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JEL Classification: G34, J30, J24, L14

Keywords: Gender Gap, networks, CEO compensation, Firm sorting

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1. Introduction

Research on executive pay has uncovered that men are more likely to attain top executive positions than women, at the same time as extensive evidence on the gender pay bias. Examples are Geiler and Renneboog (2015), who find that female top managers of listed UK firms earn 23% less than their male counterparts; Bell (2005) who documents a bias between 8% and 25% conditional on the gender of the Chief Executive and Corporate Board Chair for US listed firms; and Bertrand and Hallock (2001) who find a 45% gap in US firms, which is reduced to below 5% after accounting for all observable differences, where gender segregation by firm size plays a crucial role.[1] However, the literature has neglected the possible role of professional networks in determining gender differences in executive pay. A few authors have shown that female presence in leadership positions can lead to positive spillovers in terms of the progress of other women and the general within-firm pay gaps (Matsa and Amalia 2011; Magda and Cukrowska-Torzewska 2018). Other authors have acknowledged the role of networks for the gender gap, using very particular network measures such as co-authorships, e-mail exchanges, or same high-school attendance as a firm's chair (Lindenlaub and Prummer 2020; Keloharju *et al.* 2016). However, the exact role of broader professional networks in explaining gender pay differences amongst top managers has not yet been addressed. This is an important omission to overcome, as empirical and theoretical work have shown how critical networks are for the professional advancement of managers (Renneboog and Zhao 2011; Engelberg *et al.* 2013; Hwang and Kim 2009).

A related key issue is whether networks differ only in size, or whether the benefits drawn from networks are gender specific, particularly whether the gender composition of a manager's own network is important. Understanding these issues opens the possibility for female managers leveraging their networks' size and composition to reduce the gender pay gap. Matsa and Amalia (2011) show that top managers are primarily male, which may derive from, and lead to tacit discrimination against female managers. The authors stress that the historic absence of women in leadership positions may lead to hysteresis, with the predominantly male composition of existing networks and male-dominated firms further preventing advancement in overcoming the gender pay gap at the top. In sum, networks may play a key role as a tool for female managers to overcome existing barriers.

In this study, we compute the gender pay gap at the top of the corporate ladder for the sample of Portuguese firms. In 2017 female top managers in Portugal earned on average around 80 cents for every euro earned by their male counterparts. This difference in pay is made more salient as we consider

1. Elkinawy and Stater (2011) find a similar figure as Bertrand and Hallock (2001) with a more recent sample of US firms.

the rising trend in females' education levels and labor market experience, so that when we adjust the gender pay gap by age, tenure and schooling, it reaches 25%. Cardoso *et al.* (2016) and Card *et al.* (2015) have shown that firm sorting plays a large role in explaining the overall gender gap in the Portuguese labor market. We will advance a similar analysis as Cardoso *et al.* (2016), extending it to top managers, and precisely quantifying the importance of the firm sorting channel. More specifically, we will estimate a conventional wage equation for top managers and then compute the contribution of sorting into firms with heterogeneous pay policies, combining the estimates of high-dimensional fixed effects regression models with the omitted variable bias decomposition, as suggested in Gelbach (2016). We will contribute to the existing literature by isolating the network effect among managers, discussing how the gender pay gap is impacted.

We rely on two characteristics of networks: size and gender composition. The former is given by the number of all past professional interactions, within the same firm, with co-workers who later became top managers. In other words, a top manager's current network size depends on how often she or he was present in the same firm with workers who later became managers. Our network metric benefits from a key conceptual advantage over the definitions in the existing literature: it changes over time for reasons exogenous to the manager herself, and her choices, as past co-workers become managers – or leave the job market. Additionally, our comprehensive sample of firms and the considerable time interval analyzed allows us to register variations in network size across time, and estimate network effects while controlling for manager and firm fixed effects.

The network size allows us to assess the role of the number of connections in explaining pay differences, but we go one step further and investigate whether the gender composition of the network matters. We see this as unveiling the relative strength of factors such as same-gender empathy and gender diversity in determining the value of a network. In our case, gender composition is defined as the ratio of male connections in a manager's network. In a male-dominated job, can a female manager's advancement depend not only on how many people she is connected to, but also whether she is well-connected to male or female top managers?

We find that, of the 25% (22 log points) of the pay gap amongst top managers in Portugal, approximately 30% can be attributed to male top managers sorting into firms with more generous pay policies. This firm sorting channel can result both from gender discrimination and stereotyping, as well as other corporate preferences, for instance, related to a specific clientele (Matsa and Amalia 2011). The manager pay gap drops to 20% (18 log points), when we account for differences in network metrics across genders. The contribution of firm sorting to the pay gap more than halves. These results suggest that networks are important: they are used to access better paying firms, in line with the generally accepted notion that being part of a large network translates into greater opportunities for materializing rewarding job changes (Bartlett and Miller 1985). We explore further the link between networks and firm sorting by focusing on the transitions of top managers between firms, using a nearest neighbor matching procedure. The bulk of the gender gap is created precisely during the hiring process when managers transition between firms, and is only slightly increased by the biased career progression within the firm. This gender bias for new hires is present even when we compare top managers with the same years of schooling, similar education, age and networks, and coming from and moving to firms that are similar in size and wage policies. By comparing managers with the same pay prior to the transition, we are able to control in part for unobservable characteristics – to the researcher and the hiring firm – including ability and accumulated human capital. Our view is that the gender gap that persists after this careful comparison can be legitimately equated to gender discrimination.

Our evidence suggests the existence of a large premium associated with network size, manifested primarily as managers transition across firms. Female and male top managers with more connections than the sample median obtain a 22% and 17% average higher pay, respectively, than otherwise similar managers with thinner networks. We find no penalty as to how females benefit from networks. Controlling for firm characteristics, we confirm that most of the network premium is related to gaining access to firms with more generous pay policies.

Finally, we discuss how the gender composition of networks impacts managers' pay. Despite the existing bias in favor of male managers in top corporate positions, our results suggest that female top managers benefit more from having females rather than males in their 'inner circle'. This suggests gender empathy may trump gender diversity in network value, and suggests an increased presence of females in top management jobs will further facilitate overcoming gender bias at the top. This virtuous cycle stemming directly from the gender composition of networks is here empirically tested for the first time, suggesting fruitful avenues for future research.

This paper is structured as follows: Section 2 carefully describes the construction of the network, as well as the underlying data; Section 3 computes the gender pay gap amongst top managers and documents results from Gelbach's decomposition; the role of networks during firm transitions is explored in Section 4, and Section 5 concludes.

2. Data and network description

2.1. Network definition

We follow the same approach as in Chapter 2, and define manager i's network in year t as all past co-workers, who are themselves top managers in year t.

In other words, we backtrack all the firms a manager has worked at in the past, and identify all the employees that coincided at those firms. Next, we exclude from the yearly network all acquaintances who have not reached a management position by year t or are in the same firm as manager i at time t. Yearly variations in a manager's network are driven by firm transitions, that result in the managers of the prior firm being added to the manager's network and by past co-workers being promoted to or ceasing management positions. The latter is a source of exogenous variation as it is completely independent from the manager's choices.

The network size of a manager is given by the total number of connections in a given year – denoted as *Degree* centrality in network theory:

$$\mathrm{D(i)} = \sum_{j \neq i} x_{ij}, \tag{1}$$

where x_{ij} is 1 for the presence of a link between i and j.

For the gender composition of networks, we will consider the share of male connections:

$$\mathrm{G(i)} = \frac{\sum_{j \neq i} x_{ij}}{D(i)}, \tag{2}$$

where x_{ij} is 1 for the presence of a link between i and any male manager j.

2.2. Sample

Our data draws on information from *Quadros de Pessoal* (henceforth denoted *QP*), a micro longitudinal dataset that contains mandatory information collected by the Portuguese authorities. The matched employer-employee dataset covers all private firms and each of its wage-earners operating in Portugal between 1986 and 2017, containing information regarding the firm and each of its workers. *QP* includes a personal identification number that enables tracing individuals across time, which allows us to observe the entire professional history of a worker (since 1986).

