Do Informal Referrals Lead to Better Matches? Evidence from a Firm's Employee Referral System[1]

Meta Brown, Elizabeth Setren and Giorgio Topa
Research and Statistics Group
Federal Reserve Bank of New York
33 Liberty Street
New York, NY 10045

February 2012

[1]Corresponding coauthor Giorgio Topa may be contacted at Giorgio.Topa@ny.frb.org. *This paper is dedicated to the memory of Linda Datcher Loury, a pioneer in this literature, an excellent scholar and a great person.* Fabian Lange, Charles Bellemare, Manolis Galenianos, Uta Schonberg, Wilbert van der Klaauw and seminar participants at the Society for Economic Dynamics and the Federal Reserve Bank of New York provided valuable comments. The views and opinions offered in this paper do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System.

Abstract

The limited nature of data on employment referrals in large business and household surveys has so far restricted our understanding of the relationships among employment referrals, match quality, wage trajectories and turnover. Using a new firm-level dataset that includes explicit information on whether a worker was referred by a current employee of the company, we are able to provide rich detail on these empirical relationships for a single mid-to-large U.S. corporation, and to test various predictions of the theoretical literature on labor market referrals. We find that referred workers enter at higher wage levels, all else equal, but that the referred wage advantage dissipates by the third year of employment. After the fifth year the referral-wage relationship is reversed. Referred workers experience substantially less turnover, and this effect is relatively long-lasting. Despite higher predicted productivity for referred workers in the theoretical literature, we find, if anything, slightly slower promotion rates for referred than for non-referred workers. Finally, the wide range of skill and experience levels represented in this corporation permit detailed analysis of the role of referrals for workers from support staff to executives.

JEL codes: J30, J63, J64

1 Introduction

There is wide empirical consensus, both in economics and in sociology, on the widespread use of informal referrals in the labor market.[1] For instance, Corcoran et al. (1980) analyze national data from the Panel Study of Income Dynamics (PSID) and find that between 52% and 58% of male workers under the age of 45 heard about their current job from friends or relatives; for their first job these estimates range between 55% and 67%.[2] However, the information on referrals is often indirect, and there is little direct evidence on the impact of labor market referrals on the quality of the matches between firms and workers.

The limited nature of data on employment referrals in large business and household surveys has so far restricted our understanding of the relationships among employment referrals, match quality, wage trajectories and turnover[3]. Using a new firm-level dataset that includes explicit information on whether a worker was referred by a current employee of the company, we are able to provide rich detail on these empirical relationships for a single mid-to-large U.S. corporation, and to test various predictions of the theoretical literature on labor market referrals.

We find that referred workers enter at higher wage levels, all else equal, but that the referred wage advantage dissipates by the third year of employment. After the fifth year the referral-wage relationship is reversed. Referred workers experience substantially less turnover, and this effect is relatively long-lasting. Despite higher predicted productivity for referred workers in the theoretical literature, we find, if anything, slightly slower promotion rates for referred than for non-referred workers. Finally, the wide range of skill and experience levels represented in this corporation permit detailed analysis of the role of referrals for workers from support staff to company executives.

The plan of the paper is as follows. Section 2 relates this paper to the rich and varied empirical literature on employee networks in general and referral in particular. In Section 3 we review existing theory on labor market referrals and note several testable predictions. Section 4 describes our new firm-level data on employee referral status, tenure outcomes, and promotion and salary trajectories.

[1] See Ioannides and Datcher Loury (2004) and Topa (2011) for surveys of the economics literature, and Marsden and Gorman (2001) for a survey of the sociology literature.

[2] See also Datcher (1983). Pellizzari (2004) analyzes a large panel dataset of European households (the European Community Household Panel) and finds that between 25% and 40% of respondents in most countries heard about their current job through informal contacts. On the employer side, Marsden (2001) and Holzer (1987b) use national surveys of U.S. firms and find that a little over one third of firms surveyed in 1991 and in 1982 (respectively) often used referrals from current employees when publicizing vacancies.

[3] A notable exception is Datcher (1983)

The empirical specifications used to test the various predictions generated by models of employee referrals, results of these tests and other empirical findings are found in Section 5, and Section 6 concludes.

2 Related empirical literature

Empirical research on labor market referrals has emphasized the identification of effective proxies for referred worker status, as a result of the difficulty of measuring referral status in most relevant data sources. Recent research focuses on whether neighbors cluster in the same firm or area as an indication of the strength of informal referral networks (Bayer et al. 2008 and Hellerstein et al. 2008). Others study family based networks (Kramarz and Nordstrom Skans 2007) and educational institutions (Oyer and Schaefer 2009). Giuliano et al. (2009) and Aslund et al. (2009) find a relation between the ethnic status of managers and the ethnic composition of new hires using data from one large U.S. retail firm and Swedish social security data, respectively. Dustman, Glitz, and Schonberg (2011) use ethnic minority groups as a source of variation in network distance between current employees and new hires in German employment data.

With regard to the impact of referrals on hiring probabilities, Holzer (1987a) finds that that the probability of obtaining a job or receiving an offer through personal contacts is higher than that through formal methods. Holzer (1988) also finds that among all search methods, informal methods (personal contacts and direct applications) generated the most offers and acceptances conditional on offer. The high fraction of jobs found through informal means reflects both high usage and high productivity of these methods. With regard to match outcomes, Datcher (1983) uses PSID data and finds lower turnover (quit rates) in jobs found through personal contacts rather than formal means, for blacks and for college educated but not for those with high school or less.

A few richly informative studies of referral based on firm-level data and explicit referral information address the subject from a sociological perspective. Fernandez and Weinberg (1997), Fernandez and Castilla (2000, 2001) and Castilla (2005) use data from a retail bank and a call center to study the role of referral networks in hiring for low to moderate skill jobs. Much of the focus of these papers is on the hiring stage, and on initial productivity. Major findings include that referred applicants are more likely to be hired after controlling for other observables, that referrers

do have relevant information about referred employees and that there is some evidence of assortative matching between referrer and referred. Castilla has direct measures of worker productivity from a call center and finds that referred workers are in fact more productive.

However, these studies do not follow employees for long post-hire periods, and they generally do not rely on the tools of labor economics. This study is the first, to our knowledge, to use explicit data on individual employees' referral status to relate referrals to immediate and long-term employment outcomes including starting salary, salary trajectory over time, promotion patterns and stability of the job match, and hence we are the first, again to our knowledge, to be able to test the collection of predictions generated by the theoretical literature on employee referrals regarding salary trajectories, promotion and turnover using explicit data on employees' referral status.

3 Theoretical models of employment referrals and their predictions

Simon and Warner (1992) is an early and relatively influential example of the theory of labor market referrals. They embed employee referrals in a Jovanovic (1979, 1984) model of job matching and turnover, and use this partial equilibrium framework to derive predictions for differences in salary and match duration between referred and non-referred workers. They emphasize three predictions that we will be able to address directly using our explicit referral information below. Their model predicts that referred workers, or workers hired through the "old boy network", will (i) earn higher starting salaries, (ii) gradually lose their salary advantage and (iii) display longer tenure in the firm than comparable workers hired through other means. As a result of their partial equilibrium, dynamic framework, testing the types of predictions generated by the Simon and Warner model involves immediate and ongoing observation of referred and non-referred workers in a single employment spell, a task for which our panel of firm-level data is well suited.[4]

Montgomery (1991) is another seminal paper on the role of referrals in the labor market. He argues that referrals from current employees may reduce the adverse selection problem an employer

[4] Note that Simon and Warner test the predictions of their old boy network model using the 1972 Survey of Natural and Social Scientists and Engineers, a collection of retrospective self-reports on employment experiences. We discuss their findings in conjunction with our own empirical results below. While our data have the advantages of being roughly 30-50 years more recent, being derived from an administrative source and representing a considerably wider range of worker skill levels, their data have the obvious advantage of representing more than one firm.

faces when trying to hire someone, if there is uncertainty about worker or match quality. He formalizes this idea in a labor market model in which formal and informal search methods coexist in equilibrium. Firms set their wages before observing a new worker's productivity; current employees are likely to know someone of similar quality given assortative matching in personal networks. This implies that by relying on referrals employers can alleviate the adverse selection problem they face. In equilibrium, the model implies that wages of jobs obtained through referrals are higher than wages of jobs found through other means. Montgomery (1991) also derives some interesting comparative statics: an increase in either network density or assortative matching increase referral wages relative to market wages, and increases the dispersion in the wage distribution.

3.1 Prediction 1: Referred applicants are more likely to be hired

More recent theoretical papers on employee referrals include Galenianos (2011) and Dustmann et al. (2011). Galenianos models worker and firm search with and without productivity heterogeneity in the presence of networks that yield (informative) referrals. As the (exogenous) rate at which referrals are generated increases, the aggregate job finding rate rises and labor market tightness decreases. Together, these imply that a higher prevalence of referrals will be associated to higher estimated matching efficiency – in estimates of an aggregate matching function. Other predictions include that referrals are associated with the hiring of more productive workers. Access to referral networks both decreases a worker's unemployment probability and increases the worker's wage. Further, a worker's job-finding rate increases with the rate of employment among members of her network.

Importantly, the Galenianos model with worker heterogeneity delivers the theoretical implication that workers who meet a firm through referrals are more likely to be hired than workers who meet the firm through random matching. This is because high productivity workers are more likely to be employed and therefore are more likely to refer one of their social contacts. Because of assortative matching, those who are referred are more likely to be other high productivity workers. Therefore, when a worker and a firm meet, a referred job candidate is more likely to be hired than a non-referred one, all else equal. We will be able to test this hypothesis directly with our data. Note that the Galenianos model emphasizes the roles of the job seeker and potential employer in the context of a matching model, where referrals affect the aggregate job finding rate and the properties

of the equilibrium matching function. Therefore, some of its predictions may be best tested using the business and household survey data on which much of the referral network has relied to date.

3.2 A simple model of employee referral

We briefly present here a simple model of job matching, adapted heavily from Dustmann et al. (2011). Dustmann et al. model both initial worker-firm contact in referral and external markets and the ongoing wage negotiation over time between a matched worker and the firm. In this sense, their approach fits our current purposes more closely. They generate richer predictions for the employment trajectory than other available models of employee referral, and they have more to say about the wage renegotiation process within a single employment spell. For these reasons, we focus on the Dustmann et al. model and intuitions behind its various predictions.

Let us begin by laying out the fundamental features of the Dustmann et al model, after which we will provide some intuition for its main empirical predictions. The Dustmann et al. model draws heavily on the specification in Simon and Warner, which in turn is based on the job matching model of Jovanovic. Hence the various approaches on which we pin our tests share common assumptions and intuition. Consider an economy consisting of N workers and L firms producing according to a constant returns to scale technology, and in which firms may enter (by posting a vacancy) and leave freely. Firms and workers are risk neutral payoff maximizers. When unemployed, workers receive unemployment benefit b. Firms experience cost of an unfilled vacancy k. True underlying productivity y is match-specific and drawn from distribution $N(\mu, \sigma_\mu^2)$.

When a worker and firm meet, they observe a noisy signal of the match's true productivity, $\widehat{y}_j = y + \varepsilon_j$, where $\varepsilon_j \sim N(0, \sigma_j^2)$ and $j \in \{R, E\}$ indicates the worker's referred or external market status. Given a posting, a referral may or may not be available to the firm according to an exogenous process. The effect of the referral is to modify the informativeness of the productivity signal observed by the worker and firm, so that $\varepsilon_R \sim N(0, \sigma_R^2)$ and $\varepsilon_E \sim N(0, \sigma_E^2)$, with $\sigma_R^2 < \sigma_E^2$.

In the interest of expositional simplicity, we abstract from several features of the problem included in Dustmann et al. We assume a zero rate of match destruction and that employers and employees observe the true match quality in the second period of employment with certainty, rather than with a positive probability in each subsequent period of employment. Further, we limit the time horizon to the two period case, where Dustmann et al. model infinitely lived firms and workers.

Finally, we set aside some structure on the employee network used by Dustmann et al. to allow for equilibrium effects of employment levels on job finding rates and the like. These simplifications allow us to reproduce and discuss certain central intuitions of the Dustmann et al. model briefly in our context. Where more extensive modeling is valuable, we simply refer to the original and discuss its predictions in less specific terms.

Suppose, then, that the (somewhat simplified) timing of events is as follows:

1. A firm chooses to post a vacancy. With positive probability the firm receives an employee referral for the vacancy. Firm and referred worker observe signal $\widehat{y}_R$ of the referred worker's quality. The firm makes a wage offer. If the worker turns down the offer, the position remains open and the worker remains unemployed for the duration of the period.

