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JEL Classification: J30, J24, L14

Keywords: Manager Pay, networks, Rent extraction, productivity

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1. Introduction

High executive pay has gained increasing salience in the media and in academia. In the public mind, abnormally high and rising levels of executive pay stem mostly from abusing managerial power to secure excess rents, not rising productivity. Indeed, high levels of pay may compensate for a unique set of capabilities and responsibilities, in a stressful environment, or arise just from a combination of personal power and lack of scrutiny, which create room for rent extraction (Bebchuk *et al.* 2002).

This paper provides an in-depth analysis of a specific indicator of managerial power — the professional network. Strong professional networks may increase both managers' productivity, as well as their ability to extract rents from the firm, in the form of high pay.

Jackson (2014) argues that the ability to accurately model human behavior requires recognizing the social nature of humans, which in turn implies understanding the interaction patterns shaping behavior and decisions. While networks have long been the subject of study in sociology, only more recently has their analysis gained momentum in the finance and economics literature. Network analysis aims to identify the structure of interactions, and consider how observations are connected, not isolated. Several studies have analyzed the social ties of top executives, including authors such as F. Hallock (1997), Core *et al.* (1999) and Liu (2014), who have explored observable, formal business settings, such as boards of directors. Other authors explored informal settings, such as connections through a common background, including attendance of educational institutions (Engelberg *et al.* 2013), region of origin (Hwang and Kim 2009), experience in civil service (Kramarz and Thesmar 2013). Brown *et al.* (2012) has proposed a broader concept of social network that includes all acquaintances from employment, education and social activities. Gomez-Mejia *et al.* (2001) analyze closer and deeper bonds, such as family ties.

We build a new indicator of a manager's network as the number of all past professional interactions, within the same firm, with co-workers who later become top managers. At the time of the interaction as co-workers, one or both workers may have not yet become top managers, but we interpret their later investiture as top manager as revealing a valuable connection. In other words, in our paper, a top manager's current network is larger, the more often they coincided in the past with other workers who have also become managers.

Our study benefits from a vast country-wide micro-level dataset that collects the full set of information on a worker's employment history. We are able to verify whether any two current managers have worked in the same firm in the past, during the same year. If that is the case, we consider that there is a tie between the two current top managers. Our definition has clear conceptual advantages over existing definitions in the literature. First, and most important, our network metrics evolve over time for reasons exogenous to the manager, avoiding endogeneity problems associated to self-selection. This is because a specific manager experiences changes in her network when other workers she met in the past become managers, or leave the job market. Second, the comprehensive and large sample of firms and years allows us to capture variations across a long time horizon, in addition to the cross-sectional variation most studies rely on. Third, it avoids issues of simultaneity and reverse causality, as it focuses on past professional encounters, at a time when the future potential of each worker was yet to be fulfilled. Other studies are vulnerable to reverse causality, as it is hard to establish whether it is the large network that allows the manager to extract higher wages, or if managers that are well-paid naturally build stronger networks. The very rich and comprehensive dataset also allows us to define networks in a manner that avoids circular/perfectly overlapping groups, and as explained in Bramoullé *et al.* (2009) that allows us to overcome the 'reflection problem' identified by Manski (1993).[1] In sum, our measure is comprehensive, varies over time and across top managers, and addresses the issue of endogeneity by using past events and capturing changes in a manager's network that are exogenous to the manager, his ability, and choices.

It is important to notice that in any kind of setting, people cannot count on all the members of their network for help or exchange of information. Not only because some of the elements of the network may not be willing to help, but also because, in this particular case, there is no guarantee that having worked with someone at the same firm at the same year implies having met that person. We propose, as a novelty in the literature, to weigh these past encounters by the time future top managers have worked in the same firm, in the same year, as well as inversely by the firm's size. This allows us to understand how working together for longer in smaller firms, thus likely establishing longer and deeper links may, or not, affect the results. In addition, we argue that it is also important to consider those weaker links, defined as few years in common in large firms. While there is a chance, that any two workers who have worked at a large firm, didn't actually meet, there is a virtual link between them that can be activated at any given moment. We advocate that it is much easier to approach someone to ask for information or to create a business connection if there exists some vague link that allows to break the initial ice and unlock the channel of information.

We hypothesize that a higher number of ties provides an effective channel for the exchange of information or transmission of ideas, which empowers the manager and increases her bargaining power (Fracassi 2016), leading consequently to a higher pay. According to Engelberg *et al.* (2013) one of the assumptions needed for a top manager's network to influence their wage is that it must accrue value to the firm. We argue that a network mustn't necessarily add value to the firm, but the firm has to believe it does. In accordance, we organize the potential benefits of a larger network into three types, which add objective and subjective value to the manager.

1. If all members of a group are linked, and the pay of one manager depends on the average pay of the group, then an identification problem arises, making it impossible to disentangle the network effect.

A larger network provides information on business opportunities, objectively increasing the value of the manager to the firm.[2] A well-positioned manager in a network can act as bridge between the firm and their connections, and therefore the cost of losing this manager gets amplified by the number of other potentially valuable connections that will be lost.

While access to a larger information set objectively increases the competence and productivity of the manager, the increase in bargaining power of the manager may include a subjective attribution of value. As firms cannot unequivocally connect results to manager competence, they may infer the latter from the manager's network. Manager wages can thus increase with the size of the network for objective or subjective reasons. This view is congruent with the idea that a large network reflects reputation and experience and can thus be regarded as an indirect measure of quality (Renneboog and Zhao 2011). This is specially relevant during the recruitment process, where despite all the efforts put into hiring the most capable top managers, the firm faces a problem of incomplete information regarding the quality of the manager-firm match.

Finally, there is also the sole bargaining power granted by networks. Since networks reduce job search frictions, highly connected managers are better informed about their outside options and can leverage this information in their favor to negotiate higher pay. In sum, regardless of the specific mechanism, theory predicts a wage-premium for managers who are able to leverage their connections to potentially benefit the firm.

While the literature is mostly consensual regarding the positive impact of networks on wages, this paper advances several key contributions. Firstly, we address endogeneity concerns thoroughly, through the inclusion of high-dimensional fixed effects, including firm and manager fixed effects and an instrumental variable approach, aside from the network definition *per se* that explores exogenous changes in the networks. The use of a unique micro-level dataset allows the use of a richer, time-varying definition of networks, encompassing professional connections that are not restricted to present ties, like most studies thus far. Moreover, we assess the impact of connections with potentially distinct values to the manager, a question not addressed in the literature. Relying on different measures of network theory, we analyze whether it is the quantity or quality of connections that prevails, where quality is defined in terms of either the depth or the power status of the connection. In addition, we look into whether it is the number of direct ties that plays the main role, or the manager's global position in the aggregate network. This is an important angle of analysis, given that the latter is a better proxy for the information value of networks, allowing us to shed some light on whether firms can actually benefit from the manager's network or not. We also unveil the type of firms that value more their manager's networks.

2. In addition to present benefits, the firm might benefit in the future from these connections provided certain conditions materialize - for instance, when planning mergers, acquisitions or expanding into new markets.

Our empirical analysis generates three main insights. First, results suggest a consistent impact of managers' networks on their total pay. This result is robust across different specifications. A one standard deviation increase in the crude network measure that accounts for the number of connections is associated to a 8% higher bonus - the more volatile component of compensation. Part of the network premium is closely linked to being better informed about job opportunities and thus having better outside options that allow to match to higher paying firms. While this is a direct benefit derived from the network, it will be absorbed by the firm fixed effect. The individual and firm fixed effects control for any innate manager characteristics and time-invariant firm characteristics, at the cost of clearly sub-estimating the network premium. Nonetheless, even including these high-dimensional fixed effects, we still find a statistically significant 8% network premium for the compensation bonus and 5% for total pay. Second, we find that quality prevails over quantity. In particular, deeper connections - i.e. longer and closer connections - are more valuable to the manager. Third, indirect measures that reflect better access to valuable information are also associated to higher pay, suggesting that it is not only who they know, but also what they know through them that matters. Our results are not firm-specific, and hold across different kinds of companies, however evidence suggests that those who pay most for well connected managers are large young firms in the services sector. Finally, a preliminary analysis suggests that networks are not overpaid and translate into higher firm productivity.

The remainder of this paper proceeds as follows. In Section 2, we carefully define the manager's network and explain the metrics underlying its topology that are used in the analysis. In Section 3, we describe the database. Section 4 presents the empirical results relating manager networks to a pay premium and several robustness checks. Concluding remarks are provided in Section 5.

2. Networks

2.1. Network definition

Our network is a set of managers (referred to as 'nodes' in network theory) and the connections between them ('edges', formally).To construct a manager's yearly network we take various sequential steps: first, we identify all the firms where top managers have worked at in the past; we then list all the employees who worked at the firms identified in the first step, at the same time as our managers; finally, we construct yearly network measures for the manager in question, considering as connections only past co-workers who are currently managers as well (excluding same-firm managers to avoid simultaneity problems). We assume that a connection is activated - or becomes 'valuable', only when both parties are managers and it remains a connection until one or both parties cease to be a manager - by being demoted or leaving the job market entirely. This procedure allows us to define all the managers that form part of a network and, once they are identified, characterize each connection by the depth of the link itself and the power of the link (as defined below). Note that, for a connection to be established between two managers, they need not have been managers when they met, but they are so at the moment they count as part of each other's network (see Figure 1).