Each worker is classified according to the National Classification of Occupations and assigned a professional grade level in *QP*. Professional grade levels are defined by law, and each firm is obliged to classify each worker accordingly. We restrict our sample to all managers between 1995 and 2013. We define managers as top decision makers or as top management. The available 6-digit occupational classification system identifies all types of managerial occupations. Additionally we restrict the sample to those workers who are classified in the highest hierarchical grade level, that is, top managers. While we include in the global network self-employed managers, *i.e.* firm owners, they are excluded from our final sample used for our regression analysis due to the lack of data regarding their wages, and the different wage-setting mechanism in place. Put differently, firm owners add value to other managers' networks, but we cannot analyze the impact of their network on pay. Our final sample consists of 665,150 manager-firm-years, representing around 29,785 firms and 102,989 top managers.

In *QP*, for the period between 1986 and 2017 the national classification of occupations was revised several times, the last change having occurred in 2010. From this year onwards, we use the latest classification of occupations and are able to identify the workers who are managers using unchanged criteria. For the prior period, we used the official table of harmonization published by Statistics Portugal, to ensure that we minimize manager movements in and out of the network due to these changes.

2.3. Statistics

Table 1 summarizes key statistics on top manager and firm characteristics, by gender. Several facts emerge from the table. First, there is a clear under-representation of females in corporate leadership. Indeed, female top managers represent only 25% of our sample. Second, female top managers earn approximately 80% of their male counterpart's pay.

Table 1. Summary statistics

	Female Top Managers			Male Top Managers		
	Obs.	Mean	Median	Obs.	Mean	Median
Manager characteristics						
Age	168 638	42.5	42.0	496 512	45.5	45.0
Education (categorical 1-5)	168 638	4.6	5.0	496 512	4.4	5.0
Tenure	168 638	10.5	8.0	496 512	11.0	8.0
Network size	168 638	90	21	496 512	102	30
Share of male connections	168 638	0.62	0.69	496 512	0.72	0.78
Total pay (euros)	168 638	3249	2754	496 512	4195	3373
Firm characteristics						
Firm size (no of workers)	168 638	1790	110	496 512	1575	126
% of female top managers	168 638	0.52	0.43	496 512	0.16	0.14

This table presents the summary statistics of firm and manager characteristics for 665,150 firm–year observations between 1995 and 2017. Education is a categorical variable where: 1 - less than primary education; 2 - 1st and 2nd cycle of primary education; 3 - lower secondary education; 4 - upper secondary education; 5 - tertiary education. See Appendix A for definitions of the other variables.

The median female manager is 42 years old – 3 years younger than her male counterpart, holds a college degree and has been at the same firm for 8 years. While the majority of top managers have tertiary education, female top managers have on average more years of schooling. On the other hand, the networks of female top managers have on average fewer connections, and a lower share of male connections. Notwithstanding, networks of both genders are dominated by males, in line with male over-representation in management positions.

In terms of firm heterogeneity across gender, females work on average for larger firms, though dispersion in firm size is also larger amongst females. Finally, the share of female managers per firm suggests sorting of gender into different kinds of firms.

3. Is there a gender gap in top management compensation?

As shown in Figure 1, in 1995 total pay of female top managers stood slightly above two thirds of the pay of their male counterparts. Interestingly, the raw gender pay gap between top managers followed a similar trend to the overall gap for all the workers in the economy, narrowing by more than 10 p.p. in the period under study, such that female pay represented almost four fifths of male wages by 2017. One should note that the gender pay gap amongst top managers was always around 3 p.p. above the overall gap, or about 10% higher.

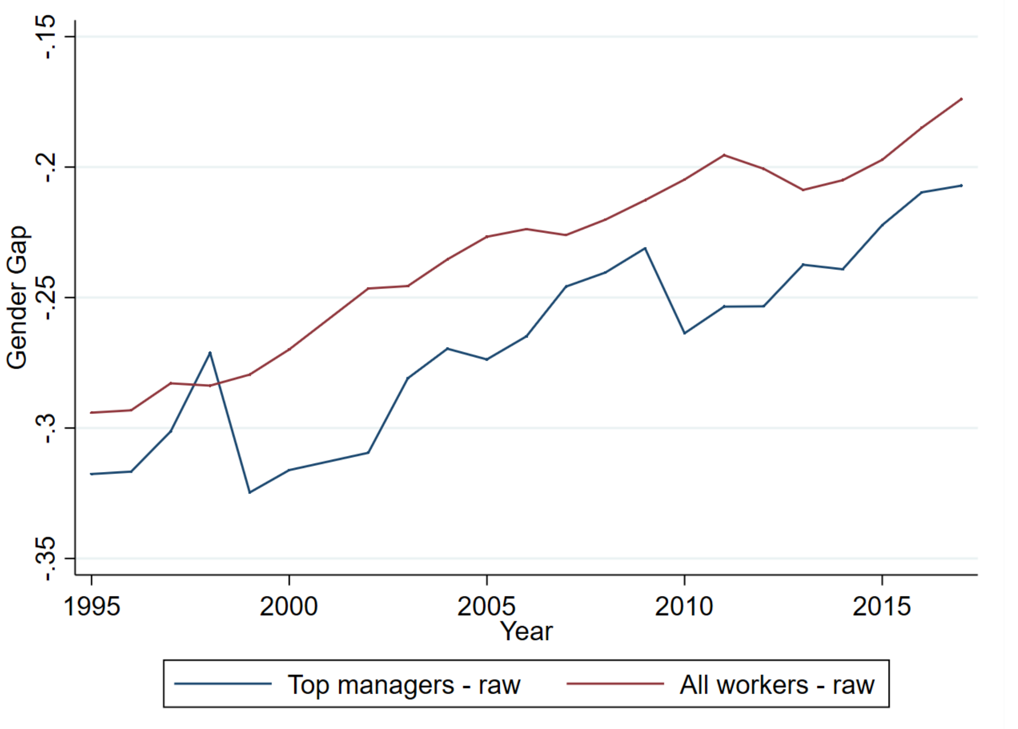

Figure 1: The gender pay gap

The story changes, however, if we take observable characteristics into account, and compute an 'adjusted' gender pay gap, as depicted in Figure 2. While there is an indication of a minor decrease in the overall gender gap over time, that is not the case amongst top managers, quite the contrary. The wage gain achieved by female top managers over this period is due to the catching up of their skills, not due to a reduction in the unexplained component of the wage difference, equated to gender discrimination (Cardoso *et al.* 2016).

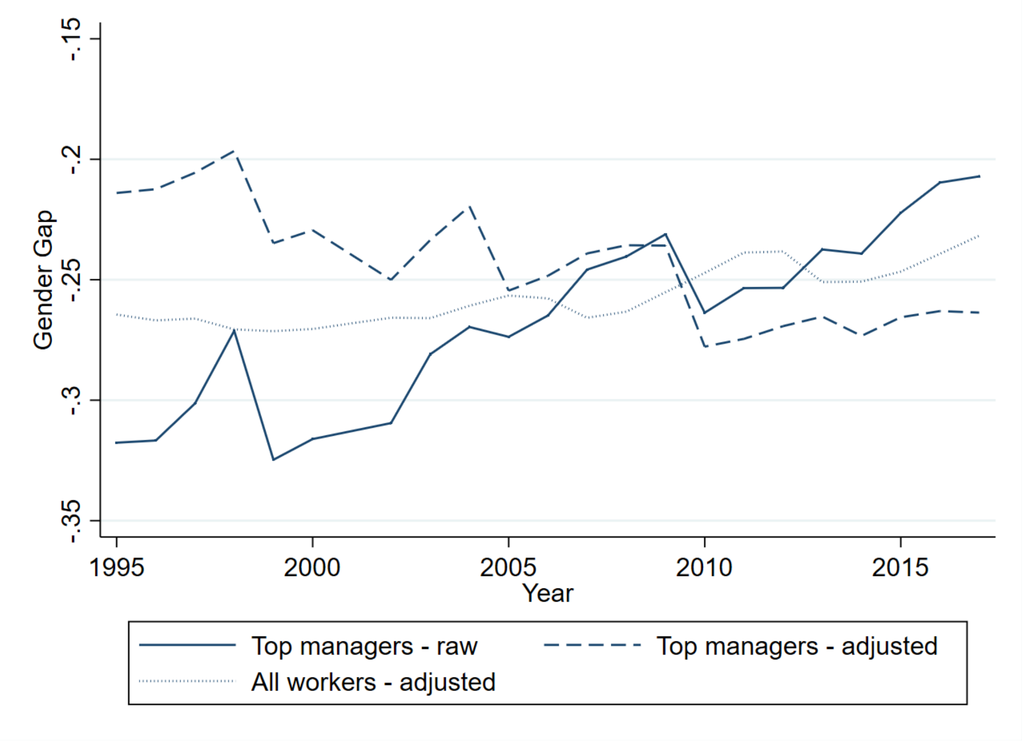

FIGURE 2: The unexplained gender pay gap

So far, to compute the 'adjusted' gap we have controlled for characteristics usually included in wage equations – age, tenure and education, following Cardoso *et al.* (2016). Next, we propose to augment the analysis, taking into account professional networks, which have been identified as crucial drivers in the wage setting process at the top of the corporate ladder (Renneboog and Zhao 2011; Engelberg *et al.* 2013).

