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Abstract

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 data set 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 U.S. corporation, and to test various predictions of theoretical models of labor market referrals. Predictions with which our results align include: 1) referred candidates are more likely to be hired, 2) referred workers experience an initial wage advantage, 3) the wage advantage dissipates over time, 4) referred workers have longer tenure in the firm, and 5) the variances of the referred and nonreferred wage distributions converge over time. The richness of the data permits analysis of the role of referrer-referee relationships, and the size and diversity of the corporation permit analysis of referrals at a variety of skill and experience levels.

Key words: referrals, networks, personnel, wage mobility, turnover

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Brown, Topa: Federal Reserve Bank of New York. Setren: Massachusetts Institute of Technology. Address correspondence to Giorgio Topa (e-mail: 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 wonderful person.* Stefania Albanesi, Laura Gee, Kevin Lang, Fabian Lange, Charles Bellemare, Manolis Galenianos, Bentley MacLeod, Uta Schoenberg, Wilbert van der Klaauw, Thijs van Rens, and seminar participants at Autonoma, Bocconi, Columbia, the New York Fed, Pompeu Fabra, Sevilla, SED, and SOLE provided valuable comments. The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System.

1 Introduction

There is an 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.[3]

We present new evidence on the empirical relationships among employment referrals and outcomes for workers based on a novel panel dataset on a single U.S. corporation, in which we observe both explicit referral status and a detailed picture of the hiring process and employment spell. We use these uniquely rich data to test the predictions of a long-established theoretical literature on labor market referrals, and to provide new descriptive evidence on the role of referrals at different skill levels and by provider-recipient relationship.

We find that referred candidates are more likely to be hired, and hired referred workers experience an initial wage advantage, all else equal, relative to non-referred workers. The initial referred wage advantage shrinks over time and dissipates by the third year of employment; starting with the fifth year the referral-wage relationship is reversed. Referred workers experience substantially less turnover, and their salary variance converges to that of non-referred workers over time. Each of these findings is consistent with the predictions of established labor market referral models, particularly those that view the distinction between referred and non-referred workers from the perspective of Jovanovic-style learning about match productivity. On the other hand, we find on average no differences in promotion rates between referred and non-referred workers: insofar as promotions reflect productivity, this finding is at odds with the theoretical literature, which tends to predict higher match productivity for referred workers.

[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) using national surveys of U.S. firms report that a little over one third of firms surveyed in 1991 and in 1982 (respectively) use referrals from current employees in hiring.

[3] A notable exception is Datcher (1983), which we discuss below.

Further, the wide range of skill and experience levels represented in this corporation permits detailed analysis of the role of referrals for workers from support staff to company executives. Overall, referrals appear to play substantially different roles in the hiring of support staff and executives. Their relationship with the probability of a job offer follows something of a U-shape, with sizable, significant positive associations between referral and offer probability for both lower skilled and executive positions. Most rank-and-file workers experience substantial referral salary advantages, with the largest estimated advantage going to support staff. The association between referral and tenure in the firm is large and positive for support staff, and it decreases more or less monotonically with staff level.

Our dataset also enables us to match referral providers and recipients within the firm, and therefore to construct measures of affinity between referrers and referred along various dimensions. Our analysis of the different types of referral matches yields some additional insights. First, we find that most referrals take place between a provider and a recipient with similar characteristics in terms of age, gender, ethnicity, education, as well as division and staff level within the corporation. This is consistent, on the one hand, with the well-documented extent of assortative matching in social networks, and on the other hand with the idea that referrals tend to be used by firms when they can provide a better signal about the referred worker's match productivity (assuming that higher affinity is associated with more informative signals). Second, we find some indication that referred workers may be more productive than non-referred, for some types of referral match: referrals from a higher to a lower staff level are associated with faster promotions; further, the salary trajectory of referred workers stays persistently higher than that of non-referred when referral providers are in a higher staff level, have relatively low tenure, or work in a different division. The tenure and division findings in particular are difficult to reconcile with a "favoritism" or "influence" interpretation of referrals.

It is important to note here that this paper does not attempt to make any causal claims about the impact of job referrals on outcomes. We do not have, in our data, any exogenous source of variation in job candidates' or hired employees' referral status, nor do we observe a rich enough set of demographic or labor market characteristics to hope to control for selection into different job search methods. Our goal in this paper is to test the equilibrium predictions of leading models of labor market referrals, as well as to enrich our descriptive understanding of the behavior of referrals by provider-recipient relationship and across skill levels. Our results, by and large, support the predictions of learning-based models of labor market referrals.

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 referrals 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 job candidates and employee referral status, tenure outcomes, and promotion and salary trajectories. 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. 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. 2011). Others study family based networks (Kramarz and Nordstrom Skans 2007) and educational institutions (Oyer and Schaefer 2012). Giuliano et al. (2009) and Aslund et al. (2010) 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 Schoenberg (2011) use ethnic minority groups as a source of variation in network distance between current employees and new hires in German employment data. Heath (2011) uses direct data on referrer-referred pairs from the Bangladeshi garment industry to test the predictions of a model in which referrals alleviate a moral hazard problem (the employer makes the referrer responsible for the referred worker's effort).

With regard to the impact of referrals on hiring probabilities, Holzer (1987a) finds 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) generate 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.[4] 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 black and college educated workers but not for those with high school educations or less.

Three revealing 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.[5] 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. Our study is the first, to our knowledge, to use explicit data on individual employees' referral status to relate referrals to both 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. In addition, we observe various measures of affinity between referrer and referred along several dimensions, so we can study whether and how these referral effects vary depending on the nature of the match between referral provider and receiver.

[4] In a seminal paper, Granovetter 1973 shows that information transmission about jobs is more likely to occur through weak rather than strong social ties. Gee and Jones 2012 revisit the "strength of weak ties" hypothesis using Facebook data and find that, while more matches are produced by weak ties as a result of their prevalence, an individual strong tie is more likely to produce a match than an individual weak tie.

[5] In addition, Fernandez and Galperin (2012) take a stab at studying the causal effect of referrals on the probability of being hired by using data on repeat applicants to a large retail bank. They find that referral applications are about five times as likely to result in interviews than non-referred ones.

3 Theoretical models of employment referrals and their predictions

The two leading descriptions of the role of referrals in the labor market, learning and homophily, are modeled in Simon and Warner (1992) and Montgomery (1991). Simon and Warner embed employee referrals in a Jovanovic (1979, 1984) learning 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. 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 particularly well suited.[6] Montgomery models employers who rely on referrals from high ability workers to alleviate a potential adverse selection problem in hiring (not being able to observe the "type" of a prospective employee). Homophily in worker networks implies that high ability employees will be more likely to refer other high ability workers.

More recent theoretical papers on employee referrals also favor one of these approaches or the other. Dustmann, Glitz and Schoenberg (2011) and Galenianos (forthcoming) allow referrals to affect firms' information in models of employer and employee learning about worker productivity. Galenianos (2012), on the other hand, drives the referral effect through homophily, and generates results that address the relationship among network density, aggregate employment and job search outcomes. Other conceptualizations of the role of referrals include alleviating a moral hazard problem via monitoring (Heath 2011 and Kugler 2003) and favoritism towards social network members, e.g. relatives (this possibility is explored, in an experimental setting, by Beaman and Magruder 2012). We discuss the predictions of these alternative models alongside the learning and homophily models, wherever possible, in light of our empirical findings.

[6] 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.

3.1 A simple learning model of employee referral

We now present a model of job matching that is adapted from the parsimonious model of Simon and Warner (1992) and the enriched specification of 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 particularly well. 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.[7]

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 $N(\mu, \sigma_y^2)$.

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 increase the informativeness of the productivity signal observed by the worker and firm, so that $\sigma_R^2 < \sigma_E^2$.

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 external market. On matching, worker and firm receive match quality signal $\widehat{y}_E$. The firm makes a

[7] In the interest of expositional simplicity, we abstract from several features of the problem included in Dustmann et al. Specifically, we assume a zero rate of match destruction and that, as in Simon and Warner, 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. 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.

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 an existing 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.

3.1.1 Wage and employment determination after true productivity is revealed

Following Jovanovic and Simon and Warner, we impose a zero expected profit condition on the firm, which implies that the expected stream of payments to the worker over the worker's tenure with the firm is equal to the worker's expected value of marginal product. Jovanovic demonstrates that the following pay strategy satisfies this condition: In the first period, the firm offers the worker a wage equal to the worker's expected productivity, conditional on the firm's signal, or $w_j = m_j = E(y|\widehat{y}_j)$. In the second period, the firm offers the worker a wage equal to true productivity y.[8]

Let $J(y)$ represent the value to the worker of remaining employed at known productivity y, and let Q represent the value to the worker of rejecting an offer in favor of unemployed search. The value of unemployed search is stationary and independent of the worker's current productivity match. Therefore, if it is currently optimal for the worker to remain employed at productivity y then it will always be optimal for the worker to remain employed at productivity y. This leads to a reservation productivity y^r, and a value of employment

$$J(y) = \begin{cases} \frac{y}{1-\beta} \text{ when } y \geq y^r \\ \beta Q \text{ when } y < y^r, \end{cases}$$

where β is the worker's discount factor. Hence $y^r = \beta(1-\beta)Q$ is common to matches produced by referrals and matches produced by the external market.

3.1.2 Wage and employment determination with unknown productivity

Define W_{1j} as the value of initial wage offer m_j from source j for a worker. Given the above,

$$W_{1j}(m_j) = \max\{m_j + \beta E[J(y)], \beta Q\}.$$

[8] As in Jovanovic and Simon and Warner, the equilibrium pay strategy is not unique.

Since $m_j + \beta E[J(y)]$ increases with m_j, while βQ is constant in m_j, there exists a unique reservation wage, m_j^r, above which the worker accepts an offer from source j, and below which he does not.

Next we discuss several predictions of referral models. Each prediction arises from some subset of the specifications we have discussed, including our learning model, its more comprehensive cousins, and models of homophily, monitoring, and favoritism. These predictions are tested below using our firm-level data. We summarize all predictions, and our main empirical findings, in Table 10.[9]

3.1.3 Predictions

Prediction 1: Referred applicants are more likely to be hired

In the context of the simple learning model, and as demonstrated in Lundquist and Sargent (2000),

$$\Pr(m_j \geq m_j^r) = \int_{m_j^r}^{\infty} dF\left(m_j|\mu, \frac{\sigma_\mu^4}{\sigma_\mu^2 + \sigma_j^2}\right). \tag{1}$$

The probability of an acceptable offer, conditional on the worker and firm meeting through source j, decreases in both the reservation wage and the variance of the noise in the initial productivity signal. Since (as we show below) $m_R^r > m_E^r$ and $\sigma_R^2 < \sigma_E^2$, the prediction for the relative rates at which a referred and an external market worker accept initial offers is ambiguous. This is presumably also true for the Simon and Warner (1992) and the Dustmann et al. (2011) models. Galenianos (forthcoming), on the other hand, generates (reasonably weak) conditions under which referred matches will more likely lead to hires. In general, hiring probabilities are not a primary target of learning models of referral, and the models have mixed predictions regarding relative hiring probabilites.

