THE VALUE OF HIRING THROUGH EMPLOYEE REFERRALS*

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Using personnel data from nine large firms in three industries (call centers, trucking, and high-tech), we empirically assess the benefit to firms of hiring through employee referrals. Compared to nonreferred applicants, referred applicants are more likely to be hired and more likely to accept offers, even though referrals and nonreferrals have similar skill characteristics. Referred workers tend to have similar productivity compared to nonreferred workers on most measures, but referred workers have lower accident rates in trucking and produce more patents in high-tech. Referred workers are substantially less likely to quit and earn slightly higher wages than nonreferred workers. In call centers and trucking, the two industries for which we can calculate worker-level profits, referred workers yield substantially higher profits per worker than nonreferred workers. These profit differences are driven by lower turnover and lower recruiting costs for referrals. *JEL* Codes: J24, M51, J30, J63.

I. INTRODUCTION

Firms often use referrals from existing employees to hire new workers: about 50% of U.S. jobs are found through informal networks and about 70% of firms have programs encouraging

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referral-based hiring.[1] A large and growing theoretical literature seeks to understand hiring through referrals, as well as draw out implications of referrals for many central issues in labor economics, including wage inequality, duration dependence in unemployment, racial gaps in unemployment, and the quality of worker-firm matching over the business cycle.[2] While there is a rich and growing empirical literature on referrals (see Ioannides and Loury 2004 and Topa 2011 for excellent reviews), particularly for questions on how networks affect worker outcomes (such as job finding), relatively little is known empirically about what firms may gain from referral-based hiring. There are two main data challenges. First, referrals are difficult to directly observe. Second, understanding what firms gain from referrals requires data on productivity, which are also rare.

We overcome these challenges by assembling personnel data from nine large firms in three industries: call centers, trucking, and high-tech. Spanning hundreds of thousands of workers and millions of applicants, our data combine direct measurement of employee referrals, high-frequency measurement of worker productivity on multiple dimensions, and surveys conducted by the firms and by the authors on different aspects of worker ability, including aspects that are not observed by the firm at time of hire. We organize our findings around answers to three main questions:

(i) How do firms treat referred versus nonreferred applicants? Compared to nonreferred applicants, referred applicants are substantially more likely to be hired, and, conditional on receiving an offer, they are more likely to accept it. This occurs even though on most characteristics, both

1. Granovetter (1974) showed that roughly 50% of workers are referred to their jobs by social contacts, a finding that has been confirmed in more recent data (Topa 2011). A leading online job site estimates according to their internal data that 69% of firms have a formal employee referral program (CareerBuilder 2012). Employee referral programs encourage referrals from existing employees, often by offering monetary bonuses for when referred candidates get hired.

2. Montgomery (1991) and Calvo-Armengol and Jackson (2007), among many others, analyze how referrals affect wage inequality. Calvo-Armengol and Jackson (2004) analyze referrals and duration dependence in unemployment. Holzer (1987b) and Zenou (2012) study referrals and racial gaps in unemployment. Galenianos (2012) analyzes how referrals affect the quality of worker-firm matching over the business cycle. For a detailed treatment of the growing theoretical literature on social networks in economics in general, see Jackson (2008).

observable and unobservable to the firm at time of hire, referred and nonreferred applicants are similar, as are referred and nonreferred workers.

(ii) Are referred workers more productive than nonreferred workers? On many productivity measures, referred and nonreferred workers have economically similar performance. There are two main exceptions: (a) in trucking, referred workers have fewer accidents than nonreferred workers, and (b) in high-tech, referred workers are more likely to invent patents than nonreferred workers.

(iii) How costly to the firm are referred vs. nonreferred workers in terms of turnover, wages, or other aspects? In all three industries, referred workers are significantly less likely to quit than nonreferred workers. Referred workers have higher wages than nonreferred workers only in high-tech, where the difference is relatively modest.

Having documented these results, we move toward quantifying differences in profits between referred and nonreferred workers. We focus on call centers and trucking, where the production process is relatively simple. Referred workers produce substantially higher profits than nonreferred workers. In both call centers and trucking, profit differences are driven by lower turnover and lower recruiting costs. Turnover is costly since quitting workers need to be replaced and because new workers require training and time to reach peak productivity. Referrals also reduce recruiting costs, as it requires substantially fewer applicants to be screened to produce a hire among referrals compared to nonreferrals. Higher productivity is not a significant driver of profit differences in call centers and trucking.

We close by considering two sources of heterogeneity in the value that firms gain from referrals. The first source we consider is the referrer, that is, the employee making the referral. In high-tech and trucking, referrers tend to have higher productivity than workers who don't make referrals. In trucking, where we know who referred whom, we find that referrers tend to refer people like themselves in productivity. Consequently, there are large differences in profits between referrals from high-productivity referrers compared to low-productivity referrers. The second source is local labor market conditions. In trucking, we find that differences between referrals and nonreferrals in hiring rates, offer acceptance rates, and trucking accidents are larger when the local economy is strong instead of weak.

Theory has identified a number of reasons firms may benefit from hiring through referrals. In learning theories (Simon and Warner 1992; Dustmann, Glitz, and Schoenberg 2012; Brown, Setren, and Topa 2013; Galenianos 2013), referrals reduce uncertainty about match quality for potential workers. With less uncertainty about match, referred workers will have higher reservation wages than nonreferred workers, as well as higher productivity and wages. In homophily theories (Montgomery 1991; Casella and Hanaki 2008; Galenianos 2012), firms seek referrals from their highest ability workers, which they do given a tendency of people to be socially connected with those of similar ability. Homophily is the pervasive tendency of people to associate with those like themselves (McPherson, Smith-Lovin, and Cook 2001). Referred workers will have superior unobservables and productivity and will produce positive profits for firms. In a third class of theories, which we call peer benefit theories (Kugler 2003; Castilla 2005; Heath 2013), referrals are valuable because of benefits that referrers and referrals derive from working in the same organization. For example, referrers may mentor referrals or monitor their behavior, or it may simply be more enjoyable for referrers and referrals to work together.[3]

In empirical work, a relatively small but growing literature explores referral-based hiring from the perspective of the firm.[4] Beaman and Magruder (2012) and Pallais and Sands (2013) conduct field experiments using workers in India and in an online marketplace, respectively, to study whether and why referred

3. Besides what we consider the three leading classes of theories, it could also be the case that referrals reflect favoritism (e.g., Beaman and Magruder, 2012). Paralleling Becker's taste-based model of racial discrimination, it could be that incumbent employees persuade firms to hire social contacts, even if these social contacts may not be the best suited for the job. If referrals reflect favoritism, then referred applicants may receive a "lower bar" in getting hired, and referred workers may end up having lower productivity.

4. Pioneering work on referrals was conducted by Rees (1966) in economics and by Granovetter (1973, 1974) in sociology. There is also substantial more recent work by sociologists, for example, Fernandez, Castilla, and Moore (2000) and Castilla (2005). In economics, there is now a significant literature on the effects of worker social networks in individual job search; see Ioannides and Loury (2004) and Topa (2011) for surveys, as well as Kramarz and Skans (2014) and Schmutte (2015) for noteworthy recent examples. This literature is connected to but we believe conceptually separate, from work on why firms use referral-based hiring.

workers are more productive. Turning to nonexperimental studies, recent contributions include Dustmann, Glitz, and Schoenberg (2012), Heath (2013), and Hensvik and Skans (2013).[5] Most similar to our paper in using direct measures of referral status and developed country workers is Brown, Setren, and Topa (2013), who use personnel data from one U.S. firm to provide a rich analysis of wages, turnover, and hiring. Relative to Brown, Setren, and Topa (2013), we use a much larger sample over nine firms, direct measures of productivity, and detailed data on applicant and worker skill characteristics.

The main contribution of our article is to assess the benefits that firms receive from referrals versus nonreferrals and to quantify those benefits in terms of profits. Past work has compared referred and nonreferred workers in terms of wages. However, wage differences alone are not enough to compute whether there are profit differences, since productivity may differ importantly from wages (e.g., Lazear, 1979; Medoff and Abraham, 1980, 1981; Flabbi and Ichino, 2001; Shaw and Lazear, 2008) and there are often multiple dimensions to productivity. Several of our findings would be overlooked with only wage data. For example, in high-tech, referrals have substantially higher levels of innovation than nonreferrals, whereas they have only modestly higher wages.

Although there are differences across industries that we highlight along the way, the facts we document are surprisingly consistent across firms and industries. This suggests that our findings may be relevant for many firms in the economy, although we certainly acknowledge that questions of generalizability may remain, even with nine firms.