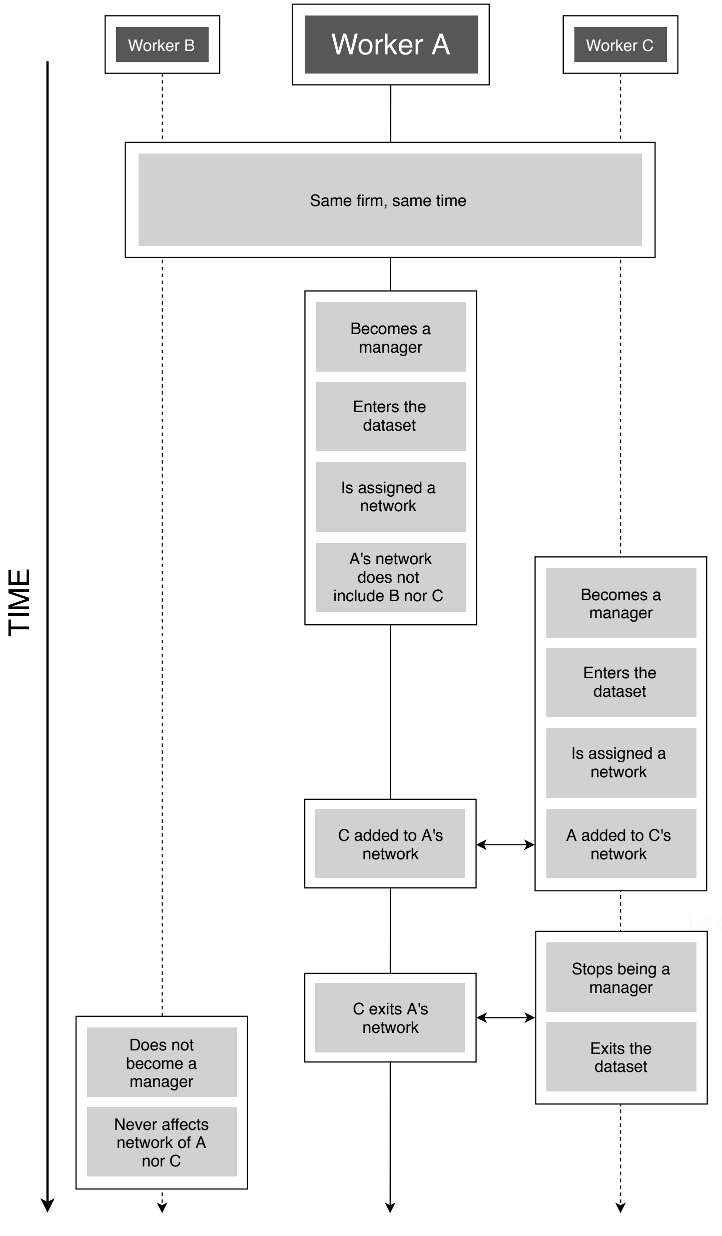

Figure 1: Network definition

Notice that the procedure to construct the network is computationally very intensive and extremely time consuming. The vector containing all interactions (every two managers who worked in a given same firm at the same year) is composed of approximately 563 million observations. All network metrics were computed using the R package igraph (Csardi and Nepusz 2006).

2.2. Network metrics

Figure 2 depicts the network of a random manager in our sample in 2017. In the figure, each manager is denoted by a node, and a connection between two nodes - signaling the two managers have worked together in the same firm, in the past, is a line in the picture. The particular manager represented has 34 connections, *i.e.* 34 past co-workers who also occupy a management position in 2017.

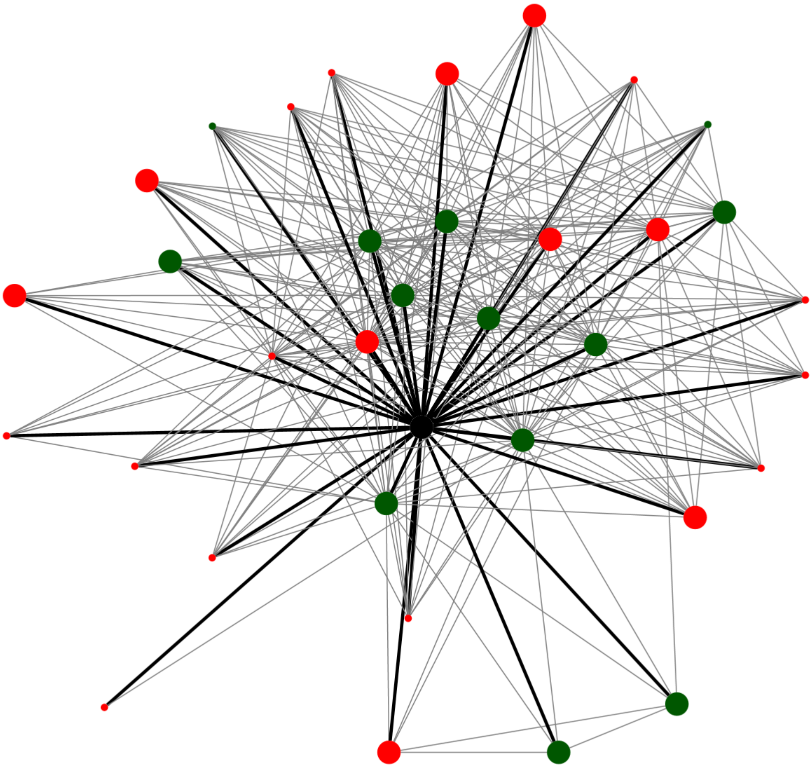

Figure 2: A fragment of the network of a top manager
The black node represents a randomly selected manager in the top quartile of the pay distribution. The black lines correspond to his direct connections. Green/red nodes are managers who earn more/less than the black node in 2017. Large/small nodes have a higher/lower level of *Degree* in 2017 than the black node. Grey lines represent connections amongst the direct connections of the black node.

The *Degree* centrality of a node is composed of the number of connections:

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

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

A node's *Depth* is computed as the sum of weights on all direct links, where each weight is defined as the number of years any two managers coincided in the same firm, divided by the firm's size. This weighted network measure attributes a higher value to connections who are likely to be stronger, either because the two managers worked together for a longer period of time, or because they did so in a smaller firm, facilitating more frequent and closer interactions between co-workers.

$$\mathrm{S(i)} = \sum_{j \neq i} w_{ij} x_{ij}, \tag{2}$$

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:

$$w_{ij} = \frac{Years_{ij}}{FirmSize_{ij}}, \tag{3}$$

Finally, a node's *Power* is derived from how powerful the connections of a manager are. It is computed as the sum of weights on all direct connections, where each weight is the average size of the firm managed, divided by the average number of managers at those firms. This weighted network measure attributes higher values to connections likely to be more valuable as implied by the average size of the firm managed by that connection. In sum, whereas a node's strength is related to the intensity of the past connections between managers, power is a proxy for the importance in corporate leadership of the nodes that form part of a manager's network.

$$\mathrm{P(i)} = \sum_{j \neq i} w_{ij} x_{ij}, \tag{4}$$

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:

$$w_{ij} = \frac{\sum_j FirmSize_j}{\sum_j NumberManagers_j}, \tag{5}$$

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

As a more global network measure, which takes into account indirect ties, we consider *Betweenness centrality*. The *Betweenness* of node *i* is defined as the sum of betweenness ratios, *i.e.* the number of geodesic paths - shortest path, which is not necessarily unique, between any two nodes passing through node *i*, divided by the total number of geodesic paths between those two nodes. This is:

$$B_i = \sum_{j \neq i \neq k} \frac{g_{jik}}{g_{jk}}, \tag{6}$$

where g_{jik} are the number of geodesic paths between *j* and *k* that pass through *i*. Given the dimension of our graph, we considered only paths of lengths smaller than 3. *Betweenness centrality* is commonly used as a measure of control over the network, as a higher *Betweenness* implies that more information will pass through that node.

PageRank is the algorithm behind the Google search engine and can be easily extended to a social network setting as in Eckbo *et al.* (2016). The *PageRank* centrality PR_i of node i is given by:

$$PR_i = \alpha \sum_j \frac{x_{ji}}{D_j} PR_j + (1 - \alpha) \tag{7}$$

where α is a constant (the damping factor), x_{ij} is 1 for the presence of a link between *i* and *j*, D_j is the *Degree* of node j if such *Degree* is positive, or $D_j = 1$ if the *Degree* of j is null. *PageRank* measures the quantity and quality of a node's connections.

3. Sample and data description

Our data draws on information from *Quadros de Pessoal* (henceforth *QP*), an official micro longitudinal dataset, with matched employer-employee data that include all private firms and workers operating in Portugal. The survey is mandatory for all establishments with wage-earners, and contains information regarding the firm - including size, and each of its workers - including gender, age, education, total compensation and hours worked. *QP* includes a personal identification number that enables tracing individuals across time, allowing the use of the entire professional history of a worker since the dataset's inception in 1986, that is, for a total of more than 30 years.

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 mandated to classify each job in accordance. We restrict the sample to all managers between 1995 and 2017. We define a top manager as a top decision makers or as top management, as inferred from the available 6-digit occupational classification system that identifies all types of managerial occupations.[3] For the classification of top managers, we restrict the sample to

3. In *QP*, in the period between 1986 and 2017 the national classification of occupations was revised several times and the last change occurred in 2010. From this year onwards, we use the

workers classified in the highest hierarchical grade level. While self-employed managers, i.e. firm owners, are included in the global network of each manager, they cannot be included in our regression analysis given the lack of data regarding wages, stemming from the specific compensation mechanism in place in owner-managed firms.[4] Our final sample consists of 1 077 233 manager-firm-years, representing around 135 424 firms and 2 776 44 top managers.

