Social Networks and Employee Performance in a Call Center[1]

Emilio J. Castilla
University of Pennsylvania

Much research in sociology and labor economics studies proxies for productivity; consequently, little is known about the relationship between personal contacts and worker performance. This study addresses, for the first time, the role of referral contacts on workers' performance. Using employees' hiring and performance data in a call center, the author examines the performance implications over time of hiring new workers via employee referrals. When assessing whether referrals are more productive than nonreferrals, the author also considers the relationship between employee productivity and turnover. This study finds that referrals are initially more productive than nonreferrals, but longitudinal analyses emphasize posthire social processes among socially connected employees. This article demonstrates that the effect of referral ties continues beyond the hiring process, having long-term effects on employee attachment to the firm and on performance.

For decades, we have seen a stream of theoretical and empirical studies in economic sociology and labor economics examining how recruitment sources relate to employees' outcomes such as turnover and tenure, starting wages, and wage growth (for a detailed review of these studies, see

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Granovetter [1995], and more recently, Petersen, Saporta, and Seidel [2000] and Fernández, Castilla, and Moore [2000]). Although many of these studies have sought to determine whether hires made through personal contacts are better matched than those made through other channels, none have focused specifically on the performance implications of hiring new employees by using current employees' connections.

Examining information on employee productivity promises to advance research in this area constructively. Such information is crucial because social relations and productivity can be related in complicated ways (and more important, they are likely to be confounded). In general, economists believe that social networks are not independent of productivity and are therefore valuable proxy variables when performance data is not available. For instance, the better match argument common in labor economics argues that social connections provide high-quality information that will improve the match between the job and the person. Under this theory, social relations act as a proxy for information about the job candidate that is difficult and expensive to measure or observe directly, such as employee productivity. However, a more sociological explanation suggests that regardless of whether personal connections reliably *predict* future employee performance, connections among employees can still *produce* more productive employees even after they have been screened and hired. Social interactions that occur among socially connected employees at the new job setting may enrich the match between the new hire and the job, and may thus affect employee performance over time. This "embeddedness" account emphasizes how the presence of personal contacts and their departure at times facilitates and at times lessens employees' productivity and attachment to the firm. However, the field's lack of direct measures of employee productivity renders us incapable of adjudicating between these two competing theoretical accounts.

One way to make progress on this subject is to directly examine the relationship between personal networks and worker performance. Using comprehensive employees' hiring and productivity data from a large call center in the United States, I examine, for the first time, the performance implications of hiring new workers via employee referrals, using referrals as indicators of preexisting social connections. My study also provides a further understanding of how workers' interdependence influences their performance. I structure my argument as follows. First, I test the central prediction of the "better match" theory in economics. The proposition here is that if referrers help to select better-matched employees, one would expect that, after controlling for observable human capital characteristics, workers hired via employee referrals should be more productive than nonreferrals at hire. Second, I examine whether referrals' performance advantages are manifested in a steeper posthire performance improvement curve. If productivity improvements occur as a result of employees' acquiring knowledge and skills, network ties might affect both potential levels of performance as well as the rate at which employees learn. Third, since turnover and performance are likely to be related, I consider the process of turnover when assessing whether referrals are better than nonreferrals (i.e., the fact that referrals might exhibit lower turnover than nonreferrals). Finally, I test a more sociological proposition which presumes that interaction between the referral and referrer at the workplace enriches the match between the new hire and the job.

My present study uses a direct measurement of what constitutes a "better" employee, one that is an *objective* measure of productivity. Thus, this is an exceptional opportunity to tackle an important research question that has never been addressed before. Consistent with the better match argument, I find that employee referrals are initially more productive than nonreferrals. In the long run, however, my analyses do not seem to support the better match explanation. Instead I find support for the more sociological argument that stresses how posthire dynamics of social relations among socially connected employees influence employee productivity over time. Given the results of my analyses, I suggest that the better match mechanism should be complemented by the social interaction and embeddedness arguments in sociology. Even if one assumes that referrals and nonreferrals have equivalent work abilities, perform equally well in the interview, or even exhibit similar performance trajectories, employers may still prefer to hire referrals at a higher rate simply because of the benefits of social integration in the workplace. Referrers might mentor and train their referrals. At the same time, the social support provided through networks might also increase positive work attitude and job satisfaction (and therefore productivity) and minimize turnover in an organization. In this study, I show that the effect of referral ties goes beyond the hiring process, having significant long-term effects on employee attachment to the firm and on performance. I find that the referral effect on performance is contingent on the referrer's continued presence in the firm. The departure of the referrer has a negative impact on the performance of the referral, even after the referral has been working in the organization for some time.

HYPOTHESES

Better Match Implies Better Performance

It has been argued that the social connections inherent in referral hiring benefit the hiring organization by improving the quality of the match between worker and job. In the economic literature on referral hiring, this argument is known as the "better match" account. It proposes that personal contact hires perform better than isolated hires because social connections may help to obtain difficult and more realistic information about the job and the candidate.[2] Wanous (1978, 1980), for example, posits that individuals who possess more accurate and complete information about a job will be more productive and satisfied with the organization than will individuals who have less accurate and complete information. This is mainly because job candidates who have more complete, relevant, and accurate information will have a clearer understanding of what the job entails and will thus be more likely to perform well on the job than will candidates lacking such information.

Ultimately, the better match theory posits that employers may benefit from referral hiring because referrals simply exhibit superior performance and are therefore better workers than nonreferrals. However, the traditional posthire indicators of employees' better matches used in existing empirical studies have been anything but direct measures of productivity; consequently, evidence for the better match hypothesis is quite mixed.[3] Perhaps the main reason for the inconclusive nature of these studies is that none has satisfactorily analyzed performance, the most important indicator of whether a referral employee is a better worker than a nonreferral employee. Therefore, it is difficult to claim to have examined the match quality in depth without having measured productivity, one of the bases upon which employees are evaluated and compensated. Here, I use a direct measurement of what constitutes "better": an objective measure of employee productivity.[4] Thus, I can provide a strong test of whether referrals are better matched than nonreferrals. If referrals are better matched to the job than nonreferrals, one would then expect some performance advantage associated with referrals at hire:

Hypothesis 1.—Referrals initially perform better than nonreferrals.

This hypothesis could be questioned on the grounds that all hires (re-

[2] Previous theoretical accounts of the role of networks in screening and hiring discuss in detail the different mechanisms that could be producing the better match (see Fernández et al. [2000] for a review).

[3] The traditional posthire indicators of employees' better matches used in this literature have been higher starting wages and slower wage growth (Quaglieri 1982; Simon and Warner 1992), lower turnover (Corcoran, Datcher, and Duncan 1980; Datcher 1983; Decker and Cornelius 1979; Quaglieri 1982; Gannon 1971; Simon and Warner 1992; Sicilian 1995; Wanous 1980), different time path of turnover (Fernández, et al. 2000), and even better work attitudes and lower absenteeism (Breaugh 1981; Taylor and Schmidt 1983).

[4] Admittedly, some studies have shown that people hired through social contacts received better *subjective* performance evaluations (Breaugh 1981; Breaugh and Mann 1984; Caldwell and Spivey 1983; Medoff and Abraham 1980, 1981; Swaroff, Barclay, and Bass 1985).

ferred and nonreferred) have been screened on performance-based criteria. Employees are selected on observable individual characteristics gathered from their résumés or observed during the interview. Nonetheless, if one does not take into account the selection process—the fact that employers hire the survivors of the organization's screening process—the effect of the referral variable on initial performance might be biased (Berk 1983; Heckman 1979). For this reason, previous studies analyzing only hires when relating recruitment source and employee's outcomes are likely to be biased (Breaugh 1981; Breaugh and Mann 1984; Quaglieri 1982; Taylor and Schmidt 1983; for an exception, see Fernández and Weinberg [1997]). The present study tests hypothesis 1, correcting for the selection of hires in prehire screening. This correction will help to perform the mental experiment of what the initial performance of all applicants would have been had they been hired without screening, and to determine whether there exists any difference in initial performance between referrals and nonreferrals at the time of hire.

Hypothesis 1 emphasizes referrals' advantages over nonreferrals at the beginning of their work contract with the organization. However, these accounts of the better match story are still incomplete because they ignore the tendency for networks to recruit employees with superior performance careers. In this sense, cross-sectional analyses may miss the role of personal contacts in building such a performance career. If the benefits of good early jobs found through contacts later translate into labor market advantages, the effect attributable to social networks is attenuated in the cross-section. The possibility that network ties themselves influence productivity over time needs to be further explored with longitudinal data on employee performance. Following the better match predictions, if referrals are better matched to the job than nonreferrals, they might not only perform better right after being hired, as suggested in hypothesis 1—they should also perform better than nonreferral hires in the long run. Even if hypothesis 1 was not supported, the advantages of social ties could be manifested over the tenure of the newly hired employee in two ways. First, referrers may provide information that helps employers choose recruits who can potentially reach a higher level of performance than nonreferrals. Second, referral hires might be able to learn the job and adjust to its requirements more quickly than nonreferrals. These two propositions imply:

Hypothesis 2.—Referrals have better performance trajectories than nonreferrals.