2. Workers who have received no offers and firms that have received no referrals meet in the non-referral market according to a constant returns to scale matching function. On matching, worker and firm receive match quality signal $\widehat{y}_E$. The firm makes a wage offer. If the worker rejects the offer then the vacancy remains open and the worker remains unemployed for the rest of the period.

3. In the next period, each worker-firm pair in a surviving match learns the true productivity of the match. The firm makes a new wage offer. If the employee turns down the wage offer then the match is dissolved, the employee becomes unemployed and the position becomes vacant.

3.3 Wage and employment determination after true productivity is revealed

Following the revelation of true productivity y, workers and firms allocate the surplus of the match according to

$$\begin{aligned} W_2(y) &= w_2(y) \\ V_2(y) &= y - w_2(y), \end{aligned}$$

where W_2 represents the value to the worker following match quality revelation, V_2 the value to the firm and w_2 the wage. Total surplus from the match is y. Given a value of unemployment in this period of b and that free entry drives the value of a vacancy to zero, only matches whose productivity meet the total of worker and firm outside options are continued after match quality revelation, so

that only matches such that $y > y^*$ where $y^* = b + 0$ survive. Note that this reservation value is common to matches produced by referrals and matches produced by the outside market.

3.4 Wage and employment determination with unknown productivity with and without referral

Define m_j to be the expected value of match productivity for a worker and firm who have just met through mechanism $j \in \{R, E\}$. Let w_j represent the wage the firm pays the worker in the current period. Then

$$W_{1j} = w_j + \beta \int \max(W_2, b) dF_j(y|m_j, \sigma_j^2), \tag{1}$$

where W_{1j} represents the value of accepting the match for the worker, β is the discount rate and $dF_j(y|m_j, \sigma_j^2)$ is the density of true match productivity given current expected productivity m_j and variance of the external market signal σ_j^2.

Similarly, the value to the firm of an accepted wage offer w_j is

$$V_{1j} = m_j - w_j + \beta \int \max(V_2, 0) dF_j(y|m_j, \sigma_j^2).$$

We assume wages are determined by Nash bargaining, with share γ of the surplus going to the worker, so that

$$W_{1j} - U = \gamma(W_{1j} - U + V_{1j}),$$

where U represents the value of first period unemployment and is common to referred and external market matches. Dustmann et al. demonstrate that there exists a reservation match quality m_j^* such that, if $m > m_j^*$, workers prefer to accept the wage offer and firms prefer to hire the worker, where m_j^* satisfies $W_{1j}(m_j^*) - U = V_{1j}(m_j^*) = 0$.

3.5 Prediction 2: Referred workers receive higher initial wages

Observe that the second term in expression (1) is increasing in the variance of the signal, σ_j^2, and that the worker's value only need meet $w_j(m_j^*) + \beta \int \max(W_2, b) dF_j(y|m_j^*, \sigma_j^2) = U$ in order for the match to be sustained. Hence the reservation wage demanded by referred workers is higher than the

reservation wage demanded by non-referred workers as a result of $\sigma_R^2 < \sigma_E^2$.[5] The intuition behind this result is that, for the external market worker, the greater uncertainty in future productivity and therefore in the future wage implies greater probability mass over higher second period wages, while she or he is insured against the greater probability mass in the lower tail of the match distribution by the ability to quit in response to low match productivity realizations. In other words, the external market worker faces a higher upside potential while being insured against bad draws, so she has a lower initial reservation wage.

Both Simon and Warner and Galenianos also predict higher starting wages for referred workers. The intuition driving this result is similar in Simon and Warner, while the source of the difference in Galenianos relies on homophily in referral networks and the higher average productivity of employed than of unemployed workers.

3.6 Prediction 3: The referred worker wage advantage diminishes over time

As noted, Dustmann et al. employ a more complex version of the model than we have described here. As a result, they are only able to generate predictions for the salary trajectory using numerical methods. In an appendix to the paper, on page 34, they report numerical results indicating that the wage advantage accruing to the (still employed) referred worker over the (still employed) non-referred worker diminishes with tenure in the firm.

In a simpler framework more closely resembling what we have described here, Simon and Warner generate some intuition for this result by considering the limiting cases. Suppose, for example, that referrals perfectly reveal true match productivity in the first period, so that $\sigma_R^2 = 0$. In this case the referral market reservation match value reverts to $y^* = b$, and as a result the first and second period reservation productivity values for the referred case are identical. Further, in this case referral wages are identical in the first and second periods, with no new information on match productivity revealed at the start of the second period. Assuming a less than perfectly informative signal for the external market ($\sigma_E^2 > 0$). this clearly implies a flatter wage profile for referred than for non-referred workers. Further, as we discuss in Prediction 4, the model predicts lower separations for referred than non-referred workers. Relatively more external market workers will separate over time, from the low end of the match quality distribution: thus, those external market

[5] We leave proof that the reservation wage increases in the reservation match quality to Dustmann et al.

workers who stay with the firm will exhibit higher wage growth on average because of the non-random differential attrition.

Note that Simon and Warner also consider the predicted effect of referral where signals regarding referred and non-referred workers' match productivities are equally informative, but referred workers are on average of better match quality. This model generates an initial wage advantage for the referred but similar wage growth for referred and non-referred workers, and Simon and Warner interpret findings on the time path of the wage advantage of referred workers as a test of the relative importance of mean productivity differences and productivity signal informativeness in explaining the referral advantage.

3.7 Prediction 4: Turnover is lower for referred workers

The lower turnover prediction in Dustmann et al. is analogous to the higher starting salary prediction in Dustmann et al. As discussed above, they demonstrate that the reservation match productivity in the referral market is higher than the reservation match quality in the external market, $m_R^* > m_E^*$, owing to the fact that greater uncertainty in true match productivity creates greater opportunity for wage growth for external market hires. Given that referred workers are better matched to their firms than non-referred workers, the probability mass below the common match productivity reservation value that applies to all workers after productivity is revealed is greater for external market than for referred workers, and so more workers initially hired through the external market separate from their matches following productivity revelation.

Returning to Simon and Warner's limiting cases, suppose again that referrals perfectly reveal true match productivity in the first period, so that $\sigma_R^2 = 0$. As discussed, in this case the referral market reservation match value reverts to $y^* = b$, the first and second period reservation productivity values for the referred case are identical, and wages are identical in the first and second periods. No new information on match productivity is revealed at the start of the second period. As a result, no referred worker separates from the firm at the start of the second period. Assuming a less than perfectly informative signal for the external market ($\sigma_E^2 > 0$), this limiting case generates the extreme prediction that all turnover takes place among external market hires, and all referred workers remain employed.

Alternatively, consider the case in which the external market productivity signal is completely

uninformative. Then the external market expected productivity distribution collapses to $N(\mu, \sigma_\mu^2)$ and all external market job candidates meeting firms are hired and draw the same wage (presuming a sufficiently favorable underlying match quality distribution for employment to take place). If the referral market productivity signal contains any information, then workers and firms meeting by referral, unlike those meeting in the external market, will be able to reject some lower segment of signalled productivities. Therefore when match quality is fully realized for both external market and referred worker-firm pairs in the second period, the proportion of referred workers with realized match productivities below the common reservation value of $y^* = b$ will be smaller than the proportion of external market workers with match productivities below $y^* = b$ (which will simply equal $\Phi(\frac{b-\mu}{\sigma_\mu})$). Therefore the separation rate for referred workers following productivity revelation will be smaller than the separation rate for non-referred workers following productivity revelation.

3.8 Prediction 5: The referred worker turnover advantage also diminishes over time

Though our simple two period model, and the simple model of Simon and Warner, cannot address patterns in turnover as tenure in the firm varies more finely, Dustmann et al. model a gradual process of true productivity revelation. This approach allows members of the populations of referred and non-referred workers to be subjected to the common post-revelation reservation match standard gradually over time. As a result, surviving referred and non-referred employees gradually become more similar. Dustmann et al. provide evidence, again numerical, that the difference in the rate of separation from the firm between referred and non-referred workers should diminish over time.

3.9 Prediction 6: Referred workers have higher expected productivity

The higher reservation match productivity of referred workers ($m_R^* > m_E^*$) predicted by the model of Dustmann et al. would seem to predict higher expected match productivity for referred workers in general. Simon and Warner make similar predictions regarding reservation match productivity, and the link to expected match productivity over the full distributions of referred and non-referred workers is more direct in their simpler context. Further, Galenianos generates higher employer predictions of referred worker initial productivity in a decidedly different context. As discussed above, in a lower skilled pool of call center workers, Castilla (2005) finds evidence of higher productivity

(in a piece-rate sense) for referred than for non-referred workers. Greater initial or expected productivity of referred workers appears to be a common prediction of the employee referral literature.

4 Data and descriptive statistics

This study utilizes a unique dataset that includes all of the hires and applicants of a U.S. corporation which employs between 2,000 and 5,000 people. The corporation hires people for a broad range of tasks with all levels of educational backgrounds and years of work experience. This makes it an ideal sample to study the effect of referrals across a variety of skill and education backgrounds.

4.1 Applicant data

The dataset covers all applicants to the corporation from 2006 to 2010. The data contain information about how the applicant found the position, whether through the corporation's website, campus recruiting, internet job boards, employee referrals, their own initiative, or another source. In our data, an applicant can be associated to an employee referral in one of two ways: either if the applicant indicated the name of a current employee as the source of a referral, or if a current employee "claimed" that candidate as a referral (or both). In either case, once the applicant gets to the interview stage, the information on the referral source is verified by the corporation's human resources department.[6]

With the data, we calculate the number of applicants for each position and the portion of the applicants that were referred.[7] We have measures of the staff level associated to each position, which we group into five categories: support, junior, mid-level, senior, or executive staff. The data also details the required years of job experience and education level. The outcomes of applicants, including whether they received an interview or offer and whether they accepted the offer, are also included. Lastly, the timing of the job posting appears in the data.

The estimation sample is restricted to include only job postings that result in a hire and those

[6] For many positions, if the employee referral leads to a hire and the newly hired worker stays at the organization for longer than six months, the employee who provided the referral receives a small monetary bonus. However, family members, company executives, direct supervisors or recruiters are not eligible for the award. We discuss below other potential sources of bias.

[7] For any given open position at the company, there may be multiple vacancies that the corporation is trying to fill. However, 91 percent of positions are associated with a single vacancy. From here on, we refer to a "position" as a job posting for which there may be a single or several active vacancies.

that received more than one applicant. We remove internship postings and positions that were only posted internally in the corporation. When former interns, former employees, or current employees apply for a position, we include them in the calculation of the size of the applicant pool, but we remove their individual observations from the estimation sample. If a former intern, former employee, or current employee ultimately is hired for the position, then that job is excluded from the sample. This reflects our impression that these types of applicants likely experience different hiring processes. We also exclude from our data postings for positions for which workers were hired in bulk.

The final sample used in our analysis includes 62,127 job applicants for 340 positions. Therefore the corporation hired 0.55% of applicants. Table 1 summarizes the key statistics of the applicant data. Of all the applicants, 2.91% received interviews and 0.69% got job offers. Almost 50% of the applicants applied to junior staff positions, followed by 27.8% to mid-level staff positions, 18.4% for senior staff jobs, 2.79% for support staff and 1.7% for executive positions. Comparatively, 39.0% of jobs postings were for junior staff positions, followed by 33.7% for mid-level staff, 20.3% for senior staff, 4.8% for support staff, and 2.2% for executives. Similar patterns exist for the education requirements, with 86.1% of postings requiring at least a Bachelor's degree. The mean years of experience required is 5.3. On average, 185 applicants apply for a given posting and 6.7 people interview.

4.2 Employee data

The data also contain information on all of the hires from 2000 to the first half of 2011. The data detail how the employee applied for the job, whether through internet job boards, the organization's website, college or career fairs, employee referrals, or other methods. As with the applicant data, in order for a worker to be considered an employee referral, either the new hire must have reported the referral when applying for the job, or a current employee must have referred that worker through the company's internal referral system (or both). The referral source is verified by the corporation's human resources department at the interview stage of the hiring process. The employees' rank in the organization, shifts, office locations, full or part-time status, and on-leave status are observed at six month intervals. If the worker leaves the organization or receives a promotion, this information and the timing of the event appear in the data.

We restrict our estimation sample to include only first time hires because of likely differences in the referrals and promotions of former employees and interns compared to other employees. The sample is also restricted to employees in the main location of the company. Interns are excluded from the sample because they are never promoted and they are attached to the corporation for a brief and externally determined period. Finally, we exclude the very top executives in the corporation.