Other approaches, however, yield a clear prediction that referred workers are more likely to be hired. Montgomery (1991) and Galenianos (2012) emphasize worker homophily, leading workers referred by high productivity employees to be more likely to be hired. Heath (2011) explains referrals through moral hazard, and also would seem to predict that referred workers are more likely to be hired. Finally, in a favoritism interpretation of referrals, referred candidates would be more likely to be hired because of the influence exerted by the referrer.

[9] Since the central objective of this study is empirical, and many of these claims were first made elsewhere, we provide only modest detail on the derivation of each model result. More information is available from the authors.

Prediction 2: Referred workers receive higher initial wages

Given the reservation wage property, as in Lundquist and Sargent, the initial reservation wage can be related to the ongoing reservation wage according to

$$m_j^r = y^r - \frac{\beta}{1-\beta}\int_{y^r}(y - y^r)dF(y|m_j^r, \sigma^2_{m_j}), \tag{2}$$

where $dF(y|m_j^r, \sigma^2_{m_j})$ is the density of true productivities conditional on current predicted productivity m_j^r. Note that the second term on the right hand side of (2) is negative, and hence the initial reservation wage is lower than the ongoing reservation wage. Part of the value to the worker of an initial wage is the possibility that the match productivity will exceed the expected productivity, leading to a higher ongoing wage. The worker is shielded from worse than expected productivity matches by the ability to separate from the firm. The probability mass above the reservation value is increasing in the variability of the conditional productivity distribution. The assumption that $\sigma_R^2 < \sigma_E^2$ implies $\sigma^2_{m_R} < \sigma^2_{m_E}$, and therefore that the amount subtracted in the second term in (2) is larger for the external market than for the referred candidate. External market job candidates mark down their reservation wages, relative to those of referred candidates, in response to the greater upside potential of their productivity signals. This leads to the result that $m_R^r > m_E^r$: external market workers are willing to accept worse matches because the larger uncertainty in their productivity signal implies greater upside potential for future wages. Therefore, conditional on acceptance, referred workers have higher starting wages than external market workers.

Dustmann et al., Simon and Warner, Galenianos (2012, forthcoming), and Montgomery all predict higher starting wages for referred workers. The intuition driving this result is similar in Dustmann et al., Simon and Warner, and Galenianos (forthcoming), while the source of the difference in Galenianos (2012) and Montgomery relies on homophily in referral networks and the higher average productivity of employed than of unemployed workers.

The implications of the moral hazard and favoritism models for initial wages are unclear: in the favoritism story in particular, if influence is focused solely on having a friend or relative hired, the candidate may be of lower quality on average and the initial wage may be lower than for a non-referred worker – but other forms of favoritism may result in higher initial wages as well. Under moral hazard, referred workers may be less productive in other jobs where they lack network connections, and their weaker outside options may result in lower wages. Other forces, however, may override this mechanism: for instance, in the context of the Heath 2011 model, if the minimum wage is binding then we would observe no differences in initial wages between referred and non-referred.

Prediction 3: The referred worker wage advantage diminishes over time

Following Simon and Warner, consider 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 $y^r = \beta Q(1-\beta)$, 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. Assuming a less than perfectly informative signal for the external market ($\sigma_E^2 > 0$), this implies a flatter wage profile for referred than for non-referred workers. A related intuition applies for the limiting case of perfectly uninformative external market signals.

Dustmann et al., Simon and Warner, and Galenianos (forthcoming) all make this prediction. Dynamic predictions including this one, prediction 5 involving relative turnover between referred and external market workers, and prediction 7 regarding relative wage variances over time are a primary means of distinguishing learning from other descriptions of the role of referrals. We know of no competing non-learning models that generate these differential wage, tenure, and wage variance trajectories.[10] Selection models based on homophily (favoritism) can generate wage and tenure advantages (disadvantages) for referred workers relative to non-referred, but – crucially – such differentials do not close with tenure in these models. Finally, the moral hazard model described in Heath (2011) generates the opposite predictions: it implies that both the level and variance of wages for referred workers *increase* with tenure relative to those of non-referred workers.

Prediction 4: Turnover is lower for referred workers

[10] Note that Simon and Warner also consider the predicted effect of referrals 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.

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, $m_R^r > m_E^r$. 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.

More specifically, the probability that a worker separates once true productivity has been revealed is

$$\int_{-\infty}^{y^r} dF(y|m_j, \sigma_{m_j}^2) = \Phi\left(\frac{y^r - m_j}{\sigma_{m_j}}\right).$$

A higher mean of the true productivity distribution for referred workers, $m_R > m_E$, decreases the above separation rate for referred relative to external market workers. Presuming that this mean exceeds reservation productivity level y^r, so that the argument of $\Phi(\cdot)$ is negative, the probability of separation increases in σ_{m_j}. Note that σ_{m_j} is an increasing function of σ_j^2. Hence the lower signal variance for referred workers, $\sigma_R^2 < \sigma_E^2$, would further decrease the separation rate, and on net lead referred workers to have a lower probability of separation following the revelation of true productivity than external market workers.[11]

Non-learning models that generate higher referred than external market worker productivity may also predict lower referred worker turnover. For example, if homophily-based referrals lead to better matches, then such matches may also be slower to dissolve. Matches based on the mutual monitoring potential of a referrer and referee may similarly lead to greater productivity and less fragile attachment to the firm. The implications of the favoritism story for turnover are again unclear: if influence was exerted merely to get a lower quality candidate hired, then turnover may be higher for such hires – but this may depend on the form of influence and on the position of the referral provider.

Prediction 5: The referred turnover advantage also diminishes over time

[11] Some ambiguity arises from the fact that $y^r > m_j^r$, and therefore, for some subset of $m_j \geq m_j^r$, $y^r > m_j$ and the probability of separation decreases in σ_j. Dustmann et al. defend prediction 4, above, using numerical methods.

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 numerical evidence that the difference in the rate of separation from the firm between referred and non-referred workers should diminish over time. Galenianos (forthcoming) also predicts that referred and external workers become more similar over time.

Like the prediction for wage dynamics, this prediction regarding turnover dynamics offers an opportunity to distinguish among learning and other models of referrals. Models in which referred workers are more productive in a permanent sense may generate a referral turnover advantage, but this advantage generally does not decline over time. Hence prediction 5 applies to our class of learning models and not, for example, to Galenianos (2012), Montgomery, and Heath.

Prediction 6: Referred workers have higher expected productivity

The higher reservation match productivity of referred workers ($m_R^r > m_E^r$) 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 (2012) generates higher employer predictions of referred worker initial productivity in a homophily context. Greater initial or expected productivity of referred workers appears to be a relatively common prediction of the employee referral literature. In contrast, Heath (2011) predicts that referral recipients on average have lower quality that non-referred, because thanks to monitoring the firm can make positive profits with observably worse workers that it would not otherwise hire. However, in terms of observed productivity on the job, monitoring by the referrer may reverse some of the underlying productivity differentials by inducing high effort.

Predictions of the favoritism model are often ambiguous, as they rely in part on the preferences and level of involvement of the influential referral provider. This makes it a particularly difficult model to refute. However, the prediction of the favoritism model for relative productivity is, arguably, unambiguous. Favoritism, definitionally, involves balancing the preferences of some influential party against the productivity of the potential hire when making a hiring decision. Hence one would expect on average lower productivity for referred than non-referred workers under favoritism.

Prediction 7: The variances of referred and non-referred workers' wages converge over time

Two forces influence the relative variances of referred and non-referred workers' wage distributions. The first is the noisiness of the signal. Consider the expected productivity variances of a referred and an external market candidate, $Var(m_R) = \frac{\sigma_y^4}{\sigma_y^2+\sigma_R^2} > \frac{\sigma_y^4}{\sigma_y^2+\sigma_E^2} = Var(m_E)$. A noisier signal leads the firm to place more weight on the population distribution of productivities when determining the initial offer. Since the population distribution is common across candidates, a noisier signal leads the firm to make more similar offers to candidates, which leads to less varied initial wages for external market workers.

The second force arises from the difference in referred and external market acceptance thresholds. The distribution of realized initial wages after the offer acceptance decision is a truncation of the normal distribution of expected productivity m_j (which has mean μ and the above variance) at reservation wage m_j^r. The variance of a truncated normal distribution is decreasing in the truncation value, so, recalling that $m_R^r > m_E^r$, we find that the effect of the reservation wages is to lower the variance of initial wages for referred workers relative to those of external market workers.

On net, the relationship between $Var(w_R)$ and $Var(w_E)$, where w_j represents initial wage, is ambiguous in the context of the theory. One thing that the theory does allow us to say, however, is that the variances will become more similar over time. Once underlying productivity is revealed, and all workers apply ongoing reservation wage $y^r = \beta Q(1-\beta)$, the remaining difference in ongoing wage variances will arise from differences in the initial acceptance thresholds for the two groups. In fact, the closer the initial signal for a group was to being either perfectly informative or perfectly uninformative about true productivity, the closer the ongoing wage distribution will be to a $N(\mu, \sigma_y^2)$ truncated at the ongoing reservation wage of $y^r = \beta Q(1-\beta)$.[12]

Turning to another source on the relative variances of referred and non-referred worker wage distributions, Datcher (1983) posits a simple model of "job shopping", in which "information gathered

[12] This assumes that μ is an acceptable wage offer in the perfectly uninformative signal case. More detail on the variance convergence prediction has been omitted for length, and is available from the authors.

through knowing someone at the place of employment before hiring lowers the uncertainty about the quality of the match between worker and job." She finds that the variance of the unobserved component of the returns of a job to an individual worker is lower for referred than non-referred workers. With regard to other models of referrals, the moral hazard model of Heath (2011), as noted earlier, generates the prediction that the variance of wages for referred workers increases with tenure relative to non-referred workers. This is in contrast to the convergence prediction in learning models.

Given the ambiguous prediction regarding the relative variances of the referred and non-referred wage distributions in the above model, and the prediction of lower referred wage variance from Datcher's work, we investigate the relative levels of referred and non-referred wage variances in our data. In addition, we test the learning model prediction that referred and non-referred wage variances converge over time.

4 Data and descriptive statistics

This study utilizes a unique dataset that includes all of the 2000-(April) 2011 hires and 2006-2010 applicants of a U.S. corporation which employs between 2,000 and 5,000 workers in the steady state. The vertically integrated corporation hires people for a broad range of tasks with all levels of educational backgrounds and years of work experience. The corporation operates in the financial services industry, is set in an urban labor market, and has been active for several decades.

4.1 Applicant data

The applicant data include 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.[13] The outcomes for the applicant are then traced through the interview, offer, and acceptance stages. Observed characteristics of the applicant are limited, but the data include detailed information on the position, including education and experience requirements, date of posting, and staff level. We divide the range of staff levels into support, junior, mid-level, senior, and executive positions. Referrals may be reported by the applicant, the referrer, or both. In any case, once

[13] All but two of the roughly 62,000 applications in our sample indicate a single source.

the applicant gets to the interview stage, the information on the referral source is verified by the corporation's human resources (HR) department. For many positions, if the employee referral leads to a hire, the employee who provided the referral receives a small monetary bonus.[14] The (nominal) bonus from 2000-(April) 2011 ranged between $500 and $4,000, with a mode of $1,000 and a median around $2,000.