II. Data

For each of the three industries, we discuss (i) the nature of the data; (ii) how productivity is measured, how workers are paid, and what survey data were collected; and (iii) how referrals are

5. Dustmann, Glitz, and Schoenberg (2012) develop a dynamic search model of learning through referrals, which they test using coethnic hiring patterns in German matched employer-employee data. Heath (2013) develops a model where referrals reduce limited liability problems, which she tests using data on Bangladeshi garment workers. Hensvik and Skans (2013) investigate homophily models by studying past coworker linkages between entering and incumbent workers using matched employer-employee data from Sweden.

measured and how the bonuses for making referrals (i.e., the employee referral programs) are structured. Some details about the firms cannot be given due to confidentiality restrictions. For brevity, we provide variable definitions in Appendix B (all appendix material is in the Online Appendix).

II.A. Call Centers

We obtained our call center data from an HR analytics firm called Evolv, which provides call center firms with job testing software.[6] The data provided to us are composed mainly of data from seven large call center firms, and we restrict our sample to these seven firms.[7] The data run from July 2009 to July 2013. Across the firms, data coverage begins at different dates, reflecting when the firms begin using Evolv's job test. Five firms adopt Evolv by Q1 of 2011, whereas the other two adopt in 2012.[8] Restricting to the seven large firms, our sample comprises about 350,000 applicants and 74,000 hires. The large majority of the workers (about 85%) are located in different parts of the United States, with a small number located abroad (primarily in the Philippines). Each of the seven firms has multiple locations (in the data each firm has, on average, about 15 locations) and provides service to large end-user companies, for example, large credit card or cellphone companies. Within each location, different workers may work for different end-user companies.

In the call centers, the production process consists of inbound and outbound calls, with workers doing primarily customer

6. Evolv was purchased in late 2014 by Cornerstone OnDemand. One of the article's authors, Michael Housman, is the current chief analytics officer for Cornerstone OnDemand.

7. The seven large firms comprise 93% of the applicants and 97% of the workers in the data provided to us, and we restrict our sample to these firms. The average number of hires among the seven large firms is 10,514 workers per firm. In addition to the seven large firms, the data provided to us include six additional firms, hiring an average of only 400 workers per firm across all years of the data. All our results are very similar regardless of whether we restrict to the seven large firms or whether we include the additional firms, as seen in Online Appendix Table C.25.

8. The firms begin using the Evolv test (i.e., the firms enter the sample) in the following months: 2009/07, 2010/09, 2011/01, 2011/02, 2011/03, 2012/02, and 2012/09. Within firms, there is also cross-location variation in when Evolv's job testing is implemented; thus, different locations within a firm enter our sample at different times. Online Appendix A.12 gives further discussion and provides evidence that the presence of variation in when firms and locations enter our sample does not seem important for the interpretation of our results.

service or sales work. Performance is measured using five industry-standard productivity measures (three objective, two subjective), though which productivity measures are available varies by firm.[9] The three objective productivity measures are schedule adherence, measuring the share of work time a worker spends performing work; average handle time, with a lower average call time indicating higher productivity; and the share of sales calls resulting in a successful sale. The two subjective productivity measures are a manager's assessment from listening in of whether the service was of high quality (quality assurance) and the customer satisfaction score. Workers are primarily paid by the hour. Turnover is high in call centers and is costly for firms—in our data, roughly half of workers leave within the first 90 days. A great deal of information on applicant skills is available from applicant job tests, including numerous questions on cognitive and noncognitive ability (though some skill characteristics are not collected by the job tests at some call center locations).

Referral status is measured via a self-report on the applicant's job test ("Were you referred to this job application by someone that already works for this company?") Referral bonuses vary by firm and by location within the firm, but are typically around \$50–\$150. The applicant must be hired for a referrer to be paid, and there is typically some tenure requirement (e.g., 30 or 90 days) that the referral must stay to yield a bonus for the referrer. A referral bonus of \$100 is about 0.5% of annual earnings for our sample.

II.B. Trucking

The data are from a very large U.S. trucking firm, covering all driver applicants and hires over the period 2003–2009. To preserve the firm's anonymity, we do not release the exact total number of applicants, employees, or employee-weeks in the sample. The baseline data include weekly miles, accidents, quits, and a number of background characteristics and are available for tens of thousands of workers. In addition, we collected very detailed survey data one week into training for a subset of roughly 900 new drivers starting work in late 2005 and 2006. Data collected include cognitive and noncognitive ability,

9. For some workers, no productivity measures are available. In Online Appendix A.5, we provide evidence that this is unlikely to be a source of bias for our productivity analysis.

experimental preferences (collected through incentivized lab experiments), and more detailed information on worker background, all of which were not observed by the firm at time of hire.[10]

Production consists of delivering loads between locations. Drivers are paid almost exclusively by the mile (a piece rate), are nonunion, and are away from home for long periods of time. The standard productivity measure in long-haul trucking is miles driven per week. Even though most drivers work about the same number of hours (i.e., the federal legal limit of about 60 hours/week), there are substantial and persistent productivity differences across workers in miles per week, which are due to several factors, including speed, skill at avoiding traffic, route planning, and coordinating with people to unload the truck. Beyond miles, another important performance metric is accidents. Turnover is high, both in quits and fires, though quits outnumber fires 3 to 1. Roughly half of workers leave within their first year. Workers who have poor performance, either in miles or accidents, risk getting fired.

Referral status for truckers is recorded both using a survey question in the job application (how the worker found out about the job) and using administrative data from the firm's employee referral program. These two measures of referral status are highly correlated, suggesting that both are reliable (see Online Appendix B.1). For our analysis, we use the job application survey question measure of referral status, since it is available for the entire sample period, whereas we only have data from the employee referral program for October 2007–December 2009. A limitation is that we are missing information from the job application survey question for 37% of the applicants and 33% of the workers. Observations with missing referral status information are excluded from the sample. Fortunately, referral status does not

10. The data were collected during commercial driver's license training at one of the firm's regional training schools. The participation rate was high; 91% of those offered the chance to participate in data collection chose to do so. See Burks et al. (2008) and Online Appendix B.3 for more on the data collection. Online Appendix Table C.1 compares drivers in the full dataset to drivers in the subset with very detailed data. Drivers in the subset have a higher share of being referred. They also have lower earnings, reflecting that they are new drivers, as well as somewhat different demographics (reflecting that they are primarily from one region of the United States). From the subset of 895 drivers, referral status is observed for 628 drivers, and we restrict attention to these drivers.

appear to be missing in a systematic way that would affect our findings.[11] Out of the three industries, only for trucking do we have matched data on who referred whom (via the administrative data from the employee referral program), and we only have the match for October 2007–December 2009. For referring an experienced driver, an incumbent worker generally receives $500 when the driver is hired and $500 if the referred driver stays at least six months. For referring an inexperienced driver, an incumbent worker generally receives $500 if the worker stays three months.[12] For our sample, a referral bonus of $1,000 is about 3% of annual earnings.

II.C. High-Tech

We use data from a large high-tech firm. The data have about 25,000 workers and 1.4 million applicants. For 2003–2008, we have data on all new regular employee hires, as well as on all applicants that are interviewed for those positions. In addition, for June 2008–May 2011, we have data on all applicants who apply (instead of just those interviewed) for engineering and computer programmer positions.

Most of the high-tech workers are high-skill individuals with advanced education. The largest share are engineers, computer programmers, and technical operations personnel. In addition, some workers are in sales and customer support. Unlike in call centers and trucking, much of production occurs in teams. Productivity measures include both subjective performance reviews and detailed objective measures of employee behavior, including the number of times one reviewed or debugged other people's code, built new code, or contributed to the firm's internal

11. The job application survey question on referral status is optional (as are a number of other questions on the job application). Online Appendix Table C.2 shows that although there are some slight demographic differences between those with and without referral status information from the job application survey question, there is no significant correlation between trucker productivity (miles or accidents) and whether referral status is missing. Furthermore, the article's results are qualitatively similar if we measure referral status using information from the administrative employee referral program where there is no missing data (Online Appendix Table C.23). For the other eight firms (the seven call center firms and the high-tech firm), we only have one measure of referral status, but it has essentially no missingness. See Online Appendix A.3 for further details.