The resulting estimation sample includes 1,774 unique employees, 29% of whom were referred by current employees before being hired. Table 2 provides descriptive statistics for our employee data estimation sample. Annual salary is reported in 2010 dollars. The salary figures and the rates reported in the top panel of Table 2 are based on our 12,447 pooled employee semiannual observations. The mean and median annual salaries in the pooled data are similar, at $102,740 and $97,377 2010 dollars respectively. The standard deviation of salaries is substantial, at $45,551, and the salary range, from about $20,000 to over $300,000, is quite broad.

This salary range indicates a wide range of positions held in the corporation. Three percent of observations represent employees who entered as support staff, 36 percent employees who entered as junior staff, 41 percent employees who entered as mid-level staff, 18 percent employees who entered as senior staff and two percent employees who entered at the executive level. The overwhelming majority of employees are full time, day shift workers who are not on leave. However, the sample includes 50 night shift, 99 graveyard shift, 194 on leave and 111 part time employee-observations.

Of the 1,774 unique workers ever observed in our sample, 1,005 (57 percent) are observed to be promoted during the sample window, and 638 (36 percent) are observed leaving the corporation. The mean observed tenure in the organization by 2011 or exit, whichever occurs first, is 3.01 years. The mean time to promotion is 1.66 years. This averages the time between starting at the corporation or between promotions for all occurrences of promotions in the data. For those that receive a promotion, it takes on average 1.62 years to get promoted for the first time. In our sample an average of 151 new employees join the corporation and 56 leave each year. Since our sample contains only employees who began working at the organization in 2000 or later, the actual average number of employees who leave each year is higher.

One meaningful shortcoming of our data in the context of the broad literature on employment is the absence of data on hours of work. Our only measures of hours of work are indicators for whether the employee is working part time and whether the employee is currently on leave. However,

there appears to be only modest variation in work hours in this sample. Roughly 97 percent of our sample of semiannual observations represents full time workers. Of course, there could be substantial unobserved hours variation among those workers whom the corporation classifies as full time. As a result of our lack of hours data, we are unable to infer hourly wages from annual salaries. We consider annual salary (or log annual salary) as our primary outcome variable for the earnings analysis portion of our empirical work.

In addition, the data do not include either education at the date of first employment or work experience before applying to the organization. In order to estimate the log earnings regressions that are standard in the literature, we require schooling and experience variables. Further, employees of the corporation staff a wide range of positions, from support through executive, which clearly require a wide range of schooling and experience levels. We address this data limitation using the staff category indicators described above. Since we observe the education and experience requirements for each job posting, we have a clear idea of the schooling and experience requirements associated with each staff level. We find that staff categories summarize schooling and experience requirements fairly effectively. Hence we use staff level at entry indicators in our earnings estimation to proxy for the schooling, experience and experience squared regressors employed by the majority of the literature.

A potentially important issue concerns the way in which an employee referral is recorded in our data. As mentioned above, for an applicant (or new hire) to be considered an employee referral in our data it must be the case that either the applicant indicated the referral source when applying for the job, or a current employee referred that person for a position at the company through the organization's internal referral system (or both). There are several potential measurement issues here, that may affect our estimation results.

First, there may be under-reporting: someone may be hired through a referral even though the referrer did not bother to fill out the relevant form with the company's referral system, *and*, in addition, the referred worker did not indicate the referral source at the time of the application. The combination of the two events seems unlikely: the referral recipient has the incentive to mention the referral as it likely raises the chances of being offered the job; the referrer, on the other hand, has the incentive to "claim" the referral either for the monetary bonus or for other non-pecuniary benefits. If there is any under-reporting, as long as it is uncorrelated with the referred worker's

characteristics, then it will likely only lead to an attenuation bias in our estimates.[8] Second, and perhaps more importantly, it is possible that a current employee's decision to formally refer someone may be related to the candidate's success during the various stages of the recruiting and interviewing process for a given posting. This possibility is limited by the details of the referral process: the latest that a current employee can "claim" someone as a referral is at the interview stage, when the recruiter reviews the candidate's initial application. Therefore, the referrer cannot decide ex-post to refer someone, after observing whether the person is actually hired or not.

5 Empirical specification and findings

5.1 Prediction 1: Referred candidates are more likely to be hired

A central prediction of Galenianos, as discussed above, is that referred workers are more likely to be hired, all else equal. Our first empirical step is to test this prediction using our data on the corporation's applicant pool and resulting hires. Note that Castilla, Fernandez and Weinberg, and Fernandez and Castilla all confirm this prediction in their bank and call center single-firm hiring studies. Our test of this prediction extends the analysis to a broad range of skill levels and more recent hiring data, and, in addition, informs our findings regarding longer-term worker experiences for this particular corporation.

An initial perspective on the question of whether referrals increase the odds of being hired is provided by the raw interview and job offer rates reported in Table 3. The most common application source in the sample by far is internet job boards. Job board applicants constitute 60 percent of the applicant sample. Moving from left to right in the job board row of Table 3, these job board applicants also constitute 41 percent of interviewees, 26 percent of offer recipients and 27 percent of final hires. In other words, there is a decisive downward trend over the hiring process in the proportion of candidates achieving increasingly serious consideration who are sourced from job boards. Similar downward trends over the hiring process can be seen for those who applied through the corporation's website and those who employed via their "own initiative". Referred employees demonstrate the opposite pattern. While only 6 percent of applicants are referred by a

[8] However, if the employee's decision to report a referral is correlated with something unobservable about the candidate that in turn affects her likelihood to be hired, then it will be difficult to sign the direction of the bias.

current employee of the corporation, 21 percent of interviewees, 28 percent of those receiving offers and 29 percent of those who are hired are referred. The only other applicant sources showing this type of increasing trajectory are the campus recruitment and "other" sources categories. Campus recruitment is a very small proportion of this organization's hiring efforts, and neither campus recruitment nor other sources demonstrate as steep an increasing trajectory across the hiring process as we observe for referred employees. The "other" category includes a variety of search methods that comprised a small proportion of applicants. These methods include staffing agencies, job fairs, print advertising, and professional affiliations. Though it is necessary to control for observable differences among applicants and positions before making final inferences regarding the relationship between referrals and hiring outcomes, the unmanipulated data in Table 3 indicate a strong association between referral and the odds of an interview or offer.

Next we adopt a more formal approach, modeling the probability of being hired by the corporation in a linear probability framework.[9] Specifically, we estimate

$$H_{ij} = X_i^H \alpha^H + Z_j^H \beta^H + \{\gamma_t^H \chi(t_j^H = t)\}_{t=2006}^{2010} + \delta^H \chi(t_j > 2007) + \varepsilon_{ij}^H, \tag{2}$$

where X_i^H is a vector of characteristics of applicant i including indicators for applicant source among the set {referral, internet job board, corporate website, own initiative, other source}, Z_j^H is a vector of characteristics of job posting j including number of applicants for the position, proportion of the applicant pool that is referred, the staff level of the position, the experience requirement of the position and the educational requirement of the position, $\{\chi(t_j^H = t)\}_{t=2005}^{2010}$ is a set of year indicators for the posting date of the position, $\chi(t_j^H > 2007)$ is an indicator for whether the position was posted since the start of the 2008-9 recession and ε_{ij}^H is an idiosyncratic error associated with the applicant i - posting j match.

The estimates generated using expression (2) are reported in Table 4. We estimate three versions of the model. In the first, we define outcome H_{ij} as an indicator for whether applicant i was interviewed for position j, and we estimate using the full sample of applicants.[10] In the second,

[9] Our qualitative results are generally robust to a logistic specification, and we include these estimates as appendix tables 1 and 2.

[10] We do impose the sample requirement that we observe all variables included in the Table 4 estimation for the applicant-position pair. The most restrictive of these sample requirements is that we observe the experience indicated for the position; 7302 of 69,429 applicants are applying to a job with missing experience requirement data.

we define outcome H_{ij} as an indicator for whether the applicant was offered position j, and we again estimate using the full sample of applicants. In the third, we condition the estimation sample on applicant i having been interviewed for position j. This leaves us with a sample of 1,811 interviewees. Of these 1,811 interviewees, 428 are offered the position for which they interviewed. We again define H_{ij} as an indicator for whether the applicant received an offer. In this manner we are able to examine not only whether referrals are associated with a greater job offer probability, but also at what stage of the hiring process any estimated referral advantage is manifested.

Our central finding is that referred applicants are indeed more likely to be hired.[11] Among the set of applicant sources, internet job boards produce the largest number of observed applicants, and so we employ job boards as the omitted category. Relative to job board applicants, referred applicants are estimated to be 7.3 percentage points more likely to be interviewed for the position, and 2.3 percentage points more likely to receive an offer. Conditional on having been interviewed, referred applicants are 13.9 percentage points more likely than job board applicants to receive offers.[12] Each of these coefficient estimates for the referred category is significant at the one percent level. Applicants sourced from the corporate website and who applied through their own initiative have interview and offer rates similar to those of job board applicants. As hinted by the Table 3 transition rates, however, "other" applicants, including those produced by campus recruiting, have interview and offer probabilities that are significantly higher than those of job board applicants.

Other regressors in Table 4 pertain to the characteristics of the posting, and therefore their coefficient estimates indicate the characteristics of more and less competitive job postings within the corporation. Unsurprisingly, a larger number of applicants significantly increases the competitiveness of the position. However, the magnitude of this effect is small: 100 more applicants for a position are associated with a 0.1 percentage point decrease in the probability that an applicant is interviewed. Surprisingly, the proportion of applicants that are referred increases the likelihood that an applicant for the position receives either an interview or an offer, and this effect is significant. A 10 percentage point increase in the proportion referred is associated with a 0.88 percentage point increase in the probability of an interview, and a 0.44 percentage point increase in the probability

[11] To be precise, we focus here on two outcomes, being interviewed and receiving an offer. Most people who receive an offer end up accepting it and thus being hired, but we want to abstract here from the candidate's decision on whether or not to accept an offer.

[12] Note that 23.6 percent of interviewees receive offers.

of an offer.

Staff level coefficient estimates indicate that support staff positions are significantly less competitive than mid-level staff positions, but that junior, senior and executive level staff positions are comparably competitive to mid-level staff positions. Similarly, positions that require a high school diploma are significantly less competitive than positions that require a college degree, particularly at the interview stage, while associate's degree, college degree and other education requirement positions are similarly competitive. However, we do find that positions that require a graduate degree are significantly more competitive than positions that require a college degree, particularly at the interview stage.

Screening from the application to interview stage becomes stronger over time in our data, with the probability of being interviewed conditional on applying decreasing by 0.5 percentage points per year. Yet the probability of receiving an offer conditional on having been interviewed increases significantly over time, and the overall offer probability for applicants does not vary significantly over time. Finally, we see a lower probability for the applicant of being interviewed following the start of the recession, with, again, no significant change in the overall probability of an offer. Together these estimates suggest that screening resources are being shifted to earlier points in the hiring process over the course of the panel.

5.2 Prediction 2: Referred workers receive higher starting salaries

We begin by testing the prediction that referred workers receive higher starting salaries. First consider the simple linear specification

$$S_{i0} = \alpha^S r_i + X_{i0}^S \beta^S + \gamma_t^S + \varepsilon_{i0}^S,$$

where S_{i0} represents the starting salary of worker i, r_i is an indicator for whether worker i was referred by a current employee of the corporation, X_{i0}^S is a vector of controls measured at job entry including a staff level indicator (as a proxy for schooling and experience at job entry) and indicators for company division, shift, work schedule and leave status, γ_t^S is a calendar year fixed effect and ε_{i0}^S is an idiosyncratic error. Coefficient estimates for the linear starting salary specification are reported in the first column of Table 5, with salary measured in thousands of 2010 dollars. We

find that having been referred is associated with a $1,326 salary premium that is close to being statistically significant at the conventional levels (the p-value equals 0.107).

A more conventional specification in the context of the literature is the following log earnings regression:

$$\ln S_{it} = \alpha_0^L r_i + \alpha_1^L \tau_{it} + \alpha_2^L r_i \tau_{it} + \alpha_3^L \tau_{it}^2 + \alpha_4^L r_i \tau_{it}^2 + X_{it}^L \beta^L + \gamma_t^L + \varepsilon_{it}^L, \tag{3}$$

where t represents calendar time and τ_{it} indicates tenure in the corporation for employee i at time t. Again, r_i is an indicator for whether worker i was referred by a current employee of the corporation, X_{it}^L is a vector of controls including entering staff level indicators (which again proxy for schooling and experience at job entry) and indicators for entering company division, shift, work schedule and leave status, γ_t^L is a calendar year fixed effect and ε_{it}^L is an idiosyncratic error. This log earnings regression is estimated using pooled data on employee half years, and allows us both to compare starting salaries for the referred and non-referred and to follow the effect of referral on employees' salary trajectories over time.