The estimation sample is restricted to include only job postings that receive more than one applicant and result in a hire.[15] We remove internships because they have very short durations (hence the hiring process is arguably different), and postings that were only internal. The meaning of a referred, or a non-referred, former employee is unclear both practically and in the context of the theory. Hence when current or former employees apply, we include them in the calculation of the applicant pool size, but drop their individual observations from the estimation.[16]

The final sample used in our analysis includes 62,127 applications for 315 positions, which resulted in 340 hires. Summary statistics appear in Table 1. On average, 185.2 individuals apply, and 6.7 interview, for a given posting. Though the table reflects substantial heterogeneity in posting characteristics, it is worth noting that most postings require at least a bachelor's degree, and just over half of the applications are for junior or support level staff positions.

4.2 Employee data

The employee data include a worker's referral status, staff level, shift, office location, full time, part time, or on leave status, salary, promotions, and turnover from the time of hire, which is left censored in April 2000, through departure, which is right censored in April 2011.[17] Again, we include only first time hires and non-interns.[18] Further, the employee data include only the main location (because other minor locations were significantly scaled down over the sample period) and

[14] The newly hired worker must stay at the organization for longer than six months for the bonus to be paid. This condition does not seem to affect behavior: the separation rates for referred vs. non referred at 6 and 12 months of tenure are not statistically different. Family members, company executives, direct supervisors, and recruiters are not eligible for the award.

[15] Though a posted position may be associated with multiple vacancies, 91 percent of positions are associated with single vacancies.

[16] If a current or former employee is hired, we drop that position from the estimation. We also exclude postings through which workers were hired "in bulk".

[17] Workers are observed semiannually, in April and October. However, promotion and termination or departure calendar dates are available.

[18] 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.

exclude the top executives of the corporation. Finally, we include only workers entering in 2000 or later, in order to follow each employment trajectory from the date of hire.

The resulting estimation sample includes 1,774 unique employees, 29% of whom were referred by current employees. All monetary variables in the paper are reported in 2010 U.S. dollars. Annual salary includes base salary but not any performance-based pay. The salary figures and transition 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 are similar, at $102,740 and $97,377, 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 reflects the breadth of worker staff levels represented in the data.

Of the 1,774 unique workers ever observed in our sample, 1,005 (57 percent) are promoted during the sample window, and 638 (36 percent) leave the corporation. The mean observed tenure by 2011 or exit, whichever occurs first, is about three years. The mean time to first (any) promotion is 1.62 (1.66) years.

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 part time and leave status. Roughly 97 percent of our pooled semiannual worker observations are full time, limiting the possible variation in hours.[19] As a result of our lack of hours data, we are unable to infer hourly wages from annual salaries, and we take annual salary as our primary outcome variable in the earnings analysis.[20]

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. 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 reasonably well. Hence we use staff level at entry indicators in our earnings estimation to proxy for the typical schooling, experience and experience squared regressors

[19] Of course, there could be substantial unobserved hours variation among those workers whom the corporation classifies as full time.

[20] Most employees at this corporation are paid on a biweekly basis.

employed by the majority of the literature.

Finally, the reader should bear in mind possible measurement problems surrounding candidate referral. In order for a referral to go unreported, both the referrer and the candidate must fail to report it. 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.[21] Second, and perhaps more importantly, it is possible that a current employee's decision to refer someone formally may be related to the candidate's success during the various stages of recruiting and interviewing. 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.[22]

5 Empirical specification and findings

5.1 Model predictions

Prediction 1: Referred candidates are more likely to be hired

A central prediction of Galenianos (2012, forthcoming), Heath (2011), and Montgomery (1991), as discussed above, is that referred workers are more likely to be hired, all else equal. This is also likely the case in a favoritism story. Our first empirical step is to test this prediction using our data on the corporation's applicant pool and resulting hires. Note that Castilla (2005), Fernandez and Weinberg (1997), and Fernandez and Castilla (2000, 2001) all confirm this prediction in their bank and call center single-firm hiring studies. Our test of this prediction extends their analysis

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

[22] It is still possible, in general, that referral recipients may be "selected", as employees may choose to refer high quality candidates for a position in order to maintain or enhance their reputation within the company. This would be consistent with homophily models a la Montgomery 1991. It is also consistent with a learning model in which the means of the underlying productivity distributions differ between referred and non-referred. As we mentioned in Section 3, a key difference between homophily and learning models is whether any referral advantages persist or dissipate with tenure. Our data enable us to distinguish between these alternative interpretations.

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 this prediction is provided by the raw interview and job offer rates reported in Table 3. Job board applicants constitute 60 percent of the applicant sample. They also constitute 40 percent of interviewees and 24 percent of offer recipients and final hires. By contrast, referred employees constitute only 6 percent of the applicant sample, but 21 percent of interviewees, 27 percent of offer recipients, and 29 percent of hires. In other words, the pool of candidates receiving serious consideration increasingly favors the referred over the course of the hiring process.[23]

Adopting a more formal approach, we model the probability of being hired by the corporation in a linear probability framework.[24] Specifically, we estimate

$$H_{ij} = X_i^H \alpha^H + Z_j^H \beta^H + \gamma_t^H + \varepsilon_{ij}^H, \tag{3}$$

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, γ_t^H is a calendar year fixed effect, and ε_{ij}^H is an idiosyncratic error associated with the applicant i - posting j pair.

The estimates generated using expression (3) 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.[25] In the second, 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.[26] We again define H_{ij} as an indicator for

[23] No other applicant source shows as steep a consideration trajectory. Campus recruitment and other methods, relatively minor applicant sources for this firm, each produce more successful applicants than the job boards. However, neither achieves the conditional interview and hiring probabilities of the referral category.

[24] Our qualitative results are generally robust to a logistic specification, and we include these estimates as Appendix Tables A1 and A2.

[25] We impose the sample requirement that we observe all variables included in the Table 4 estimation for the applicant-position pair.

[26] This leaves us with a sample of 1,811 interviewees. Of these 1,811 interviewees, 428 are offered the position 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. Relative to job board applicants, referred applicants are estimated to be 7.3 percentage points more likely to be interviewed for the position, and 2.4 percentage points more likely to receive an offer. Conditional on having been interviewed, referred applicants are 14.0 percentage points more likely than job board applicants to receive offers.[27] Each of these coefficient estimates for the referred category is significant at the one percent level. Other regressors in Table 5 pertain to other applicant sources and the characteristics of the posting. They are discussed in a brief appendix to the paper.

Prediction 2: Referred workers receive higher starting salaries

Next we test 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. We find that having been referred is associated with a \$1,326 salary premium that approaches significance at conventional levels (the p-value equals 0.107).

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

$$\ln S_{it} = \alpha_0^L r_i + \alpha_1^L \tau_{it} + \alpha_2^L r_i \tau_{it} + \alpha_3^L \tau_{it}^2 + \alpha_4^L r_i \tau_{it}^2 + X_{it}^L \beta^L + \gamma_t^L + \varepsilon_{it}^L, \tag{4}$$

which they interviewed.

[27] Note that 6.0 percent of job board applicants receive interviews and 32.3 percent of interviewees from internet job boards receive offers. Thus, relative to job board applicants, referral recipients are more than twice as likely to be interviewed and – conditional on interview – about 40% more likely to receive an offer.

where t represents calendar time and τ_{it} indicates tenure in the corporation for employee i at time t. Other variable definitions are analogous to those above. 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 both learning models, like Dustmann et al., Simon and Warner, and Galenianos (forthcoming), and homophily models, such as Montgomery and Galenianos (2012).[28]

Prediction 3: The referred worker salary advantage diminishes over time

As discussed in Section 3.1.3, however, learning-based theories of labor market referrals predict that the referral effect will dissipate over time, and the salaries of referred and non-referred workers who 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.[29]

We find that the referral effect does indeed diminish over time. In all linear tenure 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

[28] 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.

[29] Estimates of a fixed effects specification of the above model, intended to account for unobserved heterogeneity in worker productivity and other characteristics, are available from the authors. Findings for the referred and non-referred salary trajectories are qualitatively similar to the estimates reported in Table 6.

are not estimated very precisely.

Figure 1 depicts predicted salaries for referred and non-referred workers as tenure increases.[30] 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., Simon and Warner, and Galenianos (forthcoming) learning-based models of labor market referrals, and seems at odds with the selection, favoritism and moral hazard models discussed above.

From five years of tenure on, the estimates predict a statistically 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 some 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 5.1 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.[31]

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 corporation for both worker categories. It may be worth noting that an increasing wage trajectory is the central prediction of Jovanovic and other learning models.

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

$$S_{i\tau} = \alpha^s r_i + X^s_{i\tau}\beta^s + \gamma^s_t + \varepsilon^s_{i\tau},$$

[30] Note this figure is based on specification (3) in Table 6. Confidence intervals are generated using the delta method.

[31] At the same time, such a finding is not inconsistent with a favoritism interpretation: if lower quality workers are hired through favoritism their quality may eventually be observed, leading to lower wages at longer tenures. Notice that this story would still have a learning element to it.

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 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.[32]

Prediction 4: Turnover is lower for referred workers

Next we turn to the theoretical prediction, reviewed in Section 3.1.3, 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

$$\lambda_{i\tau}^{D} = \lambda_0^{D}(\tau) \exp(Z_{i\tau}^{D} \delta^{D}), \tag{5}$$

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 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 (5). Estimates in columns (1) and (3)-(8) assume tenure dependence $\lambda_0^{D}(\tau)$ to be linear.[33] In addition, the estimated values reported in Table 7 are

[32] 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.

[33] We specify the tenure dependence of baseline hazard $\lambda_0^{D}(\tau)$ in two different ways. Column (2) includes separate

in terms of $\exp(\delta)$, for ease of interpretation. Where the regressor is an indicator variable, given (5), 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.[34]

Table 7 estimates indicate that referred workers do indeed experience lower separation rates. Specifications (1) and (2) show that referred workers are only about 85 percent as likely to leave the corporation as non-referred workers, and these findings are significant at the ten percent level in each case.[35]

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 5.1 is to test the equilibrium predictions of models like Dustmann et al. and Simon and Warner. Therefore, in the empirical exercise we do not need to correct our salary trajectory estimates for differential attrition, as the model predictions are predicated on differential turnover. Hence our estimates of the salary trajectories of retained employees are, arguably, the appropriate objects with which to test these predictions. Importantly, and consistent with the theory, when we control for differential separation among referred and non-referred workers, any salary differences disappear: see Figure A1 in the Appendix, which plots salary slopes for employees who stay at the corporation at least five years.

Prediction 5: The referred 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 learning-based models.

dummies for each observed six month interval with the corporation. Comparing the estimates in columns (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 in columns (3) through (8) with both linear and fully nonparametric assumptions on the baseline hazard, and our qualitative results are essentially unchanged.

[34] 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.