When assessing whether referrals perform better than nonreferrals, I will consider the issue of turnover. The obvious relationship between turnover and performance has not been explored in empirical studies.[5] Generally, productivity can appear to improve through two separate processes. Under the first process, particular individuals show true improvement in performance over time. This process is consistent with the learning theory (Arrow 1962). However, there is a second process whereby performance growth is affected by turnover. Since turnover may change the composition of the workplace, the observed positive correlation between tenure and performance when measured across the cohort of workers (not for any particular individual) could be entirely a result of population heterogeneity. If low-productivity performers are leaving first (Tuma 1976; Price 1977; Jovanovic 1979), then what looks like productivity improvement is actually caused by a selectivity effect.[6] Thus, the average worker's productivity will improve as long as low-productivity employees leave the organization at a higher rate than good employees. The net effect of the different rates at which low- and high-productivity employees leave the firm could *look* like productivity improvement over time when measured across the cohort of workers. But this is not *true* longitudinal productivity improvement because of the change in the composition of the workforce.[7] Any attempt to assess whether referrals are better matched in this dynamic context requires separating these two processes. Therefore, hypothesis 2 will be tested controlling for the risk of turnover.

Posthire Interdependence in Performance

The last mechanism by which referral hiring might affect performance is sociological; it emphasizes posthire social processes that occur among socially connected employees. This proposition presumes that interaction between the referral and referrer at the new job setting enriches the match between the new hire and the job. The experience of the referral hire might simply be a richer and more gratifying one because the referrer is

[5] A number of authors began a conceptual exploration of the positive organizational consequences of turnover (Dalton and Todor 1979; Mobley 1980, 1982; Staw 1980).

[6] Bartel and Borjas (1981) already introduced the question about the effect of labor turnover on wage growth within the job. They argue that the observed positive relationship between tenure and wage growth could be entirely caused by population heterogeneity. There exist some unobserved individual characteristics that lead to low wages and high turnover rates for some workers, and to high wages and low turnover rates for others.

[7] Few researchers have conceptually examined this individual performance-turnover relationship in depth (Porter and Steers 1973; Price 1977). In general, the findings of such studies are quite mixed. For example, Bassett (1967, 1972) found that high-productivity performers were more likely to leave the organization; Seybol, Pavett, and Walker (1978) found higher performers less likely to leave; and Martin, Price, and Mueller (1981) found no relationship between performance and turnover.

around and available to help, answer questions, provide feedback, and participate in non-work-related social activities. In addition, referring employees can serve as informal mentors and enhance training and performance in the workplace. This process, termed the “social integration” or “social enrichment” process (Fernández et al. 2000), is distinct from the better match argument because it takes place after hiring has occurred. Thus, social relations between referrals and referrers affect new hires’ attachment to and performance in the organization.

Fernández et al. (2000) present evidence for interdependence of referrals’ and referrers’ turnover patterns. They show that referral ties affect employees’ attachment to their firm, but suggest that referrer turnover may have some implications for referral performance, even after the referral has been in the organization for some time. For example, the departure of the referrer may in itself prompt the referral to reevaluate her own satisfaction with the current job; such a reevaluation may subsequently lower her commitment to the job, and consequently, her performance. Another mechanism could be that the referrer’s exit reduces the quality of the work setting to an unsatisfactory level, again lowering the referral’s performance and possibly leading her to quit. Even if the referrer’s employment termination does not affect the referral’s performance, it may still increase her likelihood to quit; referrers who leave the organization may convey information about external job opportunities back to friends and colleagues, increasing the chance that the referral herself will be lured away to another company (Fernández et al. 2000). One final possibility is that the referral employee may feel a sense of obligation not to embarrass the referrer; such a sense of obligation might decline or even disappear after the referrer departs, lowering the referral’s performance.[8] All previous scenarios suggest that referrer turnover has negative consequences for referral performance.

However, the Fernández et al. study does not focus on the fact that referrer turnover could also have some positive impact on the attitudes and performance of those referrals who remain in the organization. Krackhardt and Porter (1985) found in their study of three fast-food restaurants that the closer the employee was to those who left the restaurants, the more satisfied and committed she would become. This observation has support in dissonance studies: if a person observes a friend leaving and attributes dissatisfaction to the friend’s decision to quit, that person’s decision to stay may require more justification. One way the person could justify her decision to stay is to develop stronger positive attitudes toward the job and the workplace.

Clearly, it is difficult to predict the effects of referrer turnover on the

[8] I thank one anonymous reviewer for pointing out this mechanism.

performance of the referral. In this study, I examine what happens to the performance curve of employees whose referrer leaves; this involves comparing the performance curves among nonreferrals, referrals whose referrer leaves, and referrals whose referrer stays. If the referrer's decision to quit has a negative impact on the productivity of the referral, this leads to:

Hypothesis 3a.—The turnover of the referrer worsens the referral's performance improvement trajectory.

Assessing the social enrichment effect requires analyzing whether or not it is the presence of the referrer that improves referrals' performance. Thus, all the previous hypotheses about the better match argument could be complemented as being about social enrichment. For instance, if the referrer teaches the referral the ins and outs of the job at the beginning of the job contract or during the training, it is the presence of the referrer that accounts for any performance differential between referrals and nonreferrals—even between referrals whose referrer is present and referrals whose referrer is not present during the first months in the organization. Similarly, the referrer could help the referral along a quicker performance improvement trajectory. In fact, one could argue that if the referrer were to influence the referral, this influence should be strongest at the very beginning. Nonreferrals might subsequently build a social network that dissipates the referral's initial advantage. This leads to an alternative hypothesis:

Hypothesis 3b.—The presence of the referrer improves the referral's performance improvement trajectory.

Finally, I explore whether the positive effect of workplace interaction between referrer and referral is enhanced when the referrer's level of performance is taken into account. After careful analysis of the classic Hawthorne plant data, Jones (1990) demonstrated that workers' productivity levels were highly interdependent. In my setting, Jones's finding suggests that there might be a relationship between the performance of the referred and referring employees: if referrals are exposed to high-performance referrers, their performance should be much higher than the performance of nonreferrals or individuals referred by low-productivity referrers. Conversely, social interactions with a low-productivity referrer at work might have a negative effect on referrals' productivity. If referrals' performance is affected by the amount of exposure to the referrer, the difference in results from exposure to a high-performance referrer as compared to a low-performance referrer should be explored.

RESEARCH SETTING

The job I study is the phone customer service representative (CSR), an entry-level job at a large phone center within a large international financial services organization in the United States. CSRs are full-time employees, paid by the hour, whose duties consist of answering customers' telephone inquiries about credit card accounts. New hires are given approximately two months of classroom and on-the-job training before working on the phone. CSRs are trained in order to improve their accuracy, speed, and efficiency while processing phone calls. Managers often monitor phone calls to ensure that CSRs achieve the phone center's courtesy and accuracy goals.

I wish to highlight two important features of the organization under study. First, the phone center is a single site with a centralized human resources function. It keeps particularly clean and orderly databases, which allow every phase of the CSR hiring process to be identified. A second feature of the phone center particularly relevant to this study is that in addition to recording supervisors' subjective ratings of employee performance, the phone center collects objective and precise measures of productivity for the CSRs. This should greatly improve the estimates of the impact of recruitment source on employee productivity. I have also been able to learn about the phone center's screening criteria and performance expectations. Consequently, I can more precisely specify the set of appropriate individual control variables that affect labor market matching. In addition, I can consider the extent to which an applicant's referral status is a proxy for other characteristics that might make the applicant desirable to the recruiters at the phone center.

In the remainder of this section, I describe the employment process at the phone center as illustrated in figure 1. I start with the records of the phone center's hiring activities during the two years from January 1995 until December 1996. The phone center's human resources (PCHR) department tracked 4,165 external employment inquiries for CSR jobs over this two-year period. Only 8% (336) of the original applicants were hired. I tracked 334 of these employees from the time of their hire until June 1997, when I ended the performance data collection. Around 290 hires completed the two-month training period at the phone center. For those hired CSRs, I examine two of the most relevant posthire outcomes at the phone center: turnover and productivity. Whenever possible, I incorporate evidence that I gained through observation and interviews of the different professionals at the phone center (mainly from the PCHR staff).