The estimated coefficient on referral in the log salary regression, reported in Table 6, indicates a 2.1 percent starting salary premium for referred workers. The coefficient is significant at the one percent level. The magnitudes of the referral coefficient estimates in the linear and log salary regressions are roughly consistent, given mean and median salaries of $102,740 and $97,377, respectively. Of course, there is wide dispersion in employee salaries in this corporation. Hence it is useful to consider the initial referral premium in both level and percentage terms, and the combination of the linear and the conventional log salary estimates allows us to do so. In sum, we find that an employee referral is associated with a starting salary premium of 2.1 percent, or more than $1,300. This result bears out the predictions of not only Dustmann et al., but also Simon and Warner and Galenianos.[13]

5.3 Prediction 3: The referred worker salary advantage diminishes over time

As discussed in Section 3.6, however, current theory of labor market referrals predicts that the referral effect will dissipate over time, and the salaries of referred and non-referred workers who

[13] Simon and Warner also show evidence of higher initial wages when recollected jobs were based on referrals in their retrospective 1972 survey of scientists and engineers.

remain with the corporation will converge. The log salary estimates reported in Table 6 provide a test of the referred salary premium's time trajectory.

We find that the referral effect does indeed diminish over time. In all linear specifications in Table 6, α_2, the coefficient on the interaction between the referral indicator and tenure in the organization, is negative and significant at the one percent level. In the quadratic specification with tenure squared, reported in column (3), the estimated values of α_2 and α_4 (i.e., the coefficients on the referral indicator multiplied by tenure and tenure squared) are both negative but the coefficients are not estimated very precisely.

Figure 1 depicts predicted salaries for referred and non-referred workers as tenure increases. While the referred salary initially lies above the non-referred salary, referred and non-referred salaries are roughly equivalent after three years of tenure with the corporation. Indeed, 95 percent confidence intervals only rule out common referred and non-referred salary levels for the first two years of tenure in the corporation. This convergence of salaries after an initial advantage for the referred is consistent with the theoretical predictions of the Dustmann et al. and Simon and Warner models of labor market referrals.[14]

From six years of tenure on, the estimates predict a significant salary advantage for the non-referred. It is not clear what to make of this eventual non-referred advantage in the context of the theory discussed earlier. Models like Dustmann et al. and Simon and Warner predict eventual convergence in referred and non-referred salaries, but do not include a source of advantage for non-referred workers who stay with the corporation. As we show in Section 5.4 below, we also find that referred employees experience significantly lower turnover than non-referred. Taken together, these findings suggest a role for differential investments in firm-specific human capital, or perhaps for non-pecuniary gains related to differential affinity between employees already at the firm and referred vs. non-referred hires. A valuable innovation in the theory of labor market referrals, then, might be an extension of existing models that accounted for these observed patterns.

Finally, it is also evident in Figure 1 that all employees of the corporation enjoy a steep salary increase with tenure, which appears to be the dominant feature of salary trajectories in this corpo-

[14] It is important to note here that the model discussed in Section 3.2 and subsequent sub-Sections incorporates the effect of differential separations for referred and non-referred workers on salary gaps over time. Therefore, in the empirical exercise we do not need to correct our salary trajectory estimates for differential attrition as the model's prediction is conditional on turnover. We discuss this issue further in Section 5.4.

ration for both worker categories.

Unobserved heterogeneity in worker productivity and other characteristics may influence salary levels, and may itself be correlated with referral status. We examine the sensitivity of our results to underlying worker heterogeneity by re-estimating the above model with worker fixed effects:

$$\ln S_{it} = \omega_i + \alpha_1^F \tau_{it} + \alpha_2^F r_i \tau_{it} + \alpha_3^F \tau_{it}^2 + \alpha_4^F r_i \tau_{it}^2 + X_{i\tau}^F \beta^F + \gamma_t^F + \varepsilon_{i\tau}^F,$$

where ω_i is an individual worker effect, $\varepsilon_{i\tau}^F$ an idiosyncratic error and $X_{i\tau}^F$ represents the subset of expression (3) regressors X_{it}^L that time vary. Table 6a reports the resulting estimates. Though we are of course unable to identify a starting salary effect of referral using this specification, we find an estimated dependence of the referral salary effect on tenure in the corporation similar to that observed in Table 6. The coefficient on tenure times the referral indicator in each linear specification indicates a 0.7 percent decline in the salary advantage to the referred with each year of experience, and is significant at the one percent level. Hence the fixed effect specification reinforces the evidence that the referred worker salary declines relative to the non-referred worker salary with tenure in the organization.

Returning to the simpler specification in Table 5, the remaining columns report results for identical specification

$$S_{i\tau} = \alpha^s r_i + X_{i\tau}^s \beta^s + \gamma_t^s + \varepsilon_{i\tau}^s,$$

with the exception that τ (again) represents the years of tenure in the corporation at the date of observation. In other words, Table 5 shows results of the linear regression of salary level at tenure τ (in thousands of 2010 dollars) on referral status and worker characteristics at tenure τ. Again we see that the positive effect of referral on salary dissipates quickly. In the earlier years of tenure in the corporation, the referral coefficient tends to be positive, though statistically insignificant. After year four, the referral coefficient becomes negative and is statistically significant at six, eight and nine or more years of tenure in the corporation. Salary disadvantages for the referred are, on average, \$3,634, \$7,689 and \$13,343 at six, eight and nine or more years, respectively.[15]

In sum, referred workers in this corporation do in fact experience an initial salary advantage

[15] Simon and Warner also find that scientists and engineers recollect lower salary growth in their ongoing jobs when they were referred, based on their 1972 survey data. They do not attempt to determine whether the lower salary growth leads non-referred workers' salaries to overtake referred workers' salaries at any point.

followed by a decline to non-referred salary levels, confirming predictions of theoretical referral models such as Simon and Warner and Dustmann et al. However, we also find a significant and economically substantial salary advantage for non-referred workers after five years. This is certainly not consistent with the predictions of Simon and Warner, it does not appear to be consistent with the predictions of Dustmann et al, and in general it is not clear how an eventual advantage for non-referred workers who remain with the organization might be aligned with existing theory.

5.4 Prediction 4: Turnover is lower for referred workers

Next we turn to the theoretical prediction, reviewed in Section 3.7, that referred workers experience lower rates of turnover after joining a firm. We model separation from the corporation using the discrete time proportional hazard framework found in Prentice-Gloeckler (1978) and Meyer (1990). The instantaneous separation hazard at tenure τ is

$$\lambda_{i\tau}^{D} = \lambda_{0}^{D}(\tau)\exp(Z_{i\tau}^{D}\delta^{D}), \tag{4}$$

where $\lambda_{0}^{D}(\tau)$ is a baseline match dissolution hazard that is permitted to vary with tenure in the corporation and

$$Z_{i\tau}^{D}\delta^{D} = \delta_{0}^{D}r_{i} + \delta_{1}^{D}\tau + \delta_{2}^{D}r_{i}\tau + \widetilde{Z}_{i\tau}^{D}\beta^{D}.$$

Here $\widetilde{Z}_{i\tau}^{D}$ includes entering salary, company division and staff level, current shift, leave status, part time status, and in some specifications some subset of the interactions of starting staff level and the referral indicator, an indicator for recession/post-recession dates and the interaction of the recession/post-recession indicator with the referral indicator. We are primarily interested in the effect of referral on the separation hazard, and any variation in the referral effect on separation as tenure increases.

Table 7 reports estimates of hazard model (4). We specify the tenure dependence of baseline hazard $\lambda_{0}^{D}(\tau)$ in one of two ways. In Table 7 specifications (1) and (3) through (8), we impose a linear tenure dependence. Specification (2) includes separate dummies for each observed 6 month interval with the corporation, which we refer to as the fully nonparametric baseline hazard model. Comparing the estimates in specifications (1) and (2), it appears that allowing a very flexible tenure

dependence in the baseline hazard has little effect on the estimates. Further, we have estimated specifications (3) through (8) with both linear and fully nonparametric assumptions on the baseline hazard, and our qualitative results are essentially unchanged. In the interest of simplicity, we report specification (3) through (8) estimates assuming a linear baseline hazard.

In addition, the estimated values reported in Table 7 are in terms of $\exp(\delta)$, for ease of interpretation. Where the regressor is an indicator variable, given (4), the reported $\exp(\delta)$ value can be interpreted as the proportional change in the hazard associated with moving from a regressor value of zero to a regressor value of one. This is measured relative to a baseline hazard, which represents the separation hazard of a full time, day shift, not on leave, mid-level, non-referred employee who has just entered the corporation during the pre-recession period. For example, the $\exp(\delta)$ value in specification (1) associated with an on leave worker indicates that, perhaps not surprisingly, a worker currently on leave faces roughly three times the separation hazard of an employee who is not currently on leave, all else equal.

Table 7 estimates indicate that referred workers do indeed experience lower separation rates from the corporation. Specifications (1) and (2) show that referred workers are about 85 percent as likely to leave the corporation as non-referred workers, and these findings are roughly significant at the ten percent level in each case.[16]

We find that most of this referral effect arises from the pre-recession period. Turning to specification (7), we see that pre-recession referred workers are 76 percent as likely to leave the organization as pre-recession non-referred workers, and this effect has a p-value of 0.045. However, the referral effect on separations for those hired after the start of the recession is much more moderate. For people hired after 2007, referred workers are only 96 percent as likely to leave the corporation compared to non-referred people, and this difference is not statistically significant. Similarly, if one estimates using only the pre-recession sample, as in specification (5), one finds that referred workers are 77 percent as likely to leave the corporation as non-referred workers, and the p-value for this estimate is 0.056. The period beginning with the recession was one of meaningful changes in employment practices for this particular corporation, as for many others. We find substantially decreased turnover from the start of the recession, and decidedly different hiring practices. Thus

[16] Simon and Warner find that scientists and engineers in their 1972 retrospective survey recall longer job duration when they were referred, all else equal.

it is not surprising that employee referrals appear to function differently for this corporation from the start of the recession.

One might be concerned, given the predicted and observed tenure differential between referred and non-referred workers, that estimates of the salary dynamics of retained workers would reflect confounding dynamic selection effects. It may be helpful to note at this point that the goal of the salary trajectory estimates in Section 5.3 is to test the equilibrium predictions of models like Dustmann et al. and Simon and Warner. Their salary trajectory predictions pertain explicitly to the subset of referred and non-referred workers in ongoing matches, whose empirical analog is the set of referred and non-referred employees who are retained by the corporation. Hence our estimates of the salary trajectories of retained employees are, arguably, the appropriate objects with which to test these predictions. Existing theory has limited or no predictions for the average salary trajectory of all workers who were referred to a match and then stayed or left relative to the average salary trajectory of all workers who were not referred to a match and then stayed or left. Similarly, our estimates have nothing to say about average salary trajectories that are unconditional on turnover.

5.5 Prediction 5: The referred worker turnover advantage also diminishes over time

The significant negative association between employee referrals and separation from the corporation does not appear to diminish with tenure, despite the predictions of the theory. The general findings regarding the relationship between tenure and separation in Table 7 appear to be that longer-tenured workers are significantly less likely to leave the corporation from the start of the recession on, but that tenure in the corporation bears no significant relationship to departure preceding the recession. Specification (3) adds a referral indicator times tenure regressor to the estimation, and based on the specification (3) estimates we see that the separation hazard increment associated with referral does not appear to change in any noticeable way with tenure. Despite the (reasonably intuitive) theoretical prediction that the lower departure rates for referred workers diminish over time as the surviving non-referred workers become a more selected and better-matched group, the empirical results indicate that, for this corporation at least, the decreased separation rate associated with employee referrals is relatively long-lasting.

5.6 Prediction 6: Referred workers have higher expected productivity

Theoretical predictions regarding referrals generally emphasize higher initial employer approximations of worker productivity for workers hired through referrals than for workers not hired through referrals. Though both worker productivity and employers' inferences regarding workers' productivity are difficult to measure, an employer's promotion decisions may offer a source of information on perceived worker effectiveness. Our dataset includes promotion indicators at six month intervals. More than half of our estimation sample employees receive a promotion at some point in the sample window.

