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The Impact of Job Referrals on Employment Outcomes in Top Corporate Positions

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Abstract

Using an original dataset on professional networks of directors sitting on the boards of large US corporations, we examine how personal relationships are used by firms to improve job match quality in the high-skill segment of the labor market. Analyzing explicit social connection data between new hires and recruiters, we are able to test predictions of well established job referral models. We find that referred executive directors have a fifteen percent longer tenure than their non-referred counterparts. Referred executive directors also tend to be similar to their referrers on multiple dimensions, giving support to network homophily hypotheses.

Keywords: Referrals, Job Match Quality, Social Networks, Board of Directors
JEL Classification: L14, J63, M51

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1 Introduction

Networking is helpful for job seekers who can leverage their personal connections to have better access to job opportunities or obtain job referrals. This job searching strategy is widely spread among workers, with a recent estimate of half of the jobs in the US filled with job referrals (Topa, 2011). Similarly, firms also leverage social networks to improve their recruitment processes. Their use reduces screening costs for the employer (Fernandez et al., 2000), facilitate transmission of job posting information to a larger audience (Granovetter, 1973) and they improve the firm-worker job match quality because they provide both agents with less biased reciprocal information through intermediaries (Beaman and Magruder, 2012). Empirical papers show recommendations improve job match quality (Burks et al., 2015; Brown et al., 2016; Pallais and Sands, 2016) but this evidence is based on low to middle skilled jobs with clearly identifiable tasks. Recommendations are likely to be even more important for jobs with complex tasks (for instance, managerial tasks) and few empirical evidence exists on the role of job referrals on job match quality for the high-skilled segment of the labor market.

This paper investigates whether social networks help workers increase job match quality with firms through the use of job referrals and studies who refers whom. Specifically, our study aims at answering two main questions: 1/ Do referred workers exhibit higher tenure in the firm? and 2/ How similar referrers and referred workers are? To do so, we derive predictions from the existing theoretical literature and test them using an original dataset that uses a conservative but credible proxy to identify job referrals: previous working relationships between new workers and recruiters. We provide evidence on job referral effectiveness in the high-skill segment of the labour market, using a large sample of directors appointed over 15 years to boards of a wide array of US firms.

We find that referred executive directors work 15 percent longer on average (six months longer) than non-referred executive directors in the same board. This positive effect decreases to 2.5 percent for non-executive directors. Additionally, we find that the strength of the social tie leading to a job referral is positively correlated with its tenure effect and that this effect is larger for less experienced workers. Finally, executive directors are slightly more similar to their referrers than to any other recruiter and the opposite applies to non-executive directors, which is intuitively expected given their different duties.

The subject is of high relevance for corporations that have incentives to increase their employee retention rate and incentives to influence employee composition diversity. Moreover, this study is relevant for policy-makers that want to improve the job-matching process in the labour market and want to reduce frictional unemployment in the economy.

The hiring process, network creation, job searching strategy, and workers' career decisions are highly endogenous on many unobservable dimensions. Therefore, our work does not aim at making any causal claim. However, our work provides further support to the existing empirical literature with additional evidence in line with theoretical models.

The closest two papers to ours (Brown et al., 2016; Burks et al., 2015) perform similar and wider analysis but their studies are limited to a small sample of firms. Burks et al. (2015) find that referred workers are less likely to quit over three industries. Brown et al. (2016) show that referred workers are about 82 percent as likely to leave the firm as non-referred workers. Both studies are however limited by single-firms observations, whereas ours accounts for a variety of firms in different industries.

Doing wide empirical studies on recommendations has been always proven difficult because it requires precise information on job referrals, typically gathered through surveys in few firms or for small samples[1]. Our approach uses social network data to infer job referrals instead. Other studies using social networks as proxy for job referrals include Bayer et al. (2008) on neighbors, Cingano and Rosolia (2012) on previous coworkers, Kramarz and Skans (2014) on relatives, Dustmann et al. (2015) on compatriots, and Zimmerman (2019) on schoolmates to name some of the precursors. These studies hinge on the network homophily theories, in which individuals having common features are assumed to belong to same social network. However, depending on the social network type we consider, it is more or less credible that individuals refer each other for a job. For example, we argue a job referral is

[1]Beaman and Magruder (2012), Burks et al. (2015), Brown et al. (2016), Pallais and Sands (2016), and Lalanne (2018) are all studies that use explicit referrals information.

more likely to happen among individuals with a stronger relationship, such as family members, versus individuals that happen to share the same nationality. Our analysis confirms this positive correlation between relationship strength and job match effectiveness of referrals. The empirical strategy of our study is to consider previous working relationships between directors as a robust proxy for job referrals. In our setting, directors work in relatively small teams[2], so they are very likely to actually know each other if they have worked in the same firm at the same time. Our *colleague* network is therefore far more precise regarding working relationships as compared to the broader *coworker* networks often used in the literature. These coworker networks are created from joint employment at a same firm at the same time and cannot neither ensure that individuals actually worked together (Cingano and Rosolia, 2012; Hensvik and Skans, 2016; Glitz, 2017; Saygin et al., 2019) nor that the connection had any influence on the firm hiring decision. Additionally, Lalanne (2018) shows that having an employment overlap with a member of the board increases the probability of being referred by nine percentage points, which makes our proxy slightly more credible. Finally, to further increase the precision of our job referral proxy, we consider as referral-relevant not every social tie of the applicant director with the board but only with the recruiters (i.e. the members of the Nomination Committee).

Our work also examines individual relationships between referrers and referees, and with it, studies their similarity with a multi-dimensional approach, contrary to the unidimensional approach used by Brown et al. (2016) and Burks et al. (2015). The use of a multi-dimensional similarity measure is an important feature of our study because homophily in social networks is evident among multiple characteristics such as age, ethnicity and gender (McPherson et al., 2001) and it is especially relevant in studying corporate boards (Adams et al., 2018). Brown et al. (2016) study and prove similarity between referred-referee only along single characteristics (e.g. gender, ethnicity, firm division). Burks et al. (2015) evidence a positive correlation with performance indicators (i.e. miles driven and accident rate) among referrers and referees in the trucking industry and bring this as evidence of ability homophily in social networks. Hensvik and Skans (2016) use scores from a test used in the armed forces as a proxy for ability and find those are correlated among referrers and referees. Our study expands on those analysis by

[2]The average board size in our sample is 9 to give a magnitude of the team size.

introducing a more holistic approach that can inspire further research and give additional credibility to studies that use similar socio-economic characteristics to create job referral proxies. The use of such proxies is justified by the fact that similar people are more likely to belong to the same social network (McPherson et al., 2001). Similarly, our results confirm that individuals share more similar characteristics with members of the nomination committee with whom they had a professional tie prior to the hire.

The different usage of informal job searching methods across skill levels might provide an explanation for the ambiguous effects found on wages and turnover of referred workers. Elliott (1999) argues that searching through informal channels is a solution of last resort for lower skilled applicants. Therefore, referred workers will have higher turnover because the referral status is negatively correlated with education. Casella and Hanaki (2006) investigate how signaling compares to recommendations from personal connections. Their model suggests that low-skilled workers will have higher incentives to network because their cost of signalling is larger. As a result, referred workers are more likely to be low-skilled. Heath (2018) predicts that firms are more likely to hire workers with observably lower skills through the referral channel. In her experimental setting featuring low-skills workers in Bangladesh, firms use referrals to mitigate moral hazard. The employer will lower the referrer's wage if the referee performs poorly and will therefore avoid paying above productivity wages overall. Nevertheless, she points out that in other settings, firms use referrals to learn about the job match quality with the worker, as evidenced by Simon and Warner (1992), Pinkston (2012), Brown et al. (2016) or Dustmann et al. (2015), in "developed country labor markets, where the prevalence of heterogeneous higher-skilled jobs likely makes this match quality more important". Among these, Brown et al. (2016) find that job referrals are more useful to communicate information about low-skilled workers rather than high-skilled ones[3]. Focusing indeed on the importance of the suitability of the worker to the job, Galenianos (2013) introduces firm productivity to propose an explanation for the mixed results on wages, productivity and separation rates by referral status. Productive firms, which offer high paying jobs, invest more in recruiting through the formal market

[3]Referred executives in Brown et al. (2016) sample show higher separation rates than their non-referred counterparts, contrarily to what happens for other lower-skill positions.The authors admit though that there were few observations for executives in their sample and results seems driven by post-recession observations.

because the cost of a bad match are higher for them. These investments increase the evaluation precision of formal recruitment, which cause non-referred workers to exhibit greater productivity on average. Still, the author argues that "it is unclear why jobs differ in the amount of information that can be transmitted through a referral". In particular, the type of skills that are required for the job might be more or less easy to observe and to report through recommendations. Our analysis fills an empirical gap in the literature and provides evidence that referrals are relevant even for the job match of workers in high-skilled positions.

The rest of the paper is organized as follows. The next section reviews the existing theory about job referrals with a focus on model predictions related to both tenure and social network homophily. Section 3, describes the data, the empirical specifications to test the predictions previously laid down, and discusses the results. Section 4 concludes.

2 Theoretical Framework

In the context of hiring, firms need to collect information about applicants and our theoretical framework highlights the mechanisms through which job referrals are used to acquire privileged information. We draw from two kind of models in the literature that describe the role of referrals in labour markets: the learning model and the homophily model. In the description offered by the former, firms ask employees for a referral to have more precise information about applicants. In the description offered by the latter, firms ask their best employees for a referral under the assumption that high-ability workers have a social network of people with similar ability. We use these models to lay down specific predictions on employee tenure and on the homophilic structure of social networks.

These models are based on the presence of a social network in the economy composed of two types of nodes: firms and workers. Two nodes of the network form a connection when they meet and increase their knowledge about each other. This way, information about each node is not exclusive to the agent itself but is available to each node connected to it in the social network. Firms cannot make connections nor share information between each other because they are in competition whereas workers are not. Hence, the firm can access to the information in the social network about a worker only through its (present) employees connected to him/her by asking them for job referrals. Hiring firms have an advantage using this channel because workers themselves can have incentives to hide information from the employer whereas their connections do not.

Over the course of the manuscript we define the provider of the job referral as referrer and its recipient as referee.

