q}|s) > 1/2 > \Psi_f(\overline{q}|s)$ for all $s \in (\overline{s}_m, \overline{s}_f)$, hence the crossing of the distributions must occur outside of this range, that is where either (i) $\Psi_g(\overline{q}|\overline{s}) > 1/2, g = m, f$, or (ii) $\Psi_g(\overline{q}|\overline{s}) < 1/2, g = m, f$. Case (i) is displayed in Figure 1. In case (i) both male and female workers with signal $s \leq \widehat{s}$ are employed in the simple task, and $w(s; \sigma_{\epsilon m}) < w(s; \sigma_{\epsilon f})$ holds because of (A.1). But then it must also be the case that $\overline{s}_m < \overline{s}_f$.[30] For $\overline{s}_m < s < \overline{s}_f$, we have male workers employed in the complex task and female workers employed in the simple job. Because $\Psi_m(\overline{q}|s) < 1/2 < \Psi_f(\overline{q}|s)$, we have $l\,(1 - 2\Phi_f(\overline{q}|s)) < h\,(1 - 2\Phi_m(\overline{q}|s))$ hence $w(s; \sigma_{\epsilon m}) > w(s; \sigma_{\epsilon f})$. For $s \geq \overline{s}_f$ all workers are employed in the complex task and since the crossing of $\Psi_m$and Ψ_f occurred at $\overline{s} < \overline{s}_f$, we must have $w(s; \sigma_{\epsilon m}) > w(s; \sigma_{\epsilon f})$. Case (ii) can be proved symmetrically, by observing that both male and female workers with $s \geq \widehat{s}$ are employed in the complex task and receive wages $w(s; \sigma_{\epsilon m}) > w(s; \sigma_{\epsilon f})$. In this case, it must be the case that $\overline{s}_f < \overline{s}_m$, and wages below $\overline{s}_m$ must satisfy $w(s; \sigma_{\epsilon m}) < w(s; \sigma_{\epsilon f})$ by an argument similar to that made for case (i). □

This "single-crossing" property of the wage functions of signals of different preci-

[29] Consider two normal distributions F, G with different variance ($\sigma_F > \sigma_G$). Then, 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 $x > \overline{x}$. 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 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.

[30] Case (i) holds whenever $\overline{q} > \mu$, that is whenever employers without signals would place workers in the simple job, hence a more precise signal implies more workers in the complex job.

sion rely to some extent on the assumptions of symmetry of the production function and of the signaling technology distributions. However the result that a more precise signal implies higher wages at the top of the distribution, and lower wages at the bottom, is more general, and will hold even if the wages cross more than once.

B Appendix: additional results

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: Full set of estimates on female wages, benchmark specification