	Mean	Median	Std. Dev.
Firm Characteristics			
Number of workers	1035.26	37	3005.09
Number of managers	151.50	3	573.53
Number of establishments	43.36	1	142.22
Manager Characteristics			
Gender	0.28	0	0.45
Age	44.61	44	10.30
Education	4.10	4	1.06
Tenure (years)	10.29	8	9.09
Hourly total compensation	21.10	16.05	30.20
Hourly base wage	16.82	13.51	16.13
Hourly bonus	4.61	1.16	23.67
Degree	65.96	9	137.35
Depth	0.17	0.09	0.25
Power	1123.63	112.67	2780.73
Betweenness	96334.29	937.11	365166.40
PageRank ($\times 10^6$)	6.30	4.41	6.71

Table 1. Summary statistics

This table presents the summary statistics of firm and manager characteristics for 916,511 firm–year observations between 1995 and 2017. *Degree*, *Depth*, *Power*, *Betweenness* and *PageRank* are network metrics defined in Section 2.2. 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.

Table 1 and 2 present the descriptive statistics of firm and top managers characteristics, including the network variables. The average firm has around 1035 workers, of which roughly 15% have top management positions. However, half of the sample consists of small firms with less than 37 workers and 3 top managers. As shown in Table 1, the average age of top managers in the sample is 45 years old and the average tenure is 10 years. Around 28% of the sample are women, and 40% hold a college degree. The base salary accounts, on average, for 80% of a

latest classification of occupations and are able to identify accordingly the workers classified as managers. Before that, we proceeded by using the official table of harmonization published by Statistics Portugal, to minimize entry and exit of managers attributable to this change.

4. In other words, in our exercise, firm owners add value to other managers' networks, but we cannot analyze how their networks impact their wages.

top manager's total compensation. While bonus pay plays a smaller role in total compensation, it displays a wider variability and is a significant fraction of total pay for part of the sample.

	Degree	Depth	Power	Betweenness	PageRank
Degree	1.0000				
Depth	0.1715	1.0000			
Power	0.8093	0.0969	1.0000		
Betweenness	0.4171	0.2842	0.4161	1.0000	
PageRank	0.6038	0.3393	0.6378	0.5505	1.0000

Table 2. Correlation matrix of network variables

The network metrics are defined in Section 2.2.

As for network measures, a top manager benefits on average from 66 connections to other managers, but there is significant variation in the number of connections across the sample. Indeed, the standard deviation of direct connections is 137, and around half of the sample has 9 or fewer connections. Table 2 presents the correlation between top managers' network measures in the sample. *Degree*, *Power*, and *PageRank* have correlations in excess of 0.60, while *Depth* displays very low correlations with the remaining measures.

Figure 3 depicts developments in the average network measures for each additional year of experience at a top management job. It shows that *Degree* and *Betweenness* centrality are the metrics that present larger increases during the first years at the job. While the latter continues growing steadily, *Degree* seems to increase on average less after the first 8 years of experience. *PageRank* presents the lowest growth rates.

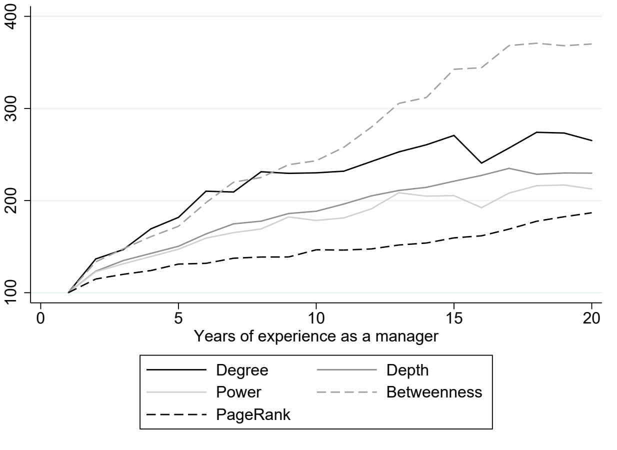

Figure 3: Average network metrics by years of experience: index 100

Descriptive statistics comparing managers with high centrality to managers with low centrality, according to each of three network metrics: *Degree*, *Depth*, and *Power*, are presented in Table 3. Managers of larger firms are, on average, better connected, and better connected managers are more likely older, educated, males, with longer tenures. Better connected managers are also paid more, about twice as much per hour as poorly connected managers. Also, note that filtering a manager's network into high and low according to *Depth*, leads to a reversion of the split of managers into large and small firms, with higher network managers associated with small firms, where interactions are more frequent and, possibly, intense.

	Degree centrality			Depth centrality			Power centrality		
	High	Low	Difference	High	Low	Difference	High	Low	Difference
Firm charact.:									
No. of workers	2108.22	118.61	1989.61***	733.23	1316.70	-583.49***	2069.60	109.48	1960.13***
No. of managers	314.93	11.88	303.05***	74.54	223.24	-148.70***	304.77	14.32	290.45***
No. of establishm.	88.99	4.39	84.60***	42.10	44.54	-2.44***	87.63	3.75	83.88***
Manager charact.:									
Gender	0.23	0.32	-0.08***	0.24	0.31	-0.07***	0.24	0.31	-0.07***
Age	45.05	44.23	0.82***	44.88	44.36	0.52***	44.92	44.33	0.59***
Tenure (anos)	11.15	9.55	1.60***	9.24	11.26	-2.03***	11.02	9.63	1.39***
Education	4.49	3.76	0.73***	4.27	3.94	0.33***	4.49	3.75	0.73***
Hourly total pay	29.86	13.62	16.24***	25.51	16.99	8.52***	29.44	13.64	15.81***
Hourly base wage	22.95	11.57	11.38***	20.32	13.54	6.77***	22.65	11.59	11.06***
Hourly bonus	7.11	2.46	4.65***	5.48	3.80	1.68***	7.00	2.47	4.53***

Table 3. Highly connected managers: statistics

This table presents the mean of manager and firm characteristics for the sample of high and low centrality managers and the associated difference. High-centrality is defined as having a centrality level higher than the sample median. Variable definitions are provided in Appendix A. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

4. Is there a wage premium associated to manager networks?

Figure 4 shows the empirical distributions of the log hourly wages of managers in the economy for different *Degree* centrality quartiles. As expected, raw wages for managers with larger networks, *i.e.* with a higher number of connections, are displaced to the right. Managers with a *Degree* level in the top (4th) quartile present additionally less dispersed wages. Given that the statistical evidence corroborates the existence of a network effect, we next propose to quantify more precisely this effect.

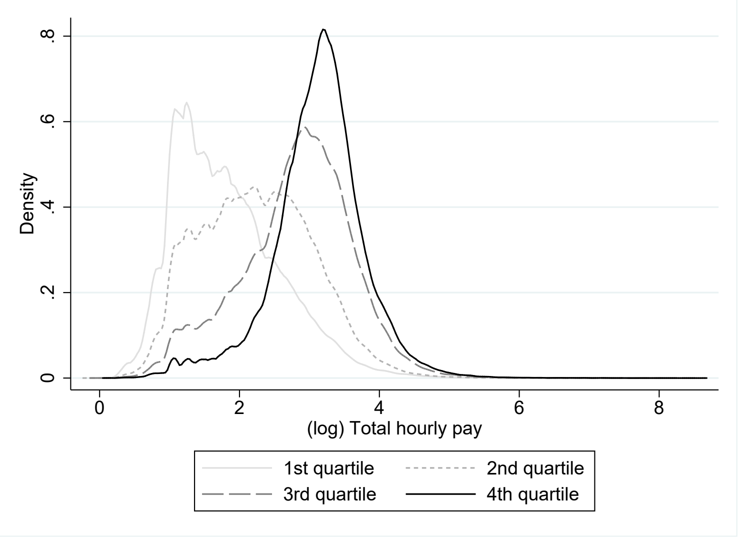

Figure 4: Distribution of (log) wages by *Degree* quartile
This figure reports kernel densities of log hourly total wages of managers for different *Degree* quartiles.

4.1. Baseline regressions

We now proceed to examine the effect of a manager's network centrality on her compensation, using a standard Mincerian wage equation to which we add high-dimensional firm and manager fixed effects, following Torres *et al.* (2018), as well as the network measures of interest:

$$\begin{aligned} Ln(w)_{ijt} = \beta_1 Network\, Measures_{ijt} + \beta_2 Manager\, Characteristics_{ijt} \\ + \beta_3 Firm\, Characteristics_{jt} + \eta_t + \gamma_j + \alpha_i + e_{ijt} \end{aligned} \tag{8}$$

In the above equation the outcome variable is the natural logarithm of the real hourly wage of manager *i*, in firm *j*, at year *t*.[5] *Network Measures* stand for the different network metrics presented in the previous section. *Manager characteristics* is a vector of the manager's observed attributes, present in the standard wage regressions in the literature, including a gender dummy that takes the value of 1 for females, a categorical education variable that increases with the level of education - as defined in Appendix A, tenure at the current firm, tenure squared and age squared. Notice that the linear term age has to be dropped as it will be absorbed

5. Wages were deflated using the consumer price index (base 2017), but this correction is inconsequential for the regression analysis, since we always include year dummies.

when manager fixed effects are added in a model that includes both manager and year fixed effects. *Firm characteristics* include the number of establishments, and the logarithm of the number of workers in the firm. It is key to control for firm size, as larger firms tend to be more complex and require more skilled and hence more highly paid managers (Gabaix and Landier 2008). η_t are year dummies, $gamma_j$ are firm fixed effects - capturing observed and unobserved firm constant heterogeneity, and $alpha_i$ are manager fixed effects - capturing observed and unobserved manager constant heterogeneity. e_{ijt} is the error term, assumed to follow the conventional assumptions. T-statistics use robust clustered standard errors, thus adjusting for heteroskedasticity and within-manager correlation.[6] Estimation of Equation 8 by ordinary least squares (OLS) is complicated due to the inclusion of two high-dimensional fixed effects. However, by using an algorithm proposed by Guimarães and Portugal (2010) that consists of an iterative procedure (that alternates between the estimation of the fixed effect and of the coefficients, taking as given the last estimates of the coefficients or the fixed effects, respectively) estimates converge to the true OLS solution.