2.1 Learning Models

In learning models, the role of the referral is to reduce the variance of the applicant's estimated productivity signal to the employer that learns over time about the true productivity of the employee.

Following Jovanovic (1979) job matching model[4], the market has two categories of profit-maximizing agents, firms and workers, that behave optimally but have initially incomplete information about each other and learn over time. Firms need to fill costly vacancies and workers get compensated by firms with a salary if they fill those vacancies.

The timing is as follows:

First Stage The two agents meet as a result of a search in which the worker sends a signal y about their match productivity θ to the firm, which decides if to employ him/her with a wage ω. At this stage, both agents use the signal y to formulate an estimate on the match productivity $y = \theta + \epsilon$ with ϵ as random variable uncorrelated with θ. The firm will estimate the posterior probability distribution of the real productivity of the match θ conditional on the signal received y and will offer a wage conditional on the estimate formulated. The distribution has mean ω

$$\omega = \mu_\theta + \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\epsilon^2} (y - \mu_\theta) \tag{1}$$

[4]Its discrete form is described by Ljungqvist and Sargent (2012).

and variance σ_1^2:

$$\sigma_1^2 = \frac{\sigma_\theta^2 \sigma_\epsilon^2}{\sigma_\theta^2 + \sigma_\epsilon^2} \tag{2}$$

that is increasing in σ_ϵ^2 because

$$\frac{\partial \sigma_1^2}{\partial \sigma_\epsilon^2} = \frac{\sigma_\theta^2(\sigma_\theta^2 + \sigma_\epsilon^2) - \sigma_\theta^2 \sigma_\epsilon^2}{(\sigma_\theta^2 + \sigma_\epsilon^2)^2} = \frac{\sigma_\theta^4}{(\sigma_\theta^2 + \sigma_\epsilon^2)^2} > 0 \tag{3}$$

ω is a random variable Normally distributed with mean μ_θ and variance σ_ω^2 where:

$$\sigma_\omega^2 = \frac{\sigma_\theta^4}{\sigma_\theta^2 + \sigma_\epsilon^2} \tag{4}$$

Together, the variables follow the distributions:

$$\theta \sim N(\mu_\theta, \sigma_\theta^2), \qquad \epsilon \sim N(0, \sigma_\epsilon^2), \qquad \theta \mid y \sim N(\omega, \sigma_1^2), \qquad \omega \sim N(\mu_\theta, \sigma_\omega^2).$$

of which the derivation is explained in the Appendix A.1.

Second Stage The worker decides if to accept the offer or reject it and search again next period.

Third Stage If the worker accepts the offer, the two agents learn about the true θ at the second period of employment. The firm commits to pay a wage equal to θ after it learns about the match productivity.

At stage 3, let it be Q the expected present value of wages for an unemployed agent, $J(\theta)$ the expected present value of wages for an agent that behaves optimally after θ is revealed, and β the time discount factor. The employed worker will make the decision each period if to keep the compensation θ and earn the present value of future wages or to become unemployed and search again next period. Searching again is a valid choice because the match productivity θ is not dependant only on the worker's ability but differs with each firm. If the worker accepts the offer the first period, it will continue to do so indefinitely because the wage cannot change. We define as θ^* the minimum match productivity for the agent to be indifferent between the choice of quitting after the second period of employment and stay in the firm forever.
The choice can be modelled as follows:

$$J(\theta) = \begin{cases} \theta + \beta J(\theta) = \sum_{n=0}^{+\infty} \beta^n \theta = \frac{\theta}{1-\beta} & \text{if } \theta \geq \theta^* \\ \beta Q & \text{if } \theta \leq \theta^* \end{cases} \tag{5}$$

such that:

$$\frac{\theta^*}{1-\beta} = \beta Q \tag{6}$$

Therefore, the probability of a worker to quit the job at stage 3 is:

$$Pr(Quit \mid Stage = 3) = Pr(\theta < \theta^*) = \int_{-\infty}^{\theta^*} dF(\theta \mid \omega, \sigma_1^2) = \mathbf{\Phi}\left(\frac{\theta^* - \mu_\theta}{\sigma_1}\right) \tag{7}$$

Jovanovic (1979) model shows in (5) that quits are negatively correlated with tenure because the workers with low productivity $\theta < \theta^*$ left between the first and second period of employment and those who do not leave, will never do any subsequent period. This mechanism also bias upwards the productivity of the group of employees in their second period of employment, so that even their wage is higher.

Simon and Warner (1992) extend the Jovanovic (1979) model by including a stage before the firm and worker meet: the referral stage. In this new stage, the agent is recommended to the firm by someone in his/her social network with probability p, together with the assumption that referred applicants R have lower productivity uncertainty σ_ϵ^2 at the moment of hire than applicants found in the external market M (i.e. $\sigma_R^2 < \sigma_M^2$). This assumption makes the probability of quitting the job specified in (7) lower for applicants recruited through referrals because the aforementioned probability decreases with σ_ϵ^2 (since σ_1^2 increases with σ_ϵ^2 as shown in equation (3)).

The employer naturally gets better information on the worker after the match is evaluated because the updated belief $\theta \mid y$ has a lower variance than θ, since $\frac{\sigma_\epsilon^2}{\sigma_\theta^2+\sigma_\epsilon^2} < 1$ in (2). Moreover, note in (1) that the smaller σ_θ^2 is relative to σ_ϵ^2, the more the employer is sure of μ_θ and less it will rely on the data observed y. This because $\frac{\sigma_\theta^2}{\sigma_\theta^2+\sigma_\epsilon^2}$ approaches zero the closer the posterior mean is to the prior mean. The employer will then ask for a referral if σ_ϵ^2 is sufficiently low because it can then trust more the data y on the single worker rather than the prior productivity mean of the population it observes before. Thus, it can offer the worker the right compensation at stage 2, so to attract more workers with higher θ than average who can accept the job.

Dustmann et al. (2015) extend the Simon and Warner (1992) model and include a probability α for the two agents to learn about the true θ at each period after the match. Additionally, they include a probability δ for the match to be dissolved for exogenous reasons at each period after the match. Hence, the true productivity θ is not necessarily revealed at stage 3 in Dustmann et al. (2015) model and the probability of a worker to quit in each period of employment is:

$$\begin{aligned} Pr(Quit) &= \delta + \alpha(1-\delta)\frac{Pr((\theta < \theta^*) \cap (\omega > \omega^*))}{Pr(\omega > \omega^*)} \\ &= \delta + \frac{\alpha(1-\delta)\int_{\omega^*}^{\infty}\int_{-\infty}^{\theta^*} dF_y(\theta|\omega, \sigma_1^2)}{\int_{\omega^*}^{\infty} dG_y(\omega)} \end{aligned} \quad (8)$$

which sums the exogenous probability of the match to be dissolved δ with the probability of the match in which the firm paid the employee a wage ω higher than his/her reservation wage ω^* at the second stage but the revealed true productivity θ at the third stage is lower than the reservation productivity θ^*. Numerical simulations performed by the authors show that the probability of quitting the job expressed in (8) diminishes with lower values of σ_ϵ^2.

We can now introduce our first prediction:

Prediction 1 *Referred workers have longer tenure than non-referred ones*

Building upon the same framework of Dustmann et al. (2015), where the firm has probability α to learn about the match's true productivity each period, we can apply the same principle of learning with respect to the relationship between referrer and referee. Hence, we posit that the information each referrer has about his/her referee is on average more precise with the amount of periods they worked together in the past. Hence, we make the assumption that σ_ϵ^2 decreases with the strength of the social tie defined as periods worked together. It is worth noticing that our definition of strength does not refer to the degree of separations between referrer and referee like the literature does when discussing 'weak ties' and 'strong ties' (Granovetter, 1973). Lalanne and Seabright (2016) use the same definition as here. This leads to our next prediction:

Prediction 2 *The positive tenure effect of referral increases with the strength of the connection between referrer and referee*

Pinkston (2012) develops a similar model but extends in time the learning process for the employer, in which it is not able to fully determine the match productivity at any specific point of time. The author introduces on-the-job training Z_t weighted by the coefficient γ in the quantification of the productivity of the employee at time t. The worker gives an initial signal y_i of its true productivity θ_i with noise ϵ_{it} at the moment of hire. The employee increases his/her productivity u_{it} each period t due to the on-the-job training Z_{it} such that $u_{it} = \theta_i + Z_{it}\gamma$. The employer has perfect information over $Z_{it}\gamma$ and will estimate the initial productivity θ_i by factoring out the effect of Z_t, such that $u_{it} = \theta_i + \psi_{it}$, where $\psi_{it} \sim N(0, \sigma^2_\psi)$. At tenure t, the employer will retrospectively form an updated signal S_{it} on its beliefs on θ_i,[5] which is a variance-weighted average of y_i and the later signals u_{it}:

$$S_{it} = \theta_i + \eta_{it} \tag{9}$$

where $\eta \sim N(0, \sigma^2_\eta)$. This generalises the match y to be evaluated at each time t after employment and this cause the posterior update of θ given the signals y and u_{it} to be calculated for multiple measurements t.[6] Analogously to how σ^2_1 in (2) is lower than σ^2_θ because it is a posterior update of θ after observing a single observation y, the variance of the updated signal σ^2_η decreases with each period of observation.[7] Additionally, the variance σ^2_η increases with σ^2_ϵ at a slower rate with t,[8] which means the precision in initial performance estimation increases with tenure and increases quicker for referred workers because they have lower initial variance. Moreover, suppose the employer makes a performance evaluation at time t defined as $P_{it} = S_{it} + Z_{it}\gamma$ and decides if to fire the employee and, if not, decides his/her wage. The variance of P_{it} is equal to the variance of S_{it} because the employer has perfect information over $Z_{it}\gamma$. Hence, the more accurate initial information is, the less employer learning will affect wages (and so, turnover) as tenure increases.

This will lead us to the next prediction:

[5] S_{ij} takes the Bayesian updating form (DeGroot, 2005):

$$S_{it} = \frac{\sigma^2_\psi}{t\sigma^2_\epsilon + \sigma^2_\psi} y_i + \sum_{\tau=1}^{t} \frac{\sigma^2_\epsilon}{t\sigma^2_\epsilon + \sigma^2_\psi} u_{i\tau}$$

[6] Mathematical derivations can be found in the Appendix A.1.

