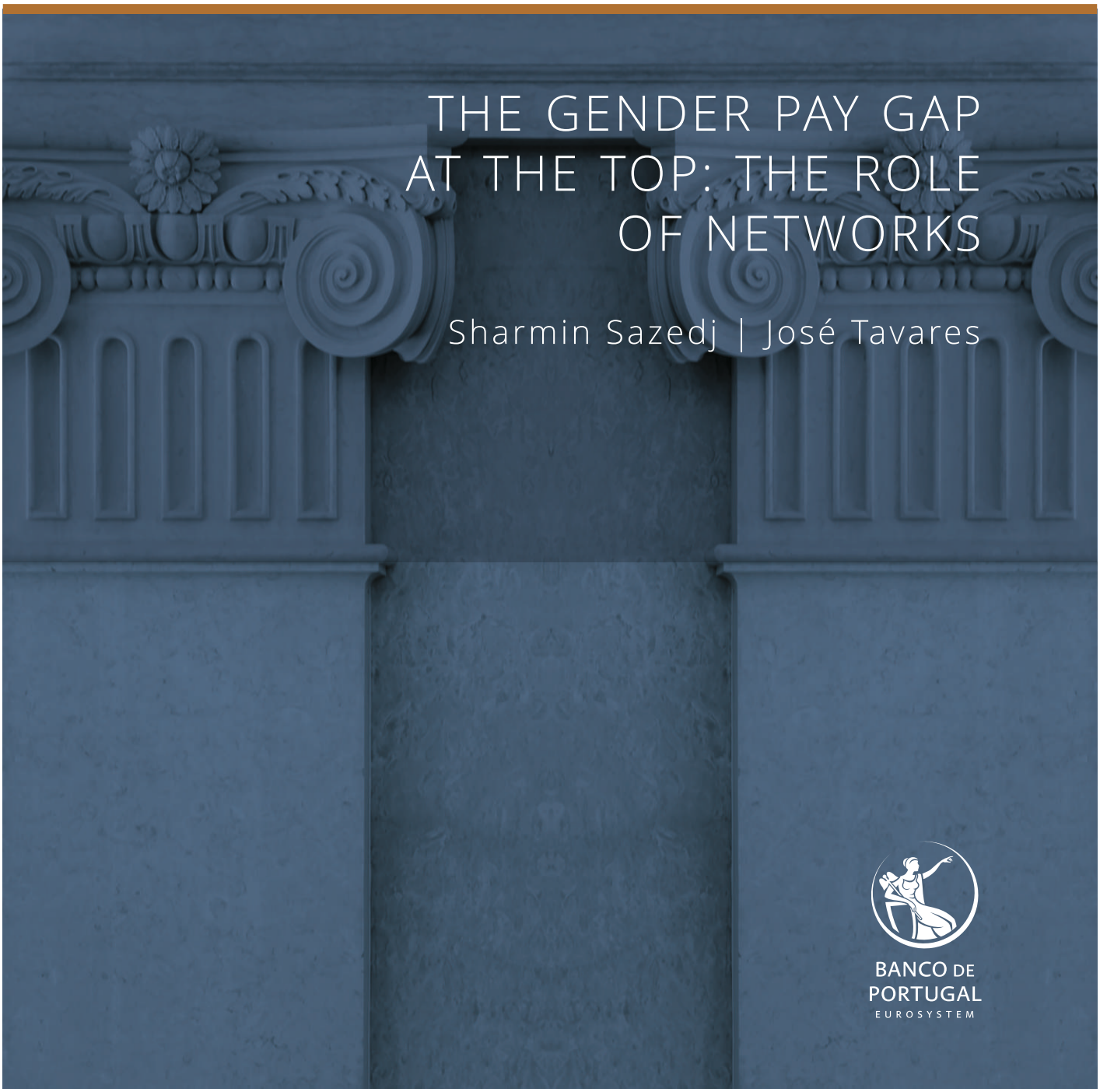
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WORKING PAPERS 2024

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Sharmin Sazedj | José Tavares



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The analyses, opinions and findings of this paper represent the views of the authors, and not necessarily those of the Banco de Portugal or the Eurosystem.

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The gender pay gap at the top: the role of networks

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Abstract
This paper assesses the relevance of professional networks for the gender pay gap amongst top managers. Using data on the universe of firms in Portugal, we show that female top managers earn 25% less than their male counterparts, and that 20% of this gap is due to differences in networks. Using Gelbach's decomposition, we find that the network effect can be ascribed to firm sorting, i.e. well-connected managers tend to be associated to higher paying firms. By examining the gender composition and the type of connections of top manager networks, we find that same gender connections are important. We conclude that connections between females can play an important role in the existing corporate framework where males are overrepresented, and thus policies furthering female representation in leadership positions can have positive spillover effects for other women.

