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Professional Networks and their Coevolution with Executive Careers: Evidence from North America and Europe

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Abstract

This paper examines how networks of professional contacts contribute to the development of the careers of executives of North American and European companies. We build a dynamic model of career progression in which career moves may both depend upon existing networks and contribute to the development of future networks. We test the theory on an original dataset of nearly 73 000 executives in over 10 000 firms. In principle professional networks could be relevant both because they are rewarded by the employer and because they facilitate job mobility. Our econometric analysis suggests that, although there is a substantial positive correlation between network size and executive compensation, with an elasticity of around 20%, almost all of this is due to unobserved individual characteristics. The true causal impact of networks on compensation is closer to an elasticity of 1 or 2% on average, all of this due to enhanced probability of moving to a higher-paid job. And there appear to be strongly diminishing returns to network size.

JEL codes: D85, J31, J62, M12
Keywords: professional networks, labor mobility, executive compensation

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1 Introduction

How important are networks of professional contacts in the development of an individual's career? Substantial evidence has accumulated in recent years that social networks have a statistical association with various aspects of professional success, notably the outcomes of job-search activities. However, little is know about how much of this association reflects a true causal role that networks might play, and if so through what causal channels this might operate.

In this paper we develop a dynamic model of career progression that distinguishes between a potential direct channel in which networks are rewarded by an individual's current employer, and an indirect channel whereby networks overcome information asymmetries and enable the individual to take advantage of employment opportunities he or she might otherwise not hear about (mobility channel). The dynamic aspect of the model is particularly important since networks not only contribute to career progression but are themselves enhanced when an individual moves from one firm to another. We then test the model using a panel of nearly 73 000 executives in over 10 000 North American and European firms.

Our dataset not only provides us with a large amount of socio-economic information about individuals, but also allows us to estimate how many currently senior executives in other firms are their former colleagues, which

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measures the size of their professional networks. Ordinary Least Squares regression of individuals' remuneration on network size yields an estimated elasticity of about 20%. However, it seems likely that some of this correlation may be due to unobserved individual characteristics - more dynamic individuals may both develop larger networks and have higher salaries, even if the networks did not contribute to their higher salaries.

In order to control for the unobserved individual characteristics we need to use the panel structure of our data. This econometric analysis suggests that only the mobility channel has a significantly positive causal effect in practice, with the direct effect of network size on executives' remuneration being even slightly negative. We estimate an elasticity of executive compensation with respect to the size of their professional networks of around 2% via this mechanism. An increase in individuals' numbers of network connections will not be rewarded by their current employers, but will slightly increase their chances of moving to a higher-paid job.

As we show in section 2, where we review the existing literature, much of the existing work on executives' networks looks at their impact on firm outcomes, whereas here we are considering the impact on individuals' careers. Our dataset allows us to perform this analysis for a larger sample of executives than has been possible to date, and to deal in a way we believe to be convincing with the identification problems that have beset many previous studies. Section 3 of this paper develops a theoretical model of an individual's dynamic career choices and derives an econometric specification. Section 4 describes our dataset. Section 5 presents the results. Section 6 concludes.

2 Literature review

The literature on social and professional networks has been growing very rapidly in recent years, both in sociology and more recently in economics.[1] The boom in network research has been seen as part of a general shift, beginning in the second half of the 20^{th} century, away from individualist explanations of economic outcomes toward more relational, contextual and systemic understandings.

Labor market outcomes are among the most carefully studied examples of the importance of networks in economics. There is substantial empirical evidence of the use of social networks as a hiring channel. Pioneering work by Rees (1966), Granovetter (1973) and Corcoran et al. (1980) found that about half of the jobs in the United States were filled through personal contacts, tendency confirmed in more recent years and for other countries by Topa (2011), and Ioannides and Datcher Loury (2004) have shown that the role played by networks has increased over time.

Networks represent an important mechanism for reducing asymmetries of information between workers and employers, in both directions. They can help compensate for workers' lack of information about available job vacancies and their characteristics, thereby reducing search frictions in labor markets (Calvo-Armengol and Jackson (2004), Galenianos (2014)). In the other direction, they may reduce employers' imperfect information about employee characteristics. In particular, a well-established literature argues that they help to screen candidates and improve the quality of matching on unobservable characteristics (Saloner (1985), Montgomery (1991), Simon and Warner (1992), Beaman and Magruder (2012), Galenianos (2013), Dustmann et al. (2015), Hensvik and Skans (2016)). They can also reduce moral hazard, since a social network may monitor and exert pressure on a worker who

[1] Because the term "social networks" has recently acquired the specific connotation of digital media platforms such as Facebook and Twitter, we shall mainly speak here of "professional networks". At all events "networks" here will always refer to contacts between individuals without any presumption that these are pursued through digital media.

was hired through it (Kugler (2003), Bandiera et al. (2013), Berardi (2013), Heath (2018)) or foster on-the-job complementarities (Bandiera et al. (2005), Pallais and Sands (2016)).[2]

Networks not only affect the probability of getting a job or a promotion, but they may have an impact on wages in a given job. However, there is no consensus as to the sign of the effect when a position is filled through networks or referrals. Simon and Warner (1992) and Kugler (2003) find higher wage rates on average, Brown et al. (2016) find no differences, and Bentolila et al. (2010) and Burks et al. (2015) find lower wages. Different modelling assumptions are consistent with either a wage penalty (Calvo-Armengol and Jackson (2004)) or a wage premium (Montgomery (1991), Simon and Warner (1992), Kugler (2003)). Using data on several European countries, Pellizzari (2010) presents evidence that the variation in wage effects of recruitment through networks seems to reflect differences in the efficiency of formal search.

The characteristics of individual networks are crucial in determining the effects on labor outcomes. Network size is the primary measure. Munshi (2003) shows that social interactions improve labor market outcomes among migrants and, in particular, that a larger network at the destination substantially increases the probability that the individual will be employed. Similarly, Bayer et al. (2008), Beaman (2011) and Laschever (2013) find that a larger network helps in job search.

Other aspects of networks may matter apart from their size. In particular, labor market characteristics of contacts might be crucial for job search. Munshi (2003) shows that migrants who benefit from a longer-established network at their destination, which is therefore more likely to be integrated into the labor market, have a substantially higher probability of employment. Schmutte (2014) show that workers are more likely to move to higher-paying

[2]Social networks could also be used for nepotism and other forms of favoritism, as shown empirically by Beaman and Magruder (2012), Berardi (2013) or Kramarz and Thesmar (2013).

firms when their neighbors are themselves working for high-paying firms. Exploiting firm closures, Cingano and Rosolia (2012), Laschever (2013) and Glitz (2017) highlight that a higher employment rate among network contacts increases the chances of finding a new job once displaced. Finally, Hensvik and Skans (2016) test the network homophily prediction of Montgomery (1991) and indeed find evidence that high-ability workers are likely to know other high-ability workers (Beaman and Magruder (2012) also find evidence of high-ability workers referring other high-ability workers).

This paper focuses specifically on the role of professional networks for top executives' careers. Professional networks are often used for recruitment at these high-level positions. Indeed, such individuals constitute "a tiny group of about a dozen individuals holding unusual power in overseeing a company's future and corporations make all efforts to recruit well-connected and experienced directors. (...) This interlocked network of board members plays a crucial role in spreading corporate practices and maintaining the political and economic clout of big corporations" (Barabasi (2003)).

Executive compensation has attracted much attention since the 90s, particularly due to growing disparities between CEO pay and average worker pay. Various theories of rent extraction by CEOs have been developed (Edmans et al. (2017)). Therefore, the finance literature interested in executives' social networks mainly investigates how these networks affect firm performance and corporate governance. For instance, Hwang and Kim (2009), Fracassi and Tate (2012) and Kramarz and Thesmar (2013) focus on connections between the CEO and directors to show that they are generally detrimental to shareholders' interests (the CEO compensation is higher and firm performance worse when more connections are present).