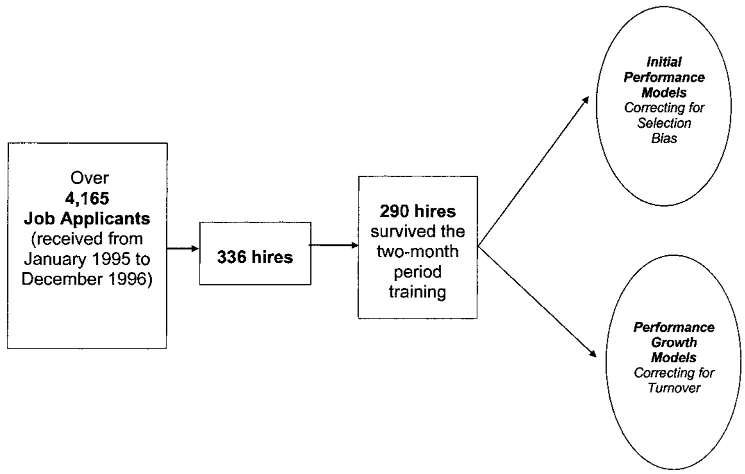

FIG. 1.—Employment process under study

Recruitment and Training

As a part of their standard operating procedures, PCHR professionals record the recruitment source for every employment inquiry. This information is recorded when a potential employee makes her initial contact with the phone center. I interviewed PCHR recruiters to determine the screening criteria and performance evaluations that were used to recommend candidates for employment. They informed me that given that the CSR job involves significant customer interaction, PCHR screens applicants based on verbal and interpersonal skills from brief interviews or phone interactions. PCHR recruiters also look for people with prior customer service experience. They also tend to look for applicants who they believe will be reliable employees, preferring applicants who are currently employed and who have had some previous work experience. In addition, they look for evidence of basic keyboarding and computer skills on the application. Very relevant to this study, the PCHR personnel emphasize that "referrals are treated the same as everyone else."

The phone center runs the training session for a cohort or "class" of about 15–20 new hires. The training consists of about six weeks of classes and two weeks out of class, working in a controlled area (what they refer to as "on-the-job training" or OJT). The OJT takes place on the first floor of the phone center and not in the main area where the CSR would work (the main call area is located on the second floor of the building). The OJT period is important in this study for various reasons. First, during the training, performance is never measured or evaluated, and most important, both referrals and nonreferrals go through an identical hiring and training process. As one of the PCHR managers put it: "Nothing will prevent a new hire [whether referral or nonreferral] from having to go through all the weeks of training. Our training is designed to better prepare our new hires to perform their duties as excellent CSRs." Second, during the training, recent hires learn about the CSR job, getting very clear information about what the job entails, including job content and responsibilities. Simultaneously, the employer learns whether the new employee is well suited for the job. As one PCHR member put it: "We can get a good idea of who is not going to be a good match to the CSR job; some hires do not even bother to show up to complete their training!" Quite a few new hires quit during the training period—during the period of my analysis, over 10% (44 of 334) of the hires left the firm during training. Therefore, I coded performance histories only for those 290 employees who were hired and completed the training process.

Turnover and Performance

PCHR personnel are concerned about the performance of their hires. However, recruiters do not seem to learn much about the quality of the employee once she has passed through the hiring process, even though, as one of the PCHR managers joked: "It is all a selection issue; if recruiters were doing their job right, we would not see so much turnover in our phone center" (field quotation from a PCHR manager). Regardless of whether recruiters are screening candidates using the "right information" or not (quoting one PCHR member), PCHR professionals are aware of the limitations associated with the screening of candidates.

PCHR personnel are also concerned about the costs of high employee turnover (although turnover at this setting is low by call center standards). Answering phone call after phone call in a high-pressure, highly structured environment demands a set of skills for which it is difficult to screen. As the PCHR director put it: "People leave their jobs because of the working environment. The job burns you out!" The numbers confirm statements like these; almost half of the CSR terminations at the phone center were the result of job abandonment or job dissatisfaction (45.7% in 2000). One of the PCHR managers remarked: "People do not want to be in [the phone center] all day. So the question is how we can change the bonus structure so that we can help reduce turnover." In previous years, PCHR professionals have dealt with the issue by hiring more people when turnover is high. Although this hiring practice might help to keep a stable number of CSRs answering the phones, it does not solve the problem of the high costs associated with employee turnover.

In terms of performance, unit supervisors at the phone center pay close attention to the average handle time; that is, the amount of time in seconds that it takes a CSR to complete a phone call with a client. A PCHR manager stated: “Average handle time is the ultimate variable we are looking at, always controlling for the quality of the call.” Every year, one of the PCHR managers computes simple statistics (i.e., means) for the whole year, taking into account the tenure of the employee. This manager prepares a report that is presented and discussed at PCHR meetings. Henceforth, PCHR managers try hard to understand the main predictors of handle time and quality so they can better screen for well-performing employees. PCHR staff, however, do not seem to have any clear idea about the observable characteristics that could help them identify and hire individuals with higher productivity potential. As the head of the PCHR department put it: “Based on our experience of 30 years, what you see in the résumé or during the interview is not a predictor of performance at all.” Although PCHR closely monitors performance, CSRs are hardly ever fired because of low productivity: only slightly more than 1% of all hires are terminated each year for performance issues. Still, supervisors intervene with poorly performing employees by rebuking them about their low productivity and/or low quality; they are also in charge of helping these CSRs to improve their performance. In addition to this monitoring and control, the phone center has a basic incentive plan where those employees with the highest performance ratings (i.e., highest average number of calls answered per hour) in a given time period get an increase of 5–10% in their salaries. Normally such salary revision occurs once or twice a year, and very few employees—less than 10%—get a raise.

Measuring Tenure and Employee Performance

For hires, I coded the two main dependent variables in the posthire analysis: duration in the organization and performance during their tenure with the phone center from hire up until June 1997 when I ended the collection of performance data. Objective and subjective performance measures were examined at the beginning of each month. Because hires go through a training period of about two months, I have a maximum of 27 months of performance observations per employee hire.[9] Almost half of the hires were still with the organization at the end of my study. For hires, the days of tenure with the phone center range from a minimum

[9] The maximum number of performance observations is for those employees who were hired at the very beginning of my hiring window (January 1995) and who stayed in the organization until my last month of performance observation (June 1997). Because performance measures are available at the beginning of each month, the performance of hires is not available for the first three months (i.e., the two months of training, plus the first month after their training).

of 3 days up to a maximum 1,104 days, with a median of 480 and a mean of 528 days.

I measure performance using the average number of calls a CSR answers per hour in any given month (corrected for call quality).[10] This measure is calculated using handle time. The phone center computer automatically calculates the average time a CSR takes to complete a phone call. Compared with other available performance measurements, the average handle time provides a good measurement of how efficient a CSR is. This measure is exceptionally accurate: it is measured across a large number of calls that are randomly routed to CSRs by the phone center computer (over 5,000 calls per month for the typical CSR at about 2.5 minutes per call), and thus equates the difficulty of tasks across CSRs. In addition, it is measured automatically, and therefore is not subject to the normal problems of subjective performance ratings (e.g., supervisor evaluations). The maximum value observed in any month of tenure was approximately 26.5 calls answered in an hour, and the minimum was 19.5, with a mean of 20.3 phone calls per hour (SD = 3.63). The number of phone calls answered per hour is on average initially low but tends to improve over the first year on the job, peaking at the fifteenth month, when an average CSR answers over 24 phone calls per hour. After the fifteenth month, the level of productivity worsens slightly—although variance in productivity also widens and the number of employee survivors decreases.

Independent Variables

Two different sets of variables are used in this study to predict an employee's performance trajectory. The first set of variables includes human capital variables that are believed to influence not only screening decisions but also an individual's productivity. Years of education and previous job experience are two of the most important variables. Experience includes variables such as months of bank experience, months of nonbank

[10] Unit managers listen to a sample of calls for each CSR and rate the quality of their calls, evaluating each CSR on a monthly basis across courtesy and accuracy. Both measures of quality are typically at ceiling and exhibit little variance across people or over time. The evaluation scale ranges from zero up to one (when all monitored calls are of maximum accuracy or courtesy) for the whole sample during the months of observation. Because of the lack of variation across observations, I do not use such measures of employee productivity as dependent variables in this study. Instead, I divide the average number of calls answered per hour by the product of both quality measures to compute a quality-adjusted average handle time for each employee. This calculates the number of calls answered per hour, adjusted for quality. As expected, both measures (number of calls quality and non–quality adjusted) are highly correlated (with a correlation coefficient of .99).

experience, number of previous jobs, whether the hire was working at time of application, and tenure and wage in the last job (as a proxy for job status prior to the job at the bank site; these variables are coded as zero for people who had not had a previous job). Since work in the human capital tradition argues that the value of human experience declines over time, I captured this effect in the analyses by entering a squared term for months of nonbank experience. In the analysis, I also include measures of different individual skills and capabilities such as having some computer knowledge or speaking another language (both are dummy variables). I also include a dummy variable to distinguish repeat applicants from first-time applicants (one for repeat applicants; zero otherwise). The maximum number of applications from individuals is three. An important demographic variable is gender (coded one when male; zero when female). Finally, I also control for the state of the market; that is, the number of job openings and the number of applications on the date the candidate applied.[11]

The second set of variables includes those measuring the availability as well as the characteristics of referrers, not only at the time of the referral's application, but also during her employment at the phone center. The first network variable included is a dummy variable indicating whether the respondent is a referral. My analyses are conservative tests (given the fact that I have only one of an employee's network ties) of the effects of social embeddedness of workers on productivity. The second set of variables measures the characteristics of the referrer, including variables such as wage, education, tenure in the firm, and performance rating in the organization. I also include variables about the referrer's structural accessibility to successful referrals, such as previous employment as a CSR.[12] All of the referrer's characteristic variables are allowed to change over time except for education, which is considered constant. For nonreferrals, all these variables are coded zero. Hence, the effects of referrers' characteristics are conditional on the applicant's being a referral. I also coded a dummy variable to distinguish those referrers who received a

[11] One might expect that the higher the supply of jobs in the organization, the less selective the organization can be. This may possibly worsen the employee-job match, leading to increased turnover of the hires and a worsening of the hires' performance. The demand side of the state of the labor market economic argument implies that the higher the demand for jobs in the organization, the more selective the organization can be. This increased selectivity should be reflected in an overall better match of hires to their jobs, in lower employee turnover, and in improved performance.

