Space and Networks in the Labor Market

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Abstract

Agglomeration economies occur when advantages are created and exploited due to the geographic clustering of firms within the same industry. We focus on one of the Marshallian micro-foundational processes which produces agglomeration economies, i.e., labor market pooling. According to economic theory, advantages are created between geographically clustered, same-industry firms on the demand side, and local workers with industry-specific skills on the supply side. These advantages result in reduced labor search costs and improve the quality of matches between firms and workers. Other theories of agglomeration often cite the importance of social networks for labor market mobility. In this study, we take advantage of a strategic research site using unique data on the hiring process of high-technology companies in California. We study how spatial agglomeration interacts with labor market referral networks. Prior theories posit that space and networks reinforce each other so that firms in agglomerated industries would tend to hire people who are both local and networked.

We find a subtle, multi-step process at play. Consistent with agglomeration accounts, at the first stage in which the applicant pool is formed, we find that networked candidates are more local than non-networked candidates. However, contrary to past understandings of the spatial aspect of embedded labor markets in agglomerations, on the demand side, networks are not spatially exclusionary. When firms screen these candidates, we find that networks serve as a substitute for space, with networked candidates having significantly higher hiring chances among more distant candidates. This, in essence, allows firms to geographically extend their recruiting horizon. But job offers are more likely to go to local applicants so that the net result of these two stages does not show networks as reinforcing spatial dynamics. To the extent that networks interact with space, it is in attracting skilled labor from outside of the local area, as firms in agglomerated industries do not rely exclusively on local labor markets to staff their rapid growth.

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INTRODUCTION

Labor market dynamics are central to studies about agglomerations, or “spatial concentrations of economic activity” (Strange 2008). The economics literature suggests that firms co-locate into industrial clusters (Stigler 1951, Ellison et al. 2010) and cities (Diamond and Simon 1990, Helsley and Strange 1990), to benefit from agglomeration economies, or positive externalities that arise from the geographic clustering of firms (Marshall 1920). One such agglomeration economy is from labor market pooling, or “thick” local labor markets, which contain a large number of workers with similar skills (Overman and Puga 2010). Networks, too, are alleged to contribute to local agglomerations (Henry and Pinch 2000, Sorenson and Audia 2000, Sorenson and Stuart 2001, Whittington et al. 2009) in part by facilitating labor mobility and subsequent knowledge spillovers (Saxenian 1994, Castilla et al. 2000).

These accounts suggest that space and networks reinforce each other in thick local labor markets. That is, firms in agglomerations tend to hire those who are both local and networked. In so doing, firms may be able to take advantage of positive externalities from local labor market pooling (Marshall 1920, Duranton and Puga 2004, Rosenthal and Strange 2004) through mechanisms such as a reduction in risk (Krugman 1991), better matches (Helsley and Strange 1990), or both (Costa and Kahn 1999). At the same time, firms may benefit from supply-side information networks (Granovetter 1995, Fernandez et al. 2000, Fernandez and Weinberg 1997) and also realize positive post-hire outcomes from network-based recruiting (Castilla 2005, Fernandez et al. 2000, Fernandez and Weinberg 1997, Petersen et al. 2000).

However, there is cause for doubt about this prediction. Although there is extensive theoretical work on the potential mechanisms giving rise to the benefits of local labor market pooling, there
is limited empirical work testing these mechanisms (for a review of theoretical work, see Duranton and Puga 2004; and for a review of empirical work, see Rosenthal and Strange 2004). In addition, prior empirical studies of hiring in the local labor market, including those facilitated by networks, rely on completed matches (e.g. Angel 1991, Hanson and Pratt 1992, Saxenian 1994, Granovetter 1995, Combes and Duranton 2006). As Fernandez and Weinberg (1997) elucidate, start-with-hire studies may suffer from selection bias (Berk 1983, Heckman 1979). Hired workers are survivors of a screening process in which a firm’s goal is to hire the best possible candidate from the application pool. Thus, if local, networked applicants are systematically better qualified as compared to the rest of the applicant pool, then we expect them to be overrepresented among those who are hired. However, if local, networked candidates are less qualified but preferred for other reasons, we expect to see the same overrepresentation in the pool of hires. Thus, it is unclear if supply-side labor pooling or demand-side screening processes might be driving the prediction of complementary space and networks in the labor market.

If networked candidates are plentiful in the candidate pool, then even when screeners have no preference for such candidates, we would see a similarly large proportion of candidates among hires. Without observing the baseline of who could have been hired, it is difficult to conclude whether the large representation of networked candidates among hires is due to their being favored by demand-side screeners or is simply a result of their prevalence in the candidate pool. The same point holds for local candidates—without observing the applicant pool, it is difficult to draw conclusions regarding screeners’ preferences regarding this population.

Indeed, space and networks are seen as important facilitators but also potential constraints in the labor market (for a review, see Fernandez and Su 2004). On the supply side for example, networks
might complement space in restricting access to job information (Newman 1999, O'Regan and Quigley 1991, 1998, Smith 2000, 2005). On the other hand, networks might substitute for space, providing access to jobs when candidates are excluded from local opportunities (Kasinitz and Rosenberg 1996). Agglomerations provide a unique opportunity to consider the interaction between space and networks in the labor market.

In this paper, we investigate the interaction of networks and space at different stages of the application-to-hire process for jobs located in California in high-technology firms. Current literature suggests a preference for local hires in agglomerations, and given barriers to labor mobility, perhaps this is to preserve the benefit of lower search costs. In addition, networks are identified as a potential contributor to agglomeration benefits and are an important facilitator of local labor markets. In this way, local networks may be an important mechanism for agglomeration economies to draw benefits from labor market pooling.

We find a subtle, multi-stage process in which space and networks interact differently at different points during the hiring process. Consistent with the agglomeration account, networked applicants are more local than non-networked applicants. During the demand-side evaluation process, however, there is a shift. At the first screening step, the interview, we find that networks substitute for space by expanding the recruitment horizon and bringing distant candidates in for consideration. Although the results are not statistically reliable, we observe that space and networks also substitute at the offer stage (conditional on interview) and complement at the hire stage (conditional on offer). In addition, we find a strong preference for distant candidates at the conditional offer stage. Interestingly, the unconditional offer and unconditional hire results are
similar to the results at the interview stage, suggesting that the interview stage affects the final outcome in a meaningful way.

Thus, contrary to the assumption that agglomeration benefits depend exclusively on local labor, these findings suggest that hiring from outside of the local area and social networks are important contributors to labor market processes in agglomerations, in effect, drawing non-local talent into the local labor pool. First, we provide evidence that candidates apply for jobs outside of their local labor market, perhaps with some expectation that the hiring firm will defray their relocation costs. In addition, instead of excluding distant candidates at the screening stage, we find that firms respond positively to a pool of candidates seemingly made richer through social networks. Although we do not observe the interviews, it is striking that firms seem to prefer to offer a job to distant candidates. Consequently, firms may benefit from co-location even if hiring from outside of the area. In this case, firms may realize supply-side benefits from social networks as they contribute to a richer, albeit more distant pool of applicants.