[35] Simon and Warner find that scientists and engineers in their 1972 retrospective survey recall longer job duration when they were referred, all else equal. Datcher (1983) also finds lower turnover in referred jobs, using PSID data.

Additional results regarding the referral turnover effect are discussed in the appendix.

In Table 7, 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.

Prediction 6: Referred workers have higher expected productivity

The theoretical predictions of the learning and homophily models generally emphasize higher initial employer approximations of worker productivity for workers hired through referrals than for workers not hired through referrals. On the other hand, the monitoring and favoritism models tend to predict lower expected productivity for referred workers. 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.[36]

We model the promotion process using approximately the same approach we applied to the tenure process in Section 5.1. In the discrete time proportional hazard framework we apply, the instantaneous promotion hazard is assumed to be

$$\lambda_{i\tau}^{P} = \lambda_0^{P}(\tau)\exp(Z_{i\tau}^{P}\delta^{P}), \tag{6}$$

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

[36]It would be prefereable to have performance review data, as in Kahn and Lange (2010), for example, but these are not currently available. Fredericksen, Lange, and Kriechel (2012), however, deomonstrate a positive correlation between performance ratings and promotions in each of six large firms.

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 statistically significant at standard levels. So, despite the predictions of higher initial perceived productivity that arise from learning and homophily models, we cannot reject the hypothesis of equal promotion rates for the referred and non-referred, and, if anything, referred employees achieve promotion slightly more slowly than their non-referred peers. Instead, other employee characteristics appear to drive promotion, and these are discussed in the appendix to the paper.

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.[37]

Prediction 7: The variances of referred and non-referred workers' wages converge over time

Table 9 reports the comparison of the variances of initial salaries for referred and non-referred workers. We find that, for all workers in our sample, the variance of initial salaries for non-referred employees is 1.2 times the variance of initial salaries for referred workers, and this ratio differs from one at the one percent level. Hence initial salaries are more dispersed for non-referred workers. In the context of the theory in Section 3, the variance-lowering noisiness of the external market signal is not great enough to overwhelm the variance-raising effect of the external market reservation

[37] 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.

wage. As shown in Table 9, this pattern also holds for two out of four of the largest divisions in the corporation, as well as among shorter- and longer-tenured workers.

Figure 2 shows the trajectories of referred and non-referred salary variances from the hire date through 7 years of tenure, along with 95 percent confidence bands around the variance trajectories. We find that the referred salary variance lies below the non-referred salary variance, with non-overlapping confidence bands, for each of the first five years. This finding aligns with the predictions of Datcher (1983). At six years the referred variance rises toward the non-referred variance, and their confidence intervals intersect. By seven years the salary variances of referred and non-referred workers are approximately identical. Thus the data for this firm are consistent with the model prediction that salary variances for referred and external market workers converge over time.[38] Note that this type of wage variance convergence is peculiar to the learning model, along with the "job shopping" model of Datcher. It is difficult to imagine a model of referred worker ability advantage that generates similar wage variance convergence. Further, the observed variance convergence is at odds with the prediction of the moral hazard model, which generates wage variance for referred workers that increases with tenure relative to non-referred.

Table 10 summarizes the seven theoretical predictions considered above, the models generating each prediction, and whether the empirical evidence generated by this study is consistent with the prediction. In sum, the empirical evidence aligns with the broad prediction of the theoretical literature that referred workers are both more likely to be hired and less likely to separate from the firm. Initial wages for the referred are significantly higher, confirming a shared prediction of learning and homophily models of referral. The diminishing referred worker wage advantage and the wage variance convergence we observe arguably favor a learning over a productivity-based interpretation of referrals. However, the lack of evidence of a diminishing turnover advantage over time for referred workers is consistent with a productivity-based but not a learning-based interpretation of referrals. Finally, insofar as promotions reflect observed productivity, the finding that promotions do not occur significantly faster for referred than non-referred is not prima facie consistent with (simple versions of) any of the models considered here.

[38] The salary variances reflect the increasing pattern documented by Kahn and Lange (2010) only in the longer run, and only for referred workers.

5.2 Referral effects by skill level

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.[39] 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 learning model of referrals in Galenianos (forthcoming) includes predictions for the varying roles of referrals at high and low productivity firms. Presuming an association between firm productivity and employee skill in equilibrium, the Galenianos model can be interpreted to predict more prevalent referral use in low skill job markets, and a larger difference in wages and separation rates between referred and external workers at lower skill jobs.[40]

The range of staff levels available in our data 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 the hiring, salary, promotion, and turnover models above.

Looking first at the hires data, Table 11 reports estimates of expression (3) 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). 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

[39] 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.

[40] Galenianos predicts higher referral use, and greater wage and separation differentials between referred and non-referred workers, at less productive firms. This is consistent with a puzzling empirical finding in the literature, namely that referrals are associated with higher wages in firm-level studies or when controlling for firm fixed effects; whereas the wage advantage is weaker or even reversed in analyses that do not control for firm characteristics. See Dustman et al. and Galenianos (forthcoming) for a discussion.

to postings requiring college and graduate degrees. The additional effect of referral for high school, associate's 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.[41]

At the same time, referrals 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 on hiring 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. This would be an interesting area for future research.

Turning to the staff levels, 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.[42] 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.

In the employee log earnings regressions reported in Table 6, analysis of referral effects by staff level also 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 other staff levels. 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 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.

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

[41] 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.

[42] 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. Notice that there is only partial overlap across positions in terms of their education requirements and associated staff levels.

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.

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.

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. The wage and tenure results appear to confirm predictions of Galenianos (forthcoming) regarding the prevalence and evident impact of referrals for low skill positions. 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.[43]

5.3 Referral match analysis

In this Section we investigate whether different degrees of similarity between referral provider and receiver along various observable dimensions are associated with different referral effects, in terms

[43] One important 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.

of the various theoretical predictions we have studied. We first look at some descriptive measures of the degree of similarity between referrer and referred, and then we consider salary levels and trajectories, and separation and promotion hazards.

Table 12 reports the degree of similarity between referral providers and receivers along the dimensions of gender, ethnicity, corporate division, age,staff level, and education. The majority of referral matches are between people of the same gender (63.5%), the same race or ethnicity (71.5%), and the same division (73.2%), indicating a high degree of homophily in referrals.[44] For confidentiality purposes, age comparisons were provided to us in 10 year brackets.[45] In Table 12 we see that the distribution of providers' ages is slightly skewed towards older providers (younger receivers). Most referrals are provided by employees in higher (48.1%) and in the same (47.9%) staff levels. Only 4.1% of referrals came from lower level staff. Forty-nine percent of receivers are referred by providers with the same education level. The rest are referred by providers with more education (17.6%), less (11.2%), or an unknown education level (22.5%).[46]

Table 13 reports the results of our log salary regressions, augmented by a set of dummy variables that describe the nature of the match between referral provider and receiver. Column (1) is a copy of Table 6 column (3); column (2) replicates column (1) with the (smaller) sample for which we have referral match information; column (3) adds the referral match variables. We find that employees who received the referral from an older provider, someone in a higher staff level, someone in the same division, or someone who has been at the organization for less than two years have higher initial salaries than their counterparts. The magnitude of the effects ranges from an additional 1.8 percent salary advantage for referred workers when the referrer is in the same division, to a 4.8 percent additional salary advantage when the referrer is in a higher staff level.[47]

The age, staff level and division results seem very intuitive, as one would expect that older

[44] In the interest of confidentiality, the corporation prefers not to provide us with explicit demographics for individual employees. Referral match measures, therefore, indicate only whether provider and recipient share the same characteristic. Thus we are unable to compare, for example, the degree of similarity of referral pairs in the data to the degree of similarity that would result by chance among a hiring pool and employee pool that resemble the demographics of the corporation's current employee pool.

[45] Specifically, we were given data indicating whether the provider and referred are within 10 year of the same age, the provider is 10 or more years older, or the provider is 10 or more years younger than the referred.

[46] Providers' tenure in the firm ranges from 0 to 11 years, with a mean of 3.1 years. Ten individuals in the sample were referred by two people. For these cases, we consider the referrer that is of the same gender, the same ethnicity, the same company division, older, a higher staff level, more educated, and with longer tenure.

[47] These results are qualitatively consistent with those in Datcher (2006). She looks at the wage effects of referrals for different types of referral providers, and finds that older workers (who typically have higher incomes) tend to provide referrals for jobs associated with higher wages.

employees, those in higher positions in the organization, and those in the same division as the referral receiver may have a better understanding of the sort of skills that are required to succeed in the organization. At the same time, it is also possible that these sorts of providers can exert more influence and secure a higher initial salary for the referred worker. This would be consistent with a "favoritism" interpretation of referrals. The result for tenure is also interesting: it may indicate that workers who have spent relatively less time at the corporation have better connections with the outside labor market and are better able to provide referrals for workers who are good matches for the organization.

These results, however, are based on *mean* salary differences. We are also interested in seeing how these different provider-receiver matches affect the salary slope of referred employees over time. Therefore we also run our log salary regressions interacting the referral match dummies with tenure and tenure squared at the organization. In Figure 3 we report salary slopes for different types of matches.[48]

Our findings are quite interesting. For those who are referred by someone in a different division, with less tenure at the organization, or in a higher staff level, the salary advantage relative to a non-referred employee seems to persist much longer than average: the difference is statistically significant up to seven years after being hired, whereas when we do not differentiate by the characteristics of the referral match the referral salary effect tends to dissipate after about three years at the company. In particular, the referral effect is initially stronger if the provider is in same rather than different division (consistent with our earlier result), but it reverses after three years. The referral effect is also stronger for providers with less tenure (vs. more) or in a higher staff level (vs. same or lower), especially if the provider is two or more salary levels higher.

The finding that after a few years those who were referred by someone in a different division tend to enjoy a significant salary advantage relative to the non-referred is particularly important to distinguish between a learning or homophily story as opposed to a mere favoritism story. If the initial referral providers work in a different division of the organization, it is less likely that they are able to exert direct influence over the employee's salary progression during her stay at the company. Thus this is perhaps our cleanest piece of evidence against a favoritism interpretation

[48] We only report results for which there is a statistically significant difference between various referral matches. The full set of regression results and the tests of statistical significance are available from the authors upon request.

of referrals. At the same time, the finding that the referral salary advantage is more persistent in this case is consistent with a homophily model where referral providers choose to refer high quality workers.[49] Finally, these findings on wage trajectories for specific referrer-referee pairs seem difficult to reconcile with the monitoring model.

Figure 3 also shows that if employees are referred by someone a decade or more older, or of the same race/ethnicity, then the initial referral advantage gets absorbed more quickly, within four to five years. Consistent with our previous finding, the referral effect is stronger if the provider is older (than same age or younger) and if the provider is of the same rather than different race or ethnicity. The same ethnicity result could be tied to the fact that social networks tend to be very assortative in the U.S. along racial and ethnic lines, so a signal about prospective match quality may be more informative for this type of referral matches, leading to a higher initial reservation wage and to a higher salary progression over time.[50]

Tables 14-16 report the impact of referral matches on promotion and separation hazards. In particular, Table 14 reports our baseline hazard models when we include all referral match dummies jointly. The only match characteristics that have a significant impact on the likelihood of a promotion are age, race/ethnicity and staff level. We do not find any significant effect of referral match differences on separations. Consistent with our salary regressions, those who received a referral from an employee of the same race/ethnicity are more likely to get promoted than a non-referred worker, and those who received the referral from someone in a lower staff level are much less likely to get promoted.

