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 analyze a matched employer-employee panel data set and find that female leadership has a positive effect on female wages at the top of the distribution, and a negative one at the bottom. Moreover, performance in firms with female leadership increases with the share of female workers. This evidence is consistent with a model where female executives are better equipped at interpreting signals of productivity from female workers. This suggests substantial costs of underrepresentation of women at the top: for example, if women became CEOs of firms with at least 20% female employment, sales per worker would increase 6.7%.

JEL Codes: M5, M12, J7, J16.

Keywords: executives' gender, gender gap, firm performance, glass ceiling, statistical discrimination

*Flabbi: Inter-American Development Bank and IZA, lucaf@iadb.org. Macis: Johns Hopkins University and IZA, mmacis@jhu.edu. Moro: Università Ca' Foscari di Venezia and Vanderbilt University, andrea@andreamoro.net. Schivardi: Bocconi University, IGIER, EIEF and CEPR, fabiano.schivardi@unibocconi.it. We thank Manuel Bagues, John Earle, Stephan Eblich, Nicola Lacetera, Giovanni Pica, Kathryn Shaw, and seminar participants at many conferences and institutions for very useful comments and suggestions. Partial funding from the Economic and Sector Work RG-K1321 at the IDB, the PRIN grant 2010XFJCLB_001 and the RAS L.7 project CUP: F71J11001260002 is gratefully acknowledged. The opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the Inter-American Development Bank, its Board of Directors, or the countries they represent.

1 Introduction

This paper investigates how the gender of a firm's CEO affects the workers' gender-specific wage distributions and the firm's performance using a unique matched employer-employee panel dataset representative of the Italian manufacturing sector.

A growing literature shows that executives' characteristics such as management practices, style, and attitudes towards risk can have an effect on firm outcomes.[1] Our focus on gender follows from the abundant evidence of systematic gender differentials in the labor market.[2] Research has highlighted that women are almost ten times less represented than men in top positions in firms.[3] For example, recent U.S. data show that even though women are a little more than 50% of white collar workers, they represent only 4.6% of executives.[4] Our own Italian data show that about 26% of workers in the manufacturing sector are women compared with only 3% of executives and 2% of CEOs. Together, these facts suggest that gender is a potentially relevant characteristic and that women's underrepresentation among executives may have important productivity and welfare implications.

This paper provides four contributions to the existing literature. First, we develop a theoretical model highlighting a potential channel of interaction between female executives, female workers, wage policies, job assignment, and overall firm performance. The model implies efficiency costs of women's underrepresentation in leadership positions, and generates empirical predictions that can be tested and compared with implications from possible alternative mechanisms. Second, we investigate the empirical predictions of the model for the relationship between female leadership and the gender-specific wage distributions at the firm level. Different

[1] Bloom and Van Reenen (2007) is one of the first contributions emphasizing differences in management practices. See also a recent survey in Bloom and Van Reenen (2010). A growing literature showing the effects of CEO characteristics follows the influential paper of 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 executive and firm characteristics, see Bandiera et al. (2011) and Lippi and Schivardi (2014).

[2] For an overview of the gender gap in the U.S. 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, and 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), Ahern and Dittmar (2012) and Matsa and Miller (2013) (Norway), Smith et al. (2006) (Denmark). 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.

from previous literature, and consistent with our model, the main focus is not on the effects on average wages, but on differential impacts over the wage distribution. This is important because different theoretical mechanisms have different predictions for what the effects of female leadership should be at different parts of the wage distribution. Third, we investigate the empirical predictions of the model on the relationship between female leadership and firm performance. Unlike previous literature, which focused generally on measures of financial performance, we focus on indicators that are less volatile and less likely to be affected by gender discrimination: sales per worker, value added per worker and Total Factor Productivity (TFP) (Wolfers, 2006). Finally, we perform a series of partial equilibrium counterfactual exercises to compute the cost of women's underrepresentation in top positions in organizations.

In Section 2 we present our theoretical model and derive its empirical implications. Our model extends the seminal 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 there is a comparative advantage to employ higher human capital workers in complex tasks. 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. Females at the top of the wage distribution receive higher wages when employed by a female CEO than when employed by a male CEO. Females at the bottom of the wage distribution receive lower wages when employed by a female CEO. The impact of female CEOs on the male distribution has the opposite signs: negative at the top and positive at the bottom of the distribution.

2. The performance of a firm led by a female CEO increases with the share of female workers.

These results follow from the assumption that female CEOs are better at processing information about female workers' productivity. Therefore, wages of females em-

[5] We discuss this assumption in Subsection 2.3.

ployed by female CEOs are more sensitive to individual productivity, delivering the first implication. Moreover, female CEOs improve the allocation of female workers across tasks, delivering the second implication.

Our data, described in detail in Section 3, includes all workers employed by firms with at least 50 employees in a representative longitudinal sample of Italian manufacturing firms between 1982 and 1997.[6] Because we observe all workers and their compensation, 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 several measures of firm performance. We merge this sample with social security administration data containing the complete labor market trajectories of all workers who ever transited through any of the sampled firms. This allows us to identify firm, worker and executive fixed effects in a joint two-way fixed effects regressions *à la* Abowd et al. (1999) and Abowd et al. (2002). These fixed effects and controls help address 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 which would otherwise bias the estimates.

We describe our empirical strategy and present the estimation results in Section 4. 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: 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. These effects are consistent with our model, and not consistent with alternative mechanisms through which female CEOs could affect women's wages, as we discuss in detail in Section 5. Also, consistent with our model's predictions, female CEOs are associated with lower wages for men at the top, and higher wages for men at the bottom of the wage distribution. As a result, we find that, as implied by our model, female CEOs reduce the gender wage gap at the top and widen it at the bottom of the wage distribution, with essentially no effects at the mean. Our results are robust to alternative specifications, such as an alternative measure of female leadership (the proportion of the firm's executives who are female) and to the selection induced by entry and exit of firms and workers.

We also analyze the impact of female leadership on firm performance, measured by sales per worker, value added per worker, and total factor productivity (TFP). We find that, as predicted by the model, the impact of female CEOs on firm performance

[6]This is the only period over which our data are available and this is the reason why we cannot provide an analysis using more recent data.

is a positive function of the proportion of female workers employed by the firm. The magnitude of the impact is substantial: a female CEO would increase overall sales per employee by about 3.7% if leading a firm employing the average proportion of women.

Using our estimates, we perform a partial equilibrium counterfactual exercise to compute the cost of women's underrepresentation in leadership positions. Our results indicate that if female CEOs were in charge of all firms with at least a 20% proportion of female workers (about 50 percent of the sample), sales per worker would increase by 14% in the "treated" firms, and by 6.7% in the overall sample of firms.