HIRING PROCESSES IN THICK LOCAL LABOR MARKETS

Agglomeration Economies

Agglomeration economies are said to arise from three Marshallian (1920) micro-foundational processes: decreased costs from vertical supply chain co-location, knowledge spillovers, and labor market pooling. Theoretically, these three sources of agglomeration economies have broad support (see Quigley 1998 and Duranton and Puga 2004 for reviews) and there are a few careful empirical studies that support their existence (Ellison et al. 2010, Rosenthal and Strange 2001, for a review
see Rosenthal and Strange 2004). However, much of this work is limited to large urban areas and industrial and manufacturing clusters (Locke 1995, Ellison and Glaeser 1997).

The main mechanisms for labor market theories of agglomeration in high-technology clusters is labor market pooling (Overman and Puga 2010) and knowledge spillovers (Audretsch and Feldman 1996). Although originally conceived as being “in the air” (Marshall 1920: 156), knowledge spillovers, often operationalized as some measure of innovation, are later proposed to be the result of high levels of local labor mobility, itself a result of labor market pooling (Combes and Duranton 2006, Freedman 2008, Bleakley and Lin 2012). As such, we focus on models exploring the mechanisms for why labor market pooling might be beneficial for firms in agglomerations.

**Local Labor Market Pooling**

Theoretical work in economics proposes four mechanisms contributing to the benefits of local labor market pooling. First, agglomerations may allow for the reduction in risk of unemployment for workers while also protecting firms’ ability to react to changes in supply and demand (Krugman 1991, Simon 1988, Diamond and Simon 1990). Next, agglomerations may facilitate better matches between employers and workers (Helsley and Strange 1990). Third, agglomerations may increase worker specialization, resulting in higher overall productivity (Rotemberg and Saloner 2000). Finally, learning may account for in-migration to agglomerations while restricting outmigration as young workers seek to learn from experienced workers in these agglomerations while experienced workers can realize the rents from this process when they stay (Glaeser 1999).

The most studied mechanism in the economic literature about thick local labor markets is through “better matches” that reduce search costs. Puga (2010) identifies three ways in which better
matches can be measured. First, better matches may induce a productivity externality, resulting in reduced search costs (Henderson 1986, Bleakley and Lin 2012) due to the presence of many firms being more likely to cover the skill space of local workers (Helsley and Strange 1990). Better matches also may increase returns to scale as market thickness increases due to increased chances of finding a suitable match (David and Rosenbloom 1990, Coles and Smith 1998). Finally, higher quality matches may obtain because of the ability to be more “choosey” as a result of the higher probability of suitable matches (Wheeler 2001, Gan and Li 2016). This work is mostly theoretical, save for Gan and Li (2016) who study variations in thickness within the academic market for new economics PhDs, a national labor market context, not local.

These theoretical explanations for the benefits of labor market pooling assume that firms hire from a local labor pool, even in the case of in-migration. The assumption of local hires is supported by three different mechanisms. First, the movement of workers is assumed to be spatially constrained to the local area, resulting in local hires (Rotemberg and Saloner 2000). Second, labor is mobile across geographical space but such mobility is assumed to be frictionless and instantaneous so firms bear no transaction costs (Helsley and Strange 1990, Krugman 1991, Simon 1988, Diamond and Simon 1990, Glaeser 1999, Moretti 2011). Finally, some economic models assume that any mobility costs are borne by the worker, resulting in hiring that is “as if” it is local due to the lack of hiring costs for the firm (Mortensen 1986). In any case, a key underlying assumption for models of mechanisms resulting in labor market-related agglomeration benefits is that hires are local, which is assumed to minimize hiring costs.

Indeed, limited evidence suggests a pattern of local hires in agglomerations (Angel 1991, Hanson and Pratt 1992, Henry and Pinch 2000). For example, Combes and Duranton (2006) find that about
75% of French workers who change employer stay in the same employment area, although they note that scientists are more mobile. In addition, geographic mobility in the U.S. is quite low, reaching 12 percent between the years 2007 and 2008, for reasons including a lack of job opportunities and demographic changes (Jacobsen and Mather 2010). Likewise, Gregg et al. (2004) find very low mobility rates in the U.K. in a study using data from the British Household Panel Study.

However, in start-with-hire and residential movers studies, it is not clear what is driving local hiring and lack of mobility. It might be a supply-side mechanism, such as applicants only applying locally, local applicants being more appropriate or more qualified, or applicants with job offers outside the area choosing not to move. On the other hand, local hiring might be related to a demand-side mechanism, such as an employer preference for local candidates. Data that includes the applicant pool is needed in order to disentangle these potential drivers (Fernandez and Weinberg 1997, Fernandez et al. 2000).

In addition, it is precisely because of the assumption of lower geographic mobility that local labor mobility is predicted to be rather high in agglomerations (Combes and Duranton 2006, Bleakley and Lin 2012). In Silicon Valley, for example, there is evidence that the local labor market is quite fluid between employers (Almeida and Kogut 1999) and between occupations (Bahrami and Evans 2000). Another study finds that in California and outside of the computer industry, mobility rates are no higher than elsewhere, whereas college educated men in Silicon Valley have higher rates of job hopping as compared to computer clusters out of state (Fallick et al. 2006). As a result, there is evidence that one of the benefits of firm co-location is localized knowledge spillovers (Almeida and Kogut 1999, Freedman 2008).
Although an assumption of exclusively local hiring may provide benefits for the tractability of a model, it is not realistic. David et al. (2010) report that as of the 2000 U.S. Census, 30% of individuals in the U.S. reside in a different state from where they were born. In addition, empirical evidence suggests that speculative movers are quite rare and mobility seems to be driven by first gaining employment outside the local area and then moving to the new locality (Gregg et al. 2004). As Rosenthal and Strange (2004) note, “it is, of course, precisely the mobility of labor that leads to agglomeration in the presence of external increasing returns in production. Or in reverse: external increasing returns lead to the agglomeration of labor” (2146).

Thus, a high level of local labor market mobility does not necessarily preclude distant applicants or distant hires, especially if the labor market is growing. Indeed, technology agglomerations are often marked by high rates of growth (Bresnahan et al. 2001), have labor markets that are national or international (1999), and still exhibit high frequency local labor markets (Saxenian 1994, Casper 2007). In addition, firms may be able to access geographically “localized” knowledge by hiring from outside of their area (Song et al. 2003).

Even if thick labor markets are dominated by local labor, in-migration is an important component underlying labor market theories of agglomeration economies. However, current theories of agglomeration do not account for distant hires as they assume exclusively local hires. In addition, theories of in-migration in agglomerations (Glaeser 1999, Mortensen 1986) do not account for labor market frictions like hiring costs (Manning 2011).

Finally, internet-based recruiting potentially poses a problem for labor market theories of agglomeration. Since the search process is no longer spatially bounded, internet job postings may
receive more distant applicants (see Autor 2001 for a review), especially if applicants or their future employers are willing to pay for the cost of a move. If employers’ search costs are contingent on the cost of posting a job (Manning 2011), which is fairly low when using internet job postings, and employers are adept at sorting through applications, they may benefit from reduced costs from better matches (David and Rosenbloom 1990, Helsley and Strange 1990, Coles and Smith 1998). However, expanding the recruiting horizon by soliciting more numerous applicants may not yield more qualified applicants, whether they are local or distant (Autor 2001).

