Referrals and Search Efficiency: Who Learns What and When?*

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Abstract

Referrals can impact employment outcomes at various stages of the hiring process. We develop a model to estimate the role of referral information on job offers, acceptances, turnover, and performance. Using rich data from a call center company, we show that referrals generate a superior pool of applicants. Performance differences between referred and non-referred employees decline with tenure, and vanish after about six months. Estimates from our multi-stage hiring model reveal that referrals induce positive sorting at the job offer stage on hard-to-observe information about performance and thus referred applicants complete much of the sorting during the hiring process.

KEYWORDS: Referrals, employer learning, learning about match quality

JEL CODE: J31, J33, M51

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1 Introduction

Referrals are a common feature of labor markets and the subject of a resurgent research agenda. Topa (2011) reports that about 70 percent of all US firms have programs to encourage hiring through referrals, while more than half of all new jobs in the US are found through informal networks. More recent research – including Brown, Setren, and Topa (2016) and Burks, Cowgill, Hoffman, and Hausman (2015) – has extensively documented the positive effects of referrals on labor market outcomes. For example referred applicants are more likely to be hired, have longer tenure, and higher starting wages compared to their non-referred counterparts. Moreover, Hansvik and Skans (2016) and Pallais and Sands (2016) have shown that decisions made within referral processes are based on information that may not be observable to employers and job applicants. There are however a number of issues related to the transmission and content of referral information, and on the job performance that remain unexplored. In particular, there has been no close examination of the effects of referral information on screening and self-selection at the job offer and job acceptance stages, respectively.

In this paper, we explicitly model the role of referrals within a multi-stage hiring process, and derive several testable implications related to the decisions made during this process. We develop an estimation framework that allows us to recover the underlying productivity distributions at each of these decision points. Thus, we are able to quantify the impact of referrals on both applicant quality and on selection at the different stages of the hiring process. We also characterize the nature and properties of the referral-induced selection during the hiring process. Moreover, we examine the relative importance of these two channels for the total effect of referrals.

Our model builds on a standard search theoretic framework. We assume that match quality (idiosyncratic productivity) between a firm and a job candidate is initially unknown, and that the meet-and-greet of recruiting and hiring potentially resolves some of this information uncertainty for one or both parties. The firm then decides whether to extend a job offer and, conditional on such an offer, the applicant decides whether to accept it. Although true match quality is revealed over the course of the employment relationship, initial beliefs about match quality, based on information signals, determine these decisions. Hence information signals exchanged during hiring are implicated in the offer, acceptance, and turnover decisions; the latter is of course also determined by on-the-job signals.

Referrals can affect the match quality of new hires in two ways. First, referred applicants may come from a pool whose distribution of productivity is stochastically superior to non-referred applicants. Second, the referral process may provide additional information to the applicant, the firm, or both about the quality of the potential match. Either party may use this information to screen and select, but this referral information may be differentially observed by each party as well as the econometrician. We derive various testable implications related to the transmission of referral information for hiring, turnover, and performance.

We test our model implications using personnel records of US customer service center employees of a large global BPO company. Our data provide a multi-stage breakdown of the hiring process, including job offer and acceptance decisions, as well as post-hire information such as termination dates, and a performance measure for those who stay long enough. The data also include standard demographic controls, information on work experience, educational attainment, cognitive and non-cognitive skills, and a set of local labor market variables for each candidate at the county and zip code level. Moreover, we have information on whether a candidate was referred by a current employee through a formal company-provided referral bonus program.

We find that for both referred and non-referred, the productivity distribution of employees who survive six months on the job is superior to that of their respective applicant pool. At the applicant stage, the referred are significantly better than the non-referred, while after six months on the job, the referred are only marginally better than the non-referred. The productivity improvements over time from the pool of applicants to the pool of employees are driven by selection, both during the hiring process and through turnover on the job. By recovering productivity at each stage (application, offer, acceptance, stay), we show that for referrals, much of the selection takes place during the hiring process, while for non-referrals, almost all of the selection takes place through turnover on the job. In particular, we find that the pre-employment selection among the referred occurs primarily at the stage of job offers, but not of acceptances. Finally, we show that this pre-employment, productivity-based selection is overwhelmingly driven by unobservable attributes, consistent with the idea that referrals provide relevant information about hard-to-observe characteristics of the potential employment relationship.[1]

Our estimates suggest that prior to employment, neither the firm nor the candidates are fully informed about their potential match quality, but that the referral process provides some of this missing information. More specifically, referrers transmit signals regarding characteristics that are match-specific, which help the firm to make job offers to applicants who eventually turn out to have high performance.[2] In contrast, whatever the information referrers may or may not have communicated to the applicants they have referred, it does not seem to induce a similar selection on unobservables at the stage of job acceptance.[3] Conversely, selectivity on unobserved dimensions for non-referred applicants happens post-hire.

The rest of the paper is organized as follows. Section 2 relates the results of our paper to the rest of the literature. Section 3 investigates the econometric implications of informative referral signals within a model of learning about match quality. Section 4 presents the data and a basic descriptive analysis. Section 5 reviews our estimation approach, while Section 6 presents our empirical results. Section 7 concludes.

[1] The information set of the econometrician (observables) includes the data contained in the online job application, which is submitted before any communication during or after the hiring process may take place. The private information and information transmitted during and after the hiring process is not available to the econometrician, and thus is called unobservable.

[2] It is possible that the employee attributes themselves are not firm-specific, but that the referred employer is in a unique position to observe them; if other employers could also view these attributes, then we would expect high performers to get poached and have higher turnover.

[3] Note however that this finding is also consistent with the story that referred candidates select into becoming applicants on the basis of referral information, and the subsequent acceptance decision is based on any additional information provided by the meet-and-greet. Since the data do not include candidates who were referred but did not apply, we cannot address this question.

2 Related Literature

Our work contributes to a large body of experimental and non-experimental literature on referrals. Recently, Burks et al. (2015) review referral practices across companies within several industries and show that referrals boost profits by cutting hiring and turnover costs. Along with Brown et al. (2016), they confirm a widely documented pattern: referred candidates are more likely to be hired, enjoy higher starting wages, and have longer tenure. Hansvik and Skans (2016) provide strong evidence, in addition to the descriptive statistics in Burks et al. (2015), that referrals have better hard-to-observe characteristics but worse observable characteristics. An earlier strand of the literature has investigated referrals from a sociological perspective, including Fernandez and Weinberg (1997), Fernandez and Castilla (2000, 2001) and Castilla (2005). In contrast, Pallais and Sands (2016) perform a set of field experiments that show that referrals contain positive information about performance that cannot be inferred from observable characteristics. Thus, they warn that screening and self-selection during the hiring process may induce selection on unobservables. The flip side of this empirical framework is that Pallais and Sands (2016) could not fully explore the associated implications for search dynamics, since by experimental design they abstract away from the actual hiring process and turnover.[4] By jointly estimating the decisions of the employer and job candidates, we contribute to the literature in several ways. We recover in a non-experimental setting the distributions of expected performance of referred and non-referred applicants. Then we track how sorting on observable and unobservable characteristics contributes to the evolution of these distributions at each stage of the hiring process and early employment. In this way, we can quantify the contribution of referrals to search efficiency.

Our paper also contributes to the literature that has directly tested predictions of models in which referrals transmit information about match quality. This research is an extension of the theoretical literature on search by experience (Jovanovic (1984)). Simon and Warner (1992)

[4] In their setting Pallais and Sands (2016) rely only on implicit incentives to motivate individuals to provide referrals, while Beaman and Magruder (2012) show that the referral of high quality performers is highly sensitive to pay incentives. Thus, the bias due to selection on unobservables may be larger when firms give an explicit bonus for successful referrals.

present an early analysis of referral networks within a search framework, while Montgomery (1991) offers an alternative but closely related analysis based on employer learning about the quality of applicants from their contacts in the firm. Among more recent contributions is Galenianos (2013, 2016), who explores the equilibrium implications of referrals when workers learn about match quality, and Munasinghe (2006), who investigates the impact of different priors on labor market outcomes. Based on firm level data, Brown et al. (2016) report a large set of findings that are consistent with various predictions generated by these models. Hansvik and Skans (2016) test the hypothesis that referrals convey information that would otherwise remain unknown to employers until after the beginning of the employment relation. Their work uses administrative data on Swedish military test scores that the econometrician observes but potential employers presumably do not. Other papers that explore testable implications of referral models using indirect proxies for referral networks include Dustmann et al. (2016), Kramarz and Skans (2014), Oyer and Schaefer (2012), and Bayer et al. (2008).[5]

Compared to the theoretical literature above and the related tests of its implications in Hansvik and Skans (2016) and Brown et al. (2016), we focus on the dynamics of the hiring process at a level of detail not yet considered. Moreover, by following the path of both observable and unobservable information through this process and beyond, we are able to identify the moments at which referral information plays a crucial role in search efficiency.

3 Model

We revisit the theoretical framework of standard models of search in the tradition of Jovanovic (1984). Our setting is very close to the one investigated in Simon and Werner (1992), Galenianos (2013), Brown, Setren, and Topa (2016), and Dustmann et al. (2016). Unlike these papers, we focus on the testable implications of referral signals for the dynamics of the hiring process and early turnover.

[5] This paper abstracts away from issues related to social networks, investigated recently in Gee et al. (2016) and Galenianos (2014) and from issues related to the formation of social networks and their equilibrium implications, central to research in the tradition of Calvo-Armengol and Jackson (2004). Still, we point out that our results are consistent with the equilibrium predictions of Galenianos (2013).