There is a large literature studying gender differentials in the labor market, and a fairly developed literature studying 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 is scant and has focused on the effect on average wages, not on the effect over the entire wage distribution. Bell (2005) studies the impact of female leadership in US firms but only on *executives'* wages. Cardoso and Winter-Ebmer (2010) consider the effect on all workers in a sample of Portuguese firms but without allowing for heterogeneous effects over the distribution. Fadlon (2010) tests a model of statistical discrimination similar to ours and assesses the impact of supervisors' gender on workers' wages using U.S. data but does not focus on the wage distribution and does not look at wages at the firm level. 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. They find that the effect of female leadership is heterogeneous and depends on the share of women in the second layer of the organization: Women in the top layer who are surrounded by men reduce wages of both men and women, while the effect is reversed as the share of women in the second layer increases. A related literature, sparked by recent reforms in European countries, looks at the impact of the gender of a firm's board members instead of its executives. Bertrand et al. (2014) documents that a reform mandating gender quotas for the boards of Norwegian companies reduced the gender gap in earnings within board members but did not have a significant impact on overall gender wage gaps.

Existing literature on the effect of female leadership on firm performance is also limited. Many contributions focus on financial performance looking at the impact on stock prices, stock returns and market values.[7] By conditioning on a wide range

[7] 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). Rare exceptions are Matsa and Miller (2013), which looks at operating profits, Smith et al.

of firm-level controls and using less volatile measures of firm performance, we can run firm-level regressions closer to our model's implications.

In Section 5, we present alternative explanations for gender inequality and illustrate why they do not perform as well as our model in explaining the evidence we uncover. In Section 6 we conclude by discussing some policy implications of our findings.

2 Theoretical Framework

We present a simple signal extraction model where inequalities are generated by employers' incomplete information about workers' productivity and where employers' gender matters. The main assumption of our model is that female and male executives are better equipped at assessing the skills of employees of their same gender. As discussed in greater detail below, 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 allows us to obtain implications for efficiency (productivity), which is one focus of our empirical analysis.[8] 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. To capture the importance of correctly assigning workers to tasks, we assume that mismatches are costlier in the complex job, where workers with higher ability are more productive. One way to model this requirement is by

(2006), with information on value added and profits on a panel of Danish firms, and Rose (2007), which looks at Tobin's Q.

[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.

assuming that the dollar value of productivity of workers in the complex (simple) job is h (l) if workers have ability $q > \overline{q}$, and $-h$ $(-l)$ otherwise, with $h > l \geq 0$.[9]

Firms compete for workers and maximize output given wages. Workers care only about wages and not about job assignment *per se*.

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 of the same gender, let us assume male; in subsection 2.3 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 $\alpha_g = \sigma^2/(\sigma^2_{\epsilon g} + \sigma^2)$. 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 expected ability is increasing in both q and s.

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 $\Phi_g(q|s)$.

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 precision. The worker with signal $\overline{s}(\sigma_{\epsilon g})$ has the same expected productivity (zero) in both jobs.[11] Competition ensures that wages w are equal to expected marginal products,

[9] 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.

[10] See Eaton (1983)

[11] 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.

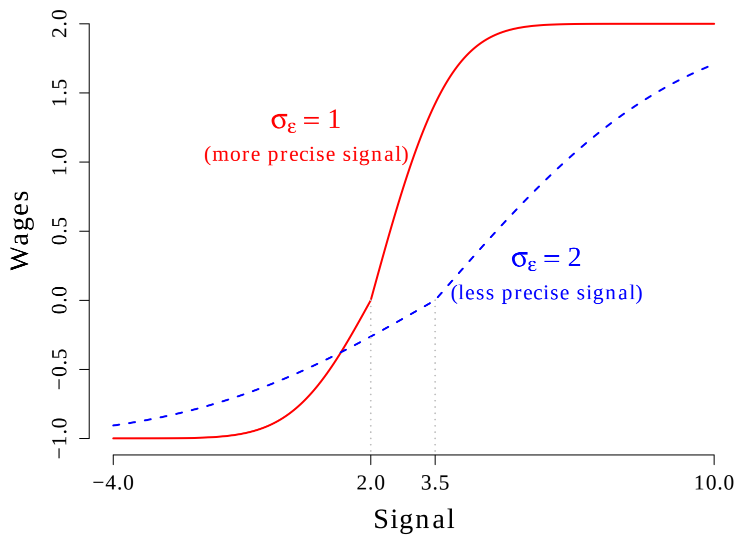


Figure 1: Simulation of the solution to the problem with parameters σ=1, $\overline{q} = 1.5$, $\mu = 1, h = 2$, $l = 1$.

which are functions of the signal received and the worker's gender:

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

We now explore 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 red continuous line displays the equilibrium wages resulting from a more precise signal than the blue dashed line. As standard in statistical discrimination models, the line corresponding to the more precise signal is steeper than the line corresponding to the less precise signal. This is the direct implication of putting more weight on the signal in the first case than in the second. As a result of one of our extensions - the presence of job assignment between simple and complex jobs - the two lines also display a non-standard feature: a kink in correspondence to the threshold signal. The kink is a result of the optimal assignment rule: workers with signals below the threshold are assigned to the simple job, where ability affects productivity less than in the complex job, therefore both wage curves are flatter to the left of the thresholds than to the right of the thresholds.

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 Appendix A. This "single-crossing" property of the wage functions of signals of different precision relies 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.

Proposition 2. *Let $y_g(\sigma_{\epsilon g})$ be 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 $\sigma_{\epsilon g}$.*

For example, 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. Because there are fewer females than males in the right tail of the quality distribution conditional on any given signal, more females are mismatched, therefore males' total value of (log) production is equal to -0.29, whereas females' is -0.35. To assess the inefficiency cost arising from incomplete information, consider that if workers were efficiently 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.[12] We assume that 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 $\sigma^2_{\epsilon F} < \sigma^2_{\epsilon f}$

[12] 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.

(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 between people of the same gender to provide a better understanding of personal skills and attitudes, improve conflict resolutions, assignment to job-tasks, etc. A large socio-linguistic literature has found differences in verbal and non-verbal communication styles between groups defined by race or gender that may affect economic and social outcomes (see e.g. Dindia and Canary (2006) and Scollon et al. (2011)).[13] Recent employee surveys also indicate that significant communication barriers between men and women exist in the workplace (Angier and Axelrod (2014), Ellison and Mullin (2014)). In the economics literature, several theoretical papers have adopted an assumption similar to ours. Lang (1986) develops a theory of discrimination based on language barriers between "speech communities" defined by race or gender. To motivate this assumption, 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. Morgan and Várdy (2009) discuss a model where hiring policies are affected by noisy signals of productivity, whose informativeness depends (as in our assumption) on group identity because of differences in "discourse systems". 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 can also provide a foundation to our assumption if female workers are more likely to excel on the same dimensions as female executives.