[7] As shown in equation (31) in the Appendix A.1.

[8] As shown in equations (30) and (32) in the Appendix A.1.

Prediction 3 *The positive tenure effect of referral decreases with the experience level of the referee*

Supposing previous on-the-job training is perfectly observable by the employer through experience, then the performance evaluation of the firm to decide to fire the worker will reduce the uncertainty reduction advantage coming from job referrals on the initial productivity because θ_i has a lower effect in magnitude on P_{it}. In fact, part of the screening costs on performance have been already paid by previous employers and the information is not anymore bilateral with the past employer but is disclosed with the whole market, since the decision of hiring the worker is a public signal.

So far, the choice of the hiring method has been exogenous and the firms homogeneous. Galenianos (2013) introduces a different setting from the previous models in which firms of different productivity endogenously choose their hiring channel and later learn about the match quality. Hiring any applicant from market i has probability p to result in a good match. The applicant sends a signal to the firm that has probability q_i to be correct. The firm maximize the present value of the job vacancy and exerts a heterogeneous linear amount of effort h in searching the referral R or non-referral M market to increase the probability $q_i(h)$ of the productivity signal sent by the worker in market i to be correct. The author assumes that the referral channel increases the probability to have good matches p because of empirical studies supporting the assumption. Thus, referred workers have lower turnover in the company because the separation rate of referred worker at each period is defined as $Pr(Quit \mid i = R, M) = \alpha(1-p_i)+\delta$ where $p_R > p_M$. The model shows that highly productive firms invest more in screening (i.e. have higher levels of h) and are less likely to use the referral hiring channel. Moreover, the tenure premium is lower without controlling for the productivity of the firm.

2.2 Homophily Models

Homophily models show that firms maximize their probability of hiring a high-ability worker by asking for job referrals to high-ability employees for which the firm has already information about. This strategy is based on the assumption that workers' social network is composed of similar peers. The seminal paper of this category of economic models is the work of Montgomery (1991), while the seminal work McPherson et al. (2001) supports the validity of the assumptions laid down in these models.

We follow Montgomery (1991) model which has two periods in which each worker lives for one and each firm can employ up to one worker. There is an equal amount of workers each period and half of them are of high ability H that produce 1 and half are low ability L that produce 0. Firms in period-1 have perfect knowledge over their employees and want to fill a job vacancy next period but have imperfect knowledge over the workers of workers in period-2. Firms maximize their profits, equal to worker productivity minus its wage, by deciding if to hire through the external market M, offering a wage w_M, or through the referral market R, offering a wage w_R, if they ask a reference from one of their employees. The social network structure of each employee in period-1 depends on the network density τ and the inbreeding bias α. The former quantifies the number of connections of each worker and the latter quantifies the similarity between the worker and the connections in his/her social network. Each worker in period-1 has probability $\tau \,\epsilon\, [0;1]$ to know one worker in period-2 and probability $\alpha \,\epsilon\, \left(\frac{1}{2};1\right]$ that the connected worker is of the same type.

This assumption on α leads us to our last prediction:

Prediction 4 *Referred workers are similar to their referrers*

In equilibrium, firms hire through the referral market with a higher wage $w_R > w_M$ only if they employ a high-ability worker in period-1. This behaviour explains the positive wage effect of the job referral because referred workers are more likely to be of high ability, since $\alpha > \frac{1}{2}$, and because using the referral market removes high-ability workers from the external market, that is in turn populated by more low-ability workers. This implies that when firms decide to ask for job referrals, there is a higher probability that referrers and referees are of similar ability and firms will select accordingly the employee to ask for a job referrals because it wants to receive an applicant similar to the referrer it asked to. It is worth noticing that this positive wage effect is independent from the actual ability of workers of period-2 but only comes from the structure of the social network of period-1 workers which shapes the belief firms have of period-2 workers.

This positive wage (and with it, tenure) effect for referred workers supports Prediction 1 because referred workers are more likely to be of high ability, since the firm will ask for job referrals only to high ability referrers, who are more likely to be connected to high ability workers. The wage premium becomes stronger for higher values of τ and α because it increases competition for referred workers and we posit that this outcome also supports Prediction 2. Firstly, because the probability of each period-1 worker to hold a social tie with a suitable period-2 worker τ can be seen as a measure of social tie strength, since the referrer is more likely to refer a specific applicant after they developed a stronger bond together. Secondly, the probability of each period-1 worker to hold a social tie with a period-2 worker of its own type α is a positive function of the social tie strength, since the referrer has more time to evaluate if the applicant is of his/her same type.

Casella and Hanaki (2006) extend the Montgomery model by including the additional possibility for workers to signal their ability and endogenize the creation of networks. Workers in period-2 pay a cost λ_N to create a connection[9] and pay a cost λ_S to take a trial that, if successful, signals the employer to be a high-ability type. The worker successfully passes the trial with probability $\alpha_S > \frac{1}{2}$ if he/she is of H type and $(1 - \alpha_S) < \frac{1}{2}$ if he/she is of L type where α_S represents the precision of the certification to express ability. The trial can be associated with formal education and it becomes information publicly known when completed. In the specification of a model with no networking costs λ_N, suppose there is an equilibrium for a given signalling cost λ_S where $\alpha = \alpha_S$ and where H workers are indifferent to take the trial or not (i.e. $w_C\alpha_S - \lambda_S = w_U(1 - \alpha_S)$) where w_C and w_U are the wages offered, respectively, in the certified and the uncertified market. In this situation, the certified market C offers the highest wage because all workers inside this market are of H type, since L workers prefer not to take the trial. In the uncertified market U there is a small proportion of H workers but the firm has still incentives to search into this market because it can offer a wage w that is $\alpha > w > w_U$ to workers hired through the referral channel. This way, the firm extracts rent $\alpha - w$ from the worker because the probability of a referred worker to be of high ability is α but the firm can pay the referred worker a wage w lower than α. Each H worker has in fact a reservation referred wage w_R^* that is less than α and equal to the uncertified market U

[9]This has the same probability α to connect two workers of the same ability type.

wage w_U, since the worker is indifferent between taking the certification or not. The uncertified market wage is equal to the probability of hiring a H worker in the same market that is composed by $(1-\alpha_S)$ H workers that failed the trial and the $\frac{1}{2}$ L-type workers that did not try. The wage is equal to:

$$w_R^* = w_U = Pr(Hiring\ a\ H\ worker \mid U\ market) = \frac{(1-\alpha_S)}{(1-\alpha_S)+0.5} < \alpha \tag{10}$$

Networking represents another way other than a certification for the worker to achieve greater probabilities of being hired with a higher wage than average. Additionally, networking is a way for the firm to acquire privileged information because the relationship between referee and referrer (and thus, with the firm) is bilateral whereas the signal is of public domain. This way, the firm acquires an information advantage over other firms that it is used to earn a rent out of the worker. However, the cost of networking λ_N is borne by the worker only but the benefits are shared with the firm, therefore, the worker will choose to network only if the rent they can personally extract is higher. Hence, H workers will start prefer using signalling, rather than networking, with higher values of λ_N or with higher values of certification signal effectiveness α_S (the probability of finding a H worker in the uncertified market in (10) decreases in α_S).

These considerations can provide support to Prediction 3 because, holding constant the parameters λ_N, α, λ_S, and α_S, all firms will offer higher wages to experienced hires but only the firm having access to referral information will offer a higher wage than the market to the less experienced workers hired through the referral channel.

2.3 Additional Theories

Previous theories assume that the incentives of the worker and the firm are aligned, so that the referrer will correctly give a precise signal about the referee or will recommend a high ability worker, whereas this might not necessarily hold true.

Beaman and Magruder (2012) evidence the moral hazard problem of referrers that could use job referrals to advantage people in their network at the expenses of the company (i.e. favouritism). One worker could in principle refer a relative to obtain greater non-monetary benefits outside the worker-firm relationship and disregard productivity as a selection criteria for his/her choice. The authors ran an experiment in a factory in India where they employ workers for a one-time employment spell and provide financial incentives to the workers for good job referrals. The incentives are randomized over the amount received for a job referral and if they were based on the referee performance or not. The authors find indeed that referrers were more likely to recommend family members to the firm only when there were no financial incentives for the referrers based on the referee productivity. The role of the incentives is to reward the transfer of correct information from the worker to the company. This experiment design removes the reputation risk of the employee because the workers are engaged in short term employment and are not expected to work with the firm again after the contract is over.

However, moral hazard is reduced if the models include this reputation risk that referrers face in case they would bring a bad hire to the company. Saloner (1985) develops a model where referrers are in competition with each other to screen applicants in a world where signalling is not possible. The objectives of the firm and the referrer are, in theory, different; the former maximizes the quality of workers filling job vacancies whereas the referrer maximises the probability that his/her referred applicants are hired and maximize the average quality of his/her referees finally hired. In practice, the interests are aligned because the reputation of the referrer is at stake when he/she recommends someone and the referrer also feels entitled to be relevant for the firm decision-making when he/she is asked to give a job referral. The referrer has a trade-off between recommending many workers to the firm to maximize the probability it will hire one of his/her referees and lowering the average quality of the applicants by doing so. As a result, the model predicts that the referrers will provide the employer with a correct quality ranking of the applicants and the hired workers are of high ability.

In light of this effect, Heath (2018) develops a model that uses job referrals as a way that firms use to mitigate this moral hazard problem also from the referees' side. Networks hold relevant social pressure within members and can have greater rewards to good behaviour than the relationship firm-worker. In fact, workers can leave the company if they have bad performance due to excessive shirking and the firms cannot share this personal information easily to other firms. Conversely, social networks can share easier this information and relationships can be longer lasting than employment spells. Hence, firms mitigate moral hazard if they use job referrals because the referred worker will exert high effort. If he/she does not, then he/she will pay costs coming from his/her network, that is, the referrer will feel resentment towards the referee because the referrer will lose reputation to the employer for having recommended a bad worker.