3.1 Environment

Some job candidates have a referral, $r = 1$, while others do not, $r = 0$. Production surplus depends on characteristics x, known to everyone, and firm-worker specific match quality θ, which is unknown to the firm and the candidate at the beginning of the hiring process. The firm and the individual learn about this match quality through the hiring process and post-hire performance (productivity). In addition, their beliefs are influenced by referral information that may or may not be the same for the two sides in the market. In the literature, referrals are associated with two distinct phenomena: on average referred applicants may (or may not) be of superior quality, which market participants are likely to know; and referrals may also provide informative signals about each specific potential match. We focus on the latter issue below in order to derive the testable implications of information transmission.

Match quality θ_r of both referred and non-referred candidates is drawn from a common normal distribution, $N\left(\mu, \sigma^2\right)$, which is independent of x and its true value is revealed after the candidate is hired. The model can easily be extended to incorporate differnces in the quality of referred and non-referred applicants.[6] Indeed, the specification that we take to the data allows for differences in both applicant quality and information transmission.The firm and each applicant share a common prior which lies within the distribution of θ. They learn about the specific match quality through Bayesian updating. All candidates go through the same hiring process which generates a signal that may or may not be the same for the different sides of the market. The candidate receives a signal $\theta_r + \xi_c$, where $\xi_c \sim N\left(0, \sigma^2_{\xi c}\right)$, while the firm receives a signal $\theta_r + \xi_f$, where $\xi_f \sim N\left(0, \sigma^2_{\xi f}\right)$. Referrals provide additional information to the firm and the candidate, which also may or may not be the same: the referred candidate receives a signal $\theta_1 + \zeta_c$, where $\zeta_c \sim N\left(0, \sigma^2_{\zeta c}\right)$, while the firm receives a signal $\theta_1 + \zeta_f$, where $\zeta_f \sim N\left(0, \sigma^2_{\zeta f}\right)$.

Based on the available information, the firm decides whether to make an offer or not. If the candidate obtains an offer, she decides whether to accept it or not. For simplicity, match quality becomes known after hiring, and the econometrician observes a performance signal for

[6] See Proposition 1' in Appendix A.

those who stay upon learning their true match quality:

$$y = \theta_r + f(x) + \epsilon \quad \text{for} \quad r = 0, 1$$

where ϵ and x are independent from match quality and from each other. Profits and individual utility are linear functions of output. Finally, the firm and its candidates have an outside option, normalized to zero.

We assume that the signals and match quality are normally distributed in order to simplify the exposition and preserve the closed-form formulas of the posterior beliefs. We also consider an additive technology in match quality, since this specification conforms to the statistical properties of our data. It also happens to be the most commonly used specification in the preceding empirical literature. The econometrician knows whether a candidate is referred or not, whether she receives an offer or not, whether she accepts it, if such is extended, how long she stays in the firm, and her performance, conditional on sufficiently long tenure. However, we allow for the possibility that during the hiring process, the employer and the applicant possess information about the quality of their potential employment match that remains unobserved to the econometrician.

3.2 Testable Predictions

This general environment has already generated a number of testable predictions summarized in Brown, Serten, and Topa (2015). Our key new insight is that the informational content of referrals generates strong testable predictions for the dynamics of the hiring process. Individuals and the firm update their beliefs about match quality following Bayes' rule. For non-referred candidates, the posterior belief after observing the signal from the hiring process is $N\left(\mu_{0c}, \sigma_{0c}^2\right)$, where

$$\sigma_{0c}^2 = \left(\frac{1}{\sigma^2} + \frac{1}{\sigma_{\xi c}^2}\right)^{-1} \text{ and } \mu_{0c} = \left(\frac{\mu}{\sigma^2} + \frac{\theta + \xi_c}{\sigma_{\xi c}^2}\right)\sigma_{0c}^2$$

In contrast, referred applicants have an additional signal and form posterior beliefs about the match quality $\theta_{1c} \sim N\left(\mu_{1c}, \sigma_{1c}^2\right)$, where

$$\sigma_{1c}^2 = \left(\frac{1}{\sigma^2} + \frac{1}{\sigma_{\xi c}^2} + \frac{1}{\sigma_{\zeta c}^2}\right)^{-1} \text{ and } \mu_{1c} = \left(\frac{\mu}{\sigma^2} + \frac{\theta_1 + \xi_c}{\sigma_{\xi c}^2} + \frac{\theta_1 + \zeta_c}{\sigma_{\zeta c}^2}\right)\sigma_{1c}^2$$

The posterior mean is just the weighted average of the prior and the informative signals about match quality. Since referred candidates observe strictly more informative signals, their posterior means are more strongly correlated with actual match quality than the posterior means of non-referred candidates. The variance of the posterior beliefs of referred individuals is also lower than the variance of posterior beliefs of non-referred individuals. This observation plays a crucial role in the derivation of the testable implications below. The same argument extends to the posterior beliefs of the employer, $N\left(\mu_{rf}, \sigma_{rf}^2\right)$, $r = 0, 1$. If they share the same information during the hiring process, the firm and the candidate have the same posterior beliefs, $N\left(\mu_r, \sigma_r^2\right)$, and agree on the value of employment.

Suppose that after all signals are observed the value to the firm of employing a candidate of type r is $v\left(\mu_{rf}, \sigma_{rf}^2, x\right)$. The applicant receives an offer if $v\left(\mu_{rf}, \sigma_{rf}^2, x\right) > 0$ and not otherwise. Following Jovanovic (1984), we solve for the threshold posterior mean $\underline{\mu}_{rf}$ that makes the firm indifferent between the two alternatives:

$$v\left(\underline{\mu}_{rf}, \sigma_{rf}^2, x\right) = 0 \;\Rightarrow \underline{\mu}_{rf} = \underline{\mu}_{rf}(x)$$

where σ_{rf}^2 is absorbed into the functional form of $\underline{\mu}_{rf}$, since the posterior variance does not depend on the specific signals. As the precision of beliefs increases, the option value of employment decreases which, pushes up the threshold posterior mean. As a result, when the firm has more precise posterior beliefs for referred than for non-referred candidates, $\sigma_{0f}^2 > \sigma_{1f}^2$, it requires higher posterior mean for entry from the referred than from the non-referred, $\underline{\mu}_{0f}(x) < \underline{\mu}_{1f}(x)$. In a similar way, we obtain the thresholds for the acceptance and stay decisions, $\underline{\mu}_{rc}(x)$ and $\underline{\theta}(x)$.[7] For simplicity, we maintain that candidates are 'shortsighted' in

[7] Most testable predictions in the existing literature are derived from these threshold conditions.

the sense that they do not update their beliefs after receiving an offer.

Thus, the optimal decision rules give rise to a multistage model of offer, acceptance, stay and performance for both referred and non-referred candidates, $r = 0, 1$:

$$\begin{aligned} o &= 1\left[\mu_{rf} > \underline{\mu}_{rf}(x)\right] \\ a &= 1\left[\mu_{rc} > \underline{\mu}_{rc}(x)\right] \\ s &= 1\left[\theta_r > \underline{\theta}(x)\right] \\ y &= f(x) + \theta_r + \epsilon \end{aligned}$$

where o is a binary indicator for offer, a for acceptance, s for stay, and y denotes performance. The acceptance decision is observed if $o = 1$, the stay decision is observed if $a = 1$, and performance is observed if $s = 1$. The functions $\underline{\mu}_{rk}(x)$ and $\underline{\theta}(x)$ decrease in x, $\underline{\theta}(x) > \underline{\mu}_{rk}(x)$, and $\underline{\mu}_{1k}(x) > \underline{\mu}_{0k}(x)$, where $k = f, c$ and $r = 0, 1$.

This representation of the optimal decision rules highlights how the accumulation and transmission of information introduces factors in both parties' decisions that are unobservable to the econometrician but may propagate through the successive stages of the hiring process. The fact that some observationally equivalent candidates are hired, while others are not, provides information to the econometrician about future performance, stay, and promotions, even conditional on observed characteristics. Since referred applicants have more precise beliefs about their match, their hiring has greater predictive power about stay and performance than the hiring of a non-referred candidate, even conditional on all observable characteristics. The following proposition states these observations formally.

Proposition 1 *Under the assumptions of the model, if referrals provide an informative signal about match quality, there is stronger positive dependence between offer, acceptance, stay, and* *performance for the referred than for the non-referred candidates:*

$$Corr(\mu_{1f}, \theta_1) \geq Corr(\mu_{0f}, \theta_0)$$

$$Corr(\mu_{1c}, \theta_1) \geq Corr(\mu_{0c}, \theta_0)$$

These relations hold with equality when the signal during the hiring process becomes perfectly informative, i.e. as $\sigma^2_{\xi k} \to 0$ *and* $\mu_{rk} \to \theta_r$ *for* $k = c, f$*. Also, if the hiring signals are informative,* $Corr(\mu_{0k}, \theta_0) > 0$ *for* $k = c, f$ *. When the candidate and the firm observe the same signal during the hiring process,* $Corr(\mu_{0f}, \mu_{0c}) = 1$*. When they also observe the same referral signal,* $Corr(\mu_{1c}, \mu_{1f}) = 1$*.*

This proposition incorporates several special cases of interest. Suppose that referral signals are informative but those associated with the hiring process are not, i.e. $\sigma^2_{\xi k} \to \infty$ for $k = f, c$. Then controlling for observable characteristics, offer, acceptance, and stay decisions of non-referred individuals are completely independent: entry has nothing to do with the underlying match quality on the difficult to verify or observe dimension. In contrast, the decision of a referred candidate has predictive power for the decision to stay, even after controlling for observable characteristics and the referral status. This difference in the stochastic dependence of entry and stay decisions between the referred and non-referred individuals extends to the more general case when the hiring process provides at least some information about the potential value of the employment relation. In another extreme case, when the hiring process resolves all uncertainty, $\sigma^2_{\xi} \to 0$, all candidates are hired on the basis of their true match quality. Thus, the association between the entry, stay, and performance is exactly the same for both referred and non-referred individuals.[8]

[8] In the theoretical model, we have assumed that the referred and non-referred applicants have identical initial distributions of performance and that the only differences between them are informational. Our empirical model allows for both informational differences and differences in expected performance between referred and non-referred applicants.