[12] Studies show that when employees find their jobs through contacts with high rank and prestige, they tend to get better jobs themselves (Lin 1999; Marsden and Hurlbert 1988). Referrers may also vary in their accessibility to successful referrals (Fernández and Castilla 2001).

good subjective evaluation, as recorded in the phone center's computer files.[13] Finally, a time-varying dummy variable is coded as one once the referrer has left the organization.

Table 1 presents descriptive statistics for the independent variables included in the performance and selection models for applicants and hires. The job is female dominated—only 22% of the hires are male. Hires on average have about 13.6 years of education, with about three months of bank experience, 71 months of nonbank experience, and 48 months of customer service experience. Less than 14% have a bachelor's degree, and 74% have some computing experience. Sixty-seven percent of the hires were working at time of application; their number of previous jobs is three on average, with approximately two years of tenure in their last job. Half of the hires were referred by an employee in the firm. The table also includes the initial performance variables for the new hires. The average number of calls answered per hour is initially 20 calls, with courtesy and accuracy levels close to one.

METHODS

My hypotheses pertain to the performance implications of hiring new employees using referral programs. Accordingly, my methodological approach is to break down the posthire employment process into individual components and to model each of these pieces to understand performance careers within organizations (see figure 1). For those hired CSRs, I examine turnover and productivity, the two most relevant posthire outcomes at the phone center. I estimate (1) models for initial performance; and (2) models for performance growth. The initial performance models are estimated controlling for the screening of employees. The performance growth models are corrected for the turnover propensity of employees.

Initial Performance Models

In order to analyze the determinants of starting performance, the dependent variable I use is the starting average number of phone calls answered

[13] In preliminary analyses, I also used the firm's information about bad evaluations. But this bad evaluation dummy variable is almost always zero; only 16 out of the 4,165 applications (.39%) were referred by employees who got bad evaluations. One of those candidates was hired and completed the training. In the case of good evaluations, 31 out of 350 applications made by "good" referrers were hired and completed the training.

TABLE 1
Means and SDs for Variables in the Performance Models

	Applicants		Hires		Hires Surviving One Year	
	Mean	SD	Mean	SD	Mean	SD
Independent variables:						
Gender (1 = male)	.337	.473	.224	.418	.216	.413
Repeat application (1 = yes)	.096	.295	.072	.260	.025	.157
Marital status (1 = married)	.423	.494	.420	.494	.443	.497
Skills:						
Computer	.731	.443	.741	.439	.784	.413
Language	.196	.397	.138	.345	.131	.338
Years of education	13.750	1.866	13.607	1.723	13.528	1.768
Bachelor's degree (1 = yes)	.185	.388	.138	.345	.146	.354
Experience:						
Works at time of application	.550	.498	.679	.468	.714	.453
Months of bank experience	2.102	14.402	3.335	14.649	2.374	10.561
Months of nonbank experience	64.629	62.361	71.721	60.136	72.631	55.334
Nonbank experience, squared	8,064.834	28,859.890	8,746.934	20,540.150	8,321.410	14,600.030
Months of customer service	34.195	44.877	48.085	53.577	47.272	47.023
No. of previous jobs	3.224	1.139	3.048	1.240	3.031	1.226
Tenure in last job (in days)	576.968	1,032.603	776.493	1,264.242	815.091	1,234.666
Salary in last job	6.431	3.659	6.086	3.450	6.426	3.198
Application behavior:						
No. of applications	19.937	16.783	18.534	15.246	18.126	13.624
No. of job openings	18.198	10.672	18.469	10.477	19.131	10.602
Application source:						
External referral	.374	.484	.510	.501	.548	.499

Referrer's characteristics at time of application:*						
Tenure (in years)	4.019	3.984	3.478	3.523	3.819	3.622
Wage	9.749	5.635	9.536	4.816	9.821	5.257
Years of education	12.430	1.218	12.432	1.202	12.422	1.189
Performance (1 = good evaluation)	.228	.419	.209	.408	.211	.410
Ever worked as a CSR (1 = yes)	.297	.457	.351	.479	.330	.472
Terminated	.034	.182	.041	.198	.028	.164
Dependent variables:						
No. of calls answered per hour			20.291	3.629	20.312	3.501
No. of calls answered per hour (quality adjusted)			20.044	3.594	20.059	3.477
Maximum level of performance			26.497		27.949	
Minimum level of performance			19.458		19.319	
Courtesy (worst level = 0; best level = 1)			.998	.007	.998	.008
Accuracy (worst level = 0; best level = 1)			.983	.024	.963	.022
No. of cases	4,114		290		199	

NOTE.—"Hires" includes those who survived the original training period (approx. two months). "Hires Surviving One Year" stayed in the company at least 12 months after their hiring date.

* The means and standard deviations for these characteristics are calculated only for referrals (these referrer's characteristics are coded as zero for individuals who were not referred).

per hour (adjusted for call quality) immediately after the initial two-month training period.[14] I estimate the parameters of models of the form:

$$Y_0 = B'\mathbf{X} + \varepsilon, \quad (1)$$

where Y_0 is the first available performance measure in the job as a CSR after training, $\mathbf{X}$ is a vector of covariates that contains characteristics of the individual at the time of entry into the phone center as coded from their job applications, and ε is the disturbance term assumed to be normally distributed and well behaved (uncorrelated with the covariates).

The performance equation proposed above has traditionally been estimated for the hires using the basic ordinary least squares (OLS) technique, a choice predicated on a lack of information about job applicants. As a result of observing performance only for the applicants who got hired, these past models do not correct for selection bias. To correct for such selection bias, I use the Heckman selection model (Gronau 1974; Lewis 1974; Heckman 1976). This model assumes a regression like the one described in equation (1). However, the dependent variable, *performance*, is not observed for all applicants or hires who were terminated during the two-month training. So there is a selection equation, and the applicant is hired and completes the initial training period in the organization if:

$$Y'\mathbf{Z} + \mu > 0, \quad (2)$$

where $\mathbf{Z}$ is a vector of covariates that affect the chances of observation of performance for a given applicant, and μ is normally distributed (mean $= 0$; SD $= 1$).[15] Presumably, firms hire those applicants who, based on available information from their résumés, are expected to be most productive. But firms may also take into consideration the state of the labor market: that is, the number of job openings that need to be staffed and the number of available applications (demand for jobs). Therefore, $\mathbf{Z}$ is a vector of covariates that contains the characteristics of the job applicant ($\mathbf{X}$) plus two variables controlling for the state of the market at the time of application. The correlation between ε and μ is some parameter ρ; so that when $\rho \neq 0$, only the Heckman selection model provides consistent, asymptotically efficient estimates for the parameters in equation (1).

[14] The performance measure is normally distributed and no logarithm transformation was therefore required. Nevertheless, in addition to the modeling of starting performance, I also modeled the logarithm of starting performance and obtained very similar results (available upon request). I also used the number of phone calls per hour (without adjusting for the quality of the call) and obtained similar results.

[15] Following Stolzenberg and Relles (1997) and Winship and Mare (1992), I run several tests using different sample selection models to ensure my results are robust.

Performance Growth Models

For the study of performance growth, I analyze longitudinal data using regression models of change. While a comparison of cross-sectional analyses at different points in time provides some insight into this process, models of change represent it explicitly. The performance data structure is a pooled cross-section and time series. The data are unbalanced: the number of observations varies among employees because some individuals leave the organization earlier than others (while many workers opt to stay in the organization). Research studies typically model such data with fixed-effect estimators, which analyze only the within-individual over-time variation. This choice is unappealing in this context because the majority of the independent variables (i.e., those variables coded from the application) do not vary over time.