The equilibrium features described in Section 2.2 carry through in the environment with heterogenous CEOs. In this new environment we can compare the equilibrium wages and firm performance in firms with CEOs of different gender. Focus for example on the wage distributions of female workers. Figure 2 displays the wage distributions of female workers employed at firms with female or male CEOs. The distribution displayed by the dashed blue line was computed using a signal with noise variance $\sigma^2_{\epsilon f} = 3$, 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. As stated in Proposition 1, Figure 2 shows that

[13] 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)).

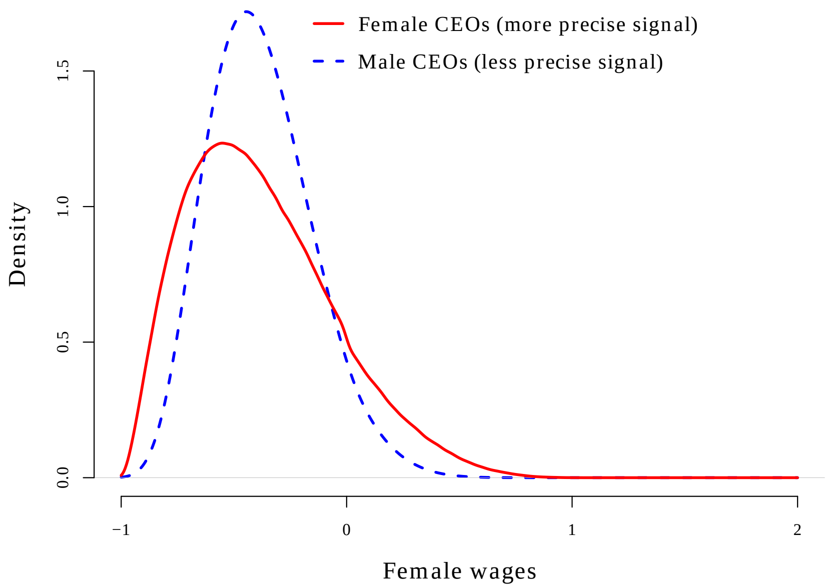


Figure 2: Simulation of the wage distributions of female workers

the wage distribution of female workers employed at female CEOs firms has thicker tails.[14] Women working for a female CEO are more likely to be assigned to the complex task and they earn higher wages at same signals for all the signals above the single crossing reported in Figure 1. This generates the fatter right tail. Below the threshold corresponding to the single crossing, women working for a female CEO earn lower wages at same signal than women working for a male CEO because the female CEO has a better assessment of how low productivity really is in those cases. This generates the fatter left tail.

The following prediction follows directly from Proposition 1:

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.*

As a result, and as Figure 2 makes clear, we should also expect the variance of

[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.

the wage distribution of female workers employed by female CEOs to be higher than the variance of the wage distribution of female workers employed by male CEOs. The opposite should be true on the variance of male wages.

The model has implications for firm performance as well. Proposition 2 states that total production is higher the lower the signal noise since CEOs can better match workers to jobs. As a result, we should observe that female CEOs can improve firm performance by implementing a better assignment of female workers.[15] Therefore, we will test the following empirical prediction:

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

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 (Flabbi et al. (2014)), we derive the same empirical implications assuming a dynamic model where signals are extracted every period. Assuming all firms initially have male CEOs, firms acquiring female CEOs update the expected productivity of female workers with higher precision. The implications follow because female CEOs will rely on a larger number of more precise signals from female workers than male CEOs.

We do not model explicitly the selection process into executive positions (although in the empirical part we will take into account that such process might differ by gender) or how labor force dynamics are affected by CEO gender in a "general equilibrium". The change of a CEO's gender in our model will affect incentives for workers to leave the firm hoping to extract a more advantageous signal. Our results therefore assume rigidities in workforce mobility, which can be motivated by costs of hiring and firing. However, the equilibrium wages by CEO and worker's gender derived in our propositions are nevertheless optimal and are indicative of the directions of wage changes we should expect when a CEO of different gender is appointed.[16]

[15] Of course female CEO's assignment of male workers has the opposite implication, but female CEOs, upon assuming leadership, could "trust" the previous assignment of male workers made by a male CEO. We do not model explicitly job reassignment, but the following proposition holds regardless of whether or not the female CEO's reassigns men to different tasks from those chosen by a previous male CEO.

[16] This motivates in the empirical analysis the inclusion, in our benchmark specification, only of data from workers that were not hired after the new CEO was appointed. We check the robustness of our results to the inclusion of all workers.

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 *National Social Security Institute* which provided the work histories of all workers ever employed at an INVIND firm in the period 1980-1997,[17] 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[18], 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 for workers younger than 15, 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 companies of which we only know the firm identifier.

In Table 1 we report summary statistics on workers' characteristics for the INVIND-INPS data set. About 67% of observations pertain to production workers, 31% to non-production employees, and 2.2% to executives. Even though they represent about 21% of the workforce, women are only 2.5% of executives. On average, workers are 37 years old and have 5 years of tenure. Average gross weekly earnings at 1995 constant prices are around 388 euros, with women earning about 24% less than men (309 euros vs. 408 euros).

CADS, the third data source we use, stands for *Company Accounts Data Service*

[17]The provision of these work histories data for the employees of the INVIND firms was done only once in the history of the data set and therefore can only cover firms and workers up to 1997. This is the reason why we cannot work on more recent data.

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

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 1988-1997. In Table 1 we report summary statistics both on this sample and on the entire, unbalanced INVIND-INPS-CADS sample for the same period. Notice that the unit of observation on the sample is a firm in a given year while in the INVIND-INPS was a worker in a given firm in a given year. 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 405 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 collar, 30% white collar, and 2.5% are executives. The corresponding statistics in the balanced sample are very similar.