**Space and Networks in the Labor Market**

Networked industrial systems may also reinforce agglomeration benefits, particularly in Silicon Valley (Angel 1991). Like labor market pooling, networks are an important component of labor market mobility, especially in agglomerations. As such, spatially constrained networks contribute to the localization of economic activity (Sorenson and Stuart 2001, Whittington et al. 2009). Saxenian’s (1994) seminal study of Silicon Valley points to the networked nature of the area as a driver of localized innovation and growth, especially due to high local labor mobility and subsequent knowledge spillovers. Accordingly, networks may play a role in structuring thick local labor markets.

However, much like the empirical work on local hires, this work starts with completed matches to infer supply-side processes (Angel 1991, Hanson and Pratt 1992) which may result in selection bias (Fernandez and Weinberg 1997). Early work on the supply-side benefits of networks emphasizes the role of information in search and matching in the labor market (Granovetter 1973, 1995) although it also relies on start-with-hire data. More recent work separates supply-side and demand-side processes by starting with the application pool and ascertaining the effect of networks.
on each stage of the hiring process (Fernandez and Weinberg 1997, Fernandez et al. 2000, Petersen et al. 2000, Castilla 2005). However, like early work on networks, it does not explicitly account for space. Finally, these studies do not account for internet-based recruiting, which might also affect supply-side processes.

There is a robust literature on the importance of social networks for general labor market mobility with respect to search and matching. Networks are a key coordinating mechanism providing access to the local labor market via information (Granovetter 1973, 1995, Simon and Warner 1992, Fernandez and Weinberg 1997, Fernandez et al. 2000, Schmutte 2015). Networks also can influence multiple steps in the screening process, from interview to hire (Fernandez and Weinberg 1997, Burks et al. 2015), as well as post-hire outcomes, such as wage growth, promotions, and turnovers (Bridges and Villedrz 1986, Fernandez et al. 2000, Petersen et al. 2000, Castilla 2005, Loury 2006, Burks et al. 2015, Brown et al. 2016).

Supply-side studies of the benefits of referrals address labor market frictions as they relate to search and labor market outcomes for potential applicants (see Marsden and Gorman 2001 for a review). Search theories emphasize the role that referrers play in disseminating extensive and intensive information (Rees 1966) about open positions. Thus referrals may help prospective applicants overcome labor market frictions such as asymmetric information from a lack of knowledge about vacancies or they may provide hard-to-obtain information about the job or the employer (Fernandez et al. 2000, Greenberg and Fernandez 2016). Other studies examine reasons why potential job applicants might use referrals, such as an increase in likelihood of securing a job, higher wages, and longer on-the-job tenure (Granovetter 1973, 1995, Bridges and Villedrz 1986, Loury 2006).
Within a local labor market, networks may contribute to labor mobility (Granovetter 1973, 1995, Angel 1989, Castilla et al. 2000, Henry and Pinch 2000) and knowledge spillovers (Saxenian 1994, Whittington et al. 2009). In Motor Sport Valley, a regional agglomeration of Formula One racing teams in England, Henry and Pinch (2000) note that “the industry labor market is made up of people networks such that it pays to be well connected” (196). In addition, access to local job networks seems to be an important influence on firm location decisions, resulting in agglomeration (Hanson and Pratt 1992, Sorenson and Audia 2000). Castilla et al. (2000) argue that networks facilitate high labor mobility in Silicon Valley, resulting in higher firm founding rates.

Supply-side studies of the effects of networks on labor market outcomes such as these start with completed matches or job changers and as such, potentially conflate supply-side and demand-side processes. Instead, data is needed that starts with the applicant pool to compare the distribution and characteristics of the applicants with those who are hired. It may be that referrals are more qualified in obvious ways, they prefer certain jobs for idiosyncratic reasons (Manning 2011, Greenberg and Fernandez 2016) or that employers prefer referrals for more hard-to-measure reasons. In any of these cases, local and networked candidates may be overrepresented in the pool of hires. What is not clear is whether this overrepresentation is the result of a supply-side or a demand-side process.

Demand-side studies attempt to ascertain organizations’ preferences for networked applicants and account for the benefits of referrals to the organization in search and matching processes (Fernandez and Weinberg 1997, Fernandez et al. 2000, Petersen et al. 2000, Castilla 2005, Fernandez and Sosa 2005, Fernandez and Fernandez-Mateo 2006). Fernandez et al. (2000) outline three theories for why referrals may be beneficial to firms. First, referrals may expand the firm’s
recruiting horizon by contributing to a richer pool of applicants who are better qualified and more appropriate (Fernandez and Weinberg 1997), reducing screening costs. Referrals may also provide the firm with better matched applicants who are more informed about the nature of the job (Rees 1966) and therefore should be more likely to accept the job and less likely to turnover than non-referrals. Finally, the referrer may provide social enrichment by mentoring the referral after hire resulting in lower turnover and increased productivity (Castilla 2005).

Studies that capture referral behavior in relation to the applicant pool may shed some light on expectations for referrals in agglomerations. The percentage of referrals in these studies range from 18% (Fernandez and Weinberg 1997) to roughly one-third of applicants (Fernandez et al. 2000, Fernandez and Sosa 2005, Castilla 2005, Fernandez and Fernandez-Mateo 2006, Fernandez and Campero 2017) to 51% (Petersen et al. 2000). However, the location of the applicants in relation to the job is either not report or not central to these studies.

One group of studies looks the effect of referrals during the hiring process at entry-level, low-to-medium skilled jobs at a retail bank (Fernandez and Weinberg 1997) and a call center (Fernandez et al. 2000, Castilla 2005, Fernandez and Sosa 2005), both of which presumably function within a local labor market. Petersen et al. (2000) use data from a high-technology firm to investigate the effect of referrals on labor market outcomes. Although they do not know the level of the job postings, they infer that it is a broad range of levels. The study also does not comment on the location of the applicants in relation to the jobs.\footnote{One might infer that the applicant pool includes both local and distant candidates given that the location of the interviews include college campus, human resources, placement department, or upper management (Petersen et al. 2000, 779).} In any case, applicant distance to job is not included in any of these studies.
Two recent studies include measures of distance in analyses of hiring processes. Fernandez and Fernandez-Mateo (2006), in a study of the effect of race and networks on hiring for lower-wage workers at a plant, are the first to incorporate distance in analyzing an applicant pool. They find that space and networks are complements as the number of referrals to the positions at the plant decreases as the distance of the workers’ home from the plant increases (see also Fernandez and Su 2004 for a review). Finally, Fernandez and Campero (2017) study gender sorting as it relates to the glass ceiling for individuals who apply to high-technology firms at a variety of levels. Although they do not consider space and networks as it relates to the applicant pool, they do use distance and referral status as control variables for the outcomes of interview and offer conditional on interview. In contrast, we consider how space and networks interact at each step of the hiring process, starting with the applicant pool, for high-technology firms with open positions at different levels.

Finally, these studies do not use internet-based recruiting (except see Fernandez and Campero 2017). During the search stage, internet-based recruiting potentially reduces asymmetrical information about job openings by democratizing access to such information, thus broadening the pool of applicants along an extensive information margin (Rees 1966). As with the concern regarding local and distant applicants, more (non-referred) applicants may not be better. If employers’ search costs are driven by the selection process (Manning 2011) and internet-based recruiting brings a surfeit of applications, referrals may help alleviate adverse selection concerns through informational advantages (Montgomery 1991, Fernandez et al. 2000, Autor 2001, Marsden and Gorman 2001). Thus, the resulting applicant pool may be richer from a broadening of the recruiting horizon as referrals bring in applicants who might otherwise have not applied (Fernandez and Weinberg 1997, Fernandez et al. 2000). When passing on job information,
referrers may act as initial screeners for the employer, potentially reducing employers’ adverse selection through employees’ reputation concerns or homophily (Fernandez et al. 2000).