In Figure 3 we adjust the gender pay gap for the size and the gender composition of a manager's network. We find that networks play an extremely important role, with the number and composition of network connections associated with about a 8 p.p. lower gap in 2017.

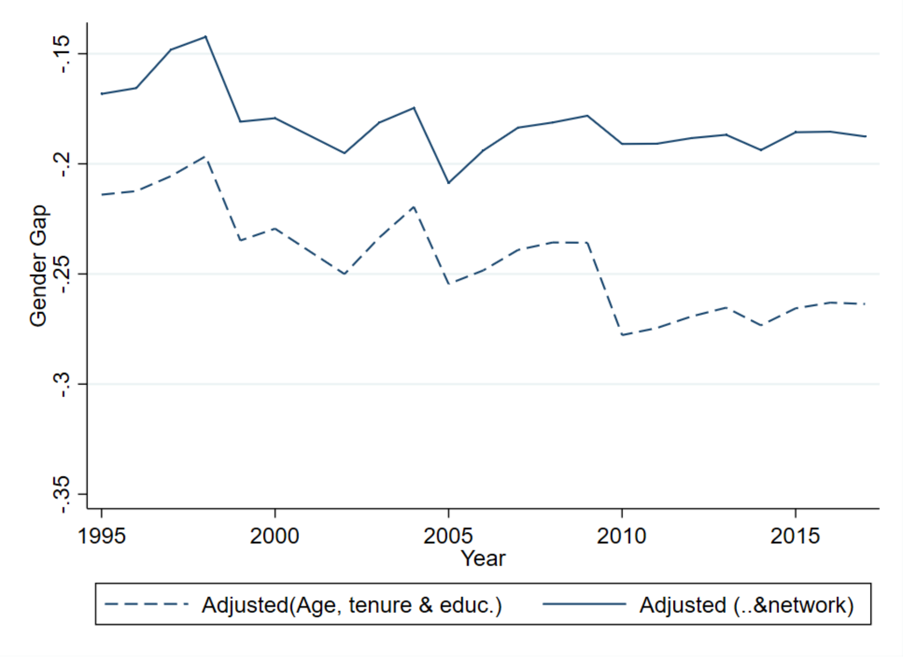

FIGURE 3: The unexplained gender pay gap: the role of networks

3.1. The role of firm heterogeneity

The adjusted gender gap in Figures 2 and 3 above corresponds to the average differential between the wages of two otherwise observably identical managers. However, another potential source of divergence might lie in unobserved heterogeneity. We propose to decompose the gender wage gap into the contributions of each of two sources of unobserved heterogeneity: firm and manager fixed effects. The former captures the time-invariant wage policy of the firm, *i.e* positive firm fixed effects will be generated for firms with more generous executive pay policies, while negative firm fixed effects will be attributed to low-wage firms. The latter is a proxy for the ability/productivity of the manager herself or himself, or simply reflects discrimination not associated with gender sorting across firms, as pointed out by Cardoso *et al.* (2016).

In this section, we follow closely the methodology presented in Cardoso *et al.* (2016) based on the Gelbach decomposition proposed in Gelbach (2016) to understand the contribution the allocation of managers across firms has on the observed gender pay differential.[2] We start out with the estimation of a

2. The main difference to Cardoso *et al.* (2016) is that our analysis focuses solely on top managers and excludes job title fixed effects.

conventional wage regression, augmented by high dimensional manager and firm fixed effects:

$$\ln Y_{ift} = \mathbf{X}_{ift}\beta + \varphi_i + \alpha_f + \tau_t + \varepsilon_{ift}, \tag{3}$$

where $\ln Y_{ift}$ is the natural logarithm of the real hourly wage of individual i (i=1,...,N), working at firm f (f=1,...,F), at year t (t=1,...,T). The vector $\mathbf{X}_{ift}$ contains observed time-varying characteristics of individual i, such as, age, education, tenure and squared terms on age and tenure. The terms φ_i and α_f stand for the manager and firm fixed effects, respectively, and are meant to capture time-invariant observed and unobserved manager and firm heterogeneity. The term τ_t refers to year dummies and the error term component ε_{ift} is assumed to follow the conventional assumptions.

For ease of presentation, this can be expressed in matrix notation as:

$$\mathbf{Y} = \mathbf{X}\beta + \mathbf{D}_i\varphi + \mathbf{D}_f\lambda + \varepsilon. \tag{4}$$

where $\mathbf{D}_i$ and $\mathbf{D}_f$ are the design matrices for the manager and firm fixed effects, respectively. We will restrict our estimations to the largest connected set, *i.e.*, the analysis is restricted to the set of firms that are connected by manager mobility to ensure comparability of the fixed effect estimates (Abowd *et al.* 2002).[3]

Gelbach's decomposition relies on the omitted variable bias formula, and requires the estimation of a benchmark regression excluding the high dimensional manager and firm fixed effects. Such that:

$$\mathbf{Y} = \mathbf{X}\beta + \gamma\mathbf{G} + \varepsilon. \tag{5}$$

where $\mathbf{G}$ refers to a gender dummy which was dropped in the *Full Model* in Equation 4 as it is fully absorbed by the manager fixed effect, and γ measures the pay gap conditional on the other observable factors $\mathbf{X}$ in the model.

Then, an estimate for γ can be obtained through a two-step regression. First, we regress $\mathbf{Y}$ on $\mathbf{X}$ and $\mathbf{G}$ on $\mathbf{X}$ to obtain the residuals of both regressions ($\mathbf{M_X Y}$ and $\mathbf{M_X G}$, respectively, where $\mathbf{M_X}$ is the residual-maker matrix). Next, we regress $\mathbf{M_X Y}$ on $\mathbf{M_X G}$ and obtain the OLS estimate for γ in our benchmark model. In other words, γ is estimated through a simple regression of $\mathbf{Y}$ on $\mathbf{G}$, after removing the impact of $\mathbf{X}$ from both variables.

Such that:

3. Notice that the estimated coefficients of fixed effects are not comparable across different mobility groups. Since in our work, in addition to controlling for individual and firm heterogeneity, we are interested in using the estimated fixed effects in further analysis, a widely used solution is to restrict the sample to the largest connected set. We confirm that this restriction does not change qualitatively our results to ensure that these are not driven by a sample selection bias.

$$\widehat{\gamma} = \mathbf{P_X Y} \tag{6}$$

where $\mathbf{P_X} = (\mathbf{G'M_X G})^{-1}\mathbf{G'M_X}$ and $\mathbf{M_X}$ is the residual-maker matrix.

Then, if we replace the coefficients and error terms of the *Full Model* 4 by their OLS estimates, and multiply this fitted model by $\mathbf{P_X}$ we obtain:

$$\mathbf{P_X Y} = \mathbf{P_X X}\widehat{\beta} + \mathbf{P_X D}_i\widehat{\varphi} + \mathbf{P_X D}_f\widehat{\lambda} + \mathbf{P_X}\widehat{\varepsilon}, \tag{7}$$

where $\mathbf{D}_i\widehat{\varphi}$ and $\mathbf{D}_f\widehat{\lambda}$ are column vectors containing the least-squared estimates of the fixed effects for managers and firms. We have obtained on the left hand side the OLS estimate for γ and $\mathbf{P_X D}_i\widehat{\varphi}$ and $\mathbf{P_X D}_f\widehat{\lambda}$ are the coefficients of the regressions of the manager and firm fixed effects on the gender dummy, conditional on the set of variables $\mathbf{X}$. Notice that $\mathbf{P_X X}\widehat{\beta} = 0$ and $\mathbf{P_X}\widehat{\varepsilon} = 0$. We can then rewrite Equation 7 more succinctly, using Equation 6:

$$\widehat{\gamma} = \widehat{\delta}_{\varphi} + \widehat{\delta}_{\lambda}. \tag{8}$$

Above the gender pay gap is partitioned into the contribution of individual and firm fixed effects, conditional on all $\mathbf{X}$ covariates.