4 Data

Our empirical environment provides several advantages: there is a formal referral system with verifiable information, both the referred and non-referred candidates go through the same hiring process, and we capture detailed information on all candidates and on the quality of the referral relationship.

4.1 Environment and Referral Program

The data come from ten US-based call centers of a large multinational company, whose main activity is debt collection. The personnel records allow us to track hiring and employment outcomes for any individual who applied for a job at the company. The company instituted its current version of its formal referral system in August 2011. While all candidates go through the same hiring process, some of them may be referred by current employees in the company. The referrers complete a detailed form in which they indicate the name of the referred individual, the context in which they met, and the duration of their acquaintance. If a referred candidate is hired and stays for more than one year, the referrer obtains a sizable bonus: for example, when someone is hired through a referral at the lowest hierarchy level and stays for one year, the cash reward is 1000 US dollars. The bonus is higher if the referred candidate enters the company at a higher hierarchical level.

Potential employees are requested to fill in an online survey of around 50 questions on background, employment and education history, reading comprehension, math, logic, response to work situations, language, and non-cognitive skills. The individual answers are then aggregated into a score to determine whether a candidate should be rejected. Crucially, the scores remain for internal use only and are never communicated to the candidates or the newly-hired employees. Each location determines its threshold score, which fluctuates monthly, largely due to demand shocks for the services of the company. Those who pass the threshold score go through an interview. The approved candidates receive job offers, mostly within two weeks from the interview. We consider an offer to be accepted if the candidate starts working at the company. Those who accept the job offer attend a two week training program. They get introduced to the work, take some obligatory courses related to their and the company's legal obligations and rights, and pass an exam to certify that they have a good understanding of these matters. Most new employees enter the company at the bottom of the hierarchy, but some deemed to be of high quality start at higher levels. These early promotions are finalized after the completion of the training. More than 95% of all employees work full time. Each workstation consists of a computer, a telephone, and a recording device. Importantly, only one worker handles a given call and an automatic switchboard assigns inbound and outbound calls by matching the call at the top of the queue with the longest waiting operator, making the distribution of tasks effectively random across workers.

We use as our performance measure an indicator designed by the firm that aggregates productivity signals on multiple dimensions, such as total debt collection, average handling time of a call, adherence to schedule, quality of customer service, etc. Individual performance is evaluated and recorded regularly, once every three months. In our empirical work, we focus on average performance during the first six months of employment, which also coincides with the tenure horizon at which the hazard rate of quitting levels off. Performance is recorded on a scale from zero to four, where higher numbers correspond to superior outcomes and the spread of outcomes over its fine scale allows us to treat average performance as a continuous variable in the following empirical work. Thus, our measure of performance shares common features with schooling grades. It also has some major advantages including multiple observations of the performance of most individuals at a given task and a great similarity in the tasks assigned to different individuals. We take as given that the firm is using the correct formula to arrive at its indicator.

Promotions are closely related to the performance measure: those who receive 3 or more are considered for promotion to the next hierarchical level. Compensation consists largely of a base pay linked to the hierarchy level and it is relatively high for low-skilled workers and comparable to that in the manufacturing sector: workers of tenure longer than six months receive between 14 and 21 dollars per hour. Importantly, the performance measures are completely unrelated to the recruitment process or the people involved in it, and the promotion decisions are made by a committee of supervisors who are generally not involved in the interview and hiring decisions of potential subordinates.

4.2 Descriptive Analysis

We limit our analysis to the candidates and employees engaged in the main activity of the firm, debt collection. Furthermore, we restrict our attention to referrals made by regular call operators, which account for more than 92 percent of all referrals. These restrictions are imposed in order to limit concerns about favoritism and heterogeneity in tasks across the workforce. The resulting sample includes information on 145 730 candidates who have applied in the period from August 2011 to July 2013.

Table 1 reveals that at all stages of the hiring process the share of referred candidates who remain under consideration is larger than the corresponding share of non-referred candidates. Moreover, it also shows that conditional on reaching a particular stage of the hiring process, the referred candidates are more likely to proceed to the next stage than the non-referred candidates. As a result, the probability that a referred candidate starts work at the end of the hiring process is approximately 0.19 compared to 0.07 for the non-referred. The comparison between the absolute numbers is even more revealing. While the firm considers 115, 893 non-referred and only 29,837 referred applicants, it actually hires 8,906 non-referred and 5,844 referred individuals. The bottom part of Table 1 presents the stay rates for referred and non-referred workers at various tenure horizons. Its striking feature is that there appears to be little difference between the referred and non-referred individuals conditional on being hired.

At first sight, this finding seems to suggest that referrals play a role only at the hiring stage due to the successful screening practices of the firm. Yet, if referrals provide a positive signal about the quality of the potential employment relation that is otherwise difficult to observe, then non-referred candidates start with a disadvantage. Consequently, if they are to pass the hiring criteria of the firm, they would have to have an advantage on other dimensions. We explore this issue further in Table 2 which summarizes the observable characteristics of referred and non-referred individuals at different stages of the recruitment and the employment relation. The table shows that as the hiring process progresses the characteristics of the remaining non-referred candidates are superior to those of the remaining referred candidates. While the differences may not be statistically significant each time, they persist consistently across the various hiring stages and during the employment relation itself.

At each stage of the hiring process and early employment, the referred individuals are more likely to have only high school education than non-referred individuals. Similarly, non-referred candidates are more likely to have prior call center experience. We also note that the same pattern persists for general work experience. Throughout the hiring process referred individuals are also more likely to be with little or no work experience than non-referred candidates. Interestingly, referrals also allow the firm to attract candidates who live further away from the premises of the call center. Among the applicants, those with an offer, the new hires, and the stayers, the distance from home to work for the referred is about 2-3km greater than the corresponding distance for the non-referred. Finally, we note that the discrepancies between the observable qualifications of the referred and non-referred pools of hires persists during the employment relation itself.

Table 3 verifies that the key observable characteristics (education, prior work and call center experience, and commuting distance) do in fact correlate with a candidate's value: Having more than a high school degree, having some work experience, having call center experience, and having a shorter commute distance all increase the probability of both accepting an offer and of staying for both referred and non-referred workers. Still, we can see that the difference in offers, acceptance, and turnover between referred and non-referred workers remains even conditional on any single one of these characteristics. Finally, the last column of Table 3 reports average performance for workers who stay at least 6 months. Conditional on a worker surviving this weeding-out period, only low education and low experience negatively impact performance. Moreover, there is virtually no difference in the performance of the remaining referred and non-referred workers.

Together, Tables 1, 2 and 3 lead to several observations that motivate the estimation model in the following section. Clearly referrals have a major impact on the hiring process, but the differences in turnover between the referred and the non-referred after that are smaller. Crucially, the observable qualifications of the non-referred individuals are consistently superior to those of the referred. Finally, there appear to be no differences in the performance of referred and non-referred stayers in the long run. In combination, these facts suggest that referred and non-referred long-run stayers may end up with different mixes of observable and unobservable characteristics that still yield similar performance. These are the classical signs of selectivity.

5 Estimation

The testable implications that we explore relate the information set available to each party at each stage of the hiring process. The differences in the information sets of the employer, the candidates, and the econometrician may induce correlations of the error terms across the equations that represent each stage of the hiring and employment decisions and outcomes. Without controlling for the resulting selection on unobservables, single-equation methods yield biased estimates and cannot test the model predictions about these cross-equation correlations.

Consistent with the theoretical model, we maintain that the error processes for the referred and non-referred differ and that the observable characteristics have differential impact for referred and non-referred individuals. However, we do not impose additional restrictions on the model, since our primary interest lies in controlling for and quantifying the aforementioned effect of unobserved heterogeneity induced by referral-based hiring. We model the outcomes from the hiring process and the employment relationship by conditioning on information available at the time someone applies for a job at the company.[9] Let subscript i denote observations associated with candidate i. As before, subscript $r = 0, 1$ indicates whether a candidate is not referred or referred, respectively. We define X_{ir}^{k} to be a vector of characteristics observable to the econometrician that impact outcome k, where $k = o, a, s, y$

[9] In this sense, our specification follows the approach of Pakes and Ericson (1999) to identifying the presence of Bayesian learning about time-invariant productivity parameter.

stand for offer, acceptance of an offer, stay, and performance.

The following sequential choice model is taken to the data. First, the firm decides to make an offer to candidate i who is referred or not, $r = 0, 1$:

$$o_i = 1\left[F_{or}\left(X_{ir}^o\right) + \varepsilon_{ir}^o > 0\right] \tag{1}$$

If the candidate receives an offer, she chooses whether or not to accept it:

$$a_i = 1\left[F_{ar}\left(X_{ir}^a\right) + \varepsilon_{ir}^a > 0\right] \tag{2}$$

If the offer is accepted, the worker decides whether to stay at the firm sufficiently long that her performance is:

$$s_i = 1\left[F_{sr}\left(X_{ir}^s\right) + \varepsilon_{ir}^s > 0\right] \tag{3}$$

If that is the case, her performance is observed:

$$y_i = F_{yr}\left(X_{ir}^y\right) + \varepsilon_{ir}^y \tag{4}$$

Formal discussion of identification conditions can be found in Maddala (1983) and Heckman and Navarro (2007), where the emphasis is on the identification of information sets and treatment effects in the presence of dynamic selection. As usual in choice models, it is impossible to identify scale and location parameters, so the standard normalization for offer, acceptance, and stay applies: $\varepsilon_{ir}^k \sim N(0,1)$ for $k = a,\ o,\ s$. To achieve nonparametric identification, there must be at least one variable that affects offer but not the subsequent outcomes, another variable that affects acceptance but not stay and performance, and yet another that affects stay but not performance. In other words, X_{ir}^y is a strict subset of X_{ir}^s, which is a strict subset of X_{ir}^a, which is a strict subset of X_{ir}^o. We discuss our exclusion restrictions at the beginning of the next section.