The Hiring Process

These accounts suggest that space and networks interact in the labor market. What is unclear from these accounts is at what stages in the hiring process space and networks may interact. There are three distinct stages in the hiring process—search, evaluation, and hire. Each stage potentially represents different aspects of the search and matching process. Although search and matching are often theoretically separate, they are are difficult to disentangle in practice. The pre-evaluation stage is a supply-side process in which the applicant pool is formed. During this stage, both employers and potential applicants engage in search behavior as firms create and post job descriptions and applicants seek out these job postings. They may do so through referrals, finding the job online, or visiting a job fair. Screening may also occur, for example, as referrals select who to tell about opportunities and prospective applicants choose which websites or fairs to visit. Applicants then decide to which jobs to apply, creating an applicant pool.

The evaluation stage is a supply-side process that is separated into two steps—the interview and the offer steps. During the evaluation stage, the employer screens the applicants, selects applicants to interview, and selects which interviewees will receive an offer for a job. Although the employer decides which applicants advance to the next round during this stage, the matching process is often two-sided as applicants seek more information about the employer. Finally, candidates who receive offers and choose to accept them are hired.
STRATEGIC RESEARCH SITE

We examine the hiring process across a sample of 259 small and medium-sized firms, many in the high-technology industry, that use a common applicant tracking system (Fernandez and Campero 2017). Firms used the system to track posted jobs and applicants throughout the hiring process. Job postings were available on the companies’ websites as well as Internet job boards. When a potential applicant clicked on the link of a job title, they were taken to a webpage with information about the company and a short job description. Salary information was not provided. Applicants applied through the companies’ websites, either by visiting them directly or by clicking through to the website from an Internet job board.

We restrict our analysis to 1,524 job openings located in California, excluding internship positions due to their transient nature. We choose to focus on California because it is home to many clusters of high-technology firms within a common institutional framework. The map of job locations in California (Figure 1) shows the extent to which jobs in these firms are agglomerated. There are four distinct clusters in our dataset. Silicon Valley is the largest cluster along the northwest coastline. There is a small cluster located in the Central Valley area, northeast of Silicon Valley around Sacramento. Finally, there are two clusters in southern California. Silicon Beach is the area that includes Los Angeles and Orange County, while San Diego is farthest south and just north of the border with Mexico.

[Figure 1 Here]

The jobs in this dataset opened for application during a 50-month period from February 2007 through March 2012. The data are collected during the recovery period after the Great Recession, exhibiting a pattern of higher numbers of applications during the early months that gradually...
decline over time (see Fernandez and Campero 2014). In addition to excluding internship job postings, internal and demand-side candidates are excluded because they may not be subject to the type of thick labor market, space, and network effects as discussed by Saxenian (1994). Internal candidates should have much lower information asymmetry, which referrals may be used to overcome, than external candidates. Demand-side candidates increase search costs, negating the benefits from pooled labor markets. The resulting applicant pool consists of 149,175 applications, excluding internal candidates and demand-side candidates (purchased from search firm or otherwise solicited).

During the application process, race and gender were collected through voluntary self-identification. The applicant tracking system also collected the applicants’ home address as well as the address of the position and calculated the distance between them in air miles. We code the applicant as local if their residence is within 50 airline miles of the job for which they’ve applied. Thus, the applicant is close if they are less than 50 miles from the job and far if they are greater than or equal to 50 miles from the job. This cut-off serves to delineate if the applicant is local or if they would either bear an extensive commute or seek to relocate.

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2 We begin with an initial dataset of 1,270 firms, 13,368 job postings, and 544,462 applications. We exclude 540 internship positions (23,162 applications), internal applicants (37,527 applications) and demand-side applicants (14,425 applications). We remove an additional 6,647 jobs located outside of California (193,397 applicants) and 80 jobs associated with 18 firms that are not high-technology (3,471 applications). From the remaining 5,132 jobs (272,480 applications), we exclude 3,608 positions that were not filled in the 50-month time frame (123,305 applications). The resulting dataset consists of 148,175 applications from 138,635 unique applicants for 1,524 positions at 259 firms (1.08 applications per applicant).

3 Applicants chose “Decline to Identify” for race in 25.01% of the cases and for gender in 20.62% of the cases. An additional 4.60% of the applicants are missing both race and gender. First names were then coded using the IBM InfoSphere Name Management Tool (http://www-03.ibm.com/software/products/en/infosphere-global-name-management) resulting in gender identified for 99.22% of the final sample (see Fernandez and Campero 2017).

4 The results are robust at five mile intervals between 30 and 60 miles.
The network status of the applicant is coded from their self-identification as a referral during the application process. Because the data is anonymized, it is possible for the person referring the applicant to be an employee or external to the firm. Therefore, we follow Fernandez and Campero (2017) in considering any referral to be a “network referral.” The outcomes of interest are successes at each stage of the application process. Starting with the realized applicant pool, we consider if the applicant receives an interview, an offer, or a hire.

RESULTS

Pre-Hire: Application Stage

The hiring process starts with the formation of the applicant pool. During this time, the employer and the potential applicant participate in search. For example, an employer or a recruiter may post information to an online job board or the company’s website, or they may attend a job fair to solicit applications. A potential applicant may attend a job fair or search for job postings online or a referrer may pass on information about open positions. It is during this stage that extensive information may be passed on to the applicant (Rees 1966). We cannot observe who might have applied but chose not to so we start at the next step, the realized applicant pool.

Prior empirical work provides limited explicit guidance on the distribution of applicants over space and network status in agglomerations. Many studies start with hires or job changers and thus cannot speak to the composition of the applicant pool. In addition, theoretical work assumes local hires but does not comment on the applicant pool. Nevertheless, given the assumptions of thick local labor markets as well as the purported prevalence of spatially-bound job networks in agglomerations, we expect to find a preponderance of local and networked applicants.
The distance in air miles for the applicant pool is reported in Table 1. As expected, we find the large majority of applicants to be local (67.6%), although not exclusively, as 32.4% of the applicants are from outside of the area. In addition, the local applicants are more networked than the distant candidates. Local candidates, or those living within 50 air miles of the job for which they applied, are 71.3% of the referrals but only 64.9% of the non-referrals (chi-square p<0.001). These results at the application stage are consistent with the account that thick local labor markets are both local and networked (Saxenian 1994).

Space may constrain networks in that networks that provide access to information about jobs can be spatially limited (Fernandez and Su 2004). These constraints may operate in a number of ways. If the network is spatially constrained, job access through information flows along the network may be limited by neighborhood effects (O'Regan and Quigley 1991). Conversely, the spatial effect may be bounded by social, informational, or mobilization considerations (Newman 1999, O'Regan and Quigley 1998, Smith 2000, Smith 2005).