Tables 15 and 16 focus on age and staff level respectively: here we run the hazard model regressions only including match dummies for these characteristics one at a time. This allows us to compare the effect of a particular referral match to both non-referrals and other types of referral matches. We find that referred workers with older providers are associated with a lower chance of promotion both relative to non-referrals and relative to employees who received referrals from same-decade or younger providers. Therefore, while receiving referrals from older providers is associated

[49] Datcher (1983) also finds evidence consistent with a learning model, and inconsistent with a "clout" theory of referrals, in which the referrer "can facilitate promotion, earnings opportunities, and receiving nonpecuniary benefits".

[50] Marsden (1987), (1988) using General Social Survey data shows that social networks of Americans exhibit a high degree of homophily (or assortative matching) with respect to race and ethnicity: individuals are much more likely to interact with members of the same racial or ethnic group than with other racial/ethnic groups (relative to random matching).

with an initial salary advantage, it is also associated with a lower chance of promotion over time. Thus, this particular type of referral match does not seem to denote the hiring of more productive workers for the organization.

On the other hand, when the referral comes from someone in a higher staff level, it is associated with a significantly higher likelihood of promotion, with respect to both non-referrals and providers in strictly lower staff levels. This effect is convex: those with referral providers who are two or more staff levels higher are even more likely to get promoted than those with providers in the same level or just one level higher. Therefore, this particular type of referral match (from a higher to a lower staff level) is associated with both steeper salary growth over time and faster promotions. Again, this finding is consistent with these referral recipients being more productive (or better matches for the organization) as predicted by the learning and homophily models, but we cannot exclude an influence interpretation of the referral.[51]

We have also explored whether referral providers are systematically different from other employees who do not provide referrals for new hires (see Tables A3 and A4 in the Appendix). We find that those employees who provide a referral, all else equal, tend to be less senior in the organization, with less tenure, and with a higher salary than non-referrers at the time of the referral provision. They are also more likely to be promoted. Thus, referrals seem to originate from relatively better-than-average employees in the organization, who may have relatively better connections with the external labor market (having joined the firm more recently). These findings seem more consistent with referrals being used by firms to reduce uncertainty about prospective hires (as in the Simon and Warner, Dustman et al, Galenianos forthcoming, and Montgomery models) rather than as the result of patronage.

Interestingly, even *after* the referral provision, referrers continue to be more likely to be promoted and to experience higher salaries (controlling for other observed attributes), continue to be less likely to be in higher staff levels within the organization, and tend to have longer tenure at the corporation. The latter finding may signal that those who provide referrals are generally more satisfied at the workplace (enough to be willing to recommend the company to others) and therefore tend to stay longer with the organization.

[51] Referrals from higher staff levels are as likely to come from providers in different divisions as referrals from same or lower staff levels, so we cannot use this additional source of variation to further distinguish these possibilities.

6 Conclusion

Our unique firm-level data on job candidate referral and subsequent careers in the firm allow us to address a series of open questions in the literature on job market referrals. We find that, in one sizable, diverse U.S. corporation, referred candidates are more likely to be hired, and hired referred workers enjoy a wage advantage for their first three years on the job. They stay with the firm longer, and their salary variance converges to that of non-referred workers over time. Each of these results is consistent with the predictions of established labor market referral models, particularly those that view the distinction between referred and non-referred workers from the perspective of Jovanovic-style learning about match productivity.[52]

Results that go beyond the confines of standard labor market referral theory include several findings on the role of referrals at different levels of skill and experience. Overall, referrals appear to play substantially different roles in the hiring of support staff and executives. Their relationship with the probability of a job offer follows something of a U-shape, with sizable, significant positive associations between referral and offer probability for both lower skilled and executive positions. Most rank-and-file workers experience substantial referral salary advantages, with the largest estimated advantage going to support staff. Executives actually experience a substantial starting salary disadvantage with referral. Finally, the association between referral and tenure in the firm is large and positive for support staff, and it decreases more or less monotonically with staff level. Executives are significantly more likely to leave the firm if they are referred.

Our analysis of the different types of referral matches (between referrer and referred) yields some additional insights. First, we find that most referrals take place between a provider and a recipient with similar characteristics in terms of age, gender, race/ethnicity, education, and staff level. This is consistent, on the one hand, with the extent of assortative matching in social networks, and on the other hand with the idea that referrals tend to be used by the firm when they can provide a better signal about the referred worker's match productivity (assuming that higher affinity is associated with more informative signals). Second, we find some indication that referred workers may be more productive that non-referred, for some types of referral match: referrals from a higher

[52] More difficult to reconcile with existing theory are our findings that referred workers are typically not promoted any more quickly than non-referred workers, that after five years' tenure the referred experience a wage disadvantage, and that the (predicted) referral tenure advantage fails to decline over time.

to a lower staff level are associated with faster promotions; further, the salary trajectory of referred workers stays persistently higher than that of non-referred when referral providers are in a higher staff level, have relatively low tenure, or work in a different division. The tenure and division findings in particular are difficult to reconcile with a favoritism interpretation of referrals.

One would like to make some inference regarding whether referrals are good for firms and workers. Though we believe that our data offer a considerably more complete picture of the behavior of referrals than was previously available, at least for one sizable and diverse U.S. corporation, we do not have access to exogenous variation in workers' referral status. (It is difficult to imagine a source of such variation in standard labor market contexts.) As a result, we cannot make causative claims about the impact of job referrals. What we have done so far is to test the equilibrium predictions of leading models of labor market referrals, as well as to enrich economists' descriptive understanding of the behavior of referrals by provider-recipient relationship and across skill levels. Our results, by and large, support the predictions of learning-based models of labor market referrals. Such models, for example Dustmann et al. and Simon and Warner, predict that referred candidates are hired in equilibrium only where such hires increase total surplus to the firm and worker. While we cannot claim to have demonstrated, in a direct sense, a positive effect of referral on wages or firm profits, we can say that our results support a family of models that predict worker-firm surplus gains from the use of referrals.

Our findings suggest a few interesting avenues for further research. First, we find that on average 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 constructing measures of affinity between the referred worker's attributes and those of his or her proximate 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, both theoretical and empirical.

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A Additional Results

A few more findings regarding the firm's hiring process and employees' experiences, though not of direct relevance to model predictions, may be of interest.

First, following Section 5.1, prediction 1, the Table 4 estimates of the probabilities of being interviewed and receiving an offer provide some ancillary information on the corporation's hiring process. 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 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.

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.

An interesting side question is whether the corporation views referrals as substitutes or complements to other inputs in the recruiting technology. We find some (weak) evidence of substitution between referrals and other inputs into the screening process: controlling for applicant pool size, the percentage of applicants who get interviews is negatively correlated with the presence of referrals in the pool.

Turning to Section 5.1's prediction 4, regarding the effect of referral on tenure in the corporation, we find that most of this referral effect arises from the pre-recession period. In specification (7) of Table 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 it is not surprising that employee referrals appear to function differently for this corporation from the start of the recession.

Despite our failure to identify a significant effect of referral on promotion under Section 5.1's prediction 6, the Table 8 results on promotion are informative regarding which employee characteristics do 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.

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.

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	2.9%		
Number of Offers	428	0.7%		
Number of Hires	340	0.6%		
Unique Positions	315			
Support Staff	1,732	2.8%	15	4.8%
Junior Staff	30,685	49.4%	123	39.1%
Mid-level Staff	17,269	27.8%	106	33.7%
Senior Staff	11,398	18.4%	64	20.3%
Executive	1,052	1.7%	7	2.2%
High School Required	1,537	2.5%	18	5.7%
Associates Degree Required	935	1.5%	6	1.9%
Bachelors Degree Required	38,057	61.3%	175	55.6%
Graduate Degree Required	18,478	29.7%	96	30.5%
Education Requirement Not Indicated or Other	3,120	5.0%	20	6.3%
Year Job Posted Range	2006-2010		2006-2010	

Years of Experience Required- mean: 5.3; median: 4; SD: 3.4; min: 1; max: 12

Number of Applicants for a Position- mean: 185.2; median: 113; SD: 245.2; min: 1; max: 2,283

Number of Interviews for a Position- mean: 6.7; median: 5; SD: 7.0; min: 1; max: 52

Notes: Excluding one person pools and postings that did not result in hires

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	1,005	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	56.71	

Salary: mean: \$102,740; median: \$97,377; SD: \$45,551

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

Source	Applicant	Interview	Offer	Hired
Internet Job Board	60.1	40.0	23.6	23.5
Firm Website	14.8	10.1	9.6	10.6
Own Initiative	10.1	7.7	7.0	5.6
Other	6.9	13.9	21.3	23.5
Referred by Current Employee	6.1	21.4	27.3	29.1
Campus Recruitment	2.1	6.9	11.2	7.6
Sum	100.0	100.0	100.0	100.0

Total Sample: 62,127

Table 4: Linear Model of Interview and Offer Probability

	(1) Interview	(2) Offer	(3) Offer/Interview
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 Degre 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	62,127	62,127	1811

Notes: * p≤0.10, ** p≤0.05, *** p≤0.01. P-values in parentheses. Excludes job postings that did not result in hires and one person pools. Specification (3) only includes those who received interviews. Omitted category: Internet job posting, college required, mid-level staff.

Table 5: Salary Regressions in Levels, in Thousands of 2010 dollars

	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	-9.060	-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	5.660	4.574	1.612	-2.050	-10.208	-10.990	-3.800	-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	1.330	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	11.540	-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≤0.10, ** p≤0.05, *** p≤0.01. P-values in parentheses. One year specification regresses the salary levels with observations from six months and one year, the subsequent years' regressions follow similarly. Omitted category is not referred, day shift, full time, not on leave, mid-level staff, in the largest division. Controls include company divisions and calendar year.

Table 6: Pooled Log Salary Regressions

	(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	12,443	12,443	12,443	12,443

Notes: * p≤0.10, ** p≤0.05, *** p≤0.01. P-values in parentheses. Omitted category is not referred, day shift, full time, not on leave, mid-level staff. Controls include company divisions and current year. Specification (2) includes a dummy for each six months of tenure.

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

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Value	Coeff.	P-Val
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
Suprt * Referral							0.088	0.022			0.092	0.029			0.092	0.025
Junior * Referral							1.001	0.997			1.046	0.880			1.009	0.967
Senior*Referral							0.997	0.992			0.801	0.640			0.985	0.962
Exec*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*Ref.													1.255	0.238	1.165	0.434
Log Likelihood	-2397		-2357		-2397		-2391		-1338		-1333		-2397		-2391	
Observations	12,443		12,443		12,443		12,443		5746		5746		12,443		12,443	

Notes: Coefficient is the exp(coefficient). Omitted category is not referred, day shift, full time, not on leave, mid-level staff, in the largest division. Controls include company divisions. Column (2) includes indicators for every six months of tenure. Columns (5) and (6) estimate using only pre-2007 data. Salary is in \$1000s.