Our paper enriches this literature by looking at the consequences for individuals' careers instead of focusing on firm outcomes. Papers show that CEOs' networks have a sizeable effect on their compensation (Brown et al. (2012), Engelberg et al. (2012)) and their connectedness affects their outside job opportunities (Liu (2014)). Horton et al. (2012) find a positive relationship between connectedness and compensation not only for CEOs but for directors in general. The endogeneity of networks and career outcomes leads to only a few existing studies that credibly assess the causal impact of social contacts (both Shue (2013) and Zimmerman (2019) focus on university connections).

3 Theoretical framework

The key idea underlying our modeling of career dynamics is that career choices and professional networks coevolve. We develop a dynamic framework where the utility of a worker is affected by the choices she makes during her career and by the characteristics of her professional network. In particular, we distinguish two potential channels whereby professional networks may affect wages. First, a potential direct channel where connections are rewarded by the current employer. One reason could be that an employee's personal contacts with workers in another firm may increase the likelihood of new contracts or facilitate transactions between the two firms. Another possibility, even if contacts do not improve business, is that they may affect the bargaining power of a worker.[3] Second, an indirect channel where networks increase an employee's chances of moving to a higher-paid job. This is particularly true in the case of executive positions, which are often filled through head hunting and professional acquaintanceship, rather than through formal advertisement of openings.

3.1 Setting

An individual's career is modeled as a sequence of periods from $t = 0, ..., T$. In $t = 0$ the individual starts her career and at the end of $t = T$ she retires. At many points in time during an individual's career, she may have a choice

[3] This interpretation is explored for CEOs by Engelberg et al. (2012).

whether or not to change her job. While professional dynamics may entail continuous progressions within the current firm and even within the current job position, we simplify by focusing on discrete progressions. Indeed, changing firm is usually the kind of professional mobility that most actively involves and affects an individual's professional network.[4]

We thus simplify the space of career choices, restricting our attention to a worker's decision to accept an offer from another firm. Between the beginning and the end of the career, the individual may have the opportunity to change firm several times. That is, at each time $0 \leq t < T$, she may receive news of opportunities in an alternative firm. In this case, she evaluates the best outside option and compare it with the continuation in the current firm. In $t+1$ she will either still work in the current firm or have changed firm. We begin by ignoring uncertainty for the moment. The individual maximizes the sum of the discounted utility during her whole career:

$$V_1 \left(n_0 \right) = max_{\{a_t\}_{t=0}^{T-1}} \sum_{t=0}^{T-1} \gamma^t \; U_{t+1} \left(n_t, a_t \right)$$

subject to $a_t \in \{ S \left(n_t \right), M \left(n_t \right) \}$ and $n_{t+1} = \varphi \left(n_t, a_t \right) \; \forall t = 0, ..., T-1$, where γ is the discount factor, n_t are the characteristics of the relevant employment network and a_t is the decision to stay (S) or move (M) in t, which affects utility in $t+1$.

Intuitively, a worker's utility depends on mobility choices, and the probability of changing job may depend on a worker's professional network, if the information about new job opportunities spreads through it. Moreover, professional connections may directly affect utility if rewarded by the employer as part of the wage.[5] At the same time, an employee's decision to

[4]Another crucial reason why this paper restricts attention to mobility across firms is that from an empirical point of view it is possible to identify with more precision this type of mobility than promotions within a firm.

[5]Notice that unless labor markets are perfectly competitive, the value to the employer of an employee's professional network that it is possible to identify does not necessarily correspond to the marginal value of that network to the employer, but rather to the value

stay or move in t will in turn affect the shape of her professional network in $t+1$. Indeed, when a worker decides to move to a new firm, her professional network is likely to expand, since new connections will be created with new colleagues. Thus, mobility choices affect workers' networks.

Bellman's Principle of Optimality suggests that the maximization can be rewritten as:

$$V_1(n_0) = max_{a_0}\ U_1(n_0, a_0) + \gamma \left[max_{\{a_t\}_{t=1}^{T-1}} \sum_{t=1}^{T-1} \gamma^{t-1}\ U_{t+1}(n_t, a_t) \right]$$

subject to $a_0 \in \{S(n_0), M(n_0)\}$, $n_1 = \varphi(n_0, a_0)$, and $a_t \in \{S(n_t), M(n_t)\}$, $n_{t+1} = \varphi(n_t, a_t)\ \forall t = 1, ..., T-1$.

The optimal value that can be obtained is therefore:

$$V_1(n_0) = max_{a_0}\ [U_1(n_0, a_0) + \gamma\ V_2(n_1)]$$

subject to $a_0 \in \{S(n_0), M(n_0)\}$ and $n_1 = \varphi(n_0, a_0)$. In the case where time is infinite we could drop time subscripts and write
$V(n) = max_{a \in \{S(n), M(n)\}}\ [U(n, a) + \gamma\ V(\varphi(n, a))]$.

In fact an individual's career horizon is finite so the maximization problem is solved backward starting from the last period of career. In fact also, uncertainty matters to individual choices since not all possibilities are available for sure.

We assume that the individual can always choose to stay in the current firm with probability one. While not strictly realistic, this allows us to ignore firing or firm bankruptcy and focus on voluntary career moves. The decision taken in t whether or not to change job in $t+1$ arises with the probability $p(n_t)$, which is an increasing function of the number of professional ties in t.

that the employer is induced to bid for an employee at equilibrium.

Thus, in t the expected value is:

$$\mathbb{E}\, V_{t+1}\left(n_t\right) = p\left(n_t\right) max_{a_t}\left[V_{t+1}\left(n_t|a_t = S\right), V_{t+1}\left(n_t|a_t = M\right)\right] + \left[1 - p\left(n_t\right)\right] V_{t+1}\left(n_t|a_t = S\right)$$

We further assume that there always exists a potential offer that gives at least the value provided by staying in the current firm, *i.e.* $V_{t+1}\left(n_t|a_t = M\right) \geq V_{t+1}\left(n_t|a_t = S\right)$. In this case, $p\left(n_t\right)$ represents the probability that a job opportunity better than the current one arises and the expected value simplifies to:

$$\mathbb{E}\ V_{t+1}\left(n_t\right) = p\left(n_t\right) V_{t+1}\left(n_t|a_t = M\right) + (1 - p\left(n_t\right))V_{t+1}\left(n_t|a_t = S\right) \qquad (1)$$

where $V_{t+1}\left(n_t|a_t = S\right) = U_{t+1}\left(n_t|a_t = S\right)\ +\ \gamma\ \mathbb{E}\ V_{t+2}\left(n_{t+1}|a_t = S\right)$ and $V_{t+1}\left(n_t|a_t = M\right) = U_{t+1}\left(n_t|a_t = M\right)\ +\ \gamma\ \mathbb{E}\ V_{t+2}\left(n_{t+1}|a_t = M\right)$.

The optimal value depends on current utility and expected future value. That is, when a worker is considering an offer to change job, she takes into account the proposed compensation (which may be directly affected by her professional network if the employer rewards it), and also the dynamic effect of moving, through the changes in her network. Indeed, changing jobs is likely to increase her professional network, which in turn will increase the probability of receiving interesting offers in the future (and, thus, the expected future value), so that network and career coevolve. And she may choose to move to increase her network even if the immediate wage benefit would not have been enough to persuade her to move.