These models also support Prediction 1, that is referred workers will work for the firm longer, since referrers are incentivized to recommend good workers that the firm does not want to fire, while the same referred workers are not incentivized to quit in fear it would make the referrers lose their reputation with the employer. Moreover, the models also support Prediction 2, that is the positive effect of a job referral is increasing in the strength of the social tie between referee-referral because with it, so are increasing the network costs applied if the referee worker shirks at work.

3 Empirical Analysis

3.1 Data

The sample used in our analysis contains 39,784 appointments to the boards of directors of 7,141 different US companies over the 2000-2015 period. The data has been collected and re-elaborated from BoardEx, a company that holds information over boards of directors of over one million companies of high capitalization worldwide. The database includes information about the board members on their demographics, education, roles, other activities, career history, and connections.

Two directors are recorded to have a connection if they have an overlap in their education, employment spell or other activities history in the same institution at the same time. Our sample contains all the directors appointed to the board of a company they have never worked in before the hire. This is meant to exclude promotion hires (or internal hires), as we are focusing on the incomplete information the firm and worker have about each other.

For the empirical analysis, we use a proxy for job referrals. The job referral dummy variable R_{ijt} is equal to one when a director has at least one connection with at least one member of the Nominating Committee of the company recruiting him/her (and zero otherwise). The Nominating Committee selects the directors for election at the annual shareholders meeting. Thus, it is essentially the recruiting body of the company for the board of directors[10]. Concretely, we consider that there is a job referral when the following scenario applies:

- Consider two directors i and m holding a social tie at time t_1 in company k
- Director m is member of the Nominating Committee of company j at time $t > t_1$
- Director i joins the board of company j at time t

Together with the job referral dummy variable, we identify the referrer director m and collect the same set of information over him/her as we have for the referred director i. In case the referee had connections with multiple members, we isolated the referrer director that worked the longer amount of years with the referred worker. In case of parity, we isolated the most recent connection.

Using past co-working relationships as network ties is an approach taken by other scholars, such as Cingano and Rosolia (2012), Hensvik and Skans (2016), Glitz (2017), and Saygin et al. (2019) but we argue that our proxy is more precise, because it links the information on the applicant directly with the recruiter instead of linking the referee with a worker that might not have had any contact with the hiring committee. Moreover, as the referee will be directly working with the referrer on the board, the moral hazard problem is likely to be reduced in our case. If the referee was about to shirk, the first people to be penalized by such behavior would be his/her direct team members i.e. the other board members, including the referrer. Thus, making it a perfect setting to test the models predictions shown in the Subsections 2.1 and 2.2.

[10]Cai et al. (2010) show that nominated directors almost never fail to be elected, thus justifying our focus on connections to the Nominating Committee and abstracting from connections to shareholders.

Theoretical models, such as the one of Casella and Hanaki (2006), include the networking cost as a parameter in their models to account for endogeneity in job search strategy. In fact, workers exert effort to form connections if they see a higher return in searching the informal labour market. In our analysis, we therefore include the network size of the applicant director as a control variable in the empirical models. This measure counts the number of workers present in the database he/she worked together with, during his/her lifetime. The variable correlates positively with the tendency of the worker to switch jobs (and with it, negatively with the tenure the director will have with the hiring company) and positively with the probability of being referred, as shown in Table 7. We use this variable as a proxy to control for heterogeneity in networking efforts.

We exclude observations from 2016 to 2018 to avoid having a truncated tenure distribution and we also exclude appointments in non-US companies to concentrate on a more homogeneous company sample under the same corporate law. As done by Hensvik and Skans (2016), we exclude from the sample all observations where the company hired more than 5 directors a single year to avoid counting cases of merger and newly established companies.[11] Finally, this dataset is then merged with firm level data from Compustat, a database providing information on company-level fundamentals, stock prices and other market data.

Table 1 provides an overview of the data with some summary statistics while Table 8 in the Appendix A.2 provides the definitions of the dataset variables.

The sample includes both executive and non-executive directors. The former have management responsibilities whereas the latter do not. In fact, Non-executive directors are not employed or affiliated with the company and must give proof of their independence from it. They must supervise the Management (agent) and safeguard the interests of the shareholders (principal) by providing expert advice. However, their incentives are not clear because they need to appear as expert monitors but also have advantages in

[11]In a merger, for instance, there would not be any job referral because managers of the acquired company would enter the board of the acquiring company with a different hiring process and would naturally have worked already with a colleague in the previous company the year before.

Table 1: Sample Summary Statistics

	No.Obs	Mean	Std. Dev.
Number of Appointments	39,784		
Number of Directors	29,033		
Number of Companies	7,141		
Number of Industries	47		
Number of Years of Observation	16		
Tenure	39,784	5.088	3.629
Referred	39,784	0.138	-
Executive Director	39,784	0.077	-
Female	39,784	0.136	-
Age	39,784	55.668	8.685
No. of Qualifications	39,784	2.165	1.179
Years of Experience	39,784	4.866	13.208
Director Network Size	39,784	1,652	1,916

supporting the CEO's decisions (Hermalin and Weisbach, 2003). Therefore, we make a clear distinction between the two kinds of directors, given the different nature of their work, the different skill-set required for their job and their different job performance evaluation (Lalanne, 2018).

Table 2 evidences such differences between the two groups. It presents a mean comparison with t-tests on observable director characteristics by role (executive versus non executive). Table 9 in the A.2 shows the same mean comparison by referral status (referred versus non referred) and Table 10 displays the mean comparison by role and referral status.

3.2 Methodology and Results

In the following subsection, we review the theoretical predictions laid down in Section 2, describe the empirical models to test them and present their results.

3.2.1 Job Referral and Impact on Tenure

Prediction 1 *Referred workers have longer tenure than non-referred ones*

Table 2: Director Characteristics Mean Comparisons (by Role)

	Executives		Non-Executives			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	Std. Error
Tenure	3.259	2.545	5.241	3.664	1.983***	0.050
Referred	0.198	0.399	0.133	0.340	-0.065***	0.007
Female	0.043	0.202	0.144	0.351	0.101***	0.004
Age	51.854	7.611	55.978	8.694	4.124***	0.144
Qualifications	1.961	1.114	2.182	1.183	0.221***	0.021
Experience	2.285	9.133	5.083	13.472	2.798***	0.179
Director Network Size	1,234	1,377	1,687	1,950	453.044***	26.825
Observations	3,079		36,705		39,784	

Notes. Two-sample t test with unequal variances. Statistical significance levels: + p<0.10 * p<0.05 ** p<0.01 *** p<0.001

In order to test Prediction 1, we firstly estimate the main model with a fixed effects regression:

$$y_{ijt} = \beta_0+\beta_1 R_{ijt}+\beta_2 EX_{ijt}+\beta_3 R_{ijt}\times EX_{ijt}+\beta_4 X_{it}+\beta_5 Z_{jt}+\beta_6 W_{ijt}+\theta_j+\delta_t+\epsilon_{ijt} \tag{11}$$

The dependent variable y_{ijt} represents the tenure of the director, here calculated as the number of years the director i hired in year t will work in company j.[12] R_{ijt} is the job referral dummy described in the subsection 3.1 and EX_{ijt} is a dummy variable equal to one if the director i is hired in year t as an executive director in company j and zero otherwise. The coefficients of interest are β_1 and β_3. The former will capture the effect of the job referral on non-executive directors while $\beta_1+\beta_3$ captures the effect of the job referral on executive directors.

X_{it} is a vector of director characteristics evaluated at time t. Variables include demographic information such as age and gender, but also years of experience in quoted boards, education, and network size. Z_{jt} is a vector of firm characteristics evaluated at the end of the fiscal year t. The variables capture the time-variant tenure effect coming from firm performance

[12]The sample only counts full-years of employment and not partial years to ensure comparability of data. This because the dataset does not always record start and end dates of employment with the full date but sometimes recording the month or the year only. Thus, the dependent variable is a natural number in the sample.

and characteristics. Those include firm size, market capitalization, net sales and board independence. The relevance of such controls can be seen, for instance, in the model of Hermalin and Weisbach (1998), where CEO tenure is endogenously dependent on board independence. Hermalin and Weisbach (2003) provide a literature review on endogeneity in board composition with firm performance. W_{ijt} is a vector of board's roles held by director i hired in year t in company j at the moment of his/her hire. δ_t is a vector of year controls used to capture the cohort effect and to account for the maximum amount of years a director can be observed still working in 2018, the year of the last update of the entire dataset. Finally, ϵ_{ijt} represents unobservable characteristics that influence y_{ijt} and are assumed to be independent from other variables. The model is estimated with firm fixed effects (θ_j). This will allow to remove the effect of time-invariant firm characteristics from the estimation of the parameters such as the propensity of using the referral channel to hire new directors. The panel is composed by firms appointing different directors (not necessarily in different years) and is unbalanced because 952 companies appear only once in the dataset, thus, removing 2.8 percent of the sample from the estimation of the constant term β_0 of the model. Standard errors are clustered at firm level to adjust for the potential non-random sample selection process done by the data providers. We do not estimate a count model because each year of tenure is correlated with the previous ones.

We could not track turnover over time using instantaneous separation hazard rate from the firm like Brown et al. (2016), Loury (2006) and Heath (2018) did because we could not ensure complete data every year. Unfortunately, it was not also possible to test whether being referred increases the probability to be hired, like Burks et al. (2015) and Brown et al. (2016) did, because our sample contains only the applicants that have been successfully been appointed and not those who have been rejected. Finally, it was impossible to calculate wage differences due to a lack of complete salary information.

The results of the model estimation (11) are shown in Table 3.