In Table 4, we regress managers' total hourly compensation on their number of connections - *Degree*, following Equation 8. In specification 1 we only control for the observable covariates, as specified above. In specification 2, we add firm fixed effects, such that additionally within-firm changes in compensation are taken into account and in specification 3 we add manager fixed effects. In specification 4, aside from all standard firm and manager characteristics, we include both firm and manager fixed effects to address the issue of time-invariant unobservables, which may drive the manager-firm match. Our preferred specification 4 minimizes the possibility that firm-specific omitted variables, as well as innate manager characteristics, such as talent, are driving our results.

Our results show that *Degree centrality* displays a positive and statistically significant association with a manager's hourly wage throughout all specifications. The quantitative impact is of 1.9% for an increase of one standard deviation in the *Degree* measure. When we add firm fixed effects alone, that coefficient decreases to 1.1%, but it is 2.6% when we add manager fixed effects alone. More relevant, the introduction of both firm and manager fixed effects leads to an estimate of a 2.4% increase in a manager's total hourly wage. In the last column of the table, we add the squared network measure to the specification, as suggested in Engelberg *et al.* (2013). In this way, we account for diminishing returns, *i.e.* while a certain connection may yield valuable benefits, additional connections will deliver marginally less valuable benefits. Our estimate of the negative squared term, confirms decreasing returns to connectivity in manager wage regressions. Once we take this into account, a one standard deviation increase in a manager's *Degree*

6. Clustering the standard errors at the firm level has no impact on the significance of the main results.

will lead to an approximately 5% increase in pay, reaching the maximum at 766 connections.

	Manager hourly pay				
	OLS (1)	Firm fixed effects (2)	Manager fixed effects (3)	Manager & firm fixed effects (4)	(5)
Degree	0.0001***	0.0001***	0.0002***	0.0002***	0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Degree squared					-0.0000***
					(0.0000)
Gender	-0.2106***	-0.1400***			
	(0.0032)	(0.0025)			
Age	0.0642***	0.0589***			
	(0.0010)	(0.0009)			
Age squared	-0.0005***	-0.0005***	-0.0005***	-0.0005***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure	0.0002***	0.0003***	0.0010***	0.0005***	0.0005***
	(0.0000)	(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)	(0.0000)	(0.0000)
Education	0.3119***	0.1010***	0.0229***	0.0080***	0.0081***
	(0.0015)	(0.0016)	(0.0031)	(0.0022)	(0.0022)
No. of workers (ln)	0.1846***	0.0523***	0.0906***	0.0804***	0.0805***
	(0.0008)	(0.0023)	(0.0018)	(0.0020)	(0.0020)
No. of establishments	-0.0009***	-0.0004***	-0.0003***	-0.0002***	-0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Year dummies	✓	✓	✓	✓	✓
Manager fixed effect			✓	✓	✓
Firm fixed effect		✓		✓	✓
Observations	1,077,233	1,077,233	1,077,233	961,029	961,029

Table 4. Managers' total pay and the network premium

This table presents estimates of ordinary least squares (OLS) and firm and manager fixed effects panel regressions of the logarithm of manager total hourly pay on the network measure *Degree* and other manager- and firm-level control variables. The sample consists of all firms, for which data on their top managers is available in the 1995-2017 period. Variable definitions are provided in Appendix A. Robust standard errors adjusted for manager-level clustering are reported in brackets. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

Our estimates compare well with the literature, which finds an effect of 9%, as in Renneboog and Zhao (2011) and Engelberg *et al.* (2013). Note that existing papers analyze more restricted samples, made up of UK and US listed firms only and mostly relying on cross-sectionl-variation, without firm and manager fixed-effects.[7] Thus,

7. Renneboog and Zhao (2011) consider more specific links, namely sitting on the same director board, and finds that a one standard deviation increase in the *Degree* measure leads to a 9% increase in the total compensation of CEOs of listed firms in the UK. Similarly, using a sample of US firms, Engelberg *et al.* (2013) find a 9% network wage premium associated to a one standard deviation increase in the number of connections, including past professional, university and social

for a very wide sample of firms in a country characterized by smaller, mostly not listed firms, we confirm the existence of a quantitatively significant wage premium associated to a manager's time varying network, controlling for firm and manager time-invariant unobservables.

A number of papers have emphasized the role of fixed effects when it comes to management compensation. Graham *et al.* (2012) find that firm and, especially, manager fixed effects explain most of the heterogeneity in executive pay. Our results, using the time variation in network variables, as opposed to cross-section variability, are thus new and important.

Notice that the firm fixed effects capture firm heterogeneity in terms of pay standards. A large positive firm fixed effect corresponds to high-wage firms, *i.e.* firms that reward their managers above what would be expected taking into account the time-invariant heterogeneity of managers, as captured by the individual fixed effects, and all observable time-varying manager and firm characteristics. Figure 5 displays the distribution of the firm fixed effects, revealing considerable heterogeneity across firms, where well-connected managers are systematically overrepresented in firms with more generous pay policies. For the least well connected managers the distributions are smoother and very dispersed, reflecting the existence of a wide range of wage policies.

Given this evidence that networks grant access to better paying firms, it is also important to keep in mind that, by including fixed effects, we are clearly under-estimating the network premium, as part of the benefits derived from a network are associated to the time invariant firm heterogeneity. These include the outside option channel which allows better connected managers to match to higher paying firms. Notice that our network measure, when controlling for the fixed effects, only varies in response to circumstances completely exogenous to the manager, as other managers enter and exit manager positions or the labor market. In conclusion, we find that a manager's *Degree*, through time, in the same firm, unequivocally impacts her hourly pay, and our estimates can be read as a lower bound for the network effect.

Finally, it is also worth noting that wages are relatively rigid in the Portuguese labor market (see Marques *et al.* 2012), making our results particularly relevant as evidence of the importance of networks to manager pay. In order to explore the impact of networks on the more variable component of pay, we now decompose total compensation into the base salary and any extras – such as seniority compensation, other benefits, and extra-hour pay – which we label for simplicity as bonus. Table 5 shows that, while the network premium is present for both components of pay, it is more substantial in the case of the bonus, which displays much higher within firm and manager variability compared to base salary. The coefficient in specification (1), with no fixed effects, stands at 6.4%, and is more directly comparable to

connections. Both studies focus on cross-sectional variation, with little time-series variation, and do not include firm nor manager fixed effects.

the above cited studies. When both firm and manager fixed effects are taken into account, the estimate of the impact for a one standard deviation increase in *Degree* stands at 8.2%.

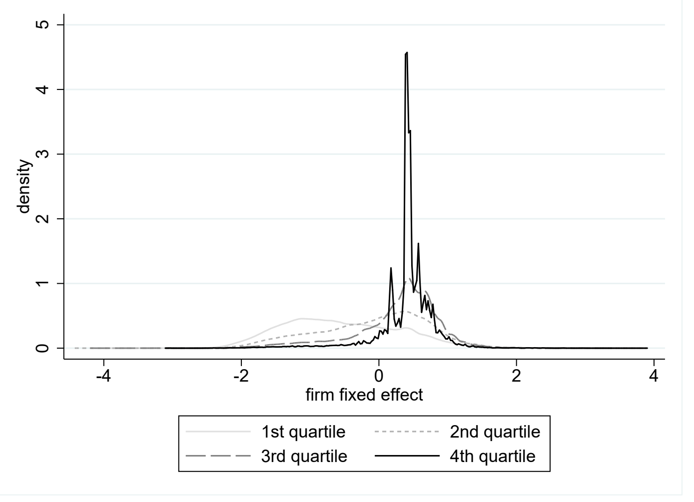

Figure 5: Distribution of firm fixed effects by *Degree* quartile
Reports kernel densities of the firm fixed effects for managers for different *Degree* quartiles. These figures follow from the estimation reported in Table 4.

Panel A	Manager hourly bonus			
	(1)	(2)	(3)	(4)
Degree	0.0005***	0.0002***	0.0007***	0.0006***
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Observations	1,077,233	1,077,233	1,077,233	961,029
Panel B	Manager hourly wage			
	(5)	(6)	(7)	(8)
Degree	0.0001***	0.0000***	0.0001***	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	1,077,233	1,077,233	1,077,233	961,029
Year dummies	✓	✓	✓	✓
Firm and Manager controls	✓	✓	✓	✓
Manager fixed effect			✓	✓
Firm fixed effect		✓		✓

Table 5. Total compensation components and the network premium

This table presents estimates of OLS and firm and manager fixed effects panel regressions of the logarithm of manager hourly wage (Panel A) and hourly bonus (Panel B) on the network measure *Degree*. Manager- and firm-level control variables are included. The sample covers the 1995-2017 period. Robust standard errors adjusted for manager-level clustering are reported in brackets. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

4.2. Power or depth: is it who you know or how well you know them?

In the previous section, we have unveiled that the number of connections managers form throughout their careers matters for the compensation they receive at each moment in time. The question that arises is which are the most important names in one's network, who convey the most relevant information or prestige, and thus the highest wage premium? In this section we create two new indicators, weighing the *Degree* indicator previously computed along two dimensions: the depth of the connection and the power of those to whom the manager is connected to. The new two network measures are weighted *Degree* metrics - commonly referred to as a tie's strength in network theory. The variable *Depth* attributes a higher weight to the connections with whom the manager is likely to have contacted more intensively, whereas the variable *Power* assigns a higher weight to ties with managers' who have gained a greater influence in corporate leadership.