3.2 Female Leadership

We identify female leadership from the job classification *executive*[19] 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 executives are registered in a separate account with the social security administration agency (INPS). We identify the CEO as the executive with the highest compensation in a firm-year. 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) The firm's CEO is classified 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 is correctly reported); iv) We have access to all the workers employed by a given firm in a given year.[20]

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

[20]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 irrelevant for our final estimation sample at the firm level since for other reasons explained below we limit our main empirical analysis to a

Table 1: Descriptive statistics: INVIND-INPS sample and 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.	2.5		3.3	(10.3)	3.4	(10.1)
% Female CEO			2.1		1.8	
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)	429.3	(92.7)	433.9	(97.5)
Wage (females)	309.5	(146.6)	343.3	(67.0)	346.4	(68.5)
Firm size (empl.)			675.0	(2,628.6)	704.2	(1,306.9)
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					
N. Years	17		15		10	

Using these definitions, we find that although 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 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[21] data for the U.S.

subset of INVIND firms.

[21] 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).

Table 2: Descriptive statistics: Firms with Male and Female CEO in INVIND-INPS-CADS sample

	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 annual earnings	199,385	(144,508)	128,157	(54,643)
% 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)
% Female executives (excl. CEO)	3.3	(10.3)	15.9	(28.6)
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 60		33	
N. Years	15		10	

Women's representation in executive positions in Italy has increased over time but remains 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.[22]

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

[22] See Table B1 in Flabbi et al. (2014) for details.

revenues, pay lower wages, and employ a larger share of blue collar workers. 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 revenue is on average about 3 times higher in firms with a male CEO than in firms with a female CEO, but revenue per 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 workers' wage distributions and firms' performance.

We will estimate regressions of the following form:

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

where: y_{jt} is the dependent variable of interest (either moments of the workers' wage distribution or measures of firm performance) and β is the coefficient of interest. The regressors and controls are defined as follows: $FLEAD_{jt}$ is the measure of female leadership used in the regression: 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, 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 used in the regression (age and tenure as CEO or executive) plus CEO's or executives' fixed effects estimated in the first stage regression described in detail below;[23] λ_j are firm fixed effects; η_t are year dummies and $\tau_{t(j)}$ are industry-specific time trends.

The main challenge in estimating the impact of female CEOs (or female leadership in general)[24] on workers' wages and firms' performance is the sample selection

[23] When the female leadership measures is the female CEO dummy we simply use the CEO's value of the listed regressors; when the leadership measure is the proportion of female executives at the firms, we use the average of the listed regressors over the firm's executives.

[24] To simplify the discussion, we present the identification for the case in which female leadership is represented by the dummy female CEO. The same discussion carries through when we use the

bias induced by the non-random assignment of CEOs to firms. In particular, it is possible that (a) unobservable firm characteristics may make some firms more productive than others, and this unobserved firm-level component may not be randomly assigned between male- and female-led firms, (b) the workforce composition of firms led by women might systematically differ from that of firms led by men, and (c) the selection on unobserved individual ability in the position of CEO may not be the same by gender so that women CEOs may be of systematically higher or lower ability than men CEOs, and female leadership indicators might be capturing such differences rather than gender effects.

Our strategy to address these issues is to control for firm fixed effects, workforce composition effects, and CEO effects. Thanks to the panel structure of the data, we can control for time-invariant firm-level heterogeneity by estimating equations (4.1) as firm fixed effects regressions; we can also include controls for a set of time-varying, observable firm characteristics, workforce characteristics, and CEO characteristics. Moreover, as we describe in the next paragraph, we exploit the employer-employee nature of our data to construct controls for unobservable workforce and CEO ability.

Our matched employer-employee data includes the *entire* work history of *all* the workers who ever transited through one of our J INVIND firms. This large matched employer-employee data set (almost 19 million worker-year observations) contains a large number of transitions of individuals across (INVIND and non-INVIND) firms and is thus well suited to estimate two-way fixed effects as in Abowd et al. (1999)(henceforth, AKM). An individual fixed effect estimated from such a regression has the advantage of controlling for the firms the worker or executive has ever worked for. As a result, it can capture those scale effects in individual productivity which are usually captured by education, other time-invariant human capital or other proxies for “ability” and skills.[25]

Our strategy is to use the individual fixed effects from an AKM regression to construct proxies for CEO/executive and average worker heterogeneity at the firm-year level to include as controls in regression 4.1. Specifically, we perform the two-way fixed effect procedure proposed by Abowd et al. (2002) by estimating the following equation:

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

fraction of female executives as a measure of female leadership.

[25] Including these controls as described in detail below also helps alleviate the fact that our data set, as is frequently the case with administrative data, does not include a particularly rich set of controls at the individual worker level. For example, we have no measure of education or other formal training in the data which are usually included as controls in wage regressions.

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 original sample consists of essentially one large connected group (comprising 99% of the sample). Thus, in our estimation we focus only 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 relatively long period under consideration: about 70 percent of workers have more than one employer during the 1980-1997 period, and between 8 and 15 percent of workers change employer in a given year. The $\hat{\alpha}_i$ obtained by this procedure for the firms' CEOs and executives are included in the vector $EXEC_{jt}$ to control for CEO's individual heterogeneity. Moreover, we also used them to compute the mean $\hat{\alpha}_i$ on the workers of a given firm j in time t, which we then include among the controls for workforce composition ($WORK_{jt}$).[26]

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. Tests and results are reported in detail in the Flabbi et al. (2014). The two-way fixed effect regressions generate expected results: wages exhibit concave age and tenure profiles, and there

[26] Under our model, the workers' wages from which we have estimated these worker fixed effects are affected by statistical discrimination. This does not introduce a bias in the estimate of the mean $\hat{\alpha}_i$ on the workers of a given firm j in time t because the model, as common in standard statistical discrimination models, does not imply "group discrimination". Moreover, the group of workers we have at each firm is large enough to deliver credible estimates: Our firms are relatively large by construction (firms are included in the INVIND sample only if they employ at least 50 employees) and the median number of workers in INVIND firms is around 250.

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 CEOs 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 CEOs. Women at the bottom of the wage distribution, on the other hand, should see lower wages when employed by female CEOs. As a result, the overall wage dispersion of female workers in each firm should be higher if in firms managed by women CEOs.