To test my hypotheses about the determinants of change in productivity, I estimate various cross-sectional time-series linear models using generalized estimating equations (GEE). These models allow estimating general linear models with the specification of the within-group correlation structure for the panels. I report the robust estimators that analyze both between- and within-individual variation. Specifically, I use the method of GEE developed by Liang and Zeger (1986). This methodology requires the inclusion of a correlation structure when estimating these models.[16] Any of these estimated longitudinal models will be corrected for the turnover process. So following Lee (1979, 1983), Lee, Maddala, and Trost (1980), and Lee and Maddala (1985), I control for the retention of employees over time by including the previously estimated turnover hazard when I estimate such longitudinal models. This results in a two-stage estimation procedure. The models I will be presenting are:

$$Y_{i,t} = \alpha Y_{i,t-1} + B'\mathbf{X}_{i,t} + \delta\bar{\pi}(t, \mathbf{Z}_{i,t}) + \varepsilon_{i,t}, \tag{3}$$

where Y_t is the performance measure in the job at time t and $\bar{\pi}$ is the estimated turnover hazard rate (using event-history analysis):

$$\pi(t, \mathbf{Z}_{i,t}) = \exp[\Gamma'\mathbf{Z}_{i,t}]q(t), \tag{4}$$

where π is the instantaneous turnover rate. This rate is commonly specified as an exponential function of covariates multiplied by some function of time, $q(t)$. The log-linear form for the covariates is chosen to ensure that predicted rates are nonnegative. $\mathbf{Z}$ is a vector of covariates that affect the hazard rate of turnover for any given hire. $\mathbf{Z}$ is indexed by i to indicate heterogeneity by case and by t to make clear that the values of explanatory

[16] Under mild regularity conditions, GEE estimators are consistent and asymptotically normal, and they are therefore more appropriate for cross-section time-series data structures.

variables may change over time.[17] I estimate the effect of the explanatory variables in model 2 using the Cox model that does not require any particular assumption about the functional form of $q(t)$ (Cox 1972, 1975). I tested for the effect of turnover across different specifications, functional forms, and measures of turnover and always found similar results.

RESULTS

Initial Performance

Table 2 shows the differences in the levels of initial productivity by application source. The performance of referral workers appears superior to the performance of nonreferrals, especially if we look at both quality-adjusted and non-quality-adjusted number of calls: referrals' average number of calls answered is higher than nonreferrals' (although the difference of a half call is barely statistically significant at the .1 level). The table shows little difference between referrals and nonreferrals on other dimensions of performance such as courtesy or accuracy. In table 2, the exploration of performance differences between referrals and nonreferrals does not control for other individual variables or the screening process that CSR applicants undergo before starting to work at the phone center. In the next tables, multivariate regression models are used to further explore this difference in initial performance between referrals and nonreferrals.

Table 3 provides the results of the initial performance regressions correcting for both the selection of candidates from a pool of applicants and their retention during the training.[18] Employees are selected on observable individual characteristics from their résumés or during the interview. One needs to account for the fact that employers hire people who passed the organization's screening process. In table 3, I correct for the selection of hires in prehire screening by including the factors for which PCHR says they screen and the control variables that affect labor market matching in the selection equation of the Heckman model.[19] The first model includes

[17] The model in 2 is the most general form of any parametric models that are generally distinguished by the different choices of $q(t)$.

[18] OLS multivariate regressions were also estimated to examine the impact of the referral variable on initial performance (Castilla 2002). From the results of these traditional models, the only significant variable in the prediction of employee performance is nonbank experience, which has a negative impact. These results are available upon request, although I argue that these traditional OLS results might be biased because these traditional OLS models do not take into account the selection process, i.e., the fact that employers hire the survivors of their screening process.

[19] My analyses reported in table 3 do not change much when I exclude the two variables measuring the state of the market in the outcome equation.

TABLE 2
MEANS AND SDs FOR MEASURES OF INITIAL PERFORMANCE BY APPLICATION SOURCE

	All Hires		Referrals		Nonreferrals		Performance Differences between Referrals and Nonreferrals	
Dependent Variable	Mean	SD	Mean	SD	Mean	SD	Difference	t-test
No. of calls answered per hour	20.291	3.629	20.561	3.584	20.009	3.666	.552	1.296^{+}
No. of calls answered per hour (quality adjusted)	20.044	3.594	20.290	3.478	19.787	3.706	.502	1.191^{+}
Courtesy (worst level = 0; best level = 1)	.998	.007	.998	.007	.999	.008	.001	.600
Accuracy (worst level = 0; best level = 1)	.983	.024	.983	.023	.984	.025	.002	.579
No. of cases	290		148		142		290	

NOTE.—To be classified as a hire (All Hires), workers must survive the training period.
$^{+}$ $P < .10$ (one-tailed test).
* $P < .05$.
** $P < .01$.

only the referral variable in the performance equation (col. 1 of the table). The second model includes all controls (col. 3); the third and final model (col. 5) includes only those individual controls with a z-value more than one in model 2 (i.e., language and months of nonbank experience).[20]

Referral appears to be an important variable at both the prehire and posthire stages of the employment process. First, referrals are more likely to be hired and to complete the initial training. More important, once I control for the other "observable characteristics," referrals show a better level of performance, as measured by a higher quality-adjusted average number of calls answered. Referrals answer, on average, an additional phone call per hour when compared to nonreferrals—the difference in the number of calls is slightly over .7. This is true for any of the three models of performance. The referral effect is significant ($P < .05$, one-tailed) in the model without controls or with those controls with a z-value higher than one (i.e., language and nonbank experience). When all control variables are included in the model (col. 2 of the table), the referral effect

[20] The effect of any independent variable with a z-value less than one can be considered very insignificant, and therefore negligible.

TABLE 3

INITIAL PERFORMANCE REGRESSION MODELS CORRECTING FOR SCREENING AND COMPLETION OF TRAINING

(OLS Models with Sample Selection)

	Only Referral		Referral and All Controls		Referral and Some Controls	
	Coef.	SE	Coef.	SE	Coef.	SE
Main model:						
Constant	18.551***	2.091	21.410**	11.491	19.481***	2.002
External referral	.745*	.435	.703+	.465	.737*	.436
Gender (1 = male)			.598	1.413		
Repeat application (1 = yes)			−.404	1.058		
Computer			−.090	1.047		
Language			−1.030	.777	−1.076+	.624
Years of education			−.046	.162		
Works at time of application			.118	1.673		
Months of bank experience			−.016	.015		
Months of nonbank experience			−.018*	.009	−.01**	.004
Nonbank experience, squared			.000	.000		
Months of customer service			.002	.014		
Number of previous jobs			−.047	.433		
Tenure in last job (in days)			.000	.000		
Salary in last job			.077	.106		
Number of applications			.001	.021		
Number of openings			.039	.020		
Selection model:						

Constant	−1.457***	.257	−1.449***	.257	−1.443***	.257
External referral	.250***	.064	.248***	.064	.248***	.064
Gender (1 = male)	−.256***	.074	−.254***	.074	−.257***	.074
Repeat application (1 = yes)	−.130	.112	−.133	.112	−.132	.112
Computer	.176*	.080	.174*	.080	.175*	.080
Language	−.189*	.087	−.200*	.086	−.200*	.086
Years of education	−.012	.019	−.013	.019	−.013	.019
Works at time of application	.310***	.069	.314***	.069	.311***	.069
Months of bank experience	.000	.002	.000	.002	.000	.002
Months of nonbank experience	.002	.001	.002	.001	.002	.001
Nonbank experience, squared	.000*	.000	.000*	.000	.000*	.000
Months of customer service	.003***	.001	.003***	.001	.003***	.001
No. of previous jobs	−.075*	.031	−.076*	.031	−.076*	.031
Tenure in last job (in days)	0.000*	.000	.000*	0.000	.000*	.000
Salary in last job	−.015	.010	−.015	.010	−.015	.010
No. of applications	−.003	.002	−.003	.002	−.003	.002
No. of openings	−.001	.003	.000	.003	−.001	.003
Wald chi-square statistic:	3.20		21.88		14.26**	
$P>\chi^2$	.074		.147		.003	
Rho	−.202	.236	−.231	.373	−.183	.226
Test of independence of equations:	.66		.27		.57	
$P>\chi^2(1)$	.417		.602		.451	
No. of job applicants (employees)	3,972 (272)		3,972 (272)		3,972 (272)	

Note.—Performance is measured as the average number of calls answered per hour (quality adjusted).
[+] $P<.10$ (two-tailed tests except the z-test for the effect of the "external referral" variable, which is one tailed).
* $P<.05$.
** $P<.01$.
*** $P<.001$.

is still about .7 quality-controlled calls, but the difference is now barely significant ($P < .10$).[21]

The results in the selection part of the Heckman model show that applicants are more likely to get hired and complete training if they are employed at the time of application, if they have more months of customer service experience and work experience outside the financial services sector, or if they report longer tenure on their last job. In the study, the number of previous jobs that candidates report has the expected negative sign (significantly related to being selected). This is consistent with the recruiter's preference for candidates with a lower number of previous jobs (since those who change jobs a lot during their work histories might be more likely to leave). While education did not emerge as a significant predictor, the dummy variable reporting some computer experience is a significant negative predictor of being selected. However, applicants with foreign language skills are less likely to be selected than applicants without such skills. The final human capital variable—candidate's last salary on the job—is not significant, although its coefficient has the expected sign. Applicants who report a higher wage on their last job seem less likely to be selected. This is consistent with recruiters' concerns that such candidates might be overqualified and more likely to leave the firm.