Table 1 Here

Pre-Hire: Evaluation Stage

The second stage after the formation of the applicant pool is the evaluation stage. This stage consists of an interview stage and an offer stage. The interview stage is the point at which the first screening decision is made by the firm and therefore the first point at which the firm considers the spatial and network attributes of each applicant. Each candidate who advances to subsequent stages of the hiring process is first interviewed and as such, it is here that the applicants first pierce the organizational boundary of the firm. As shown in Table 2, out of 146,255 applicants, 6.13% are interviewed (N=8,972).
The offer stage is also a demand-side process that is based on additional information gained during the interview process. At this stage, the firm makes another screening decision in selecting an applicant for the position. We cannot observe interactions at the interview stage, although we do collect information on who survives the interview process. In this sample, 25.03% of interviewed candidates and 1.54% of total applicants are given offers (N=2,245), as shown in Table 2. This selection process is more competitive than that of Ivy-League university admissions (Jackson 2017).

[Table 2 Here]

**Referral Effect**

The results in Table 3 show the referral effect odds ratios for three outcomes of interest, interview, offer conditional on interview, and hire conditional on offer, by three categories, all of the applicants, local applicants, and distant applicants. If space and networks are complements, we expect to find a stronger and significant referral effect for local applicants than distant applicants. If, however, space and networks substitute for each other, we expect to find a stronger and significant referral effect for distant applicants.

At the interview stage, we find a strong referral effect across all applicants (p<0.001), with a much stronger effect for those who are distant (p<0.001) than those who are local (p<0.001). We also find that the difference in referral effect between local applicants and distant applicants is statistically significant (p<0.001). Although local candidates in the applicant pool in thick local labor markets are more networked, our initial results suggest that it is the distant applicants who benefit more from their networks than the local applicants. Thus, these results suggest that at the interview stage, networks substitute for space by expanding the recruitment horizon.
The next two stages are the offer and hire stages. The results from the interview regressions hold for the unconditional offer and unconditional hire analyses which suggest that securing an interview affects subsequent outcomes in a meaningful way. In addition, at the offer stage conditional on interview, the referral effect is positive for those who are local but negative for those who are distant. However, these results are not statistically meaningful which reinforces our suggestion that the screening process at the interview stage is crucial to understanding the interaction between space and networks in the hiring process.

Finally, at the hire stage conditional on offer, we find a negative but statistically insignificant referral effect. The referral effect for those who are distant is not statistically significantly different from the referral effect for local applicants. This result is surprising in light of “better match” theories that imply referrals will accept offers at a higher rate due to a reduction in information asymmetry, specifically along intensive dimensions (Rees 1966). That is, referrals should have more information about the job and their fit for the job and thus be more likely to accept an offer than a non-referral. Our results provide support for prior work that finds that the rate of acceptance of offers by referrals is not statistically significantly different from that of non-referrals (Fernandez and Weinberg 1997, Fernandez et al. 2000).

Thus, initial results suggest space and networks as substitutes at the interview stage of the hiring process. We find that the referral effect is much stronger for distant candidates than local candidates at this stage. This effect holds for the unconditional offer and unconditional hire stages, implying that the referral effect for those who are distant has no statistically significant differences as compared with the referral effect for those who are close at any stage after the interview stage. However, if we focus on each stage conditional on the prior stage, we find something different.
First, the referral effect, though not statistically meaningful, has a slightly positive effect at the offer stage conditional on securing an interview for those who are local but is negative for those who are distant. We also find that the referral effect does not seem to be a factor at the conditional hire stage and is, perhaps surprisingly, negative. Thus, although networked applicants are preferred, the difference in effects of networks on local and distant is quite stark which might indicate that a different logic is used for the initial screening of local candidates than distant candidates.

[Table 3 Here]

**Multivariate Analyses**

We test these results using multivariate analysis to control for a number of observable characteristics of the job and the applicants. We include gender, race, the level of the position for which the applicant applies\(^5\), mean years of work experience and mean years of management experience (and squared terms to capture potential non-linearities in these variables), and the job function of the position for which the applicant applies.\(^6\) We also include an interaction variable between gender and job level to capture potential glass ceiling effects (see Fernandez and Campero 2017).

Table 2 reports summary statistics for the outcome and control variables we analyze. Without controls, local and networked applicants are most likely to secure an interview (6.99%) while distant non-referrals are least likely to secure an interview (3.86%). In addition, local applicants

---

\(^5\) The job levels include entry-level (e.g., customer service representatives, sales associates, social media coordinators, junior software engineers), mid-level (e.g., social media account managers, sales account executives, customer support specialists), experienced (e.g., software engineers, social media strategists, product managers), manager (e.g., regional sales manager, senior managers, marketing managers), executives (e.g., vice presidents, executive directors, head of customer support), and senior executives (e.g., chief product officer).

\(^6\) The job functions include sales, IT or engineering, product or operations, marketing, client services, human resources, administration, and a catchall category of other.
are more likely to secure an interview as compared with distant candidates (6.74% vs. 4.87) while referred candidates are more likely to secure an interview than non-referrals (6.88% vs. 5.61%).

However, the percent of candidates who are offered a job tells a slightly different story. At this stage, referrals are still more likely to secure an offer (1.76% vs. 1.38%), as are distant candidates (1.60% vs. 1.42%). However, distant and networked applicants are now most likely to secure an offer (1.89%), followed by local referrals (1.71%), local non-referrals (1.50%), and finally, distant non-referrals (1.14%). The percent hired follows the same pattern where referrals are more likely to be hired (1.48% vs. 1.19%) and the order of the probability of being hired is in the same order as offer: distant referral (1.51%), local referral (1.47%), local non-referral (1.32%), and distant non-referral (0.93%). Similar to the interview stage and the offer stage, local applicants are also slightly more likely to be hired (1.39 % vs. 1.15%). In addition, distant candidates are less likely to be female than local candidates. Although we have no information about partners, this fits with research on the “two-body problem” that suggests that women in relationships are more likely to be a “trailing partner” (Sorenson and Dahl 2016), particularly because men are more likely to work in agglomerated occupations (Benson 2014; see also Fernandez and Su 2004 for a review of space, networks, and gender in the labor market).

In terms of qualifications, referrals have lower mean years of work experience (8.06 vs. 8.52) and mean years of management experience (3.97 vs. 4.23) than do their non-referral counterparts. Referrals also apply for positions at slightly higher levels than non-referrals (2.18 vs. 2.10, not shown). On its face, this seems surprising because we might expect referrals to be more qualified. However, work on the “richer pool” mechanism explaining the preference for referrals in the labor market argues that referrals will be more appropriate, which may include under- and over-
qualification (Fernandez and Weinberg 1997, Fernandez et al. 2000). Indeed, Autor (2001) argues that internet-based recruiting may increase the number of inappropriate applicants. In addition, local applicants have higher years of work and management experiences (8.89 vs. 7.15 and 4.35 vs. 3.65, respectively) but apply for lower level positions on average (2.08 vs. 2.24). As the job position level correlates with percent female, we control for an interaction effect in our multivariate models.

During the evaluation stages, we expect thick market effects such as improved search, increased mobility, and reduction of search costs, to manifest as a greater likelihood of local candidates securing interviews and subsequent offers than distant candidates. This is because of two reasons. First, the hiring process is costly, averaging $4,129 for fiscal year 2015 (Management 2016). Thus the opportunity cost of screening a candidate is non-zero. Those who live outside of commuting distance cost more to hire—they might be flown in for interviews and the company may offer a relocation package that they might otherwise not make to a local candidate.