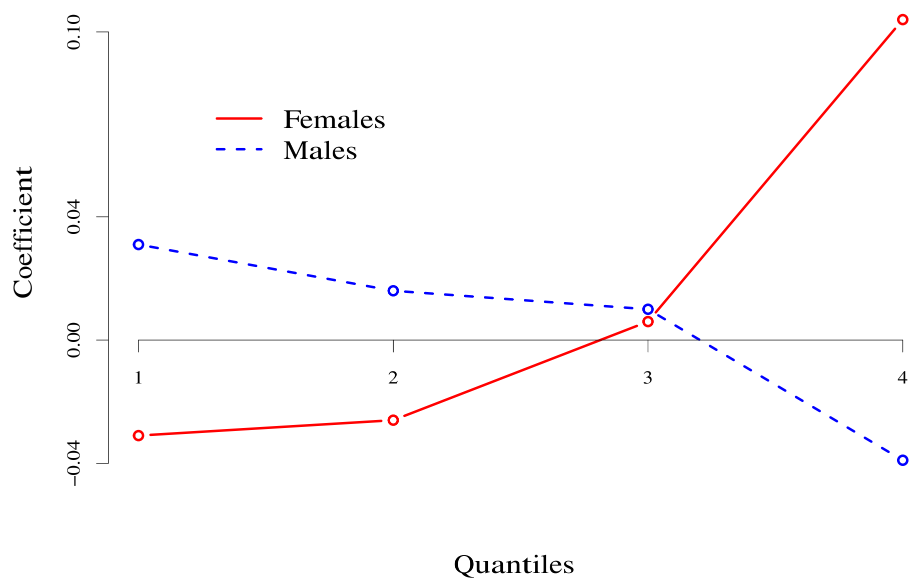
To test this prediction, we estimate equation (4.1) where the dependent variable y_{jt} is a set of firm- and gender-specific statistics of the workers' wages distribution: standard deviation, average wages below and above the median, below the 10th and above the 90th percentile, and average wages within each quartile of the wage distribution. Our main regressor of interest is the measure of female leadership: a female CEO dummy or the share of female executives. As described in Section 4.1, all regressions include firm fixed-effects, time-varying firm controls, workforce composition controls and controls for CEOs' characteristics.[27]

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 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

[27]The complete set of controls includes: 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 AKM fixed-effects regression, a set of 15 region dummies, 20 industry dummies, 4 firm-size dummies, year dummies, and industry-specific time trends.

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



4, according to six different specifications (panels (a) through (f)).[28] 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 to avoid the selection of firms entering and exiting the sample. To eliminate possible confounding effects induced by workers being hired or leaving after the appointment of the female CEO, this specification uses only observations on workers hired under the previous CEO and who stay at the firm during the female CEO's tenure. The other specifications inform the reader whether and how this sample selection and choice of variables affect our results. The specification in panel (b) comprises 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

[28] 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.

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 estimated 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.[29] Finally, results in panel (f) are obtained from regressions that do not include the controls for unobserved workforce heterogeneity and CEO ability.

For each specification, the tables report the coefficient on the measure of female leadership. 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 report the p-values of 1-tailed tests of the model's predictions.[30] Specifically, we test the null hypothesis that female leadership has zero impact on the dependent variable 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 at the top of the female wages distribution and a negative impact at the bottom. On the corresponding moments of the male wage distribution, the alternative hypothesis is that the impact of female leadership has the opposite signs. Top and bottom are defined as above and below the median.[31]

The results can be summarized as follows.

(i) Female leadership has a strong, economically and statistically significant positive effect on the variance of women's wages, as predicted by the theory; the effect is robust in all specifications (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 23 percent) and, as predicted by our model, consistently of the opposite sign, but less precisely estimated in most specifications. The null hypothesis that the

[29]Because there are more firms with at least some female executives than firms with a female CEO, this specification includes a larger number of firms providing a source of variation in female leadership compared to the other specifications.

[30]Given that individual CEO effects are generated regressors from a first stage estimation, in all specifications except (f), P-values are computed using bootstrapped standard errors with 300 replications. As described in detail in the Appendix, our bootstrapping procedure resamples firms, stratifying by firms that never had a female CEO and firms that had a female CEO. In specification (f), standard errors are clustered at the firm level. Standard errors are reported in the Appendix for the benchmark specification and in the Web Appendix for the other specifications.

[31]Note that the theory predicts that the effects of female leadership should be positive or negative at the top or bottom but does not predict non-parametrically where the change of sign should occur. Therefore, choosing the median is arbitrary. This is the reason why we add other possible cuts to the wage distribution: top and bottom 10% and quartiles.

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

Dependent variable: →	Standard deviation	Average wages: Median Below	Median Above	Decile 1	Decile 10	Quantiles 1	Quantiles 2	Quantiles 3	Quantiles 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
1-tail P-value	0.000	0.090	0.003	0.124	0.004	0.147	0.112	0.424	0.001
(b) All workers									
Coefficient	0.418	-0.032	0.049	-0.038	0.121	-0.036	-0.027	-0.020	0.072
1-tail P-value	0.000	0.041	0.062	0.146	0.009	0.108	0.043	0.824	0.027
(c) With controls for new CEO									
Coefficient	0.477	-0.030	0.079	-0.043	0.168	-0.030	-0.026	0.007	0.105
1-tail P-value	0.000	0.090	0.003	0.124	0.004	0.148	0.112	0.410	0.001
(d) Full panel									
Coefficient	0.403	-0.016	0.073	-0.004	0.170	-0.007	-0.022	0.006	0.096
1-tail P-value	0.000	0.206	0.000	0.448	0.000	0.390	0.121	0.370	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
1-tail P-value	0.000	0.188	0.000	0.109	0.000	0.172	0.286	0.571	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
1-tail P-value	0.000	0.037	0.009	0.086	0.007	0.093	0.051	0.481	0.004

Dependent variables are in logs. Dependent variables in columns (4-9) are defined in Footnote 28. Coefficients for a larger set of explanatory variables and standard errors are reported in Appendix and the online appendix (Flabbi et al. (2014)). Number of observations: 2,340 (234 Firms, 10 years), all specifications except (d); specification (d): 5,029 observations (795 firms). P-values are computed using bootstrapped standard errors with 300 replications.

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

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)
(a) Benchmark									
Coefficient	-0.107	0.021	-0.027	0.029	-0.069	0.031	0.016	0.010	-0.039
1-tail P-value	0.130	0.118	0.188	0.091	0.116	0.047	0.193	0.667	0.148
(b) All workers									
Coefficient	-0.113	-0.016	-0.037	-0.023	-0.071	-0.016	-0.015	-0.014	-0.047
1-tail P-value	0.095	0.894	0.080	0.919	0.078	0.901	0.870	0.183	0.076
(c) With controls for new CEO									
Coefficient	-0.105	0.022	-0.027	0.029	-0.067	0.031	0.016	0.010	-0.039
1-tail P-value	0.133	0.115	0.194	0.090	0.120	0.046	0.188	0.670	0.153
(d) Full panel									
Coefficient	-0.152	0.030	-0.038	0.058	-0.092	0.049	0.019	0.005	-0.054
1-tail P-value	0.021	0.002	0.069	0.000	0.035	0.000	0.038	0.630	0.049
(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
1-tail P-value	0.132	0.409	0.067	0.648	0.039	0.539	0.303	0.550	0.048
(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
1-tail P-value	0.013	0.154	0.059	0.148	0.027	0.077	0.231	0.629	0.037

Dependent variables are in logs. Dependent variables in columns (4-9) are defined in Footnote 28. Coefficients for a larger set of explanatory variables and standard errors are reported in Appendix B and in the online appendix (Flabbi et al. (2014)). Number of observations: 2,340 (234 Firms, 10 years), all specifications except (d); specification (d): 5,029 observations (795 firms). P-values are computed using bootstrapped standard errors with 300 replications.

effect on the male wage variance is zero against the alternative that it is negative is rejected in specifications (d), and (f) with p-values below 5%, and in the other specifications with p-values close to 10%.

