# Network hiring, firm performance and growth*

Ines Black
Duke University
Fuqua School of Business
Durham, NC
ines.black@duke.edu

Sharique Hasan
Duke University
Fuqua School of Business
Durham, NC
sharique.hasan@duke.edu

January 26, 2022

**Abstract**

Network hiring—i.e., the preference for hiring workers who are referred by existing employees or have shared affiliations with them—is a prevalent practice across many industries. Considerable research shows that hiring within a firm's network provides soft information about potential hires and informal mechanisms of control once they join a company. While research shows that in-network hires perform better, little is known about the firm-level performance implications and the associated trade-offs of this practice. In this article, we study the impact of network hiring by using data on the universe of firms in Portugal between 1994 to 2017. We find that network hiring appears to increase firm performance but at the expense of growth. Furthermore, network hiring seems to provide firms with information on intrinsic motivation traits of the candidates rather than information on skills. We conclude with a discussion on how this practice should affect firm strategy, particularly young ones'.

*Authorship in alphabetical order. Both authors contributed equally to the manuscript.

# 1 Introduction

Finding and retaining talent is one of the most critical challenges for organizations. A large body of research shows that talent matters for firm performance (e.g., Coff, 1997; Koch and McGrath, 1996) and informational asymmetries in the hiring process make it hard to uncover (e.g., Castilla, 2005; Pallais and Sands, 2016). To address this challenge, firms often leverage the networks of their existing employees to find new ones (Granovetter, 1973). Indeed, referral and network-based hiring make up a significant share of how firms hire workers. In the United States, recent figures suggest that firms hire over 30% of all workers through referrals (Black, Hasan and Koning, 2020), and this share appears to be equally significant in other developed economies (Hoffman, 2017). Indeed, considerable empirical research using detailed case studies of firms' hiring practices suggests that firms prefer in-network candidates and that these individuals perform better once hired (Hoffman, 2017; Castilla, 2005; Fernandez and Sosa, 2005; Petersen, Saporta and Seidel, 2000).

However, a parallel literature suggests that network-based hiring may lead to narrower and often biased search by firms (Fernandez-Mateo and Fernandez, 2016; Rubineau and Fernandez, 2013; Fernandez and Sosa, 2005; Petersen, Saporta and Seidel, 2000). By considering only candidates with whom they have a network "connection," a firm may constrain its talent pool size, which is likely to compound over time. By gaining information on the intensive margin—e.g., about the quality of workers in the pool—they may lose information on the extensive margin—e.g., about workers with whom they do not have some link. These competing mechanisms suggest that firms may differ in how much they benefit from using networks to hire; however, evidence is limited.

This article takes a firm-side approach and asks what and how firms benefit from network hiring. We argue that the benefits of network hiring depend on whether the balance of a network's value lies in providing firms with information about the intensive or extensive margin during the hiring process. On the one hand, like much other work, we posit that firms that use networks to hire can choose better quality workers among those in their pool. On the other hand, we argue that firms may limit their growth by relying on network hiring—because they rely disproportionately on employee networks to find workers. Moreover, young and entrepreneurial firms may be most susceptible to this trade-off because they depend on founders or early employees to find and vet new employees. Finally, we expect the impact of network hiring to be most crucial in hiring workers who do creative knowledge-intensive tasks. In such tasks, worker ability is harder to measure *a priori*.

To test our arguments, we use matched employer-employee data from Portugal between 1994 and 2017. We use data on 941,403 firms and close to 6,329,089 workers to examine the impact of network hiring on firm performance. Since network hiring is hard to observe, we develop a method to identify firms that engage in network hiring using workplace affiliation networks. We consider a firm to participate in network hiring when a recruit comes from a firm from which the firm has already hired existing employees in recent years. This method is replicable in other employer-employee data sets and can be used to infer the lower-bound of network hiring practices of firms.

We take advantage of the panel structure of our data set to implement a rich fixed-effects approach. Specifically, we estimate panel regressions of network hiring on firm outcomes —sales, firm growth, and employee retention— with firm and year fixed effects. This approach allows us to compare the impact of network hiring on our outcomes of interest within firms, which cleans our estimates of possible between-firm variation in network hiring adoption.

Our findings suggest a positive and statistically significant improvement in firm performance when they engage in network hiring. The magnitude of this effect appears to be about 21 percent, but with meaningful heterogeneity depending on the firm's age. We find that young firms appear to benefit less from network hiring than large firms. This difference, we posit, is likely a consequence of younger firms exploring less due to relying on the smaller set of networks of their founders and early employees. Thus, they are limited in their ability to hire high-quality but more socially distant workers. Our results also point to our predicted trade-off between performance and growth. Firms that engage in network hiring see a 120% lower growth rate, and this effect is particularly stark for younger firms. Lastly, we find evidence that the actual value of network hiring for firms lies in its acquisition of information on non-cognitive traits (e.g., Deming, 2017; Farkas, 2003) rather than candidates' specialized skills (Ferguson and Hasan, 2013).

Our results contribute to four streams of literature on human capital and firm performance. First, most of the research on referrals has focused on single firms and the returns to network hiring for individual employees (Fernandez and Weinberg, 1997; Hoffman, Kahn and Li, 2018; Pallais and Sands, 2016). Based on economy-wide data, our results provide evidence that this practice is prevalent and impacts the performance of a wide range of firms. Second, our results speak to recent theoretical work suggesting that networks may increase and decrease information, which may have consequences for individual and organizational outcomes (Chandrasekhar, Morten and Peter, 2020). Third, our results indicate that young entrepreneurial firms may face the most significant trade-offs from network hiring. This finding contributes to the growing literature on the human capital strategy of new ventures (Chatterji et al., 2019; Marx and Timmermans, 2017; Baron, Hannan and Burton, 2001). Finally, our work speaks to the growing literature on the changing nature of skills in the labor market and suggests that hiring practices may improve the ability of firms to acquire information about some skills rather than others. In particular, we find that the benefits of network hiring accrue primarily to firms that rely on creative and knowledge-based workers.

# 2 Theoretical framework

Firms need high-quality employees to be successful. However, finding, hiring, and then retaining high quality-workers is difficult. This challenge is particularly significant for young firms that do not have established processes for recruiting. Thus, their performance may be considerably affected because they cannot find suitable workers. To address this perennial challenge, firms often rely on the networks of their employees in the hiring process. Not surprisingly, a large body of research shows that network-driven hiring makes up a significant portion of how firms recruit workers (Bewley and Bewley, 1999; Henly, 2000; Marsden and Gorman, 2001) and how workers search for jobs (Franzen and Hangartner, 2006; Fernandez and Weinberg, 1997; Granovetter, 1995). Indeed, recent estimates suggest that even in the age of digitally-enabled labor markets, network or referral-based hiring continues to make up at least one-third of hiring across the economy (Black, Hasan and Koning, 2020).

## 2.1 Network hiring and firm outcomes

The benefits of network hiring to firms come from two primary informational mechanisms, operating at both the intensive and extensive margins of the hiring process. First, network ties provide firms access to information about worker quality on the intensive margin. Referees allow firms to gather more and difficult-to-observe details on each candidate. Second, network ties additionally provide information on the extensive margin of the labor market by making firms aware of new potential candidates. Collectively, existing employees have many connections to acquaintances, friends, and family (e.g., Lin, 1999; Granovetter, 1973) that they can use to source talent for the firm.[1] Both mechanisms increase the likelihood that the firm can find high-quality workers and include them in their hiring pool.

### 2.1.1 Intensive margin: choosing between workers

One benefit of network hiring is that it allows firms to acquire difficult-to-observe information about workers. Consider the information a firm can learn from a resume or a job application. A resume or an online profile (e.g., LinkedIn or Indeed) can provide information about education or skills and can serve as an initial filter in the hiring process. However, this type of information is limited in meaningful ways. A resume rarely reveals information about whether an individual is hard-working, trustworthy, careful, creative, or has a good personality. Using referrals can help decrease the cost of acquiring this non-cognitive information by providing a screening mechanism that reduces the information asymmetry that is inherent to the hiring process (Beaman and Magruder, 2012;

[1]For a recent review of the literature on networks and careers, see Hasan (2019).