The second reason for a preference for local candidates is that thick labor markets imply qualified candidates are available locally. Since the benefits of agglomeration are purported to outweigh the costs of locating in high cost areas, we expect to see the benefits from labor market pooling as a higher likelihood of interview for local candidates, after controlling for observables. In addition, if local labor markets are the ultimate source of better matches, we might expect that they will be favored during the offer stage as well. Finally, it is unclear if local or distant candidates would be more likely to accept the offer. Local candidates might have more outside options while distant candidates, if they are less likely to get an interview, may not secure as many offers. This sort of
calculation may affect the likelihood of offer if employers are concerned about offering candidates whom they think are more likely to accept.

**Interview Stage**

Table 4 reports the odds ratios for the interview stage. If thick local labor markets are so bountiful as to provide better matches through easily signaled quality and quantity, we expect to find that local candidates are favored over distant candidates and we do not expect to find a referral effect for local candidates. Distant candidates are presumably more costly to hire and may provide quantity but not quality while referrals seem to be unnecessary in a thick local labor market.

If, however, screening is difficult, perhaps due to quantity or increased adverse selection from internet-based recruiting (Autor 2001), we might expect referrals to provide a richer pool of applicants (Fernandez and Weinberg 1997, Fernandez et al. 2000) or better match on the intensive margin (Rees 1966). In addition, frictions in the local labor market, such as high hiring costs (Manning 2011), may shift preferences to distant candidates.

In Table 4, the referral effect odds ratio is positive and significant for all specifications of the model, including controls. Thus, for local applicants, the odds of a referral securing an interview is 1.069 times higher than the odds of a non-referral (Model 5, p<0.05). Although we cannot comment on the mechanism driving this result, it does suggest that at the interview stage, agglomerated firms prefer referrals to non-referrals for local applicants, controlling for observable factors.

In addition, although the odds of a distant candidate securing an interview is 29.2% less than the odds of a local candidate (Model 2, p<0.001), the referral effect for distant candidates is 1.560
times the referral effect for local candidates as shown by the interaction term between distant and referral, net of controls (Model 5, p<0.001). Even though distant candidates have much lower odds of securing an interview as compared with local candidates, a referral provides a 66.8% increase to the odds of a distant candidate securing an interview as compared with a distant non-referral, although not as much as being local (91.6% increase for a non-referral).

Thus, within agglomerations, the hiring process within local labor markets does not seem to rely exclusively on higher quantity, locally available labor, that is better matched on skills for the job, and is therefore of higher quality. Instead, firms seem to be expanding their recruiting horizon locally and by bringing distant candidates in, both through the use of referrals. However, contrary to the agglomeration account in which networks and space reinforce each other, the referral effect is much stronger for distant candidates than for local candidates. Thus, these results suggest that despite (or perhaps because of) a preference for local candidates, referrals substitute for space at the interview stage.

[Table 4 Here]

**Offer Stage**

The next step in the hiring process after the firm interviews one or more candidates is the offer. The firm takes all of the information about the candidates into account to decide to whom to extend an offer for a given position. The predictions at this step are similar for those at the interview step in that we expect local and networked candidates to be more likely to be offered a job. It is possible that the effect would be stronger at this step than at the interview step if referred candidates are given courtesy interviews but are not seriously considered. In addition, it is at this step that firms
more explicitly face frictions such as hiring costs, which may include potentially costly relocation packages.

We report the results of multivariate logistic regressions on offer conditional on previously receiving an interview in Table 5. Although the odds ratios for referrals are positive, none of them are statistically significant. In addition, it is distant candidates who have 32.2% higher odds of securing an offer than local candidates (Model 2, p<0.001). Finally, the referral effect for distant candidates is negative but not statistically significantly different from the referral effect for local candidates.

These results stand in stark contrast to the interview stage. Although the odds are lower to secure an interview as a distant candidate, the effect of a referral is stronger for a distant candidate than for a local candidate. However, it is the distant candidates, regardless of network status, who are more likely to secure an offer. These results are especially surprising considering that the agglomeration literature is all but silent on distant candidates under the assumption that firms co-locate to take advantage of thick local labor markets with plenty of mobile, skilled workers. Although in-migration is seen as important for the growth of agglomerations (Glaeser 1999, Rosenthal and Strange 2004), it is assumed to occur prior to securing a job offer. However, we find that many people apply to jobs from outside of an agglomeration and, although they have lower odds of receiving an interview, they do see some success at procuring a job offer before moving to the agglomeration. Given that the recruitment horizon is expanded in the interview stage, these findings suggest that firms do not always find the “better match” in the thick local labor market, relying on distant applicants instead.

[Table 5 here]
The unconditional offer multivariate logistic regression in Table 6 reiterates the results from the interview analysis and the conditional offer analysis. Across all specifications, there is a positive and significant referral effect on the odds of securing an offer (p<0.001 for Models 1 and 3, p<0.01 for Models 4 and 5). In contrast, the distant effect is negative and significant (p<0.05 for Models 2 and 3, p<0.001 for Models 4 and 5). Finally, there are positive interactions between space and networks (p<0.001 for Models 4 and 5). Although at the conditional offer stage the referral effect for those who are distant is no longer any more or less strong than the referral effect for local applicants, that the conditional offer results mirror the interview stage suggests that the decisions made at the interview stage have lasting consequences.

[Table 6 Here]

DISCUSSION

Although we find support for the spatial reinforcement of network processes emphasized in the extant literature, space is not simply exclusionary. Instead, in breaking out the stages of the hiring process, we find a persistent substitution effect for space and networks in the labor market. At the interview stage, referrals help in expanding the recruiting horizon, drawing distant candidates into the consideration set. However, this is surprising given the “better match” theory derived from the dynamics of thick local labor markets in agglomerations. Instead of simply mining the local network of employees, high-technology firms located in thick local labor markets are attracting candidates from beyond the commuting zone to find potential candidates and as such, rely on referrals to inform the first stage of the screening process. Local candidates are not afforded the same treatment.
Angel (1991) finds that “Silicon Valley firms fill the majority of their job vacancies (at least 85 percent in all occupations [production, technical, and engineering]) from within the local labor market, drawing upon the large pool of specialized labor skills viable within the region” (1506). However, thick local labor markets are not exclusively spatially constrained, especially in growing areas. Although migration may be limited, it should be accounted for in economic models of the labor market. In particular, labor market theories of agglomerations cannot account for these results.

It is possible that firms in agglomerations favor distant candidates because they provide access to new streams of knowledge (Rosenkopf and Almeida 2003, Burt 2004). Especially if knowledge is localized (Jaffe et al. 1993, Almeida and Kogut 1999), then someone from outside the area may act as a “bridge” (Burt 1992) by funneling new information into the organization. And indeed, there is some evidence that knowledge spillover effects, quite robust already within agglomerations (Saxenian 1994, Audretsch and Feldman 1996), are more pronounced when hiring across regions rather than within region (Rosenkopf and Almeida 2003, Corredoira and Rosenkopf 2009).