JEL: J16, J30, J24, L14

Keywords: Gender gap, Networks, Managers, Firm sorting.

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1. Introduction

Research on executive compensation consistently demonstrates that men are more likely than women to attain top executive positions, accompanied by substantial evidence of gender pay disparities. Examples are Geiler and Renneboog (2015), who find that female top managers in UK-listed firms earn 23% less than their male counterparts; Bell (2005) who documents a bias ranging from 8% to 25% conditional on the gender of the Chief Executive and Corporate Board Chair in US-listed firms; and Bertrand and Hallock (2001) who find a 45% pay gap in US firms, which narrows to below 5% when accounting for all observable differences, with gender segregation by firm size playing a critical role.[1] Despite this extensive research, the literature has overlooked the potential role of professional networks in explaining gender differences in executive pay.

Some studies suggest that the presence of women in leadership positions can generate positive spillovers, benefiting other women and reducing within-firm pay gaps (Matsa and Amalia 2011; Magda and Cukrowska-Torzewska 2018). Additionally, a few authors have examined the impact of networks on the gender pay gap, albeit using specific and limited network measures, such as co-authorships, email exchanges, or shared high school attendance with a firm's chair (Lindenlaub and Prummer 2020; Keloharju *et al.* 2016). However, the broader role of professional networks in influencing gender pay disparities among top managers remains underexplored. This omission is significant, as both empirical and theoretical work have highlighted the critical role networks play in the professional advancement of managers (Renneboog and Zhao 2011; Engelberg *et al.* 2013; Hwang and Kim 2009).

A related and equally important question is whether network characteristics differ by gender and whether the benefits derived from networks are gender-specific. In particular, it is crucial to understand whether the gender composition of a manager's network affects their career outcomes. Addressing these questions could provide insights into how female managers might leverage the size and composition of their networks to mitigate the gender pay gap. Matsa and Amalia (2011) argue that the predominance of male top managers may perpetuate tacit discrimination against women, suggesting that the historical absence of women in leadership roles may have lasting effects, with male-dominated networks and firms continuing to obstruct progress toward closing the gender pay gap at the executive level. Thus, networks could serve as a key tool for female managers to overcome these barriers.

In this study, we examine the gender pay gap at the top of the corporate ladder for a sample of Portuguese firms. In 2017, female top managers in Portugal earned, on average, approximately 80 cents for every euro earned by their male counterparts. This pay disparity becomes more pronounced when considering the rising trend in

1. Elkinawy and Stater (2011) corroborate these findings with a more recent sample of US firms, showing similar results to Bertrand and Hallock (2001).

female education levels and labor market experience; adjusting the gender pay gap for age, tenure, and schooling increases it to 25%. Previous research by Cardoso *et al.* (2016) and Card *et al.* (2015) has shown that firm sorting plays a significant role in explaining the overall gender gap in the Portuguese labor market. Building on their work, we extend the analysis to top managers, precisely quantifying the importance of firm sorting in contributing to the pay gap. Specifically, we estimate a conventional wage equation for top managers and then compute the contribution of sorting into firms with heterogeneous pay policies, using high-dimensional fixed effects regression models and the omitted variable bias decomposition as suggested by Gelbach (2016). Our study contributes to the existing literature by isolating the network effect among managers and examining its impact on the gender pay gap.

We analyze two key characteristics of networks: size and gender composition. Network size is defined by the number of past professional interactions within the same firm with coworkers who later became top managers. In other words, a top manager's current network size depends on how frequently they worked in the same firm with individuals who subsequently advanced to managerial positions. Our network metric offers a significant conceptual advantage over previous definitions in the literature: it evolves over time due to exogenous factors, such as former coworkers becoming managers or leaving the job market, rather than solely reflecting the manager's own choices. Furthermore, our comprehensive sample of firms and the extended time period covered in our analysis enable us to capture variations in network size over time and estimate network effects while controlling for manager and firm fixed effects.

While network size helps us understand the role of connections in explaining pay differences, we take our analysis a step further by investigating whether the gender composition of networks matters. This approach allows us to explore the relative importance of factors such as same-gender empathy and gender diversity in determining the value of a network. In our study, gender composition is defined as the ratio of male connections in a manager's network. We ask whether, in a male-dominated environment, a female manager's advancement depends not only on the size of her network but also on whether her connections are primarily with male or female top managers.