Below, we present the estimation method in the context of the model of offer, acceptance, stay and performance. However, as a first step in our empirical analysis, we lump together decisions (1) and (2) into a joint entry decision:

$$e_i = 1\left[F_{er}\left(X^e_{ir}\right) + \varepsilon^e_{ir}\right] \tag{5}$$

Eventually, we test the restriction and reject it.

To estimate this multi-stage model, we use simulated maximum likelihood (SML) based on the Geweke-Hajivassiliou-Keane smooth recursive conditioning simulator. To save computing time, we generate Halton draws for the SML. Our motivation for doing so is that, as discussed in Train (2003), Halton draws provide the same accuracy with fewer draws. Let Λ be a set that contains the parameters of the model. The derivation of the loglikelihood can be found in Appendix B.

6 Results

This section presents the specification that we take to the data and its identification. By jointly estimating job offers, acceptance, stay, and performance, we characterize how referrals induce selection on unobservables. The section concludes by discussing counterfactuals that illustrate the impact of referrals on the hiring process.

6.1 Specification and Identification

We use the six month tenure horizon to define early quitters because the hazard rate of quitting levels off by the sixth month of employment, suggesting that any transitional dynamics associated with learning end by then. If employees stay for at least six months, we observe their average past performance for that period. Since compensation is tightly linked to meeting certain performance standards and job titles, we prefer to focus on the analysis of performance itself rather than its derivatives. To address possible concerns about favoritism, we exclude from the sample referrals made by someone from the management, which account for only about 8 percent of all referrals.

We also estimate the effect of both observable and unobservable characteristics separately for referred and non-referred candidates. The explanatory variables include years of past work experience and of past call center experience, educational attainment, age, race, ethnicity, gender, and distance between work and home in kilometers. In addition, we try to control extensively for differences in the local labor markets by including county and zip code level median income, shares of men and women below 25 in the labor force, shares of women and men below 25 with at least some college education, total labor force, and unemployment rate. Finally, we include the entry-level test score used by the firm to decide on interview invitations and offers, as well as the associated ranking relative to the other job candidates.

Our strategy for identification of the sequential decisions in our model is based on the nature and timing of the hiring process. The intuition for the identification of selection on unobservables is that, controlling for their characteristics, individuals who get unexpectedly hired also turn our to have (unexpectedly) high performance. The multistage choice model is identified nonparametrically through exclusion restrictions. The first exclusion restriction relates to the way the firm determines who is to be interviewed. Soon after the entry test, the employer decides who receives an invitation to an interview. This decision is based on a comparison between the score of a candidate and a historically determined threshold. The technical explanation is that the distribution of scores and the associated rankings for each wave of candidates is aggregated and becomes known to the recruiters only by the time the firm makes offer decisions or, sometimes, even post-hire. For this reason, we include in our model two variables that affect the offer decision but not the subsequent stages of the hiring process: the average test score of recently interviewed individuals in the same location in the past 90 days before the candidate applied, and the associated ranking of the candidate relative to the distribution of these past test scores.[10] Undoubtedly one's test score and ranking relative to the other current candidates affect decisions during the hiring process and

[10] In practical terms, we explore several time horizons: interviewed candidates in the preceding 30, 60, and 90 days before a specific individual applies for a job.

we include them as controls wherever necessary. Still, we believe that, once we control for their impact on the offer decision, the test scores of past interviewed candidates should have no residual effect on subsequent outcomes.[11]

The second exclusion restriction is based on the time between the date of completing the test and the date on which the offer is generated. This waiting period depends on the day of the hiring cycle on which a given candidate takes the test, and the schedule of the hiring cycle is not public. Since the average waiting time is around two weeks, the time to offer likely has an impact on extending and accepting a job offer through the likelihood that a candidate is still looking for a job, but not on the prospects of remaining employed in the firm in the long run.

To identify performance from the hiring and stay decisions, we explore the fact that the test score is used internally by the HR teams throughout the hiring process, but it is never communicated to the candidates. Obviously, the test score affects the likelihood of an interview, job offer, and possibly separation decisions in the first months of employment. At the same time, as it remains unknown to candidates and employees, the hiring test score has no residual impact on acceptance and performance once we control for the direct effect on of the variables that are its constituent elements. Finally, we also explore an argument similar to those used by Heckman and Honoré (1989) to achieve identification in the classical Roy model. Specifically, we verify empirically that local labor market conditions affect both the hiring outcomes and the stay decisions, but not performance. This fact suggests that these control variables capture in a reduced-form the alternative employment possibilities available to a particular individual without an indirect effect on performance.

[11] In our preliminary work, we did not find that the characteristics of the other employees in the company have any effect on the probability that a particular individual receives an offer, accepts it, stays long, and performs well. Consequently, we did not include them as controls. These findings conform to what we know about the operations of the company and the industry. Similarly to the rest of the industry, the biggest concern of the company is filling in its positions and reducing turnover. As a result, the entry-level questionnaire and the associated score have been primarily motivated by the need of the company to evaluate how likely a particular candidate is to remain employed for a long time. For these reasons, the firm also does not engage in relative performance evaluation in order to put pressure on low performers to quit.

6.2 Effect of Referrals on Screening and Self-Selection

6.2.1 Selection on Unobservables

The results in Table 4 show that selection on unobservables plays a crucial role during the hiring process and early employment. For both referred and non-referred employees, we find that even after controlling for observable characteristics, individuals with unexpectedly high performance are also less likely to quit in the first six months of employment. Specifically, the correlations between the errors in the stay decision and in the performance equation are highly statistically significant with point estimates of 0.87 and 0.84 for the referred and non-referred employees, respectively. These correlation coefficients are statistically different from each other at the five percent significance level according to Welch's unequal variance t-test, but economically they are very similar.

Moreover, after controlling for observable characteristics, referred individuals who are more likely to receive a job offer also turn out to have high performance. The correlation between the associated errors is statistically significant at the five percent level with a point estimate of 0.35. In contrast, we do not find such a relationship between performance and job offer decision for the subsample of non-referred employees. Formally, the correlation between the errors in the job offer and performance equations for the subsample of non-referred candidates is statistically different from its counterpart for the subsample of referred candidates. At the same time, there is no significant correlation between the errors in the acceptance equation and the errors in the performance equation for either group of applicants.

Controlling for their observable characteristics, referred individuals who receive a job offer from the firm are also more likely to stay in the firm for more than six months. We find a correlation of 0.58 between the associated errors in the job offer decision and the decision to stay. This estimate is significantly different from zero at the one percent significance level. In contrast, for non-referred individuals we do not find a significant correlation between the errors in the stay decision and the errors in the job offer or the job acceptance equation. Again, Welch's unequal variance t-test rejects the null hypothesis that the correlation coefficients between the errors in the offer and stay equations for the subsamples of referred and non-referred candidates are the same.

For all types of applicants, the unobserved component in the acceptance decision appears unrelated to stay and performance. Interestingly, the correlation between the errors in the job offer and acceptance equations is positive for all candidates but borderline statistically significant only for the non-referred. Thus, these results formally reject the hypothesis that the referred applicants and the employer make their decisions on the basis of the same information. Again, the Welch's unequal variance t-test rejects the null hypothesis that the correlation coefficients between the errors in the offer and acceptance equations for the subsamples of referred and non-referred candidates are the same.

6.2.2 Selection on Observables

The rest of the results in Table 4 reveal that having more general work experience increases the chances that a non-referred candidate receives a job offer. Such positive effects of experience are not present in the case of referred candidates. Not surprisingly, all candidates who previously worked at call centers are more likely to receive a job offer. At the same time, the marginal impact of such specific experience is much higher for non-referred candidates than referred candidates. In addition, the likelihood of getting a job offer increases monotonically with experience in the case of non-referred applicants. The results also show that educational attainment has a positive effect on the probability that both referred and non-referred applicants receive a job offer. Race and ethnic background also seem to play some role in the decision of the employer to extend job offers. The estimates show that the score on the test that candidates take online has a very strong positive effect on the probability of receiving a job offer. The magnitude of this effect does not differ significantly between referred and non-referred job candidates. With respect to the exclusion restrictions, the time between the submission of an application and the offer decision has a statistically significant negative effect on the probability of receiving an offer. Finally, an increase in the mean test score of recently interviewed job candidates has a significant but small negative effect on the probability of receiving a job offer.

With respect to offer acceptamce, the effect of observables differs slightly between the two types of applicants: unlike their non-referred counterparts, referred candidates with prior call center experience are more likely to accept an offer than referred candidates without it. Race and ethnic background continue to play a role in the decision of non-referred candidates to accept or not an offer. Again, the time between the submission of an application and the offer decision has a statistically significant but economically small negative effect for both groups on the probability of accepting an offer.

With respect to remaining in the firm beyond the first six months of employment, we find that having more general work experience increases the chances that a candidate, referred or non-referred, stays employed for a long time. Once hired, non-referred individuals with prior call center experience are more likely to quit sooner rather than later. In contrast, referred employees with prior call center experience are more, not less, likely to stay with the firm in the long run. Race and ethnic background do not affect stay. The results also show that having higher educational attainment increases the chances that both referred and non-referred workers remain employed longer. In addition, they reveal that the initial test score has a small positive and statistically significant effect on the probability that a referred worker remains employed. In contrast, the test score has again small but negative statistically significant effect on the probability that non-referred workers stay longer in the firm. These findings highlight the need for interactions between the referral indicator and observable individual characteristics, and suggest that the information contained in the referral may cause employers to interpret observable characteristics differently.