Marmaros and Sacerdote, 2002; Montgomery, 1991; Simon and Warner, 1992). As a result, by using referrals, firms can acquire valuable but challenging-to-learn information that is predictive of a worker's future productivity (Pallais and Sands, 2016).

Complementing the information that network hiring provides are several social mechanisms that operate before and after a firm makes a hire. First, research suggests that high ability workers are more likely to make referrals (Burks et al., 2015). This is because career concerns provide employees with inherent incentives to refer contacts with high ability (Ekinci, 2016), augmenting the value of network-acquired information. Moreover, a connection to someone at the firm may increase the non-pecuniary benefits of working there (Galenianos, 2018; Brown, Setren and Topa, 2016; Burks et al., 2015; Dustmann et al., 2016). These factors also contribute to network hires exhibiting higher performance and lower turnover (Pallais and Sands, 2016; Burks et al., 2015). Finally, having social connections at work may also serve as a form of social control that can lead to higher performance through informal influence and monitoring.

Thus, we should expect that firms that rely on network hiring should have higher performance and that their ability to retain workers should also be higher.

### 2.1.2 Extensive margin: searching for workers

Although there are many benefits to network recruiting, recent research also suggests that relying on employees to find new workers may limit a firm's ability to search broadly. In recent theoretical work, Chandrasekhar, Morten and Peter (2020) suggests this may happen because part of the inputs of a formal, application-driven hiring process is to provide the firm with two pieces of information. The first is a consideration set of potential candidates previously unknown to the firm. The second is the expected quality of an average candidate in this set. When firms rely on referrals, their pool of potential hires is drawn from the networks of their existing employees. Using networks limits the size of the consideration set and its composition and, thus, quality. If a firm relies heavily on in-network recruiting, this will lead to an increasing overlap between the networks of existing employees and future employees. As a result, the total size of the referral pool a firm can potentially target will increase at a decreasing rate over time. Furthermore, because of homophily in the formation of social ties, relying on network hiring should lead to a less diverse—in terms of demographics, skill, as well as quality—consideration set (Rubineau and Fernandez, 2013; Fernandez and Sosa, 2005).

One key consequence of this narrowed pool is a reduction in the firm's ability to grow. As workers refer the best among their contacts to the firm, the remaining pool of workers may be limited both in terms of quantity and quality. As a result, firms that rely on network recruiting, which achieving higher performance and better retention, should also grow more slowly as the reliance on the employees' networks limits their access to a broader pool of high-quality workers unknown by their present organization.

## 2.2 Network hiring and entrepreneurial firms

While these mechanisms should impact a broad range of firms that rely on network hiring to recruit workers, they are most likely to be consequential for younger, more entrepreneurial firms. Young firms depend heavily on the networks of their founders and early employees to acquire essential resources—especially talent and human resources (e.g., Leung et al., 2006; Hansen, 1995). Founders, for instance, often rely on their networks of connections from prior companies they have worked for to hire new employees (Rider, 2012). Relying on their networks allows new ventures to find workers that they can both trust to have essential cognitive and non-cognitive skills, but also with whom they have prior experience working together (Marx and Timmermans, 2017). Moreover, in a younger company where formal roles and processes are not yet in place, a selection process based on referrals should also increase the amount of social control and intrinsic motivation of the worker pool. Consequently, the value of network hiring for firm performance should be higher for younger firms than more mature ones.

On the other hand, the reliance on network hiring will likely have a more significant impact on the growth of young firms. Whereas older firms are more likely to have formal mechanisms to hire as they deplete their ability to recruit workers purely through networks, young firms may not. As a consequence, young firms that rely on networks to hire should grow more slowly than those that do not (e.g., Chandrasekhar, Morten and Peter, 2020).

## 2.3 Network hiring and information asymmetries

Network hiring helps firms acquire hard to observe information about potential hires. For what types of skills does network hiring help the most? Research highlights that several characteristics of workers are difficult to observe. Work on specialization, for example, highlights that a critical challenge for employers is determining whether a worker has the relevant skills to perform a task (Ferguson and Hasan, 2013). To the extent that a worker's observable experience is a weak signal of this information, referrals may provide greater nuance as to whether a potential hire has the knowledge or skill to perform a specialized task. If firms are using referral hiring to learn about workers' specialized skills, then we should expect that the impact of network hiring should be larger for firms that rely on high-skilled labor.

On the other hand, the performance of workers depends on more than just their skill and knowledge. Work suggests that traits that drive intrinsic motivation, such as commitment, effort, social skill, as well as perseverance, all predict performance independently of a worker's skill in a specific task (Deming, 2017; Cobb-Clark and Tan, 2011; Farkas, 2003). Research suggests that social networks are a crucial source of this type of information and that information on intrinsic motivation may be difficult to acquire from other sources. Suppose firms are using referral hiring to learn about intrinsic motivation. In that case, we should expect the benefits of network hiring to vary little based on the skill requirements but vary based on the level of intrinsic motivation required or expected of the worker's occupation.

For what types of work is intrinsic motivation most important? Research shows that performance in creative occupations, such as computer programming, advertising, research, and science, is less susceptible to high-powered incentives because intrinsic motivation proportionally more drivers workers (Erat and Gneezy, 2016). Similarly, Cohen, Sauermann and Stephan (2018) and Sauermann and Cohen (2010) suggest that innovative output varies considerably according to the inventor's intrinsic motivation. Therefore, if firms use referrals to gather difficult-to-observe information on intrinsic motivation, we should expect that the effects of network hiring on firm outcomes are greater for firms with more creative and knowledge-intensive employees.

# 3 Data & Setting

This paper analyzes the relationship between network hiring and firm performance using economy-wide data from Portugal. Portugal is a small open economy with a set of labor market and market economy characteristics that may be generalized to other European Union or OECD economies. Alongside labor market features, Portuguese economic activity is similar to other small EU countries. Portugal has been part of the European Common Market and Schengen Agreement since 1986, allowing free movement of goods, services, and people. It has also belonged to the Monetary Union (euro) since its inception in 1999. Small and medium-sized firms represent close to 99% (95% OECD average) of the total number of firms in Portugal. They have accounted for between one-half and two-thirds of its total value creation over the past decade[2]. Most (68.2%) of these firms' employment is dedicated to services, comparable to a 72% in the EU[3]).

Besides closely representing a small open economy, the Portuguese labor market presents features that we believe make it a particularly suitable setting to study questions related to network hiring. First, the relatively inflexible labor laws in place in most EU countries and Portugal— means decisions connected to how to hire talent are also more consequential. Second, informal network hiring is quite prevalent in the labor market, giving us a large sample to study.

[2]Source: PORDATA (2018) *Empresas, Pequenas e Médias Empresas.*
[3]OECD (2015), Employment in the services sector.

## 3.1 Data sources

Our data set links two sources: a matched employer-employee data set and a firm-level data set with information from balance sheets and profit and loss statements. Pairing the two sources yields a longitudinal data set at the worker-firm-year level, covering all sectors —except public service— of the Portuguese economy from 1994 to 2018.

Employer-employee data are sourced through *Quadros de Pessoal* (henceforth, QP), a proprietary data set administered and collected by the Portuguese Ministry of Labor Solidarity and Social Security[4]. This data set draws on an annual compulsory employment census of the universe of firms that have at least one employee on payroll during the survey reference week[5]. Thus far, the survey has compiled information on approximately 3 million firms and 13 million employees; in 2018 alone, the survey collected responses from 1.2 million firms. Our final sample contains 941,403 firms across all years and 6,329,089 workers[6], and we detail out sample selection criteria in Appendix 1. Reported data cover each firm (location, sector, total employment, sales, and legal form) and each of its workers (gender, age, education, skill, occupation, tenure, hours worked, overtime, and wages). Firms and workers entering the database are assigned a unique, time-invariant, and anonymized identifier that allows us to track firms and workers over time.