In our benchmark regression, we find, in accordance with the literature, that manager pay increases with age and tenure at a decreasing rate.[4] Higher levels of education are also associated to higher pay. Regarding our key variable of interest – the dummy on females – we estimate a wage penalty of 22 log points for female top managers, conditional on age, tenure and schooling.[5]

TABLE 2. Conditional decomposition of the top manager gender pay gap

Pay Gap	Firm FE	Manager FE
-0.2196***	-0.0733***	-0.1463***
(0.0046)	(0.0050)	(0.0043)

Decompositions based on Gelbach (2016). The corresponding regressions are presented in Table B.1 in Appendix B. The benchmark model includes a gender dummy variable and controls for age, tenure, education, a squared term on age and tenure, and time fixed effects. The *Full Model* further includes fixed effects for the manager and the firm. The number of fixed effects are as follows: 29,785 for the firm and 102,989 for the manager. Robust standard errors adjusted for manager-level clustering are reported in brackets. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

4. See Table B.1 in Appendix B.

5. Cardoso *et al.* (2016) find a similar pay gap (23 log points) for the entire labor market and a less recent sample (1986-2008).

Gelbach's decomposition suggests that a significant fraction of the gender pay gap is explained by the heterogeneity of the firms' compensation policies (see Table 2). The sorting of managers into firms is responsible for 7.3 out of 22 log points of the gender pay gap. Put differently, female managers are disproportionately allocated to firms with less generous wage policies. If managers were randomly assigned to firms, the gender pay gap would be reduced by one third.

The unobserved permanent characteristics of the managers explain the remaining two thirds of the gender pay gap. In line with Cardoso *et al.* (2016) these unobserved – from the researcher's viewpoint – manager characteristics can be equated both with unobserved skills as well as forms of gender discrimination not associated with sorting of managers across firms.

3.2. The role of networks in explaining the Gender Gap

In what follows, we propose to explore the role of professional networks for the gender pay gap. Figure 4 displays the distribution of the firm fixed effects previously estimated. It is clear that larger networks give access to firms with more generous pay policies and that the dispersion amongst top managers with smaller networks is much higher. Another important takeaway is that amongst the less connected top managers – that is, those with smaller networks – male top managers seem to be over-represented in higher paying firms. Gender selection is less evident between well connected top managers. With regard to the distribution of manager fixed effects depicted in Figure 5, the gender penalty is very striking and there is no evidence of a different distribution for well connected managers.

Building on the evidence drawn from Figure 4, we augment the conventional wage equation with network metrics, henceforth augmented benchmark. Departing from the benchmark model and controlling additionally for the network size – *Degree* and *Degree* squared[6] – and network composition – share of male connections – reduces the estimated pay gap by almost 4 log points.[7] Relying again on Gelbach's decomposition, we find that 25% of the reduction is driven by the network size, while the remaining 75% stem from the gender composition of the network (Table 3).

Finally, adding manager and firm fixed effects to the augmented benchmark model allows us to conclude that only 20% of the pay gap is due to an uneven distribution of managers across firms, as shown in the specification denoted *Full Model* in Table 3. More importantly, notice that the contribution from the individual fixed effect, which represents, at least partly, discrimination, did

6. As suggested in Engelberg *et al.* (2013), and confirmed in Chapter 2, network size impacts positively pay at a decreasing rate.

7. See Table B.1 in Appendix B.

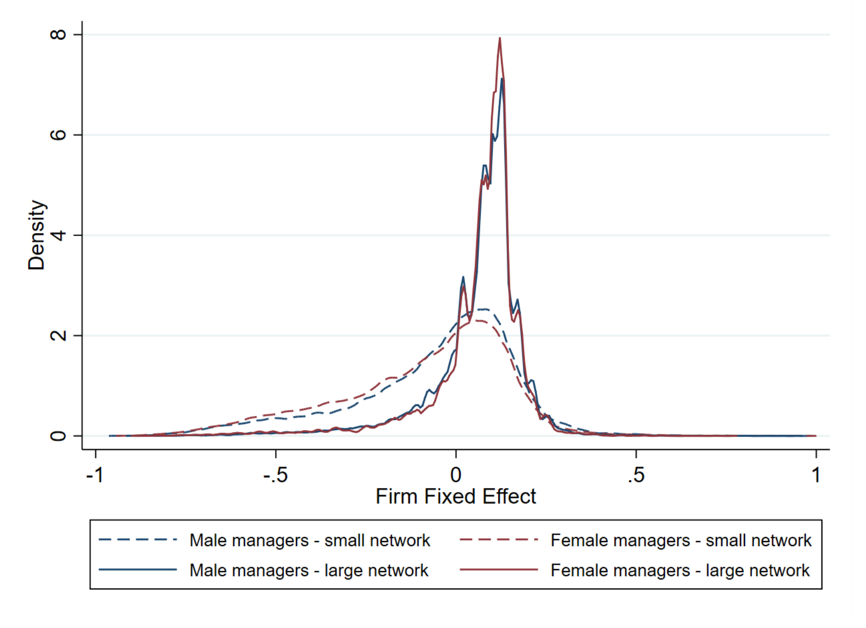

Figure 4: The distribution of firm fixed effects

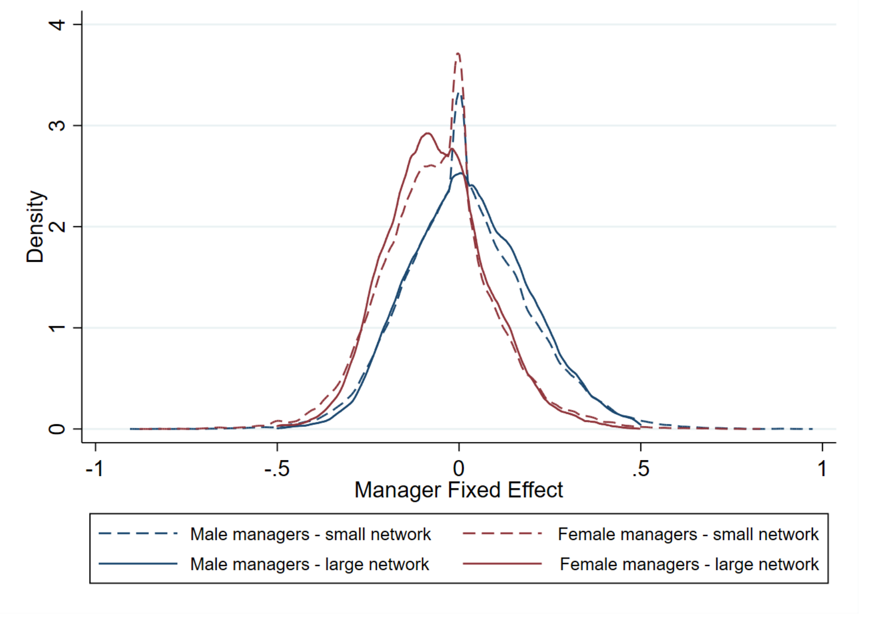

Figure 5: The distribution of manager fixed effects

Table 3. Conditional decomposition of the top manager gender pay gap: the role of networks

	Benchmark γ_0	Augmented benchmark γ_1	Full model γ_2
Gender Gap	-0.2196***	-0.1821***	0.0000
	(0.0046)	(0.0044)	
Observations	665,150	665,150	665,150
Adjusted R^2	0.2772	0.3193	0.8649
Gelbach decomposition			
$\gamma_0 - \gamma_1$		-0.0375	
Network size		-0.0095	
Network composition		-0.0281	
$\gamma_1 - \gamma_2$			-0.1821
Firm FE			-0.0356
Manager FE			-0.1465

Decompositions based on Gelbach (2016). The regressions are presented in Table B.1 in Appendix B. The ‘benchmark model’ includes a gender dummy and controls for age, tenure, education, a squared term on age and tenure and year dummies. The ‘augmented benchmark’ further includes the network metrics, and the *Full Model* also includes fixed effects for managers and firms. Robust standard errors adjusted for manager-level clustering are reported in brackets. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

not change. The entire network effect took place through the firm contribution. In other words, networks contribute to the matching of male top managers to higher paying firms. Therefore, by including the network metrics in our model, the contribution of the firm fixed effect was almost halved.