12. These referral bonuses were generally standard over 2003–2009, though there were occasional cases when drivers were paid different amounts (e.g., different regions paid slightly different amounts), as described in Online Appendix B.3.

wiki. We also have data on worker innovation, an important aspect of performance in many high-tech fields. Worker innovation is measured primarily using patent applications since getting hired.[13] We analyze the objective performance and innovation measures at the monthly level, whereas the subjective performance reviews are given by quarter. The vast majority of workers are paid by salary. Unlike in our call center or trucking data, turnover is low, with workers staying years with the firm. Incumbent workers are surveyed occasionally by the HR department; a 2006 survey provides data on personality traits, which are not directly observed by the firm at time of hire.[14]

Referral status at the high-tech firm is measured using administrative data from the company's employee referral program (i.e., a current employee provided an applicant's résumé to the HR department). Referral bonuses have varied over time, but are usually a few thousand dollars and are paid to referrers for an applicant getting hired (no tenure requirement). We have data on receipt of referral bonuses, so we know which employees made successful referrals and when; however, we do not know whom an employee referred.

II.D. Summary

Table I summarizes the data elements available for the three industries. Certain elements such as cognitive ability and personality are available for workers in all three industries. Other elements are only available for particular industries. For example,

13. At the high-tech firm, employees who create an invention file an Invention Disclosure Form. Attorneys from the firm then decide whether to file a patent application. Most of these patent applications are later approved as patents, but the process usually takes several years. For the analysis, our variable of interest is patent applications per employee. This is advantageous in two respects. First, patent applications are observed right away (whereas actual patent award occurs usually multiple years later). Second, it allows us to compare referrals and nonreferrals in terms of the ideas that the firm thought were most valuable to patent, instead of merely all the ideas that an inventor chose to disclose.

14. The survey also provides us with SAT scores. We do not have personality or SAT score data for employees who joined the company after the survey was administered. The survey was voluntary. The participation rate was only about one-third, but the participation rate was very similar for referred and nonreferred workers (regressing whether one responds to the survey on referral status and the controls in Table IV, Panel C, the response rates of referrals and nonreferrals differ by less than 1 percentage point). Also, some people who answered the survey chose to answer the personality questions but left the question about SAT scores blank.

TABLE I
SUMMARY OF DATA ELEMENTS

	Call centers	Trucking	High-tech
Referral status	W,A	W,A	W,A
Productivity	W	W	W
Demographics	A	W,A	W,A
Cognitive ability	W,A	W	W
Personality	W,A	W	W
Experimental games		W	
Who makes referrals		W	W
Who referred whom		W	

Notes. This table summarizes the data elements from the three industries. W means a data element is available for workers. A means a data element is available for applicants. For details on data collection and more on why different elements are available for different industries, see the Online Data Appendix (Appendix B).

trucking is the only industry where we know who referred whom, and where we have measures of worker behavior in lab experiments. Table II provides sample means for workers. The share of workers referred is 36%, 20%, and 33% in call centers, trucking, and high-tech, respectively. During our sample period, 51% of truckers are observed ever having an accident and 6% of high-tech workers are observed ever developing a patent.

III. APPLICANT QUALITY AND HIRING

Table III shows that referred applicants are substantially more likely to be hired. We analyze linear probability models of being hired on referral status and observables. Throughout the article, standard errors are clustered at the applicant or worker level (depending on whether we are analyzing applicants or workers).[15] In call centers, referred applicants are 6.3 percentage points more likely to be hired (up from a base of 19% for nonreferred applicants), and falling to 6.0 percentage points once demographics are controlled for. In trucking, referred applicants are 10 percentage points more likely to be hired, up from a base

15. We do this because referral status, the main regressor of interest, varies at the individual level. When we analyze the interaction term of referral times the annual state unemployment rate, we show results clustering by state. In addition, we include dummy variables for missing instances of control variables.

TABLE II

SAMPLE MEANS

	Call center firms	Trucking firm	High-tech firm
Referred	36%	20%	33%
Years of schooling	13	13	17
Female	62%	8%	Confidential
Black	21%	18%	Confidential
Hispanic	21%	5%	Confidential
Age at hire	26	39	29
Log(salary)	4.32	6.53	Confidential
Accidents		0.024	
Preventable accidents		0.011	
Patents			0.0047
Have accident or patent		51%	6%
Number of workers	73,595	N	25,282

Notes. This table provides sample means for workers as well as the sample size for workers. For applicants, the sample size is 349,562 applicants for call centers; A applicants for trucking; and 1,415,320 applicants for high-tech. Some information cannot be shown in the table due to confidentiality requirements. For the trucking firm, exact sample sizes are withheld to protect firm confidentiality, $A \gg 100{,}000$, $N \gg 10{,}000$. Entries are blank if a variable is not applicable. In all three industries, means for referral status, schooling, gender, race, and age are calculated at the worker level. For call centers, we can calculate sample means of demographics at the worker level, but we cannot link demographic information to our main data on worker outcomes (explained in Online Appendix B.2). Call center mean salary is calculated at the worker-day level. For trucking, mean salary and accidents are calculated at the worker-week level. Accidents is the share of worker-weeks where a driver has an accident. The company's definition of an accident is quite broad and includes serious as well as relatively minor accidents. Preventable accidents are accidents the driver had control over. For high-tech, mean patents is calculated at the worker-month level (i.e., patents is the average number of patent applications per worker-month). Have accident or patent equals 1 if the worker has at least one trucking accident or one patent in the sample.

of 17%. In high-tech, referred applicants are 0.27 percentage point more likely to be hired, which is sizable relative to the base of 0.28%. Because the coefficients remain large after observables are controlled for, this suggests that firms recognize that referrals may be better along unobserved dimensions.

Table III also shows that referred applicants are more likely to accept offers, conditional on receiving them. In baseline specifications without demographic controls, referred applicants are 5.1, 7.3, and 2.7 percentage points more likely to accept an offer in call centers, trucking, and high-tech, respectively. Results are similar after demographic controls are added.

These differences in hiring and offer acceptance are interesting because in terms of characteristics, referred and nonreferred applicants look similar. In addition, referred and nonreferred workers look similar. We focus our comparison here on schooling, cognitive ability, and noncognitive ability, analyzing additional

TABLE III

REFERRED APPLICANTS ARE MORE LIKELY TO BE HIRED AND MORE LIKELY TO ACCEPT JOB OFFERS

	(1) Hired	(2) Hired	(3) Accept offer	(4) Accept offer
Panel A: Call centers				
Referral	0.063***	0.060***	0.051**	0.050**
	(0.002)	(0.002)	(0.025)	(0.025)
Demographic controls	No	Yes	No	Yes
Observations	349,562	349,562	2,362	2,362
R-squared	0.062	0.066	0.208	0.210
Mean dep. var. if ref = 0	0.19	0.19	0.56	0.56
Panel B: Trucking				
Referral	0.101***	0.098***	0.073***	0.073***
	(0.002)	(0.002)	(0.003)	(0.003)
Demographic controls	No	Yes	No	Yes
Observations	A	A	$0.22A$	$0.22A$
R-squared	0.067	0.068	0.070	0.071
Mean dep. var. if ref = 0	0.17	0.17	0.80	0.80
Panel C: High-tech				
Referral	0.0027***	0.0027***	0.027**	0.026**
	(0.0003)	(0.0003)	(0.011)	(0.011)
Demographic controls	No	Yes	No	Yes
Observations	1,175,016	1,175,016	5,738	5,738
R-squared	0.586	0.586	0.597	0.598
Mean dep. var. if ref = 0	0.0028	0.0028	0.74	0.74

Notes. This table presents linear probability models analyzing whether referred applicants are more likely to be hired and, conditional on receiving an offer, whether they are more likely to accept. An observation is an applicant. Robust standard errors in parentheses. In Panel A, regressions include month-year of application dummies and location fixed effects. In columns (1) and (2), demographic controls are race, age, gender, and years of schooling. For columns (3) and (4), the only available demographic control is years of schooling. In Panel B, regressions include month-year of application dummies, work type controls, and state fixed effects. Demographic controls are age and gender. The exact number of applicants, A, is withheld to protect firm confidentiality, $A \gg 100{,}000$. In Panel C, regressions include month-year of application dummies, job position ID dummies, and office location dummies. Demographic controls are race and gender. The sample is applicants for engineering and computer programmer positions from June 2008 to May 2011. *significant at 10%; **significant at 5%; ***significant at 1%.

characteristics in Online Appendix C. Schooling is observed by firms at time of hire, whereas cognitive and noncognitive ability are generally not directly observed by the firm at time of hire.[16]

16. With the exception of SAT scores in high-tech, our data on cognitive skills, noncognitive skills, and experimental preferences were not directly observed by firms at time of hire. In the call-centers, data on cognitive and noncognitive skills, as well as substantial other information about work-relevant skills and job fit, are collected by the job testing company, Evolv; however, only overall job test scores on each applicant are shared with the call-center firms. In trucking, the data were collected by the authors on workers during training. In high-tech, the data on noncognitive skills were collected in a survey of existing workers by the HR

For applicants, data on applicant schooling, cognitive ability, and noncognitive ability are mostly only available for call centers, so we focus the analysis there.[17] For trucking, data on worker characteristics are only available for the subset of 900 new drivers described in the data section. For high-tech, data on SAT scores and Big 5 personality traits come from a survey by the HR department.