3.2 The role of professional connections

We turn now to a more analytical understanding of the different channels whereby professional connections affect career outcomes. From expression (1) it is easy to see that the professional network plays a role in several ways. Indeed, the derivative of the value in $t+1$ with respect to professional connections in t is:

$$\frac{\partial \mathbb{E}V_{t+1}(n_t)}{\partial n_t} = \frac{\partial p(n_t)}{\partial n_t}\left[V_{t+1}(n_t|a_t=M) - V_{t+1}(n_t|a_t=S)\right] + \\ + p(n_t)\left[\frac{\partial V_{t+1}(n_t|a_t=M)}{\partial n_t} - \frac{\partial V_{t+1}(n_t|a_t=S)}{\partial n_t}\right] + \frac{\partial V_{t+1}(n_t|a_t=S)}{\partial n_t} \tag{2}$$

If we assume that the way connections affect the value does not depend on mobility decisions,[6] *i.e.* $\frac{\partial V_{t+1}(n_t|a_t=M)}{\partial n_t} \approx \frac{\partial V_{t+1}(n_t|a_t=S)}{\partial n_t}$, then expression (2) simplifies to:

$$\frac{\partial \mathbb{E}V_{t+1}(n_t)}{\partial n_t} = \underbrace{\frac{\partial V_{t+1}(n_t|a_t=S)}{\partial n_t}}_{connection\ direct\ effect} + \underbrace{\left[V_{t+1}(n_t|a_t=M) - V_{t+1}(n_t|a_t=S)\right]}_{mobility\ effect} \underbrace{\frac{\partial p(n_t)}{\partial n_t}}_{connection\ indirect\ effect} \tag{3}$$

Expression (3) means that the overall impact of connections results from two channels and three effects. The first term constitutes the direct effect that professional connections have on value beyond mobility, that is, the extent to which they directly affect the career value. It captures the extent to which the employer rewards a worker's contacts (direct channel). The second term captures the role that professional networks play through mobility (mobility channel) through two effects: the gain from changing job with respect to staying in the current firm (mobility effect) multiplied by the extent to which connections affect the probability of getting the information about a better

[6]If this hypothesis were not true, the same network would have a different effect depending on whether a worker changes firm or not. That is, the connection direct effect would be different for stayers and movers. In this case, empirically we would need to allow for potentially different effects on connections on the salary for movers and stayers. We should then estimate an endogenous switching model. However, since there are few observations for movers, convergence is not achieved. Therefore, to the extent that it is reasonable to assume that connections have the same effect on salary for movers and for stayers, it is possible to interpret the difference in the impact of connections on value for movers and stayers as a measure of the probability of moving.

job opportunity (connection indirect effect).

3.3 From the theoretical framework to the empirical specification

In order to assess the relative role played by the different channels that are identified in the theoretical framework, it is necessary to disentangle the three effects. Indeed, if we simply estimated $Y_{t+1} = \beta_0 + \beta_1 n_t + \beta_2 X_{t+1} + \epsilon_{t+1}$, where Y_{t+1} is the career value (for the moment, it can be useful to think of it as simply the wage) and X_{t+1} the standard determinants, the estimated coefficient $\widetilde{\beta}_1$ would combine the three effects whereby connections affect a worker's value.[7] Nor it is sufficient to include explicitly the mobility decisions (*i.e.*, $Y_{t+1} = \beta_0 + \beta_1 n_t + \beta_2 X_{t+1} + \beta_3 A_t + \epsilon_{t+1}$, where A_t is the decision taken in period t, or $Y_{t+1} = \beta_0 + \beta_1 n_t + \beta_2 X_{t+1} + \beta_3 A_t + \beta_4 n_t * A_t + \epsilon_{t+1}$), since A_t may be endogenous with respect to Y_{t+1}. Indeed, beyond professional networks, some unobserved individual or firm characteristics may affect both mobility and salary.

Instead, our theoretical framework suggests a benchmark empirical specification that takes into account the dependence of utility on connections and on mobility decisions. It consists of two stages. The first stage estimates the probability of being offered a better job opportunity:

$$A_t = \delta_0 + \underbrace{\delta_1}_{connection\ indirect\ effect} n_t + \delta_2 Z_t + \zeta_t \tag{4}$$

where Z_t includes the controls X_{t+1} and some determinant of mobility that is legitimately excluded from the second stage. The second stage is then represented by:

$$Y_{t+1} = \beta_0 + \underbrace{\beta_1}_{connection\ direct\ effect} n_t + \beta_2 X_{t+1} + \underbrace{\beta_3}_{mobility\ effect} \widehat{A}_t + \epsilon_{t+1} \tag{5}$$

[7] Table 1 in the Results section shows this exact estimated coefficient. It is positive and significant but does not tell anything about whether professional networks are valuable directly, indirectly through mobility decisions or both.

The three components singled out in the theoretical framework (see expression (3) in section 3.2) correspond to the estimated coefficient $\widehat{\beta_1}$ (connection direct effect), $\widehat{\beta_3}$ (mobility effect), and $\widehat{\delta_1}$ (connection indirect effect). .

One final issue needs to be resolved, and this is the choice of the dependent variable. The dependent variable in equation (5) is the career value, not the wage in period $t+1$. However, the career value is not observed directly, though it will be positively correlated with the wage in $t+1$. We therefore propose to use the wage in $t+1$ as our dependent variable but to bear in mind that there may be biases linked to the imperfect measurement of career value by the current wage. In particular if the current wage over-reacts to a change of firms, the parameter estimate with respect to the current wage will represent an over-estimate of the impact of a change of firm on the career value; and conversely, if the current wage under-reacts, it will represent an under-estimate. This should be borne in mind in interpreting the results that follow.

4 Dataset and empirical strategy

Our analysis is based on an original dataset describing the career history of nearly 73,000 executives of over 10 000 North American and European publicly listed companies between 2000 and 2008. It was build from a larger database provided by BoardEx Ltd, a UK supplier of data to headhunting companies (which we refer to hereafter as the 'main' database), consisting of information on more than 300 000 executives and board members of over 16 000 companies across the world.

We exclude private firms because they do not have to report remuneration of top executives and board members.[8] We restrict our sample period to the pre-crisis one (i.e. until 2008), to avoid contamination by the way in

[8]They represent 25% of firms in the main database.

which many firms had to adopt drastic measures, including limiting executive compensation, in response to the new conditions.[9] Moreover, our analysis discards individuals with no executive responsibilities during the 2000-2008 period.[10]

Our econometric analysis uses panel estimation, not just because we are interested in the dynamic nature of career development, but also because cross-sectional correlations between network size and career advancement might easily be due to unobservable characteristics of individuals. For instance, more talented, dynamic or energetic individuals (qualities we cannot see in our dataset) might be able both to develop larger professional networks and to advance further in their careers. Panel estimation can enable us to control for all such factors that have a constant impact on outcomes.

Unfortunately, information on individuals is often not available each year between 2000 and 2008. Moreover, even individuals who are always present in the executive panel may have remuneration information in some years but not in others, as disclosure depends on regulation. Since individuals drop in and out of our executive and compensation panels, and there is every reason to think that they do not do so at random but in response to precisely those evolving career opportunities that it is our aim to study, it is important to carry out our analysis also on the unbalanced panels of a larger set of executives who do not hold executive positions in all years or who do not always have their compensation disclosed.[11]

[9] We have 268 388 individuals and 11 283 firms in the 2000-2008 period.

[10] Non-executives have very different compensation schemes from executives, often composed of a standardized board meeting fee, and usually hold a position in many boards at the same time. Moreover, since the transition between executive and non-executive positions is often used as a pre-retirement period, we focus on workers that keep executive positions over time. Vancil (1987) estimates that 80% of exiting (non-deceased) CEOs remain on their firms' boards of directors; and 36% continue serving on the board as chairman. In the 2000-2008 period, around 40% of individuals never had an executive position in publicly listed companies. Our analysis is based on the remaining individuals, who were either "always executives" or "sometimes executives" in publicly listed companies during the 2000-2008 period.

[11] Fortunately, it turns out that these different estimation strategies deliver very similar results.

Therefore, in the following section we present results for four different but complementary panels. Two of these are balanced, with all individuals observed in all years. The first one is the Executive panel and includes all executives present in the dataset in all years between 2000 and 2008, whether or not we have information about their compensation (19,031 individuals). The second one, the Compensation panel, further requires executives to have disclosed annual compensation for all years between 2000 and 2008 (1,731 individuals).

The remaining two panels provide the unbalanced equivalents of the above two balanced panels. The Executive unbalanced panel includes all executives present in the dataset in at least 2 of the years between 2000 and 2008, whether or not we have information about their compensation (72,652 individuals). The Compensation unbalanced panel consists of 22,905 individuals for whom we have annual compensation for at least 2 years between 2000 and 2008. This is the panel for which we have in our view the best compromise between sample size and informativeness of the outcome variable.

Tables 1 and 2 show the descriptive characteristics at the individual level for the four samples.[12] Beyond information about individuals' demographic characteristics such as age and gender, about their job and education, the special feature of our dataset is the information provided on networks. In general, each individual is simultaneously embedded in very different types of social networks. In the present context we are particularly interested in the professional network, that is, the connections resulting from one's professional activity.[13]

[12]Notice that some variables considerably differ between the Compensation (table 1) and the Executive (table 2) samples, because the former is a highly selected subset of the latter. They also differ considerably between the balanced and unbalanced panels, for the same reason.