In sum, controlling for network metrics, we estimate a gender pay gap of approximately 20% (18 log points) between female and male top managers. Gelbach’s decomposition suggests that a random assignment of managers across firms would reduce the gap to 16% (15 log points), which represents a 20% reduction. This is a very striking result, as the role of sorting into firms is substantially reduced when controlling for networks. This highlights the importance of networks as an instrument to allow female top managers to overcome part of the bias they face.

4. Manager mobility: top managers transitioning between firms

So far results highlighted the role of networks in matching male top managers to firms with more generous pay policies. In what follows, we propose to focus solely on manager mobility to examine further the role of networks during transitions between firms, and investigate how female top managers can overcome some of he existing biases, leveraging on their networks.

More specifically, we start by estimating the gender pay gap during firm transitions. The purpose of this analysis is threefold. First, we verify whether the gender pay gap widens or shrinks as a result of career progression inside a firm. Second, we provide further evidence, confirming the robustness of our previous finding, as regards the role of networks in sorting into higher paying firms. And finally, we acknowledge that other important factors unobservable to the researcher might play a role, and we estimate a lower bound for how much of the gap can be attributed to discrimination.

Then, in the remainder of this section (Subsection 4.2), we turn our focus to networks and estimate a gender specific network premium. In other words, we will answer how much being connected to other top managers impacts total pay at a new firm, and to what extent the extracted benefits might be gender specific. Finally, an important question remains, namely whether both genders benefit equally from networks in terms of gender composition.

In the analysis that follows, we will rely on matching procedures to obtain credible estimates for the unobserved counterfactuals: for example, how a female manager's transition to a new firm compares in terms of pay to a transition were she not a female? Or what would have been her pay under the alternative of having a different kind of network? Without credible answers to these questions, we are unable to determine whether the differences in pay would have occurred irrespectively. The solution followed here is the estimation of the counterfactual outcome relying on a comparison group, which needs to be statistically identical to our treatment group, *i.e.*, we use a nearest-neighbor matching estimator approach.[8] As pointed out by Custódio *et al.* (2013), top manager transitions are a natural application for a matching procedure as the hiring process relies mostly on observable information.[9] Since the number of covariates is large, we define the comparison groups based on exact matching on the categorical variables and the probability of being in the treatment group in the case of the continuous covariates (the propensity score). After performing balancing tests on our matched sample, we tightened the matching procedure by forcing exact matches by age quartile, to ensure that there are no statistically significant differences between the treatment and control groups.[10]

This kind of matching procedure faces the risk of identifying a closest neighbor that is actually not that similar. We minimize this problem by imposing a maximum propensity score distance of 0.05 (caliper), avoiding bad matches. We confirm that this is enough to balance the distribution of the relevant covariates and that more stringent levels for the caliper do not alter significantly our results. To determine the region of common support we

8. Based on (Abadie and Imbens 2011).

9. Custódio *et al.* (2013) refers, in particular, to the case of CEO selection.

10. We have checked with stricter matching rules for other variables, including exact matching within quartiles for the continuous variables. Results are available upon request.

exclude all observations for which the propensity score lies below the minimum or above the maximum of the opposite group. Our approach eliminates a very low number of observations, having only a marginal impact on our results.

Table B.2, B.3 and B.4 in Appendix B focus on the balancing properties of the matching procedure. These tables present the mean for the treatment and control groups for the unmatched and matched samples and a t-test on the differences, together with the standardized bias measure suggested by Rosenbaum and Rubin (1985). While the matching is not perfect for all variables, the clear ex-ante difference in averages between the treatment and control groups is reduced to statistical insignificance for all variables and the standardized bias is below 5%. Finally, following Sianesi (2004), we also confirm that the pseudo-R^2 of the propensity score in the matched sample is very low, suggesting that, after the match, there are no systematic differences in the distribution of covariates between the two groups. Overall, we conclude that the matching procedure was successful, as it increased substantially the similarity between the observables of the treatment and the control groups.

4.1. Manager mobility and the gender pay gap

We start by computing the existing gender pay gap amongst top managers, restricting the sample to episodes of transition between firms. As we cannot compare the pay of a female manager when she changes firms with her pay under the alternative were she a male top manager, we compute the counterfactual. More specifically, we estimate a first-stage logit regression of the likelihood that the appointed manager is a female, using observable manager and firm characteristics. We then obtain a propensity score based on the predicted probabilities. Finally, we impute the missing hypothetical counterfactual for each subject by using the outcome of the nearest neighbor from the control group – made up of male top managers, relying on the propensity score for continuous variables and exact matches for categorical variables. The average pay gap is calculated as the average of the difference between the observed and imputed hypothetical wages for each manager.

Table 4 summarizes the results. We sequentially add variables to the matching procedure to disentangle the impact of different factors. We start by the basic manager characteristics – age and education, then analyze the network effect, and finally take into account the heterogeneous nature of firms. We control for the size of the previous firm in all specifications as it proxies for experience, in the sense that the human capital accumulated from managing a firm is related to the nature of the firm, including it's size. Additionally, the manager's previous firm also has an impact on the network metrics, as a manager's network increases by the number of managers from the firm it is departing. Comparing managers from similarly sized firms allows us to disentangle the network effect from the experience effect. The drawback is underestimating both the importance of networks and firm sorting, as both also relate to the choice of working at the previous firm.

In column (1) we compute the equivalent to the pay gap from the benchmark model in the previous section, but restricting the sample to transition episodes. The estimated gender gap is around 22% (19.6 log points), close to the figure from our previous benchmark model. Considering that this figure is restricted to transition episodes, while the benchmark model included the entire executive career of a manager, we can conclude that around 90% of the gender gap originates in the hiring process, and is then slightly aggravated by biased career progressions.

Table 4. Manager mobility and the gender pay gap: propensity score matching

	Pay Gap	Pay Gap adjusting for		Unexplained Pay Gap[1]
		networks	firm sorting	
	(1)	(2)	(3)	(4)
Gender Pay Gap	-0.1956***	-0.1309***	-0.1271***	-0.1083***
	(0.0106)	(0.0104)	(0.0135)	(0.0125)
Observations	43,185	40,549	23,040	20,462
Matching based on:				
Year, age, educ. & prev. firm size	✓	✓	✓	✓
Network size and composition		✓		✓
New firm size&FE; Prev. firm FE			✓	✓

[1]The unexplained Pay Gap is adjusted for both networks and firm sorting.
This table presents the second stage estimates of a propensity score model of the logarithm of manager total hourly pay at the new firm on the gender dummy, which takes the value of 1 for female top managers. The matching procedure was based on a caliper of 0.05. The matching on year, education, age and *Degree* quartile is exact. Firm FE refer to the fixed effects estimated in 'Full Model' in Table B.1. First-stage results are presented in Table B.5. The sample consists of all top managers who transitioned between firms in the 1995-2017 period. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

We then add our network metrics to our matching procedure in column (2), where network size is measured by total number of connections and gender composition by the share of male connections. The gender gap is reduced by 6.5 log points, when we compare managers with similar networks, both in terms of size and composition (column (2)-(1)). Notice that this reduction encompasses two different mechanisms through which networks impact wages: (i) the increased outside options that lead a manager to higher paying firms, *i.e* the firm sorting channel and (ii) the bargaining power derived from one's network that allows a manager to negotiate a higher pay within a firm. Due to the former, the estimated network effect is larger during transition years, as one would expect. We propose to control for this sorting into higher paying firms by controlling additionally for the previous and new firm size and pay policies

– proxied by the previously estimated firm fixed effects from the *Full Model* in Subsection 3.2. If we do not control for network size and composition, in column (3), we find that the gap falls to below 13 log points taking into account the type of firm the manager transitions to, suggesting that around 7 log points of the base gap is explained by sorting into firms (column (3)-(1)). Notice, however, that matching on the firm' characteristics, in addition to the network metrics, reduces the gap only by 2 log points (column (4)-(2)), suggesting that around two thirds (4.6 log points) of the bias driven by firm sorting is due to differences in networking. This allows us to decompose the network effect (6.5 log points) into 70% associated to accessing higher paying firms and the remaining 30% to bargaining higher wages within a firm. Comparing, on the other hand, the results in column (4) – where we take into account all characteristics – with column (1), we find that the pay gap was reduced by 8.8 log points, which can be roughly decomposed into 75% associated to networks and 25% to sorting into firms, conditional on the network.