To define the *Depth* of a connection we consider the number of years the two managers worked simultaneously in the same firm, and the corresponding firm size. Having worked more years together, in smaller firms, translates in a higher *Depth* indicator. While the number of years increases the probability of actually having met someone and created a strong bond, the size of the firm reduces the odds of having worked side by side. The *Power* of a connection is defined also on the basis of two dimensions: in the firms where the connection works, how many other managers are present, and how large that firm is. The size of the firm is a measure of its power in industry and by also considering the number of managers we assess how powerful the connection might be in the decision making process of the firm. Therefore, working in large firms with fewer managers is assumed to translate into higher *Power*.

Figure 6 depicts the impact on pay given a one standard deviation increase in the weighted network measures, *Depth* and *Power*, derived from the model as specified in Equation 8.[8] For ease of comparison the results regarding the crude unweighted *Degree* measure, discussed in the previous section, are also depicted. We find that both weighted network measures have consistent positive and statistically significant impacts on pay, whether this means total pay or its components, wage and bonus.

More: *Depth* has a quantitatively larger impact on total compensation than *Power*, suggesting that deeper connections increase a network's value by more than powerful connections. This result is even more relevant as *Depth* displays low variability throughout a manager's career. Indeed, considering only firm fixed effects, not manager fixed effects, nearly doubles the coefficient on *Depth*.[9] Second, deeper connections have a similar impact on the base salary – the wage, and the

8. The table with the detailed results is presented in Appendix 2.

9. When we interact *Depth* and *Power*, we confirm that deep links to powerful managers are more valuable than deep links to less powerful managers. results are available upon request.

more variable component- the bonus, whereas *Power* has a low impact on the base salary, but impacts the bonus more than does *Depth*.

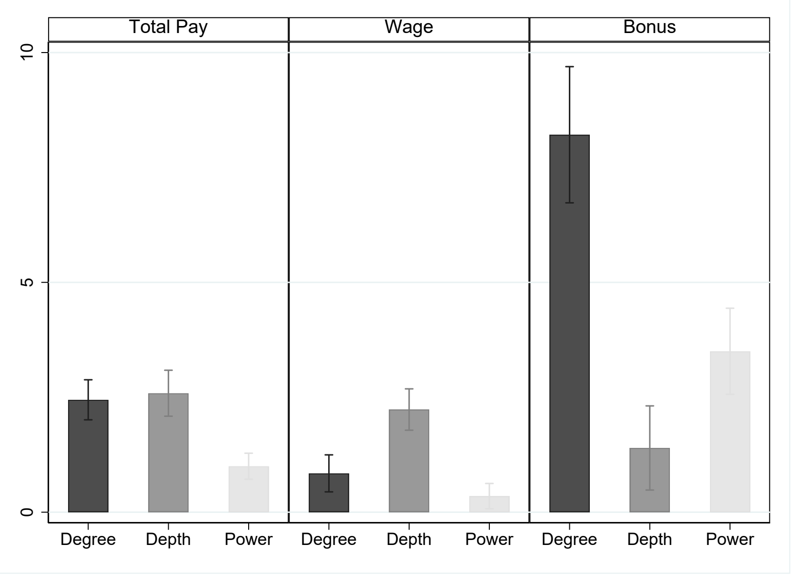

Figure 6: Network measures
The columns stand for the estimated coefficients for a one standard deviation change in the variable and the lines represent the 95 per cent confidence interval. Detailed estimation results can be found in Table B.1 in the Appendix.

Networks impact a manager's pay, as previously mentioned, through different channels, which can be grouped into 2 theories: (1) being more connected in a network implies higher productivity and (2) more connections facilitate rent extraction. We can speculate that the rent extraction portion of the network effect is more likely associated to the bonus, while the productivity portion of the network effect can impact more easily the base wage, given the variability of the former and the rigid nature of the latter. Indeed, a simple exercise allows us to verify this hypothesis. By measuring the contribution of the manager fixed effect to base wage and bonus variability, we can confirm which compensation component is more closely linked to a manager's ability or time-invariant productivity. Table B.2 in Appendix B suggests that indeed, the role of manager heterogeneity, including ability, is more prominent for base wage, than for bonus payments, despite being also very important for the determination of the latter. Thus, results suggest that perhaps *Depth* is more closely related to a manager's actual productivity, for example given the ease of exchanging valuable information with closer links. Regressing the estimated manager fixed effects on the network metrics together with the set of controls confirms that, indeed, the network metric more closely related to a manager's ability is *Depth* (Figure B.1 in Appendix B.1).

To further validate our results on powerful ties, we pursued two strategies. First, we use an alternative measure of network power, regarding just the last firm managed by the connection, not the average firm managed. Our results are unchanged. Second, we restricted the scope of firms defining network power to firms with 250 workers or more, i.e. a weight of 0 is given to ties with firms smaller than 250 workers. Results do not suggest that ties to large firms are more valuable. Thus, we find no evidence that firms pay a higher premium to managers with connections to large firms, as suggested by Engelberg *et al.* (2013).

To this point, we have concluded that connections to other managers (*Degree*) are valuable, and the more acquainted those connections are (*Depth*) the higher the benefit. It is intuitive to consider that those deeper links are the ones more likely to transmit high-quality relevant information or favors. Although we do not report these results, we have analyzed whether the value of these deep connections increases even further when both managers share the same industry. Industry connections are much more rare (the median manager has 11 connections, of which only 2 are from the same industry), but do not seem to increase more the network premium compared to other connections.

In addition, we have posed the question of whether ties to the financial sector are specifically more valuable due to the financing need of firms, particularly for smaller firms with higher credit constraints. We find no evidence to support this hypothesis. On the contrary, larger firms seem to be willing to pay more for connections to the financial sector.

4.3. The value of indirect ties

So far we have restricted our analysis to the direct ties that managers form throughout their careers. It is only natural to question how valuable the indirect ties are. Indirect ties proxy for a fuller range of connections the manager has access to, with just one degree of separation. While in the literature direct measures are used as a proxy for managerial influence, indirect connections capture the information collection ability. Therefore, indirect ties may be more related to actual added value for the firm. Also, given that it is more difficult for firms to observe these indirect metrics, any impact on pay will be less related to a subjective attribution of value to managers, and more to objective results for the firm.

In this section we analyze two centrality measures of manager networks. They are known in the literature as *Betweenness* and *PageRank*. A manager with high *Betweenness* or *PageRank* has a higher probability of receiving information that is circulating in the network. These measures capture not only the volume, but the variety of information that is accessible. *Betweenness centrality* is frequently used in the literature as the main proxy for information collection efficiency, as suggested in (Renneboog and Zhao 2011), and defined as the total number of shortest paths between any two other managers that pass through a given manager, normalized by the total number of shortest paths between them. It assesses how central a certain individual is in the network. Individuals with a higher *Betweenness* measure not only have access to richer and more diverse information (Intintoli *et al.* 2018), but may wield considerable influence in the network by virtue of their position as a go-between for others.

Considering that access to information is one of the channels through which a firm can benefit from a manager's network, then the most relevant names in a manager's *Degree* are those that have access to high-quality information and are likely to transmit that information. The indicator *PageRank* takes both these dimensions into account. More specifically, there are three distinct factors that determine a manager's *PageRank*: her number of connections, that is, her *Degree*; the centrality (*PageRank*) of her connections; and their *Degree*. Finally, a manager's *PageRank* also takes into account that, the more widely connected is a given connection, the less likely it is that it passes valuable information only to the manager in question. Thus, *PageRank* depends not just on the quantity of links, but also on their qualities, and a high *PageRank* can be the result of a few highly ranked connections.

Figure 7 depicts the impact on pay of a standard deviation increase in the *Betweenness* and *PageRank* measures. Both are positively correlated to total compensation, and significantly so, though the impact of *PageRank* is considerably higher.[10] The impact on total pay is driven mainly by the impact on base wage, as with the *Depth* measure, in the previous section. Thus, indirect centrality measures seem to play an important role in wage setting. Given that these indirect measures are not observable, even less so by firms, rent extraction is not likely to be behind their impact on wages, rather, these results suggest that there is indeed a positive productivity effect stemming from a more valuable network. Finally, we proceed with a simple exercise presented in Appendix B.3 to validate this hypothesis. We propose to estimate a productivity-wage gap as in Kampelmann *et al.* (2018) to gauge whether the network effect on the firm's wage bill is in line with firm-level productivity gains, or whether instead manager's with large networks are simply overpaid. Results suggest that there is a statistically significant productivity-wage gap, *i.e.* firm rents increase when small-network managers are substituted by large-network managers.[11] Indeed, the gap is largest for the indirect network metrics (in particular *PageRank*) and for the closer direct connections (*Depth*), while it is only marginally significant for the crude number of connections (*Degree*).

10. The impact of *PageRank* is robust to controlling simultaneously for network size (using any of the direct metrics), while the coefficient for the *Betweenness* metric becomes statistically insignificant.