Controlling for other factors, males are less likely to be selected than females. PCHR recruiters speculate that females have a better sense of how to conduct customer service interactions, even though the substantive part of the equation demonstrates that females do not seem to perform any differently from males. The recruiters' preference for female employees may be an effect of gender stereotyping in the service industry. Even when there are no objective reasons showing that women perform better in any given service job, women are more often recruited for such positions. None of the variables controlling for the state of the market at the time of application has any significant impact on the likelihood of the candidate to be hired and to complete the training period. Finally, the dummy variable distinguishing between referrals and nonreferrals is statistically significant. Referrals are more likely to be hired and to complete

[21] Even when applicants with foreign language skills are less likely to be selected than applicants without such skills, foreign language skills seem to have a negative effect on CSR performance. Candidates with foreign language skills answer fewer phone calls per hour than candidates without such skills (the difference is not significant at the .05 level though). Work experience outside the financial services sector worsens the CSR average number of calls answered ($P < .01$); customer service experience is never significant, although it has the expected sign.

their training than nonreferrals.[22] Although referrals appear to be more appropriate candidates for the CSR job, referrals' advantages at the interview and training stage cannot be explained by the individual background control variables alone.[23]

There are clear productivity advantages in the hiring of employees using referral programs (and the bonus associated with the referral program). In this setting, the referral program seems to bring measurable posthire advantages in the hiring of employees, even though certain PCHR representatives express their belief that the referral bonuses are counterproductive since people refer others for money. Only after completing my analyses on initial performance that control for the selection of hires, could I determine that these perceptions do not reflect reality. In actuality, the use of the referral program seems to provide two advantages in this particular phone center. First, there is evidence that the referral program increases the quantity of job applicants. Second, the referral program seems to recruit better-matched employees; there are definite initial performance advantages in the hiring of employees using the referral program. I show a net productivity gain of .7 phone calls per hour. Over an eight-hour day, this corresponds to five to six calls a day; over a 40-hour week to about 28 calls, or about an hour's worth of work that has been saved. So I estimate an initial productivity increase of about 2.5%.

Finally, there is another way in which referring employees can signal information about the performance quality of referral candidates. Employees can access "upstream" information that could be available because of the tendency of people to refer others like themselves. According to this homophily mechanism, referrals are more likely to be like referrers, and since referrers have already survived a prior screening process, the homophily mechanism would lead the applicants referred by employees to be better performers than nonreferred applicants (see Montgomery 1991; Ullman 1966). To address whether the referrer's characteristics and level of performance might influence the initial performance of the employee, I ran several Heckman regression models adding referrer's char-

[22] I estimated the same Heckman regression models excluding those 44 hires who were terminated during their training. The selection coefficient for referral is still statistically significant and has about the same magnitude. Moreover, the deletion of those 44 cases does not change the pattern of the effects of all the variables in both the selection and the substantive equations in the Heckman model.

[23] To complete my test of the better match argument at the time of hire, I analyzed terminations during the training period (Castilla 2002). There were 44 terminations during this period. My probit models with sample selection suggest that referrals seem less likely than nonreferrals to leave their job during the training. In termination models beyond training, however, the effect is not significant (consistent with Fernández et al. 2000).

acteristics to the main performance equation. I find no evidence that additional information about referrers improves the fit of the initial performance model.[24] The fact that recruiters never contact referrers or look up their information explains why I see no support for the homophily mechanism in this phone center.

Performance Trajectory

I now analyze whether referrers help to recruit better-performing employees over time. Table 4 presents the results of the several performance growth regression models correcting for the turnover rate. I estimate the turnover-hazard-rate selection-regression models to test hypothesis 2—whether referrals have better performance trajectories than nonreferrals once we control for the risk of turnover. There does not, therefore, seem to be any support for the better match theory in the long run. In addition, most of the appropriate individual human capital characteristics have insignificant effects on employee performance over time. By looking at the results on table 4, it seems that the three significant variables in the prediction of employee performance growth are nonbank experience (which has a negative impact; $P < .05$), customer service experience (which has a positive impact; $P < .001$), and the number of applications at time of application (which has a positive impact; $P < .05$). Looking at the coefficient for the estimated hazard rate in the performance growth model, one can see that the likelihood of turnover is associated with higher performance growth over time. In other words, the model seems to suggest that those employees who are more likely to leave the phone center are those whose performance improves over time.

By examining the results of the turnover-hazard-rate part of these selection-regression models (reported in the last two columns of table 4), I do not find statistically reliable evidence of referrals having a lower turnover rate.[25] As in the performance models, very few of the appropriate individual human capital and other control variables seem to have any significant effect on turnover. Additional months of bank experience seem

[24] These results are available in Castilla (2002). Referrers' characteristics do not seem to provide any additional information about the future performance of the referral ($P < .776$; incremental $\chi^2 = 1.78$; $df = 4$); nor does information about the referrer's evaluation by the firm ($P < .727$; incremental $\chi^2 = 0.12$; $df = 1$).

[25] Results do not change across a variety of parametric transition rate models (the Cox model presented in the table, the proportional exponential model, or the proportional Weibull model). I also performed these tests separately for voluntary (quitting) vs. involuntary (fired or laid off) turnover and found no reliable differences. Most of the turnover was voluntary, though; only 18 (11%) of the overall job terminations were involuntary.

to increase the rate of turnover, whereas months of customer service experience improve an employee's chances of staying in the phone center.

The model of employee performance reported in table 4 represents an important step toward correcting for a lack of empirical research concerning both the evolution of productivity and turnover decisions of hires within organizations. My model attempts to control for the process of turnover. I find that neither poor performers nor good performers are more likely to leave the phone center; the effect of the performance at time $t - 1$ on the turnover rate is not significant. This finding seems to suggest that the performance of the employee is not a good predictor of turnover in this research setting. However, as pointed out above, the coefficient for the estimated hazard rate in the performance growth model shows that those employees who are more likely to leave the phone center tend to significantly improve their performance over time ($P < .1$).

The initial performance models show clear productivity and early turnover advantages when employees are hired using referral programs. The analyses of performance growth, however, show that referrals do not perform any better than nonreferrals over time at the phone center. Moreover, the path of performance estimated for the employees at the phone center does not seem to reflect any improvement and/or skill acquisition (i.e., "learning by doing"; see Arrow 1962). In this phone center, on-the-job tenure does not seem to make a worker more productive, especially in the long run. My findings suggest that an inverse U-shape curve is very descriptive for the CSR performance curve (consistent with the findings in many other studies of service-oriented jobs; see Staw 1980). The performance improvement mostly occurs during the first three months at the job (including the training). After that, the performance tends to decrease (the coefficient for tenure is negative and significant in all estimated models; also the coefficient for average performance in the previous month is below one and significant in all models).

To address whether referrer's characteristics and level of performance might influence the performance trajectory of the employee referral, I also ran several models adding referrer's characteristics to the main performance equation. The results were similar to those in the initial performance models; I found no evidence that information about the referrer improves the fit of any performance improvement model.[26]

[26] Referrer's characteristics do not seem to predict or provide any information about the future performance of the referral ($P < .575$; incremental $\chi^2 = 2.90$; $df = 4$); nor does information about the referrer's evaluation by the firm ($P < .255$; incremental $\chi^2 = 1.29$; $df = 1$). These results are available in Castilla (2002).

TABLE 4

Turnover-Hazard-Rate Selection-Regression Models Predicting Performance Correcting for Turnover Rate

	Only Referral		Adding Controls		Adding Some Controls		Turnover Rate Model (Cox Regression Model)	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Main model:								
Constant	5.890***	.340	6.148***	.545	5.844***	.351		
Performance, month $T-1$	.762***	.015	.748***	.015	.768***	.014	.012	.048
Tenure in months	−.054***	.019	−.060***	.020	−.055***	.019		
External referral	.037	.111	−.009	.113	−.015	.107	−.435	.320
Gender (1 = male)			.103	.146			.254	.340
Repeat application (1 = yes)			−.225	.194	−.179	.174	.541	.565
Computer			−.074	.138			.168	.456
Language			−.167	.157	−.161	.139	.510	.440
Years of education			.013	.039			.052	.093

Works at time of application			−.009	.131			−.075	.369
Months of bank experience			−.002	.004			.018***	.006
Months of nonbank experience			−.005*	.002	−.004***	.001	−.009*	.005
Nonbank experience, squared			.000	.000			.000*	.000
Months of customer service			.004***	.001	.003**	.001	.004	.004
No. of previous jobs			−.013	.051			−.211	.157
Tenure in last job (in days)			.000	.000			.000	.000
Salary in last job			.024	.019			−.055	.049
No. of applications			.006*	.003	.006*	.003	−.001	.013
No. of openings			−.001	.006			−.014	.019
Turnover hazard rate[a]	1.767^{+}	1.199	1.762^{+}	1.028	1.417^{+}	1.011		
Wald chi-square stastistic	3,298***		3,732***		3,680***		39.11***	
$P > \chi^2$	.000		.000		.000		.002	
Person-month observations (employees)	2,983 (257)		2,983 (257)		2,983 (257)		3,188 (260)	

NOTE.—Performance is measured as the average number of calls answered per hour (quality adjusted).
[a] The turnover hazard rate is estimated from the turnover Cox Regression Model reported in the table.
[+] $P < .10$ (two-tailed tests except for z-test on effect of "external referral" variable, which is one tailed).
* $P < .05$.
** $P < .01$.
*** $P < .001$.