The unexplained pay gap in column (4), after taking into account all observables, networks and firm sorting, is close to 11% during episodes of manager mobility. This figure compares well with the almost 15% gap found in the *Full Model*, after parceling out the impact from the firm fixed effects, suggesting again that the bulk of the bias is formed during the hiring process.

We perform one last exercise in Table 5, where we add to the matching procedure performed in column (4) of Table 4 the total pay received from the prior firm. We find that, even when we compare a female top manager to a male top manager with similar pay at the previous job, a 6% (5.8 log points) gap persists at the new job. By controlling for the previous wage, we are not only taking into account individual heterogeneity, such as differences in ability, accumulated experience, or any other unobservable that we are neglecting, but also the best observable indicator that the hiring firm has on the manager's skills. Therefore this remaining gap can be easily equated to gender discrimination beyond any bias associated to sorting across firms. More precisely, this should be considered a lower bound for discrimination as here we are assuming that differences in prior wages are not a result of discrimination.

4.2. Manager mobility and the role of gender specific networks

In this subsection we quantify the network effect on a manager's compensation when transitioning to a new firm. This network effect, as previously discussed includes both: (i) the matching to higher paying firms, as networks reduce search frictions, while increasing outside employment options and (ii) the added bargaining power that allows a manager to negotiate a higher pay at the new

TABLE 5. Top manager gender pay gap: considering unobservables

	Discrimination
Gender Pay Gap	-0.0577***
	(0.0119)
Observations	19,405
Matching based on:	
Year, age, education and prev. firm size	✓
Network size and composition	✓
New firm size and prev. and new firm FE	✓
Previous pay	✓

This table presents the second stage estimates of a propensity score model of the logarithm of manager total hourly pay at the new firm on the gender dummy, which takes the value of 1 for female top managers. The matching procedure was based on a caliper of 0.05. The matching on year, education, age and *Degree* quartile is exact. Firm FE refer to the fixed effects estimated in 'Full Model' in Table B.1. First-stage results are presented in Table B.5. The sample consists of all top managers who transitioned between firms in the 1995-2017 period. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

job. We present separate estimates for male and female top managers to assess whether there exists a gap in the benefits drawn from networks.

Similarly to before, we follow a matching procedure, pairing well connected to poorly connected managers with similar observable characteristics, as well as, similar unobservables as captured by previous pay. We define a well connected manager as someone with a higher than sample median number of connections.

We find that well connected top managers' compensation is between 16 and 20 log points higher than their poorly connected peers, with similar characteristics in terms of experience and education (see Table 6, column (1) and (2)). This estimate of the effect of networks on pay is both statistically significant and economically relevant, specially as we are comparing top managers with similar compensation levels at their prior jobs. Notice that the network effect is larger for females than males, suggesting that the network contribution to the gender gap is not related to intrinsic differences in the capacity of women to benefit from networks, but rather to actual differences in the networks.

Table 6 also reports results for the impact of networks on pay, beyond the firm sorting channel. In the last two columns of the table, the matching procedure also takes into account the size of the new firm, as well as the firm fixed effects of both firms from the *Full Model* in Table B.1. The size of the firm is relevant as managing larger firms is likely to involve higher responsibilities and therefore higher pay, while the firm fixed effect is intended to capture the heterogeneity of the time unvarying wage policies of firms. The network effect is significantly reduced after accounting for the characteristics of the firm the manager is transitioning to, suggesting that a large part of the network premium is associated with the match to higher paying firms. Notice, however, that the network effect remains relatively larger for females, confirming that women's networks are not per se less productive.

Table 6. The network size effect: propensity score matching

	Network size effect		Network effect adjust. for firm sorting	
	Women	Men	Women	Men
Total Hourly Pay	0.1985***	0.1601***	0.1118***	0.0604***
	(0.0223)	(0.0156)	(0.0258)	(0.0166)
Observations	4,654	23,512	2,234	13,249
Matching based on:				
Year, age, educ. & prev. firm size	✓	✓	✓	✓
Network gender composition	✓	✓	✓	✓
Previous pay	✓	✓	✓	✓
New firm size, prev. & new firm FE			✓	✓

This table presents the second stage estimates of a propensity score model of the logarithm of manager total hourly pay at the new firm on the network dummy, which takes the value of 1 for a *Degree* higher than the sample median. The matching procedure was based on a caliper of 0.05. The matching on year, education and age quartile is exact. Firm FE refer to the fixed effects estimated in 'Full Model' in Table B.1. First-stage results are presented in Table B.6. The sample consists of all top managers who transitioned between firms in the 1995-2017 period. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

Gender composition of networks

We have established that networks play an important role in explaining the gender pay gap at the top, and that accessing higher paying firms is a big part of the story. We have also uncovered that there is no penalty in the way female top managers benefit from networks. Now we turn to a different aspect of networks, which has not been addressed thoroughly in the literature yet, namely their gender composition. Is there any evidence of gender empathy, such that females benefit more from being connected to other female top managers? Does the persistent over-representation of males in corporate leadership and their bias towards females, create room for women serving at management positions to help advance other females? Or on the contrary, does the over-representation of men in powerful positions turn them into a more valuable asset in a female manager's network?

We proceed as before, only now our treatment group is defined as having a higher than median share of male connections, controlling for the total network size. We also take into account age, education and previous firm size and pay, and focusing only on gender composition, we find that both genders benefit more from male connections than female connections (see Table 7). We also find that the gender composition of networks only matters for firm sorting, *i.e*, after controlling for the type of firm the manager transitions to, there is no significant difference associated to male-dominated networks.

Now, we question whether this result stems from male manager's larger networks and the associated access to information, *i.e.*, just a direct effect of male's predominance in top management, or whether gender per se is relevant. We propose to investigate this further, by considering a weighted network metric –labeled as *Power*– that attributes a higher weight to connections who manager larger firms. More specifically, a manager's *Power* derives from how powerful their connections are, and is computed as the sum of weights on all direct connections, where each weight is defined as the average size of the firm's managed divided by the average number of managers at those firms. That is:

$$\mathrm{P(i)} = \sum_{j \neq i} w_{ij} x_{ij}, \tag{9}$$

where $\mathrm{w_{ij}}$ is greater than 0 for the presence of a link between i and j and the value represents the weight of the tie defined as:

$$w_{ij} = \frac{\sum_j FirmSize_j}{\sum_j NumberManagers_j}, \tag{10}$$

TABLE 7. Network gender composition: propensity score matching

	Male vs. Female connections		Composition effect adjust. for firm sorting	
	Women	Men	Women	Men
Total Hourly Pay	0.0328**	0.0429***	0.0189	0.0245
	-0.0186	(0.0121)	(0.0295)	(0.0178)
Observations	7,318	27,945	4,372	17,126
Matching based on:				
Year, age, educ. & prev. firm size	✓	✓	✓	✓
Network size	✓	✓	✓	✓
Previous pay	✓	✓	✓	✓
New firm size, prev. & new firm FE			✓	✓

This table presents the second stage estimates of a propensity score model of the logarithm of manager total hourly pay at the new firm on the network dummy, which takes the value of 1 for a male share higher than the sample median. The matching procedure was based on a caliper of 0.05. The matching on year and education is exact. Firm FE refer to the fixed effects estimated in 'Full Model' in Table B.1. First-stage results are presented in Table B.7. The sample consists of all top managers who transitioned between firms in the 1995-2017 period. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

where *$FirmSize_j$* represents the size of all firms managed by manager j and *$NumberManagers_j$* the number of managers of these same firms, to account for the number of managers' amongst which decision making power is divided.

Table 8 reports the results considering this alternative weighted network metric. As suspected, we find that gender composition becomes irrelevant for females, suggesting that females only benefit from having more male connections than female ones given the status quo that has more males as powerful top managers, and not because male connections, per se, are more valuable. Male top managers do, however, continue to benefit more from same gender connections. While this results needs to be deepened further in future research, it strongly suggests that, in the male-dominated management environment, male top-managers tend to benefit other males more than females, perpetuating gender bias.[11]

Finally, we complement the previous analysis with an alternative weighted metric, which instead of weighing more heavily powerful connections, takes into account the proximity to connections. This measure, which we label *Depth*, has weights increase as the years two top managers coincided in a firm are higher, scaled by the firm's size. This weighted network measure allows us to attribute a higher value to connections who are more likely stronger, either because the two managers worked together for a longer period of time, or because the firm was small, or both, thus suggesting deeper interactions between co-workers. Such that:

$$w_{ij} = \frac{Years}{FirmSize}, \tag{11}$$

Comparing as before female top managers who have a share of high *Depth* connections to male managers above the sample median with comparable females, as far as observables, including the generic *Depth* level and previous wage, we find that both genders benefit more from same gender connections. Male top managers benefit similarly from connections to powerful male managers as to managers who they have interacted with extensively. While the result for females contrasts with our previous result, as now females benefit more from longer past interactions with other female managers, in line with the hypothesis that female representation in corporate leadership has positive spillovers for other women (Kunze and Miller 2017).