In addition, labor markets are imperfect in many ways. Manning (2011) argues that two frictions in particular are important to understanding rents in the labor market. On the supply side, he argues that prospective applicants have idiosyncratic preferences about the position, such as the employer, the geographic location, or non-monetary attributes. On the demand side, he argues that employers’ hiring costs stem from the selection process rather than the search process.
These frictions also provide some insight into how space and networks may work in the labor market. Idiosyncratic preferences may result in a preference for remaining in a local labor market or they may compel a prospective applicant to apply to positions in distant locations, perhaps to be near network connections (Dahl and Sorenson 2010). In addition, in the face of hiring costs, potentially heightened from internet-based recruiting, referrals may provide a way to expand the recruiting horizon and draw in qualified applicants (Fernandez et al. 2000).

**SUMMARY AND CONCLUSION**

Prior work suggests that hires are more likely to be local and networked. Although more local candidates are hired in absolute numbers, supporting the start-with-hire predictions of local hires, the absolute numbers do not support the networks story. Indeed, there are more local applicants and fewer networked applicants who apply.

Our analysis tells an additional story. Using a unique dataset of applicants to high-technology firms in California, we find a subtle, multi-step process. While applicants are more likely to be local and networked, networks are not only a local phenomenon. At the interview stage, networks are an important factor in drawing distant candidates into the hiring process, even more so than for local candidates. Thus, we find that space and networks are substitutes at the interview stage of the hiring process.

Likewise, we find that space and networks are substitutes at the unconditional offer and unconditional hire stages. At these stages, not conditional on surviving the prior round, the referral effect for those who are distant is stronger than the referral effect for those who are local. Taken together, the finding that space and networks are substitutes at different stages of the hiring practice
provide limited support for thick local labor market mechanisms while also challenging a key assumption of benefits from labor market pooling more generally. In addition, these findings also provide evidence of the demand for and realization of in-migration. Finally, these findings support Fernandez et al.’s (2000) theory of how networks contribute to a richer pool of applicants.

Table 7 shows that starting with hires, as the extant literature does, it appears that networks are spatially distributed in the same way (Chi-square test is not significant). Stopping here, we would wrongly conclude that the interaction of space and networks is null. However, this pattern is the result of a set of processes working at an earlier stage. As this paper shows, networks do matter in terms of spatial distribution at an earlier stages. The applicant pool shows that referrals are more local than non-referrals. In addition, networks substitute for space, expanding the recruiting horizon and pulling people into the consideration set from farther away at the interview stage.

[Table 7 Here]

That networks substitute for space at certain stages of the hiring process in agglomerations suggests that while thick local labor markets are less reliant on networks, perhaps due to the quality and quantity of the local applicants, hiring is not exclusively local, as the key assumption in models of hiring in agglomerations assumes. In-migration, while not costless as the model assumes, seems to be an important driver of growth in agglomerations. Distant candidates apply in great numbers and their network status is an important component of successfully entering and navigating the hiring process. Indeed, networks not only enrich the pool of applicants but they also interact with space. Thus, space and networks may be important mechanisms through which network theories and space-based theories of hiring operate, respectively.
While a vibrant, networked local labor market is no doubt a part of the agglomeration success story, to the extent that networks interact with space, it is in attracting skilled labor from outside of the local areas into the consideration set. We find evidence that firms in agglomerated industries do not rely exclusively on local labor markets to staff their rapid growth.
FIGURE 1

Job Locations in California
### TABLE 1

Distance in Air Miles for the Applicant Pool

<table>
<thead>
<tr>
<th></th>
<th>Referrals</th>
<th>Non-Referrals</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Local</td>
<td>71.3%</td>
<td>64.9%</td>
<td>67.6%</td>
</tr>
<tr>
<td>% Distant</td>
<td>28.7%</td>
<td>35.1%</td>
<td>32.4%</td>
</tr>
<tr>
<td>N</td>
<td>60,501</td>
<td>85,754</td>
<td>146,255</td>
</tr>
</tbody>
</table>

Chi-square p=0.001
### TABLE 2
Summary Statistics of Variables Used in Multivariate Analysis

<table>
<thead>
<tr>
<th>Variables</th>
<th>Local Referrals</th>
<th>Non-Referrals</th>
<th>Distant Referrals</th>
<th>Non-Referrals</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Distance</td>
<td>146,255</td>
<td>18.20</td>
<td>16.64</td>
<td>1783.96</td>
<td>2146.98</td>
</tr>
<tr>
<td><strong>Dependent variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent offered job</td>
<td>1.712</td>
<td>1.501</td>
<td>1.885</td>
<td>1.144</td>
<td>1.536</td>
</tr>
<tr>
<td>Percent hired</td>
<td>1.474</td>
<td>1.322</td>
<td>1.510</td>
<td>0.935</td>
<td>1.309</td>
</tr>
<tr>
<td><strong>Control variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent female</td>
<td>38.28</td>
<td>45.93</td>
<td>23.70</td>
<td>28.31</td>
<td>37.42</td>
</tr>
<tr>
<td>Race</td>
<td>146,255</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent Black</td>
<td>3.21</td>
<td>5.48</td>
<td>2.02</td>
<td>3.67</td>
<td>4.03</td>
</tr>
<tr>
<td>Percent Hispanic</td>
<td>4.15</td>
<td>6.92</td>
<td>2.39</td>
<td>4.16</td>
<td>5.00</td>
</tr>
<tr>
<td>Percent Other</td>
<td>4.18</td>
<td>5.63</td>
<td>2.21</td>
<td>3.15</td>
<td>4.29</td>
</tr>
<tr>
<td>Percent White</td>
<td>28.84</td>
<td>31.94</td>
<td>24.78</td>
<td>35.42</td>
<td>30.89</td>
</tr>
<tr>
<td>Percent missing</td>
<td>31.15</td>
<td>28.45</td>
<td>36.04</td>
<td>26.14</td>
<td>29.67</td>
</tr>
<tr>
<td><strong>Work and Management Experience</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean years of work experience</td>
<td>145,129</td>
<td>8.62</td>
<td>9.10</td>
<td>6.62</td>
<td>7.44</td>
</tr>
<tr>
<td>Mean years of management experience</td>
<td>141,685</td>
<td>4.25</td>
<td>4.43</td>
<td>3.27</td>
<td>3.86</td>
</tr>
<tr>
<td>Mean level of job application (1-5)</td>
<td>146,255</td>
<td>2.15</td>
<td>2.03</td>
<td>2.26</td>
<td>2.23</td>
</tr>
<tr>
<td><strong>Job Function</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales</td>
<td>9.66</td>
<td>9.27</td>
<td>11.16</td>
<td>15.09</td>
<td>10.80</td>
</tr>
<tr>
<td>IT/Engineering</td>
<td>32.30</td>
<td>21.79</td>
<td>51.77</td>
<td>40.63</td>
<td>32.32</td>
</tr>
<tr>
<td>Product/Operations</td>
<td>15.30</td>
<td>16.08</td>
<td>11.33</td>
<td>12.76</td>
<td>14.60</td>
</tr>
<tr>
<td>Client services</td>
<td>12.56</td>
<td>15.99</td>
<td>7.58</td>
<td>9.29</td>
<td>12.60</td>
</tr>
<tr>
<td>Human resources</td>
<td>4.70</td>
<td>5.73</td>
<td>1.60</td>
<td>1.96</td>
<td>4.16</td>
</tr>
<tr>
<td>Administration</td>
<td>9.10</td>
<td>15.26</td>
<td>2.49</td>
<td>4.79</td>
<td>9.78</td>
</tr>
<tr>
<td>Other</td>
<td>2.00</td>
<td>3.65</td>
<td>1.37</td>
<td>2.22</td>
<td>2.60</td>
</tr>
</tbody>
</table>
### TABLE 3