Our findings indicate that approximately 30% of the 25% (22 log points) pay gap among top managers in Portugal can be attributed to male managers sorting into firms with more generous pay policies. This firm sorting channel may result from gender discrimination, stereotyping, or other corporate preferences, such as catering to a specific clientele (Matsa and Amalia 2011). When accounting for differences in network metrics across genders, the pay gap narrows to 20% (18 log points), and the contribution of firm sorting to the gap is more than halved. These results underscore the importance of networks, which are instrumental in accessing better-paying firms, aligning with the broader understanding that being part of a large network enhances opportunities for securing more rewarding job transitions (Bartlett and Miller 1985). We further explore the link between networks and firm sorting by analyzing the transitions of top managers between firms, using a nearest

neighbor matching procedure. Our analysis reveals that the bulk of the gender pay gap is created during the hiring process when managers transition between firms, with only a slight increase due to biased career progression within firms. This bias in hiring persists even when comparing top managers with similar years of schooling, education, age, and networks, and who transition between firms of similar size and wage policies. By comparing managers with the same pay prior to the transition, we partially control for unobservable characteristics – such as ability and accumulated human capital – that are not directly observable to researchers or hiring firms. The remaining gender gap after this careful comparison can be reasonably attributed to gender discrimination.

Our evidence points to a substantial premium associated with network size, which manifests primarily during managers' transitions across firms. Female and male top managers with networks larger than the sample median earn, on average, 22% and 17% more, respectively, than otherwise similar managers with smaller networks. We find no evidence of a gender penalty in how managers benefit from their networks. After controlling for firm characteristics, we confirm that most of the network premium is related to accessing firms with more generous pay policies.

Finally, we examine how the gender composition of networks affects 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 female connections in their "inner circle" than male ones. This finding implies that same-gender empathy may outweigh gender diversity in enhancing network value, indicating that an increased presence of women in top management roles could further facilitate the reduction of gender bias at the executive level. This virtuous cycle, driven by the gender composition of networks, is empirically tested here for the first time, suggesting promising avenues for future research.

This paper is structured as follows: Section 2 provides a detailed description of the network construction and underlying data; Section 3 computes the gender pay gap amongst top managers and documents results from Gelbach's decomposition; Section 4 explores the role of networks during firm transitions; and Section 5 concludes.

2. Data and network description

2.1. Network definition

We define manager i's network in year t as comprising all former coworkers who have attained top management positions by year t. In other words, we backtrack all the firms where the manager has worked, identifying all employees who were at those firms during the same period. From this group, we exclude those who have not reached a management position by year t or who are currently employed at the same firm as manager i in year t. The year-to-year changes in a manager's network are primarily driven by transitions between firms, which introduce new

managers from previous firms into the network, and by former coworkers either being promoted to or leaving management positions. The latter introduces a source of exogenous variation, as these changes are entirely independent of the manager's own decisions.

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

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

where x_{ij} equals 1 if there is a link between manager *i* and manager *j*.

To measure the gender composition of the network, we consider the proportion of male connections:

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

where x_{ij} equals 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* (hereafter *QP*), a comprehensive micro-level longitudinal dataset that contains mandatory information collected by the Portuguese authorities. The matched employer-employee dataset covers all private firms and their wage-earners operating in Portugal between 1986 and 2017, containing detailed information on both firms and their employees. The *QP* includes a unique personal identification number that enables tracing individuals over time, and observe their entire professional history dating back to 1986.

In *QP*, each worker is categorized according to the National Classification of Occupations and assigned a professional grade level. These grade levels are defined by law, and firms are required to classify each worker accordingly. For our analysis, we focus on managers between 1995 and 2013, defining managers as individuals occupying top decision-making or senior management positions. The 6-digit occupational classification system available in *QP* allows us to accurately identify various managerial roles. To ensure consistency, we restrict our sample to workers classified within the highest hierarchical grade level, specifically top managers. While we include self-employed managers, such as firm owners, in the overall network, they are excluded from our regression analysis due to the absence of wage data and the distinct wage-setting mechanisms applicable to them. In essence, firm owners contribute to the value of other managers' networks, but we are unable to analyze the impact of their network on pay. Our final sample comprises 665,150 manager-firm-year observations, representing approximately 29,785 firms and 102,989 top managers.

It is important to note that the National Classification of Occupations in *QP* underwent several revisions between 1986 and 2017, with the most recent

update occurring in 2010. From 2010 onward, we apply the latest classification criteria to identify managers consistently. For the earlier periods, we utilized the official harmonization table published by Statistics Portugal to minimize artificial movements of managers in and out of the network due to these classification changes.

2.3. Statistics

Table 1 summarizes key statistics on top manager and firm characteristics, by gender. Several noteworthy facts emerge. First, there is a clear under-representation of women in corporate leadership, with female top managers comprising only 25% of our sample. Second, there is a pronounced gender pay gap, with female top managers earning roughly 80% of what their male counterparts earn.

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 tend to have more years of schooling on average. However, their are generally smaller, with fewer connections and a lower proportion of male connections. Despite this, both male and female networks are predominantly male, reflecting the overall male dominance in management positions.