11. This is in line with Horton *et al.* (2012) who don't find evidence on rent extraction for a sample of listed UK firms, but rather argue that firms compensate their directors for the resources these better connections provide.

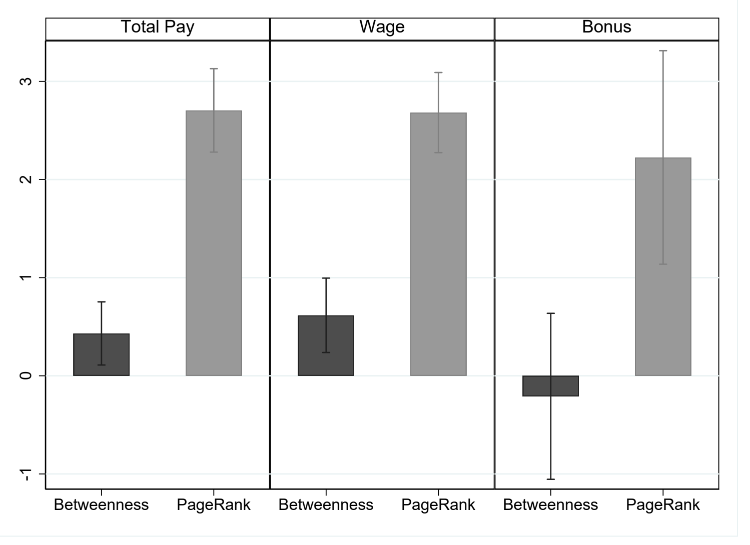

Figure 7: Indirect network measures: Betweenness and PageRank
The columns stand for the estimated coefficients for a one standard deviation change in the variable and the lines represent the 95 per cent confidence interval. Detailed estimation results can be found in Table B.3 of the Appendix.

4.4. Additional robustness checks

To reach our goal to test whether a highly connected manager is paid a premium over a more isolated manager with otherwise similar characteristics at a similar firm, we have used 5 different network measures. Next, we create an index of the global network position of the manager, based on these 5 proxies: *Degree*, *Depth*, *Power*, *Betweenness* and *PageRank*, to maximize the information content of our index. To reduce these variables into a unique informative index, we extract common components, using principal component analysis. Using this method, we obtain only one component with an eigenvalue higher than one (2,83), indicating higher explanatory power than the original input variables. We find that this broad network index is positively and significantly associated with manager total compensation. A one standard deviation increase in this index is associated with an additional 4% in hourly total pay, in line with our previous results.[12]

Finally, as an additional robustness test, we restrict the network to connections formed during the last 5 years. Liu (2014) argues that including all past connections can be problematic, because: (i) a gap of many years can weaken the connection and (ii) a cumulative network measure can create a spurious relation with pay. The latter argument is not directly an issue in our setting, because a given connection is only

12. Results are available upon request.

activated in our yearly network, if they are a manager at the time, thus our network measures can decrease over time, depending on the connections career choices. Notwithstanding, we do test whether the rolling window approach suggested by Liu (2014) changes results and conclude that our estimates remain qualitatively robust when a 5-year window is examined. We do not find any evidence that these more recent connections are more valuable for the network effect on pay.[13]

Next we investigate whether the previously estimated network premium is a horizontal result, or whether it is heterogeneous across different types of firms. Table 6 presents a set of results, where we have run specification 8 for groups of firms, according to their size, age and capital.

	Firm size		Foreign capital		Firm age	
	Small	Large	No	Yes	Young	Old
	(1)	(2)	(3)	(4)	(5)	(6)
Degree	-0.0000	0.0001***	0.0001***	0.0001***	0.0001***	0.0001***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	(7)	(8)	(9)	(10)	(11)	(12)
Depth	0.0569***	0.1439***	0.0829***	0.1352***	0.0792***	0.0763***
	(0.0108)	(0.0114)	(0.0089)	(0.0194)	(0.0099)	(0.0126)
	(13)	(14)	(15)	(16)	(17)	(18)
Power	0.0729**	0.0206***	0.0127**	0.0859***	0.0285***	0.0179*
	(0.0299)	(0.0048)	(0.0064)	(0.0075)	(0.0056)	(0.0100)
	(19)	(20)	(21)	(22)	(23)	(24)
Betweenness	0.0007***	-0.0000	0.0002***	-0.0001	-0.0000	0.0002**
	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	(25)	(26)	(27)	(28)	(29)	(30)
PageRank	1.4833**	2.3834***	4.4770***	-0.2212	4.4891***	3.0808***
	(0.7341)	(0.3522)	(0.3923)	(0.5203)	(0.4234)	(0.4892)
Observations	447,865	498,067	760,438	189,906	469,487	470,235
Year dummies	✓	✓	✓	✓	✓	✓
Firm and Manager controls	✓	✓	✓	✓	✓	✓
Manager fixed effect	✓	✓	✓	✓	✓	✓
Firm fixed effect	✓	✓	✓	✓	✓	✓

Table 6. Firm type and the network premium

This table presents estimates of firm and manager fixed effects panel regressions of the logarithm of manager total hourly pay on the network measures and other manager- and firm-level control variables, as specified in Table 4. The sample is split according to firms characteristics, where small and large, young and old firms consist of those that are below or above the sample median. Foreign capital refers to all firms with any percentage of foreign capital above nil. The sample covers the 1995-2017 period. Robust standard errors adjusted for worker-level clustering are reported in brackets. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

Columns 1 and 2 display results for the sample split into firms with a number of workers below or above the median, labeled as small and large, respectively. We find that larger firms pay a higher network premium, which is in line with more talented managers being matched to larger firms (Gabaix and Landier 2008). This finding

13. Results are available upon request.

is also consistent with the idea that larger firms have more need for external links, given the scope and complexity of their operations (Coles *et al.* 2008). Columns 3 and 4 present results for firms with and without foreign capital. A positive relation between pay and networks exists in both groups. In terms of the size of the network premium, we find no consistent evidence that any of the two groups of firms are willing to pay more or less for highly-connected managers. Finally, in columns 5 and 6 we examine how the firm's experience (age) affects the manager pay - network relation. We rank firms into young or old firms according to the median of the sample. Results point towards a higher network premium in less experienced firms. This result seems plausible, as younger firms are less well established in the market and thus more in need of a central position in the global network to access high quality information. Overall, the coefficient of interest is positive and significant in most specifications suggesting that our results are not firm-specific, but rather consistent across different firm types.

In addition, in Table 7, we analyze whether the industry in which the firm operates plays a role. We find that the network premium is driven mostly by the tertiary sector, where results are consistently positive across several industries. On the contrary, there is no evidence for a premium in the primary nor secondary sectors of activity, with the exception of the construction industry (results available upon request).

Industry	Primary	Secondary	Tertiary
	(1)	(2)	(3)
Degree	-0.0012	0.0001	0.0002***
	(0.0013)	(0.0001)	(0.0000)
	(4)	(5)	(6)
Depth	-0.0212	0.0744***	0.1126***
	(0.1057)	(0.0177)	(0.0097)
	(7)	(8)	(9)
Power	-0.0875	0.0081	0.0422***
	(0.2028)	(0.0245)	(0.0050)
	(10)	(11)	(12)
Betweenness	0.0002	0.0002*	0.0001*
	(0.0005)	(0.0001)	(0.0000)
	(13)	(14)	(15)
PageRank	3.7176	3.8684***	4.1475***
	(5.7053)	(0.6279)	(0.3580)
Observations	7,619	264,133	681,724
Year dummies	✓	✓	✓
Firm and Manager controls	✓	✓	✓
Manager fixed effect	✓	✓	✓
Firm fixed effect	✓	✓	✓

Table 7. Firm industry and the network premium

This table presents estimates of firm and manager fixed effects panel regressions of the logarithm of manager total hourly pay on the network measures and other manager- and firm-level control variables, as specified in Table 4. The sample is split according to the industry the firms operate in: primary, secondary and tertiary. Robust standard errors adjusted for worker-level clustering are reported in brackets. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

4.5. Alternative method: an instrumental variable approach

A source of endogeneity in the network literature is that common factors affect both a manager's network and pay. In other words, an unobservable variable, such as the manager's ability, has an impact on the type of firms the manager works for, determining simultaneously his network and his pay. In our study this endogeneity problem is minimized given how the network measure is defined: though influenced by a manager's career choices, yearly changes are ultimately exogenous to the manager since they are mostly driven by how past colleagues are promoted to management positions, demoted, or leave the labor market. Given the inclusion of manager and firm fixed effects, it is exactly these yearly changes that are most relevant and drive our results.

To overcome any remaining source of potential endogeneity generated by common correlated group effects, we also resort to an instrumental variable (IV) approach. A good instrument for our network measures should affect the manager's pay only by influencing their network. We follow a similar approach to Liu (2014), using the network measure of the manager's 'initial peers' as the instrument. This strategy is also in line with the approach suggested by Bramoullé *et al.* (2009) for the identification of peer effects. Specifically: we define the initial peers as all the co-workers – those working at the same time in the same firm that later become managers, who coincided with our manager in the first year of her career[14]; we compute the average network measures for these peers; we predict the manager's network measures using the network measure for those peers; finally, we use the predicted network measures from the first stage with pay as the dependent variable. Notice that to instrument *PageRank* of managers, we chose to use the average *Degree* of their initial peers, instead of their *PageRank* as the latter depends also on their own *PageRank*, causing a simultaneity problem.