We model the promotion process using approximately the same approach we applied to the tenure process in Section 5.4. In the discrete time proportional hazard framework we apply, the instantaneous promotion hazard is assumed to be

$$\lambda_{i\tau}^{P} = \lambda_{0}^{P}(\tau)\exp(Z_{i\tau}^{P}\delta^{P}), \tag{5}$$

where $\lambda_{0}^{P}(\tau)$ is a baseline promotion hazard that we again allow to vary either linearly or completely non-parametrically with tenure in the organization. This time

$$Z_{i\tau}^{P}\delta^{P} = \delta_{0}^{P}r_{i} + \delta_{1}^{P}\tau + \delta_{2}^{P}r_{i}\tau + \widetilde{Z}_{i\tau}^{P}\beta^{P},$$

with $\widetilde{Z}_{i\tau}^{P}$ including entering salary, company division and staff level, current shift, leave status and part time status, and in some specifications some subset of the interactions of starting staff level and the referral indicator, an indicator for recession/post-recession dates and the interaction of the recession/post-recession indicator with the referral indicator. Unlike separations as measured in our data, promotions may arrive more than once for some employees. Our model admits repeated failures, and second and later promotions do contribute to the reported coefficient estimates. We are primarily interested in the effect of referral on the promotion hazard, and any variation in the referral effect on promotion as tenure increases.

Table 8 reports the promotion model estimates. Looking first at our baseline specification in column (1), we find that referred employees are 93 percent as likely to be promoted over a given interval as non-referred employees, all else equal. This difference is not significant at standard levels

of confidence. So, despite the predictions of higher initial perceived productivity that arise from the theory, we cannot reject the hypothesis of equal promotion rates for the referred and non-referred, and, if anything, referred employees achieve promotion more slowly than their non-referred peers.

Instead, other employee characteristics appear to drive promotion. Employees with longer tenure in the corporation are significantly more likely to be promoted. One year of tenure increases the promotion probability over the next six months by five percentage points, all else equal. Employees with higher starting salaries, conditioning on staff level, are more likely to be promoted. Not surprisingly, full time, day shift, and active status workers are more likely to be promoted. The relationship between staff level and promotion rate is non-monotonic. Support staff are promoted at only 52 percent the rate of mid-level staff, and this difference has a p-value of 0.003. Junior and executive staff are promoted at insignificantly higher rates than mid-level staff. However, senior staff are promoted at only 84 percent of the rate of mid-level staff, and this difference is significant at the ten percent level. Finally, the rate of promotions at this corporation increased following the start of the recession.

As in the case of separation, specification (2) indicates that the promotion results described in this section are robust to linear and non-parametric specifications of the tenure dependence of the hazard. Turning to specification (3), we find no significant difference in the tenure dependence of promotion rates between the referred and non-referred. Theoretical predictions regarding whether the initial higher productivity of referred workers would be sustained are unclear. In any case, the data for this corporation do not support a meaningful difference in employers' promotion decisions for referred and non-referred workers over time.

Of course, the extent to which the promotion results provide a test of the theoretical predictions regarding perceived worker productivity depend critically on the extent to which promotion decisions are a valid measure of perceived worker productivity. To the extent that promotions are a valid perceived productivity measure, our results do not support the claim that referred workers' perceived initial productivity is significantly higher than non-referred workers' perceived initial productivity.

5.7 Referral effects by skill level

The range of staff levels available in these data, and associated range of starting education and experience levels, in combination with sample sizes of 62,127 applicants, 1,774 workers and 12,447 worker-half years, allows us to make some inferences regarding differences in the role of employee referrals across the markets for different employee skill levels. In the interest of studying the role of referrals in lower and higher skilled labor markets, we introduce staff level-referral interactions in models (2) (3), (4) and (5) above.

There is strong empirical evidence that informal search methods are used more by workers with lower socioeconomic status and lower education levels, and for 'lower-status' jobs.[17] However, there is very limited work on the effect of referrals on outcomes by skill or education level. Using an indirect approach, Topa (2001) studies the magnitude of referral effects across neighboring census tracts in Chicago. He finds that the estimated spillover effects are stronger in tracts with lower education levels and with higher fractions of minorities. Using a different identification strategy to identify neighborhood effects in labor market outcomes, Bayer et al. (2008) find that the estimated referral effects are stronger for less educated workers, younger workers, and Asian or Hispanic workers. The advantage of this study is that it uses direct information on referrals together with detailed measures of job outcomes.

Looking first at the hires data, Table 9 reports estimates of expression (2) in which we have added either education requirement and referral interactions, in columns 1-3, or staff level and referral interactions, in columns 4-6. Again, outcomes are an indicator for whether the applicant interviewed in columns 1 and 4, an indicator for whether the applicant received an offer in columns 2 and 5 and an indicator for whether the applicant received an offer restricting the sample to interviewees in columns 3 and 6. Our first observation is that referrals have a significantly greater impact on the overall probability of offer receipt for positions with lower education requirements. Applicants to postings requiring high school diplomas, associate's degrees and other educational credentials show significantly larger referral effects on offer probability than applicants to postings requiring college and graduate degrees. The additional effect of referral for high school, associate's

[17] Corcoran et al. (1980), Datcher (1983), Marx and Leicht (1992), all report higher usage for less educated job seekers. Elliot (1999) finds that informal contacts are more frequently used in high-poverty neighborhoods than in low-poverty ones. Rees and Schultz (1970) and Corcoran et al. (1980) both find that informal search methods are used more often for blue-collar than for white-collar occupations.

degree and other requirement postings relative to college postings is 2, 4 and 3 percentage points, respectively, and each estimate is significant at the five or the one percent level. The high school and other education requirement effects appear to operate mainly through the effect of the referral on being interviewed, while the associate's degree effect operates primarily between the interview and the offer stage.

Secondly, referrals also have a significantly larger positive impact on the probability of being interviewed for positions with a graduate rather than college degree requirement. Thus, referral effects seem to have a U-shaped relationship with skill level. We conjecture that the corporation may rely on referrals for different reasons at different points of the skill distribution. For positions with lower education requirements, the corporation may use referrals to detect worker traits such as reliability, punctuality, etc. At the high end of the skill distribution, the corporation may be looking for things like initiative, leadership, and strategic thinking. This would certainly be an interesting area for future research.

Turning to the staff levels, referrals have a similar relationship to offer receipt for support, junior and senior staff as for mid-level staff. Point estimates for support, junior and senior staff indicate a one percentage point smaller referral effect than for mid-level staff, and are in some cases significant.[18] For executives, however, the referral effect on offer receipt is 4.5 percentage points higher than the referral effect on offer receipt for mid-level staff, and this difference is significant at the one percent level. Estimated increments to the referral effect for executives relative to mid-level staff are large at both the interview and offer stages. Thus the estimates suggest that referrals play a substantially different role in the hiring of executives than in the hiring of rank-and-file staff, and are again consistent with the idea that the corporation may use referrals to detect qualities such sh leadership and strategic thinking.

Analysis of referral effects by staff level in the employee log earnings regression reveals a non-monotonic pattern. Support staff experience a particularly strong salary referral advantage relative to mid-level staff. Junior staff and executives show significantly lower initial salary referral advantages than the reference category. The estimated referral advantage of 3.4 percent of initial salary is offset for junior staff by a significant 2.5 percent, indicating that junior staff have a net

[18] The point estimates also indicate a large negative effect of referral at the interview to offer stage for support staff, but, given the small and insignificant difference in the overall referral effect on offers for support and mid-level staff, it is not clear how much to make of this result.

referral advantage of only about 0.9 percent of initial salary. More strikingly, the coefficient on the referral-executive interaction is -7.9 percent of starting salary, and is significant at the one percent level. On net, the referral effect on initial salary for executives is -4.5 percent relative to non-referred executives, and it is significantly different from zero. Hence for executives there seems to be a negative effect of referrals on initial salary.[19] While the estimate for junior staff is not far out of line with the referral effects for the other staff levels, the estimates indicate decisively that referrals play a different role in determining executive salaries.

Returning to the separation results in Table 7, we find that the negative separation effect of referral we observe for the full sample appears to be largest among the support staff. The Table 7 column (4) point estimates for the referral and the referral times the support staff indicator interaction together indicate that referred support staff are *eight percent* as likely to leave the corporation as non-referred mid-level staff, and this estimated difference is significant at the five percent level. Further, the association between referral and the probability of separation increases roughly monotonically in staff level, going from a large negative association at the support staff level to a large positive association for executives. While support staff are much less likely to separate from the corporation if referred, referred junior, mid-level and senior staff are only somewhat less likely to separate if referred, with separation rates relative to non-referred mid-level staff of 87 to 88 percent. Echoing the results for initial salary, executives also demonstrate a unique referral-tenure relationship. We find that referred executives are substantially more likely to leave the corporation than non-referred mid-level staff. Based on the point estimates, referred executives are more than twice as likely to leave as non-referred mid-level staff. However, as a result of the relatively small sample of referred executives, this difference is not quite significant at conventional levels. Overall, the separation results indicate large differences in the role of employee referral in labor markets for different skill levels, with a large positive association between referral and tenure in lower-skilled jobs and some evidence of a negative association between referral and tenure in higher-skilled jobs.

Moving to the promotion results in Table 8, we observe no significant differences between referred and non-referred promotion rates by staff level. In general, promotion practices appear to be quite similar for the referred and the non-referred.

[19] There are only 9 unique executive referrals and 57 unique executive non-referrals in our data, therefore it is not feasible to study the entire salary trajectory for executives separately from other employees.

In sum, employee referrals are associated with strong positive tenure effects for lower skilled workers. For most rank-and-file workers they also tend to be associated with higher starting salaries. However, referrals appear to function quite differently in the market for executives. Their referrals are associated with, if anything, *shorter*-lived matches and lower starting salaries. Our estimates clearly indicate different roles for referrals across markets for different worker skill levels.[20]

Finally, we have also run our empirical analysis separately for some of the largest divisions within the company, to see whether our results are robust to possibly different management practices within the company. Our findings are qualitatively very similar across the four largest divisions of the corporation, with some variation in the size of the estimated referral effects on outcomes. For instance, the estimated initial salary advantage for referred vs. non-referred workers ranges between 0.8 and 5.4 percent of initial salary across divisions. There is also some evidence in one division that referrals are associated to a higher promotion hazard, suggesting higher perceived productivity for referred hires. Overall, the results are remarkably similar across the entire corporation.

6 Conclusion

The limited nature of data on employment referrals in large business and household surveys has so far limited our understanding of the relationships among employment referrals, match quality, wage trajectories and turnover. Using a new firm-level dataset that includes explicit information on whether a worker was referred by a current employee of the company, we are able to provide rich detail on these empirical relationships for a single mid-to-large corporation, and to test various predictions of the theoretical literature on labor market referrals.

We find that referred workers enter at higher wage levels, all else equal, but that the referred wage advantage dissipates by the sixth year of employment, after which the referral-wage relationship is reversed. Referred workers experience substantially longer tenure in the corporation. Despite higher predicted productivity for referred workers in the theoretical literature, we find, if anything, slightly slower promotion rates for referred than for non-referred workers. Finally, the wide range of skill and experience levels represented in this corporation permit detailed analysis of

[20] One caveat is that, as noted above, we have relatively few observations for executives in our sample. Further, some of our results – for instance on the negative association between referrals and job tenure for executives – seem to be driven mostly by the post-recession period.

the role of referrals for workers from support staff to company executives.

Our findings suggest a few interesting avenues for further research. First, we find that referred workers tend to stay longer with the company, but eventually experience slower salary growth than non-referred ones. This seems puzzling. As we discussed above, one possible explanation is that referred workers may invest relatively more in firm-specific human capital, which would limit their outside options over time and therefore reduce their bargaining power within the corporation. Another possibility is that the eventual salary disadvantage is compensated by non-pecuniary aspects of the job match, such as a more enjoyable work environment because the referred worker has social contacts within the corporation. We plan to explore this possibility in future work by matching demographic information for the referrer and the referred, and constructing measures of affinity between the referred worker's attributes and his or her co-workers.

Second, we find some evidence of a U-shaped relationship between education or skill level, and the size of the referral effect on hiring outcomes. We conjecture that this non-monotonic relationship may be explained by different roles played by referrals at different points in the skill distribution. At low education or skill levels, referrals may be used to better detect desirable worker traits such as punctuality and reliability, whereas at the higher end of the distribution they may be used to screen for traits such as leadership and strategic vision. This could be another interesting area for future research.

References

[1] Aslund, Olof and Oskar Nordstrom Skans (2009): \Will I See You at Work? Ethnic Workplace Segregation in Sweden 1985-2002", *Industrial and Labor Relations Review*, forthcoming

[2] Bayer, Patrick, Stephen L. Ross and Giorgio Topa (2008). "Place of work and place of residence: informal hiring networks and labor market outcomes." *Journal of Political Economy* 116 (6), 1150-1196.