Female managers are, on average, employed by larger firms, although there is greater variability in firm size among females. Lastly, the distribution of female managers across firms suggests a pattern of gender sorting, with women and men likely working in different types of firms.

	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

Table 1. Summary statistics

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.

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

As depicted in Figure 1, in 1995, the total pay of female top managers stood slightly above two thirds of the pay of their male counterparts. Notably, the raw gender pay gap among top managers followed a similar trend to the overall gap across all workers in the economy, narrowing by more than 10 p.p. over the analysed period. By 2017, female top managers earned nearly four-fifths of what male top managers earned. It is important to highlight that the gender pay gap among top managers consistently remained approximately 3 p.p. higher than the overall gap, or about 10% larger.



Figure 1: The gender pay gap

The narrative shifts, however, when we account for observable characteristics and compute an "adjusted" gender pay gap, as shown in Figure 2. While there is some evidence of a modest decline in the overall gender pay gap over time, this trend does not extend to top managers; in fact, the opposite is true. The wage gain achieved by female top managers during this period is due to the catching up of their skills, rather than a reduction in the unexplained portion of the wage difference, which is often interpreted as gender discrimination (Cardoso *et al.* 2016).

Thus 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 further adjust the gender pay gap for the size and the gender composition of a manager's network. Our findings reveal that networks

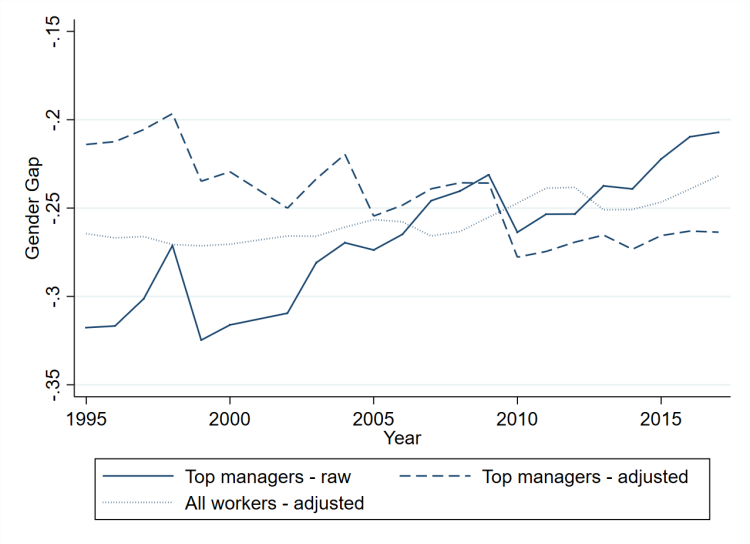


Figure 2: The unexplained gender pay gap

play a significant role, with the number and composition of network connections contributing to a roughly 8 p.p. reduction in the gap by 2017.

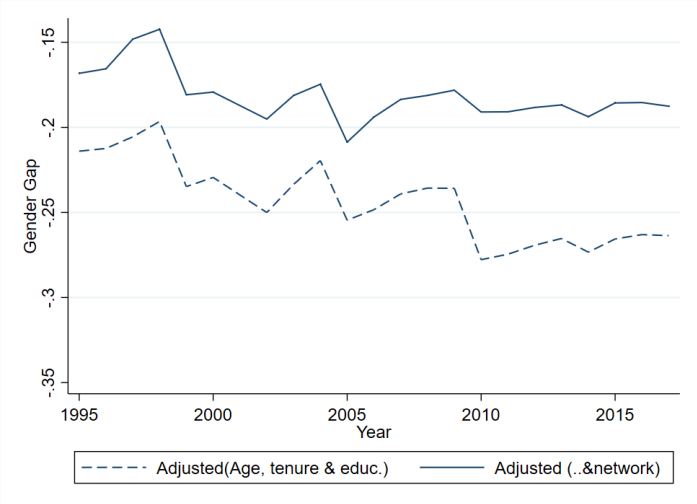


Figure 3: The unexplained gender pay gap: the role of networks

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, unobserved heterogeneity may also contribute to this divergence. To explore this, we propose decomposing the gender wage gap into the contributions of two key sources of unobserved heterogeneity: firm and manager fixed effects. The firm fixed effects capture the time-invariant wage policies of firms—where positive firm fixed effects indicate more generous executive pay policies, and negative effects are associated with lower-wage firms. Manager fixed effects, on the other hand, serve as a proxy for the ability or productivity of the manager, or they may reflect discrimination not related to gender-based sorting across firms.

In this section, we closely follow the methodology presented in Cardoso *et al.* (2016), utilizing the Gelbach decomposition approach from Gelbach (2016) to assess the impact of manager allocation across firms on the observed gender pay differential.[2] We begin by estimating a 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:

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

2. The main difference from Cardoso *et al.* (2016) is that our analysis focuses exclusively on top managers, excludes job title fixed effects, and adds network variables.