11. Results are statistically insignificant after we adjust for firm sorting, taking into account firm characteristics.

Table 8. Network gender composition: *Power* and *Depth*

	Male vs. Female Connections	
	Women	Men
Power	-0.0191	0.0318**
	(0.0202)	(0.0127)
Observations	7,249	28,005
Depth	-0.0361*	0.0377***
	(0.0216)	(0.0116)
Observations	7,305	28,019
Matching based on:		
Year, age, educ. & prev. firm size	✓	✓
Network size	✓	✓
Previous pay	✓	✓

This table presents the second stage estimates of a propensity score model of the logarithm of manager total hourly pay at the new firm on the network dummy, which takes the value of 1 for a male share higher than the sample median. The matching procedure was based on a caliper of 0.05. The matching on year and education is exact. First-stage results are presented in Table B.8. The sample consists of all top managers who transitioned between firms in the 1995-2017 period. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

5. Concluding remarks

We advance the existing literature on the gender pay gap amongst top managers by investigating an additional source of divergence between male and female manager pay: professional networks. We rely on new indicators of network size and network gender composition, making use of information on the entire history of past interactions between each manager and former co-workers who have themselves also become managers.

We estimate a standard wage equation to find that female top managers in Portugal are paid, on average, 25% less than their male counterparts, conditional on age, education and tenure at the firm. This figure is especially alarming as one would expect the few high-potential females who break the firm promotion glass ceiling to be especially skilled and talented, as argued in (Bertrand and Hallock 2001). Next, we augment the standard model with network metrics, considering both the size and the gender composition of each manager's network. We find that networks account for 20% of the pay gap. After adding high-dimensional manager and firm fixed effects to the model, we estimate networks to have most of its differentiated impact on pay through firm sorting, i.e, networks give a manager access to firms that follow more generous executive compensation policies.

By then focusing on episodes of transitions between firms, and using a propensity score matching procedure, we estimate a pay gap around 22%, validating that the bulk of the manager gender gap arises during the hiring process and is only slightly aggravated thereafter, due to biased career progression. We also estimate one third of the gap to be associated to firm sorting, two thirds os which are explained by differences in networks. Put differently, the benefits of networks are access to higher paying firms and bargaining power to negotiate within the new firm a higher pay. Differences in networks between male and female managers explain almost 5 p.p. of the pay gap through firm sorting and another 2 p.p. through negotiations for higher pay. After taking into account all observables and both firm sorting and networks, we are left with an unexplained pay gap among top managers close to 11%. If we take into account previous compensation levels to proxy for unobserved individual heterogeneity, a 6% pay gap persists. We interpret this figure as a lower bound for pure gender discrimination among top managers, not associated to sorting across firms. Notice that by considering previous pay, we are not only accounting for unobservable characteristics to the researcher, but we are also taking into account a key observable indicator that the hiring firm may use as proxy for the manager's skills.

After establishing the important role of networks in explaining the gender pay gap among top managers, we further investigate how female managers can best leverage their networks to overcome gender segregation across firms. We find no evidence that females benefit differently from network size than males, considering otherwise comparable managers, also in terms of network gender composition. However, we do find an important new result suggesting the importance of the gender composition of a manager's network. While both genders seem to benefit more from male connections, once we take into account the importance of the connections, female top managers benefit equally from male or female dominated networks, whereas male managers continue to benefit more from same gender connections. Moreover, when the depth of the connections is considered, proxying for the 'inner circle' of a given manager, we find that both female and male managers benefit most from connections to managers of their own gender. Our results demonstrate that, in a male-dominated corporate world, gender bias can be perpetuated. On the other hand, however, with appropriate policies in place that envisage higher female presence in leadership positions, there is evidence for positive spillovers as women become especially supportive of the advancement of their close female connections. Our line of research, data, and methodology, suggests several fruitful avenues for future research.

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Appendix

Appendix A: Variable definitions

Variable	Description
Firm Characteristics	
Number of workers	Log of number of workers registered as working at the firm in October of each year.
Total hourly pay	The ratio of the sum of base wages, regular benefits (including seniority benefits), and overtime pay over total hours (normal and overtime hours worked).
Manager Characteristics	
Gender	Dummy variable: equals 1 for females and 0 otherwise.
Age	Current year minus birth year.
Tenure	Defined as the difference between the current year and the year of admission in the current firm.
Education	Categorical variable where: 1 - less than primary education; 2 - 1st and 2nd cycle of primary educ.; 3 - lower secondary educ.; 4 - upper secondary educ.; 5 - tertiary educ.;
Network Measures	
Network size	The sum of total connections the manager has on the annual executive network.
Network gender composition	Share of total male connections in a manager's annual network
Depth	The weighted sum of connections the manager has on the annual network, where the weight equals the number of years worked together over the number of workers at the same firm.
Power	The weighted sum of connections the manager has on the annual network, where the weight equals the average number of workers at the managed firms over the average number of managers.

Appendix B: Additional results

B.1. Gender Pay Gap: benchmark and full model results

Table B.1. Gender Pay Gap: benchmark and full model

	Total Hourly Pay			
	(1)	(2)	(3)	(4)
Female	-0.2196***		-0.1821***	
	(0.0046)		(0.0044)	
Age	0.0863***		0.0662***	
	(0.0017)		(0.0016)	
Age squared	-0.0008***	-0.0005***	-0.0006***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure	0.0011***	0.0005***	0.0008***	0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure squared	-0.0000	-0.0000***	0.0000	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Schooling	0.3484***	0.0078***	0.3013***	0.0079***
	(0.0027)	(0.0028)	(0.0026)	(0.0028)
Network size			0.0018***	0.0003***
			(0.0000)	(0.0000)
Network size squared			-0.0000***	-0.0000***
			(0.0000)	(0.0000)
Network comp.			0.3469***	0.0206***
			(0.0068)	(0.0036)
Observations	665,150	665,150	665,150	665,150
R^2	0.2772	0.8918	0.3193	0.8918
Year fixed effects	✓	✓	✓	✓
Manager and firm fixed effects		✓		✓

This table presents in column (1) the OLS estimates of a benchmark specification of the logarithm of manager hourly pay on gender, age, age squared, tenure, tenure squared and schooling. Column (2) shows the full specification including manager and firm fixed effects. Gender and age are absorbed by the manager fixed effects (the latter due to the combination of manager and year fixed effects). Columns (3) and (4) augment the previous specifications with network metrics and column (4). Standard errors are clustered at the manager level. The sample consists of all top managers (excluding firm owners) in the 1995-2017 period. Variable definitions are provided in Appendix A. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

B.2. Balancing properties of the matching procedure

Table B.2. Balancing properties of the propensity score matching: gender

Variable	Sample	Mean Treated	Mean Control	%bias	Bias reducation	t-test	p-value
Age	Unmatched	41.229	44.186	-34.6		-20.74	0.000
	Matched	41.198	41.103	1.1	96.8	0.57	0.570
Education	Unmatched	4.707	4.564	21.8		12.77	0.000
	Matched	4.744	4.744	0.0	100.0	0.00	1.000
Network size	Unmatched	159.760	147.330	6.3		3.88	0.000
	Matched	166.080	168.660	-1.3	79.3	-0.60	0.546
Network composition	Unmatched	0.690	0.752	-33.8		-21.58	0.000
	Matched	0.704	0.710	-3.0	91.2	-1.51	0.130
Firm size	Unmatched	5.466	5.054	15.9		9.99	0.000
	Matched	5.532	5.638	-4.1	74.3	-1.90	0.058
Prev. firm size	Unmatched	5.423	5.146	11.2		7.06	0.000
	Matched	5.502	5.534	-1.3	88.7	-0.58	0.559
Firm fixed effect	Unmatched	0.120	0.112	1.5		0.94	0.347
	Matched	0.143	0.138	1.0	37.6	0.49	0.626
Prev. firm fixed effect	Unmatched	0.169	0.156	2.8		1.72	0.085
	Matched	0.188	0.177	2.2	23.6	1.09	0.278
Prev. Pay	Unmatched	2.849	3.008	-23.2		-13.89	0.000
	Matched	2.880	2.893	-1.9	91.8	-0.98	0.326

This table presents the mean for the treatment (females) and control (males) groups for the unmatched and matched samples and the corresponding standardized bias measure as suggested by Rosenbaum and Rubin (1985) reported together with the achieved reduction.