More detailed firm-level data are obtained from two additional surveys, the *Inquérito Anual às Empresas* (henceforth, IEH), from which we gather data

[4] *Ministério do Trabalho, Solidariedade e Segurança Social.*

[5] Typically, the last week of October of each year.

[6] Note that each regression described in the below is bound by the amount of data available for each firm and each variable used in the specifications. Namely, we do not have information for each variable used in Equations (3) through (8), for each firm. More detailed information is presented in Appendix 1.

for the 1996-2004 period. This survey was discontinued and replaced by the *Sistema de Contas Integradas das Empresas* (henceforth, SCIE), from which we gather information for the 2005-2017 period. Both surveys are administered and collected by the Portuguese National Statistics Institute[7]. The surveys report data on the balance sheet and profit and loss statements. The latter includes data on date of incorporation, capital, raw materials, and other consumables, services used in production, employment, added value, gross revenues, profit, or loss. These data sources are then merged with the QP data set using a common anonymized firm identifier. Table 1 shows the descriptive statistics of the main variables we use.

[Table 1 about here.]

## 3.2 Network hiring

Our primary independent variable of interest is whether —and the extent to which— a firm engages in network hiring. While our administrative data set does not allow us to observe each workers' network directly, the panel structure of our data will enable us to identify ties between workers and firms through shared workplaces. Therefore, we consider a shared workplace between two workers as a network link. We build two measures of network hiring: one at the firm level, which we describe here, and another at the individual level, which we explore in Appendix A2 as a further robustness check on our results. These two measures yield comparable results in terms of the magnitude and direction of estimates.

[7] *Instituto Nacional de Estatística, Departamento de Estatísticas Económicas, Serviço de Estatísticas das Empresas.*

Our first measure draws on the fact that the majority of the firm's new hires have, at some point, worked for other firms in the past. We consider a firm to be engaging in network hiring if it repeatedly hires over time from the same source firms. Specifically, for each new hire by firm $j$ in year $t$, we start by identifying the new hire's origin firm $j'$. If firm $j$ hired from $j'$ in the five years before hiring worker $i$, we consider this to be an in-network hire. If firm $j$ presents one or more in-network hires at time $t$, our binary Network Hiring variable takes value one; and zero otherwise. We use a continuous version of the network hiring variable, which corresponds to the share of hires obtained in-network by firm $j$ at year $t$-in our robustness checks.

[Figure 1 about here.]

Figure 1 displays an illustration of a network of firms and workers. In this example, the two firms $j$ and $j'$ only appear in our data set for three periods: $\{t-2, t-1, t\}$. Since $j$'s first new hire in the data set is worker $i = 5$ in year $t-1$, we consider this worker as coming from outside of the network. In year $t$, firm $j$ hires worker $i = 6$ from a repeated origin firm, $j'$. Therefore, we consider $i = 6$ as firm $j$'s in-network hire.

## 3.3 Variable construction

### 3.3.1 Dependent variables

**Gross Revenues**

We use both the QP and IEH/SCIE data sets as sources of gross revenue information. Both databases record gross revenues from product and/or service sales; however, one complements the other as some years show missing information in both panels. Using both sources guarantees maximum coverage. To avoid outliers, we windsorize the data at the 5% and 95% level. Table 1 shows the descriptive statistics of gross revenues.

**Growth**

The QP matched employer-employee data set lists all workers employed at firm $j$ during year $t$. This enables us to obtain the total number of workers employed at each firm-year pair. We measure firm growth as the net job creation from $t-1$ to $t$, where net job creation is the result of new hires and employee exits. We use the following formula to construct firm growth:

$$FirmGrowth_{j,t} = \frac{Emp_{j,t} - Emp_{j,t-1}}{Emp_{j,t-1}} \tag{1}$$

where $Emp_{j,t}$ is total employment at firm $j$ in year $t$ and $FirmGrowth_{j,t}$ is the rate of employment growth in firm $j$, from $t-1$ to $t$.

**Retention**

We compute the average retention rate for each firm $j$ from each year $t-1$ to $t$. Consider a firm $j$ which employs $n_j$ workers, $i \in \{1, ..., n_j\}$. If worker $i$ is employed at firm $j$ at year $t-1$, we consider retention to be equal to one if $i$ still works at $j$ at $t$, and zero otherwise. The retention dependent variable is then an average across all workers at the firm-year level:

$$Pr[Retention]_{j,t} = \frac{1}{n_j} \sum_{i=1}^{n_j} \mathbf{1}\{i \in (j, t-1)\} \tag{2}$$

### 3.3.2 Independent variables

**Firm age**

The data sets IEH and SCIE described in this Section provide each firm's date of incorporation. The panel structure of the data thus allows us to compute firm age at each year $t$. Following the hypotheses exposed in the previous section, we use the calculated firm age to separate firms into two types: the first, we call “young" firms, with less than five years of operation; and the second, we call “mature" firms, with five or more years.

**Workers’ skill levels**

As explained in Section 2, network hiring should affect firms differently depending on the skill composition of their workforce. We measure workers’ skills using the QP data set, which records broad occupation classes, including high-skill workers. For each firm, $j$ and year $t$, we compute the share of high-skilled workers. For robustness, we add a specification with a measure of skill-based on educational attainment. Specifically, we take the percentage of college graduates at each firm $j$ and year $t$.

**Workers’ occupations**

It is possible that hiring through networks provides firms with information not (just) on workers’ qualifications or skills, but also on their non-cognitive attributes. Specifically, we hypothesize in Section 2 that firms rely on in-network hiring may do so to gather information on intrinsic motivation, such as commitment, effort, social skill, or perseverance, which are harder to observe in the limited information provided by resumes or cover letters. We test the hypothesis of firms gathering information on workers’ intrinsic motivation by focusing on two types of occupations for which research shows this type of motivation matters most: creative and knowledge-intensive.

We take the definition of creative occupations from Bakhshi, Freeman and Higgs (2013) and Florida (2002). A creative occupation is one for which processes are not strictly defined, and the output is novel[8]. We use established classification of creative occupation for SOC[9]. For knowledge-intensive occupations, we use the definition of the Bureau of Labor Statistics.

# 4 Empirical strategy

Though research shows that network hiring provides benefits to some firms that choose to engage in it (Pallais and Sands, 2016; Burks et al., 2015), these benefits may not necessarily accrue to the whole economy. Given the labor market spillovers of engaging in network hiring, compounded effects of this practice on firm-level outcomes such as gross revenue performance, growth, and employee retention are still unknown. Moreover, in Section 2, we identify a trade-off faced by firms that engage in network hiring between performance and growth. However, to our knowledge, there have been no systematic empirical accounts of this trade-off, which we now provide.

The matched employer-employee panel data set described in the previous section provides a good testing ground for the effects of network hiring on firm outcomes at the economy-wide level. Our 23-year long panel of all private sector firms presents enough variation to identify the broader role of network hiring and the trade-offs firms may face when hiring through networks.

There are two main challenges in assessing the effects of network hiring in firm performance outcomes: selection bias and simultaneity bias. First, firms that engage in network hiring may differ from those that do not, both

[8] *"A role within the creative process that brings cognitive skills to bear to bring about differentiation to yield either novel or significantly enhanced products whose final form is not fully specified in advance."* (Bakhshi, Freeman and Higgs, 2013)

[9] Occupation crosswalks are detailed in Appendix 1.

on observables— e.g., different firm size or maturity—and unobservables, and therefore pursue different market strategies. If this is the case, directly comparing firms that engage in network hiring may bias the results. Second, within firms that hire through networks, the timing of their hiring decisions is not random: there is potential simultaneity bias between input (hiring) and output (sales) determination.