Results are in Table IV. Starting with comparisons among referred and nonreferred applicants, column (1) of Panel A shows that in call centers, referred applicants have 0.10 fewer years of schooling, which is statistically significantly different from 0 but economically small in comparison to the standard deviation of schooling, which is 1.3 years for the column (1) sample. Referred applicants score 0.02 standard deviation (σ) lower in intelligence, and 0.02σ lower on the Big 5 Personality Index, our measure of noncognitive ability, which is equal to the mean of the normalized Big 5 personality characteristics. Looking one by one at the different personality characteristics in Online Appendix Table C.3, referred applicants are less conscientious, less agreeable, and less open, but are more extroverted.[18]

Turning to workers instead of applicants, Table IV shows that compared to nonreferred workers, referred workers have slightly fewer years of schooling in call centers and trucking and similar years of schooling in high-tech. Referred and nonreferred workers have similar levels of cognitive ability—referred truckers score 0.12σ lower on an IQ test and referred high-tech workers score 12 points higher on the SAT (neither difference is statistically significant). Turning to noncognitive ability, there are a few interesting patterns in personality when we look one by one at Big 5 traits in Online Appendix Table C.4—referred workers tend to be slightly less agreeable and slightly more extroverted. However, on the overall Big 5 index, differences are

department. Of course, firms may receive partial information about cognitive/noncognitive skills during recruitment, so it is more correct to think of such variables as not easily observed instead of unobserved (Altonji and Pierret 2001).

17. For high-tech, we have data on applicant schooling for a small sample of applicants, composed of applicants applying between 2008 to 2010 for entry-level jobs. In that sample, referred workers have 0.12 fewer years of schooling than nonreferred workers.

18. Of the Big 5, conscientiousness, agreeableness, extroversion, and openness are usually considered desirable, whereas neuroticism is usually considered undesirable (e.g., Dal Bó, Finan, and Rossi 2013).

TABLE IV

SCHOOLING, COGNITIVE ABILITY, AND NONCOGNITIVE ABILITY: COMPARING REFERRED VS. NONREFERRED APPLICANTS, REFERRED VS. NONREFERRED WORKERS

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Schooling in years		Intelligence (normalized)		Big 5 index (normalized)	
Applicants or workers?	App	Workers	App	Workers	App	Workers
Panel A: Call centers						
Referral	−0.100***	−0.068***	−0.024***	−0.029***	−0.017***	−0.013***
	(0.012)	(0.023)	(0.004)	(0.008)	(0.002)	(0.003)
Observations	47,360	9,956	302,022	62,110	341,788	73,214
R-squared	0.088	0.095	0.137	0.196	0.087	0.092

	(1)	(2)	(3)
Dep. var.: (sample is workers)	Schooling in years	IQ (normalized)	Big 5 index (normalized)
Panel B: Trucking			
Referral	−0.231	−0.115	−0.023
	(0.150)	(0.101)	(0.061)
Observations	628	598	628
R-squared	0.093	0.120	0.076

	(1)	(2)	(3)
Dep. var.: (sample is workers)	Schooling in years	SAT total score (mean = 1,401)	Big 5 index (normalized)
Panel C: High tech			
Referral	0.006	11.96	0.015
	(0.027)	(9.45)	(0.026)
Observations	10,890	899	1,853
R-squared	0.188	0.210	0.040

Notes. This table compares schooling, cognitive ability, and noncognitive ability among referred versus nonreferred applicants, as well as referred versus nonreferred workers. An observation is an applicant in the odd columns of Panel A, whereas an observation is a worker in all the other regressions. Robust standard errors in parentheses. For an explanation of how the different variables are measured and defined, see Online Appendix B. For the call centers, the applicant regressions (odd-numbered columns) include month-year of application dummies, location dummies, and controls for race, age, and gender. The worker regressions (even-numbered columns) include the same controls, except they include month-year of hire dummies instead of month-year of application dummies and also include client dummies. The call center schooling analysis is based on one firm, whereas the analyses of cognitive and noncognitive ability are based on seven firms. For trucking, the regressions include month-year of hire dummies, work type controls, state dummies, and controls for race, age, gender, and marital status. The drivers here are from the same training school and were hired in late 2005 or 2006. For high-tech, the regressions include month-year of hire dummies, job category dummies, job rank dummies, office location dummies, and controls for race, age, and gender. The SAT and Big 5 Index data are from a voluntary 2006 survey done by the high-tech firm's HR department. *significant at 10%; **significant at 5%; ***significant at 1%.

slight in all three industries between referred and nonreferred workers.[19]

19. Online Appendix Table C.5 shows that referred and nonreferred workers also look similar in terms of additional measures of schooling and experience.

Although referrals do not have higher levels of human capital and ability in Table IV, it could be they differ in terms of certain preferences, which we measure for truckers using lab experiments, for example, referrals might be less likely to quit because they are more patient or have a greater risk tolerance for weekly swings in trucker income. Online Appendix Table C.6 does not support this. The one significant difference is that referrals are less trusting than nonreferrals.

IV. Productivity

Table V shows that referred and nonreferred workers have similar productivity on many metrics, whereas referred workers have superior performance in terms of accidents and innovation. We regress productivity on referral status, normalizing the productivity variables when appropriate to ease comparisons across performance measures and industries.

In call centers, there are no statistically significant differences between referred and nonreferred workers on four of five productivity measures (all normalized), and on schedule adherence, referrals are slightly less productive (by 0.03σ). The number of observations varies by regression because which productivity measures are available varies by firm (and firms enter the sample at different dates), and because certain productivity measures are measured more frequently than others.[20] The estimates are precise. In Castilla's (2005) study of one call center, referrals have 3.5% more phone calls per hour than nonreferrals. Using a much larger sample, our 95% confidence interval allows us to rule out a referral performance advantage of more than 0.3%, meaning we can rule out differences 10 times smaller than in Castilla (2005).[21]

In trucking, using miles as an outcome, the coefficient on referral is essentially 0, with a standard error of 0.01σ. Although miles is the main performance indicator, another very

20. For example, sales conversion data are not available for firms that don't do sales work, and quality assurance data are only available on days where managers listen in to a worker's calls.

21. Castilla (2005) finds that referrals have 0.7 more calls/hour (off a base of 20), or about 3.5% more. See Online Appendix A.5 for more on comparing our estimates with Castilla (2005). Holzer (1987a) and Pinkston (2012) show that referrals have higher subjective productivity ratings, using data from the Employment Opportunity Protection Project. Pallais and Sands (2013) show that referrals have higher productivity on oDesk.

TABLE V

REFERRALS AND PRODUCTIVITY

Dep. var.:	(1) Adherence share	(2) Average handle time	(3) Sales conversion	(4) Quality assurance	(5) Customer satisfaction
Panel A: Call centers					
Referral	−0.027**	0.001	−0.014	0.016	0.003
	(0.013)	(0.010)	(0.008)	(0.017)	(0.003)
Observations	152,683	749,616	134,386	31,908	603,860
Clusters	3,136	12,496	3,192	2,864	11,859
R-squared	0.142	0.563	0.725	0.175	0.034

Dep. var.: (accident coeffs are multiplied by 100)	(1) Miles	(2) Accident	(3) Preventable accident	(4) Nonpreventable accident (placebo)
Panel B: Trucking				
Referral	−0.001	−0.136***	−0.121***	−0.008
	(0.009)	(0.032)	(0.021)	(0.018)
% reduced accident risk	NA	6%	11%	1%
Observations	0.83*M*	*M*	*M*	*M*
Clusters	0.85*N*	*N*	*N*	*N*
R-squared	0.082	0.0032	0.0039	0.0008

Dep. var.:	(1) Subjective performance	(2) Objective performance	(3) Patents	(4) Citation-weighted patents
Panel C: High-tech				
Referral	0.035***	0.004	0.236***	0.272***
	(0.012)	(0.007)	(0.077)	(0.091)
Observations	104,255	289,689	333,492	333,492
Clusters	16,546	11,123	17,190	17,190
R-squared	0.093	0.170		