[3] Castilla, Emilio (2005). "Social networks and employee performance in a call center." *American Journal of Sociology* 110 (5), 1243-1283.

[4] Corcoran, Mary, Linda Datcher and Greg Duncan (1980): "Information and Influence Networks in Labor Markets," in *Five Thousand American Families: Patterns of Economic Progress*, edited by Greg Duncan and James Morgan, vol. 7, 1-37, Ann Arbor, MI: Institute For Social Research.

[5] Datcher, Linda. (1983): "The Impact of Informal Networks on Quit Behavior," *The Review of Economics and Statistics*, 65 (3), 491-495.

[6] Datcher, Linda Loury. (2006): "Some Contacts are More Equal than Others: Informal Networks, Job Tenure, and Wages," *Journal of Labor Economics*, 24 (2), 299- 318.

[7] Dustmann, Christian, Albrecht Glitz and Uta Schoenberg (2012). "Referral-based job search networks," manuscript, University College London.

[8] Fernandez, Roberto M., and Emilio J. Castilla. 2001. "How Much Is That Network Worth? Social Capital Returns for Referring Prospective Hires." Pp. 85–104 in *Social Capital: Theory Research*, edited by Karen Cook, Nan Lin, and Ronald Burt.Hawthorne, N.Y.: Aldine De Gruyter.

[9] 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.

[10] Fernandez, Roberto and Nancy Weineberg (1997). "Sifting and sorting: personal contacts and hiring in a retail bank." *American Sociological Review* 62, 883-902

[11] Galenianos, Manolis (2011), "Hiring Through Referrals," manuscript, Penn State University.

[12] Giuliano, Laura, David I. Levine, and Jonathan Leonard (2009): "Manager Race and the Race of New Hires", *Journal of Labor Economics*, 27(4), 589-632

[13] Hellerstein, Judith, Melissa McInerney, and David Neumark (2008): "Measuring the Importance of Labor Market Networks", IZA Discussion Paper No. 3750.

[14] Holzer, Harry J. (1987a): "Informal Job Search and Black Youth Unemployment," *The American Economic Review*, 77 (3), 446-452.

[15] Holzer, Harry J. (1987b): "Hiring Procedures in the Firm: Their Economic Determinants and Outcomes", in *Human Resources and the Performance of the Firm*, edited by Morris M. Kleiner, Richard N. Block, Myron Roomkin, and Sidney W. Salsburg, Madison, WI: Industrial Relations Research Association.

[16] Holzer, Harry J. (1988): "Search Method Use by Unemployed Youth," *Journal of Labor Economics*, 6 (1), 1-20.

[17] Ioannides, Yannis M. and Linda Datcher Loury. (2004): "Job Information Networks, Neighborhood Effects, and Inequality," *Journal of Economic Literature*, 42 (4), 1056-1093.

[18] Jovanovic, Boyan. "Job Matching and the Theory of Turnover." *Journal of Political Economy* 87 (October 1979): 972-90.

[19] Jovanovic, Boyan. "Matching, Turnover, and Unemployment." *Journal of Political Economy* 92 (February 1984): 108-22.

[20] Kramarz, Francis and Oskar Nordstrom Skans (2007): "With a Little Help from My... Parents? Family Networks and Youth Labor Market Entry", CREST, mimeo.

[21] Marsden, Peter V. (2001): "Interpersonal Ties, Social Capital, and Employer Staffing Practices", in *Social Capital: Theory and Research*, edited by Nan Lin, Karen Cook and Ronald S. Burt, New Brunswick, NJ: Transaction Publishers.

[22] Marsden, Peter V. and Elizabeth H. Gorman (2001): "Social Networks, Job Changes and Recruitment", in *Sourcebook of labor Markets: Evolving Structures and Processes*, edited by Ivar Berg and Arne L. Kalleberg, New York, NY: Kluwer Academic/Plenum Publishers.

[23] Marx, Jonathan and Kevin T. Leicht (1992): "Formality of Recruitment to 229 Jobs: Variation by Race, Sex and Job Characteristics", *Sociology and Social Research*, Vol. 76, 190-196.

[24] Meyer, B.D. (1990), 'Unemployment insurance and unemployment spells' *Econometrica*, 58(4), 757-782.

[25] Montgomery, James D. (1991): "Social Networks and Labor-Market Outcomes: Toward an Economic Analysis", *American Economic Review*, 81(5), 1407-18.

[26] Oyer, Paul and Scott Schaefer (2009): "The Personnel-Economic Geography of US Law Firms and Law Schools", manuscript, Stanford Graduate School of Business.

[27] Prentice, R. and L. Gloeckler (1978), "Regression analysis of grouped survival data with application to breast cancer data," *Biometrics*, 34, 57-67.

[28] 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.

[29] Topa, Giorgio. (2001): "Social Interactions, Local Spillovers and Unemployment," *Review of Economic Studies*, vol. 68, no. 2, 261-295.

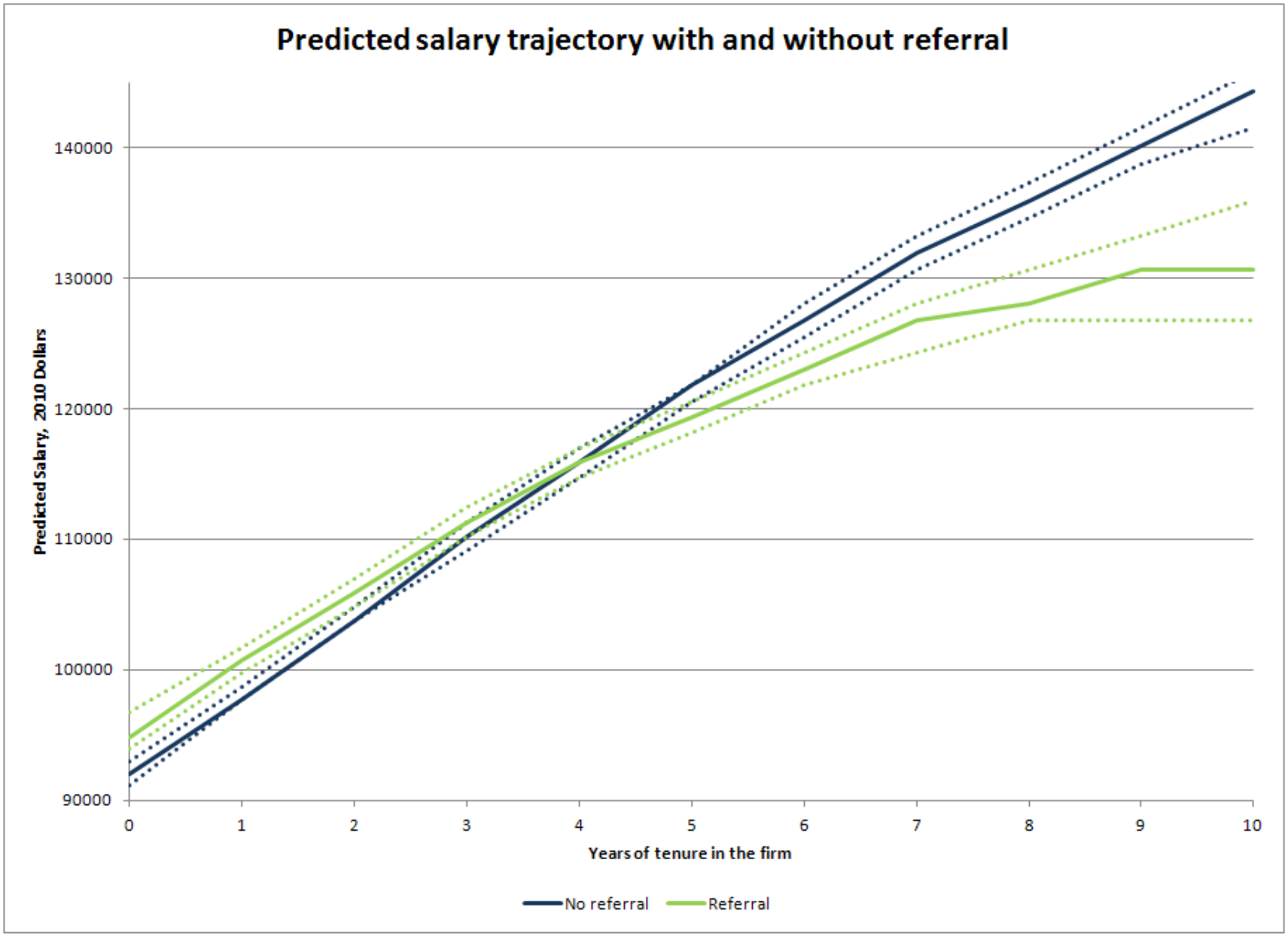
Predicted salary trajectory with and without referral
Predicted Salary, 2010 Dollars
140000
130000
120000
110000
100000
90000
0
1
2
3
4
5
6
7
8
9
10
Years of tenure in the firm
No referral
Referral

Table 1: Estimation Sample Descriptive Statistics Applicant Data

Characteristics	Obs	Proportion	Obs	Proportion
Full Sample - Number of Applicants	62,127	100%		
Number of Positions			315	100%
Number of Interviews	1,811	2.91%		
Number of Offers	428	0.69%		
Number of Hires	340	0.55%		
Unique Positions	315			
Support Staff	1,732	2.79%	15	4.8%
Junior Staff	30,685	49.39%	123	39.0%
Mid-level Staff	17,269	27.80%	106	33.7%
Senior Staff	11,398	18.35%	64	20.3%
Executive	1,052	1.69%	7	2.2%
High School Required	1,537	2.47%	18	5.7%
Associates Degree Required	935	1.50%	6	1.9%
Bachelors Degree Required	38,057	61.26%	175	55.6%
Graduate Degree Required	18,478	29.74%	96	30.5%
Education Requirement Not Indicated or Other	3,120	5.02%	20	6.3%
Year Job Posted Range 2006 - 2010			2006 - 2010	

Years of Experience Required- mean; median; SD; min; max 4.687; 4; 3.20; 1; 12

Number of Applicants for a Position- mean; median; SD; min; max 487.45; 341; 482.15; 1; 2,283

Number of Interviews for a Position - mean; median; SD; min; max 6.705; 5; 6.990; 1; 52

Notes: Excluding 1 person pools and postings for which no one was hired

Table 2: Estimation Sample Descriptive Statistics Employee Data

Characteristic	Number of observations	Proportion of observations
Full Sample	12,447	100%
Separations from firm	638	5%
Promotions	1,852	15%
Support staff	329	3%
Junior staff	4,451	36%
Mid-level staff	5,108	41%
Senior staff	2,253	18%
Executive	306	2%
Day shift	12,296	99%
Night shift	50	0%
Graveyard shift	99	1%
On leave	194	2%
Part time	111	1%
Unique individuals	1,774	-
Referred	509	29%
Ever promoted	1005	57%
Ever separated	638	36%
Average tenure in years	3.01	
Average time to promotion	1.66	
Average time to 1st promotion	1.62	
Average number of new hires per year	150.50	
Average number of promotions per year	176.91	
Average number of separations per year	56.17	
Salary: mean; median; SD; min; max	$102,740; 97,377; 45,551; 20,963; 371,750	

Table 3: Percent of Applicants at Each Stage by Method of Applying

Source	Applicant	Interview	Offer	Hired
Internet Job Board	60.08	39.98	23.6	23.53
Firm website	14.78	10.1	9.58	10.59
Own initiative	10.08	7.73	7.01	5.59
Other	6.88	13.93	21.26	23.53
Referred by current employee	6.09	21.37	27.34	29.12
Campus Recruitment	2.09	6.91	11.21	7.64
Sum	100.0	100.0	100.0	100.0
Total Sample: 62,127				