[13]While many studies focus on friends, the focus of this paper is on professional connections. Indeed, Podolny and Baron (1997) find that friendship is not the relevant network for studying career mobility. Cingano and Rosolia (2012), Hensvik and Skans (2016) and Glitz (2017) use the same notion of professional network that we adopt.

Table 1: Descriptive Statistics - Compensation sample

	Balanced		Unbalanced			
	Mean	SD	Mean	SD	Diff.	SE
Connections	60.440	88.842	88.295	137.090	27.855***	3.347
Current colleagues	27.351	22.398	32.035	31.268	4.684***	0.766
Net connections	33.089	79.593	56.260	123.143	23.171***	3.006
Placebo connections	54.931	132.896	85.269	173.066	30.339***	4.251
Conn. in sales expanding firms (prop.)	0.581	0.204	0.520	0.251	-0.061***	0.006
Conn. in employees expanding firms (prop.)	0.577	0.205	0.514	0.248	-0.063***	0.006
Salary	214.396	87.181	188.771	92.126	-25.626***	2.302
Annual compensation	860.575	633.078	869.079	819.058	8.503	20.126
Top 5 earners (prop.)	0.968	0.095	0.889	0.230	-0.079***	0.006
Changed firm dummy	0.042	0.156	0.060	0.215	0.018***	0.005
Age	51.455	7.443	49.998	7.604	-1.457***	0.189
Female (prop.)	0.040	0.197	0.063	0.243	0.023***	0.006
CEO	0.343	0.431	0.210	0.385	-0.132***	0.010
CFO, COO	0.249	0.394	0.250	0.412	0.002	0.010
President, Vice President, Chief Officer	0.178	0.346	0.299	0.439	0.120***	0.011
Director, Head, Officer	0.177	0.357	0.185	0.375	0.008	0.009
Other Executives	0.006	0.070	0.006	0.069	-0.000	0.002
Degree level: Bachelor (prop.)	0.272	0.445	0.280	0.449	0.008	0.011
Degree level: Master (prop.)	0.339	0.473	0.367	0.482	0.029*	0.012
Degree level: PhD (prop.)	0.214	0.410	0.200	0.400	-0.014	0.010
Degree major: Business (prop.)	0.238	0.426	0.264	0.441	0.026*	0.011
Degree major: Finance (prop.)	0.142	0.349	0.112	0.316	-0.029***	0.008
Degree major: Social Sciences (prop.)	0.080	0.271	0.087	0.282	0.007	0.007
Degree major: Science (prop.)	0.017	0.128	0.021	0.144	0.005	0.004
Observations	1 731		22 905			

Statistical significance levels: * $p<0.05$ ** $p<0.01$ *** $p<0.001$

There are several ways of assessing networks. Often people are asked to list their contacts. This procedure suffers however from concerns related to self-reporting and directionality of the reported ties. Moreover, such data are usually costly to collect and therefore usually identify rather small and intimate networks, or at least the networks of a relatively small sample of individuals. Here instead, connections are based on objective measures of membership in a group of co-workers.[14] In our dataset a connection is cre-

[14]This definition has the advantage of enabling us to obtain comparable measures of connections for a large number of individuals based on publicly available data for all listed companies, rather than to depend on partial and potentially unrepresentative surveys. It has the disadvantage that we have to interpret connections as opportunities, given by the fact of being colleagues, to invest time and energy in the formation of more solid personal

Table 2: Descriptive Statistics - Executive sample

	Balanced		Unbalanced			
	Mean	SD	Mean	SD	Diff.	SE
Connections	71.980	111.552	76.127	122.274	4.146***	0.978
Current colleagues	30.879	29.400	30.798	31.442	-0.081	0.253
Net connections	41.101	93.355	45.329	106.030	4.227***	0.843
Placebo connections	52.015	135.480	68.875	155.630	16.860***	1.235
Conn. in sales expanding firms (prop.)	0.445	0.264	0.412	0.274	-0.033***	0.002
Conn. in employees expanding firms (prop.)	0.428	0.264	0.399	0.271	-0.029***	0.002
Top 5 earners (prop.)	0.239	0.368	0.251	0.382	0.012***	0.003
Changed firm dummy	0.050	0.167	0.041	0.148	-0.009***	0.001
Age	47.976	7.828	47.986	8.070	0.010	0.065
Female (prop.)	0.103	0.303	0.105	0.306	0.002	0.002
CEO	0.117	0.276	0.119	0.294	0.002	0.002
CFO, COO	0.150	0.300	0.174	0.342	0.023***	0.003
President, Vice President, Chief Officer	0.348	0.383	0.371	0.428	0.023***	0.003
Director, Head, Officer	0.096	0.250	0.138	0.320	0.042***	0.002
Other Executives	0.020	0.113	0.024	0.138	0.004***	0.001
Degree level: Bachelor (prop.)	0.314	0.464	0.303	0.460	-0.011**	0.004
Degree level: Master (prop.)	0.372	0.483	0.380	0.485	0.008*	0.004
Degree level: PhD (prop.)	0.181	0.385	0.181	0.385	-0.000	0.003
Degree major: Business (prop.)	0.244	0.430	0.257	0.437	0.013***	0.004
Degree major: Finance (prop.)	0.100	0.300	0.104	0.305	0.004	0.002
Degree major: Social Sciences (prop.)	0.097	0.296	0.089	0.285	-0.008***	0.002
Degree major: Science (prop.)	0.023	0.151	0.024	0.152	0.000	0.001
Observations	19 031		72 652			

Statistical significance levels: * $p<0.05$ ** $p<0.01$ *** $p<0.001$

ated when two persons work together in a publicly listed company. While this is not equivalent to their being friends or even close colleagues, it does strongly suggest that they know each other.

In what follows we use the variable name 'Connections' to refer to the number of members of the BoardEx main database with whom an individual in our dataset has worked in the same firm at the same time.[15] This is evi-

and professional links. We cannot observe such investments directly - however, even if we could they would be endogenous decisions and therefore less useful in econometric analysis than the opportunities which are more independent of an individual's own choices.

[15]Notice that the connections are to members of the main database and not necessarily to other individuals in our restricted dataset, which would arbitrarily restrict our measure of the size of individuals' networks by whether or not members of that network are themselves executives, working for North American or European companies during the pre-crisis period.

dently not a measure of the total of an individual's colleagues, just of those who have become sufficiently influential to feature in the BoardEx database. However, some of these connections will represent current colleagues, so the main explanatory variable we shall use in the analysis that follows is 'Net connections', derived by subtracting current colleagues from total connections. This allows us to avoid problems of reverse causality, by investigating the role of past connections on future career outcomes. Executives have on average 72 professional connections, of whom 31 are current colleagues.

We also use in the analysis another network-related variable, called 'Placebo connections', which measures the number of members of the BoardEx main database with whom an individual in our dataset has worked in the same firm but not at the same time. This is the same measure as developed in Lalanne and Seabright (2016) and (independently) in Hensvik and Skans (2016). This variable captures the various characteristics that individuals share with their contacts through being hired by the same employer, except for the fact of having been employed at the same time. It can therefore be used as a control variable, in specifications in which 'Net connections' is the explanatory variable of interest, as a proxy measure of the unobserved individual characteristics that be statistically associated with individuals' having differently sized networks. We use this variable in our regressions as an alternative to fixed effects, the placebo variable acting like a placebo in clinical medical trials, which captures the effect of everything involved in a treatment but the chemical molecule under investigation.

By analogy with the medical application in which we seek to measure the effect of treatment over placebo, we should consider the true causal effect of connections to be measured by the difference between the coefficient on connections and that on placebo connections. This measures by how much more it helps an individual to have worked with others rather than merely to have been employed by the same firm as them.[16]

[16]In the same way, the treatment effect over placebo in the clinical trial of a pharmaceutical product measures the impact of receiving a particular active ingredient over the

We should not necessarily expect the coefficient on placebo effects to be zero (and in clinical trials it is often non-zero also). Being employed by the same firm as other influential individuals though not at the same time may either provide a direct career benefit, or be correlated with certain unobservable individual characteristics that reflect the firm's recruitment strategy. In fact as we shall see the coefficient on placebo connections is typically non-zero in our estimations here.