Notes. Standard errors clustered by worker in parentheses. In Panel A, all columns are OLS regressions. Productivity is one of five normalized measures. An observation is a worker-day. The controls are month-year of hire dummies, month-year dummies, a fifth-order polynomial in tenure, location dummies, client dummies, and the number of times that each outcome was measured to compute the dependent variable. In Panel B, all columns are OLS regressions. In column (1), productivity is measured in normalized miles driven per week (trimming zero mile weeks, as well as the lowest and highest 1% of the nonzero miles observations), whereas in columns (2)–(4), productivity is a dummy for having an accident in a given week. An observation is a worker-week. All regressions include month-year of hire dummies, month-year dummies, a fifth-order polynomial in tenure, driver training contracts, work type controls, training school dummies, state dummies, the annual state unemployment rate, and controls for gender, race, marital status, and age. The exact sample size is withheld to protect firm confidentiality, $M \gg 100{,}000$, $N \gg 10{,}000$. In Panel C, columns (1) and (2) are OLS regressions (with normalized subjective and objective performance) and columns (3) and (4) are negative binomial models. An observation is a worker-quarter in column (1) and a worker-month in columns (2)–(4). All regressions include a fifth-order polynomial in tenure, job category dummies, job rank dummies, office location dummies, and controls for race, age, gender, and education. In addition, column (1) includes quarter-year of hire dummies and quarter-year dummies; column (2) includes month-year of hire dummies and month-year dummies; and columns (3) and (4) include month-year of hire dummies. *significant at 10%; **significant at 5%; ***significant at 1%.

important measure of performance is driver accidents. Using a linear probability model, we estimate that referrals have a weekly accident probability that is about 0.14 percentage point below that of nonreferrals. Given a baseline accident probability of around 2.4% a week, referrals have a roughly 6% lower risk of having an accident each week. One potential explanation for this result, separate from referrals having lower underlying accident risk, is that referrals may be assigned different roles in a firm than nonreferrals. Although we control for the different types of work that different drivers are doing, it might be possible that referrals are receiving preferential treatment or work type assignment by the firm on some unobserved dimension. To address this, we take advantage of the fact that accidents are divided into "preventable", accidents the driver had control over, and "nonpreventable", accidents the driver could not control. Referrals are 11% less likely to have preventable accidents, which is substantial, but only 1% less likely to have nonpreventable accidents.

In high-tech, referrals have slightly higher subjective performance scores (by 0.04σ),[22] arguably the most important performance metric. For objective productivity, we create a single index equal to the average of six normalized objective productivity variables. Referrals and nonreferrals have similar performance on this index, and the tight standard error means we can rule out small differences in either direction. Looking one by one at the different objective productivity measures in Online Appendix Table C.7, we also see little performance difference between referrals and nonreferrals.

Column (3) of Table V, Panel C, shows that referrals are significantly more likely to file patent applications than are nonreferrals. Patents are a standard measure of innovation in firms and, though relatively rare in patents per worker, are believed to be an important driver of firm performance (Bloom and Van Reenen 2002). Given the skewed, count nature of patent production, we estimate negative binomial models. Referrals produce about 24%

22. To put the 0.04σ magnitude into perspective, we redid the regression in column (1) of Table V, Panel C, using the logarithm of the performance rating instead of standardized performance. The coefficient on referral is 0.0037 (std. err. = 0.0011), indicating that referred workers have 0.4% higher subjective performance, which is an order of magnitude less than the referral differences observed for trucking accidents and for patents.

more patents than nonreferrals.[23] To account for patent quality, we also study citation-weighted patents. Referrals produce 27% more citation-weighted patents than nonreferrals (column (4)).[24]

Our results in Table V include demographic controls, which are available for workers in trucking and high-tech. Online Appendix Table C.9 repeats Table V without demographic controls for trucking and high-tech, while adding job test score controls for call centers. The resulting estimates are mostly similar.[25]

One potential concern in estimating the relationship between referral status and productivity is differential attrition. Among nonreferrals, low-productivity workers might get "weeded out" after some period of time, whereas both low- and high-productivity referred workers may stick with the job. As a robustness check, we repeat our productivity regressions restricting to workers whose tenure exceeds some length, T, looking at productivity in the first T periods. As seen in Online Appendix Table C.8, the resulting estimates are relatively similar.

Why might referred workers be less likely to have accidents and more likely to develop patents? Why couldn't the trucking firm use past accidents to predict new accidents, and why couldn't the high-tech firm use past patents to predict who will develop new patents? In trucking, the firm requests state driving records for applicants, and applicants with past safety issues are removed from consideration. Managers believed that among driver applicants who are not excluded for safety issues, predicting who will be a safe driver is very difficult. Referrals may be providing additional information from social contacts about a driver's difficult-to-observe accident risk.

In high-tech, information about past patents is generally not requested by the firm on applications or in interviews, though applicants could potentially choose to report this information themselves. Managers highlighted to us that the workers are quite young. The median age at hire is 27, with many workers

23. The overdispersion parameter, α, is 16.9 (std. err. = 1.64) in column (3), indicating a highly significant degree of overdispersion, suggesting use of a negative binomial instead of a Poisson model (Cameron and Trivedi 2005).

24. While patents are the most standard measure of innovation, we also have data on contribution of ideas to the firm's internal idea board. On this, referrals also have superior performance (see Online Appendix A.7).

25. Our results in Table V also include tenure controls. Online Appendix Table C.10 repeats Table V without tenure controls. The resulting estimates are also mostly similar.

starting right out of college or graduate school. As we describe in Online Appendix A.7, most of these workers have no or little patenting history before joining the firm. Referrals might provide useful information about innovative potential, given that there is limited information on past innovation performance.

IV.A. Productivity Spillovers for the Referrer

Another way that using referrals may increase productivity is if there is a productivity benefit to the referrer from making a referral. A referrer may feel empowered if the person they refer is hired, or they may become more productive because they have a friend to work with. We examine whether referrers become more productive after making referrals using data from trucking and high-tech, where we know which workers are making referrals and when. We regress productivity on a dummy for having already made a first referral, worker fixed effects, and time-varying controls.

Online Appendix Table C.12 shows that there are no significant gains in productivity or salary for referrers making referrals. In trucking, miles, accidents, and earnings do not change after a referral has been made. In high-tech, subjective performance ratings, patents, and salary do not change after a referral. The zeroes we estimate are fairly precise for earnings in both industries, for miles in trucking and for subjective performance in high-tech. For accidents and patents, while the point estimates are close to zero, we are unable to rule out moderate-sized spillovers in either direction (reflecting that accidents and patents are relatively rare).

V. How Costly to the Firm Are Referred versus Nonreferred Workers?

We consider whether referred and nonreferred workers may differ in turnover, wages, and benefits, aspects which affect how costly workers are to firms.

V.A. Turnover

Despite similarities in observable characteristics, Table VI shows that referred workers are substantially less likely to quit than nonreferred workers. We estimate Cox proportional hazard models. In call centers, referred workers are about 11% less likely

TABLE VI

REFERRALS AND QUITTING

	(1)	(2)	(3)	(4)	(5)	(6)
Industry:	Call centers		Trucking		High-tech	
Referral	−0.107***	−0.108***	−0.110***	−0.103***	−0.262***	−0.253***
	(0.014)	(0.014)	(0.020)	(0.020)	(0.061)	(0.062)
Current state unemployment rate				−0.074***		
				(0.016)		
Additional controls	No	Yes	No	Yes	No	Yes
Observations	4,446,155	4,446,155	0.94M	0.94M	301,272	301,272

Notes. This table examines whether a worker's referral status predicts quitting. All specifications are Cox proportional hazard models with standard errors clustered by worker in parentheses. For call centers, an observation is a worker-day. Both columns (1) and (2) include month-year of hire dummies, location dummies, and client dummies. We restrict to workers who are with the company for 200 days or less. The additional controls in column (2) are job test score controls. For trucking, an observation is a worker-week. Columns (3) and (4) include month-year of hire dummies, month-year dummies, driver training contracts, work type controls, training school dummies, and state dummies. The additional controls in column (4) are gender, race, marital status, and age. The exact sample size is withheld to protect firm confidentiality, $M \gg 100{,}000$, $N \gg 10{,}000$. For high-tech, an observation is a worker-month. Columns (5) and (6) include month-year of hire dummies, job category dummies, job rank dummies, and office location dummies. The additional controls in column (6) are race, age, gender, and education. For all three industries, time since hire is fully controlled for (see Online Appendix A.8 for details). *significant at 10%; **significant at 5%; ***significant at 1%.

to quit, both with and without job test score controls. In trucking, referred workers are also about 11% less likely to quit. Given the coefficient on driver home state unemployment rate of –0.07, the reduction in quitting among referred workers is of the same magnitude impact as that from a 1.5 percentage point increase in the driver's home state unemployment rate. In high-tech, referred workers are around 26% less likely to quit. The coefficients in trucking and high-tech are similar after controlling for demographics.