The model in column (5) of Table 3 shows referred non-executive directors work in the company for almost two months longer (0.134 years) than non-referred non-executive directors, which is 2.5 percent higher than the sample mean of the non-executives group (5.24 years in Table 2). The effect is not high and this is likely due to the fact that their contracts are fixed-

Table 3: Job Referral Impact on Tenure

	Tenure				
	(1)	(2)	(3)	(4)	(5)
Referred	0.045	0.044	0.150**	0.165**	0.134*
	(0.051)	(0.051)	(0.049)	(0.053)	(0.054)
Executive Director	-1.340***	-1.318***	-0.765**	-0.772**	-0.847**
	(0.055)	(0.056)	(0.235)	(0.295)	(0.297)
Referred × Executive Director					0.369**
					(0.138)
Director Characteristic	No	Yes	Yes	Yes	Yes
Role in the Company	No	No	Yes	Yes	Yes
Company Characteristics	No	No	No	Yes	Yes
Year Controls	Yes	Yes	Yes	Yes	Yes
Company Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.230	0.240	0.287	0.294	0.294
Adjusted R^2	0.230	0.239	0.286	0.293	0.293
Observations	39,784	39,784	39,784	35,412	35,412

Notes. Standard errors in parentheses, clustered at the firm level. Variables Description in Table 8.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

term and their productivity is not easily observable (Hermalin and Weisbach, 2003). Conversely, referred executive directors work in the company for six months longer (0.503 years) than non-referred executive directors, which is 15.4 percent higher than the sample mean of the executives group (3.25 years in Table 2).

The results showing both β_1 and β_3 positive are consistent with the predictions of all models in Section 2 and qualitatively similar to those of other empirical studies like Burks et al. (2015), Brown et al. (2016) and Dustmann et al. (2015). Comparing the coefficient β_1 in column (3) to the one in column (4), we can mildly confirm the prediction of Galenianos (2013) on tenure effects being lower without controlling for firm productivity.

Residuals of the model in column (5) distribute very closely according to a Normal distribution, so confirming the validity of t-statistics and statistically significance of the coefficients. This model explains well the variability within firms, with a R^2 (within) of 0.294 and an $Adjusted - R^2$ (within) of 0.293 but explains poorly the variability explained between firms, with a R^2 (between) of 0.03. Hence, there is high unobserved time-variant heterogeneity in the tenure determination of directors in different firms. The F-test on firms effects does in fact reject the hypothesis that all firm effects are null and justifies our choice of an OLS Fixed Effects estimation model. Pooled OLS estimation returns similar coefficient inference results both quantitatively and qualitatively and confirms the relevance of unobservable heterogeneity tenure effects because this model has a higher R^2 of 0.554 and an $Adjusted - R^2$ of 0.458. Estimating the same model without clustering standard errors also return similar results for statistically significance.

Prediction 2 *The positive tenure effect of referral increases with the strength of the connection between referrer and referee*

Prediction 2 can be tested including measures of relationship strength in the model (11) interacted with the job referral dummy. Results of the model estimation are shown in Table 4.

Table 4 shows in column (1) small positive returns to connection strength for both non-executives and executive referred directors of 9 days (0.025

Table 4: Referrer-Referee Relationship Strength on Tenure

	Tenure		
	(1)	(2)	(3)
Referred	0.018	0.025	0.046
	(0.069)	(0.105)	(0.064)
Executive Director	-0.839**	-0.838**	-0.835**
	(0.296)	(0.296)	(0.296)
Referred × Executive Director	0.408*	0.047	0.305+
	(0.184)	(0.279)	(0.156)
Referred × Relationship Length	0.025*		
	(0.010)		
Referred × Relationship Length × Executive Director	-0.010		
	(0.029)		
Referred × No. Social Ties to Nom. Committee		0.090	
		(0.074)	
Referred × No. Social Ties to Nom. Committee × Executive Director		0.177	
		(0.133)	
Referred × Total Amount of Relationship Years			0.013*
			(0.006)
Referred × Total Amount of Relationship Years × Executive Director			0.005
			(0.009)
Controls	Yes	Yes	Yes
Company Fixed Effects	Yes	Yes	Yes
R^2	0.294	0.294	0.294
Adjusted R^2	0.293	0.293	0.293
Observations	35,412	35,412	35,412

Notes. Standard errors in parentheses, clustered at the firm level. Controls include director characteristics, company characteristics, role of the director in company and year of hire. Variables Description in Table 8. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

years) of additional tenure for each year of past relationship with the referrer. Additionally, column (2) shows referred directors have no tenure premium for the number of connections they hold with the Nominating Committee. Column (3) shows both non-executive and executive referred directors work for 4.7 days (0.013 years) longer for the total amount of years of past relationships between the referee and each one of his/her referrers.

The results suggest that there might not be an overall baseline effect of job referrals but there is a crossover interaction with the strength of the connection leading to it. This result confirms the theory of Heath (2018) in which referred workers with strong network ties have better behaviour in the workplace and confirms the model of Saloner (1985) that predicts referrers that have an information advantage over the other competitors will be asked for job referrals more often, so referrers will firstly recommend those workers they have good knowledge about, that is, the ones they hold stronger connections with. However, the evidence is not strong and the model introduced variance that increases the uncertainty of the effects.

Prediction 3 *The positive tenure effect of referral decreases with the experience level of the referee*

In order to test Prediction 3, we firstly restrict the sample for those directors with less than half a year and with less than two years of experience in quoted boards before being hired. Secondly, we estimate the same fixed effects model (11) using the full sample but adding an interaction term with experience, to capture the continuous influence of experience. Results of the model estimation are shown in Table 5.

Prediction 3 can also be seen as a conclusion deriving from Casella and Hanaki (2006) model, where there is a trial that workers can take to signal to be of high ability. Under the model framework, we can think of the certification as a continuum of achievements. Experience can model well this trial for our sample because schooling is not likely to matter much in top corporate boards as much as experience. Additionally, experience signals to the new employer that the worker is worth enough to sit on a corporate board because another company chose to appoint him/her and this signal is stronger for each year spent in quoted boards.

Table 5: Heterogeneity of Experience Level on Tenure

	Tenure		
	Experience<0.5	Experience<2	Full Sample
	(1)	(2)	(3)
Referred	0.175^{+}	0.180^{*}	0.120^{*}
	(0.090)	(0.072)	(0.058)
Executive Director	-0.682	-0.598^{+}	-0.848^{**}
	(0.415)	(0.331)	(0.297)
Referred × Executive Director	0.396^{*}	0.434^{**}	0.402^{**}
	(0.198)	(0.159)	(0.142)
Referred × Experience			0.002
			(0.003)
Executive Director × Experience			0.001
			(0.006)
Referred × Experience × Executive Director			-0.010
			(0.014)
Controls	Yes	Yes	Yes
Company Fixed Effects	Yes	Yes	Yes
R^2	0.303	0.301	0.294
Adjusted R^2	0.302	0.300	0.293
Observations	18,201	25,151	35,412

Notes. Standard errors in parentheses, clustered at the firm level. Controls include director and firm characteristics, role of the director in the company and year of hire. Variables Description in Table 8. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results show that the exclusive tenure premium of referred executive directors 0.369 slightly increase to 0.396 (7.3 percent increase) when we restrict the sample to directors with less than half a year of experience (column (1)). However, the average treatment effect of the job referral for every director increases of half a month (0.041 years) but loses its traditional statistical significance of 5 percent, not allowing us to take a clear stance on it because the data is more disperse on this sub-sample.

After restricting the sample to directors with less than two years of experience in column (2), we see the tenure effect similarly increasing of half a month more (0.046 years) for non-executive directors and one month more (0.111 years) for executive directors. However, the interaction of years of experience with both referred R_{ijt} and executive director EX_{ijt} dummies is not statistically significant on the full sample in the model in column (3). This suggests there are unobservable characteristics in the group of less experienced referral hires driving their tenure. Another possible explanation is that returns on tenure for referred workers are initially increasing and later decreasing in experience but adding quadratic terms on experience to the model does not change the results.

Finally, we test if there are heterogenous effects of the referee's role, the referrer's role, and the connection type on the referee's tenure. The results are respectively shown in Table 11, Table 12, and Table 13 in the A.2.

Table 3 and Table 5 show that there is an heterogeneous effect for executive and non-executive directors. Therefore, we estimate a model that tests if there is a specific role that benefits more from job referrals in terms of tenure. Table 11 does not show any statistically significant difference in the effect of the role assigned to the director on his/her tenure. Brown et al. (2016) show heterogeneity in quit rates among different staff levels, with support staff having the larger benefits. However, the dataset available to the authors is comprised of workers over a wide job hierarchy, whereas our selection is limited to the roles on the board.

Table 12 shows the results of a model that includes the referrer's role in the company. We want to test whether the higher influence or longer tenure of the referrer increases the tenure of the referred director. According to Prediction 4, tenured workers with higher skills will refer a better hire who will work for a longer time in the company. In fact, Beaman and Magruder (2012) show that low-ability workers are less able to refer productive peers. Additionally, it might be possible that experienced directors know best what figure would fit into the company (Brown et al., 2016) or influential referrers could ensure greater job security to their referee. However, there is no statistical difference in the effect of job referrals originating from different referrers' board roles on the referee's tenure, as can be seen in columns (1) and (2). Executive referees' tenure is instead shown in columns (3) and (4) to have a significant negative relationship with the referrer's tenure that is of approximately 25 days (0.07 years) lower tenure for each year the referrer has been in the company or has sat on the board, compared to their non-executive counterparts. Contrarily to these results, Loury (2006) shows workers referred by older workers tend to work for more than two years longer in the same company. Hensvik and Skans (2016) find that ability and schooling of the referrer positively correlates with the referee wage. Brown et al. (2016) also find that referees receive a 4.8 percent higher salary when the referral is provided by senior referrers.

In Table 4, we show results of a model that tests the relevance of connection strength in determining director's tenure. Similarly, we estimate a model that tests if there is a heterogeneous effect in the company where the connection was formed. It might happen, for example, that if two workers had an overlap in a small company, then they might have higher probability of actually knowing each other, or else, that workers having an overlap in the armed forces in youth develop a stronger bond through their lives. Table 13 shows there is virtually no statistically different impact on referee's tenure between originating places for social tie construction. Only referred directors that had a connection through a medical company display 20.4 months (1.69 years) less tenure as compared to referred directors with a connection from university. Interacting variables with the dummy for executive director EX_{ijt} yields similar results both quantitatively and qualitatively.

3.2.2 Job Referral and Homophily

Prediction 4 *Referred workers are similar to their referrers*

In order to test Prediction 4, we built a dataset of dyads for each hired director with each member of the recruiting Nomination Committee. We split this dataset into two groups: the referred group contains dyads for which the two directors had a connection previous to the hire, and the non-referred group contains dyads for which there was no connection between the two directors previous to the hire. We then measure and compare the similarity between directors among these two groups. For the ease of reading, we refer to the members of the Nominating Committee as recruiters.