Table 8: Discrete Time Proportional Hazard Model of Promotion

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-val
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	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
Suprt* Referral							1.596	0.225			1.946	0.229			1.590	0.229
Junior* Referral							0.844	0.153			0.799	0.228			0.843	0.150
Senior*Referral							0.928	0.664			0.783	0.498			0.930	0.674
Exec*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*Ref.													0.975	0.817	0.970	0.785
Log Likelihood	-5101		-4508		-5101		-5099		-2226		-2224		-5101		-5099	
Observations	12,443		12,443		12,443		12,443		5746		5746		12,443		12,443	

Notes: Coefficient is the exp(coefficient). Omitted category is not referred, day shift, full time, not on leave, mid-level staff, in the largest division. Controls include company divisions. Column (2) includes indicators for every six months of tenure. Columns (5) and (6) estimate using only pre-2007 data. Salary is in \$1000s.

Table 9: Initial Salary Standard Deviations

	Non-referred SD	Referred SD	Ratio of NR/R Variances
All	42,623	35,458***	1.20
Divison 1	35,875	34,691	1.03
Division 2	36,969	38,666	0.96
Division 3	48,362	40,731***	1.19
Division 4	44,799	31,215***	1.44
$\leq$ 3 Years Tenure	51,072	43,651***	1.17
$>$3 Years Tenure	37,868	29,726***	1.27
$\leq$5 Years Tenure	46,316	37,887***	1.22
$>$5 Years Tenure	37,077	30,646**	1.21

Notes: * p$\leq$ 0.10, ** p $\leq$ 0.05, *** p $\leq$ 0.01

Table 10: Referral Model Predictions and Estimation Results

	Referral model				
Prediction	Learning	Homophily	Moral hazard	Favoritism	Data
1. Pr(hire)	$\sim$	$R > E$	$R > E$	$R > E$	$R > E$
2. Initial wages	$R > E$	$R > E$	$R < E$ or $\sim$	$\sim$	$R > E$
3. Wage gap with τ	$\searrow$	flat	$\nearrow$	flat	$\searrow$
4. Separation	$R < E$	$R < E$	$R < E$	$\sim$	$R < E$
5. Separation gap with τ	$\searrow$	flat	flat	$\sim$	flat
6. Mean productivity	$R > E$	$R > E$	$R < E$ or $\sim$	$R < E$	$R = E$
7. Wage variance	$R < E^*$ or $\sim$, gap $\searrow$ in τ	$\sim$	$\sim$, gap $\nearrow$ in τ	$\sim$	$R < E$, gap $\searrow$ in τ

R = referral-sourced candidate, E = external market-sourced candidate; * = Datcher 1983. τ = tenure.

Table 11: Linear Model of Interview and Offer Probability - With Interactions

	(1) Interview	(2) Offer	(3) Offer/Interview	(4) Interview	(5) Offer	(6) Offer/Interview
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	0000	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	-.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	0.000	0.00	0.040	0.010	0.000	0.040
Not Indicated or Other	(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
	(0.000)	(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)
Juinor 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	62,127	62,127	1811	62,127	62,127	1811

Notes: * p ≤ 0.10, ** p ≤ 0.05, *** p ≤ 0.01. P-values in parentheses. Excludes job postings w/o hires & 1 person pools. (3) & (6) include only those who were interviewed. Omitted category: Internet postings, college required, mid-level staff.

Table 12: Characteristics of Providers and Receivers of Referrals

Provider's	% Same	% Different		
Gender	63.5	36.5		
Ethnicity	71.5	28.5		
Division	73.2	26.8		
	>10 yrs. Older	Within 10 yrs.	> 10 yrs. Younger	
Age	35.8	48.1	16.1	
	% Higher	% Same	% Lower	
Staff Level	48.1	47.9	4.1	
	% More	% Same	% Less	% Unknown
Education	17.6	48.7	11.2	22.5
	Mean	Range	Standard Dev.	
Provider Tenure	3.1 years	0-11 years	2.9 years	
	Tenure 25th Pctile	Median	75th Pctile	
	1 year	2 years	4 years	

Notes: Some referrals were dropped for missing provider data. Only 10 referees are referred by two people in our sample. For multiple providers of differing characteristics, we err on the side of matching provider and referrer characteristics, older provider age, higher staff level, and higher education.

Table 13: Pooled Log Salary Regressions with Referral Matches

	(1)	(2)	(3)
Referral	0.019***	0.020***	0.000
	(0.00)	(0.00)	(0.99)
Years * Referral	-0.005	-0.011*	-0.008
	(0.15)	(0.07)	(0.18)
Years at Firm	0.059***	0.059***	0.059***
	(0.00)	(0.00)	(0.00)
Years at Firm Squared /100	-0.208***	-0.205***	-0.205***
	(0.00)	(0.00)	(0.00)
Years Squared x Referral/100	-0.058	0.061	0.016
	(0.21)	(0.55)	(0.87)
Night	-0.088***	-0.096***	-0.098***
	(0.00)	(0.00)	(0.00)
Graveyard	0.004	-0.005	-0.008
	(0.82)	(0.74)	(0.63)
Part Time	-0.013	-0.029*	-0.022
	(0.39)	(0.06)	(0.16)
On Leave	-0.007	-0.008	-0.010
	(0.54)	(0.46)	(0.39)
Support Staff	-0.889***	-0.889***	-0.890***
	(0.00)	(0.00)	(0.00)
Junior Staff	-0.451***	-0.450***	-0.450***
	(0.00)	(0.00)	(0.00)
Senior Staff	0.344***	0.343***	0.344***
	(0.00)	(0.00)	(0.00)
Executive	0.921***	0.923***	0.929***
	(0.00)	(0.00)	(0.00)
Same Gender			-0.003
			(0.70)
Same Ethnicity			0.000
			(0.99)
Older Provider			0.041***
			(0.00)
Higher Staff Level			0.048***
			(0.00)
Same Division			0.018**
			(0.01)
Provider Tenure $\leq$ Median			-0.048***
			(0.00)
Provider More Educated			-0.015*
			(0.09)
Constant	11.354***	11.357***	11.359***
	(0.00)	(0.00)	(0.00)
R-squared	0.862	0.867	0.869
Observations	12,443	11,363	11,363

Notes: * p$\leq$0.10, ** p$\leq$0.05, *** p$\leq$0.01. Controls include company divisions.

Table 14: Referral effects on promotion and separation by affinity between provider and referred

	Promotions				Separations			
	(1)		(2)		(3)		(4)	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Tenure	1.059	0.000	1.061	0.000	0.943	0.007	0.944	0.007
Starting Salary	0.991	0.000	0.991	0.000	0.996	0.179	0.996	0.186
Night Shift	0.120	0.035	0.123	0.037	0.000	0.991	0.000	0.991
Graveyard Shift	0.193	0.005	0.195	0.005	0.601	0.384	0.606	0.392
Part Time	0.556	0.098	0.553	0.095	5.395	0.000	5.359	0.000
On Leave	0.446	0.003	0.448	0.003	2.950	0.000	2.944	0.000
Support Staff	0.476	0.003	0.479	0.003	1.163	0.671	1.162	0.672
Junior Staff	1.057	0.566	1.065	0.513	1.528	0.008	1.532	0.008
Senior Staff	0.920	0.473	0.889	0.312	1.102	0.614	1.085	0.670
Executive	1.825	0.094	1.754	0.118	2.612	0.084	2.563	0.090
Post-2007	1.141	0.013	1.126	0.027	0.618	0.000	0.617	0.000
Provider Strictly Older	0.663	0.030			1.222	0.484		
Provider Same Gender	0.995	0.960			0.870	0.474		
Provider Same Ethnicity	1.219	0.049			0.865	0.433		
Provider Same Division	0.976	0.826			1.284	0.216		
Provider Tenure $\geq$ Median	0.968	0.766			0.872	0.494		
Provider Strictly More Educated	0.967	0.818			1.058	0.830		
Provider Strictly Lower Staff Level	0.075	0.010			0.473	0.299		
Provider Younger or Same Age			1.132	0.425			0.751	0.272
Provider Opposite Gender			0.983	0.878			1.112	0.617
Provider Different Ethnicity			0.814	0.104			1.098	0.682
Provider Different Division			1.001	0.996			0.741	0.208
Provider Tenure $<$ Median			0.995	0.961			1.108	0.618
Provider same or lower education			0.861	0.254			0.866	0.564
Provider Higher or Same Staff Level			1.175	0.388			1.327	0.400
Log Likelihood	-4678		-4689		-2218		-2218	
Observations	11,363		11,363		11,363		11,363	

Notes: Coefficient is the exp(coefficient). Omitted category is not referred, day shift, full time, not on leave, mid-level staff in the largest division. Controls include comapny divisions.

Table 15: Referral effects on promotion and separation by age difference between provider and referred.

	Promotions (1)		Seaprations (2)	
	Coeff.	P-value	Coeff.	P-value
Referral	1.045	0.594	0.797	0.169
Tenure	1.061	0.000	0.943	0.006
Starting Salary	0.992	0.000	0.996	0.250
Night Shift	0.121	0.035	0.000	0.991
Graveyard Shift	0.191	0.004	0.585	0.360
Part Time	0.556	0.098	5.288	0.000
On Leave	0.450	0.003	2.953	0.000
Support Staff	0.500	0.006	1.185	0.632
Junior Staff	1.085	0.394	1.541	0.007
Senior Staff	0.878	0.263	1.046	0.813
Executive	1.636	0.170	2.314	0.131
Post-2007	1.130	0.023	0.614	0.000
Older Provider*	0.690	0.056	1.377	0.293
Younger Provider*	1.093	0.457	1.324	0.209
Log Likelihood	-4689		-2219	
Observations	11,363		11,363	

	$\exp(B1+B2)$	P-value	$\exp(B1+B2)$	P-value
Test of H0: net older referral effect is zero**	0.722	0.072	1.098	0.728
Test of H0: net younger referral effect is zero**	1.142	0.163	1.055	0.749
Test of H0: net same age referral effect is zero**	1.045	0.594	0.797	0.169

Notes: * Omitted group is people within a decade of the same age of their providers.
** Comparison group is nonreferred individuals.
Coefficient is the exp(Coefficient). Omitted category is not referred, day shift, full time, not on leave, mid-level staff, in the largest division. Controls include company division.

Table 16: Referral effects on promotion and separation by staff level difference between provider and referred.