One explanation for why referrals are less likely to quit, which is unrelated to underlying quit propensities, is that referrals postpone quitting so as to help their referrer get a referral bonus. Specifically, for truckers and many call-center workers, there are bonuses for referrers where part or all of the bonus is contingent on the referral staying for some period of time. To examine this explanation, we exploit the sharp referral bonus thresholds in trucking at six months (for experienced drivers) and at three months (for inexperienced drivers) with a regression discontinuity design. As seen in Online Appendix Table C.13, the referral bonus appears to have little impact on quitting around the bonus tenure threshold, and the zero effect is precisely estimated. In addition, the largest quitting differences in Table VI are for the high-tech firm, where referral bonuses are paid solely for the referral getting hired. These two pieces of evidence

TABLE VII

REFERRALS AND WAGES (OLS, DEP VAR = LOG(SALARY))

	(1)	(2)	(3)	(4)	(5)	(6)
Industry:	Call centers		Trucking		High-tech	
Referral	0.0002	−0.0004	0.0002	0.0041	0.017**	0.017**
	(0.0021)	(0.0021)	(0.0041)	(0.0040)	(0.0065)	(0.0065)
Additional controls	No	Yes	No	Yes	No	Yes
Observations	634,153	634,153	0.65M	0.65M	245,270	245,270
R-squared	0.275	0.284	0.064	0.067	0.518	0.524

Notes. This table examines whether referred workers earn higher salaries. Standard errors clustered by worker in parentheses. For call centers, an observation is a worker-day. Columns (1) and (2) include month-year of hire dummies, month-year dummies, a fifth-order polynomial in tenure, location dummies, and client dummies. The additional controls in column (2) are job test score controls. There are 11,174 workers. The data are from two of the call center firms. For trucking, an observation is a worker-week. Columns (3) and (4) include month-year of hire dummies, month-year dummies, a fifth-order polynomial in tenure, driver training contracts, work type controls, training school dummies, state dummies, and the annual state unemployment rate. The additional controls in column (4) are gender, race, marital status, and age. There are 0.74N workers. The exact sample size is withheld to protect firm confidentiality, $M \gg 100{,}000$, $N \gg 10{,}000$. For high-tech, an observation is a worker-month. Columns (5) and (6) include month-year of hire dummies, month-year dummies, a fifth-order polynomial in tenure, job category dummies, job rank dummies, and office location dummies. The additional controls in column (6) are controls for race, age, gender, and education. There are 10,655 workers. *significant at 10%; **significant at 5%; ***significant at 1%.

suggest (but do not prove) that differences in quit rates are unlikely to be driven by referral bonuses.

Although our analysis focuses on quits, which are more common than fires in all three industries, referred workers are also less likely to be fired.[26]

V.B. Wages

Table VII shows regressions of log earnings on referral status and controls. In call centers, referrals and nonreferrals have similar earnings. In trucking, recall that earnings are closely related to miles since truckers are paid primarily by piece rate. As for call centers, we find similar earnings for referrals and nonreferrals. In high-tech, referred workers earn around 1.7% higher wages both with and without controlling for demographics. Referred high-tech workers are paid more even conditional on their characteristics, as we would expect when there is an important unobservable component to match quality.

26. In all three industries, we can distinguish quits and fires in the data. Referred workers are 1%, 11%, and 37% less likely to be fired in call centers, trucking, and high-tech, respectively. The difference is highly statistically significant for trucking, but not statistically significant for call centers and high-tech.

As for the productivity results, we explore the importance of differential attrition for the wage results by repeating our wage regressions restricting to workers whose tenure exceeds some length, T, analyzing the first T periods. Online Appendix Table C.14 shows similar results.

V.C. Benefits

Another cost where referrals and nonreferrals might differ is in terms of employee benefits. Speaking to managers at two call center firms, the trucking firm, and the high-tech firm, benefit eligibility does not depend on referral status for any benefit. Despite this, there could still be differences in benefit utilization (conditional on benefit eligibility) between referrals and nonreferrals. Unfortunately, we were unable to obtain comprehensive data on benefit utilization for any firm. Fortunately, for the trucking firm, we obtained information on usage of a few benefits: holiday time and vacation time. Online Appendix Table C.16 shows that referred and nonreferred truckers do not significantly differ on usage of these two benefits. In addition, at the four firms we spoke to, managers had no reason to believe that referrals and nonreferrals differed in benefit utilization.

VI. Profits

Having documented several differences in behaviors, we turn to profits. We focus our profits analysis on trucking and call centers because the production process is relatively simple. For high-tech, the production process is much more complicated than in call centers or trucking, making it unfeasible to perform a profits analysis.

We compare the average profits received when a firm hires a referred worker versus when a firm hires a nonreferred worker. When a position is posted, it lies vacant for $S \geq 0$ periods, during which a vacancy cost of c_V is incurred per period. Recruitment costs are incurred to hire the worker, including all the time and money required to process and consider the applicants. After getting hired, the worker begins production, during which he produces weekly profits of Z_t. For a worker, i, who stays with a firm for T periods, the profits from that worker are:

$$\pi_i = -H_i - \delta^S RB_i + \sum_{t=S+1}^{S+T} \delta^{t-1} Z_{it}. \tag{1}$$

The first term, H_i, is the hiring cost, which is equal to the recruiting cost, R_i, plus the cost of the position being vacant. The second term, $\delta^S RB_i$, is the discounted referral bonus, where δ is the discount factor. RB_i includes referral bonuses paid at time of hire, as well as possibly paid later (if referral bonuses are contingent on the worker staying for some period of time). The third term, $\sum_{t=S+1}^{S+T} \delta^{t-1} Z_{it}$, is discounted profits from production.

The different terms in equation (1) will vary between call centers and trucking. The profit formula is somewhat more complex for trucking than for call centers, and we begin with that one first. For both industries, we assume an annual discount factor of 0.95.[27]

For trucking, the weekly profit function is $Z_t = y_t(P - mc - w_t) - FC - c_A A_t + (1 - E)\theta k_t q_t$. The first term, $y_t(P - mc - w_t)$, is per-mile earnings from operating a truck, where y_t is a driver's weekly miles, P is revenue per mile, mc is the nonwage marginal cost per mile (such as, truck wear and fuel costs), and w_t is the wage per mile. The second term, FC, is fixed costs per week (for example, back office support for the driver and the capital cost of the truck). The third term, $c_A A_t$, is weekly costs from trucking accidents, where c_A is the cost per accident and A_t is a dummy for having an accident. The fourth term, $(1 - E)\theta k_t q_t$, represents penalties collected by the firm through its training contracts when inexperienced workers quit (Hoffman and Burks 2014).[28] Based on consultation with managers at the trucking firm, we assume that $P - mc = \$0.70$ per mile, $FC = \$450$ per week, $c_A = \$1{,}000$ for nonpreventable accidents, and $c_A = \$2{,}000$ for preventable accidents.[29] In addition, for inexperienced drivers, we use a cost of \$2,500 for commercial driver's

27. Our results are robust to different discount factors; for example, as seen in Online Appendix Table C.17, our results are similar if we assume an annual discount factor of 0.90.

28. For inexperienced drivers, the firm provides free commercial driver's license training, but workers must sign a contract specifying penalties if they quit too soon (see Online Appendix A.1 for details). E is a dummy for being an experienced worker, $\theta = 0.3$ is the approximate share of quit penalties collected by the firm, k_t is the quit penalty at a given tenure level, and q_t is a dummy for quitting.

29. For profits analysis in trucking, we restrict attention to new hires during October 2007–December 2009, the period when we have information on who referred whom. We do this so we can analyze how profits vary by referrer productivity (see Table VIII). Our conclusions are robust to using the full sample period (2003–2009) for profits analysis, as we discuss further in Online Appendix A.1.

license training, plus five weeks of costly on-the-job training (details on training in Online Appendix A.1). Turning to the referral bonus, if the driver is an experienced referral, the firm pays \$500 when the driver is hired and an additional \$500 if he stays at least 26 weeks. If the driver is an inexperienced referral, the firm pays \$500 if he stays at least 13 weeks. We describe the recruiting cost further later.