To measure similarity we use the cosine similarity CS_{imjt} metric, which measures the orientation difference of two non-zero vectors. In this context, we define $\mathbf{D}$ as a vector of characteristics of the director i hired and $\mathbf{M}$ as a vector of characteristics of the recruiter m of the company j at the year the director has been hired t. The cosine similarity is equal to one if both vectors are equivalent and it is equal to zero if they are orthogonal. The formula is hereby described:

$$\cos(\mathbf{D}, \mathbf{M}) = \frac{\mathbf{DM}}{\|\mathbf{D}\|\|\mathbf{M}\|} = \frac{\sum_{i=1}^{n} \mathbf{D}_i \mathbf{M}_i}{\sqrt{\sum_{i=1}^{n} (\mathbf{D}_i)^2} \sqrt{\sum_{i=1}^{n} (\mathbf{M}_i)^2}} \tag{12}$$

The measure is calculated using the director vector of characteristics including age, gender, education attainment, number of qualifications, and experience because those are the characteristics observable by the Nominating Committee prior to the hire. We also calculate the measure including the network size and present results with and without network size. We divide each continuous variable in the director vector into five brackets, each one containing approximately 20 percent of the observations in the sample. For each of them, we create dummy variables equal to one if the value of the continuous variable falls into the specified range and zero otherwise. This is done to normalize variables with different magnitudes and to combine binary measures (e.g. gender) with continuous ones (e.g. age). We use cosine similarity as a similarity measure because it is appropriate for comparing the sparse vectors of dummies we create, where many variables are equal to zero and only non-zero dimensions are relevant[13].

In Table 6, we present t-tests on the cosine similarity distributions be-

[13] Other distance measures such as the Euclidean Distance would calculate continuous distances for each continuous term, making for more precise calculations, but we did not choose to use it because it would suffer from magnitude comparability issues between continuous and discrete dimensions.

tween the Referred and Non-Referred groups to test for the evidence of homophilic features in social networks.

Table 6: Network Similarity Mean Comparisons

	Full Sample	Referred Group	Non-Referred Group	
	Mean	Mean	Mean	Diff.
	(Std. Dev.)	(Std. Dev.)	(Std. Dev.)	(Std. Error)
Recruiter Network Size	1633.294	1652.587	1631.772	-20.815
	(2123.995)	(2115.892)	(2124.635)	(22.841)
Same Sex	0.793	0.815	0.791	-0.024***
	(0.405)	(0.388)	(0.407)	(0.004)
Cosine Similarity	0.422	0.436	0.421	-0.015***
	(0.271)	(0.229)	(0.274)	(0.003)
Cosine Similarity	0.453	0.476	0.452	-0.025***
(No Network Size)	(0.284)	(0.260)	(0.286)	(0.003)
Observations	126,644	117,380	9,264	

Notes. Two-sample t test with unequal variances. Statistical significance levels: + p<0.10 * p<0.05 ** p<0.01 *** p<0.001

First of all, we test if recruiters in the referred group have a larger network size and, even though the sample mean of the network size is higher in the referred group, we cannot reject the hypothesis that the variable has the same distribution in both groups. This test is relevant to ensure the recruiters have in both cases the same number of connections they can potentially browse for job referrals, and with it, ensure greater comparability. Secondly, the results show that referrer and referee are 2.4 percentage points (3 percent) more likely to be of the same gender than any other pair director-recruiter. Similarly, the referrer-referee pair has a cosine similarity score ranging from 0.015-0.025 higher than average depending on whether we include network size or not to calculate it, which is in line with Prediction 4.

In order to test Prediction 4, we estimate the following model:

$$\begin{aligned} y_{imjt} &= \beta_0 + \beta_1 CS_{imjt} + \beta_2 EX_{ijt} + \beta_3 CS_{imjt} \times EX_{ijt} \\ &+ \beta_4 ln(N_{it}) + \beta_5 X_{it} + \beta_6 Z_{jt} + \beta_7 W_{ijt} + \theta_j + \delta_t + \epsilon_{imjt} \end{aligned} \tag{13}$$

y_{imjt} is a dummy variable that is equal to one if the hired director i had a previous connection to the recruiter m in company j before t and it will be considered from now on, as the probability of being referred. Specifically, this represents the probability a connection could lead to being referred in a board appointment. In this model, we explicitly display the coefficient for the director i network size N_{it} at time t because the amount of connections positively correlates with the probability of having a connection with a member of the Nominating Committee.

X_{it} is a vector of (other) director characteristics evaluated at time t. Z_{jt} is a vector of firm characteristics evaluated at the end of the fiscal year t. W_{ijt} is a vector of roles held by director i hired in year t in company j at the moment of his/her hire. δ_t is a vector of year controls and ϵ_{imjt} is the error term. The model is estimated with firm fixed effects (θ_j) and standard errors are clustered at firm level.

The results of the model (13) estimation are shown in Table 7.

Table 7 shows the probability of being referred increases (decreases) with the cosine similarity between recruiters and referees for executive directors (non-executive directors). Approximately, the coefficients could be interpreted as follows for the first model in the first column: the recruiter and the appointed executive director have 2.8 percentage points higher probability to have shared work history (i.e. causing a job referral in our study) if they had one additional point of cosine similarity (i.e. if they were perfectly equal in all their observable characteristics). Considering that the average cosine similarity in the sample is around 0.42, as shown in Table 6, then, the probability of being referred would increase on average of 1.62 percentage points for executive directors and decrease of 1.97 percentage points for non-executive directors if the couple recruiter-director were instead exactly similar (i.e. if cosine similarity would increase of 0.58).

In the second column, we calculate the cosine similarity measure without taking into account the network size. Network size can be appropriately included in the similarity calculation because workers with many ties might exchange favours with each other to reap advantages from their higher network density or centrality and because it is found that structural position in a network is a dimension of homophily in social networks (McPherson et al.,

Table 7: Similarity Between Referrer and Referee

	Probability to be Referred		
	OLS	OLS	Logit
Cosine Similarity	-0.034***		
	(0.004)		
Cosine Similarity × Executive Director	0.062***		
	(0.017)		
Cosine Similarity (no Network Size)		-0.025***	-0.512***
		(0.003)	(0.054)
Cosine Similarity (no Network Size) × Executive Director		0.056***	0.787***
		(0.016)	(0.171)
Ln Director Network Size	0.004***	0.005***	0.106***
	(0.001)	(0.001)	(0.011)
Executive Director	-0.021	-0.020	-0.220
	(0.022)	(0.022)	(0.212)
Controls	Yes	Yes	Yes
Company Fixed Effects	Yes	Yes	Yes
R^2	0.011	0.011	
Adjusted R^2	0.011	0.010	
Observations	126,644	126,644	78,992

Notes. Standard errors in parentheses, clustered at the firm level. Controls include director and firm characteristics, role of the director in the company and year of hire. Variables Description in Table 8. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2001). However, it can also be inappropriately included because workers that have a higher number of connections are more likely to be connected to the board by construction and we might want to avoid this artefact in our results. Under this specification, the results decrease of magnitude. Considering that the average cosine similarity without network size in the sample is around 0.45, as shown in Table 6, then, the probability of being referred would increase on average of 1.70 percentage points for executive directors and decrease of 1.37 percentage points for non-executive directors if the couple recruiter-director were instead exactly similar.

In the last column, we estimated a Logit Fixed Effects model. This model estimates the impact of each variable in turning a non-referral connection into a referral one within each company, excluding from the model estimation the companies that would have never used the referral channel anyway. In fact, the model restricts the sample to the companies that had both referred and non-referred hires and shows similar results to the other specifications. The coefficients can be interpreted easily as odds ratios. The odds of a connection to lead to a referral for a non-executive director perfectly similar to his/her recruiter is 0.60 ($e^{-0.512}$) times that of those perfectly dissimilar to their recruiter. Conversely, the odds ratio to be referred for executive directors perfectly similar compared to those perfectly dissimilar is 1.32 ($e^{0.275}$).

A possible reason on why the coefficients β_1 and β_3 have opposite signs can be attributed to the different diversity expected in both categories of directors. In fact, as explained in the subsection 3.1, non-executive directors should advice the Management and provide external expertise that can fill the knowledge gaps of the executive board. Therefore, it is plausible that different people fill non-executive positions in order to cover a wide array of expertise. In fact, Carter et al. (2003) empirically show that boards of *Fortune 1000* companies with fewer executives are more likely to have more women and minority directors. The authors argue that directors with a different background might bring innovating ideas but also take the risk of being marginalized. Furthermore, Kang et al. (2007) suggest that non-executive directors are more diverse because they must represent different shareholder groups.

4 Conclusion

There are several explanations for the wide use of job referrals in the labour market. In some models, the firm uses referrals to reduce the profile evaluation uncertainty of an applicant. In other models, the firm carefully selects good employees to suggest a referee under the assumption that ability is correlated within social networks. Finally, the referral reduces moral hazard of the referee because the social network exerts pressure on good behaviour. All models predict that referrals improve the match between firms and workers and, thus, predict that workers hired through the referral channel will consequently work longer in the company.

Our study provides additional empirical evidence on this prediction for the high-skill segment of the labour market using a wide original dataset of directors sitting on boards of large US companies. We find that referred executive directors work fifteen percent longer than their non-referred counterparts, that stronger relationships have a greater positive effect on job match quality and that the job referral benefits are slightly larger for less experienced directors. The referral information is proxied using a career link between the referee and recruiter previous to the hire. This is a proxy more reliable than overlaps between workers in linked-employer-employee datasets that might not have any contact with the hiring committee.

Using professional network information, we study the relationship between referrers and referees to test the assumption that people sort themselves into social networks of similar peers. We find that executive directors with similar characteristics are more likely to provide each other with a job referral, while the opposite applies for non-executive directors. Our approach use a multi-dimensional measure to calculate similarity that builds on the holistic view of similarity present in the sociology literature.