Table 4: The Impact of Referrals on Interviews and Hiring - Linear Model

	(1) Interview b/se	(2) Offer b/se	(3) Offer/Interview b/se
Referral	0.073***	0.024***	0.139***
	(0.000)	(0.000)	(0.000)
Firm Website	-0.002	-0.001	0.045
	(0.417)	(0.266)	(0.219)
Own Initiative	0.000	0.001	0.070*
	(0.973)	(0.362)	(0.068)
Other Source	0.042***	0.018***	0.173***
	(0.000)	(0.000)	(0.000)
Number of Applicants/100	-0.001***	-0.000***	-0.012**
	(0.000)	(0.000)	(0.010)
Portion of Applicants Referred	0.088***	0.044***	0.107***
	(0.000)	(0.000)	(0.000)
Support Staff	0.014**	0.014***	0.130*
	(0.043)	(0.000)	(0.099)
Junior Staff	0.004	0.000	-0.019
	(0.108)	(0.960)	(0.577)
Senior Staff	0.003	-0.001	-0.039
	(0.119)	(0.240)	(0.177)
Executive	-0.007	0.003	0.108
	(0.197)	(0.304)	(0.191)
Years of Experience Required	0.003***	0.000**	-0.009**
	(0.000)	(0.025)	(0.038)
High School Required	0.023***	0.008***	-0.043
	(0.000)	(0.001)	(0.388)
Associates Degree Required	-0.013	-0.010**	0.003
	(0.120)	(0.015)	(0.975)
Graduate Degree Required	-0.004**	-0.002**	-0.027
	(0.028)	(0.036)	(0.290)
Education Requirement Not Indicated or Other	0.005	0.000	-0.047
	(0.118)	(0.817)	(0.340)
Year Job Posted	-0.005***	-0.001	0.029*
	(0.000)	(0.153)	(0.061)
Post-2007	-0.012***	-0.002	-0.076
	(0.001)	(0.168)	(0.111)
Constant	9.966***	1.500	-57.007*
	(0.000)	(0.152)	(0.062)
R-squared	0.036	0.021	0.082
Observations	62127	62127	1811

Notes:

P-values in parentheses. Excludes jobs postings that did not result in hires. Excludes 1 person pools. Reg (3) only includes those who received interviews. Excluded category: Internet job posting, college required, mid-level staff

Table 5: Yearly Salary Levels with Current Year Dummies (in Thousands of $2010)

	Starting Salary	1 Year	2 Years	3 Years	4 Years	5 Years	6 Years	7 Years	8 Years	9+ Years
Referral	1.326	0.424	-0.121	0.679	0.507	-1.401	-3.634*	-3.986	-7.689*	-13.343***
	(0.107)	(0.501)	(0.864)	(0.448)	(0.677)	(0.390)	(0.099)	(0.192)	(0.063)	(0.000)
Night	1.813	0.999	-1.806	-6.294	-9.06	-13.164	-25.275	-27.234		-34.739**
	(0.816)	(0.855)	(0.737)	(0.265)	(0.204)	(0.127)	(0.150)	(0.160)		(0.019)
Graveyard	5.66	4.574	1.612	-2.05	-10.208	-10.99	-3.8	-4.776	-3.686	-10.814
	(0.251)	(0.127)	(0.642)	(0.615)	(0.121)	(0.234)	(0.745)	(0.714)	(0.800)	(0.547)
Part Time	-5.203	1.33	1.443	2.899	5.794	6.059	-10.878	-8.756	-3.167	-11.143
	(0.207)	(0.732)	(0.668)	(0.463)	(0.269)	(0.515)	(0.205)	(0.399)	(0.823)	(0.311)
On Leave	11.54	-3.579	1.493	-2.729	-0.591	-1.145	-0.965	-4.708	7.665	-6.234
	(0.451)	(0.242)	(0.567)	(0.349)	(0.874)	(0.759)	(0.842)	(0.562)	(0.476)	(0.553)
Support Staff	-55.959***	-54.887***	-57.201***	-58.806***	-60.336***	-61.394***	-63.579***	-68.642***	-75.335***	-78.595***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Junior Staff	-39.085***	-38.224***	-38.152***	-36.889***	-35.962***	-33.862***	-33.982***	-34.086***	-33.453***	-37.810***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Senior Staff	41.336***	41.954***	40.880***	40.857***	41.494***	41.174***	43.854***	47.886***	49.548***	51.250***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Executive	145.478***	150.909***	158.668***	174.904***	177.939***	184.392***	200.195***	203.833***	211.999***	199.029***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	93.283***	92.651***	97.604***	102.793***	111.472***	120.609***	128.909***	130.182***	138.350***	152.139***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.889	0.889	0.884	0.857	0.825	0.794	0.79	0.75	0.763	0.664
Observations	1778	3010	2292	1603	1210	839	570	382	281	478

Notes:
P-values in parentheses. 1 Year regresses the salary levels with observations from 6 months and 1 year, the subsequent years' regressions follow similarly.
Excluded Category is not referred, day time shift, full time, not on leave, mid-level staff, in the largest division.
Controls included company divisions
Controls for current year are included

Table 6: Log of Salary with Current Year Dummies

	(1)	(2)	(3)	(4)
Referral	0.021***	0.023***	0.019***	0.034***
	(0.000)	(0.000)	(0.001)	(0.000)
Years * Referral	-0.009***	-0.010***	-0.005	-0.010***
	(0.000)	(0.000)	(0.151)	(0.000)
Years at Firm	0.042***		0.059***	0.042***
	(0.000)		(0.000)	(0.000)
Night	-0.087***	-0.087***	-0.088***	-0.081***
	(0.000)	(0.000)	(0.000)	(0.000)
Graveyard	0.005	0.004	0.004	0.011
	(0.758)	(0.782)	(0.819)	(0.494)
Part Time	-0.011	-0.013	-0.013	-0.009
	(0.455)	(0.386)	(0.390)	(0.528)
On Leave	-0.001	-0.006	-0.007	-0.001
	(0.930)	(0.563)	(0.535)	(0.962)
Support Staff	-0.891***	-0.888***	-0.889***	-0.913***
	(0.000)	(0.000)	(0.000)	(0.000)
Junior Staff	-0.452***	-0.451***	-0.451***	-0.445***
	(0.000)	(0.000)	(0.000)	(0.000)
Senior Staff	0.343***	0.344***	0.344***	0.348***
	(0.000)	(0.000)	(0.000)	(0.000)
Executive	0.920***	0.921***	0.921***	0.931***
	(0.000)	(0.000)	(0.000)	(0.000)
Years at Firm Squared/100			-0.208***	
			(0.000)	
Referral * Years at Firm Squared/100			-0.058	
			(0.206)	
Support Staff * Referral				0.052***
				(0.005)
Junior Staff * Referral				-0.025***
				(0.001)
Senior Staff * Referral				-0.018**
				(0.041)
Executive Staff * Referral				-0.079***
				(0.007)
Constant	11.356***	11.805***	11.354***	11.353***
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.861	0.863	0.862	0.861
Observations	12443	12443	12443	12443

Notes:
P-values in parentheses. Excluded Category is not referred, day time shift, full time, not on leave, mid-level staff.
Controls included company divisions
Controls for current year are included.
1. Parametric Model
2. Fully Non-Parametric Model (time dummies)
3. Parametric Model with non-linear Tenure * Referral
4. Interaction of Grade Level with Referral

Table 6a: Log of Salary with Current Year Dummies and Individual Fixed Effects

	(1)	(2)	(3)	(4)
Years * Referral	-0.007***	-0.007***	-0.003	-0.007***
	(0.000)	(0.000)	(0.124)	(0.000)
Years at Firm	0.046***		0.059***	0.046***
	(0.000)		(0.000)	(0.000)
Night	-0.070***	-0.044*	-0.052**	-0.070***
	(0.004)	(0.067)	(0.031)	(0.004)
Graveyard	-0.036**	-0.034**	-0.036**	-0.036**
	(0.016)	(0.018)	(0.013)	(0.016)
Part Time	0.012	0.009	0.009	0.012
	(0.242)	(0.344)	(0.368)	(0.242)
On Leave	-0.007	-0.010*	-0.010**	-0.007
	(0.217)	(0.054)	(0.046)	(0.217)
Years at Firm Squared/100			-0.158***	
			(0.000)	
Referral * Years at Firm Squared/100			-0.059***	
			(0.007)	
Constant	11.357***	11.787***	11.337***	11.357***
	(0.000)	(0.000)	(0.000)	(0.000)
R-squared	0.715	0.728	0.724	0.715
Observations	12443	12443	12443	12443

Notes:
P-values in parentheses. Excluded Category is not referred, day time shift, full time, not on leave, mid-level staff.
Controls included company divisions
Controls for current year are included.
1. Parametric Model
2. Fully Non-Parametric Model (time dummies)
3. Parametric Model with non-linear Tenure * Referral
4. Interaction of Grade Level with Referral

Table 7: Discrete Time Proportional Hazard Model of Separation From Firm

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	B	*P-value*	*B*	*P-value*	*B*	*P-value*	*B*	*P-value*	*B*	*P-value*	*B*	*P-value*	*B*	*P-value*	*B*	*P-value*
Referral	0.850	0.091	0.845	0.081	0.833	0.175	0.876	0.420	0.771	0.056	0.841	0.461	0.764	0.045	0.815	0.279
Tenure	0.931	0.000			0.929	0.001	0.935	0.001	0.995	0.857	0.998	0.933	0.932	0.001	0.935	0.001
Tenure * Referral					1.010	0.834										
Starting Salary	0.995	0.109	0.995	0.092	0.995	0.110	0.995	0.144	0.983	0.002	0.985	0.004	0.995	0.110	0.995	0.143
Night	0.000	0.991	0.000	0.994	0.000	0.991	0.000	0.991	0.000	0.991	0.000	0.991	0.000	0.991	0.000	0.991
Graveyard	0.640	0.445	0.628	0.426	0.641	0.447	0.581	0.354	0.760	0.704	0.669	0.579	0.632	0.433	0.577	0.348
Part Time	4.972	0.000	5.172	0.000	4.984	0.000	4.790	0.000	6.818	0.000	7.027	0.000	4.930	0.000	4.762	0.000
On Leave	3.144	0.000	3.029	0.000	3.148	0.000	3.219	0.000	3.972	0.000	4.174	0.000	3.153	0.000	3.220	0.000
Support Staff	0.743	0.398	0.761	0.436	0.741	0.393	1.282	0.493	0.424	0.067	0.766	0.579	0.760	0.435	1.281	0.495
Junior Staff	1.466	0.013	1.459	0.014	1.466	0.013	1.492	0.014	1.002	0.994	1.053	0.830	1.466	0.013	1.489	0.015
Senior Staff	1.101	0.606	1.125	0.528	1.101	0.606	1.090	0.666	1.811	0.029	1.809	0.035	1.100	0.608	1.093	0.657
Executive	2.901	0.044	3.045	0.036	2.898	0.044	2.292	0.140	3.047	0.360	2.664	0.424	2.907	0.044	2.316	0.136
Support Staff * Referral							0.088	0.022			0.092	0.029			0.092	0.025
Junior Staff * Referral							1.001	0.997			1.046	0.880			1.009	0.967
Senior Staff * Referral							0.997	0.992			0.801	0.640			0.985	0.962
Executive * Referral							2.577	0.136			0.000	0.998			2.430	0.165
Post-2007	0.643	0.000	0.628	0.000	0.643	0.000	0.632	0.000					0.609	0.000	0.610	0.000
Post-2007 * Referral													1.255	0.238	1.165	0.434
N	12443		12443		12443		12443		5746		5746		12443		12443	

Notes:
Excluded Category is not referred, day time shift, full time, not on leave, mid-level staff, in the largest division.
Controls included company divisions
1. Parametric Model
2. Fully Non-Parametric Model (time dummies)
3. Interaction of Tenure with Referral
4. Interaction of Grade Level with Referral
5. Just Pre-2007 - Parametric Model
6. Just Pre-2007 Interaction of Grade Level with Referral
7. Parametric Model with Post-2007*Referral
8. Interaction of Grade Level with Referral with Post-2007* Referral

Table 8: Discrete Time Proportional Hazard Model of Promotions

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	B	*P-value*	*B*	*P-value*	*B*	*P-value*	*B*	*P-value*	*B*	*P-value*	*B*	*P-value*	*B*	*P-value*	*B*	*P-value*
Referral	0.933	0.207	0.939	0.248	0.946	0.488	0.999	0.986	0.983	0.842	1.088	0.521	0.948	0.538	1.017	0.871
Tenure	1.046	0.000			1.047	0.000	1.045	0.000	1.141	0.000	1.142	0.000	1.046	0.000	1.045	0.000
Tenure * Referral					0.995	0.815										
Starting Salary (in Thous)	0.993	0.000	0.992	0.000	0.993	0.000	0.993	0.000	0.993	0.040	0.992	0.037	0.993	0.000	0.993	0.000
Night	0.128	0.041	0.118	0.033	0.128	0.041	0.134	0.045	0.000	0.991	0.000	0.991	0.128	0.041	0.134	0.045
Graveyard	0.194	0.005	0.177	0.003	0.194	0.005	0.202	0.006	0.261	0.061	0.285	0.080	0.195	0.005	0.202	0.006
Part Time	0.580	0.104	0.619	0.153	0.579	0.103	0.578	0.102	0.169	0.073	0.169	0.073	0.581	0.104	0.578	0.102
On Leave	0.503	0.006	0.447	0.001	0.502	0.006	0.506	0.007	0.599	0.179	0.608	0.192	0.503	0.006	0.506	0.007
Support Staff	0.522	0.003	0.513	0.003	0.523	0.003	0.413	0.003	0.602	0.130	0.416	0.060	0.521	0.003	0.413	0.003
Junior Staff	1.098	0.310	1.085	0.378	1.098	0.312	1.138	0.179	1.202	0.228	1.250	0.159	1.098	0.309	1.139	0.177
Senior Staff	0.839	0.115	0.851	0.154	0.839	0.116	0.857	0.203	0.664	0.040	0.702	0.093	0.839	0.115	0.857	0.201
Executive	1.470	0.266	1.655	0.151	1.473	0.264	1.462	0.288	0.980	0.980	1.051	0.950	1.469	0.268	1.459	0.290
Support Staff * Referral							1.596	0.225			1.946	0.229			1.590	0.229
Junior Staff * Referral							0.844	0.153			0.799	0.228			0.843	0.150
Senior Staff * Referral							0.928	0.664			0.783	0.498			0.930	0.674
Executive * Referral							1.256	0.717			0.000	0.998			1.267	0.707
Post-2007	1.151	0.006	1.136	0.011	1.150	0.006	1.153	0.005					1.158	0.011	1.161	0.009
Post-2007 * Referral													0.975	0.817	0.970	0.785
N	12443		12443		12443		12443		5746		5746		12443		12443	

Notes:

Excluded Category is not referred, day time shift, full time, not on leave, mid-level staff, in the largest division.