Finally, Table 4 reveals that the cumulative impact of observable characteristics during the hiring process is limited. They show that referred employees with longer work experience have higher performance. In contrast, prior work experience does not improve performance of non-referred employees. The estimates also reveal that referred women tend to have higher performance than men, but a such an effect is not present for non-referred women. Race and ethnicity appear to play no role in performance. Furthermore, educational attainment and age have a positive effect only on performance of non-referred workers. We also find that, for both referred and non-referred individuals, differences in observable characteristics explain only a small part of the variation in the performance.

6.3 Referral Quality

Our dataset contains very detailed information on how well the referrer knows the firm and how well she knows the candidate. Thus, we can evaluate how the estimates of the model for the referred candidates change as we include these controls for the quality of the referral relations. Table 5 reports the associated results for the model of offer, acceptance, stay, and performance.

We introduce as controls the referrer's job title and job tenure, which should be positively correlated with the quality of the employment relationship between the firm and the referrer. Tenure may also reflect the precision of the information about the firm that the referrer can communicate to the candidate. To control for the quality of the relationship between the candidate and the referrer, we include in our specification the time the referrer and the candidate have known each other and the context in which they formed their acquaintance. The estimates indicate that individuals referred by medium and senior level call operators are more likely to receive an offer, stay for more than six months, and perform well, but these hierarchy categories appear to have no impact on job acceptance. In contrast, job tenure of referrers has no significant effect on any of the hiring decisions, stay, or performance. With respect to the relationship between the referrer and the candidate, we find that referrals made by employees who have known the applicant for more than five years tend to be associated with superior chances of both receiving a job offer and accepting it. Interestingly, these positive and significant effects do not extend to stay and performance conditional on selection. Furthermore, referrals by a former coworker are positively related to offer, acceptance, and stay, but not performance. We do not find that close family links have any impact on recruitment and employment outcomes. These results indicate that the primary impact of a stronger referral connection is on selectivity at the stage of job application.

Moreover, the re-estimation of the model with these observable controls constitutes a test in the tradition of Altonji, Elder, and Taber (2005) for selection on unobservables that may be correlated with the already included observable characteristics. Specifically, we do not find that the introduction of the controls for referral quality significantly alters our estimates of the correlation structure between the errors in the offer, acceptance, stay, and performance equations. Similarly, there are no substantial changes in the estimated coefficients of the other observable variables. Thus, our model passes an informal specification test, in that the elimination of unobservables from one equation does not disturb the remaining model structure.

6.4 Referrals, Search Efficiency, and Counterfactuals

By jointly estimating the statistical dependencies in the offer, acceptance, and stay decisions, we are able to estimate the distributions of expected performance of referred and non-referred applicants regardless of whether they were actually hired. Such an exercise illustrates the impact of referrals on the hiring process and also allows us to separately consider the effects of observable and unobservable characteristics on performance and turnover. The results are consistent with the interpretation of referrals as signals within a model of learning about match quality. Moreover our estimation framework allows us to present various counterfactuals to isolate the two parts of the role referrals play in job matching: quality of applicants and information signals.

6.4.1 Referred vs. Non-Referred

Figure 1 plots the kernel densities of anticipated performance of referred and non-referred applicants at the following stages of the hiring and employment process: application, job offer, job acceptance, six months on the job. The corresponding means and variances can be found in Panels 1 and 2 of Table 6. Plots A.1 in Figure 1 compares the observed distributions of performance for referred and non-referred workers who remain employed for at least six months (labeled "stayers") and the corresponding distributions of performance applicants. It shows that referred applicants are of superior quality: the differences in expected performance (about a third of a standard deviation of performance) are statistically significant and economically important. Nevertheless, the hiring process and turnover act to reduce those performance differences over time. Thus, within the first six months of employment, the differences in performance vanish.

Panels A.2 and A.3 present the distributions of the component of performance associated with the observable characteristics and the component of performance associated with unobservable characteristics, i.e. the error term. The estimates show that referred applicants have superior performance relative to the non-referred applicants based on their unobservable characteristics, but that this difference disappears after six months of employment. Moreover, among both the referred and the non-referred, selection of those with high performance takes place almost entirely along the unobservable dimension: As we see in Panel A.3, according to the observable component of performance, referred applicants have nearly identical predicted performance to referred stayers, and non-referred applicants have nearly identical performance to non-referred stayers.[12]

In Panel B, we show predicted performance separately for referred and non-referred applicants at each stage of the hiring and employment process: application, job offer, job acceptance, six months on the job. Panel B.1 plots the distribution of performance of referred applicants at each of these stages. In combination with Panel B.2 (which plots the unobservable component of these items), it shows that referrals allow the employer to screen referred applicants at the job offer stage on hard-to-observe dimensions that are positively related to performance. In other words, referrals induce positive selection on unobservables and the firm makes offers to referred applicants who eventually turn out to have high performance and longer tenure. In contrast, there exists no evidence for selection on unobservables at the job acceptance stage. Panel B.1 also shows that, despite the contribution of referrals, the

[12] At first blush, the result in Panel A3 that the referred are superior along observable dimensions may appear at odds with those from Table 2 that the non-referred are superior along observable dimensions. However, these characteristics are scored differently for the two groups when estimating predicted performance, so the predicted output of a referred candidate may be higher than that of a non-referred candidate with identical characteristics.

selection on hard-to-observe dimensions that are positively related to performance still continues on the job through selective turnover. At the same time, Panel B.3 indicates that the selection on observables during the hiring process is completely orthogonal to performance: the distribution of the observable component of performance does not shift to the right during the hiring process at all. In fact, we find some statistically insignificant evidence for adverse selection on the observable component of performance.

Panels C.1-C.3 of Figure 1 reveal a completely different pattern for the sample of non-referred candidates. Panel C1 shows that while stayers have a superior distribution of performance to new hires, the distribution of performance of new hires is virtually identical to that of applicants – in other words, those offered a job and those hired are basically a random sample of the applicant pool, performance-wise. Moreover, as seen by Panels C.2 and C.3, predicted performance based on observables is the same for applicants, offers, new hires, and stayers. Thus, selective post-hire attrition of poor performers among the non-referred takes place almost entirely along unobservable dimensions.

6.4.2 Applicant Quality vs. Selection

The preceding results indicate that referrals affect employment outcomes through two different channels: the quality of the applicant pool and the effect on screening and self-selection during the hiring process due to the transmission of information. 6 reports the results from two counterfactual experiments that illustrate important features of these two channels by shutting them down one at a time and measuring the associated effects. Panel 1 shows the actual performance of non-referred employees, and the anticipated performance of non-referred applicants and hires. Panel 2 shows the same for referred hires and employees. In panels 3 and 4, we generate two types of hypothetical applicants. The first type, in Panel 3, consists of individuals whose performance is drawn from the distribution of performance of referred applicants, but who are not subject to the referral-induced selection on unobservables. The second type, in Panel 4, consists of individuals who are subject to the same selection on unobservables as referred individuals, but their performance is the same as that of non-referred applicants. The comparison between the hypothetical types and the actual referred and non-referred applicants illustrate the importance of referral-induced selection on unobservables.

Interestingly, the expected performance of workers of the first hypothetical type – applicants drawn from the referred pool, but who are not subject to the referral-induced selection on unobservables – who remain employed for at least six months is 2.82, which is significantly lower than the corresponding values for both referred and non-referred workers. The knowledge that on average they are of superior match quality makes all applicants of this hypothetical type more likely to entertain optimistic beliefs about the quality of the match with the employer than they would otherwise. A similar argument applies for the employer. In the absence of a referral-induced selection on unobservables, such optimistic beliefs make both the applicants and the employer more willing to commit to, and prolong, an employment relationship. Thus, it takes longer for poor performers of this hypothetical type to sort out of employment. Our counterfactual exercise shows that the referral-induced selection channel may be of such relative importance that shutting it down leads to an apparently paradoxical outcome: in the first months of employment, non-referred employees have observationally higher expected performance than their referred counterparts despite the fact that the latter are of superior quality.

In contrast, the second hypothetical type – applicants drawn from the non-referred pool, but with referral signals– is subject to strong selection on unobservables, leading to expected performance of 2.83 for those who receive an offer, 2.94 for those who accept a job offer, and 3.34 for those who survive at least six months in the firm. A quick comparison shows that the expected performance of this hypothetical type is highest compared to all other types after each stage of the hiring process, and even among the employees who remain employed for at least six months. Thus, in our setting the selection effect is sufficiently strong to overcome the handicap from their inferior quality.

In combination, the results in Panels 3 and 4 of Table 6 show that improved applicant quality is not sufficient to deliver the empirically documented superiority of referred individuals at each stage of the hiring process and employment. In fact, the results in Panel 4 suggest that in some cases the documented patterns may be purely driven by referral-induced selection on unobservables. Thus, the counterfactual exercise reveals that understanding the differences between hiring and employment outcomes of referred and non-referred applicants require the modeling and estimation of both referral-induced selection and initial differences in applicant quality.

7 Discussion and Conclusion

In this paper, we investigate how referral signals about difficult to observe dimensions of match quality induce statistical dependence between job offers, acceptances, early performance and stay decisions. As suggested by our model, selection on unobservables is crucial to quantifying the contribution of referral signals to search efficiency at each of the various stages of the hiring process. We find that the unexplained component of performance of referred candidates statistically dominates the unexplained component of performance of non-referred candidates. However, due to selective hiring and early turnover the differences between the distributions of the referred and non-referred virtually disappear by the sixth month of employment. The key role of referrals in the labor market is, therefore, the provision of informative signals that improve search efficiency. In particular, we find that the referral process provides informative signals to employers making job offers but not to referred applicants deciding whether to accept or reject such offers. Of course, it is possible that the referral process leads to pre-selection of candidates who apply. The point, however, is that referred employees complete much of the sorting on unobservables during the hiring process. In contrast, non-referred individuals start their employment relationship with the firm considering only observable characteristics in its selection process. In terms of external validity, the descriptive analysis and our estimates show that the patterns in our data are similar to those reported in the recent literature. Moreover, our framework for the identification of the informational content of referrals can be applied to any of the recently investigated referral settings, providing sufficient data are available.