To address these challenges, we use a fixed-effects approach. We run panel regressions with both firm and year fixed effects, which allows us to compare the role of network hiring on our outcomes of interest within the same firm and significantly reduce the potential for selection bias. Moreover, year fixed effects help us control economic fluctuations that influence a firm's overall hiring decisions. Our main specification is:

$$Y_{jst} = \beta_0 + \beta_1 NH_{jst} + \beta_2 Emp_{jst} + \beta_3 NH_{jst} Emp_{jst} + \boldsymbol{X'_{jst}} \boldsymbol{\beta_k} + \gamma_j + \gamma_s, t + \varepsilon_{jst} \quad (3)$$

where $Y_{jst}$ is the firm-level outcome —logarithm of gross revenues (sales), the logarithm of employment growth, and average employee retention— for a firm $j$, in industry $s$ at year $t$. $NH_{jst}$ is our binary network hiring variable as described in the previous section, which takes value one if firm $j$ engages in network hiring at year $t$. $Emp_{jst}$ is the total number of employees at a firm $j$, year $t$ and $NH_{jst}Emp_{jst}$ is the interaction between the network hiring variable and total employment. $\boldsymbol{X_{jst}}$ is a vector of additional controls such as $NewHires_{jst}$, the total number of hires by firm $j$ in year $t$, and $AvgWage_{j,t-1}$, the average wage at firm $j$ and year $t-1$. Lastly, $\gamma_j$ and $\gamma_s, t$ are firm and industry-year fixed effects, respectively. The error term is $\varepsilon_{jst}$, which includes idiosyncratic variation in firm-level outcomes that are not captured by time trends.

The coefficients of interest in Equation (3) are $\hat{\beta}_1$ and $\hat{\beta}_3$, which tell us the impact of network hiring on firm outcomes, allowing for heterogeneous effect throughout the firm size distribution.

## 4.1 Entrepreneurial firms

The previous specification analyzes the effects of network hiring on the whole population of firms. While the use of firm fixed effects provides a control for unobservable heterogeneity, and thus mitigate selection bias, there may be other observable or time-varying characteristics of the firm that moderate the impact of network hiring. In particular, we are interested in the effects of network hiring for entrepreneurial firms in their first five years of operation. In Section 2, we argue that, because a heavy reliance on referral hiring marks the initial stages of a firm, the effect of this practice on entrepreneurial firms' outcomes should be more economically significant. In line with our theoretical predictions, we test the interaction effect of firm age with network hiring:

$$Y_{jst} = \beta_0 + \beta_1 NH_{jst} + \beta_2 Young_{jst} + \beta_3 NH_{jst} Young_{jst} + \boldsymbol{X'_{jst}\beta_k} + \gamma_j + \gamma_s, t + \varepsilon_{jst} \tag{4}$$

where $Y_{jst}$ is the firm-level outcome —logarithm of gross revenues (sales), the logarithm of employment growth, and average employee retention— for a firm $j$, in industry $s$ at year $t$. $NH_{jst}$ is our binary network hiring variable as described in the previous section, which takes value one if firm $j$ engages in network hiring at year $t$. $Young_{jst}$ is a binary variable that takes value one if the firm is in its first five years of operation and zero otherwise. This variable is meant to capture the first years of an entrepreneurial firm. $NH_{jst}Young_{jst}$ is the interaction term between network hiring and firm age. This interaction variable takes value one if firm $j$ in industry $s$ engages in network hiring in year $t$ and is in its first five years of operation, and zero otherwise.$\boldsymbol{X_{jst}}$ is a vector of additional controls such as $NewHires_{jst}$, the total number of hires by firm $j$ in year $t$, $Emp_{jst}$ is the total number of employees at firm $j$, year $t$, and $AvgWage_{jst}$, the average wage at firm $j$ and year $t$. Lastly, $\gamma_j$ and $\gamma_s, t$ are firm and indsutry-year fixed effects, respectively. The error term is $\varepsilon_{jst}$.

The coefficients of interest in Equation (4) are $\hat{\beta}_1$ and $\hat{\beta}_3$, which together report the impact of network hiring on firm outcomes in young versus mature firms.

## 4.2 Workers' skills

The practice of hiring through referrals can provide firms with a way to mitigate information asymmetries inherent to the hiring process. Though prior research has identified several types of information gathered through referrals, we have little empirical evidence about which of those play a role in firm outcomes. If firms use referrals to gather information on worker's skills, we should observe that firms that rely on a larger share of high-skilled work should see benefit more from this practice. In line with our theoretical predictions in Section 2, we use the following specifications:

$$Y_{jst} = \beta_0 + \beta_1 NH_{jst} + \beta_2 HS_{jst} + \beta_3 NH_{jst} HS_{jst} + \boldsymbol{X'_{jst}\beta_k} + \gamma_j + \gamma_s, t + \varepsilon_{jst} \tag{5}$$

where, as before, $NH_{jst}$ is a binary network hiring variable. $HS_{jst}$ is the share of employees classified as high-skill working at firm $j$ in industry $s$ and year $t$, and $NH_{jst}HS_{jst}$ is the interaction term between network hiring and share of high-skill workers at firm $j$, year $t$. The vector of controls $\boldsymbol{X'_{jst}\beta_k}$ includes, as before, $Emp_{jst}$, $NewHires_{jst}$, and $AvgWage_{jst}$. $\gamma_j$ and $\gamma_s, t$ are firm and industry-year fixed effects, and $\varepsilon_{jst}$ is the error term.

The coefficient of interest in Equation (5) is $\hat{\beta}_3$, which displays the differential impact of network hiring for firms along the distribution of the share of high-skill workers.

#### 4.2.1 Entrepreneurial firms

We further analyze the firm's skill and composition according to firm age. We use the following specification:

$$\begin{aligned} Y_{jst} =& \beta_0 + \beta_1 NH_{jts} + \beta_2 Young_{jst} + \beta_3 NH_{jst} Young_{jst} + \beta_4 NH_{jst} HS_{jst} \\ &+ \beta_4 NH_{jst} Young_{jt} HS_{jst} + \boldsymbol{X'_{jst}\beta_k} + \gamma_j + \gamma_s, t + \varepsilon_{jst} \end{aligned} \tag{6}$$

where, as before, $NH_{jst}$ is a binary network hiring variable. $HS_{jst}$ is the share of employees classified as high-skill working at firm $j$ in industry $s$ and year $t$, and $Young_{jst}$ is an indicator variable that takes value one when firm $j$ has been operating for less then five years by time $t$. The vector of controls $\boldsymbol{X'_{jt}\beta_k}$ includes, as before, $Emp_{jst}$, $NewHires_{jst}$, and $Wage_{jst}$. $\gamma_j$ and $\gamma_s, t$ are firm and industry-year fixed effects, and $\varepsilon_{jst}$ is the error term.

The coefficient of interest in Equation (6) is $\hat{\beta}_4$, which displays the differential impact of network hiring for firms within their first five years of operation, along the distribution of the share of high-skill workers.

## 4.3 Creative Occupations

Instead, firms may engage in network hiring because it provides them with difficult-to-observe information on candidates' intrinsic motivation. Research shows that creative occupations require a high level of intrinsic motivation. To assess this hypothesis, we analyze firm outcomes as a result of network hiring for firms employing workers on creative occupations:

$$Y_{jst} = \beta_0 + \beta_1 NH_{jst} + \beta_2 Creative_{jst} + \beta_3 NH_{jst} Creative_{jst} + \boldsymbol{X'_{jst}\beta_k} + \gamma_j + \gamma_s, t + \varepsilon_{jst} \tag{7}$$

where, as before, $NH_{jst}$ is a binary network hiring variable. $Creative_{jst}$ is the share of employees holding creative occupations at firm $j$ in indsutry $s$ and year $t$, and $NH_{jst}Creative_{jst}$ is the interaction term between network hiring and share of creative occupation workers at firm $j$, year $t$. The vector of controls $\boldsymbol{X'_{jst}\beta_k}$ includes, as before, $Emp_{jst}$, $NewHires_{jst}$, and $AvgWage_{jst}$. $\gamma_j$ and $\gamma_s, t$ are firm and year fixed effects, and $\varepsilon_{jst}$ is the error term.