Interdependence at Work

The dynamic models in table 5 include the "referrer leaves" dummy variable in order to evaluate whether the departure of the referrer has a negative impact on the referral performance curve. All four models show that the referral variable does not seem to have a significant effect on employee performance. Overall, referrals and nonreferrals do not differ in their productivity trajectories. These results again do not support the better match theory in the long run. Instead, I find statistically reliable evidence of interdependence between referrals' productivity and referrers' turnover. Consistent with hypothesis 3a, referrals whose referrer has left show a worse performance trajectory than those whose referrer has stayed (and even than nonreferrals). The "referrer leaves" coefficient in the dynamic regression models—including the most significant controls only—is $-.28$ ($P < .05$, two-tailed test). I therefore find support for hypothesis 3a.[27]

This finding suggests that the effects of referral ties continue beyond the hiring process, having later effects not only on attachment to the firm but also on performance. The model shows that there are no statistically significant differences in productivity trajectories between nonreferrals and referrals whose referrer stays in the organization. I find, however, that the "breaking of the tie" between referrer and referral has important negative consequences for the productivity of the referred employee—to the extent that referrals perform worse than nonreferred employees if their referrer leaves the organization. In the last two columns of table 5, I report the event-history analysis results of the turnover process. Now the referral variable appears to have a significant negative impact on the likelihood of an employee leaving the organization. However, referrals

[27] I also tested the reciprocal effect that referrals had upstream on their referrers' turnover and performance. Consistent with the social enrichment argument, one can easily imagine that the referrers might also be affected when their referrals depart. Thus, I explored the data for evidence of whether the referral turnover decreases referrers' performance and/or increases the chances of referrer turnover. Unfortunately, the study design did not allow me to perform a robust test of this effect. First, in order to avoid problems of left censoring, I only looked at referrers who were themselves hired in the two-year hiring window ($N = 82$). Of the 119 referrals these people made, only 18 were hired, and of these, only seven terminated. Second, given that not all employee referrers were (or had worked as) CSRs before (or during the period under study), their performance was not measured as number of calls per hour. Instead I used the organization's yearly subjective employee evaluations which exhibit little variance across employees or over time. Despite the lack of statistical power, the effect of the referral's terminating in both the turnover and the performance models is as predicted (the results are never statistically significant though). This is consistent with Fernández et al. (2000).

whose referrer has left show a lower survival rate than referrals whose referrer has stayed.

Hypothesis 3a is about examining the impact of the exit of the referrer on the referral's level of performance. Assessing the social enrichment effect also requires analyzing whether the presence of the referrer is what improves referrals' performance (hypothesis 3b). I was unable to test whether the presence of the referrer during training accounts for any initial performance advantage of referrals in comparison with nonreferrals. By the time referred hires complete their training, most of their referrers are still with the company, and therefore the referral variable and the referrer presence variable are almost identical.[28] I can, however, test whether the referrer can help the referral along a quicker performance improvement trajectory. To test hypothesis 3b, I run a model similar to the one in table 5 that includes now the variables "referrer stays" and "referrer leaves." The results of such analyses are displayed in table 6. Since the effects of the control variables on performance are almost identical to the effects reported in table 5, those effects are omitted in table 6. The referrer's continued presence does not seem to help the referral along a quicker performance improvement trajectory.

As some evidence supporting the social enrichment process in this phone center, I learned from my interviews with PCHR personnel about what they thought were important posthire determinants of retention and productivity. In a high-pressure, highly structured environment where CSRs answer up to 5,000 phone calls a month and where work is closely scrutinized, the PCHR staff have indeed thought about the potential benefits of the social enrichment process. As mentioned earlier, one trainer claimed: "People leave their jobs because of the working environment. The job burns you out!" Thus, it is not surprising that prior to my study, the staff had been considering introducing a formal "buddy" system, where longtime employees would be paired with new hires as a means of reducing turnover and increasing job satisfaction. The underlying theory is identical to that of the social enrichment process. One trainer highlighted the importance of having a friend on the job: "It really helps in making the job more comfortable." This trainer did not specifically say that the referrer might play an important role in this process. But when probed about the possibility that the referrer might be acting as an informal "buddy," she said that this was "probably right" (Fernández et al. 2000). Similarly, according to one hiring manager, "I once had two employees who were dating each other come together to let me know about their decision to leave the floor." When I probed about the possibility of their being referral

[28] Only 11 referrers left the organization during the training period of their respective referrals.

TABLE 5

CROSS-SECTIONAL CROSS-TIME REGRESSION MODELS PREDICTING PERFORMANCE CORRECTING FOR TURNOVER RATE

	ONLY REFERRAL		ADDING SOCIAL INTERACTION		ADDING CONTROLS		ADDING SOME CONTROLS		TURNOVER RATE MODEL (Cox Regression Model)	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Main model:										
Constant	5.890***	.340	5.859***	.341	6.149***	.546	5.823***	.352		
Performance, month $T-1$	.762***	.015	.763***	.015	.748***	.015	.769***	.014	.015	.048
Tenure in months	−.054***	.019	−.053***	.019	−.058***	.019	−.053***	.019		
External referral	.037	.111	.061	.114	.020	.117	.012	.110	−.654*	.354
Referrer leaves (1 = yes)			−.279*	.159	−.275*	.155	−.281*	.157	.966*	.504
Gender (1 = male)					.105	.147			.271	.340
Repeat application (1 = yes)					−.220	.192	−.174	.172	.537	.562
Computer					−.065	.139			.105	.452
Language					−.171	.156	−.162	.138	.537	.445

Years of education					.013	.039			.051	.092
Works at time of application					−.007	.131			−.078	.362
Months of bank experience					−.002	.004			−.019***	.005
Months of nonbank experience					−.005*	.002	−.004***	.001	−.009[+]	.005
Nonbank experience, squared					.000	.000			.000*	.000
Months of customer service					.004***	.001	.003***	.001	.004	.004
Number of previous jobs					−.015	.051			−.186	.160
Tenure in last job (in days)					.000	.000			.000	.000
Salary in last job					.022	.019			−.053	.049
Number of applications					.006*	.003	.006*	.003	.001	.013
Number of openings					−.001	.006			−.013	.019
Turnover hazard rate[a]	1.767[+]	1.199	1.746[+]	1.024	2.076[+]	1.221	1.644[+]	1.199		
Wald chi-square stastistic	3,298***		2,098***		3,754***		3,713***		41.33***	
$P > \chi^2$	.000		.000		.000		.000		.001	
Person-month observations (employees)	2,983 (257)		2,983 (257)		2,983 (257)				3,188 (260)	

NOTE.—Performance is measured as the average number of calls answered per hour (quality adjusted).
[a] The turnover hazard rate is estimated from the turnover Cox Regression Model reported in the table.
[+] $P < .10$ (two-tailed tests except for the z-test for the effect of "external referral," which is one tailed).
* $P < .05$.
** $P < .01$.
*** $P < .001$.

TABLE 6
PRESENCE OF THE REFERRER IN PREDICTING THE PERFORMANCE OF THE REFERRAL

			Turnover Rate Model (Cox Regression Model)	
	Coef.	SE	Coef.	SE
Main model:				
Constant	6.149***	.546		
Performance, month $T-1$	.748***	.015	.015	.048
Tenure in months	−.058***	.019		
Referrer stays (1 = yes)	.020	.117	−.654*	.354
Referrer leaves (1 = yes)	−.275*	.155	.966*	.504
Control variables included[a]				
Turnover hazard rate[b]	2.076[+]	1.221		
Wald chi-square statistic	3,753.50***		41.33***	
$P > \chi^2$	.000		.001	
Person-month observations (employees)	2,983 (257)		3,188 (260)	

NOTE.—Performance is measured as the average number of calls answered per hour (quality adjusted).
[a] The effects of the control variables on performances are very similar to those effects reported in table 5. They are not reported in this table.
[b] The turnover hazard rate is estimated from the turnover Cox Regression Model reported in this table.
[+] $P < .10$ (two-tailed test except for z-test for "referrer stays" and "referrer leaves," which is one tailed).
* $P < .05$.
** $P < .01$.
*** $P < .001$.

and referrer, she said that this was "very possible given that many employees refer relatives and friends for the CSR job."

Finally, I also test whether referrer's characteristics and level of performance influence the performance trajectory of the referred employee. Again, adding the information about the productivity of the referrer who leaves the phone center does not improve the fit of any performance growth model.[29]

Limitations and Future Research

This article expands the scope of previous recruitment source studies by analyzing unique, objective measures of performance. As with the results of any study based on one sample drawn from a single organization, caution needs to be exercised when generalizing the results of this study. Thus, I believe that this research can be extended in several interesting

[29] Once again, referrer's characteristics do not seem to predict or provide additional information about the future performance of the referral ($P < .620$; incremental $\chi^2 = 2.64$; $df = 4$); nor does information about the referrer's evaluation by the firm ($P < .308$; incremental $\chi^2 = 1.04$; $df = 1$). Results are available in Castilla (2002).

directions. The first and most obvious area to be explored involves developing studies to continue testing the social integration and embeddedness arguments in more comprehensive and detailed ways. I have explored whether the effect of referral ties on employees' performance continues beyond the hiring process. A dummy variable for whether the respondent is a referral is included as a network variable. I focus on referrals as a matter of necessity. In particular, one can believe in social enrichment without believing that it has to come through a referral process. After all, once an employee enters the organization, she presumably develops a much wider network of employee connections and friendships. Studies need to look at the social enrichment process by including dynamic information about employees' multiple networks before and after they come to work at an organization. It is important to collect information about new workplace connections and personal relationships as they evolve over employees' tenure on the job. Additional research dealing with multiple ties over time (and their effect on individual performance) is much needed.