We show below that 'Placebo connections' acts as a good proxy for unobserved individual heterogeneity when fixed effects cannot be implemented because of concerns about missing observations in a panel, as in Hensvik and Skans (2016). This is because the coefficient on 'Net connections' with fixed effects is usually of similar magnitude to the difference in coefficients on 'Net connections' and 'Placebo connections' in a specification without fixed effects.

We look at two dependent variables related to the success of an executive' career. The first one, annual 'Compensation', is the sum of salary, bonus, value of shares awarded, value of long term incentives programs awarded and the estimated value of options awarded in a given year.[17] As firms are not obliged to disclose the compensation of all their executives,[18] this dependent variable is missing for many executives. The sample of executives for whom information about compensation is available allows us to quantify the effect of professional networks on career outcomes.

We also carry on our analysis on the whole sample of executives. In this case, because compensation data are not available for everyone, we use another dependent variable, which we call the 'Top 5 earners' dummy, taking value 1 if an executive's compensation is disclosed and ranks among the top

impact of being given medical attention and a sugar pill.

[17]We trim the top 5%.

[18]In the US and Canada, each publicly listed firm has to disclose compensation information of the CEO, the CFO and the next three top earners. In Europe, companies have to disclose compensation of executives who are also on the board.

five of the company in a given year, and 0 otherwise. This dummy variable conveys less information than the compensation variable, but it nonetheless tags very successful executives and allows to carry on our analysis on a much larger sample. Most executives in the Compensation sample are among the top five earners of the company, compared to about one fourth in the Executive sample.

A crucial element for our analysis of executives' career and professional networks is their choice of moving to another firm. Executives' mobility decisions are captured by a dummy variable called 'Changed firm', taking value 1 if an executive ever changed firm since the beginning of our sample period (i.e. 2000) and 0 otherwise. 6% of executives in our compensation sample changed firm within our sample period. As explained in section 3.3, we first predict these (endogenous) mobility decisions, using network-related instrumental variables; this will allow us to estimate the connection indirect effect. We then regress the estimated change firm dummy together with the net connections variable on Compensation and Top 5 earners dummy to estimate the mobility and connections direct effects.

Our instruments are based on the proportion of connections in an executive's professional network that have been working for expanding firms. The idea is that expanding firms are more likely to be hiring, and therefore professional contacts working for such firms are more likely to transmit information about job opportunities. Therefore the larger the proportion of connections working for expanding firms, the larger the probability that an executive receives information on a new job from her professional network and decides to change firm. At the same time, the proportion of connections working for expanding firms should not directly affect an executive's compensation or access to the top executive echelons, only indirectly through her mobility choices.[19] We define expanding firms in the following way: in each

[19]We also tried as instruments the proportion of connections who became CEOs, changed jobs themselves or obtained additional (non-executive board) positions. However, we believe these latter instruments to be less exogenous than the ones we use, since homophily in networks means that more talented individuals may have more contacts who

year, a firm is considered as expanding if its growth rate is higher than the median growth rate of all firms for that year. The two instruments used in the analysis are based on firm growth rates in terms of sales and number of employees. Using two instruments also allows us to calculate tests of overidentification. More than 40% of professional contacts have been working for an expanding firm.[20]

Table 3 shows the descriptive characteristics at the firm level for the Compensation and Executive unbalanced samples.[21] The large majority of firms are based in the US, followed by the UK and France.[22]

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are themselves talented and therefore more likely to have become CEOs. Our instruments here are based on firms' success rather than on individuals' success.

[20]This proportion goes up to almost 60% for the Compensation sample.

[21]Data from the databases Compustat (for North American companies) and Amadeus (for European companies) were matched to the dataset to provide extra firm characteristics such as sales or the number of employees.

[22]Table 11 in the Appendix shows that the firms in our data constitute the overwhelming majority of indexed firms in their respective countries.

Table 3: Descriptive Statistics - Firms

	Compensation unbalanced sample	Executive unbalanced sample
Country: Canada (prop.)	0.002	0.039
Country: France (prop.)	0.037	0.027
Country: Finland (prop.)	0.003	0.005
Country: Germany (prop.)	0.017	0.021
Country: Ireland (prop.)	0.014	0.009
Country: Italy (prop.)	0.014	0.011
Country: Netherlands (prop.)	0.018	0.012
Country: Norway (prop.)	0.015	0.011
Country: Spain (prop.)	0.003	0.008
Country: Sweden (prop.)	0.028	0.019
Country: Switzerland (prop.)	0.007	0.012
Country: UK (prop.)	0.288	0.187
Country: US (prop.)	0.530	0.594
Sector: Construction (prop.)	0.039	0.029
Sector: Defense (prop.)	0.009	0.007
Sector: Education (prop.)	0.002	0.003
Sector: Finance (prop.)	0.136	0.171
Sector: Health (prop.)	0.036	0.046
Sector: Information (prop.)	0.151	0.135
Sector: Manufacturing (prop.)	0.269	0.261
Sector: Mining (prop.)	0.063	0.082
Sector: Real Estate (prop.)	0.038	0.039
Sector: Services (prop.)	0.088	0.083
Sector: Technical (prop.)	0.047	0.044
Sector: Trade (prop.)	0.057	0.046
Sector: Transportation (prop.)	0.033	0.029
Sector: Utility (prop.)	0.032	0.025
Index: S&P 500 (prop.)	0.220	0.170
Index: S&P 1500 (prop.)	0.542	0.510
Index: FTSE 100 (prop.)	0.042	0.033
Index: FTSE ALL SHARES (prop.)	0.334	0.339
Index: NASDAQ 100 (prop.)	0.042	0.032
Index: EUROTOP 100 (prop.)	0.034	0.035
Index: CAC 40 (prop.)	0.016	0.014
Index: DAX (prop.)	0.008	0.011
Index: OBX (prop.)	0.006	0.006
Observations	5 024	10 416

5 Results

In this section we estimate the impact of the size of an individual's professional network on her career outcomes. We begin by reporting the results of some simple regressions using Ordinary Least Squares before considering the panel estimation. Table 4 shows that the size of executives' networks is positively and very significantly correlated with professional outcomes, whether these are measured by compensation or by presence among the top 5 earners in the firm. The coefficient in the regression where the dependent variable is Compensation has a natural interpretation. A 10% increase in network size is associated with about 2% higher compensation, which seems an empirically plausible result. The interpretation of the coefficient in the regression with the Top 5 earners dummy as dependent variable is that a 10% increase in network size increases the probability of being among the top 5 earners of the firm by about 0.2 percentage points, compared to sample average of about 25%.

It is encouraging to note that the estimates differ rather little between the balanced and the unbalanced panels. In particular, the elasticity of compensation with respect to connections is about 20% in both panels, although the balanced panel contains fewer than 10% as many individuals (1602 as opposed to 22821).

Table 4: Estimates of the relation between connections and career outcomes

	Compensation		Executive	
	Balanced Panel	Unbalanced Panel	Balanced Panel	Unbalanced Panel
(Log of) Net Connections	0.192***	0.200***	0.024***	0.029***
	(0.005)	(0.002)	(0.001)	(0.000)
Controls	Yes	Yes	Yes	Yes
Individual fixed effects	No	No	No	No
Nb of observations	15 579	104 628	171 279	423 643
Nb of individuals	1 731	22 905	19 031	72 652
R2	0.240	0.258	0.118	0.127

Robust standard errors in parentheses. Statistical significance levels: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies.

We now investigate how much of this systematic correlation between networks and career outcomes represents a true causal impact of the former on the latter. Table 5 shows, for the Compensation balanced panel, that unobserved individual characteristics account for most, if not all, of this aggregate positive correlation. Column I reproduces the result in the first column of Table 4. Column II includes fixed effects, with the result that the coefficient on connections changes from significantly positive to insignificantly positive, falling from an elasticity of 19.2% to one of just 1%. It seems likely that, overall, the correlation between larger networks and higher salaries is mostly due to the fact that more talented individuals tend to have both larger networks and higher compensation. But increases in the size of an individual's networks (because, for example, more of her previous colleagues become successful executives and enter the BoardEx database) do not, on average, have a significant positive effect on remuneration.