Table B.3. Balancing properties of the sample of female managers: network size

Variable	Sample	Mean Treated	Mean Control	%bias	Bias reducation	t-test	p-value
Age	Unmatched	41.510	40.675	9.9		3.37	0.001
	Matched	40.669	40.988	-3.8	61.8	-1.07	0.287
Education	Unmatched	4.768	4.587	28.9		10.05	0.000
	Matched	4.886	4.886	0.0	100.0	0.00	1.000
Network composition	Unmatched	0.708	0.653	24.2		9.24	0.000
	Matched	0.716	0.716	0.2	99.0	0.08	0.937
Firm size	Unmatched	6.313	3.794	110.9		34.31	0.000
	Matched	4.775	4.855	-3.5	96.8	-1.01	0.314
Prev. firm size	Unmatched	6.342	3.610	131.9		40.10	0.000
	Matched	4.623	4.525	4.7	96.4	1.63	0.104
Firm fixed effect	Unmatched	0.252	-0.140	71.1		25.64	0.000
	Matched	0.182	0.159	4.3	94.0	1.30	0.192
Prev. firm fixed effect	Unmatched	0.296	-0.081	77.7		27.99	0.000
	Matched	0.218	0.208	2.2	97.2	0.64	0.520
Prev. Pay	Unmatched	2.992	2.568	65.9		22.26	0.000
	Matched	3.014	3.021	-1.1	98.3	-0.29	0.771

This table presents the mean for the treatment (females with higher than median number of connections) and control (females with lower than median number of connections) groups for the unmatched and matched samples and the corresponding standardized bias measure as suggested by Rosenbaum and Rubin (1985) reported together with the achieved reduction.

Table B.4. Balancing properties of the sample of female managers: network size

Variable	Sample	Mean Treated	Mean Control	%bias	Bias reducation	t-test	p-value
Age	Unmatched	44.564	43.525	11.4		7.51	0.000
	Matched	43.007	43.235	-2.5	78.0	-0.99	0.322
Education	Unmatched	4.635	4.438	27.0		17.99	0.000
	Matched	4.839	4.839	0.0	100.0	0.00	1.000
Network composition	Unmatched	0.760	0.738	11.6		8.33	0.000
	Matched	0.774	0.778	-1.7	85.5	-0.84	0.401
Firm size	Unmatched	5.759	3.821	87.6		54.02	0.000
	Matched	4.459	4.580	-5.4	93.8	-2.36	0.018
Prev. firm size	Unmatched	5.973	3.698	114.4		69.77	0.000
	Matched	4.556	4.472	4.2	96.3	2.10	0.035
Firm fixed effect	Unmatched	0.221	-0.079	53.6		37.13	0.000
	Matched	0.164	0.173	-1.6	96.9	-0.74	0.459
Prev. firm fixed effect	Unmatched	0.266	-0.038	60.1		41.83	0.000
	Matched	0.207	0.186	4.2	93.0	1.87	0.061
Prev. Pay	Unmatched	3.141	2.776	51.3		33.91	0.000
	Matched	3.145	3.174	-4.0	92.2	-1.58	0.114

This table presents the mean for the treatment (males with higher than median number of connections) and control (males with lower than median number of connections) groups for the unmatched and matched samples and the corresponding standardized bias measure as suggested by Rosenbaum and Rubin (1985) reported together with the achieved reduction.

B.3. First-stage results from matching procedure

Table B.5. First-stage results: gender pay gap

	Gender				
	(1)	(2)	(3)	(4)	(5)
Age	-0.0353***	-0.0335***	-0.0404***	-0.0372***	-0.0313***
	(0.0014)	(0.0014)	(0.0020)	(0.0020)	(0.0021)
Previous firm size	0.0036	0.0320***	0.0087	0.0093	-0.0002
	(0.0048)	(0.0061)	(0.0095)	(0.0106)	(0.0109)
New firm size			-0.0874**	-0.0349	-0.0569
			(0.0386)	(0.0392)	(0.0407)
Previous firm FE			0.0639***	0.0553***	0.0516***
			(0.0093)	(0.0095)	(0.0097)
New firm FE			-0.0075	0.0358	0.2450***
			(0.0425)	(0.0430)	(0.0492)
Network size		-0.0000		-0.0000	0.0000
		(0.0001)		(0.0001)	(0.0001)
Male share		-1.0754***		-1.5870***	-1.5430***
		(0.0418)		(0.0847)	(0.0864)
Previous Wage					-0.2629***
					(0.0296)
Observations	43,281	43,281	23,562	23,562	22,815

This table presents logit regressions of the gender dummy on the variables above. The sample consists of all top managers transitions in the 1995-2017 period. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

Table B.6. First-stage results: the network effect

	Network Size			
	Females		Males	
	(1)	(2)	(3)	(4)
Age	0.9201***	-0.0004	-0.0005	0.0083***
	(0.0441)	(0.0049)	(0.0016)	(0.0021)
Previous firm size	0.5055***	0.4170***	0.4759***	0.4289***
	(0.0151)	(0.0244)	(0.0076)	(0.0117)
Male share	1.4571***	1.0966***	1.1521***	0.7481***
	(0.1223)	(0.1940)	(0.0715)	(0.1087)
New firm size		0.1495***		0.1259***
		(0.0218)		(0.0105)
Previous firm FE		0.2893***		0.1151**
		(0.1114)		(0.0494)
New firm FE		0.4388***		0.3624***
		(0.0911)		(0.0407)
Previous Wage	0.9201***	0.7574***	0.6625***	0.5534***
	(0.0441)	(0.0737)	(0.0190)	(0.0311)
Observations	8,111	4,795	29,436	18,020

This table presents logit regressions of the network dummy, that takes the value of 1 for managers with a higher than median number of connections, on the variables above. The sample consists of all top managers transitions in the 1995-2017 period. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

Table B.7. First-stage results: network composition effect

	Network Composition			
	Females		Males	
	(1)	(2)	(3)	(4)
Age	0.0149***	0.0215***	0.0223***	0.0273***
	(0.0030)	(0.0041)	(0.0014)	(0.0018)
Previous firm size	-0.1432***	-0.1432***	-0.1172***	-0.1327***
	(0.0201)	(0.0201)	(0.0064)	(0.0100)
Network size	-0.0020***	-0.0008***	-0.0004***	-0.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
New firm size		-0.0431**		-0.0835***
		(0.0176)		(0.0088)
Previous firm FE		-0.0437		0.1445***
		(0.0950)		(0.0440)
New firm FE		0.2203***		0.0641*
		(0.0773)		(0.0362)
Previous Wage	0.1158***	0.2014***	-0.0572***	-0.1293***
	(0.0327)	(0.0577)	(0.0157)	(0.0259)
Observations	7,494	4,677	28,125	17,732

This table presents logit regressions of the network dummy, that takes the value of 1 for managers with a higher than median share of male connections, on the variables above. The sample consists of all top managers transitions in the 1995-2017 period. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

Table B.8. First-stage results: network composition effect of *Power* and *Depth*

	Network Composition			
	Females		Males	
	Depth	Power	Depth	Power
	(1)	(2)	(3)	(4)
Age	0.0189***	0.0113***	0.0194***	0.0176***
	(0.0030)	(0.0030)	(0.0014)	(0.0014)
Previous firm size	-0.1743***	-0.1713***	-0.1600***	-0.1271***
	(0.0108)	(0.0107)	(0.0059)	(0.0057)
Network size	0.0000	-0.4958***	0.0000***	-0.3443***
	(0.0000)	(0.0805)	(0.0000)	(0.0383)
Previous Wage	0.0346	0.1242***	-0.1247***	-0.0484***
	(0.0340)	(0.0357)	(0.0159)	(0.0163)
Observations	7,492	7,492	28,125	28,125

This table presents logit regressions of the network dummy, that takes the value of 1 for managers with a higher than median share of male connections, on the variables above. The sample consists of all top managers transitions in the 1995-2017 period. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.