If we consider non-referred workers as some sort of socially disadvantaged group, then our model can be interpreted as a model of statistical discrimination. Thus, we believe that our methodology can be extended to the analysis of other environments of information uncertainty, such as employer learning, communication, and statistical discrimination. In contexts such as these, market participants have to learn on-the-job about their match prospects, and typically neither share nor access the same information signals. A number of related topics are left for future research. For example, referral signals may induce selection on unobservables in social networks when the matchmakers are not current employees. The distinction between internal (current employee) and external (non-employee) referrers raises further questions about the incentives that underpin individual behavior. Most internal referral systems, like the one investigated in this paper, rely on explicit incentives in the form of fixed payments whenever the referral remains employed for a certain duration with the company. Although such an incentive structure suggests that employees might recommend as many candidates as possible, the empirical evidence, including our finding of a strong informational content of referring, points to a more nuanced set of facts. The distribution of referrals across employees seem to suggests the existence of implicit (reputational or other) costs associated with a strategy of maximizing the number of referrals. An analysis of the quality and quantity of referrals between different referrers is likely to provide further insight about true match-makers in the labor market.

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Table 1: Hiring and employment outcomes of referred and non-referred candidates.

	Referred		Non-Referred	
	Marginal	Cumulative	Marginal	Cumulative
Offered	0.319	0.319	0.136	0.136
	(0.47)	(0.47)	(0.34)	(0.34)
Accepted	0.614	0.196	0.566	0.077
	(0.49)	(0.40)	(0.50)	(0.27)
Stay $>$ 6 mo.	0.400	0.078	0.389	0.030
	(0.49)	(0.27)	(0.49)	(0.17)
Obs.	29837		115893	

Note: The table reports the fraction of initial candidates who reach successive stages of the hiring process and proportion of hired workers who remain in the firm for at least 6 mo. Standard deviations are reported in parentheses.

Table 2: Observable characteristics of referred and non-referred candidates

Variable	Candidates		Offered		Accepted		Stay > 180 days	
	R	NR	R	NR	R	NR	R	NR
HSD only	0.468	0.453	0.388	0.339	0.392	0.346	0.371	0.335
	(0.50)	(0.50)	(0.49)	(0.47)	(0.49)	(0.48)	(0.48)	(0.47)
Distance	25.552	24.959	24.568	22.914	23.925	21.937	24.288	22.009
	(24.38)	(26.03)	(21.30)	(21.52)	(19.81)	(19.91)	(20.40)	(21.04)
Call exp.	0.562	0.592	0.584	0.627	0.570	0.602	0.560	0.583
	(0.50)	(0.49)	(0.49)	(0.48)	(0.50)	(0.49)	(0.50)	(0.49)
Low exp.	0.155	0.152	0.145	0.120	0.150	0.128	0.139	0.129
	(0.36)	(0.36)	(0.35)	(0.32)	(0.36)	(0.33)	(0.35)	(0.33)
Exp. > 5 yr.	0.558	0.559	0.530	0.572	0.515	0.551	0.538	0.550
	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)
Black	0.518	0.563	0.464	0.503	0.498	0.530	0.512	0.543
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Hispanic	0.099	0.082	0.127	0.121	0.121	0.127	0.121	0.137
	(0.30)	(0.27)	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)	(0.34)
Female	0.661	0.700	0.636	0.667	0.648	0.679	0.669	0.682
	(0.47)	(0.46)	(0.48)	(0.47)	(0.48)	(0.47)	(0.47)	(0.47)
Observations	29837	115893	9510	15728	5844	8906	2339	3464

Note: The table reports observable characteristics of referred (R) and non-referred individuals (NR) at each stage of the hiring process and during the first months of employment, includind indicators for having only a high school diploma (HSD only), prior experience as call center operator (call exp.), no or little work experience (low exp.), work experience of more than 5 years (exp.>5y), gender, race, ethnicity, and distance from home to work in kilometers (distance), The sample includes data on individuals who have been hired at least one year before the last date for which data are available. Standard deviations are reported in parentheses.

Table 3: Hiring and employment outcomes, conditional on observable characteristics.

Variable	Status	Offered	Accepted	Stay>0.5mo.	Stay>3mo.	Stay>6mo.	Avg. Perf.
HSD only =1	R	0.27	0.17	0.87	0.56	0.38	2.86
		(0.44)	(0.38)	(0.33)	(0.50)	(0.48)	(0.78)
	NR	0.10	0.06	0.87	0.56	0.37	2.99
		(0.31)	(0.24)	(0.34)	(0.50)	(0.48)	(0.76)
HSD only =0	R	0.37	0.23	0.90	0.58	0.41	3.02
		(0.48)	(0.42)	(0.31)	(0.49)	(0.49)	(0.78)
	NR	0.17	0.10	0.89	0.57	0.39	3.04
		(0.37)	(0.30)	(0.32)	(0.49)	(0.49)	(0.78)
Low exp. =0	R	0.33	0.21	0.89	0.58	0.40	3.02
		(0.47)	(0.40)	(0.32)	(0.49)	(0.49)	(0.78)
	NR	0.14	0.08	0.88	0.57	0.39	3.02
		(0.35)	(0.28)	(0.33)	(0.50)	(0.49)	(0.78)
Low exp. =1	R	0.31	0.20	0.89	0.54	0.37	2.93
		(0.46)	(0.40)	(0.32)	(0.50)	(0.48)	(0.79)
	NR	0.11	0.07	0.90	0.57	0.39	3.04
		(0.31)	(0.25)	(0.30)	(0.49)	(0.49)	(0.75)
Exp.<5yr.	R	0.32	0.21	0.89	0.58	0.40	3.03
		(0.47)	(0.40)	(0.31)	(0.49)	(0.49)	(0.77)
	NR	0.14	0.08	0.88	0.58	0.39	3.05
		(0.34)	(0.27)	(0.32)	(0.49)	(0.49)	(0.77)
Exp≥5yr.	R	0.33	0.20	0.88	0.55	0.40	2.87
		(0.47	(0.40)	(0.33)	(0.50)	(0.49)	(0.82)
	NR	0.15	0.08	0.86	0.52	0.35	2.88
		(0.36)	(0.28)	(0.35)	(0.50)	(0.48)	(0.77)
Call exp. =0	R	0.32	0.20	0.88	0.57	0.39	3.02
		(0.47)	(0.40)	(0.32)	(0.50)	(0.49)	(0.77)
	NR	0.14	0.08	0.88	0.58	0.39	3.04
		(0.34)	(0.27)	(0.32)	(0.49)	(0.49)	(0.77)
Call exp. =1	R	0.38	0.23	0.91	0.63	0.49	2.89
		(0.48)	(0.42)	(0.28)	(0.48)	(0.50)	(0.82)
	NR	0.16	0.08	0.85	0.52	0.35	2.90
		(0.37)	(0.28)	(0.36)	(0.50)	(0.48)	(0.79)
Distance<4km	R	0.32	0.21	0.90	0.60	0.41	2.97
		(0.46)	(0.41)	(0.30	(0.49)	(0.49)	(0.74)
	NR	0.15	0.09	0.89	0.59	0.41	3.04
		(0.36)	(0.29)	(0.31)	(0.49)	(0.49)	(0.77)
Distance≥4km	R	0.33	0.20	0.88	0.56	0.39	3.02
		(0.47)	(0.40)	(0.32)	(0.50)	(0.49)	(0.79)
	NR	0.13	0.08	0.87	0.56	0.37	3.01
		(0.34)	(0.27)	(0.33)	(0.50)	(0.48)	(0.78)

The table reports outcomes during the hirng process, stay, and performance, conditional on observable characteristics. Average performance in the first six months of employment is defined for employees who remain in the firm for at least six months. Standard deviations are reported in parentheses.