As the second stage relies on the predicted network measures, which depend on the estimates of the fixed effects, we have to guarantee that the estimated coefficients of the fixed effects are comparable across groups. Following Abowd *et al.* (2002), we have restricted our analysis to the largest connected set, *i.e.*, a mobility group that includes all managers and firms that are connected.

Our strategy relies on the assumption that the initial peers' current network measures are likely to be correlated with the manager's own network centrality, but not due to her own efforts, hence with no other connection to pay. First, given that these managers worked previously at the same firm, part of their network will overlap. Second, assuming some sorting into firms and also the reverse impact of firms shaping their workers' careers, one can assume some similarity in their professional choices thereafter, creating another link between their networks.

14. We also use as an alternative definition to define the instrument, the initial three years of a manager's career. Results remain unchanged and are available upon request.

Table 8 presents the results from two stage IV regressions. In the first stage regression, in the first column, we find that the average network measures of the initial peers have a positive coefficient that is statistically significant at the 99% confidence level, validating their correlation with the manager network measures after netting out the effects of all other control variables. The associated t-statistic for the excluded instruments suggests that the chosen IVs do not suffer from the weak instrument problem. Results confirm that there exists a positive network premium on total pay, thus the previously found results persist, mitigating any endogeneity concerns. Only *Betweenness* becomes statistically insignificant.

In Figure 8, we replicate the impact on total pay of a one standard deviation increase in the size of the network measures based on the main baseline results, together with the IV estimates, turning the estimates more comparable. As seen, each network measure, except *Betweenness*, has a positive significant impact on total pay. The measure *Depth*, together with the broader centrality measure *PageRank* are more valuable than unqualified direct ties or ties to powerful managers (*Degree* and *Power*). These results are in line with our previous results, also in size, and suggest that the quality of a manager's connections prevails over quantity.

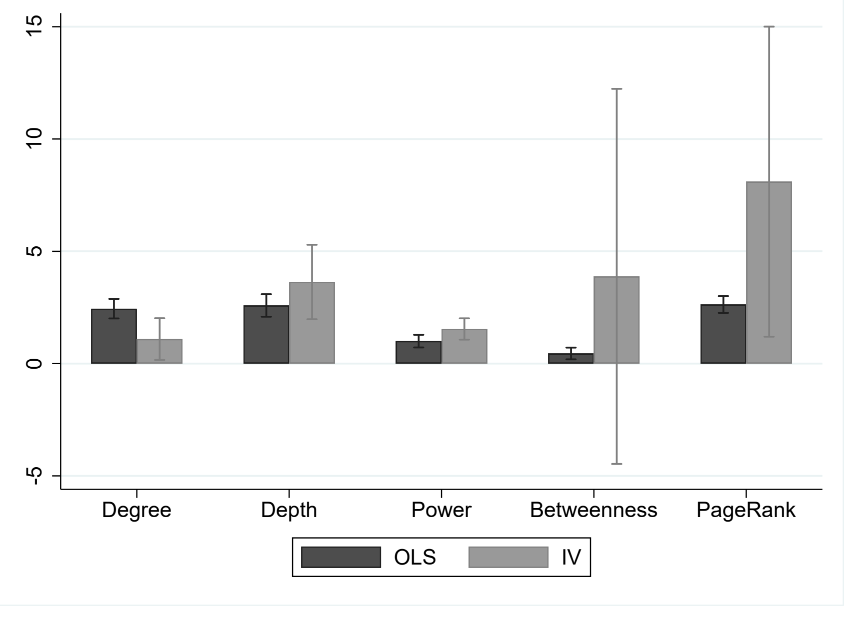

Figure 8: The network effect: OLS and IV estimations
The columns stand for the estimated coefficients for a one standard deviation change in the variable and the lines represent the 95 per cent confidence interval.

	First stage	Second stage
		Manager total pay
	(1)	(2)
Degree initial peers	0.5463***	
	(0.0102)	
Degree		0.0001**
		(0.0000)
T-stat	53.44	
Observations	665,150	665,150
	(3)	(4)
Depth initial peers	0.1270***	
	(0.0305)	
Depth		0.1444***
		(0.0337)
T-stat	4.16	
Observations	665,150	665,150
	(5)	(6)
Power initial peers	0.6078***	
	(0.0105)	
Power		0.0536***
		(0.0084)
T-stat	57.70	
Observations	665,150	665,150
	(7)	(8)
Betweenness initial peers	0.0279***	
	(0.0062)	
Betweenness		0.0033
		(0.0036)
T-stat	4.49	
Observations	665,150	665,150
	(9)	(10)
Degree initial peers	0.0033***	
	(0.0000)	
Pagerank		12.4444***
		(5.4102)
T-stat	11.84	
Observations	665,150	665,150

Table 8. The network effect: an IV approach

This table presents IV regressions of the logarithm of manager hourly pay on different network measures. The first stage regression is presented in the first column (the coefficient for *degree initial peers* in specification 9 was scaled by 10^6). Variables betweenness and PageRank have also been rescaled ($\times 1/10^3$ and $\times 10^4$, respectively). All specifications include all manager- and firm-level control variables from Table 4, as well as year, firm and manager fixed effects. The sample consists of the largest connected set of the database. Robust standard errors adjusted for manager-level clustering are reported in brackets. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

5. Concluding remarks

In this paper we add to the small but emerging body of literature that explores professional networks. Managers who are well connected enjoy better access to private information that can benefit the firm, their career options and their bargaining power. In this context, we propose to gauge the network effect on top manager's pay.

We rely on comprehensive data on the entire career of top managers, which allowed us to go beyond exploring the value of direct present connections. We consider all connections formed throughout a manager's career, unveiling which names are most valuable in a network. The analysis is based on five different network metrics, which take into account the number, *Depth* and *Power* of direct professional connections to other managers, as well as the extent and relevance of indirect connections.

The estimation of network effects is plagued by several econometric problems and data limitations. We address these concerns thoroughly. We diverge from the existing literature, by employing these network metrics in a novel way that includes substantial exogenous variation. Indeed, these measures are time-varying, increasing and decreasing over time depending on whether manager's connections become themselves managers, change firms, or exit the job market, that is, reasons exogenous to the manager. We have addressed remaining endogeneity concerns, by employing high-dimensional firm and manager fixed effects and an instrumental variable approach.

Overall, we have found consistent evidence that supports the hypothesis that networks are associated with higher base wage and bonus pay. Our findings suggest that the quality of connections prevails over quantity, where quality refers to the depth of the connections. Indirect measures that proxy better the information value of networks are also valuable. From the firm's perspective, results suggest productivity gains associated to large-network managers that go beyond the pay premium. Future research should explore further the channels through which networks create value for firms.

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Appendix

Appendix A: Variable definitions

Variable	Description
Firm Characteristics	
Sales	Log of annual sales.
Number of establishments	Number of establishments that the firm lists each year.
Number of workers	Log of number of workers registered as working at the firm in October of each year.
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.
Years of experience	Defined as the difference between the current year and the earliest year of admission found in the dataset.
Education	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.
CEO	Dummy variable that takes the value of 1 for managers who are classified as CEOs, according to the National Classification of Occupations.
Network Measures	
Degree	The sum of total connections the manager has on the annual executive network.
Depth	The weighted sum of connections the manager has on the annual executive 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 executive network, where the weight equals the average number of workers at the managed firms over the average number of managers.
Betweenness	The number of geodesics (shortest paths) going through a manager.
PageRank	PageRank is a way of measuring the importance of each manager in the network by counting not only the quantity, but also the quality of each connection. It is computed through an iterative process, where the PageRank of each manager is the sum of the PageRank of their connections normalized by their degree.

Appendix B: Additional results

B.1. Direct network metrics

	Total hourly compensation								
	Total pay			Wage			Bonus		
	Degree (1)	Depth (2)	Power (3)	Degree (4)	Depth (5)	Power (6)	Degree (7)	Depth (8)	Power (9)
Network metric	0.0001***	0.1129***	0.0399***	0.0001***	0.0938***	0.0224***	0.0002***	0.0739***	0.0942***
	(0.0000)	(0.0080)	(0.0065)	(0.0000)	(0.0073)	(0.0061)	(0.0000)	(0.0186)	(0.0196)
Age	0.0440***	0.0434***	0.0446***	0.0391***	0.0384***	0.0395***	0.0494***	0.0504***	0.0504***
	(0.0020)	(0.0020)	(0.0020)	(0.0018)	(0.0018)	(0.0018)	(0.0034)	(0.0034)	(0.0034)
Age squared	-0.0005***	-0.0005***	-0.0005***	-0.0004***	-0.0004***	-0.0004***	-0.0005***	-0.0005***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure	0.0054***	0.0055***	0.0053***	0.0037***	0.0038***	0.0036***	0.0015	0.0013	0.0013
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0011)	(0.0011)	(0.0011)
Tenure squared	-0.0000**	-0.0000**	-0.0000**	0.0000	0.0000	0.0000	0.0001**	0.0001**	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education	0.0072***	0.0075***	0.0072***	0.0083***	0.0086***	0.0083***	-0.0060	-0.0060	-0.0062
	(0.0025)	(0.0025)	(0.0025)	(0.0023)	(0.0023)	(0.0023)	(0.0053)	(0.0053)	(0.0053)
CEO dummy	0.0341***	0.0337***	0.0340***	0.0364***	0.0361***	0.0363***	0.0106**	0.0102*	0.0103**
	(0.0022)	(0.0022)	(0.0022)	(0.0020)	(0.0020)	(0.0020)	(0.0052)	(0.0052)	(0.0052)
No. of workers (ln)	0.0767***	0.0742***	0.0747***	0.0689***	0.0674***	0.0677***	0.0368***	0.0320***	0.0331***
	(0.0022)	(0.0022)	(0.0022)	(0.0020)	(0.0020)	(0.0020)	(0.0045)	(0.0045)	(0.0045)
No. establishments	-0.0002***	-0.0002***	-0.0002***	-0.0001***	-0.0001***	-0.0001***	-0.0005***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Year dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Manager fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm fixed effect	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	806,619	806,619	806,619	806,619	806,619	806,619	806,619	806,619	806,619