Controls included company divisions

1. Parametric Model
2. Fully Non-Parametric Model (time dummies)
3. Interaction of Tenure with Referral
4. Interaction of Grade Level with Referral
5. Just Pre-2007 - Parametric Model
6. Just Pre-2007 Interaction of Grade Level with Referral
7. Parametric Model with Post-2007*Referral
8. Interaction of Grade Level with Referral with Post-2007* Referral

Table 9: The Impact of Referrals on Hiring - Linear Model - With Interactions

	(1) Interview b/se	(2) Offer b/se	(3) Offer/Interview b/se	(4) Interview b/se	(5) Offer b/se	(6) Offer/Interview b/se
Referral	0.059***	0.021***	0.155***	0.071***	0.029***	0.175***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm Website	0.00	0.00	0.05	0.00	0.00	0.05
	(0.27)	(0.21)	(0.17)	(0.41)	(0.29)	(0.19)
Own Initiative	0.000	0.000	0.073*	0.000	0.000	0.071*
	(0.87)	(0.39)	(0.06)	(0.97)	(0.36)	(0.07)
Other Source	0.042***	0.018***	0.174***	0.042***	0.018***	0.173***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of Applicants/100	-0.001***	0.000***	-0.012**	-0.001***	0.000***	-0.012***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Portion of Applicants Referred	0.088***	0.044***	0.106***	0.088***	0.044***	0.108***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Support Staff	0.014*	0.014***	0.11	0.013*	0.015***	0.181**
	(0.05)	(0.00)	(0.17)	(0.07)	(0.00)	(0.03)
Junior Staff	0.00	0.00	0.02	0.004*	0.00	0.01
	(0.11)	(0.97)	(0.53)	(0.10)	(0.67)	(0.83)
Senior Staff	0.00	0.00	0.04	0.00	0.00	0.03
	(0.11)	(0.26)	(0.18)	(0.24)	(0.56)	(0.33)
Executive	0.010	0.000	0.110	-0.010*	0.000	0.060
	(0.17)	(0.32)	(0.19)	(0.07)	(0.78)	(0.51)
Years of Experience Required	0.003***	0.000**	-0.010**	0.003***	0.000**	-0.009**
	(0.00)	(0.02)	(0.03)	(0.00)	(0.03)	(0.04)
High School Required	0.010**	0.007***	0.02	0.023***	0.008***	0.050
	(0.03)	(0.01)	(0.76)	(0.00)	(0.00)	(0.36)
Associates Degree Required	0.010	-0.012***	0.040	0.010	-0.010**	0.000
	(0.13)	(0.01)	(0.74)	(0.13)	(0.01)	(0.97)
Graduate Degree Required	-0.005**	-0.002**	0.030	-0.004**	-0.002**	0.030
	(0.01)	(0.03)	(0.35)	(0.03)	(0.02)	(0.30)
Education Requirement Not Indicated or Other	0.000	0.00	0.040	0.010	0.000	0.040
	(0.96)	(0.31)	(0.52)	(0.12)	(0.81)	(0.43)
High School * Referral	0.211***	0.019**	-0.200**			
	(0.00)	(0.04)	(0.04)			
Associate * Referral	0.01	0.040***	0.33			
	(0.66)	(0.00)	(0.16)			
Graduate School * Referral	0.013**	0.000	0.010			
	(0.03)	(0.28)	(0.87)			
Other Ed Requirement * Referral	0.113***	0.030***	(0.02)			
	(0.00)	(0.00)	(0.81)			
Year Job Posted	-0.005***	0.000	0.026*	-0.005***	0.000	0.026*
	(0.00)	(0.18)	(0.09)	(0.00)	(0.15)	(0.09)
Post-2007	-0.012***	0.000	0.070	-0.012***	0.000	0.070)
	(0.00)	(0.15)	(0.16)	(0.00)	(0.18)	(0.14)
Support Staff * Referral				0.030	0.010	-0.277**
				(0.17)	(0.22)	(0.04)
Junior Staff * Referral				0.00	-0.009***	0.050
				(0.56)	(0.01)	(0.37)
Senior Staff * Referral				0.01	-0.008**	0.040
				(0.20)	(0.04)	(0.50)
Executive * Referral				0.067***	0.045***	0.150
				(0.01)	(0.00)	(0.40)
Constant	9.622***	1.410	-52.497*	9.950***	1.530	-51.764*
	(0.00)	(0.18)	(0.09)	(0.00)	(0.14)	(0.09)
R-squared	0.039	0.022	0.085	0.037	0.022	0.085
Observations	62127	62127	1811	62127	62127	1811

Notes:
P-values in parentheses. Excludes jobs postings that did not result in hires. Excludes 1 person pools. Reg (3) and (6) only include those who received interviews. Excluded category: Internet job posting, college required, mid-level staff

Appendix 1: The Impact of Referrals on Interviews and Hiring - Logit Model - Full Sample

	(1) Interview b/se	(2) Offer b/se	(3) Offer/Interview b/se
Referral	0.048***	0.011***	0.170***
	(0.000)	(0.000)	(0.000)
Firm Website	0.001	0.001*	0.071
	(0.655)	(0.085)	(0.111)
Own Initiative	0.002	0.001**	0.095*
	(0.288)	(0.030)	(0.056)
Other Source	0.030***	0.009***	0.196***
	(0.000)	(0.000)	(0.000)
Number of Applicants/100	-0.004***	-0.001***	-0.014***
	(0.000)	(0.000)	(0.009)
Portion of Applicants Referred	0.015***	0.002***	0.077***
	(0.000)	(0.000)	(0.003)
Support Staff	0.009*	0.005**	0.127
	(0.061)	(0.041)	(0.197)
Junior Staff	0.004***	0.001*	-0.019
	(0.002)	(0.051)	(0.584)
Senior Staff	0.002	0.000	-0.047
	(0.172)	(0.302)	(0.101)
Executive	-0.004	0.000	0.112
	(0.106)	(0.716)	(0.260)
Years of Experience Required	0.001***	0.000	-0.008*
	(0.000)	(0.142)	(0.067)
High School Required	0.005*	0.000	-0.043
	(0.055)	(0.654)	(0.320)
Associates Degree Required	-0.006*	-0.001**	-0.001
	(0.052)	(0.037)	(0.989)
Graduate Degree Required	-0.001	0.000	-0.030
	(0.260)	(0.246)	(0.264)
Education Requirement Not Indicated or Other	0.000	-0.001***	-0.050
	(0.918)	(0.006)	(0.272)
Year Job Posted	-0.003***	0.000	0.027*
	(0.000)	(0.109)	(0.096)
Post-2007	0.002	0.000	-0.075
	(0.232)	(0.420)	(0.175)
Observations	62127	62127	1811

Notes:

P-values in parentheses. Marginal effects displayed.

Excludes jobs postings that did not result in hires. Excludes 1 person pools. Reg (3) only includes those who received interviews. Excluded category: Internet job posting, college required, mid-level staff

Appendix 2: The Impact of Referrals on Interviews and Hiring - Logit Model - With Interactions

	(1) Interview b/se	(2) Offer b/se	(3) Offer/Interview b/se	(4) Interview b/se	(5) Offer b/se	(6) Offer/Interview b/se
Referral	0.043***	0.011***	0.183***	0.043***	0.012***	0.200***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Firm Website	0.00	0.001*	0.078*	0.00	0.001*	0.075*
	(0.87)	(0.09)	(0.09)	(0.68)	(0.07)	(0.10)
Own Initiative	0.00	0.001**	0.099**	0.00	0.001**	0.097*
	(0.37)	(0.03)	(0.05)	(0.31)	(0.03)	(0.05)
Other Source	0.030***	0.009***	0.198***	0.030***	0.009***	0.196***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Number of Applicants/100	-0.004***	-0.001***	-0.014***	-0.004***	-0.001***	-0.014***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
Portion of Applicants Referred	0.015***	0.002***	0.077***	0.015***	0.002***	0.078***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Support Staff	0.009*	0.005**	0.100	0.008*	0.006**	0.182*
	(0.06)	(0.04)	(0.31)	(0.08)	(0.04)	(0.10)
Junior Staff	0.004***	0.001*	0.020	0.004***	0.001*	0.010
	(0.00)	(0.05)	(0.54)	(0.01)	(0.06)	(0.82)
Senior Staff	0.00	0.00	-0.047*	0.000	0.000	0.050
	(0.18)	(0.31)	(0.10)	(0.22)	(0.33)	(0.17)
Executive	-0.004*	0.000	0.110	-0.006**	0.000	0.070
	(0.09)	(0.72)	(0.25)	(0.02)	(0.69)	(0.55)
Years of Experience Required	0.001***	0.000	-0.009*	0.001***	0.000	-0.008*
	(0.00)	(0.14)	(0.05)	(0.00)	(0.14)	(0.07)
High School Required	0.000	0.000	0.010	0.005*	0.000	0.050
	(0.48)	(0.46)	(0.81)	(0.06)	(0.66)	(0.30)
Associates Degree Required	-0.006**	-0.001***	0.020	-0.006*	-0.001**	0.010
	(0.03)	(0.01)	(0.83)	(0.05)	(0.03)	(0.96)
Graduate Degree Required	0.000	0.000	0.030	0.000	0.000	0.030
	(0.31)	(0.29)	(0.30)	(0.26)	(0.23)	(0.28)
Education Requirement Not Indicated or Other	0.000	-0.001***	0.040	0.000	-0.001***	0.040
	(0.18)	(0.00)	(0.49)	(0.91)	(0.01)	(0.39)
High School * Referral	0.021**	0.000	-0.134***			
	(0.03)	(0.25)	(0.01)			
Associate * Referral	0.010	0.000	0.280			
	(0.62)	(0.43)	(0.38)			
Graduate School * Referral	0.000	0.000	0.000			
	(0.95)	(1.00)	(0.98)			
Other Ed Requirement * Referral	0.018**	0.000	0.010			
	(0.04)	(0.33)	(0.88)			
Year Job Posted	-0.003***	0.000	0.020	-0.003***	0.000	0.020
	(0.00)	(0.11)	(0.13)	(0.00)	(0.11)	(0.13)
Post-2007	0.000	0.000	0.070	0.000	0.000	0.070
	(0.27)	(0.42)	(0.23)	(0.24)	(0.45)	(0.21)
Support Staff * Referral				0.000	-0.001**	-0.150***
				(0.77)	(0.02)	(0.00)
Junior Staff * Referral				0.000	0.000	0.040
				(0.20)	(0.78)	(0.43)
Senior Staff * Referral				0.000	0.000	0.010
				(0.97)	(0.90)	(0.88)
Executive * Referral				0.020	0.000	0.110
				(0.22)	(0.38)	(0.58)
Observations	62127	62127	1811	62127	62127	1811

Notes:

P-values in parentheses. Marginal effects displayed.

Excludes jobs postings that did not result in hires. Excludes 1 person pools. Reg (3) only includes those who received interviews. Excluded category: Internet job posting, college required, mid-level staff