Column III of Table 5 shows that using Placebo connections is a good alternative to using fixed effects. The coefficient on Placebo connections is positive and highly significant, and the difference between the two (the effect of treatment over placebo) yields an elasticity of about 1%, similarly to the coefficient estimated using fixed effects. This suggests that, for compensation at least, we may be on reasonably firm ground in using Placebo Connections to control for unobservable heterogeneity when using fixed effects is infeasible.

Column IV of Table 5 shows the estimates corresponding to equation (5) in section 3.3, that is: $Y_{t+1} = \beta_0 + \beta_1 n_t + \beta_2 X_{t+1} + \beta_3 \widehat{A}_t + \epsilon_{t+1}$. The insignificantly positive average impact of network size on compensation in column II masks two distinct and opposite effects, which we can untangle by looking at the decision to change firm, as suggested by our theoretical model. The connection direct effect (β_1) is in fact negative, but the mobility effect (β_3) is positive, large and very highly significant (as estimated by instrumental variables because of its evident endogeneity). It should be noted that the F-test shows a high significance of our excluded coefficients, and the Hansen overidentification test suggests they are indeed legitimately excluded from the second stage regression.

Table 6 shows that results are remarkably similar when we run the same analysis on the unbalanced panel. This has the great advantage that we now have data on 22821 individuals instead of on 1602, and that we can draw conclusions not only on a selected set of executives but on a larger set of them. We consider these results as our baseline.

Tables 8 and 9 show that qualitatively similar conclusions can be drawn from outcome variable Top 5 earners dummy for the Executives balanced and unbalanced panels respectively. The average correlation of network size with outcomes is due, on average, to unobserved individual characteristics. The connection direct effect is once again negative. And the effect of changing firm is once again positive, large, and highly significant.

In order to compute the overall impact of connections through mobility we need to multiply the coefficient of changing firm by a measure of the ex-

Table 5: Estimates of the impact of connections on compensation (balanced panel)

	Dependent variable: Log of Compensation			
	I	II	III	IV
(Log of) Net Connections	0.192***	0.016	0.104***	-0.122***
	(0.005)	(0.018)	(0.008)	(0.033)
(Log of) Placebo Connections			0.092***	
			(0.006)	
Changed Firm Dummy				3.497***
				(0.734)
Individual FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	2SLS
Nb of observations	15 579	15 579	15 579	15 579
Nb of individuals		1 731		1 731
R2	0.240	0.153	0.252	0.561
Hansen J stat				0.115
p-value				0.735
F-test(1st stage)				29.949
p-value				0.000

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies.

Table 6: Estimates of the impact of connections on compensation (unbalanced panel)

	Dependent variable: Log of Compensation			
	I	II	III	IV
(Log of) Net Connections	0.200***	0.011	0.119***	-0.094***
	(0.002)	(0.006)	(0.003)	(0.014)
(Log of) Placebo Connections			0.098***	
			(0.002)	
Changed Firm Dummy				2.452***
				(0.279)
Individual FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	2SLS
Nb of observations	104 628	104 628	104 628	104 628
Nb of individuals		22 905		22 905
R2	0.258	0.065	0.272	0.743
Hansen J stat				0.098
p-value				0.755
F-test(1st stage)				125.333
p-value				0.000

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies.

Table 7: Estimates of the impact of connections on job mobility (Compensation balanced and unbalanced panels) - First stage regressions

	Dependent variable: Changed firm dummy	
	Balanced panel	Unbalanced panel
Prop. of connections in firms with:		
Expanding sales	0.035***	0.043***
	(0.005)	(0.003)
Expanding nb of employees	0.023***	0.026***
	(0.006)	(0.003)
(Log of) Net Connections	0.041***	0.043***
	(0.004)	(0.002)
Individual FE	Yes	Yes
Controls	Yes	Yes
Nb of observations	15 579	104 628
F-test	29.949	125.333
p-value	0.000	0.000

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies.

Table 8: Estimates of the impact of connections on being Top 5 earners (Executives balanced panel)

	Dependent variable: Top 5 earners dummy			
	I	II	III	IV
(Log of) Net Connections	0.024^{***}	-0.008^{***}	-0.002^{*}	-0.109^{***}
	(0.001)	(0.002)	(0.001)	(0.011)
(Log of) Placebo Connections			0.032^{***}	
			(0.001)	
Changed Firm Dummy				2.061^{***}
				(0.212)
Individual FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	2SLS
Nb of observations	171 279	171 279	171 279	171 279
Nb of individuals		19 031		19 031
R2	0.118	0.042	0.125	0.343
Hansen J stat				1.989
p-value				0.158
F-test(1st stage)				79.070
p-value				0.000

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies.

Table 9: Estimates of the impact of connections on being Top 5 earners (Executives unbalanced panel)

	Dependent variable: Top 5 earners dummy			
	I	II	III	IV
(Log of) Net Connections	0.029***	-0.000	0.018***	-0.062***
	(0.000)	(0.001)	(0.001)	(0.005)
(Log of) Placebo Connections			0.016***	
			(0.001)	
Changed Firm Dummy				1.418***
				(0.111)
Individual FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	2SLS
Nb of observations	423 643	423 643	423 643	423 643
Nb of individuals		72 652		72 652
R2	0.127	0.024	0.129	0.565
Hansen J stat				4.866
p-value				0.027
F-test(1st stage)				188.602
p-value				0.000

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies.

Table 10: Estimates of the impact of connections on job mobility (Executives balanced and unbalanced panels) - First stage regressions

	Dependent variable: Changed firm dummy	
	Balanced panel	Unbalanced panel
Prop. of connections in firms with:		
Expanding sales	0.022***	0.032***
	(0.003)	(0.002)
Expanding nb of employees	0.018***	0.018***
	(0.003)	(0.002)
(Log of) Net Connections	0.049***	0.044***
	(0.001)	(0.001)
Individual FE	Yes	Yes
Controls	Yes	Yes
Nb of observations	171 279	423 643
F-test	79.070	188.602
p-value	0.000	0.000

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies.

tent to which networks increase the probability of changing firm. The latter corresponds to δ_1 in equation (4) in section 3.3: $A_t = \delta_0 + \delta_1 n_t + \delta_2 Z_t + \zeta_t$. Tables 7 and 10 report the first stage regressions for the instrumental variables estimation for the two outcome variables. We can see that the excluded instruments have, as expected, a positive and highly significant impact on the probability of changing firm. Individuals whose connections work for firms that are expanding are more likely to change firms themselves. To get a feel for the magnitude we can express it this way: if we compare two individuals, one of whom has 75% of her connections working in expanding firms and the other has 25% of her connections working in expanding firms, the first individual is around 1.5 percentage points more likely to change firm. This may not seem a lot, but only about 6% of executives in our sample change firm, so this represents an increase of around a quarter in the probability of doing so.

The third row reports the coefficient on Net connections (which corresponds to the connection indirect effect through mobility δ_1), which is also positive and highly significant, with a value of around 4%. Multiplying it by the coefficient of 2.8 on the Changed firm dummy in Tables 5 and 6 (corresponding to the mobility effect β_3) yields an overall elasticity of 11.2%. This is the overall causal effect of connections through mobility and is more than half the size of the raw correlation between connections and compensation as estimated by Ordinary Least Squares. It means that an increase of 10% in the number of net connections, which means an extra 3 net connections at the sample mean of 33 in the balanced panel or an extra 6 net connections at the sample mean of 56 in the unbalanced panel, results in an expected increase in compensation of 1.1% through an increased probability of moving to higher-paying job in another firm.

To quantify the overall impact of connections we need to add the direct effect of connections on remuneration and the overall impact of connections through mobility, as specified in equation (3) in section 3.2: $\frac{\partial \mathbb{E} V_{t+1}(n_t)}{\partial n_t} = \frac{\partial V_{t+1}(n_t|a_t=S)}{\partial n_t} + \left[V_{t+1}\left(n_t|a_t = M\right) - V_{t+1}\left(n_t|a_t = S\right)\right] \frac{\partial p(n_t)}{\partial n_t}$. Since our estimation of the connection direct effect is negative, the overall impact of connections is lower that through the mobility channel alone and is slightly larger than the fixed effects estimation of the overall impact of connections on remuneration, namely around 2%. The bottom line seems to be that larger networks of connections are mostly a symptom of an executive's success and do not contribute very much causally to that success; they have a very modest positive effect.