The analysis cannot rule out spurious relationships here not evidenced. Job referrals are part of a highly endogenous system that is very difficult to control for. Therefore, given the data at hands, it is not possible to show a causal link between job referrals and tenure. However, with these findings we provide empirical support to the theoretical explanations for why job referrals should help firms and workers to decrease asymmetric information in the labour market and an empirical support to theories of homophily sorting in social networks.

Our analysis may be further extended to incorporate relationship dynamics by including in the match-specific productivity the interaction of the worker not only with the firm but with the other co-workers as well. This would provide a learning framework that includes homophily elements together with moral hazard mitigation. A referrer can communicate a job referral to the employer about their joint productivity that is more precise (i.e. with lower signal variance) if the referee has a similar skill-set to the referrer that is easier to evaluate for him/her and if he/she can exert peer pressure on good behaviour of his/her referee. Moreover, this extension can also explain if referee and referrer have similar characteristics because this is correlated with the probability of belonging to the same network (McPherson et al., 2001), through which, peer pressure is applied to exhibit good behaviour. Alternatively, it can explain if firms specifically ask high ability employees to provide them a job referral that exhibits similar ability to them. In fact, the referrer that showed the employer to have the right skill-set for the job wants both to work with a similar worker for better communication (McPherson et al., 2001) and knows that a worker with similar skills will perform as well as him/her (Heath, 2018).

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A Appendix

A.1 Theory

Drawing from DeGroot (2005), consider n observations $y_1, y_2, y_3, \ldots, y_n$. The likelihood of obtaining those observations out of a distribution dependent on parameters θ and σ_ϵ^2 is:

$$P\left(y_1, y_2, y_3, \ldots, y_n \mid \theta, \sigma_\epsilon^2\right) \propto \frac{1}{\sigma_\epsilon^n} \exp\left(-\frac{1}{2\sigma_\epsilon^2} \sum \left(y_i - \theta\right)^2\right) \tag{14}$$

In our case, the observations are measures of productivity of the worker at each period, such that y_t is the productivity signal of the worker revealed in period t. The employer will observe the signal y and needs to estimate the true productivity θ of the worker using the posterior distribution of θ given y.

Firstly, we define the conjugate prior distribution of θ given the prior mean μ_θ and variance σ_θ^2:

$$P\left(\theta \mid \mu_\theta, \sigma_\theta^2\right) \propto \frac{1}{\sigma_\theta} \exp\left(-\frac{1}{2\sigma_\theta^2} \left(\theta - \mu_\theta\right)^2\right) \tag{15}$$

The distribution is conjugate because both the probability distribution y and prior probability distribution θ are both Normal.

One Measurement In learning models studied in Section 2.1, the productivity of the worker never changes and is equal to θ. The firm will measure the productivity either in the third stage (in Jovanovic (1979), Simon and Warner (1992)) or with probability α (in Dustmann et al. (2015)) but the measurement will happen only once. Therefore, the distribution of y laid down before is evaluated when $t = 1$.

The signal y is dependent on the random variable θ because $y = \theta + \epsilon$, where y is Normally distributed with mean μ_θ and variance $\sigma_\theta^2 + \sigma_\epsilon^2$. We can consider (θ, y) as distributed according to a bivariate Normal distribution, so to apply general rules for calculating conditional probabilities under a multivariate Normal distribution using facts about the Schur complement of matrices.

We put together the prior distribution (15) and likelihood (14) to obtain the posterior probability distribution of θ given y that is Normally distributed with mean ω and variance σ_1^2 where:

$$\omega = E(\theta \mid y) = E(\theta) + \frac{Cov(\theta, y)}{Var(y)}(y - E(y)) = \mu_\theta + \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\epsilon^2}(y - \mu_\theta) \quad (16)$$

and

$$\sigma_1^2 = Var(\theta \mid y) = Var(\theta) - \frac{Cov(\theta, y)^2}{Var(y)} = \sigma_\theta^2 - \frac{\sigma_\theta^4}{\sigma_\theta^2 + \sigma_\epsilon^2} = \frac{\sigma_\theta^2 \sigma_\epsilon^2}{\sigma_\theta^2 + \sigma_\epsilon^2} \quad (17)$$

because

$$E(\theta) = \mu_\theta, \qquad Var(y) = Var(\theta) + Var(\epsilon) = \sigma_\theta^2 + \sigma_\epsilon^2. \quad (18)$$

and

$$\begin{aligned} Cov(\theta, y) = E\left((\theta - \mu_\theta)(y - \mu_y)\right) = E(\theta y) - E(\theta)E(y) = E(\theta(\theta + \epsilon)) - \mu_\theta^2 = \\ = E(\theta^2) + E(\theta)E(\epsilon) - E(\theta)^2 = E(\theta^2) + 0 - E(\theta)^2 = Var(\theta) = \sigma_\theta^2 \quad (19) \end{aligned}$$

The posterior mean ω in (16) is a random variable because is proportional to the prior mean μ_θ and to the observation y, which is a random variable. Therefore, we calculate the first and second central moments of ω:

$$E(\omega) = E(\mu_\theta) + E\left(\frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\epsilon^2}(y - \mu_\theta)\right) = \mu_\theta + 0 = \mu_\theta \quad (20)$$

$$\begin{aligned} Var(\omega) &= Var(\mu_\theta) + Var\left(\frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\epsilon^2}(y - \mu_\theta)\right) \\ &= 0 + \left(\frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\epsilon^2}\right)^2 (\sigma_\theta^2 + \sigma_\epsilon^2) = \frac{\sigma_\theta^4}{\sigma_\theta^2 + \sigma_\epsilon^2} \quad (21) \end{aligned}$$

because:

$$E(y - \mu_\theta) = E(\theta) + E(\epsilon) - E(\mu_\theta) = E(\mu_\theta) + 0 - E(\mu_\theta) = 0 \quad (22)$$

$$Var(y - \mu_\theta) = Var(\theta) + Var(\epsilon) - Var(\mu_\theta) = \sigma_\theta^2 + \sigma_\epsilon^2 \quad (23)$$

We also see the variance of the distribution σ_1^2 increases in the noise σ_ϵ^2 of the signal y because

$$\frac{\partial \sigma_1^2}{\partial \sigma_\epsilon^2} = \frac{\sigma_\theta^2(\sigma_\theta^2 + \sigma_\epsilon^2) - \sigma_\theta^2 \sigma_\epsilon^2}{(\sigma_\theta^2 + \sigma_\epsilon^2)^2} = \frac{\sigma_\theta^4}{(\sigma_\theta^2 + \sigma_\epsilon^2)^2} > 0 \quad (24)$$

Multiple Measurements If we have multiple observations (i.e. $t > 1$), like in Pinkston (2012), then we use the sample mean $\bar{y} = \frac{\sum y_t}{n}$ for n observations in (15) as sufficient estimator for θ for simplicity and get back to a univariate case. Note that the single observation has variance σ_ϵ^2 but the sample mean $\bar{y}$ has sample variance $\frac{\sigma_\epsilon^2}{n}$ such that:

$$y_i \mid \theta \sim N\left(\theta, \sigma_\epsilon^2\right) \qquad \bar{y} \mid \theta \sim N\left(\theta, \frac{\sigma_\epsilon^2}{n}\right) \tag{25}$$

The posterior probability of θ then becomes:

$$\begin{aligned} P\left(\theta \mid y_1, y_2, y_3, \ldots, y_n\right) &\propto P\left(y_1, y_2, y_3, \ldots, y_n \mid \theta\right) P(\theta) \\ &\propto P\left(\bar{y} \mid \theta\right) P(\theta) \propto P\left(\theta \mid \bar{y}\right) \end{aligned} \tag{26}$$

which means that the distribution of $\theta \mid y_1, y_2, y_3, \ldots, y_n$ is proportional to the one of $\theta \mid \bar{y}$. Therefore, we find ourselves in the previous case, where we estimated the distribution of $\theta \mid \theta + \epsilon$ where $n = 1$. We can therefore substitute the variable $\bar{y}$ to the results obtained in (16) and (17). For sake of nomenclature consistency, we define the later signals of y_t as u_{it}, as in Pinkston (2012), and $S_{it} = \theta_i + \eta_{it}$ as the posterior updated signal, so that:

$$u_{it} \mid \theta \sim N\left(\theta, \sigma_\psi^2\right), \qquad \bar{u} \mid \theta \sim N\left(\theta, \frac{\sigma_\psi^2}{t}\right) \tag{27}$$

and the posterior probability distribution of θ for the sample mean $\bar{u}$ of multiple measures u_{it} has mean and variance:

$$E(S_{it}) = \mu_\theta + \frac{t\sigma_\epsilon^2}{t\sigma_\epsilon^2 + \sigma_\psi^2}\left(u - \mu_\theta\right) \tag{28}$$

$$Var(S_{it}) = \sigma_\eta^2 = \frac{\sigma_\epsilon^2 \sigma_\psi^2}{t\sigma_\epsilon^2 + \sigma_\psi^2} \tag{29}$$

σ_η^2 is increasing in the initial signal variance σ_ϵ^2 and is decreasing slower with tenure because

$$\frac{\partial \sigma_\eta^2}{\partial \sigma_\epsilon^2} = \frac{(\sigma_\psi^2)^2}{(t\sigma_\epsilon^2 + \sigma_\psi^2)^2} > 0 \tag{30}$$

$$\frac{\partial \sigma_\eta^2}{\partial t} = \frac{-\sigma_\psi^2 (\sigma_\epsilon^2)^2}{(t\sigma_\epsilon^2 + \sigma_\psi^2)^2} < 0 \tag{31}$$

and

$$\frac{\partial^2 \sigma_\eta^2}{\partial t \partial \sigma_\epsilon^2} = \frac{-4\sigma_\epsilon^2 \sigma_\psi^2}{(t\sigma_\epsilon^2 + \sigma_\psi^2)^3} < 0 \tag{32}$$