(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 with wages above the median earn on average 7.8% more when working for a female CEO than for male CEOs (Table 3 panel (a), column (3)). The effect of female leaderships is stronger 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* wage distribution (Table 4, columns 2, 4, 6, and 7) is positive and significant in most specifications.

(iii) The effect of female leadership is monotonically increasing moving from the bottom to the top of the female wage distribution (compare the 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 the 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 it is less precisely estimated than the effects at the top of the wage distribution. For example, most specifications reject the null hypothesis that the coefficient on the bottom half of the wage distribution is zero against the alternative that it is negative with less than 9% confidence. Specifications (b) and (f) reject the null with a p-value below 5%. 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 again consistent 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 non-parametrically where the change of sign should occur.

To summarize, the signs of our point estimates of the effects of female leadership correspond to the prediction of our theoretical model. These effects are strong and robust across specifications. They are also strongly statistically significant when predicted to be positive. When they are predicted to be negative, the estimates that we obtain are close and often below conventional levels of statistical significance.

Despite the lack of strong statistical significance at the bottom in all specifications, there are at least four factors that we believe work in favor of not rejecting the theory. First, the sign of the point estimates is consistent across specifications. In particular, results are robust to extending the data to include the full panel of firms, and to including all workers (not just those that were employed at the time the female CEO took charge of 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 though 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 fourth quartiles. Third, the effects are increasing from the left to the right of the female wage distribution, consistent with theory. The opposite occurs on the male wage distribution. Finally, downward wage rigidity works against finding large negative effects, especially at the bottom of the wage distribution therefore it is not surprising that the estimates are more precise when the effects are positive.

4.3 Female Leadership and Firm-Level Performance

In our model, female executives improve the allocation of female talents within the firm by counteracting pre-existing statistical discrimination. Therefore, we expect the efficiency-enhancing effects of female leadership to be stronger the larger the presence of female workers.

Table 5 presents the estimation results from firm performance regressions, i.e. coefficients from estimating equation (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.[32] The female leadership measures and the controls are the same as those used in the wage regressions. As in the previous subsection, our benchmark specification focuses on the balanced panel of firms that were continuously observed from 1988 through 1997 (panel (a) in the table). Panel (b) reports the results from the benchmark specification run on the full (unbalanced) panel. Panel (c) reports results using the proportion of women executives as a measure of female leadership, and panel (d) is obtained from regressions that do not include the controls for unobserved workforce heterogeneity and CEO ability. In Table 5 we report the coefficients only on the variables of interest for our results. The Appendix reports the complete set of estimated coefficients for the main explanatory variables.

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

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

Dependent variable: →	Sales per employee		Value added per employee		TFP	
(a) Benchmark						
Female leadership	0.033	-0.120	-0.046	-0.245	-0.059	-0.213
Std. Error	(0.039)	(0.045)	(0.038)	(0.041)	(0.029)	(0.039)
Interaction		0.610		0.795		0.616
1-tail P-value		0.000		0.000		0.000
(b) Full Panel						
Female leadership	0.029	-0.009	-0.049	-0.093	-0.061	-0.096
Std. Error	(0.024)	(0.034)	(0.026)	(0.032)	(0.024)	(0.031)
Interaction		0.123		0.144		0.115
1-tail P-value		0.066		0.022		0.041
(c) Alternative measure of leadership: fraction of female execs.						
Female leadership	0.033	-0.120	-0.046	-0.245	-0.059	-0.213
Std. Error	(0.039)	(0.045)	(0.038)	(0.041)	(0.029)	(0.039)
Interaction		0.610		0.795		0.616
1-tail P-value		0.000		0.000		0.000
(d) Without controls for unobservable workers and CEO ability						
Female leadership	0.027	-0.104	-0.064	-0.234	-0.072	-0.200
Std. Error	(0.061)	(0.071)	(0.058)	(0.057)	(0.045)	(0.051)
Interaction		0.523		0.677		0.513
1-tail P-value		0.001		0.000		0.002

Female leadership: Female CEO dummy (panels a, b, and c); Fraction of female executives (panel c); Interaction: female leadership interacted with the fraction of female workers (non-executive). Coefficients for a larger set of explanatory variables and standard errors are reported in Appendix B and in the online appendix (Flabbi et al. (2014)).

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 results from the literature: as found by Wolfers (2006) and Albanesi and Olivetti (2009),[33] female CEOs do not appear to have a significant impact on firm perfor-

[33] Recent work on the impact of gender quotas 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.

mance.[34] 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 for the impact of a 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.[35] 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 women are present at the firm, the larger the effect. The empirical prediction is thus that the interaction term should be positive. This is exactly the result we find for each of the three measures of firm performance. The magnitude of the impact is substantial: for example, based on our benchmark estimates (column (2) in panel (a) of Table 5), a female CEO taking over a firm employing the average proportion of women in the sample would increase sales per employee by about 3.2%; if half of the firm's workers were women the impact would be about 18.5%.

The results are robust to adopting an alternative measure of female leadership (the fraction of female executives reported in panel (b)) and to changing the specification to avoid using generated regressors (panel (c)). Results on the unbalanced sample (panel (d)) report the correct sign but generate smaller point estimates and larger standard errors: P-values for the alternative consistent with the model (a positive sign) are in the range of 13/18%.

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 increasing the presence of women in corporate leadership positions, for example through gender quotas, we consider a partial-equilibrium exercise using as a benchmark the parameters reported in Table 5. We performed two counterfactuals. The first is a "targeted" exercise where we allocated a female CEO to all firms whose performance would improve as a result, according to our estimates from Section 4.3 (i.e., firms with at least 20 percent of female employees). This results in 51% of firms with a woman CEO. In our second counterfactual, instead, we assign a female CEO to the same proportion of firms (51%) selected randomly.