The coefficient of interest in Equation (7) is $\hat{\beta}_3$, which displays the differential impact of network hiring for firms along the distribution of the share of creative occupation workers.

### 4.3.1 Entrepreneurial firms

We further analyze the firm's share of creative occupations according to firm age. We use the following specification:

$$Y_{jst} = \beta_0 + \beta_1 NH_{jst} + \beta_2 Young_{jst} + \beta_3 NH_{jst} Young_{jst} + \beta_4 NH_{jt} Creative_{jt}$$

$$+ \beta_4 NH_{jst} Young_{jst} Creative_{jst} + \boldsymbol{X'_{jst}\beta_k} + \gamma_j + \gamma_s, t + \varepsilon_{jst} \tag{8}$$

where, as before, $NH_{jst}$ is a binary network hiring variable. $Creative_{jst}$ is the share of employees classified as high-skill working at firm $j$ in industry $s$ year $t$, and $Young_{jst}$ is an indicator variable that takes value one when firm $j$ has been operating for less then five years by time $t$. The vector of controls $\boldsymbol{X'_{jst}\beta_k}$ includes, as before, $Emp_{jst}$, $NewHires_{jst}$, and $AvgWage_{jst}$. $\gamma_j$ and $\gamma_t$ are firm and indsutry-year fixed effects, and $\varepsilon_{jt}$ is the error term.

The coefficient of interest in Equation (8) is $\hat{\beta}_4$, which displays the differential impact of network hiring for firms within their first five years of operation, across the distribution of the share of creative occupations.

# 5 Results

## 5.1 Main results

We start by analyzing the relationship between network hiring and firm performance outcomes in the universe of firms, corresponding to the estimation of Equation (3). Table 2 shows the results of this estimation. The table displays results for two firm-level outcomes: gross revenues or sales and firm employment growth.

[Table 2 about here.]

We begin with our results on sales, column (1) present findings from the panel of Equation (3) with the logarithm of gross revenues from sales as a dependent variable. Results show a positive and significant relationship (42.19%) between network hiring and sales performance. Larger firms show a positive correlation between sales performance and network hiring, with network hiring firms adding an average of 3.57% on sales for each added employee.

We turn to the results examining the role of network hiring on firm growth in the number of employees. Column (3) shows the results on a specification using firm and industry-year fixed effects. There is a negative and significant relationship between network hiring and employment growth from $t-1$ to $t$, with firms that engage in network hiring, showing 51.89% lower average growth rates. This negative relationship is starker for larger firms, as these show an average of 1.185% lower growth rates when network hiring.

Finally, we also present results on the firm's average retention rate. In column (5) we show that the effect of network hiring is positive and significant, increasing firms' average worker retention by 17.58%. Moreover, the larger the firm, the higher the effect of network hiring on the firm's retention rate, by about 1.04% for every added employee.

### 5.1.1 Entrepreneurial firms

We report results on gross revenue performance, employment growth, and employee retention in entrepreneurial firms in columns (2), (4) and (6) of Table

2. Column (2) presents results for Equation (4) with the logarithm of gross revenues from sales as a dependent variable. The negative coefficient on the interaction term, $\hat{\beta}_3$, shows that entrepreneurial firms —firms in their first five years of operation— are not beneficially affected by network hiring when compared to their mature firm counterparts. On the other hand, column (4) shows that entrepreneurial firms' employment growth is more negatively affected when engaging in network hiring —by about 21.89%— than mature firms. Results seem to indicate that the trade-off between the intensive and extensive margin value of referrals, mentioned in Section 2, is starker for entrepreneurial firms as expected. Lastly, columns (6) of Table 2 reports results of Equation (4) with average retention rate at the firm as a dependent variable. The coefficient of interest is $\hat{\beta}_3$ on the interaction term between network hiring and the indicator variable for whether the firm is in its first five years of operation. As we predicted in Section 2, we find that average worker retention is more positively affected by network hiring at entrepreneurial firms, by about 9.06%.

## 5.2 Workers' skills and Occupation

To probe into the mechanisms through which network hiring affects firm outcomes, we analyze what type of information asymmetries network hiring helps firms mitigate. Following our prediction in Section 2, we test whether firms use network hiring primarily to gather information on workers' skills. To implement this test, we analyze whether firms that rely on a larger share of high-skill workers respond differently to network hiring. We estimate Equations (5) and (6). Table 3 presents results for the three firm outcome variables: gross revenue from sales, employment growth, and average worker retention.

[Table 3 about here.]

Results show that firms with a larger share of high-skill workers perform better, on average, both in sales and worker retention rates. However, firms that engage in network hiring do not see their outcomes of sales, growth and retention differentially affected according to their skill composition.

These results suggest that firms are not using network hiring as a means to gather information on worker skills to improve performance, growth, or retention. We turn to look at our other hypothesis: that firms regard referrals as a vehicle to obtain information on the intrinsic motivation of potential candidates.

[Table 4 about here.]

Results show that firms that have a higher share of creative occupations exhibit better performance on average. Those that engage in network hiring, in particular, show significantly larger firm gross revenues by about 15.26%. Entrepreneurial firms with a larger share of creative occupations, in particular, show improved sales performance by approximately 22%.

Together, the results on skill composition and creative occupations suggest that it is more likely that firms use referrals to gather information on the intrinsic motivation of potential workers. Evidence suggests a positive relationship between network hiring and performance or growth in companies with a larger share of creative occupations.

# 6 Discussion and conclusion

Network hiring—i.e., the preference for hiring those with social or professional connections to existing employees—is a prevalent practice across many industries (Fernandez and Castilla, 2017; Burks et al., 2015; Hoffman, 2017). Recruitment using networks provides firms with otherwise difficult-to-observe information about potential hires as well as informal mechanisms of control once they join the firm (Castilla, 2005; Fernandez, Castilla and Moore, 2000). Although a considerable body of research shows that in-network hires perform better, there is a shortage of evidence about the firm-level performance implications of this practice over time and its limits. This article uses data on the universe of firms in Portugal between 1994 and 2017 to examine the trade-offs that firms make between performance and growth when using network-based hiring.

Our results show that network hiring is associated with an increase in financial performance. We find that firms that use the practice perform 21% better in terms of gross revenues from sales. Firms that hire in-network are better able to retain employees, with a seven percentage point improvement in overall employee retention. These findings are in line with prior work that has shown the individual-level performance benefits of network hiring. However, as we predict, firms that use this practice appear to face a trade-off between performance and growth. Relying on networks seems at once to improve performance but decrease growth. Network-based hiring reduces firm growth by 120%, and this decline is larger for young firms whose primary mechanism of recruiting are the networks of their founders and employees. Finally, our results suggest that firms are not necessarily learning about workers' skills, but perhaps other characteristics labeled as intrinsic motivation, such as effort provision, commitment, or reliability, that are valuable regardless of the skill level required for a job.