How should we interpret the negative sign of the connection direct effect? Is this really a causal coefficient, telling us that, excluding any effect of mobility, individuals with larger networks suffer a salary penalty compared to smaller-networked individuals? Table 12 in the Appendix shows that some of this is likely to be a composition effect - once we include measures of the number of firms for which an executive has worked, the average board size of these firms, and the size of the current firm, the connection direct effect falls by a little over a third - but it is still negative, and highly significant.[23]

Another possibility is, as we suggested previously, that salaries might over-react to executive moves, and executives who then stay on in their new firms might see their salaries regress to a more modest level. However, Table 13, also in the Appendix, suggest this is unlikely to be the explanation. It includes the lagged value of the Changed Firm dummy, which under this hypothesis should have a substantially lower coefficient than than the current value. In fact the two values are almost identical.

Instead, Table 14 in the Appendix suggests that composition effects are particularly important for the individuals in the top quintile of the distribution of network size. The table shows connection direct effects by quintile and shows an inverted U shape - executives in the second and third quintile have positive coefficients compared to those in the bottom quintile, but those

[23]We have not included these controls in our baseline specification since some of them seem probably endogenous - in particular, current firm size may itself be a result of prior moves. However, their inclusion suggests the possibility of composition effects in explaining the negative direct effect of connections.

in the fourth and especially the fifth is negative. There are two possibilities: one is that individuals in the top quintile of net connections may really be different from others - they might have accumulated their connections through a large number of previous moves, and also be considered less reliable or loyal employees of their firms. However, controlling for number of previous firms as in Table 15, though it reduces somewhat the negative coefficient on the fifth quintile, shows that this remains substantially negative, suggesting that this is unlikely to be the main explanation.

Instead, we suggest, the linear specification of the Changed Firm dummy may be concealing significant non-linearities. Executives with a large number of connections are indeed significantly more likely to change firm but this increased likelihood does not bring with it a proportionate increase in expected salary. There may, in other words, be substantially diminishing returns to greater network size: in the fourth and especially the fifth quintiles of network size, the extra connections bring exposure to new opportunities that are not proportionately as interesting as those brought by connections in the second and third quintiles. This reinforces our previous conclusion: larger networks are modestly useful to executives in a causal sense - but the networks face diminishing returns, and the highest-remunerated individuals are not principally being remunerated because of their networks.

Robustness checks on the sample are reported in the Appendix. Results in all the specifications are qualitatively similar as far as the coefficients that have a causal interpretation are concerned, that is, that on Net connections in the fixed effects estimation in column II (as well as the difference between the coefficient on Net connections and that on Placebo connections in column III), and those on Net connection and on the Changed firm dummy in column IV. In particular, Tables 16, 17 and 18 correspond to the analysis on the unbalanced Compensation and Executive panels including the crisis (all years between 2000 and 2012). Tables 19, 20 and 21 use as dependent variable the salary component only, instead of the overall compensation.

6 Conclusions

Networks have long been considered important for executives' professional advancement, but quantifying and testing such theories rigorously has been hard because of the difficulty of obtaining large, representative datasets that allow to control for unobservable characteristics that may determine both the nature of individuals' networks and their professional advancement. We have developed a panel dataset of Executives in North American and European publicly listed firms that allows us to meet this challenge.

There is a clear statistical association between the size of executives' professional networks and their annual compensation, with an elasticity of about 20%. However, controlling for unobserved individual heterogeneity, using either individual fixed effects or placebo network controls, suggests that most of this statistical association is due to unobserved characteristics that have a positive impact on both networks and professional advancement. The true average causal impact of network size on remuneration, estimated in this fashion, appears to be small and positive, with an elasticity that we estimate at 1.1%.

In principle, this aggregate causal impact might work through several channels. In the paper we devise and test a formal model of the coevolution of executives' professional networks, in order to distinguish between the direct effect of networks on remuneration and the indirect effect through increasing employees' mobility and therefore their ability to leave their firm for a better paid job elsewhere. We estimate that all the average positive impact of networks works through the mobility channel. More specifically, there is a direct causal impact of network size on remuneration via mobility with an elasticity of around 11%. However, this is offset by a negative direct association between network size and compensation with a negative elasticity of around 9%, leaving a net impact of only around 2%. And there appear to be significant diminishing returns to network size: executives with larger networks are a lot likelier to move but do not improve their expected remuneration in proportion.

Methodologically, we have also shown that using placebo networks as a way of adjusting for heterogeneity in unobserved individual characteristics is a a fairly effective technique, producing results very similar to those of estimation using individual fixed effects. This is a valuable lesson to bear in mind in contexts in which data limitations may make the use of individual fixed effects infeasible.

To conclude, professional networks appear to have been over-hyped as determinants of executives' professional success. Although there is a substantial cross-sectional correlation between executives network size and their remuneration, almost all of this is due to unobserved differences between individals - characteristics that make an individual more likely to have large networks and also more likely to have high remuneration. It is hard to find convincing evidence for an elasticity much larger than one or two percentage points in terms of the expected compensation that an executive can receive from such networks, although those networks will increase the probability of moving to a new and better paid job.

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Appendix

Table 11: Number of firms from our samples belonging to the main indexes

Year	S&P 500	NASDAQ 100	FTSE 100	EUROTOP 100	CAC 40
		Compensation unbalanced panel			
2000	373 (74.6%)	66 (66%)	71 (71%)	36 (36%)	13 (32.5%)
2001	402 (80.4%)	67 (67%)	75 (75%)	47 (47%)	25 (62.5)
2002	423 (84.6%)	79 (79%)	79 (79%)	62 (62%)	31 (77.5%)
2003	424 (84.8%)	79 (79%)	82 (82%)	64 (64%)	32 (80%)
2004	429 (85.8%)	80 (80%)	84 (84%)	71 (71%)	33 (82.5%)
2005	441 (88.2%)	89 (89%)	86 (86%)	74 (74%)	34 (85%)
2006	439 (87.8%)	93 (93%)	85 (85%)	78 (78%)	36 (90%)
2007	447 (89.4%)	90 (90%)	89 (89%)	79 (79%)	37 (92.5%)
2008	457 (91.4%)	88 (88%)	91 (91%)	81 (81%)	37 (92.5%)
		Executive unbalanced panel			
2000	381 (76.2%)	63 (63%)	73 (73%)	79 (79%)	31 (77.5%)
2001	398 (79.6%)	67 (67%)	74 (74%)	82 (82%)	33 (82.5%)
2002	414 (82.8%)	76 (76%)	80 (80%)	88 (88%)	36 (90%)
2003	432 (86.4%)	83 (83%)	84 (84%)	91 (91%)	35 (87.5%)
2004	448 (89.6%)	86 (86%)	87 (87%)	93 (93%)	35 (87.5%)
2005	460 (92%)	91 (91%)	87 (87%)	96 (96%)	37 (92.5%)
2006	474 (94.8%)	97 (97%)	92 (92%)	98 (98%)	40 (100%)
2007	480 (96%)	99 (99%)	94 (94%)	98 (98%)	40 (100%)
2008	484 (96.8%)	96 (96%)	96 (96%)	97 (97%)	38 (95%)

Table 12: Compensation unbalanced panel - Additional controls, including firm size

	Dependent variable: Log of Compensation			
	I	II	III	IV
(Log of) Net Connections	0.082^{***}	0.013^{+}	0.056^{***}	-0.059^{***}
	(0.003)	(0.007)	(0.003)	(0.012)
(Log of) Nb of companies	0.247^{***}	0.123^{***}	0.135^{***}	-0.917^{***}
	(0.010)	(0.026)	(0.011)	(0.142)
(Log of) Avg board size	0.126^{***}	0.055	0.087^{***}	0.018
	(0.009)	(0.054)	(0.009)	(0.052)
Firm size	0.204^{***}	0.056^{***}	0.201^{***}	0.138^{***}
	(0.002)	(0.009)	(0.002)	(0.015)
(Log of) Placebo Connections			0.055^{***}	
			(0.003)	
Changed Firm Dummy				3.101^{***}
				(0.421)
Individual FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	2SLS
Nb of observations	88 353	88 353	88 353	88 353
Nb of individuals		19 196		19 196
R2	0.376	0.074	0.379	0.737
Hansen J stat				10.586
p-value				0.001
F-test(1st stage)				92.252
p-value				0.000

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies. Firm size is the log of number of employees.