Table B.1. The value of direct ties

This table presents estimates of firm and manager fixed effects panel regressions of the logarithm of manager hourly pay on the network metrics *Degree*, *Depth* and *Power* and other manager- and firm-level control variables. The sample consists of all firms for which data on their top managers is available in the 1995-2017 period. Variable definitions are provided in Appendix A. Variable *Power* has been rescaled ($\times 10^4$). Robust standard errors adjusted for manager-level clustering are reported in brackets. *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

	Degree		Depth		Power	
	Base Wage	Bonus	Base Wage	Bonus	Base Wage	Bonus
Manager fixed effect	18.1%	14.1%	17.9%	15.6%	18.1%	15.2%

Table B.2. Contribution of manager heterogeneity to compensation variation

This table presents the contribution of manager fixed effects to base wage and bonus pay variability ($cov(\ln w_{ijt}, \alpha_i)/Var(\ln w_{ijt})$), based on the estimates from specifications (4) to (9) from Table B.1.

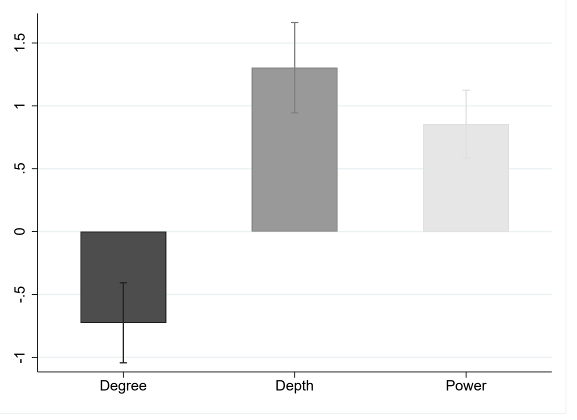

Figure B.1: Manager fixed effects and network metrics
The columns stand for the estimated coefficients for the impact of a one standard deviation change in the network metric on the estimated manager fixed effects from specifications 1 to 3 of Table B.1. The lines represent the 95 per cent confidence interval.

B.2. Indirect network metrics

	Total pay		Total hourly compensation Wage		Bonus	
	Betweenness (1)	PageRank (2)	Betweenness (3)	PageRank (4)	Betweenness (5)	PageRank (5)
Network centrality	0.0001***	5.2314***	0.0001***	4.8567***	0.0000	3.1941***
	(0.0000)	(0.2876)	(0.0000)	(0.2697)	(0.0001)	(0.7593)
Age	0.0450***	0.0429***	0.0397***	0.0378***	0.0515***	0.0502***
	(0.0020)	(0.0020)	(0.0018)	(0.0018)	(0.0034)	(0.0034)
Age squared	-0.0005***	-0.0005***	-0.0004***	-0.0004***	-0.0005***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tenure	0.0052***	0.0059***	0.0036***	0.0042***	0.0011	0.0015
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0011)	(0.0011)
Tenure squared	-0.0000**	-0.0000***	0.0000	-0.0000	0.0001**	0.0001**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Education	0.0072***	0.0072***	0.0083***	0.0083***	-0.0062	-0.0062
	(0.0025)	(0.0025)	(0.0023)	(0.0023)	(0.0053)	(0.0053)
CEO dummy	0.0340***	0.0333***	0.0363***	0.0356***	0.0104**	0.0100*
	(0.0022)	(0.0022)	(0.0020)	(0.0020)	(0.0052)	(0.0052)
No. of workers (ln)	0.0743***	0.0763***	0.0675***	0.0693***	0.0320***	0.0333***
	(0.0022)	(0.0022)	(0.0020)	(0.0020)	(0.0045)	(0.0045)
No. of establishments	-0.0002***	-0.0002***	-0.0001***	-0.0001***	-0.0004***	-0.0004***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Year dummies	✓	✓	✓	✓	✓	✓
Manager fixed effect	✓	✓	✓	✓	✓	✓
Firm fixed effect	✓	✓	✓	✓	✓	✓
Observations	806,619	806,619	806,619	806,619	806,619	806,619

Table B.3. The value of indirect ties

This table presents estimates of firm and manager fixed effects panel regressions of the logarithm of manager total hourly pay on the indirect centrality measures *Betweenness* and *PageRank* and other manager- and firm-level control variables. Variables betweenness and PageRank have been rescaled ($\times 1/10^3$ and $\times 10^4$, respectively). Robust standard errors adjusted for manager-level clustering are reported in brackets. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively.

B.3. Productivity-wage gap

A simple method to compute productivity-wage gaps is to estimate a firm-level equation, following Kampelmann *et al.* (2018):

$$\begin{aligned}&[Ln(Sales/Hours)_{jt} - Ln(Wagecost/Hours)_{jt}] \\ &= \beta_1 Network_{jt} + \beta_2 X_{jt} + \gamma_j + e_{jt}\end{aligned} \tag{B.1}$$

in which the dependent variable – the gap between firm *j*'s log hourly sales (firm sales are used as a proxy for production) and log hourly wage bill – is regressed on the shares of hours worked by large-network managers (defined as having a network metric above the yearly median) and on a set of controls X_{jt}. The latter includes firm size, the share of managers in each age and tenure quartile, the share of female managers and the share of managers by educational level. These shares account for the total number of worked hours that is accounted for by each type of manager considered. We also include firm fixed effects (γ_j) to account for heterogeneity at the firm level. Although usually in the literature a dynamic element is added to the equation, we have found no evidence for strong persistence.

Estimating Equation B.2 is equivalent to estimating separately a firm-level wage equation and productivity equation (which can be derived from a standard Cobb-Douglas production function augmented by firm-specific characteristics). The coefficient of interest β_1 determines whether marginal wage costs of large networks (the network premium) are in line with the corresponding output elasticities. A negative coefficient indicates that large-network managers are overpaid, while a positive coefficient suggests firm rents.

	Sales - Wage cost gap				
	(1)	(2)	(3)	(4)	(5)
Network metrics: share of managers					
Degree top 50%	0.0233*				
	(0.0123)				
Depth top 50%		0.0714***			
		(0.0085)			
Power top 50%			0.0517***		
			(0.0118)		
Betweenness top 50%				0.0652***	
				(0.0109)	
PageRank top 50%					0.0914***
					(0.0083)
No. of workers (log)	0.2282***	0.2289***	0.2276***	0.2274***	0.2284***
	(0.0112)	(0.0112)	(0.0112)	(0.0112)	(0.0112)
Age: share of managers					
Quartile 2	-0.0609***	-0.0663***	-0.0626***	-0.0659***	-0.0710***
	(0.0124)	(0.0124)	(0.0124)	(0.0124)	(0.0124)
Quartile 3	-0.1363***	-0.1418***	-0.1378***	-0.1421***	-0.1484***
	(0.0145)	(0.0145)	(0.0145)	(0.0145)	(0.0145)
Quartile 4	-0.2237***	-0.2288***	-0.2244***	-0.2286***	-0.2354***
	(0.0162)	(0.0162)	(0.0162)	(0.0162)	(0.0162)
Tenure: share of managers					
Quartile 2	0.0385***	0.0370***	0.0392***	0.0388***	0.0395***
	(0.0078)	(0.0078)	(0.0078)	(0.0078)	(0.0078)
Quartile 3	0.0168	0.0147	0.0189	0.0184	0.0196*
	(0.0120)	(0.0119)	(0.0119)	(0.0120)	(0.0119)
Quartile 4	-0.0708***	-0.0717***	-0.0670***	-0.0678***	-0.0670***
	(0.0175)	(0.0174)	(0.0175)	(0.0175)	(0.0174)
Share of female managers	0.0964***	0.0987***	0.0977***	0.0990***	0.1004***
	(0.0139)	(0.0139)	(0.0139)	(0.0139)	(0.0139)
Schooling: share of managers					
1st & 2nd cycle of primary education	-0.2126	-0.2269	-0.2112	-0.2108	-0.2129
	(0.1649)	(0.1628)	(0.1648)	(0.1648)	(0.1630)
Lower secondary education	-0.2174	-0.2323	-0.2164	-0.2167	-0.2194
	(0.1652)	(0.1631)	(0.1652)	(0.1651)	(0.1633)
Upper secondary education	-0.2373	-0.2502	-0.2368	-0.2373	-0.2387
	(0.1656)	(0.1635)	(0.1656)	(0.1655)	(0.1637)
Tertiary education	-0.2511	-0.2628	-0.2511	-0.2510	-0.2513
	(0.1660)	(0.1639)	(0.1660)	(0.1659)	(0.1641)
Observations	186,433	186,433	186,433	186,433	186,433
R^2	0.7999	0.8000	0.8000	0.8000	0.8002
Year dummies	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓

Table B.4. Sale-wage cost gap

The sample consists of all firms, for which data on their top managers is available in the 1995-2008 period. The sample is restricted to the period prior to 2009, due to a break in the sales series in the database. Robust standard errors adjusted for firm-level clustering are reported in brackets. *, ** and *** indicates significance at the 10%, 5% and 1% level, respectively