The second extension is closely related to the previous one. Although the current and previous studies have documented important recruitment source differences in several posthire indicators of employees' better matches, most of them exclusively focus on the bilateral nature of ties and their consequences. In my study, I only look at how the tie between two actors (referrer/referral) affects the performance for one of these actors. One point often emphasized in the "posthire interdependence" literature, however, is that the social relationships that affect outcomes are decidedly multilateral. In this regard, more research is required to understand how multilateral networks affect outcomes and how an employee's degree of integration into multilateral social networks might itself be affected by the referrer (perhaps by the referrer's status or simply by the referrer's position in the formal or informal network of the workplace). Without studies that collect and analyze data on more complex relationships, many of the intervening mechanisms are left open to speculation.

As a sociologist, my own bias is to be more interested in the "posthire interdependence in performance" aspect of this study. In order to better understand how posthire social integration lies at the root of any differential in performance, I suggest more qualitative data studies that can give us a better sense of the mechanisms at work. Despite my limited presentation of what I learned from interviews and observation at the phone center, there is no way I could have captured these more complex relationships in my data since I did not have information about these social networks over time within the phone center. In the absence of such data, many of the intervening mechanisms will thus be left open to speculation for future research on the effects of posthire personal interdependence on performance.

I do not directly address here the conditions that make network effects more or less important. Performance, turnover, and job satisfaction are much more salient in knowledge-intensive industries or jobs—or more generally, in industries that require skilled and highly paid labor, where firms are particularly concerned with attracting and retaining workers. Insofar as that is true, the present research on a specific lower-entry position at the phone center provides an especially stringent test of the hypotheses. The workplace that I chose to study does not involve particularly skilled workers, which makes its support of sociological hypotheses all the more remarkable; these are purported to be jobs in which network effects would be less salient. Future research should pay attention to the fact that the industry/job/firm-level factors might create variation in the strength of the network effects that I am investigating. This is particularly relevant given the mixed results from past studies on turnover and performance. After all, the relationships between turnover or performance and network referral may vary by industry, job, and even by location of the organization.

DISCUSSION AND CONCLUSION

Organizations frequently use referral programs to recruit new employees. Implicit in referral hiring is the assumption that social relationships among existing employees and potential employees will benefit the hiring organization. This study provides a distinctive and substantive contribution to the literature of economic sociology and labor economics by evaluating the impact of referral ties on employee performance. For the first time in this tradition of research, I have been able to code and carefully analyze unique data on direct measures of employee productivity. As an immediate result, I have been capable of empirically distinguishing among the different theoretical mechanisms by which the hiring of new employees using referrals (as an indicator of preexisting personal connections) influences employee productivity and turnover over time. The dominant argument in economics posits that personal contact hires perform better than isolated hires because social connections provide difficult-to-obtain and more realistic information about jobs and candidates. A more sociological explanation, however, emphasizes posthire social processes that occur among socially connected employees. Employers may still hire referrals at a higher rate simply because personal connections help to *produce* more productive employees in the job. The social support and interactions that occur between referral and referrer can enhance an employee's productivity and attachment to the firm.

My study begins by testing the effectiveness of labor economic models of employee referrals. My findings in the analyses of initial performance suggest that referral programs provide important economic returns to the organization at the very beginning of the job contract: not only do employees hired via referrals initially perform better than nonreferrals, but they are also more likely to complete their initial training in the organization. In the long run, however, referral programs do not seem to provide any economic returns: I provide robust evidence that employees hired via referrals do not perform any better than nonreferrals over time. In addition, I show that information from a candidate's résumé does not seem to predict her initial productivity, subsequent productivity growth, or tenure on the job.

This study is a significant step forward for the literature on social networks and employment because it illustrates the benefits of including the *posthire* dynamics of social relations to understand employee productivity over time. I argue that the finding that referrals perform better than nonreferrals initially, but not over time, does not provide adequate support for the better match argument. Instead, I show that the explanation for better performance by referrals over nonreferrals is sociological given that the initial performance differential seems to be caused by the possibility that the referrer is present to teach the referral the particulars of the job at the very beginning of the job contract or during the training period, or perhaps is simply making the workplace a better place to work. Thus, I find that the presence of the referrer seems to be the factor that accounts for any initial performance differential between referrals and nonreferrals.

Figure 2 provides a stylized representation of these findings, charting the effects of social interdependence on employee performance growth curves (note that the figure is not a plot of my model parameters, though). Referrals do appear to be better performers than nonreferrals right after their training. Any performance advantages of referrals over nonreferrals disappear soon after their first month working as a CSR at the phone center; I found no significant difference in performance careers between referrals and nonreferrals. This pattern of converging productivity for both groups of workers is very much related to the nature of the job selected for this study. Like many lower-entry jobs, working as a phone customer representative is a job with a "hard" performance ceiling. Employees hired via referrals peaked out earlier and were later caught up by those hired by nonreferrals. The performance improvement mostly occurs during the first three months at the job. The performance of the referral, however, is negatively affected by the referrer's departure at any point in time, even when the referral has been in the organization for a while. As shown in this figure, the leaving of the referrer results in a

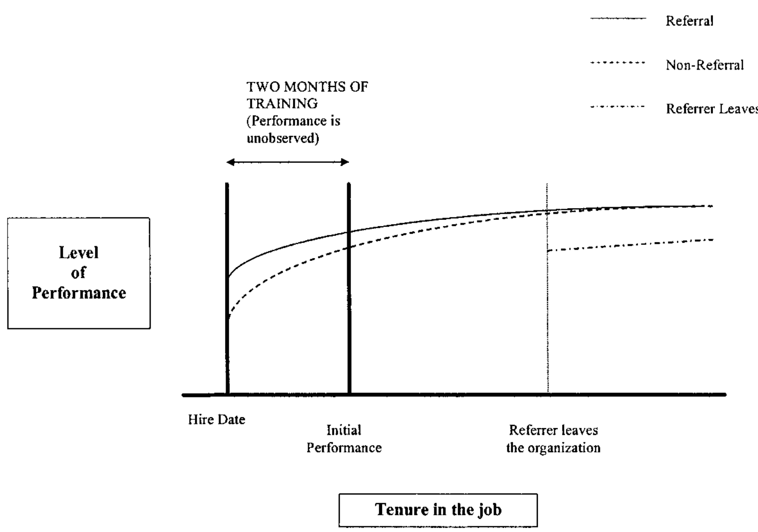

FIG. 2.—Summary graph of the effects of social interdependence on performance growth curves. Note: This figure provides a stylized representation of my findings (it is not a plot of the model parameters).

significant predicted parallel downward shift of the performance curve.[30] This finding is of interest because an important predictor of performance evolution over time appears to be the referrer's continued presence in the firm. It is the "breaking of the tie" between referrer and referral that seems to have serious negative implications for the referral employee's productivity over time.

Clearly, the role of social connections goes beyond the screening and hiring of employees: it is an important tool for understanding the dynamics of employee outcomes such as turnover, job satisfaction, and performance. For this reason, researchers should not restrict their study of employee networks to examining whether employees are connected at a given point in time. The ability to develop prominent personal connections, whether "weak" or "strong," may not be the central determining factor of individual careers (Granovetter 1973). On the contrary, the main argument in this study is that individual career outcomes may depend more on whether those contacts are present in the right place at the right time. In this sense, I suggest bringing back the original notion of embeddedness (as in Gra-

[30] There is only an effect if the referrer left. As an anonymous reviewer pointed out, this may be caused by the fact that CSRs reach very high levels of performance during the first few months of employment, and the only way to go is down. However, I still find that for those referrals whose referrer leaves, this "going down" is more pronounced than for those whose referrer stays (or even for those who were not referrals).

novetter [1985]) and conceptualizing "embeddedness" as an ongoing set of social relationships whereby employees come to organizations with preexisting social ties (some of which vanish and some of which remain over time). Once employees get hired, they develop new sets of connections that prevail when they move on to other organizations. Influential and knowledgeable contacts thus depend on one's past mobility; in turn, these contacts influence one's future career moves.

My research indicates that the presence of certain contacts at the workplace (and especially their departure) can influence one's productivity and attachment to the firm. In order to gain a better understanding of the mechanisms by which social relations matter in the hiring and posthiring of employees in organizations, future work in this field needs to consider the dynamics of these interactions of employees with both preexisting contacts as well as in new personal relationships developed at the workplace, and should use detailed longitudinal data such as those I have analyzed here. At a more general level, this type of research should continue facilitating necessary dialogue between economic and sociological theories (Baron and Hannan 1994). I also believe that such work is essential for expanding and further clarifying our current knowledge about the impact of social relations on economic behavior and outcomes.

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