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.

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:

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

where $\mathbf{P_X} = (\mathbf{G}'\mathbf{M_X G})^{-1}\mathbf{G}'\mathbf{M_X}$ 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:

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

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

Our benchmark regression results align with existing literature, showing that manager pay increases with age and tenure, though at a decreasing rate.[4] Higher levels of education are also positively correlated with higher pay. Regarding our primary variable of interest—the female dummy—we estimate a wage penalty of 22 log points for female top managers, conditional on age, tenure, and education.

Gelbach's decomposition indicates that a significant portion of the gender pay gap can be attributed to the heterogeneity in 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. Specifically, the sorting of managers into firms accounts for 7.3 of the 22 log points of the gender pay gap. In other words, female managers are disproportionately placed in firms with less generous wage policies. If managers were randomly assigned to firms, the gender pay gap would be reduced by one third.

4. See Table B.1 in Appendix B.

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

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

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.

The remaining two-thirds of the gender pay gap are explained by the unobserved permanent characteristics of the managers. These unobserved manager characteristics can be attributed to both unobserved skills and forms of gender discrimination that are not related to the 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 in 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, while the dispersion is significantly higher amongst top managers with smaller networks. Another important takeaway is that amongst the less connected top managers – those with smaller networks – male top managers seem to be over-represented in higher paying firms. In contrast, gender selection is less evident among 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 presented in Figure 4, we augment the conventional wage equation with network metrics, referred to as the augmented benchmark model. Departing from the benchmark model and controlling additionally for the network size – *Degree* and *Degree* squared[5] – and network composition – share of male connections – reduces the estimated pay gap by almost 4 log points.[6] Using Gelbach's decomposition, we find that 25% of this reduction is driven by the network size, while the remaining 75% stem from the gender composition of the network (Table 3).

5. As suggested in Engelberg *et al.* (2013), and confirmed in Sazedj and Tavares (2021), network size impacts positively pay at a decreasing rate.