Our research contributes to at least three streams of research in management and strategy. First, our findings provide rare economy-wide evidence of the implications of network hiring for firms. This work extends the considerable literature that shows the benefits to individual worker performance due to network hiring (Fernandez and Weinberg, 1997; Rubineau and Fernandez, 2013; Burks et al., 2015; Pallais and Sands, 2016). Moreover, we provide a replicable method to infer network hiring practices using administrative employer-employee data sets. Second, because we can observe variation *across* firms in this practice, we can better understand its impact at both the intensive —depth of information on a potential candidate— and extensive margins —breadth of the consideration set of candidates— of the hiring process, firms that use network hiring, while performing better, appear to grow more slowly. This effect seems most pronounced for young firms that rely heavily on networks to hire. This trade-off appears to be one faced by young firms in many of their early decisions (Belenzon, Chatterji and Daley, 2019). Given this trade-off, firms must invest in complementary capabilities that can offset the negative effect on growth. Indeed, the fact that network-based hiring limits growth for firms old and young may explain why many firms are investing in outbound recruiting (Black, Hasan and Koning, 2020; Cappelli, 2019). Finally, our results speak to the growing literature on the human capital strategy of firms (Chadwick and Dabu, 2009; Hatch and Dyer, 2004; Rosenkopf and Almeida, 2003; Koch and McGrath, 1996), and especially entrepreneurial firms (Chatterji et al., 2019; Leung et al., 2006; Hansen, 1995). Our findings suggest that the trade-offs are especially salient for young firms who need both growth and performance.

Although we can provide large-scale empirical evidence of the benefits and costs of network hiring, our research is not without limitations. Perhaps the most significant limitation of our work is the observational nature of our data and thus our inability to make strong causal claims. We alleviate some of these concerns using various fixed-effects specifications, including those with firm fixed-effects and those with year and non-parametric industry-year trends that account for time-varying heterogeneity experienced across industries. A second limitation of our study is the difficulty in identifying the exact information that firms learn through network ties. While we provide suggestive evidence that firms use network hiring to elicit information on traits related to intrinsic motivation, more research is needed to assert this evidence further.

We see many possibilities for future research. Our research has focused primarily on the impact of network hiring on young versus old firms and for high vs. lower-skilled work. However, there is likely significant heterogeneity in which firms are most likely to benefit from this practice. Future work should explore the complementary practices within firms that make this practice more effective. Moreover, there is scope for further research on the relationship between modes of hiring and labor market match quality.

# References

Bakhshi, Hasan, Alan Freeman and Peter Higgs. 2013. *A dynamic mapping of the UK's creative industries.* Nesta.

Baron, James N, Michael T Hannan and M Diane Burton. 2001. "Labor pains: Change in organizational models and employee turnover in young, high-tech firms." *American Journal of Sociology* 106(4):960–1012.

Beaman, Lori and Jeremy Magruder. 2012. "Who gets the job referral? Evidence from a social networks experiment." *American Economic Review* 102(7):3574–93.

Belenzon, Sharon, Aaron K Chatterji and Brendan Daley. 2019. "Choosing between growth and glory." *Management Science* .

Bewley, Truman F and Truman F Bewley. 1999. *Why wages don't fall during a recession.* Harvard university press.

Black, Ines, Sharique Hasan and Rembrand Koning. 2020. "Hunting for talent: Firm-driven labor market search in America." *Working paper* .

Brown, Meta, Elizabeth Setren and Giorgio Topa. 2016. "Do informal referrals lead to better matches? Evidence from a firm's employee referral system." *Journal of Labor Economics* 34(1):161–209.

Burks, Stephen V, Bo Cowgill, Mitchell Hoffman and Michael Housman. 2015. "The value of hiring through employee referrals." *Quarterly Journal of Economics* 130(2):805–839.

Cappelli, Peter. 2019. "Your approach to hiring is all wrong." *Harvard Business Review* .

Castilla, Emilio J. 2005. "Social networks and employee performance in a call center." *American Journal of Sociology* 110(5):1243–1283.

Chadwick, Clint and Adina Dabu. 2009. "Human resources, human resource management, and the competitive advantage of firms: Toward a more comprehensive model of causal linkages." *Organization Science* 20(1):253–272.

Chandrasekhar, Arun G, Melanie Morten and Alessandra Peter. 2020. Network-Based Hiring: Local Benefits; Global Costs. Technical report National Bureau of Economic Research.

Chatterji, Aaron, Solène Delecourt, Sharique Hasan and Rembrand Koning. 2019. "When does advice impact startup performance?" *Strategic Management Journal* 40(3):331–356.

Cobb-Clark, Deborah A and Michelle Tan. 2011. "Noncognitive skills, occupational attainment, and relative wages." *Labour Economics* 18(1):1–13.

Coff, Russell W. 1997. "Human assets and management dilemmas: Coping with hazards on the road to resource-based theory." *Academy of Management Review* 22(2):374–402.

Cohen, Wesley M, Henry Sauermann and Paula Stephan. 2018. Not in the job description: The commercial activities of academic scientists and engineers. Technical report National Bureau of Economic Research.

Deming, David J. 2017. "The growing importance of social skills in the labor market." *Quarterly Journal of Economics* 132(4):1593–1640.

Dustmann, Christian, Albrecht Glitz, Uta Schönberg and Herbert Brücker. 2016. "Referral-based job search networks." *The Review of Economic Studies* 83(2):514–546.

Ekinci, Emre. 2016. "Employee referrals as a screening device." *The RAND Journal of Economics* 47(3):688–708.

Erat, Sanjiv and Uri Gneezy. 2016. "Incentives for creativity." *Experimental Economics* 19(2):269–280.

Farkas, George. 2003. "Cognitive skills and noncognitive traits and behaviors in stratification processes." *Annual review of sociology* 29(1):541–562.

Ferguson, John-Paul and Sharique Hasan. 2013. "Specialization and career dynamics: Evidence from the Indian Administrative Service." *Administrative Science Quarterly* 58(2):233–256.

Fernandez-Mateo, Isabel and Roberto M Fernandez. 2016. "Bending the pipeline? Executive search and gender inequality in hiring for top management jobs." *Management Science* 62(12):3636–3655.

Fernandez, Roberto M and Emilio J Castilla. 2017. How much is that network worth? Social capital in employee referral networks. In *Social Capital*. Routledge pp. 85–104.

Fernandez, Roberto M, Emilio J Castilla and Paul Moore. 2000. "Social capital at work: Networks and employment at a phone center." *American Journal of Sociology* 105(5):1288–1356.

Fernandez, Roberto M and M Lourdes Sosa. 2005. "Gendering the job: Networks and recruitment at a call center." *American Journal of Sociology* 111(3):859–904.

Fernandez, Roberto M and Nancy Weinberg. 1997. "Sifting and sorting: Personal contacts and hiring in a retail bank." *American Sociological Review* 62:883–902.

Florida, Richard. 2002. *The rise of the creative class*. Basic Books.

Franzen, Axel and Dominik Hangartner. 2006. "Social networks and labour market outcomes: The non-monetary benefits of social capital." *European Sociological Review* 22(4):353–368.

Galenianos, Manolis. 2018. "Referral networks and inequality." *Available at SSRN 2768083* .

Granovetter, Mark. 1973. "The strength of weak ties." *American Journal of Sociology* 78(6):1360–13806.

Granovetter, Mark. 1995. "How to get a job: a study on contacts and careers.".

Hansen, Eric L. 1995. "Entrepreneurial networks and new organization growth." *Entrepreneurship theory and practice* 19(4):7–19.

Hasan, Sharique. 2019. Social Networks and Careers. In *Social Networks at Work*. Routledge.

Hatch, Nile W and Jeffrey H Dyer. 2004. "Human capital and learning as a source of sustainable competitive advantage." *Strategic Management Journal* 25(12):1155–1178.

Henly, Julia R. 2000. "Mismatch in the low-wage labor market: Job search perspective." *The Low-Wage Labor Market* p. 145.

Hoffman, Mitchell. 2017. "The value of hiring through employee referrals in developed countries." *IZA World of Labor* .

Hoffman, Mitchell, Lisa B Kahn and Danielle Li. 2018. "Discretion in hiring." *Quarterly Journal of Economics* 133(2):765–800.

Koch, Marianne J and Rita Gunther McGrath. 1996. "Improving labor productivity: Human resource management policies do matter." *Strategic Management Journal* 17(5):335–354.