Table 13: Compensation unbalanced panel - Lagged changed firm and current changed firm

	Dependent variable: Log of Compensation			
	I	II	III	IV
(Log of) Net Connections	0.215***	0.019*	0.138***	-0.204***
	(0.002)	(0.008)	(0.003)	(0.031)
(Log of) Placebo Connections			0.087***	
			(0.002)	
Lag Changed Firm Dummy				3.642***
				(0.364)
Changed Firm Dummy				3.830*
				(1.882)
Individual FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	2SLS
Nb of observations	88 170	88 170	88 170	88 170
Nb of individuals		20 454		20 454
R2	0.260	0.071	0.271	0.643
Hansen J stat				12.166
p-value				0.002
F-test(1st stage)				82.168
p-value				0.000
F-test(1st stage)				4.334
p-value				0.002

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies. Firm size is the log of number of employees.

Table 14: Compensation unbalanced panel - Quintiles of net connections

	Dependent variable: Log of Compensation			
	I	II	III	IV
Net Connections 2Q Dummy	0.156***	0.009	0.141***	0.042***
	(0.010)	(0.010)	(0.010)	(0.010)
Net Connections 3Q Dummy	0.412***	0.031*	0.350***	0.051***
	(0.009)	(0.013)	(0.009)	(0.013)
Net Connections 4Q Dummy	0.694***	0.043**	0.509***	-0.078***
	(0.010)	(0.017)	(0.010)	(0.023)
Net Connections 5Q Dummy	0.895***	0.052*	0.525***	-0.391***
	(0.010)	(0.023)	(0.012)	(0.057)
(Log of) Placebo Connections			0.113***	
			(0.002)	
Changed Firm Dummy				2.716***
				(0.313)
Individual FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	2SLS
Nb of observations	104 628	104 628	104 628	104 628
Nb of individuals		22 905		22 905
R2	0.260	0.065	0.279	0.730
Hansen J stat				0.453
p-value				0.501
F-test(1st stage)				109.929
p-value				0.000

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies. Firm size is the log of number of employees.

Table 15: Compensation unbalanced panel - Additional controls and quintiles of net connections

	Dependent variable: Log of Compensation			
	I	II	III	IV
Net Connections 2Q Dummy	0.154***	0.010	0.150***	0.027**
	(0.010)	(0.010)	(0.009)	(0.009)
Net Connections 3Q Dummy	0.366***	0.031*	0.343***	0.042***
	(0.009)	(0.013)	(0.009)	(0.012)
Net Connections 4Q Dummy	0.569***	0.039*	0.490***	-0.030
	(0.010)	(0.017)	(0.010)	(0.019)
Net Connections 5Q Dummy	0.669***	0.040^{+}	0.493***	-0.227***
	(0.012)	(0.023)	(0.013)	(0.039)
(Log of) Nb of companies	0.241***	0.097***	0.037***	-0.988***
	(0.010)	(0.026)	(0.011)	(0.121)
(Log of) Avg board size	0.438***	0.127**	0.360***	0.166***
	(0.009)	(0.049)	(0.009)	(0.046)
(Log of) Placebo Connections			0.099***	
			(0.003)	
Changed Firm Dummy				2.494***
				(0.274)
Individual FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	2SLS
Nb of observations	104 608	104 608	104 608	104 608
Nb of individuals		22 903		22 903
R2	0.280	0.065	0.290	0.749
Hansen J stat				1.830
p-value				0.176
F-test(1st stage)				153.642
p-value				0.000

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies. Firm size is the log of number of employees.

Table 16: Compensation unbalanced panel - All years

	Dependent variable: Log of Compensation			
	I	II	III	IV
(Log of) Net Connections	0.207***	0.006	0.131***	-0.072***
	(0.002)	(0.006)	(0.002)	(0.010)
(Log of) Placebo Connections			0.090***	
			(0.002)	
Changed Firm Dummy				1.562***
				(0.179)
Individual FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	2SLS
Nb of observations	132 091	132 091	132 091	132 091
Nb of individuals		26 201		26 201
R2	0.282	0.062	0.293	0.777
Hansen J stat				1.407
p-value				0.236
F-test(1st stage)				218.673
p-value				0.000

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies.

Table 17: Executives unbalanced sample - All years

	Dependent variable: Top 5 earners dummy			
	I	II	III	IV
(Log of) Net Connections	0.028***	0.008***	0.020***	-0.045***
	(0.000)	(0.001)	(0.000)	(0.003)
(Log of) Placebo Connections			0.012***	
			(0.000)	
Changed Firm Dummy				1.110***
				(0.063)
Individual FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	2SLS
Nb of observations	620 440	620 440	620 440	620 440
Nb of individuals		85 043		85 043
R2	0.137	0.031	0.138	0.497
Hansen J stat				0.036
p-value				0.851
F-test(1st stage)				408.584
p-value				0.000

Robust standard errors in parentheses. Statistical significance levels: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies.

Table 18: First stage regressions - All years

	Dependent variable: Changed firm dummy	
	Compensation	Top 5 earners dummy
Prop. of connections in firms with:		
Expanding sales	0.055***	0.042***
	(0.004)	(0.002)
Expanding nb of employees	0.039***	0.032***
	(0.003)	(0.002)
(Log of) Net Connections	0.050***	0.048***
	(0.002)	(0.001)
Individual FE	Yes	Yes
Controls	Yes	Yes
Nb of observations	132 091	620 440
F-test	218.673	408.584
p-value	0.000	0.000

Robust standard errors in parentheses. Statistical significance levels: + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies.

Table 19: Salary balanced panel

	Dependent variable: Log of Salary			
	I	II	III	IV
(Log of) Net Connections	0.122***	-0.024	0.031***	-0.126**
	(0.005)	(0.025)	(0.009)	(0.048)
(Log of) Placebo Connections			0.096***	
			(0.007)	
Changed Firm Dummy				2.074*
				(0.858)
Individual FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	2SLS
Nb of observations	18 846	18 846	18 846	18 846
Nb of individuals		2 094		2 094
R2	0.079	0.064	0.090	0.667
Hansen J stat				1.514
p-value				0.218
F-test(1st stage)				21.871
p-value				0.000

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies.

Table 20: Salary unbalanced panel

	Dependent variable: Log of Salary			
	I	II	III	IV
(Log of) Net Connections	0.377^{***}	0.003	0.368^{***}	-0.128^{***}
	(0.003)	(0.009)	(0.005)	(0.021)
(Log of) Placebo Connections			0.011^{*}	
			(0.004)	
Changed Firm Dummy				2.905^{***}
				(0.419)
Individual FE	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes
Estimation	OLS	OLS	OLS	2SLS
Nb of observations	130 894	130 894	130 894	130 894
Nb of individuals		28 601		28 601
R2	0.170	0.037	0.170	0.909
Hansen J stat				4.647
p-value				0.031
F-test(1st stage)				95.720
p-value				0.000

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies.

Table 21: Salary panel - First stage regressions

	Dependent variable: Changed firm dummy	
	Balanced panel	Unbalanced panel
Prop. of connections in firms with:		
Expanding sales	0.024***	0.034***
	(0.006)	(0.003)
Expanding nb of employees	0.027***	0.026***
	(0.006)	(0.003)
(Log of) Net Connections	0.050***	0.046***
	(0.004)	(0.002)
Individual FE	Yes	Yes
Controls	Yes	Yes
Nb of observations	18 846	130 894
F-test	21.871	95.720
p-value	0.000	0.000

Robust standard errors in parentheses. Statistical significance levels: $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Controls include log of age, log of age squared, female dummy, degree level and major dummies, country, sector and year dummies.

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