Dependent variable:	Standard deviation	Average wages							
		Median		Decile		Quantiles			
		Below	Above	1	10	1	2	3	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female CEO	0.475	-0.030	0.078	-0.043	0.167	-0.031	-0.026	0.006	0.104
	(0.131)	(0.025)	(0.032)	(0.043)	(0.069)	(0.033)	(0.024)	(0.033)	(0.039)
CEO age	0.076	0.074	0.044	-0.019	0.065	0.059	0.092	0.045	0.043
	(0.431)	(0.065)	(0.094)	(0.151)	(0.184)	(0.086)	(0.068)	(0.064)	(0.118)
CEO tenure	0.006	-0.001	-0.000	0.002	0.001	-0.000	-0.002	-0.001	0.000
	(0.004)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
CEO started <1980	-0.011	0.016	0.012	0.011	0.010	0.014	0.017	0.014	0.014
	(0.057)	(0.008)	(0.012)	(0.018)	(0.027)	(0.013)	(0.007)	(0.008)	(0.015)
CEO fixed eff.	0.049	0.013	0.015	-0.005	0.024	0.008	0.016	0.010	0.017
	(0.055)	(0.008)	(0.011)	(0.021)	(0.022)	(0.012)	(0.007)	(0.007)	(0.013)
Mean wkrs. age	0.097	0.054	0.068	0.084	0.078	0.065	0.050	0.051	0.072
	(0.070)	(0.035)	(0.042)	(0.058)	(0.049)	(0.043)	(0.032)	(0.034)	(0.045)
Mean wokrs. tenure	-0.026	-0.002	-0.007	-0.006	-0.011	-0.003	-0.003	-0.003	-0.008
	(0.016)	(0.003)	(0.004)	(0.009)	(0.007)	(0.005)	(0.003)	(0.003)	(0.005)
% white collars	0.381	-0.131	-0.014	-0.502	0.092	-0.286	-0.049	-0.038	0.019
	(0.378)	(0.065)	(0.099)	(0.197)	(0.174)	(0.107)	(0.064)	(0.071)	(0.120)
Fraction female	0.227	-0.595	-0.577	-0.623	-0.435	-0.661	-0.556	-0.541	-0.572
	(0.490)	(0.103)	(0.118)	(0.353)	(0.185)	(0.179)	(0.093)	(0.118)	(0.136)
Mean wors. F.E.	1.960	1.250	1.577	1.897	1.764	1.474	1.130	1.181	1.680
	(0.699)	(0.145)	(0.178)	(0.410)	(0.328)	(0.238)	(0.131)	(0.158)	(0.225)
Constant	1.009	4.149	3.993	3.269	3.789	3.763	4.306	4.390	3.893
	(2.083)	(0.971)	(1.173)	(1.692)	(1.408)	(1.196)	(0.870)	(0.935)	(1.270)
R^2 : Between	0.153	0.222	0.367	0.081	0.263	0.115	0.253	0.298	0.351
Within	0.100	0.448	0.500	0.086	0.277	0.270	0.515	0.528	0.443
Overall	0.105	0.413	0.486	0.070	0.273	0.222	0.481	0.507	0.432

Dependent variables are in logs. Standard Errors in parentheses. Additional controls: 15 region dummies, 20 industry dummies, 4 firm-size dummies, year dummies, industry-specific trends, and 234 firm fixed effects.

Table A.3: Full set of estimates on male wages, benchmark specification

Dependent variable:	Standard deviation	Average wages							
		Median		Decile		Quantiles			
		Below	Above	1	10	1	2	3	4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female CEO	-0.107	0.021	-0.027	0.029	-0.069	0.031	0.016	0.010	-0.039
	(0.109)	(0.019)	(0.035)	(0.023)	(0.066)	(0.019)	(0.019)	(0.025)	(0.043)
CEO age	1.815	0.046	0.317	0.069	0.787	0.053	0.041	0.056	0.433
	(0.874)	(0.058)	(0.193)	(0.085)	(0.409)	(0.070)	(0.057)	(0.079)	(0.249)
CEO tenure	-0.003	-0.001	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001
	(0.003)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
CEO started $<$1980	0.024	0.007	0.016	0.007	0.026	0.007	0.008	0.007	0.018
	(0.036)	(0.005)	(0.010)	(0.008)	(0.019)	(0.006)	(0.005)	(0.007)	(0.012)
CEO fixed eff.	0.328	0.008	0.053	0.019	0.138	0.014	0.005	0.004	0.074
	(0.032)	(0.006)	(0.011)	(0.009)	(0.019)	(0.007)	(0.006)	(0.009)	(0.014)
Mean wkrs. age	0.074	0.048	0.074	0.048	0.071	0.046	0.049	0.061	0.079
	(0.054)	(0.039)	(0.046)	(0.043)	(0.045)	(0.039)	(0.039)	(0.045)	(0.048)
Mean wokrs. tenure	0.003	-0.003	-0.004	-0.000	0.000	-0.002	-0.004	-0.004	-0.004
	(0.010)	(0.004)	(0.004)	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
% white collars	0.120	0.095	0.196	0.012	0.150	0.035	0.127	0.208	0.204
	(0.182)	(0.086)	(0.088)	(0.098)	(0.128)	(0.088)	(0.089)	(0.096)	(0.102)
Fraction female	0.219	-0.181	0.063	-0.217	0.212	-0.186	-0.176	-0.083	0.121
	(0.267)	(0.148)	(0.129)	(0.159)	(0.182)	(0.146)	(0.152)	(0.162)	(0.144)
Mean wors. F.E.	1.968	1.021	1.796	1.008	1.773	0.946	1.051	1.431	1.921
	(0.472)	(0.358)	(0.169)	(0.415)	(0.247)	(0.375)	(0.356)	(0.344)	(0.167)
Constant	2.442	4.334	3.933	4.141	4.410	4.284	4.376	4.068	3.934
	(2.088)	(1.095)	(1.513)	(1.182)	(1.712)	(1.098)	(1.097)	(1.265)	(1.654)
R^2 : Between	0.246	0.399	0.470	0.223	0.331	0.299	0.410	0.437	0.439
Within	0.293	0.522	0.426	0.361	0.265	0.434	0.537	0.507	0.383
Overall	0.275	0.509	0.427	0.332	0.264	0.415	0.525	0.502	0.384