6. See Table B.1 in Appendix B.

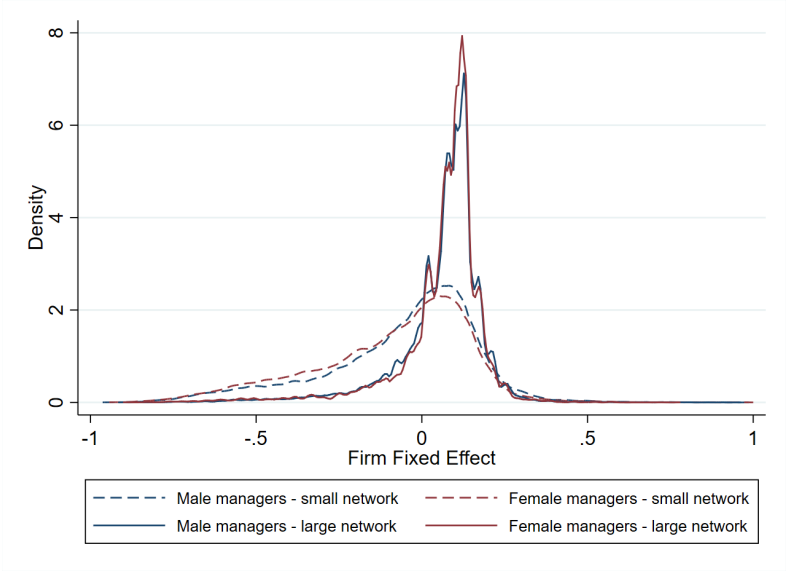


Figure 4: The distribution of firm fixed effects

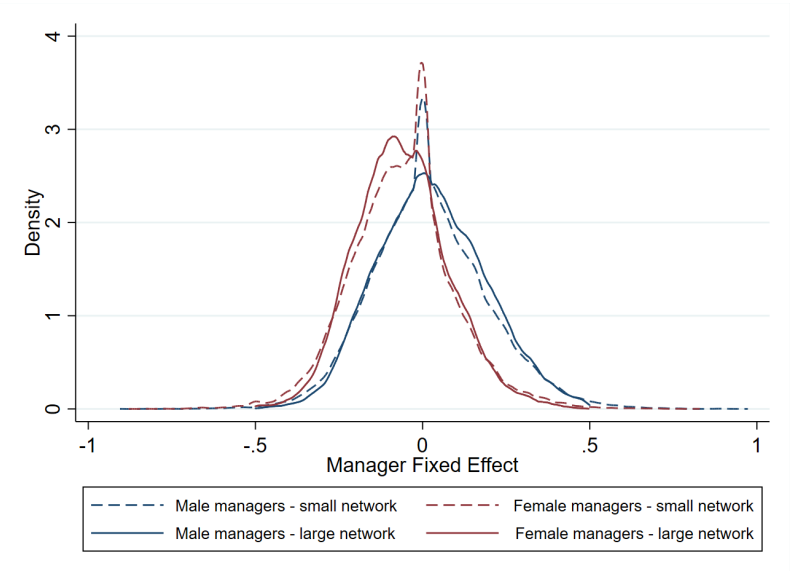


Figure 5: The distribution of manager fixed effects

Furthermore, when manager and firm fixed effects are added to the augmented benchmark model, the analysis shows that only 20% of the pay gap can be attributed to an uneven distribution of managers across firms, as demonstrated in the *Full Model* specification in Table 3. More importantly, the contribution from the individual fixed effect—partially reflecting discrimination—remains unchanged

	Benchmark	Augmented benchmark	Full model
	γ_0	γ_1	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

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

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.

(compared to the model without network controls). This indicates that the impact of networks operates entirely through the firm contribution. In other words, networks play a crucial role in facilitating the matching of male top managers to higher-paying firms. Notably, incorporating network metrics into our model nearly halves the contribution of the firm fixed effect.

In sum, after controlling for network metrics, we estimate a gender pay gap of approximately 20% (18 log points) between female and male top managers. A random assignment of managers across firms would reduce this gap to 16% (15 log points), representing a 20% reduction. This is a significant finding, as it highlights how the influence of firm sorting diminishes considerably when network effects are accounted for. This underscores the importance of networks as a mechanism for female top managers to counteract some of the biases they face.

4. Manager mobility: top managers transitioning between firms

So far, our results have highlighted the critical role networks play in matching male top managers with firms that offer more generous pay policies. In the following analysis, we shift our focus exclusively to manager mobility to further examine the role of networks during transitions between firms and explore how female top managers can leverage their networks to overcome existing biases.

We begin by estimating the gender pay gap during firm transitions, with three primary objectives. First, we assess whether the gender pay gap widens or narrows as a result of career progression within a firm. Second, we provide additional evidence to confirm the robustness of our earlier finding regarding the role of networks in

sorting managers into higher-paying firms. Lastly, we acknowledge the influence of other important factors that may be unobservable to researchers, and we estimate a lower bound for how much of the pay 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. Specifically, we seek to determine the extent to which connections to other top managers impact total pay at a new firm, and whether these benefits differ by gender. We also address an important question: do both genders benefit equally from networks in terms of gender composition?

To conduct this analysis, we use matching procedures to generate credible estimates of unobserved counterfactuals. For instance, we compare a female manager's pay following a transition to a new firm with what her pay might have been if she were not female, or if she had a different kind of network. Without credible answers to these questions, it is difficult to ascertain whether the observed differences in pay would have occurred regardless. To address this, we estimate the counterfactual outcomes by comparing the treatment group to a statistically identical comparison group using a nearest-neighbor matching estimator approach.[7] As noted by Custódio *et al.* (2013), top manager transitions are particularly suited to a matching procedure, as the hiring process is predominantly based on observable information.[8] Given the large number of covariates, we define the comparison groups using exact matching for categorical variables and the propensity score for continuous covariates. After performing balancing tests on our matched sample, we further refine the matching procedure by enforcing exact matches by age quartile to ensure no statistically significant differences exist between the treatment and control groups.[9]

One challenge with this type of matching procedure is the risk of identifying a nearest neighbor that is not truly comparable. We mitigate this issue by imposing a maximum propensity score distance of 0.05 (caliper), thereby avoiding poor matches. We confirm that this threshold is sufficient to balance the distribution of relevant covariates and that using a more stringent caliper does not significantly alter our results. To define the region of common support, we exclude observations where the propensity score lies below the minimum or above the maximum of the opposite group. This approach eliminates very few observations, with 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

7. Based on (Abadie and Imbens 2011).

8. Custódio *et al.* (2013) specifically refers to CEO selection.

9. We also tested stricter matching rules for other variables, including exact matching within quartiles for continuous variables. Results are available upon request.

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 substantially increased the similarity between the observables of the treatment and 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 mean 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 isolate the impact of different factors. We start with basic manager characteristics – age and education, then analyze the network effect, and finally take into account firm heterogeneity. In all specifications, we control for the size of the previous firm, as it serves as a proxy for experience; the human capital accumulated from managing a firm is related to the firm's characteristics, including its size. Additionally, the manager's previous firm influences network metrics, as a manager's network grows with the number of managers from the firm they are leaving. By comparing managers from similarly sized firms, we can better distinguish the network effect from the experience effect. However, this approach may underestimate the importance of both networks and firm sorting, as both are also influenced by the choice of the previous firm.