	Promotions (1)		Separations (2)	
	Coeff.	P-value	Coeff.	P-value
Referral	0.077	0.011	0.446	0.260
Tenure	1.059	0.000	0.942	0.006
Starting Salary	0.991	0.000	0.996	0.209
Night Shift	0.119	0.034	0.000	0.991
Graveyard Shift	0.196	0.005	0.589	0.366
Part Time	0.564	0.106	5.251	0.000
On Leave	0.449	0.003	2.950	0.000
Support Staff	0.474	0.003	1.166	0.664
Junior Staff	1.051	0.604	1.532	0.007
Senior Staff	0.934	0.554	1.083	0.677
Executive	1.921	0.068	2.439	0.109
Post-2007	1.140	0.015	0.617	0.000
Same or +1 Staff Level*	13.607	0.009	2.151	0.290
+2 Staff Level*	14.938	0.007	2.097	0.324
Log Likelihood	-4681		-2219	
Observations	11,363		11,363	

	$\exp(B1+B2)$	P-value	$\exp(B1+B2)$	P-value
Test of H0: net same level 1 referral effect is zero**	1.053	0.466	0.959	0.742
Test of H0: net +2 level referral effect is zero**	1.156	0.230	0.935	0.772
Test of H0: net same age referral effect is zero**	0.077	0.011	0.446	0.260

Notes: * Omitted group is people with lower staff levels.

** Comparison group is nonreferred individuals.

Coefficient is the exp(Coefficient). Omitted category is not referred, day shift, full time, not on leave, mid-level staff, in the largest division. Controls include company division.

Appendix A1: Logit Model of Interview and Offer Probability

	(1) Interview	(2) Offer	(3) Interview/Offer
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)
Log Likelihood	-7231	-2124	-917
Observations	62,127	62,127	1811

Notes: * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. P-values in parentheses. Marginal effects displayed. Excludes job postings that did not result in hires and one person pools. Specification (3) includes only those who were interviewed. Omitted category: Internet job posting, college required, mid-level staff.

Appendix A2: Logit Model of Interview and Offer Probability, With Interactions

	(1) Interview	(2) Offer	(3) Interview/Offer	(4) Interview	(5) Offer	(6) Interview/Offer
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)
Ed. missing 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)			
Ed. other * 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	9,929
	(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)
Log Likelihood	-7231	-2124	-917	-7231	-2124	-917
Observations	62,127	62,127	1811	62,127	62,127	1811

Notes: * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. P-values in parentheses. Marginal effects displayed. Excludes job postings that did not result in hires and one person pools. Specification (3) includes only those who were interviewed. Omitted category: Internet job posting, college required, mid-level staff.

Appendix A3: Probability of Providing a Referral - Logit Model

	(1) Period Referral Given	(2) Period During and After Referral
Years at Firm	-0.190***	0.067***
	(0.000)	(0.000)
Night	-	-
	-	-
Graveyard	0.725	0.27
	(0.320)	(0.529)
Part Time	-0.363	0.423
	(0.720)	(0.153)
On Leave	-0.413	0.635***
	(0.565)	(0.001)
Support Staff	-0.675	0.21
	(0.514)	(0.484)
Junior Staff	-0.016	-0.159
	(0.945)	(0.129)
Senior Staff	-0.801***	-1.045***
	(0.001)	(0.000)
Executive	-2.277***	-2.248***
	(0.001)	(0.000)
Salary in Thousands	0.018***	0.020***
	(0.000)	(0.000)
Constant	-5.359***	-4.488***
	(0.000)	(0.000)
Log Likelihood	-1004.15	-3305
Observations	12,338	12,338

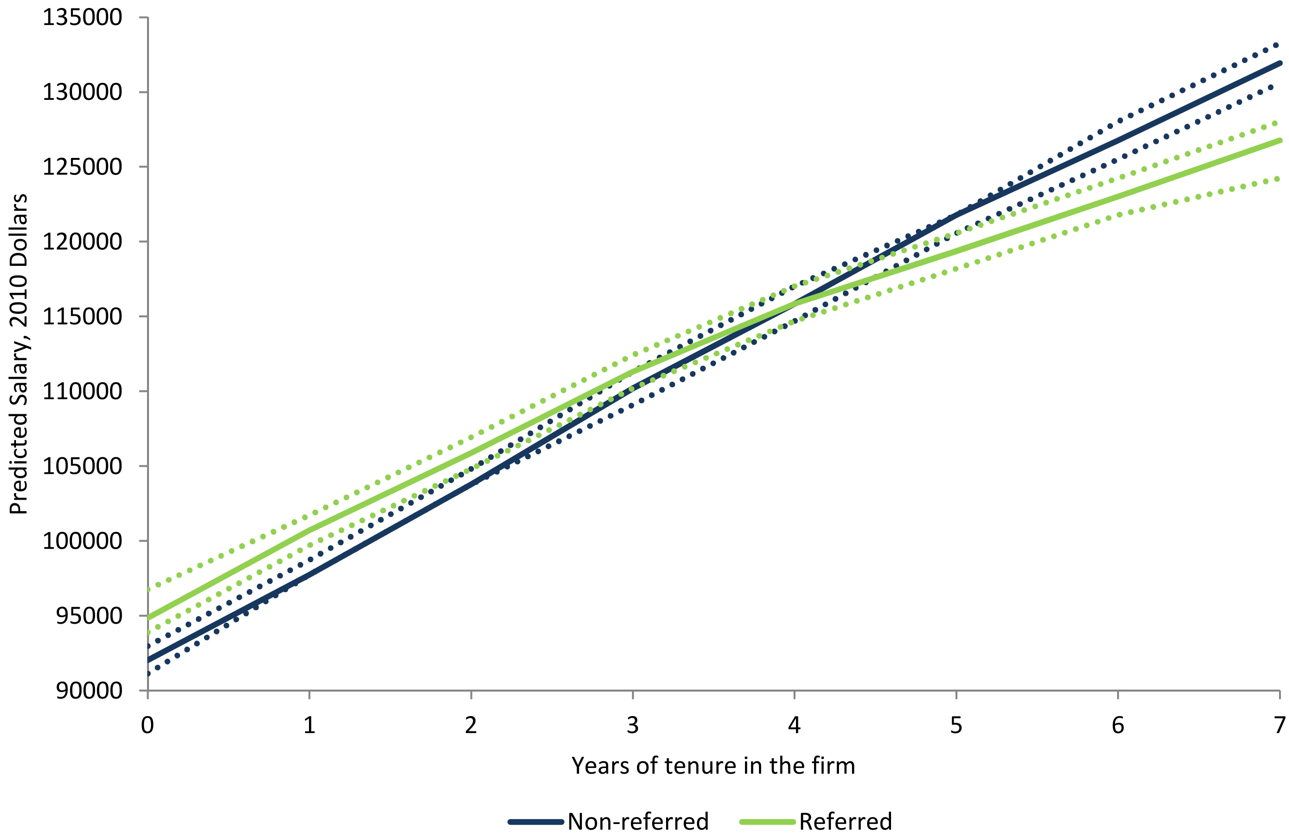
Notes: * $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. P-values in parentheses.
Omitted category: is day shift, full time, and mid-level staff.

Appendix A4: Discrete Time Proportional Hazard Model of Promotion, Adding a Referral Provider Indicator

	(1) Period of Referral		(2) Period During and After Referral	
	Coeff.	P-value	Coeff.	P-value
Gives Referral	1.46	0.02	1.60	0.00
Years at Firm	1.05	0.00	1.04	0.00
Starting Salary	0.99	0.00	0.99	0.00
Night	0.13	0.04	0.13	0.04
Graveyard	0.19	0.01	0.19	0.01
Part Time	0.58	0.11	0.57	0.10
On Leave	0.51	0.01	0.49	0.01
Support Staff	0.52	0.00	0.52	0.00
Junior Staff	1.10	0.30	1.10	0.31
Senior Staff	0.85	0.15	0.89	0.29
Executive	1.53	0.22	1.58	0.19
Post-2007	1.15	0.01	1.12	0.03
Log Likelihood	-5066		-5051	
Observations	12,388		12,388	

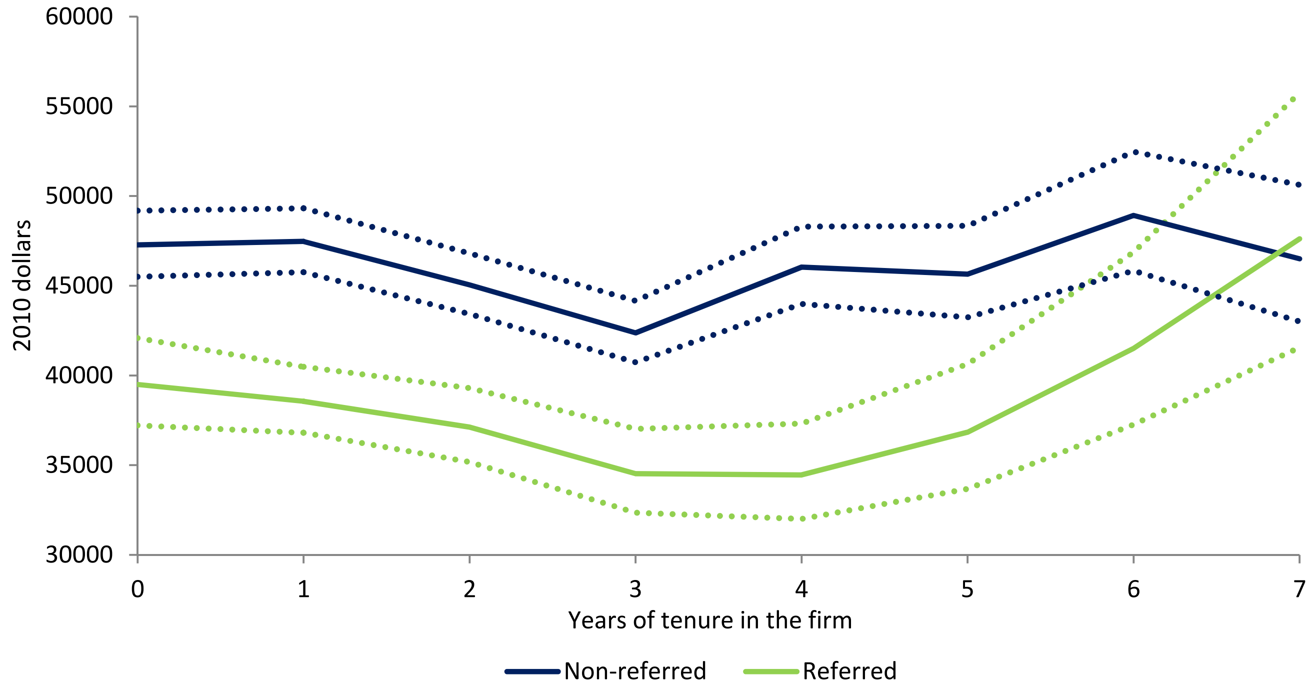
Notes: Coefficient is the exp(coefficient). Omitted category is non-provider, day shift, full time, and mid-level staff.