Leung, Aegean, Jing Zhang, Poh Kam Wong and Maw Der Foo. 2006. "The use of networks in human resource acquisition for entrepreneurial firms: Multiple âĂIJfitâĂİ considerations." *Journal of Business Venturing* 21(5):664–686.

Lin, N. 1999. "Social Networks and Status Attainment." *Annual Review of Sociology* 25(1):467–487.

Marmaros, D. and B. Sacerdote. 2002. "Peer and social networks in job search." *European Economic Review* 46(4-5):870–879.

Marsden, Peter V and Elizabeth H Gorman. 2001. Social networks, job changes, and recruitment. In *Sourcebook of labor markets*. Springer pp. 467–502.

Marx, Matt and Bram Timmermans. 2017. "Hiring molecules, not atoms: Comobility and wages." *Organization Science* 28(6):1115–1133.

Montgomery, James D. 1991. "Social networks and labor-market outcomes: Toward an economic analysis." *American Economic Review* 81(5):1408–1418.

Pallais, Amanda and Emily Glassberg Sands. 2016. "Why the referential treatment? Evidence from field experiments on referrals." *Journal of Political Economy* 124(6):1793–1828.

Petersen, Trond, Ishak Saporta and Marc-David L Seidel. 2000. "Offering a job: Meritocracy and social networks." *American Journal of Sociology* 106(3):763–816.

Rider, Christopher I. 2012. "How employeesâĂŹ prior affiliations constrain organizational network change: A study of US venture capital and private equity." *Administrative Science Quarterly* 57(3):453–483.

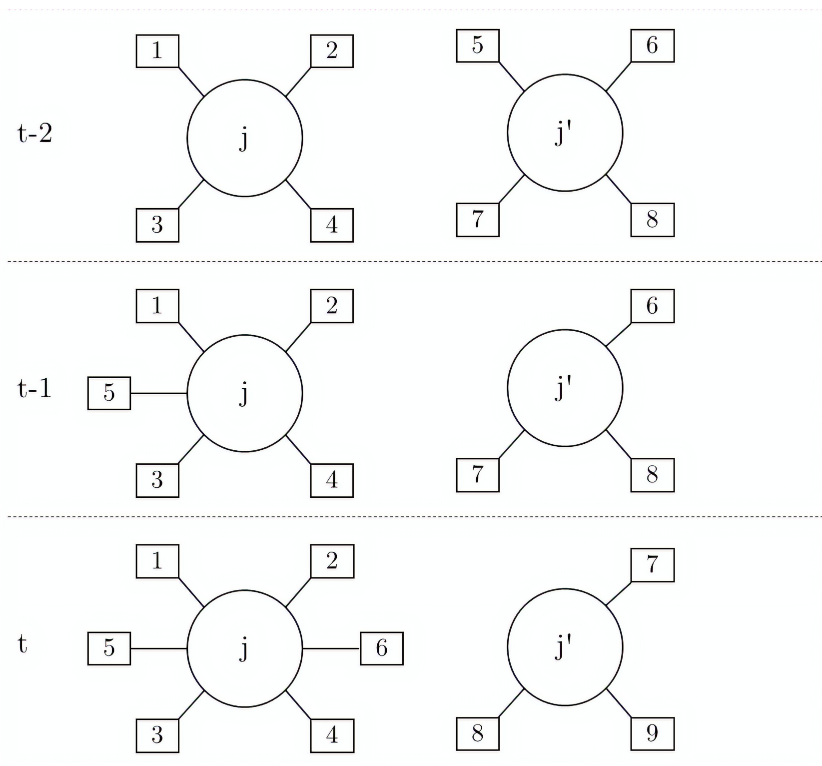
Rosenkopf, Lori and Paul Almeida. 2003. "Overcoming local search through alliances and mobility." *Management Science* 49(6):751–766.

Rubineau, Brian and Roberto M Fernandez. 2013. "Missing links: Referrer behavior and job segregation." *Management Science* 59(11):2470–2489.

Sauermann, Henry and Wesley M Cohen. 2010. "What makes them tick? Employee motives and firm innovation." *Management Science* 56(12):2134–2153.

Simon, Curtis J and John T Warner. 1992. "Matchmaker, matchmaker: The effect of old boy networks on job match quality, earnings, and tenure." *Journal of Labor Economics* 10(3):306–330.

Figure 1: Network Hiring Example




*Notes:* Figure 1 displays an illustration of a network of firms and workers. We consider the hiring of worker $i = 5$ by firm $j$ as a hire from a new origin firm $j'$, and thus not a network hire. However, worker $i = 6$ is a network hire because $j'$ is a repeated origin firm for focal firm $j$ at time $t$.

Table 1: Descriptive Statistics.

| | 1995 | | | | 2006 | | | | 2018 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | p50 | SD | N | Mean | p50 | SD | N | Mean | p50 | SD |
| **Firms** | | | | | | | | | | | | |
| Sales ( M.) | 114,332 | 0.919 | 0.192 | 4.227 | 213,887 | 0.958 | 0.189 | 4.615 | 211,095 | 1.083 | 0.201 | 5.161 |
| Firm Size | 183,398 | 12.07 | 4.00 | 101.41 | 335,668 | 9.16 | 3.00 | 78.82 | 287,168 | 10.35 | 3.00 | 110.00 |
| Network Hiring (%) | - | - | - | - | 323,212 | 0.626 | 0.00 | 7.885 | 276,843 | 0.953 | 0.00 | 9.715 |
| Young (%) | 183,398 | 18.90 | 0.00 | 39.15 | 336,356 | 11.14 | 0.00 | 31.47 | 287,168 | 43.77 | 0.00 | 49.61 |
| New Hires | 183,398 | 3.69 | 1.00 | 38.95 | 336,356 | 2.02 | 0.00 | 30.48 | 287,168 | 2.30 | 0.00 | 36.57 |
| **Workers** | | | | | | | | | | | | |
| Retention (%) | 183,398 | 67.85 | 80.00 | 36.54 | 336,356 | 76.17 | 100.00 | 35.40 | 287,168 | 88.90 | 100.00 | 21.81 |
| Tenure at firm (Years) | 183,398 | 3.15 | 2.75 | 1.95 | 336,356 | 4.39 | 3.60 | 3.22 | 287,168 | 8.29 | 7.17 | 5.19 |
| Wage (/hour) | 168,562 | 2.40 | 1.94 | 2.55 | 299,674 | 4.06 | 3.27 | 3.49 | 260,266 | 5.29 | 4.33 | 5.23 |
| Schooling (Years) | 183,398 | 7.10 | 6.00 | 3.10 | 335,668 | 7.67 | 7.33 | 2.70 | 268,692 | 8.36 | 8.43 | 2.57 |
| BA/MA (%) | 183,398 | 13.68 | 0.00 | 24.32 | 335,668 | 15.62 | 0.00 | 27.81 | 287,168 | 2.84 | 0.00 | 16.60 |

Table 2: Gross Revenues, Firm Growth, and Retention. Regression Results.