Table 4: Estimates of Model of Offer, Acceptance, Stay and Performance

Variables	Referred				Non-Referred			
	Offer	Accept	Stay	Perf.	Offer	Accept	Stay	Perf.
	dy/dx	dy/dx	dy/dx	Coef.	dy/dx	dy/dx	dy/dx	dy/dx
Call exp.>0	0.022**	-0.025	-0.046*	-0.027	-0.003	-0.006	-0.018	0.000
	(0.008)	(0.014)	(0.023)	(0.059)	(0.003)	(0.012)	(0.016)	(0.050)
2yr<Call exp.<5yr	0.001	0.034*	0.026	-0.007	0.010**	-0.007	-0.007	-0.068
	(0.009)	(0.015)	(0.029)	(0.065)	(0.003)	(0.012)	(0.016)	(0.054)
Call exp. >5yr.	0.063**	0.041*	0.173**	0.145	0.022**	-0.010	-0.008	-0.073
	(0.012)	(0.021)	(0.044)	(0.092)	(0.004)	(0.016)	(0.023)	(0.076)
2yr.<Exp.<5yr.	0.020**	0.007	0.031	0.142*	0.006	-0.002	0.000	0.058
	(0.009)	(0.017)	(0.023)	(0.067)	(0.004)	(0.014)	(0.018)	(0.059)
5yr.<Exp.<10yr.	0.002	-0.016	0.040	0.174*	0.019**	-0.032*	0.018	0.081
	(0.011)	(0.019)	(0.026)	(0.076)	(0.004)	(0.016)	(0.023)	(0.068)
10yr.<Exp.<15yr.	0.016	0.002	0.088*	0.224*	0.020**	-0.010	0.037	0.110
	(0.014)	(0.025)	(0.034)	(0.103)	(0.006)	(0.021)	(0.029)	(0.093)
Black	-0.002	0.017	0.025	-0.092	0.013**	0.041**	0.011	-0.058
	(0.007)	(0.012)	(0.018)	(0.050)	(0.003)	(0.010)	(0.024)	(0.047)
Hispanic	0.074**	-0.007	0.038	-0.025	0.032**	0.054**	0.038	0.031
	(0.010)	(0.017)	(0.026)	(0.075)	(0.004)	(0.014)	(0.033)	(0.065)
Female	-0.003	0.005	0.040**	0.130**	0.005*	0.012	-0.009	0.039
	(0.006)	(0.011)	(0.014)	(0.044)	(0.002)	(0.009)	(0.013)	(0.039)
Age	0.000	-0.003*	0.003	0.013	0.000	-0.006**	0.005	0.014*
	(0.001)	(0.001)	(0.003)	(0.008)	(0.000)	(0.001)	(0.003)	(0.007)
HSD only	-0.021**	-0.011	-0.054**	-0.059	-0.018**	-0.003	-0.025*	-0.119**
	(0.006)	(0.011)	(0.018)	(0.046)	(0.002)	(0.009)	(0.013)	(0.040)
Score	0.022**		0.009**		0.019**		-0.004*	
	(0.002)		(0.004)		(0.001)		(0.002)	
Time to offer	-0.004**	-0.001*			-0.002**	-0.001*		
	(0.001)	(0.000)			(0.000)	(0.00)		
Intw. rank, past 90d.	-0.013				0.000			
	(0.013)				(0.005)			
$\overline{\text{Score}}$, past 90d.	-0.006**				-0.002*			
	(0.002)				(0.001)			
Error Correlations:	Referred				Non-Referred			
		ϵ_s	ϵ_a	ϵ_o		ϵ_s	ϵ_a	ϵ_o
ϵ_y		0.843**	0.100	0.345*		0.873**	-0.138	-0.010
		(0.034)	(0.268)	(0.155)		(0.021)	(0.235)	(0.105)
ϵ_s			0.133	0.577*			-0.211	0.028
			(1.105)	(0.252)			(0.770)	(0.172)
ϵ_a				0.253				0.261*
				(0.176)				(0.118)

Note: The controls include the associated score rank, location and month dummies, age^2, county/zip code median income, shares of men and women below 25 in labor force, shares of college-educated men and women below 25, labor force, and unemployment. The offer equation includes the rank relative to past interviewed candidates (interview rank) and past average score ($\overline{\text{Score}}$). Stars denote stat. significance (*=5%, **=1%). Obs., r=1: 21693. Obs., r=0: 84829. Avg. marginal effects: dy/dx. Std. err. in parentheses.

Table 5: Estimates of Model with Referral Quality of Offer, Acceptance, Stay and Performance

Variables	Referred			
	Offer	Acceptance	Stay	Perf.
	dy/dx	dy/dx	dy/dx	dy/dx
Call exp.>0	0.020**	-0.023	-0.036	-0.034
	(0.008)	(0.014)	(0.022)	(0.059)
2yr.<Call exp.<5yr.	-0.004	0.035*	0.003	-0.023
	(0.009)	(0.015)	(0.028)	(0.065)
Call exp. >5yr.	0.050**	0.041*	0.133**	0.113
	(0.012)	(0.021)	(0.041)	(0.091)
2yr.<Exp.<5yr.	0.020**	0.008	0.026	0.141*
	(0.009)	(0.017)	(0.023)	(0.066)
5yr.<Exp.<10yr.	-0.004	-0.014	0.044	0.165*
	(0.011)	(0.019)	(0.026)	(0.076)
10yr.<Exp.<15yr.	0.008	0.004	0.081*	0.207*
	(0.014)	(0.025)	(0.034)	(0.103)
Female	-0.002	0.005	0.038*	0.131**
	(0.006)	(0.011)	(0.014)	(0.044)
HSD only	-0.025**	-0.010	-0.049**	-0.060
	(0.006)	(0.011)	(0.018)	(0.047)
Referral by coworker	0.043*	0.059*	0.112*	0.112
	(0.016)	(0.029)	(0.051)	(0.102)
Referred known >5yr.	0.064**	0.051*	0.054	-0.027
	(0.010)	(0.018)	(0.042)	(0.070)
Job title of referrer: low	-0.091**	0.023	-0.054*	-0.130
	(0.010)	(0.016)	(0.025)	(0.072)
Score	0.023**		0.008*	
	(0.002)		(0.005)	
Time to offer	-0.004**	-0.001*		
	(0.001)	(0.000)		
$\overline{\text{Score}}$, past 90d.	-0.006**			
	(0.002)			
Error Correlations:	Referred			
		ϵ_s	ϵ_a	ϵ_o
ϵ_y		0.841**	0.098	0.331**
		(0.035)	(0.264)	(0.158)
ϵ_s			0.156	0.475
			(0.816)	(0.251)
ϵ_a				0.260
				(0.186)

Note: The controls include the associated score rank, location and month dummies, age^2, county/zip code median income, shares of men and women below 25 in labor force, shares of college-educated men and women below 25, labor force, and unemployment. The offer equation includes the rank relative to past interviewed candidates (interview rank) and past average score ($\overline{\text{Score}}$). Stars denote stat. significance (*=5%, **=1%). Obs., r=1: 21693. Average marginal effects: dy/dx. Std. err. in parentheses.

Table 6: Counterfactuals

	Performance											
	(1) NR quality, NR selection			(2) R quality, R selection			(3) R quality, NR selection			(4) NR quality, R selection		
	Total	Obs.	Unobs.	Total	Obs.	Unobs.	Total	Obs.	Unobs.	Total	Obs.	Unobs.
Applicants	2.131	2.137	-0.006	2.472**	2.274**	0.198**	2.472**	2.274**	0.198**	2.131	2.137	-0.006
	(1.188)	(0.045)	(1.145)	(1.084)	(0.064)	(1.022)	(1.084)	(0.064)	(1.022)	(1.188)	(0.045)	(1.145)
Offers	2.091	2.107	-0.014	2.688**	2.211**	0.478**	2.463**	2.208*	0.255**	2.831**	2.100	0.731**
	(1.162)	(0.042)	(1.130)	(1.115)	(0.059)	(1.032)	(1.084)	(0.059)	(1.024)	(0.980)	(0.045)	(0.929)
Accepts	2.017	2.112	-0.094	2.752**	2.215**	0.537**	2.258**	2.205*	0.053**	2.938**	2.115	0.825**
	(1.153)	(0.042)	(1.119)	(1.092)	(0.058)	(1.016)	(1.049)	(0.060)	(0.960)	(0.980)	(0.047)	(0.925)
Stay>6mo.	3.069	2.128	0.942	3.231**	2.246**	0.985	2.824**	2.235*	0.589**	3.344**	2.136	1.204**
	(1.179)	(0.042)	(1.199)	(1.067)	(0.055)	(1.071)	(0.794)	(0.058)	(0.774)	(0.781)	(0.040)	(0.743)

Note: This table presents the expected performance and the variance (in parentheses) after each stage of the hiring process and after 6 months of employment for four types of applicants. The first two types correspond to the observed referred (R) and non-referred (NR) applicants. Type (3) applicants are of the same quality as referred applicants, but they are not subject to selection on unobservables as the referred during the hiring process. Type (4) applicants are of the same quality as non-referred applicants, but they are subject to the referred's selection on unobservables. Stayers are workers who remain employed for at least six months. Stars indicate statistically significant difference from the corresponding statistic for the nonreferred individuals (1).