In column (1), we estimate the equivalent pay gap from the benchmark model in the previous section, but restrict the sample to episodes of firm transitions. The estimated gender gap is approximately 22% (19.6 log points), which is close to the figure from our previous benchmark model. Given that this estimate is based solely on transition episodes, while the benchmark model encompassed the entire executive career of a manager, we can infer that around 90% of the gender gap originates during the hiring process and is then slightly exacerbated by biased career progressions.

	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			✓	✓

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

[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.

Next, in column (2), we incorporate our network metrics into the matching procedure, where network size is measured by the total number of connections, and gender composition is captured by the share of male connections. When comparing managers with similar networks in terms of size and composition, the gender gap decreases by 6.5 log points (column (2) vs. column (1)). This reduction reflects two distinct mechanisms through which networks influence wages: (i) the increased outside options that allow managers to access higher-paying firms—known as the firm sorting channel—and (ii) the bargaining power derived from one's network, which enables a manager to negotiate a higher salary within a firm. As expected, the network effect is more pronounced during transition years due to the former mechanism.

To further isolate the impact of sorting into higher-paying firms, we control for the size and pay policies of both the previous and new firms—using the previously estimated firm fixed effects from the *Full Model* in Subsection 3.2. In column (3), where we do not control for network size and composition, the gap decreases to below 13 log points when accounting for the type of firm the manager transitions to, indicating that approximately 7 log points of the initial gap can be attributed to firm sorting (column (3) vs. column (1)). However, when matching on both firm characteristics and network metrics in column (4), the gap is reduced by only 2 log points (column (4) vs. column (2)), suggesting that about 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 6.5 log point network effect into 70% associated with accessing higher-paying firms and 30% linked to bargaining higher wages within a firm. Additionally, comparing the results in column (4) - where all characteristics are considered - with those in column (1) reveals an overall

reduction in the pay gap of 8.8 log points. This reduction can be roughly attributed to networks (75%) and firm sorting, conditional on the network (25%).

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 is comparable to the nearly 15% gap found in the *Full Model* after controlling for firm fixed effects, further suggesting that the bulk of the bias originates during the hiring process.

Finally, in Table 5, we perform an additional analysis by adding the total pay received from the prior firm to the matching procedure. Even when comparing a female top manager to a male with similar pay at their previous job, a 6% (5.8 log points) gap persists at the new job. By controlling for the previous wage, we account not only for individual heterogeneity, but also for the best observable indicator that the hiring firm has of the manager's skills. Therefore, this remaining gap can be reasonably attributed to gender discrimination beyond any bias associated with firm sorting. It should be noted that this estimate likely represents a lower bound for discrimination, as it assumes that differences in prior wages are not themselves a result of discrimination.

	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	✓

Table 5. Top manager gender pay gap: considering unobservables

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.

4.2. Manager mobility and the role of gender specific networks

In this subsection we quantify the gender-specific network effect on a manager's compensation when transitioning to a new firm. As previously discussed, the network effect encompasses two key components: (i) the ability to match with higher-paying firms, as networks reduce search frictions and increase outside employment options, and (ii) the enhanced bargaining power that enables a manager to negotiate a higher salary at the new job. We provide separate estimates

for male and female top managers to determine whether there is a difference in the benefits they derive from networks.

Following a similar approach as before, we employ a matching procedure that pairs well-connected managers with their less-connected peers who have similar observable characteristics and comparable unobservables, as indicated by their previous pay. We define a well-connected manager as someone with a number of connections above the sample median.

Our findings indicate that well-connected top managers earn between 16 and 20 log points more than their less-connected counterparts with similar experience and education (see Table 6, columns (1) and (2)). This estimate of the network effect on pay is both statistically significant and economically meaningful, especially considering that we are comparing managers with similar compensation levels at their previous jobs. Notably, the network effect is larger for females than for males, suggesting that the contribution of networks to the gender pay gap is not due to intrinsic differences in women's ability to benefit from networks, but rather to actual disparities in the networks themselves.

	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			✓	✓

Table 6. The network size effect: propensity score matching

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.

Table 6 also presents results that isolate the impact of networks on pay beyond the firm sorting channel. In the last two columns of the table, the matching procedure additionally accounts for the size of the new firm and the firm fixed effects of both the previous and new firms, as estimated in the *Full Model* in Table B.1. Firm size is relevant because managing larger firms typically involves greater responsibilities and, consequently, higher pay, while firm fixed effects capture the time-invariant wage policies of firms. After controlling for the characteristics of the firm to which the manager is transitioning, the network effect is significantly reduced, confirming that a substantial portion of the network premium is linked to

matching with higher-paying firms. However, the network effect remains relatively larger for females, reinforcing the conclusion that women's networks are not inherently less productive.