We computed the predicted value of the dependent variable under the two scenarios. Results are in Table 6. When Female CEOs are allocated randomly, the

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

[35] Just as in the wage regressions, we only focus on non-executives because the theory presented in Section 2 is not modeling promotion to executive, executive pay or interaction within executives.

Table 6: Impact of gender quotas

Counterfactual		Average percent gain			Percent gain for treated		
		Sales	Value added	TFP	Sales	Value added	TFP
CEO Allocation	Quota						
Random	51%	1.9	-2.1	-2.7	3.7	-4.1	-5.4
Female share > 20%	51%	6.7	4.2	2.1	14.2	8.7	4.3

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

average percent change is generally small, and its sign depends on the measure of performance. In contrast, our "targeted" exercise delivers large, positive effects in the firms that are assigned a female CEO, and also positive effects overall. For example, the table shows that in this scenario sales per worker would increase by 14% in the "treated" firms and by 6.7% in the overall sample of firms. This is because our findings imply large, positive interaction effects between female leadership and the share of female workers. Although our exercises ignore general equilibrium effects, these results confirm that, based on our estimates, the order of magnitude of the efficiency gains from having a larger female representation in firm leadership can be quite large.[36]

5 Other explanations

In this section, we discuss the plausibility of possible alternative explanations for the empirical results we presented in Section 4.

5.1 Gender preferences

A possible alternative explanation for our results is that female CEOs give preferential treatment to female workers. However, such an explanation is at odds with at lest two of our findings. First, the effect of female leadership on female wages varies with the wage level, so much so that the impact at lower wages is negative. A theory based on preferences would require the ad-hoc assumption that the CEOs preferences for women are conditional on their wage level. In particular, a female CEO would need to prefer female workers at the top of the distribution, and to hold prejudice

[36]The effect on the average gender wage gap, not shown in the table, is small. In firms acquiring female leadership, the higher wages of female workers at the high end of the distribution are compensated by lower wages at the low end of the wage distribution.

against women at the bottom of the distribution. Second, preferential treatment is inconsistent with our results on firm performance illustrated in Subsection 4.3. If female CEOs gave preferential treatment to female workers, they would be prone to hire and promote female workers even if males with identical characteristics were more productive. As a result, the impact on performance of the interaction between female leadership and share of females would unlikely be positive.[37]

5.2 Complementarities between female managers and skilled female workers

Complementarities between female managers and skilled labor input from female workers may be consistent with some of our results depending on the source of such complementarities. For example, one could assume that communication is more efficient between workers and executives of the same gender. This communication technology is not in contradiction with our model. In fact, it provides a possible micro-foundation for the crucial assumption of our statistical discrimination framework: the difference in the quality of signals from workers of different gender.

However, similar effects could be also derived from a complete information model where communication skills enter directly into the production function. For example, complementarities may be generated by peer-group effects or because female managers are role models for skilled female workers.[38] These explanations can indeed generate the productivity effects we find in our results. They can also generate one result from the wage regressions: the positive effect of female leadership on female wages at the top of the distribution. However, these alternative explanations are unable to generate the two other results we obtain from the wage regressions: the negative effect of female leadership on female wages at the bottom of the distribution, and any effect of female leadership on the male wage distribution. We conclude that the balance of the evidence favors our statistical discrimination model.

6 Conclusion

Motivated by a recent literature showing the importance of executives' personal traits 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 on firm performance. We

[37] Bednar and Gicheva (2014) find support for a similar conclusion. Using a matched manager-firm data with information about the gender composition in lower levels of the job ladder, and they do not find evidence that gender is predictive of a supervisor's female-friendliness.

[38] Athey et al. (2000) introduce a model analyzing the effects of mentoring on workplace diversity.

find that female CEOs 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. In our preferred specification, female CEOs increase wages for women in the top 25% of the women's wage distribution by about 10 percentage points and they decrease wages for women in the bottom 25% by about 3 percentage points. The impact on the men's wage distribution has opposite signs. Our results are robust to alternative measures of female leadership, to different empirical specifications and to different sample selection criteria for firms and workers. When looking at the impact on firm performance, we estimate that the interaction between female CEOs and the share of female workers employed at the firm has a positive impact on firm performance. The magnitude of the impact is substantial: in our preferred specification, a female CEO taking over a firm employing the average proportion of women in the sample would increase overall sales per employee by about 3.7%. The results are robust to three different measures of firm productivity, one different measure of female leadership, and two different specifications and estimation samples. Moreover, we exploited the matched employer-employee, longitudinal structure of our data to construct a rich set of controls for firm-level, workforce-level, and executive-level heterogeneity, thereby alleviating selection bias concerns.

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 of this attenuated information asymmetry, female CEOs taking charge of previously male-led firms are able to 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.

The interpretation of our results through the implications of our theoretical model suggests that there are potentially high costs associated with the underrepresentation of women at the top of corporate hierarchies. Our findings suggest that companies with a substantial female presence would be likely to benefit from assigning women to leadership positions. Results from a partial-equilibrium counterfactual experiment based on our point estimates show if all the firms with at least 20% of female workers were lead by female CEOs, they would see their sales per worker increase by about 14.2%. From a public policy point of view, the same partial-equilibrium counterfactual experiment shows that an integrated generalized extension of women in leadership positions would lead to a much smaller,[39] but still positive effect on

[39] 3.7% instead of 14.2%, see Table 6. Results on Value Added and TFP would actually turn from positive to negative, with magnitudes always smaller than in the sales per worker case.

sales per worker.

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.[40] 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, $\widehat{s}$, as 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 $\overline{s}_m < \overline{s}_f$.[41] 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

[40] 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.

[41] 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.

an argument similar to that made for case (i). □

B Appendix: additional results on the benchmark specification.

We report below the estimation results for the benchmark specification. Results for all robustness specifications are available in the online appendix (Flabbi et al. (2014)).

All the reported standard errors are computed by a bootstrapping procedure. We need to compute standard errors by bootstrapping on specifications (a)-(e) because they include generated regressors (the CEO and worker fixed effects) from the first stage. Standard errors in the first stage can be computed only by bootstrap (AKM.) We perform the bootstrapping procedure by resampling at the firm level and by resampling separately 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. Since stratification at the first stage may generate samples with zero or very few firms with female CEOs at the second stage, identification of the parameters of interest may not be attained for some bootstrap runs. Therefore, we computed standard errors using only bootstraps with more than 10 firms with a female CEO in the second stage. We run the procedure until we reach 300 valid replications.