Figure 1: Predicted salary trajectory with and without referral



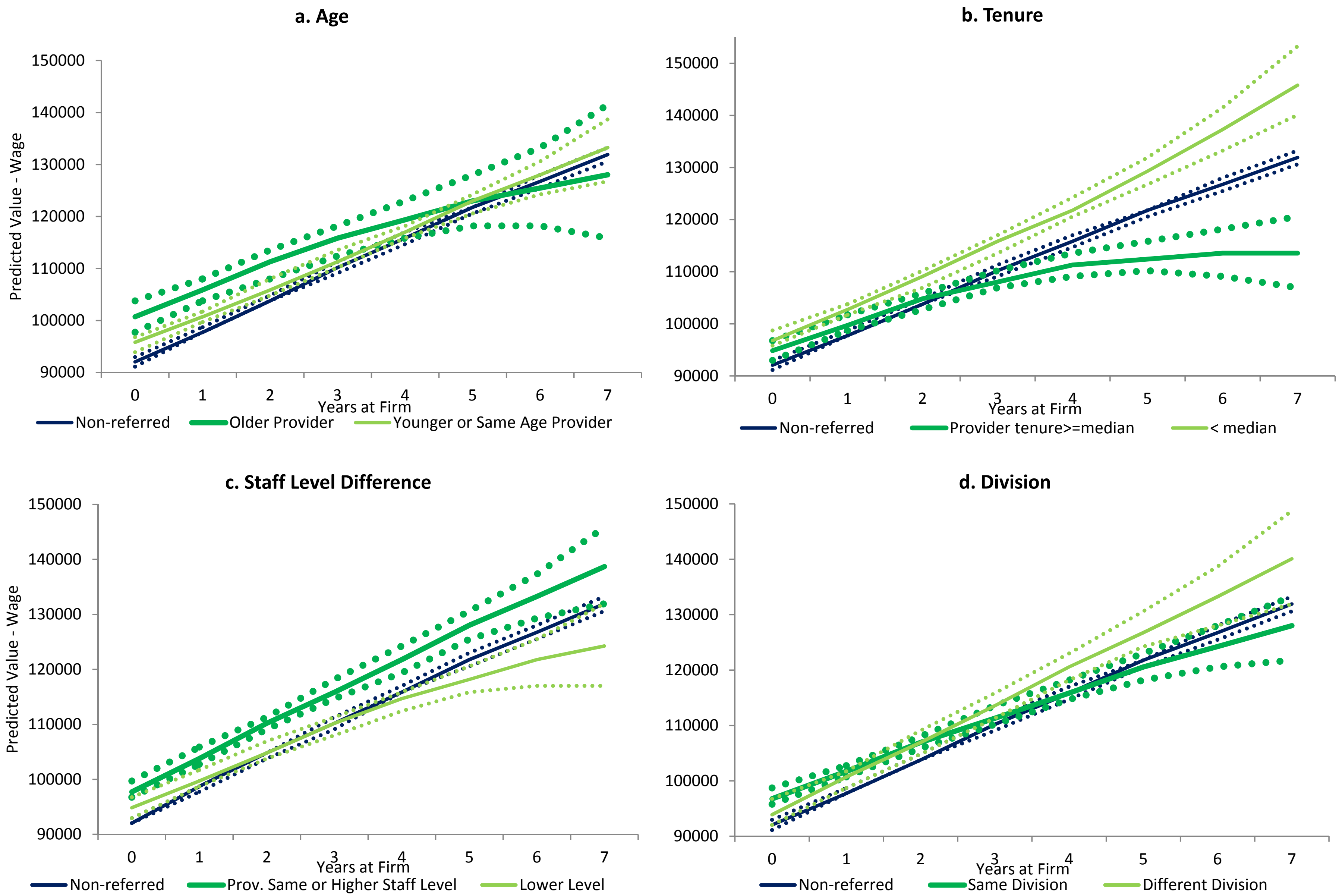
Dashed lines denote 95% confidence intervals.

Figure 2: Standard Deviation of Salary



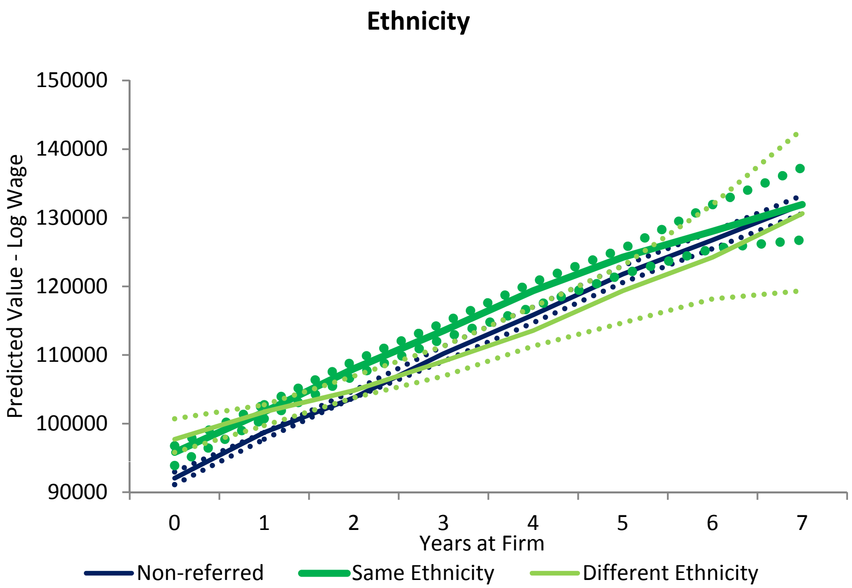
Dashed lines denote 95% confidence intervals.

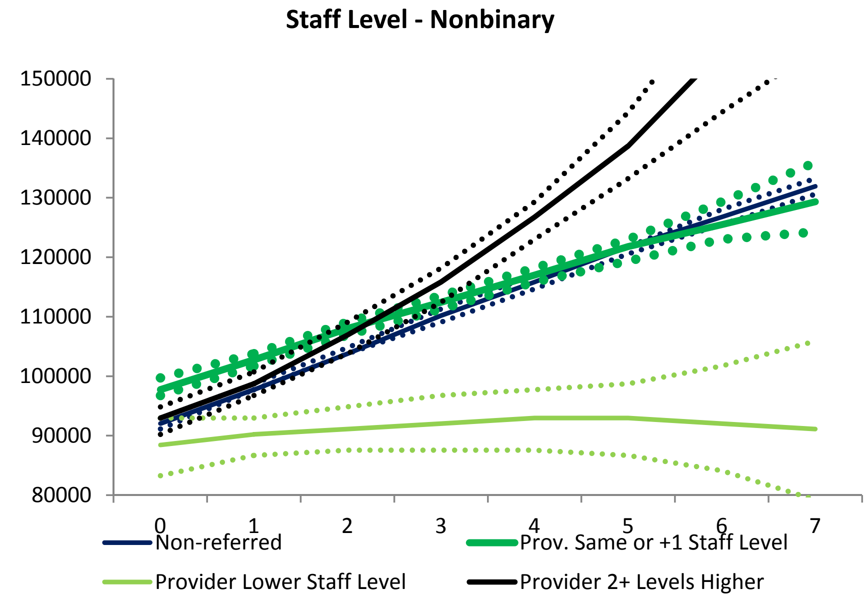
Figure 3: Predicted Salary Trajectory by Provider-Receiver Affinity



Dashed lines denote 95% confidence intervals.

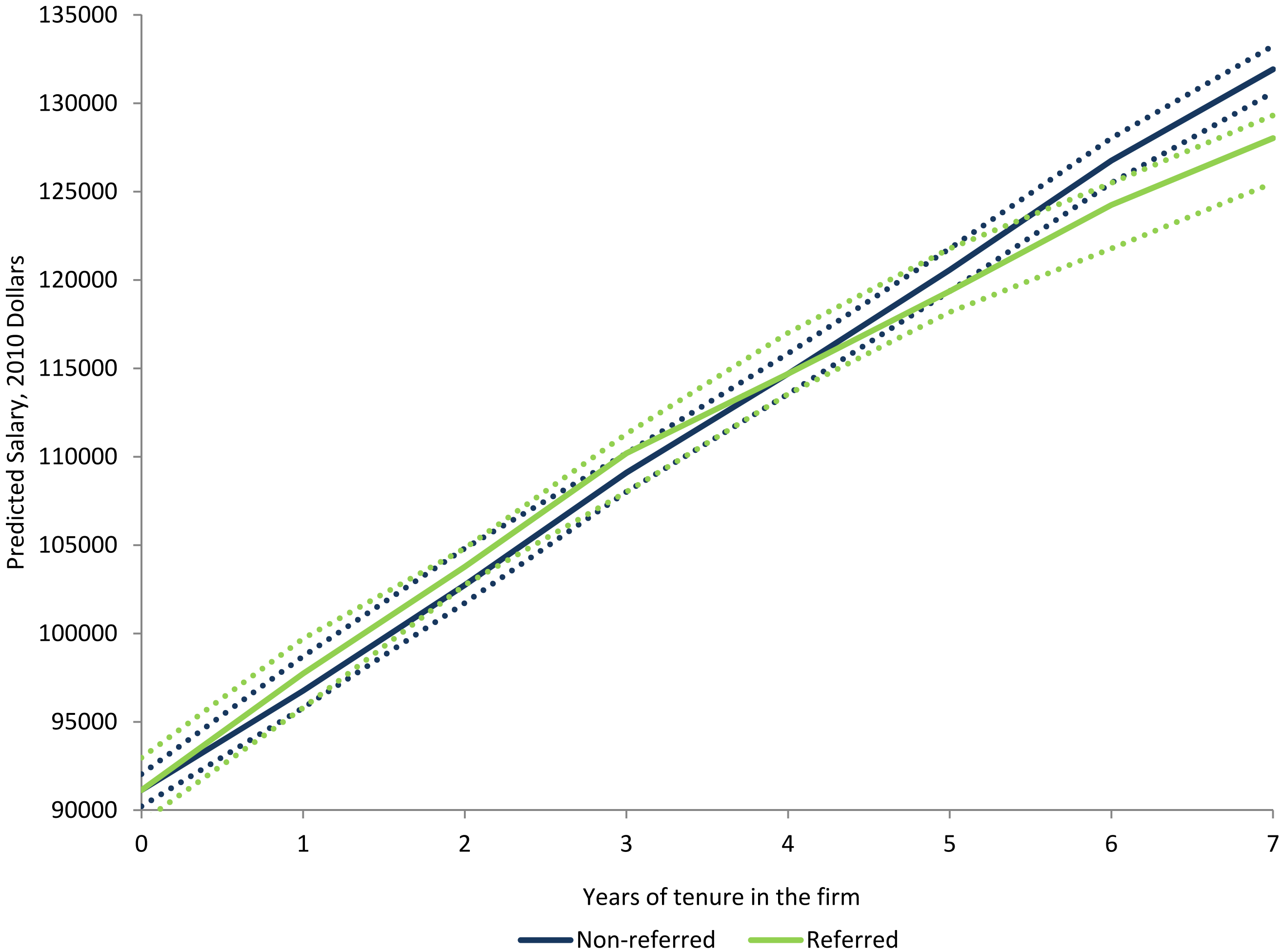
Figure 3 cont'd: Predicted Salary Trajectory by Provider-Receiver Affinity





Dashed lines denote 95% confidence intervals.

Figure A1: Predicted salary trajectory with and without referral - 5 Plus Years



Dashed lines denote 95% confidence intervals.