For call centers, our analysis is primarily based on cost and revenue information from one of the seven firms. We assume that the other firms have a similar cost and revenue structure. Workers are paid by the hour, and the weekly profit function is given by $Z_t = P_t - mc_t - w_t$. During training, the worker produces no revenues ($P_t = 0$) and has an average wage of \$9 per hour. Training lasts five weeks. After training, revenues are $P = \$26.70$ per hour and the wage is \$10 per hour. Both during and after training, there is overhead cost equal to 63% of the hourly wage (covering wages for trainers and supervisors, as well as worker benefits, building costs, and equipment costs). Weekly profits, Z_t, will solely be determined by how long a worker stays with the firm, and thus abstracts from productivity along the other dimensions (such as calls per hour or call quality). However, given that referrals and nonreferrals did not significantly differ along those dimensions, this simplification should not affect our conclusions comparing profits from referrals versus nonreferrals. The referral bonus is set to \$50 and is paid on the applicant being hired. Online Appendix A.1 provides further details.

We need to calculate R, the recruiting costs involved in making a hire, for both referred and nonreferred workers. Although it is common for firms to measure their average recruiting costs per hire, it is less common to do so separately for referred and nonreferred workers. One strategy suggested by our conversations with the firms was that hiring costs generally scale linearly with the number of people being considered.[30] We make this assumption, allowing us to compute cost per hired for referred and nonreferred workers. For call centers, the average recruiting cost per hire is \$600; given the estimates in Table III, this implies that the recruiting cost per hire for referred workers is about \$497, whereas that for nonreferred workers is \$658. For trucking,

30. The assumption that recruiting costs per hire scale linearly with the number of people being considered is a strong one and could be violated in either direction. See Online Appendix A.1 for further discussion.

the average recruiting cost per hire is about \$1,500, with a corresponding cost per hire for referred workers of \$1,063 and of \$1,609 for nonreferrals.[31]

Last before computing profits, we need to account for the cost of vacancies. The per period vacancy cost, c_V, is assumed to be the average profits earned by a randomly selected alternative worker (that is, average profits averaged over all periods and workers). For the number of vacant periods, S, recall that the call center and trucking firms have high turnover. Rather than waiting for workers to quit, the firms are usually in hiring mode, with new candidates constantly moving through the pipeline. Thus, when workers quit, they are often replaced very quickly. Based on conversations with managers, we assume a vacancy duration of $S = 1$ weeks for call centers and $S = 2$ weeks for trucking.[32]

Table VIII shows that referred workers produce substantially higher profits than nonreferred workers. To compute profits, we add up profits for each worker, and then take an average over referred workers and over nonreferred workers. In call centers, referrals yield average discounted profit of \$1,453 per worker, whereas nonreferrals yield average discounted profit of \$1,201 per worker. Likewise in trucking, referrals yield average discounted profit of \$3,547 per worker, compared to \$2,549 per worker for nonreferrals. As we show in Online Appendix Table C. 17, the results are relatively similar in robustness checks.

VI.A. Decomposition

To help understand what is driving profit differences between referrals and nonreferrals, we perform a simple decomposition. Profit differences between referred and nonreferred workers can be divided into differences in recruiting costs, productivity, and turnover. To obtain the share for each category, we divide discounted profit differences from each category over the total difference in discounted profits between referrals and

31. Let ρ be the share of workers who are referred and c_H be the average recruiting cost per hire. Then, it follows that the recruiting cost per hire is $\frac{\Pr(Hire|r=0)}{\rho \Pr(Hire|r=0)+(1-\rho)\Pr(Hire|r=1)} c_H$ for a referred worker and $\frac{\Pr(Hire|r=1)}{\rho \Pr(Hire|r=0)+(1-\rho)\Pr(Hire|r=1)} c_H$ for a nonreferred worker. See Online Appendix A.1 for a derivation, as well as for details on how we implement these formulas.

32. The durations are broadly consistent with other studies for the United States (e.g., Davis, Faberman, and Haltiwanger 2013; Wolthoff 2012). We assume vacancy duration does not depend on referral status. See Online Appendix A.1 for discussion.

TABLE VIII

PROFITS PER WORKER AMONG REFERRED AND NONREFERRED WORKERS

Industry	Profits per worker call centers	Profits per worker trucking
Referred (overall)	\$1,453	\$3,547
Nonreferred (overall)	\$1,201	\$2,549
Decomposition:		
Share profit difference from lower turnover	46.6%	64.8%
Share profit difference from higher productivity	0%	1.7%
Share profit difference from lower recruiting costs	53.4%	33.4%
Comparisons based on the referrer:		
Referred (matched sample)		\$3,810
Referred, referring worker w/ above median productivity		\$6,490
Referred, referring worker w/ below median productivity		\$1,526

Notes. We present profits per worker for call center workers and truckers. As described in Section VI, the profits for referred workers includes the cost of paying referral bonuses. The decomposition of profit differences into lower turnover, higher productivity, and lower recruiting costs is as described in Section VI. The matched sample refers to drivers for which we know who referred them (that is, it is based on administrative data from the trucking firm's employee referral program). We calculate profits when the driver referring them has above median productivity in miles and when the driver referring them has below median productivity in miles. For both industries, we assume an annual discount factor of 0.95.

nonreferrals, excluding referral bonuses.[33] Let $\overline{\pi}_i = \pi_i + \delta^S RB_i$ be profits excluding referral bonuses. Given that hiring costs equal recruiting costs plus vacancy costs, and given that we assume vacancy durations are the same for referred and nonreferred hires, the share of profit differences due to hiring costs is the same as the share of profit differences due to recruiting costs.

For call centers, recall that referrals and nonreferrals have very similar productivity (Table V, Panel A); thus, profit differences can be decomposed into recruiting costs and turnover. The share of profit differences due to recruiting costs is $\frac{E(H|r=0)-E(H|r=1)}{E(\overline{\pi}|r=1)-E(\overline{\pi}|r=0)}$, which we calculate to equal roughly 53%. The remaining 47% of profit differences between referrals and nonreferrals comes from referrals having lower turnover.

For trucking, recall that referred workers have similar miles to nonreferred workers, but have fewer accidents (Table V, Panel B). Thus, we measure the share of profit differences due to

33. Profit differences from turnover are defined as the profit differences remaining after subtracting out differences due to recruiting costs and productivity.

productivity differences using differences in accident rates. The share of profit differences due to differences in accident rates is $\frac{E\left(\sum_{t=S+1}^{S+T} \delta^{t-1} c_A A_t \mid r=0\right) - E\left(\sum_{t=S+1}^{S+T} \delta^{t-1} c_A A_t \mid r=1\right)}{E(\overline{\pi} \mid r=1) - E(\overline{\pi} \mid r=0)}$, which we compute to be roughly 2%. Differences in recruiting costs, defined the same way as in call centers, are estimated to comprise 33% of profit differences. Differences in turnover make up the remaining 65% of profit differences.

Why are differences in turnover important for profit differences between referrals and nonreferrals? Part of this reflects that a worker's profit stream is carried out longer. In addition, lower turnover makes it so that a greater share of weeks worked are profitable. In call centers and trucking, most new workers require large initial investments by the firms in training. During call center training, workers yield negative profits per week. In trucking, there is also training for new workers, as well as an initial period of increasing productivity.[34]

VII. Heterogeneity

We now discuss how the value firms gain from hiring through referrals depends on two factors: the identity of the referrer and local labor market conditions. Unlike for our main results, which were for all three industries, our heterogeneity analysis is performed primarily for trucking.

VII.A. Referrers

Before analyzing how the identity of the referrer relates to the value of the referral hired, we consider if there is a

34. If hiring were costless, and all workers yielded the same profit at all levels of tenure, then turnover would not be costly for firms. If this were the case, and if referred workers were less likely to quit, using profits per worker may overstate whether referred workers are actually more valuable to firms than nonreferred workers. As an alternative to calculating profits per worker, we have also calculated profits per worker per week, defined as the total profit produced among all workers (referred or nonreferred) divided by the total number of regular weeks worked for all workers (inclusive of weeks when the position is vacant). Using profits per worker per week, we continue to find that referred workers are significantly more profitable than nonreferred workers. For call centers, we calculate average profits per worker per week of \$85 for referred workers and \$72 for nonreferred workers. For trucking, average profits per worker per week is \$94 for referred workers and \$74 for nonreferred workers.