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, where female managers benefit more from connections with other female top managers? Does the persistent over-representation of men in corporate leadership, coupled with potential biases against women, create an opportunity for women in management positions to support and advance their female peers? Or, conversely, does the dominance of men in powerful positions make them a more valuable asset within a female manager's network?

	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			✓	✓

Table 7. Network gender composition: propensity score matching

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.

We proceed as before, only now our treatment group is defined as having a higher than median share of male connections, while controlling for the total network size. We also take into account age, education and previous firm size and previous pay. Focusing specifically on gender composition, we find that both genders benefit more from male connections than female ones (see Table 7). However, we also observe that the gender composition of networks primarily influences firm sorting; once we control for the type of firm the manager transitions to, the advantage of male-dominated networks disappears.

This raises the question of whether this result stems from the larger networks typically associated with male managers and the accompanying access to information—essentially a direct effect of male predominance in top management—or whether gender itself plays a critical role. To explore this further, we introduce a weighted network metric, labeled *Power*, which assigns greater weight to connections with managers of larger firms. A manager's *Power* is calculated as the sum of the weights of all direct connections, where each weight is defined as the average size of the firms managed by a connection divided by the average number of managers at those firms. Formally:

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

where 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:

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

where $FirmSize_j$ represents the size of all firms managed by manager *j* and $NumberManagers_j$ the number of managers of these same firms, accounting for the distribution of decision-making power among managers.

Table 8 reports the results using this alternative weighted network metric. As suspected, we find that gender composition becomes irrelevant for female managers, suggesting that the observed benefit from having more male connections arises not because male connections are inherently more valuable, but because of the existing status quo where more males hold powerful top management positions. Conversely, male top managers continue to benefit more from connections with other males. While this result warrants further investigation, it strongly suggests that in a male-dominated management environment, male top managers tend to support and benefit other males more than females, thereby perpetuating gender bias.

Finally, we complement this analysis with an alternative weighted metric that, instead of emphasizing powerful connections, focuses on the proximity of connections. This measure, which we label *Depth*, assigns greater weight to connections based on the duration of shared work experience at the same firm, scaled by the firm's size. This allows us to value connections that are likely stronger due to longer, or more intimate, professional interactions. Formally:

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

When comparing top managers with a higher than sample median share of close male connections - measured by *Depth* - to comparable managers with similar observable characteristics, we find that both genders benefit more from same-gender connections. Male top managers gain equally from connections with powerful male managers and those they have worked closely with over time.

Interestingly, the results for female managers differ from our earlier findings: they benefit more from extended past interactions with other female managers. This supports the hypothesis that greater female representation in corporate leadership creates positive spillovers for other women (Kunze and Miller 2017).

	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	✓	✓

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

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 contribute to the literature on the gender pay gap among top managers by investigating the role of professional networks. Our analysis reveals that female top managers in Portugal earn 25% less than their male counterparts, even after controlling for factors such as age, education, and tenure. This disparity is especially troubling, as the women who break through the corporate glass ceiling are likely among the most skilled and talented, as noted by Bertrand and Hallock (2001). By introducing new metrics for network size and gender composition based on managers' past interactions, we find that networks account for 20% of this pay gap, primarily through firm sorting, as networks enable access to higher-paying firms.

Focusing on episodes of transitions between firms, we estimate a pay gap of around 22%, indicating that most of the gender pay gap originates during the hiring process. We also estimate that one-third of the gap is explained by differences in networks. The network effect works through two channels: by facilitating access to higher-paying firms (70% of the effect) and by enhancing bargaining power during salary negotiations in the new firm (30%).

Having established the significant role of networks, we further explore how female managers can leverage their networks to mitigate gender segregation across firms. We find no evidence on female and male managers benefiting differently from network size, assuming other factors are comparable, including the gender composition of their networks. However, we uncover an important new insight regarding the gender composition of networks. While both genders generally benefit more from male connections, once the importance of the connections is accounted for, female top managers benefit equally from male- or female-dominated networks, whereas male managers continue to derive greater benefits from same-gender connections. Moreover, when we consider the depth of connections—representing a manager's "inner circle"—we find that both female and male managers benefit most from connections with managers of their own gender. These findings suggest that gender bias can persist in a male-dominated corporate environment, but with appropriate policies to increase female representation in leadership, there is potential for positive spillovers, as women become strong advocates for advancing their close female colleagues. Our line of research, data, and methodology, suggest several fruitful avenues for future research.

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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

	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		✓		✓

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

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

Variable	Sample	Mean		%bias	Bias reduction	t-test	p-value
		Treated	Control				
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

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

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.

Variable	Sample	Mean		%bias	Bias reduction	t-test	p-value
		Treated	Control				
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

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

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.

Variable	Sample	Mean		%bias	Bias reduction	t-test	p-value
		Treated	Control				
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

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

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

	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

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

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.

	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

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

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.

	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

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

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.

	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

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

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.

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