Table A.1: 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
Expl. variable ↓	(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
	(0.122)	(0.022)	(0.028)	(0.037)	(0.063)	(0.029)	(0.022)	(0.030)	(0.035)
CEO age	0.076	0.074	0.044	-0.019	0.065	0.059	0.092	0.045	0.043
	(0.425)	(0.067)	(0.092)	(0.152)	(0.179)	(0.090)	(0.070)	(0.063)	(0.115)
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 $<$ 1980	-0.011	0.016	0.012	0.011	0.010	0.014	0.017	0.014	0.014
	(0.056)	(0.007)	(0.012)	(0.018)	(0.027)	(0.012)	(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
	(0.054)	(0.008)	(0.011)	(0.021)	(0.021)	(0.013)	(0.008)	(0.007)	(0.013)
Avg. wrk. age	0.097	0.054	0.068	0.084	0.078	0.065	0.050	0.051	0.072
	(0.067)	(0.035)	(0.042)	(0.058)	(0.048)	(0.043)	(0.032)	(0.033)	(0.045)
Avg. wrk. tenure	-0.026	-0.002	-0.007	-0.006	-0.011	-0.003	-0.003	-0.003	-0.008
	(0.017)	(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
	(0.401)	(0.070)	(0.103)	(0.201)	(0.187)	(0.111)	(0.067)	(0.072)	(0.125)
Fraction female	0.227	-0.595	-0.577	-0.623	-0.435	-0.661	-0.556	-0.541	-0.572
	(0.488)	(0.111)	(0.126)	(0.341)	(0.188)	(0.182)	(0.101)	(0.125)	(0.145)
Avg. wkr. F.E.	1.960	1.250	1.577	1.897	1.764	1.474	1.130	1.181	1.680
	(0.714)	(0.156)	(0.190)	(0.440)	(0.329)	(0.258)	(0.136)	(0.169)	(0.232)
Constant	1.009	4.149	3.993	3.269	3.789	3.763	4.306	4.390	3.893
	(1.996)	(0.981)	(1.171)	(1.695)	(1.392)	(1.211)	(0.879)	(0.921)	(1.258)
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. Boostrap Standard Errors in parentheses; see text for details. Additional controls: 15 region dummies, 20 industry dummies, 4 firm-size dummies, year dummies, industry-specific trends, and 234 firm fixed effects.

Table A.2: 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
Expl. variable ↓	(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
	(0.094)	(0.018)	(0.031)	(0.022)	(0.057)	(0.018)	(0.018)	(0.023)	(0.038)
CEO age	1.815	0.046	0.317	0.069	0.787	0.053	0.041	0.056	0.433
	(0.869)	(0.061)	(0.197)	(0.093)	(0.412)	(0.075)	(0.060)	(0.083)	(0.254)
CEO tenure	-0.003	-0.001	-0.001	-0.001	-0.002	-0.001	-0.001	-0.001	-0.001
	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
CEO < 1980	0.024	0.007	0.016	0.007	0.026	0.007	0.008	0.007	0.018
	(0.038)	(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)	(0.012)	(0.010)	(0.019)	(0.008)	(0.006)	(0.010)	(0.014)
Avg. wrk. age	0.074	0.048	0.074	0.048	0.071	0.046	0.049	0.061	0.079
	(0.056)	(0.037)	(0.047)	(0.040)	(0.046)	(0.037)	(0.038)	(0.044)	(0.049)
Avg. wrk. tenure	0.003	-0.003	-0.004	-0.000	0.000	-0.002	-0.004	-0.004	-0.004
	(0.010)	(0.004)	(0.003)	(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
	(0.196)	(0.090)	(0.089)	(0.103)	(0.131)	(0.092)	(0.092)	(0.097)	(0.103)
Fraction female	0.219	-0.181	0.063	-0.217	0.212	-0.186	-0.176	-0.083	0.121
	(0.273)	(0.139)	(0.134)	(0.142)	(0.186)	(0.132)	(0.145)	(0.162)	(0.150)
Avg. wkr. F.E.	1.968	1.021	1.796	1.008	1.773	0.946	1.051	1.431	1.921
	(0.467)	(0.364)	(0.190)	(0.397)	(0.240)	(0.368)	(0.369)	(0.364)	(0.179)
Constant	2.442	4.334	3.933	4.141	4.410	4.284	4.376	4.068	3.934
	(2.137)	(1.051)	(1.518)	(1.103)	(1.746)	(1.036)	(1.061)	(1.228)	(1.674)
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. Boostrap Standard Errors in parentheses; see text for details. Additional controls: 15 region dummies, 20 industry dummies, 4 firm-size dummies, year dummies, industry-specific trends, and firm fixed effects.

Table A.3: Estimates on Firm-Level Performance, benchmark specification

Dependent variable → . variable ↓	Sales per employee (1)	(2)	Value added per employee (3)	(4)	TFP (5)	(6)
Female CEO	0.033	-0.120	-0.046	-0.245	-0.059	-0.213
	(0.039)	(0.045)	(0.038)	(0.041)	(0.029)	(0.039)
Interaction		0.610		0.795		0.616
		(0.142)		(0.169)		(0.172)
CEO age	0.212	0.209	0.442	0.438	0.320	0.316
	(0.154)	(0.152)	(0.162)	(0.160)	(0.146)	(0.145)
CEO tenure	-0.003	-0.003	-0.002	-0.002	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
CEO started <1980	0.028	0.028	0.012	0.011	0.010	0.010
	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)
CEO fixed eff.	0.017	0.017	0.065	0.064	0.046	0.045
	(0.019)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)
Avg. Wkr. age	0.028	0.031	0.051	0.055	0.055	0.058
	(0.027)	(0.028)	(0.031)	(0.033)	(0.029)	(0.029)
Avg wkr. tenure	0.005	0.004	-0.013	-0.014	-0.030	-0.030
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
% white collars	0.269	0.254	-0.117	-0.137	-0.082	-0.098
	(0.135)	(0.136)	(0.154)	(0.155)	(0.154)	(0.154)
Fraction female	-0.313	-0.390	-0.496	-0.596	-0.478	-0.556
	(0.234)	(0.242)	(0.157)	(0.158)	(0.164)	(0.161)
Avg. wkr. F.E.	1.217	1.284	1.636	1.724	1.438	1.506
	(0.267)	(0.264)	(0.299)	(0.305)	(0.305)	(0.299)
Constant	3.089	3.020	2.072	1.983	0.422	0.353
	(0.640)	(0.653)	(0.830)	(0.868)	(0.697)	(0.708)
R^2: Between	0.590	0.592	0.218	0.222	0.179	0.182
Within	0.013	0.015	0.044	0.055	0.270	0.268
Overall	0.070	0.073	0.070	0.081	0.248	0.247

Dependent variables are in logs. Boostrap Standard Errors in parentheses; see text for details. 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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