**Odds Ratios for the Referral Effect on Outcomes**

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Local (distance&lt;50m)</th>
<th>Distant (distance&gt;=50m)</th>
<th>Significant?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Interview</strong></td>
<td></td>
<td></td>
<td></td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>1.257***</td>
<td>1.073**</td>
<td>1.763***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(10.54)</td>
<td>(2.75)</td>
<td>(13.25)</td>
<td></td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>149,175</td>
<td>98,848</td>
<td>47,407</td>
<td></td>
</tr>
<tr>
<td>**Offer</td>
<td>Interview**</td>
<td></td>
<td></td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>1.06</td>
<td>1.091</td>
<td>0.947</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.21)</td>
<td>(1.50)</td>
<td>(-0.59)</td>
<td></td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>9,143</td>
<td>6,664</td>
<td>2,308</td>
<td></td>
</tr>
<tr>
<td>**Hire</td>
<td>Offer**</td>
<td></td>
<td></td>
<td>No</td>
</tr>
<tr>
<td></td>
<td>0.861</td>
<td>0.839</td>
<td>0.904</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-1.26)</td>
<td>(-1.17)</td>
<td>(-0.52)</td>
<td></td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>2,297</td>
<td>1,575</td>
<td>671</td>
<td></td>
</tr>
</tbody>
</table>

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

+ z-scores in parentheses

---

7 The referral effect on unconditional offer and unconditional hire logistic regressions are similar to the referral effect on interview. This suggests that securing an interview affects final outcomes in a meaningful way.
**TABLE 4**  
Odds Ratios for Interview

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b/z</td>
<td>b/z</td>
<td>b/z</td>
<td>b/z</td>
<td>b/z</td>
</tr>
<tr>
<td>Referral</td>
<td>1.257*** (10.28)</td>
<td>1.220*** (8.79)</td>
<td>1.073** (2.69)</td>
<td>1.069* (2.46)</td>
<td></td>
</tr>
<tr>
<td>Distant</td>
<td>0.708*** (-13.47)</td>
<td>0.718*** (-12.83)</td>
<td>0.573*** (-15.60)</td>
<td>0.522*** (-17.15)</td>
<td></td>
</tr>
<tr>
<td>Referral x Distant</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.643*** (9.66)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.059*** (-188.14)</td>
<td>0.072*** (-202.79)</td>
<td>0.066*** (-157.62)</td>
<td>0.070*** (-152.37)</td>
<td>0.069*** (-53.56)</td>
</tr>
<tr>
<td>Controls</td>
<td>YES</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Likelihood Value</td>
<td>-54910.604</td>
<td>-34330.172</td>
<td>-33632.596</td>
<td>33591.663</td>
<td>-33542.086</td>
</tr>
<tr>
<td>P-value</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
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</tr>
<tr>
<td>N</td>
<td>149,175</td>
<td>146,255</td>
<td>146,255</td>
<td>146,255</td>
<td>140,397</td>
</tr>
</tbody>
</table>

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

**TABLE 5**  
Odds Ratios for Offer Conditional on Interview

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b/z</td>
<td>b/z</td>
<td>b/z</td>
<td>b/z</td>
<td>b/z</td>
</tr>
<tr>
<td>Referral</td>
<td>1.06 (1.19)</td>
<td>1.048 (0.94)</td>
<td>1.091 (1.49)</td>
<td>1.108 (1.65)</td>
<td></td>
</tr>
<tr>
<td>Distant</td>
<td>1.324*** (5.10)</td>
<td>1.322*** (5.05)</td>
<td>1.416*** (4.53)</td>
<td>1.286*** (2.99)</td>
<td></td>
</tr>
<tr>
<td>Referral x Distant</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(-1.28)</td>
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<tr>
<td>Constant</td>
<td>0.326*** (-33.45)</td>
<td>0.309*** (-40.27)</td>
<td>0.303*** (-32.57)</td>
<td>0.297*** (-30.61)</td>
<td>0.391*** (-8.37)</td>
</tr>
<tr>
<td>Controls</td>
<td>YES</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log Likelihood Value</td>
<td>-6598.681</td>
<td>-5153.02</td>
<td>-5035.34</td>
<td>-5034.885</td>
<td>-5034.036</td>
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<tr>
<td>P-value</td>
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<td>8,972</td>
<td>8,972</td>
<td>8,972</td>
<td>8,481</td>
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* p<0.05, ** p<0.01, *** p<0.001
TABLE 6

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b/z</td>
<td>b/z</td>
<td>b/z</td>
<td>b/z</td>
<td>b/z</td>
</tr>
<tr>
<td>Referral</td>
<td>1.300***</td>
<td>1.277***</td>
<td>1.143**</td>
<td>1.157**</td>
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</tr>
<tr>
<td></td>
<td>(6.09)</td>
<td>(5.58)</td>
<td>(2.58)</td>
<td>(2.70)</td>
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</tr>
<tr>
<td>Distant</td>
<td>0.887*</td>
<td>0.902*</td>
<td>0.760***</td>
<td>0.646***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-2.52)</td>
<td>(-2.13)</td>
<td>(-4.16)</td>
<td>(-6.10)</td>
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<td>Referral x Distant</td>
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<td></td>
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<td>Constant</td>
<td>0.014***</td>
<td>0.016***</td>
<td>0.014***</td>
<td>0.015***</td>
<td>0.019***</td>
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<tr>
<td></td>
<td>(-144.99)</td>
<td>(-159.62)</td>
<td>(-123.30)</td>
<td>(-118.60)</td>
<td>(-41.85)</td>
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<tr>
<td>Controls</td>
<td>YES</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Log Likelihood Value</td>
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<td>-11580.669</td>
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<td>P-value</td>
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</tr>
<tr>
<td>N</td>
<td>149,175</td>
<td>146,255</td>
<td>146,255</td>
<td>146,255</td>
<td>140,397</td>
</tr>
</tbody>
</table>

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

TABLE 7

Distance in Air Miles for Offer

<table>
<thead>
<tr>
<th></th>
<th>Referrals</th>
<th>Non-Referrals</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Local</td>
<td>69.3%</td>
<td>70.8%</td>
<td>70.1%</td>
</tr>
<tr>
<td>% Distant</td>
<td>30.7%</td>
<td>29.2%</td>
<td>29.9%</td>
</tr>
<tr>
<td>N</td>
<td>1,066</td>
<td>1,180</td>
<td>2,246</td>
</tr>
</tbody>
</table>

Chi-square test is not significant

Distance in Air Miles for the Applicant Pool

<table>
<thead>
<tr>
<th></th>
<th>Referrals</th>
<th>Non-Referrals</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>% Local</td>
<td>71.3%</td>
<td>64.9%</td>
<td>67.6%</td>
</tr>
<tr>
<td>% Distant</td>
<td>28.7%</td>
<td>35.1%</td>
<td>32.4%</td>
</tr>
<tr>
<td>N</td>
<td>60,501</td>
<td>85,754</td>
<td>146,255</td>
</tr>
</tbody>
</table>

Chi-square p<0.001
REFERENCES