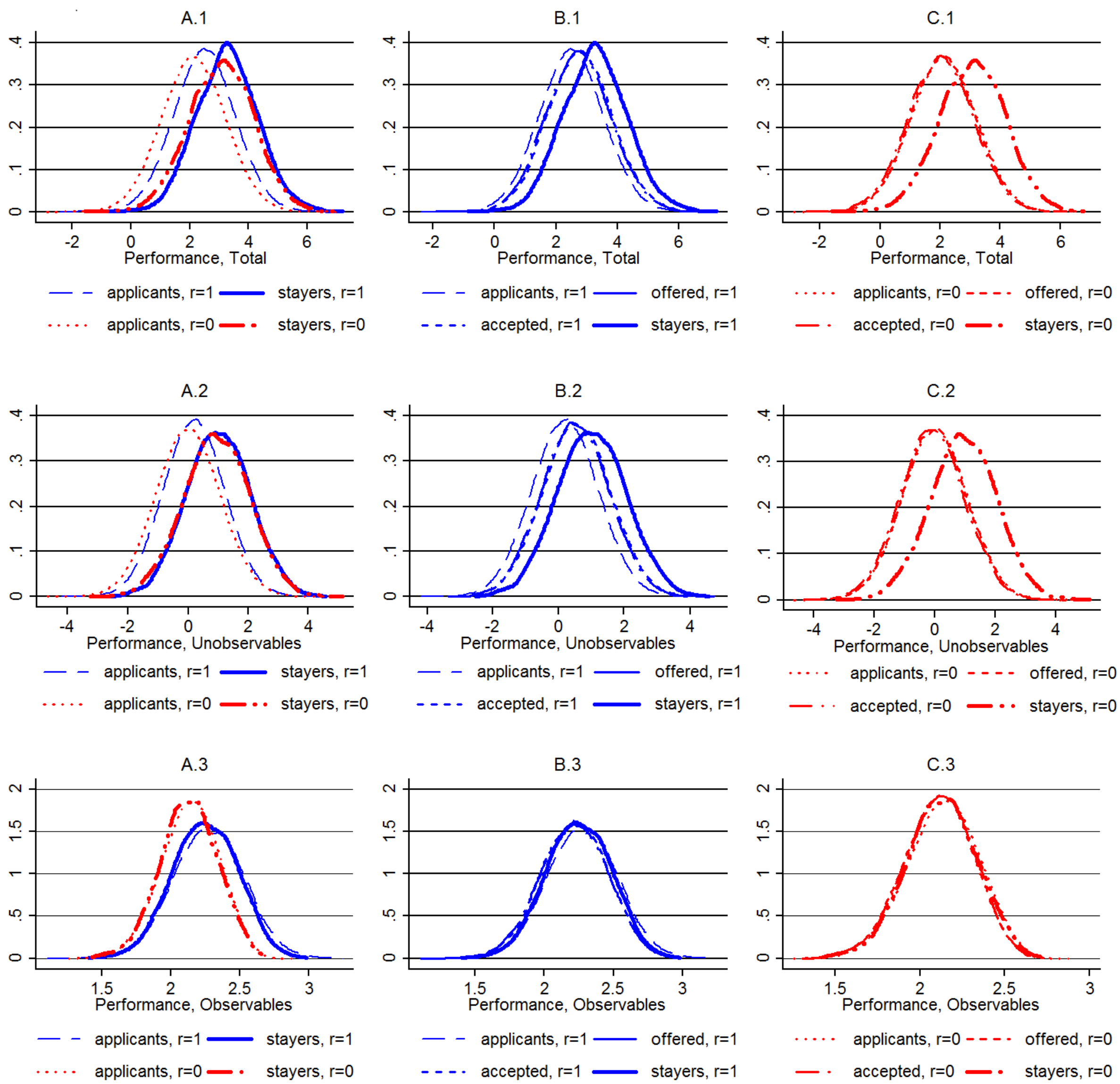

Figure 1: Dynamic selection of referred and non-referred applicants during the hiring process. The figure plots the the kernel densities associated with expected performance of referred and non-referred individuals before recruitment, after offers, after acceptances, and after six months of employment. It also presents the decomposition of expected performance into components that can be attributed to observable and unobservable characteristics (error term). Stayers are defined as workers who remain employed for more than six months.

8 Appendix A

Proof of Proposition 1: Observe that for $\sigma^2_{k\xi}$, σ^2_{ε} finite, where $k = f, c$,

$$\mu_{1k} = \frac{\sigma^2\left(\sigma^2_{\xi k} + \sigma^2_{\varepsilon}\right)}{\sigma^2_{\xi k}\sigma^2_{\varepsilon} + \sigma^2\left(\sigma^2_{\xi k} + \sigma^2_{\varepsilon}\right)}\theta_1 + \lambda_{1k} \quad \text{and} \quad \mu_{0k} = \frac{\sigma^2}{\left(\sigma^2_{\xi k} + \sigma^2\right)}\theta_0 + \lambda_{0k}$$

where λ_{0k} and λ_{1k} contain the remaining terms in the posterior means. Note that

$$\frac{\sigma^2\left(\sigma^2_{\xi k} + \sigma^2_{\varepsilon}\right)}{\sigma^2_{\xi k}\sigma^2_{\varepsilon} + \sigma^2\left(\sigma^2_{\xi k} + \sigma^2_{\varepsilon}\right)} = \frac{\sigma^2\left(\frac{\sigma^2_{\varepsilon}}{\sigma^2_{\xi k}} + 1\right)}{\sigma^2_{\varepsilon} + \sigma^2\left(\frac{\sigma^2_{\varepsilon}}{\sigma^2_{\xi k}} + 1\right)}$$

Since $\left(\frac{\sigma^2_{\varepsilon}}{\sigma^2_{\xi k}} + 1\right) > 1$, it follows that $Corr\left(\mu_{1k}, \theta_1\right) \geq Corr\left(\mu_{0k}, \theta_0\right)$. Also, if $\frac{\sigma^2}{\left(\sigma^2_{\xi k} + \sigma^2\right)} > 0$, $Corr\left(\mu_{0k}, \theta_0\right) > 0$ Note that in the limit,

$$Lim_{\sigma^2_{\xi} \to \infty}\frac{\sigma^2\left(\sigma^2_{\xi k} + \sigma^2_{\varepsilon}\right)}{\sigma^2_{\xi k}\sigma^2_{\varepsilon} + \sigma^2\left(\sigma^2_{\xi k} + \sigma^2_{\varepsilon}\right)} = \frac{\sigma^2}{\sigma^2_{\xi k} + \sigma^2} > 0 \text{ and } Lim_{\sigma^2_{\xi k} \to \infty}\frac{\sigma^2}{\sigma^2_{\xi k} + \sigma^2} = 0$$

while

$$Lim_{\sigma^2_{\xi} \to 0}\frac{\sigma^2\left(\sigma^2_{\xi k} + \sigma^2_{\varepsilon}\right)}{\sigma^2_{\xi k}\sigma^2_{\varepsilon} + \sigma^2\left(\sigma^2_{\xi k} + \sigma^2_{\varepsilon}\right)} = 1 \text{ and } Lim_{\sigma^2_{\xi k} \to 0}\frac{\sigma^2}{\left(\sigma^2_{\xi k} + \sigma^2\right)} = 1$$

which implies the limit results. ■

Assume that the original assumptions holds, except that θ_0 is drawn from $N\left(\mu, \sigma^2\right)$, while θ_1 is drawn from $N\left(\mu_*, \sigma^2\right)$, where $\mu_* > \mu$. This assumption ensures that referred candidates come from a stochastically dominant distribution of match quality.[13] Proposition **??** obviously survives.

Proposition 1' *Under the modified assumptions,the differences in performance of referred and non-referred employees who stay employed long enough to learn their true match quality are smaller than the differences in performance of referred and non-referred candidates:*

$$E\left(y|x, \theta_1 > \underline{\theta}(x)\right) - E\left(y|x, \theta_0 > \underline{\theta}(x)\right) < E\left(y|x\right) - E\left(y|x\right)$$

[13] Normal distributions with difference variances cannot be ordered in the sense of first-oder stochastic dominance. The theoretical results can be generalized by assuming that referred applicants are drawn from a distribution of performance that stochastically dominates its counterpart for non-referred applicants.

Proof of Proposition 1': Note that

$$\begin{aligned}
&E\left(y|x,\theta_1>\underline{\theta}\left(x\right)\right)-E\left(y|x,\theta_0>\underline{\theta}\left(x\right)\right) \\
&=\mu_*-\mu+\sigma\left(\frac{\phi\left(\frac{\underline{\theta}(x)-\mu_*}{\sigma}\right)}{\Phi\left(\frac{\underline{\theta}(x)-\mu_*}{\sigma}\right)}-\frac{\phi\left(\frac{\underline{\theta}(x)-\mu}{\sigma}\right)}{\Phi\left(\frac{\underline{\theta}(x)-\mu}{\sigma}\right)}\right) \\
&\leq \mu_*-\mu
\end{aligned}$$

since the inverse Mill's ratio is an increasing function. If not controlled for, this selection leads to biased estimates of the effect of referrals on entry, turnover, performance, and promotions because

$$E\left(\theta_r|\mu_r>\underline{\mu}_r\left(x\right)\right)>E\left(\theta_r\right)$$

Moreover, without explicitly controlling for the dependence induced by referrals, one cannot identify underlying differences in the quality of referred and non-referred individuals from the effects of referrals on sorting during the hiring process.■

9 Appendix B

Following Maddala (1983), the conditional likelihood for individual i with observed characteristics X_i is:

$$l_i\left(\Lambda|X_i,o_i,a_i,s_i,y_i\right)=P\left(o_i|X_{ir}^o\right)P\left(a_i|o_i,X_{ir}^a\right)P\left(s_i|a_i,o_i,X_{ir}^s\right)\left[\varphi_{y|o,a,s}\left(\frac{y_i-F_{yr}\left(X_{ir}^y\right)}{\sigma}\right)\right]^{o_ia_is_i}$$

where

$$\begin{aligned}
P\left(o_i|X_{ir}^o\right)&=\Phi_o\left(F_{or}\left(X_{ir}^o\right)\right)^{o_i}\left(1-\Phi_o\left(F_{or}\left(X_{ir}^o\right)\right)\right)^{1-o_i} \\
P\left(a_i|o_i,X_{ir}^a\right)&=\left[\Phi_{a|o}\left(F_{ar}\left(X_{ir}^a\right)\right)^{a_i}\left(1-\Phi_{a|o}\left(F_{ar}\left(X_{ir}^a\right)\right)\right)^{1-a_{ir}}\right]^{o_i} \\
P\left(s_i|a_i,o_i,X_{ir}^s\right)&=\left[\Phi_{s|o,a}\left(F_{sr}\left(X_{ir}^s\right)\right)^{s_i}\left(1-\Phi_{s|o,a}\left(F_{sr}\left(X_{ir}^s\right)\right)\right)^{1-s_{ir}}\right]^{o_ia_i}
\end{aligned}$$

where $\Phi_o\left(F_{or}\left(X_{ir}^o\right)\right)$ is the normal CDF , $\Phi_{a|o}\left(F_{ar}\left(X_{ir}^a\right)\right)$ is the normal CDF conditional on $o_i=1$, and $\Phi_{s|o,a}\left(F_{sr}\left(X_{ir}^s\right)\right)$ is the normal CDF conditional on $o_i,a_i=1$. The final piece is the conditional density of the disturbance term for the performance signal. Combining the contributions of all candidates, we obtain the conditional likelihood:

$$l\left(\Lambda|X\right)=\prod_{i=1}^{n}l_i\left(\Lambda|X_i\right)$$

where X is a collection of the vectors of characteristics, X_i, of all candidates.