| | (1) Sales | (2) Sales | (3) Firm Growth | (4) Firm Growth | (5) Retention | (6) Retention |
|---|---|---|---|---|---|---|
| Network Hiring | 0.352*** | 0.514*** | -0.418*** | -0.890*** | 0.162*** | 0.217*** |
| | (0.0363) | (0.0147) | (0.109) | (0.0327) | (0.0128) | (0.00410) |
| Log(Firm Size) | 0.707*** | 0.699*** | -0.394*** | -0.361*** | -0.0873*** | -0.0909*** |
| | (0.00221) | (0.00220) | (0.00864) | (0.00889) | (0.000609) | (0.000614) |
| NH×Log(FS) | 0.0351*** | | -0.112*** | | 0.0103** | |
| | (0.0101) | | (0.0308) | | (0.00372) | |
| Young | | -0.145*** | | 0.243*** | | -0.0643*** |
| | | (0.00152) | | (0.00398) | | (0.000491) |
| NH×Young | | -0.186*** | | 0.198*** | | -0.0867*** |
| | | (0.0224) | | (0.0558) | | (0.00653) |
| New Hires | -0.000353*** | -0.000332*** | 0.00243*** | 0.00234*** | -0.000322*** | -0.000319*** |
| | (0.0000874) | (0.0000851) | (0.000580) | (0.000563) | (0.0000572) | (0.0000565) |
| Avg. Wage$_{(t-1)}$ | 0.172*** | 0.169*** | 0.00298 | 0.00905 | -0.00439*** | -0.00552*** |
| | (0.00224) | (0.00223) | (0.00655) | (0.00652) | (0.000692) | (0.000686) |
| Constant | 11.00*** | 11.04*** | -0.426*** | -0.555*** | 1.023*** | 1.040*** |
| | (0.00510) | (0.00510) | (0.0195) | (0.0202) | (0.00129) | (0.00129) |
| Observations | 3,063,356 | 3,063,356 | 822,777 | 822,777 | 4,079,240 | 4,079,240 |
| Adjusted $R^2$ | 0.899 | 0.900 | 0.447 | 0.451 | 0.270 | 0.276 |
| Number of firms | 369,809 | 369,809 | 207,230 | 207,230 | 485,105 | 485,105 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry*Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

Standard errors in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes:* Table 2 shows the results from estimating Equation (3). Columns (1) and (2) display results for gross revenues. Columns (3) and (4) display results for firm growth. Columns (5) and (6) display results for average worker retention. Standard errors are clustered at the firm level. Outcome variables and firm size are logarithmized.

Table 3: Firms' skill composition and Network Hiring. Regression Results.

| | (1) Sales | (2) Sales | (3) Firm Growth | (4) Firm Growth | (5) Retention | (6) Retention |
|---|---|---|---|---|---|---|
| Network Hiring | 0.469*** | 0.501*** | -0.856*** | -0.895*** | 0.198*** | 0.218*** |
| | (0.0142) | (0.0155) | (0.0340) | (0.0369) | (0.00419) | (0.00452) |
| Log(Firm Size) | 0.708*** | 0.699*** | -0.397*** | -0.361*** | -0.0871*** | -0.0909*** |
| | (0.00222) | (0.00220) | (0.00882) | (0.00889) | (0.000618) | (0.000614) |
| Young | | -0.144*** | | 0.239*** | | -0.0643*** |
| | | (0.00156) | | (0.00413) | | (0.000512) |
| NH×Young | | -0.146*** | | 0.185** | | -0.0870*** |
| | | (0.0232) | | (0.0610) | | (0.00707) |
| Avg. High Skill | 0.0221*** | 0.0273*** | -0.00143 | -0.0188 | 0.00595*** | 0.00702*** |
| | (0.00413) | (0.00422) | (0.0109) | (0.0113) | (0.00119) | (0.00120) |
| HSkill×NH | 0.00713 | 0.197* | 0.148 | 0.0685 | -0.0292 | -0.0261 |
| | (0.0997) | (0.100) | (0.184) | (0.204) | (0.0237) | (0.0256) |
| Young×HSkill | | -0.0269** | | 0.0749** | | -0.000320 |
| | | (0.00909) | | (0.0235) | | (0.00296) |
| Young×HSkill×NH | | -0.630** | | 0.171 | | 0.00352 |
| | | (0.223) | | (0.348) | | (0.0402) |
| New Hires | -0.000334*** | -0.000330*** | 0.00238*** | 0.00234*** | -0.000319*** | -0.000319*** |
| | (0.0000870) | (0.0000850) | (0.000572) | (0.000563) | (0.0000568) | (0.0000565) |
| Avg. $\text{Wage}_{(t-1)}$ | 0.172*** | 0.169*** | 0.00378 | 0.00904 | -0.00449*** | -0.00560*** |
| | (0.00224) | (0.00223) | (0.00657) | (0.00652) | (0.000693) | (0.000686) |
| Constant | 11.00*** | 11.03*** | -0.419*** | -0.554*** | 1.023*** | 1.040*** |
| | (0.00511) | (0.00510) | (0.0198) | (0.0202) | (0.00129) | (0.00129) |
| Observations | 3,063,356 | 3,063,356 | 822,777 | 822,777 | 4,079,240 | 4,079,240 |
| Adjusted $R^2$ | 0.899 | 0.900 | 0.447 | 0.451 | 0.270 | 0.276 |
| Number of firms | 369,809 | 369,809 | 207,230 | 207,230 | 485,105 | 485,105 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry*Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* Table 3 shows results from estimating Equations (5) and (6) using firm and year fixed effects in all specifications.

Table 4: Creative Occupations and Network Hiring. Regression Results.

| | (1) Sales | (2) Sales | (3) Firm Growth | (4) Firm Growth | (5) Retention | (6) Retention |
|---|---|---|---|---|---|---|
| Network Hiring | 0.459*** | 0.478*** | -0.880*** | -0.895*** | 0.210*** | 0.222*** |
| | (0.0161) | (0.0172) | (0.0409) | (0.0432) | (0.00482) | (0.00514) |
| Log(Firm Size) | 0.709*** | 0.700*** | -0.386*** | -0.349*** | -0.0877*** | -0.0914*** |
| | (0.00232) | (0.00230) | (0.00892) | (0.00899) | (0.000661) | (0.000657) |
| Young | | -0.147*** | | 0.255*** | | -0.0704*** |
| | | (0.00201) | | (0.00538) | | (0.000695) |
| Young×NH | | -0.126*** | | 0.115 | | -0.0723*** |
| | | (0.0281) | | (0.0737) | | (0.00845) |
| Creative Occup. | 0.0292*** | 0.0335*** | -0.0565*** | -0.0665*** | 0.0283*** | 0.0262*** |
| | (0.00247) | (0.00252) | (0.00654) | (0.00677) | (0.000723) | (0.000724) |
| Creative×NH | 0.0305 | 0.142** | 0.144 | 0.0241 | -0.0573*** | -0.0271 |
| | (0.0457) | (0.0532) | (0.110) | (0.126) | (0.0127) | (0.0142) |
| Young×Creative | | -0.00932* | | -0.0248* | | 0.0216*** |
| | | (0.00433) | | (0.0118) | | (0.00145) |
| Young×Cr×NH | | -0.126*** | | 0.115 | | -0.0723*** |
| | | (0.0281) | | (0.0737) | | (0.00845) |
| New Hires | -0.000320*** | -0.000307*** | 0.00236*** | 0.00232*** | -0.000339*** | -0.000336*** |
| | (0.0000881) | (0.0000847) | (0.000566) | (0.000557) | (0.0000612) | (0.0000606) |
| Avg. Wage$_{(t-1)}$ | 0.171*** | 0.169*** | 0.00713 | 0.0125 | -0.00570*** | -0.00677*** |
| | (0.00232) | (0.00230) | (0.00671) | (0.00667) | (0.000726) | (0.000718) |
| Constant | 11.00*** | 11.04*** | -0.446*** | -0.581*** | 1.021*** | 1.039*** |
| | (0.00547) | (0.00546) | (0.0203) | (0.0207) | (0.00140) | (0.00139) |
| Observations | 2,854,062 | 2,854,062 | 799,743 | 799,743 | 3,763,931 | 3,763,931 |
| Adjusted $R^2$ | 0.903 | 0.904 | 0.443 | 0.448 | 0.271 | 0.276 |
| Number of firms | 358,137 | 358,137 | 202,010 | 202,010 | 468,276 | 468,276 |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry*Year FE | Yes | Yes | Yes | Yes | Yes | Yes |

Standard errors in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes:* Table 4 shows results from estimating Equations (7) and (8) using firm and industry-year fixed effects in all specifications. Creative occupations are coded based on Florida (2002). Outcomes of sales revenues and firm growth are logarithmized.