Dependent variables are in logs. Standard Errors in parentheses. Additional controls: 15 region dummies, 20 industry dummies, 4 firm-size dummies, year dummies, industry-specific trends, and firm fixed effects.

Table A.4: Estimates on Firm-Level Performance, benchmark specification

Dependent variable:	Sales per employee		Value added per employee		TFP	
	(1)	(2)	(3)	(4)	(5)	(6)
Female CEO	0.033	-0.120	-0.046	-0.245	-0.059	-0.213
	(0.074)	(0.092)	(0.069)	(0.087)	(0.054)	(0.082)
Interaction		0.610		0.795		0.616
		(0.280)		(0.343)		(0.360)
CEO age	0.212	0.209	0.442	0.438	0.320	0.316
	(0.274)	(0.271)	(0.279)	(0.276)	(0.241)	(0.238)
CEO tenure	-0.003	-0.003	-0.002	-0.002	-0.002	-0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
CEO started <1980	0.028	0.028	0.012	0.011	0.010	0.010
	(0.025)	(0.025)	(0.028)	(0.028)	(0.028)	(0.028)
CEO fixed eff.	0.017	0.017	0.065	0.064	0.046	0.045
	(0.032)	(0.032)	(0.029)	(0.029)	(0.029)	(0.029)
Mean wkrs. age	0.028	0.031	0.051	0.055	0.055	0.058
	(0.046)	(0.048)	(0.056)	(0.058)	(0.055)	(0.055)
Mean wokrs. tenure	0.005	0.004	-0.013	-0.014	-0.030	-0.030
	(0.014)	(0.014)	(0.013)	(0.013)	(0.012)	(0.012)
% white collars	0.269	0.254	-0.117	-0.137	-0.082	-0.098
	(0.219)	(0.220)	(0.274)	(0.275)	(0.276)	(0.275)
Fraction female	-0.313	-0.390	-0.496	-0.596	-0.478	-0.556
	(0.429)	(0.442)	(0.283)	(0.280)	(0.301)	(0.292)
Mean wors. F.E.	1.217	1.284	1.636	1.724	1.438	1.506
	(0.481)	(0.484)	(0.518)	(0.522)	(0.543)	(0.530)
	0.070		0.070		0.248	
	(0.048)		(0.056)		(0.150)	
Constant	3.089	3.020	2.072	1.983	0.422	0.353
	(1.085)	(1.109)	(1.486)	(1.537)	(1.298)	(1.311)
R^2 : Between	-0.071	0.592	-0.025	0.222	-0.034	0.182
Within	0.590	0.015	0.218	0.055	0.179	0.268
Overall	0.013	0.073	0.044	0.081	0.270	0.247

Dependent variables are in logs. Additional controls: 15 region dummies, 20 industry dummies, 4 firm-size dummies, year dummies, industry-specific trends, and firm fixed effects.

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