A.2 Tables

Table 8: Variables Definitions

Variable Name	Description
Variables of Interest	
Tenure	No. of years in the company since the time of hire
Referred	Dummy variable equal to 1 if the director has previous shared work history with at least one member of the Nominating Committee of the hiring company and 0 otherwise
Executive Director	Dummy variable equal to 1 if the director holds the position of Executive Director in the firm at the time of hire and 0 otherwise
Cosine Similarity	Cosine Similarity measure evaluated between the director and a member of the Nominating Committee of the hiring company at the time of hire. Variables used: *Director Characteristics*
Cosine Similarity (No Network Size)	Cosine Similarity measure evaluated at the time of hire using variables: *Director Characteristics* but without Director Network Size
Relationship Length	Maximum amount of years the director worked with any member of the Nominating Committee of the hiring company
No. Connections to Nom. Committee	Number of members of the hiring company Nominating Committee the director had previous shared work history with

Table 8: Variables Definitions, continued

Variable Name	Description
Total Amount of Relationship Years	Combined amount of years the director worked with all the members of the Nominating Committee of the hiring company
Same Sex	Dummy variable equal to 1 if the director and the member of the Nominating Committee have the same sex and 0 otherwise
Director Characteristics	
Age	Age of the director at the time of hire in years
Age^2	Age of the director at the time of hire in years squared
Experience	Total amount of years spent on quoted boards before the time of hire
Female	Dummy variable equal to 1 if the director is female and 0 otherwise
Ln Director Network Size	Number of the director overlaps through employment, other activities, and education on logarithmic scale at the time of hire
Bachelor	Dummy variable equal to 1 if the director holds a Bachelor degree and 0 otherwise
Master	Dummy variable equal to 1 if the director holds a Master degree and 0 otherwise
MBA	Dummy variable equal to 1 if the director holds a MBA degree and 0 otherwise
PhD	Dummy variable equal to 1 if the director holds a PhD degree and 0 otherwise
Role in the Company	
Chairman	Dummy variable equal to 1 if the director holds the role of Chairman in the firm at the time of hire and 0 otherwise
CEO	Dummy variable equal to 1 if the director holds the role of CEO in the firm at the time of hire and 0 otherwise

Table 8: Variables Definitions, continued

Variable Name	Description
Executive VP	Dummy variable equal to 1 if the director holds the role of an Executive Vice-President (excluding CEO) in the firm at the time of hire and 0 otherwise
Senior VP	Dummy variable equal to 1 if the director holds the role of a Senior Vice-President in the firm at the time of hire and 0 otherwise
Other Non-Ex. Director	Dummy variable equal to 1 if the Executive director is a holds a role different from Chairman, CEO, VP in the firm at the time of hire and 0 otherwise
Independent Director	Dummy variable equal to 1 if the director holds the role of Independent Director in the firm at the time of hire and 0 otherwise
Other Non-Ex. Director	Dummy variable equal to 1 if the Non-Executive director is a holds a role different from Independent Director in the firm at the time of hire and 0 otherwise
Company Characteristics	
Board NED Percentage	Percentage of non-executive directors present in the board of directors of the firm at the time of hire
Ln Employees	Number of employees working at the firm at the time of hire on logarithmic scale
Ln Market Capitalization	Total market value of the number of outstanding shares evaluated at the time of hire on logarithmic scale
Ln Net Sales	Company net sales at the time of hire on logarithmic scale

Table 9: Director Characteristics Mean Comparisons (by Referral Status)

	Referred		Non-Referred			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	Std. Error
Tenure	4.801	3.351	5.134	3.670	0.332***	0.049
Executive Director	0.111	0.314	0.072	0.258	-0.039***	0.004
Female	0.110	0.313	0.140	0.347	0.030***	0.005
Age	56.307	9.013	55.555	8.627	-0.753***	0.130
Experience	7.891	17.571	4.381	12.296	-3.510***	0.246
Chairman	0.091	0.288	0.053	0.224	-0.038***	0.004
CEO	0.077	0.266	0.050	0.218	-0.027***	0.004
Executive VP	0.021	0.143	0.013	0.114	-0.008***	0.002
Senior VP	0.002	0.040	0.002	0.043	0.000	0.001
Other Ex. Director	0.004	0.063	0.004	0.065	0.000	0.001
Independent Director	0.787	0.409	0.839	0.368	0.052***	0.006
Other Non-Ex. Director	0.092	0.289	0.085	0.280	-0.007	0.004
Observations	5,504		34,280		39,784	

Notes. Two-sample t test with unequal variances. Statistical significance levels: + p<0.10 * p<0.05 ** p<0.01 *** p<0.001

Table 10: Director Characteristics Mean Comparisons (by Referral Status and Role)

	Referred		Non-Referred			
	Mean	Std. Dev.	Mean	Std. Dev.	Diff.	Std. Error
Executive Directors						
Tenure	3.200	2.353	3.273	2.591	0.073	0.109
Female	0.031	0.174	0.045	0.208	0.014	0.008
Age	51.908	8.485	51.841	7.381	-0.068	0.374
Experience	2.774	8.972	2.164	9.170	-0.610	0.407
Chairman	0.720	0.449	0.672	0.470	-0.048*	0.020
CEO	0.692	0.462	0.698	0.459	0.006	0.021
Executive VP	0.188	0.391	0.183	0.387	-0.005	0.018
Senior VP	0.015	0.121	0.026	0.158	0.011	0.006
Other Ex. Director	0.036	0.186	0.059	0.236	0.023**	0.009
Independent Director	0.000	0.000	0.000	0.000	0.000	0.000
Other Non-Ex. Director	0.000	0.000	0.000	0.000	0.000	0.000
Observations	611		2,468		3,079	
Non-Executive Directors						
Tenure	5.001	3.403	5.278	3.702	0.277***	0.053
Female	0.120	0.325	0.147	0.354	0.027***	0.005
Age	56.857	8.927	55.843	8.650	-1.014***	0.137
Experience	8.530	18.264	4.553	12.490	-3.977***	0.270
Chairman	0.013	0.113	0.005	0.071	-0.008***	0.002
CEO	0.000	0.000	0.000	0.000	0.000	0.000
Executive VP	0.000	0.000	0.000	0.000	0.000	0.000
Senior VP	0.000	0.000	0.000	0.000	0.000	0.000
Other Ex. Director	0.000	0.000	0.000	0.000	0.000	0.000
Independent Director	0.885	0.319	0.904	0.295	0.019***	0.005
Other Non-Ex. Director	0.104	0.305	0.092	0.289	-0.012*	0.005
Observations	4,893		31,812		36,705	

Notes. Two-sample t test with unequal variances. Statistical significance levels: + p<0.10 * p<0.05 ** p<0.01 *** p<0.001

Table 11: What Role Benefits From Referrals More

	Tenure
	(1)
Referred	0.751
	(1.59)
Referred × Chairman	0.388
	(1.21)
Referred × CEO	-0.690^{+}
	(1.92)
Referred × Executive Vice-President	0.114
	(0.24)
Referred × Senior Vice-President	0.799
	(0.66)
Referred × Other Executive Director	-1.150
	(1.24)
Referred × Independent Director	-0.684
	(1.45)
Referred × Other Non-Executive Director	-0.007
	(0.01)
Executive Director	-0.752*
	(2.56)
Controls	Yes
Company Fixed Effects	Yes
R^2	0.295
Adjusted R^2	0.294
Observations	35,412

Notes. Standard errors in parentheses, clustered at firm level. Controls include director and firm characteristics, role of the director in the company and year of hire. Variables Description in Table 8. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Heterogeneity of Referrer Role on Tenure

	Tenure				
	(1)	(2)	(3)	(4)	(5)
Referred	0.127*	1.171	0.194**	0.192**	0.224**
	(0.053)	(0.762)	(0.073)	(0.074)	(0.072)
Executive Director	-0.848**	-0.851**	-0.838**	-0.837**	-0.839**
	(0.297)	(0.297)	(0.296)	(0.296)	(0.296)
Referred × Ex. Director	0.391**	0.372**	0.504***	0.499***	0.424**
	(0.137)	(0.139)	(0.151)	(0.151)	(0.153)
Referred by Ex. Director	0.360				
	(0.617)				
Referred by Ex. Director × Ex. Director	-0.627				
	(0.937)				
Referred by Chairman		-0.546			
		(0.731)			
Referred by CEO		-0.622			
		(0.594)			
Referred by Executive Vice-President		-0.245			
		(1.229)			
Referred by Other Executive Director		-2.599			
		(2.553)			
Referred by Independent Director		-1.072			
		(0.762)			
Referred by Other Non-Executive Director		-0.541			
		(0.792)			
Time in Company of Referral			-0.010		
			(0.008)		
Time in Company of Referral × Ex. Director			-0.071**		
			(0.026)		
Time on Board of Referral				-0.009	
				(0.008)	
Time on Board of Referral × Ex. Director				-0.069**	
				(0.026)	
Time in Role of Referral					-0.019+
					(0.010)
Time in Role of Referral × Ex. Director					-0.056
					(0.039)
Controls	Yes	Yes	Yes	Yes	Yes
Company Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.294	0.294	0.294	0.294	0.294
Adjusted R^2	0.293	0.293	0.293	0.293	0.293
Observations	35,412	35,412	35,412	35,412	35,412

Notes. Standard errors in parentheses, clustered at firm level. Omitted variable: 'Referred by Senior Vice-President'. Controls include director and firm characteristics, role of the director in the company and year of hire. Variables Description in Table 8. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Importance of Social Tie on Tenure

	Tenure
	(1)
Referred	0.053
	(0.148)
Executive Director	-0.845**
	(0.296)
Referred × Executive Director	0.352*
	(0.139)
Referred × Armed Forces	0.271
	(0.452)
Referred × Charities	-0.139
	(0.421)
Referred × Clubs	-0.171
	(0.298)
Referred × Government Body	-0.022
	(0.356)
Referred × Medical Company	-1.689**
	(0.529)
Referred × Partnership	-0.138
	(0.372)
Referred × Private Company	0.166
	(0.167)
Referred × Quoted Company	0.063
	(0.166)
Controls	Yes
Company Fixed Effects	Yes
R^2	0.294
Adjusted R^2	0.293
Observations	35,412

Notes. Standard errors in parentheses, clustered at the firm level. Independent Variables are dummies for each company type the referee and referrer worked before the hire. Omitted Variable: 'University'. Control variables include director and firm characteristics, role of the director in the company and year of hire. Variables Description in Table 8. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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