TABLE IX

HIGH-PRODUCTIVITY WORKERS ARE MORE LIKELY TO EVER MAKE A REFERRAL

	(1)	(2)
Panel A: Trucking		
Miles per week (normalized)	0.0047***	0.0052***
	(0.0013)	(0.0013)
Demographic controls	No	Yes
R-squared	0.031	0.033
Mean dep. var.	0.042	0.042
Panel B: High-tech		
Subjective performance rating (normalized)	0.027***	0.027***
	(0.004)	(0.004)
Patents per year	0.033*	0.030*
	(0.018)	(0.016)
Interview score (normalized)		0.012***
		(0.004)
Incumbent worker was referred		0.043***
		(0.006)
Demographic controls	No	Yes
R-squared	0.151	0.157
Mean dep. var.	0.180	0.180

Notes. This table presents OLS regressions of whether an employee makes a referral on the employee's average productivity. An observation is an incumbent worker. Robust standard errors in parentheses. In Panel A, all regressions include month-year of hire dummies, work type controls, state dummies, and tenure at the job. Making a referral is defined according to administrative employee referral program data. Demographic controls are gender, race, marital status, and age. The sample size is $0.63N$ workers. The exact sample size is withheld to protect firm confidentiality, $N \gg 10{,}000$. In Panel B, all regressions include month-year of hire dummies, job category dummies, job rank dummies, office location dummies, and tenure at the job. Demographic controls are race, age, gender, and education. The sample size is 15,810 workers. *significant at 10%; **significant at 5%; ***significant at 1%.

relationship between worker productivity and whether a worker makes referrals. Table IX shows that workers with higher productivity are more likely to ever make a referral, both for truckers in miles (Panel A) and for high-tech workers in average subjective performance scores and patents per year (Panel B). We do not have information on who makes referrals for call centers.

Table X shows that referred workers tend to have similar performance to their referrers on particular productivity metrics. We focus on trucking where we know who referred whom. We regress a driver's productivity in a given week on the average productivity of their referrer and controls. Panel A shows that if a referrer's average lifetime productivity is 100 miles a week above the mean, the person they refer is on average around 35 miles a week above the mean. Panel B shows that if the referrer has an accident at some point, the person they refer is roughly

TABLE X

Homophily in Truck Driver Referrals

	(1)	(2)	(3)
Panel A: Miles			
Avg. miles per week of referring driver	0.350***	0.339***	0.356***
	(0.037)	(0.039)	(0.039)
Mean dep. var.	1,652	1,652	1,652
Demog. controls for referred driver	No	Yes	Yes
Demog. controls for referrer	No	No	Yes
R-squared	0.187	0.191	0.194
Panel B: Accidents			
Referring driver ever had an accident	0.00383*	0.00373*	0.00371*
	(0.00209)	(0.00211)	(0.00209)
Mean dep. var.	0.0218	0.0218	0.0218
Demog. controls for referred driver	No	Yes	Yes
Demog. controls for referrer	No	No	Yes
R-squared	0.010	0.010	0.011

Notes. This table presents OLS regressions of the productivity of referred workers on the productivity of referrers. The sample is restricted to matched referred truckers hired in October 2007–December 2009. Furthermore, the sample is restricted to workers whose referrer was hired between 2003 and 2009. In Panel A, the dependent variable is worker productivity in miles per week (the estimated coefficients are similar if we exclude zero-mile weeks from the sample). An observation is a worker-week. The sample size is 0.017M worker-weeks. All regressions include month-year of hire dummies, month-year dummies, a fifth-order polynomial in tenure, driver training contracts, work type controls, training school dummies, state dummies, and the annual state unemployment rate for the referred driver. They also include work type controls, state dummies, and tenure at date of referral for the referring worker. Demographic controls refer to controls for gender, race, marital status, and age for both the referred and referring worker. In Panel B, we present linear probability models where the dependent variable is whether the worker has an accident in a given week. An observation is a worker-week. The sample size is 0.018M worker-weeks. Controls are the same as in Panel A. Exact sample size is withheld to protect firm confidentiality, $M \gg$ 100,000. *significant at 10%; **significant at 5%; ***significant at 1%.

17% more likely to have an accident. A confound to identifying behavioral homophily would be if there were a common shock affecting referrers and referrals (e.g., a shock to trucker productivity in a given area). We assuage this concern by including geographic controls for both referrers and referrals (see Online Appendix A.10 for further discussion).[35]

In Table VIII, we see that truckers referred by above median productivity drivers (measured in terms of miles) yield $6,490 in average profits, whereas referrals from below median productivity workers yield $1,526, which is below average profits from nonreferred workers.

35. Pallais and Sands (2013) also find a correlation between the productivity of referrers and referrals.

VII.B. Labor Market Conditions

For trucking, the data contain workers living all over the United States over a seven-year timeframe, allowing us to examine referral differences in varied local labor market conditions. As seen in Online Appendix Table C.19, not only are referred applicants more likely to be hired and more likely to accept offers, but these differences are greater where unemployment is lower at time of application. Likewise, for trucking accidents, nonreferred worker performance is negatively correlated with unemployment at time of hire, whereas for referred workers, there is less cyclical correlation.

For nonreferred workers, our finding on accidents is consistent with asymmetric information models of firing and hiring (e.g., Gibbons and Katz, 1991; Nakamura, 2008), where those looking for work in good times tend to be of lower quality. As to why referred worker quality appears to be less countercyclical, trucking firm managers suggested that referred worker quality may be constrained by reputational concerns for incumbent workers. In the terminology of one manager, incumbent workers may be generally unwilling to refer a “doofus”, even in booms when the average quality of those looking for work may be lower. To the extent that offer acceptance reflects match quality, that referrals differ in offer acceptance in booms is consistent with this interpretation. If firms anticipate these differences in match quality, referred applicants may be differentially more likely to be hired in booms.

VIII. CONCLUSION

Employee referrals are a topic of interest for many social scientists. Although we know that referral-based hiring is common, relatively little is known about what firms gain from hiring referred versus nonreferred workers. Our article takes a step toward filling this gap by combining personnel data from nine large firms in three industries.

In all three industries, referred applicants have a higher chance of getting hired than do nonreferred applicants, and referred workers are less likely to quit than nonreferred workers. On a few productivity dimensions, most notably trucking accidents and high-tech innovation, referred workers have superior performance, but on many dimensions, referrals have similar productivity to nonreferrals. In call centers and trucking, referred workers produce significantly higher profits per worker than nonreferred workers, with differences driven primarily by referrals having lower turnover and requiring less money to recruit. Productivity differences are either absent or do not play a first-order role in profit differences for these two industries.

For high-tech, it is not feasible to calculate worker-level profits, due to the complexity of high-tech production. Thus, we are unable to assess the relative importance of recruiting costs, productivity, and turnover for the value of hiring through referrals in high-tech. We speculate, though, that the relative importance of productivity may be higher for high-tech, due to the importance of innovation for high-tech production.

Although it is not the goal of our article to test theories of referral-based hiring, our results are still relevant for theory. Consistent with learning, homophily, and peer benefit theories, referred applicants are more likely to be hired than nonreferred applicants and referred workers are less likely to quit compared to nonreferred workers. Consistent with homophily theories, high-ability workers are more likely to make referrals, as is the tendency of workers to refer those of similar ability. Potentially consistent with all three classes of theories, referred workers yield higher profits per worker than do nonreferred workers.

However, we also find results that seem inconsistent with existing theories. Referred workers do not consistently have higher wages than nonreferred workers, nor are referrals consistently more productive across different metrics. In addition, in seeming contrast with learning and homophily theories, referrals do not have superior scores on dimensions of quality that are unobserved by the firm. Part of this could reflect that existing theories do not generally include referral bonuses, which are observed in all three industries. When workers receive bonuses for making referrals, they may sometimes recommend unqualified candidates, which may work against referred workers having higher wages or being more productive.[36]

36. It does seem possible, however, that having referral bonuses could increase referral quality relative to having no bonus, particularly if bonuses are conditional on being hired or on worker performance (e.g., if it is costlier for an incumbent worker to find a high-quality candidate to refer than to find a low-quality candidate to refer). The only theory we are aware of that incorporates referral bonuses is that in the recent field experiments of Beaman and Magruder (2012) and Beaman, Keleher, and Magruder (2013). See Online Appendix A.11 for more discussion on the relevance of our results for existing theories.

Outside of learning, homophily, and peer benefit theories, another explanation that has been proposed to explain differences between referrals and nonreferrals is that referrals may have worse outside options (Loury 2006). The worse outside option explanation is consistent with referred workers being less likely to quit and with referred applicants being more likely to accept job offers; however, it does not explain why referred workers have fewer trucking accidents and are more innovative than nonreferred workers.

Methodologically, we illustrate both the promise and limitations in combining large personnel data sets. Personnel data can provide large-scale, inside-the-firm information, which may be valuable for bringing data to bear on a whole host of economic questions. Although using personnel data often leads to questions of external validity, by combining data from different industries, we can examine whether results are consistent across industries, which is largely the case for our findings. Still, even with nine firms in three industries, we acknowledge that our results may not be generalizable to all firms in the economy, though we believe our methodology represents a significant advance relative to existing knowledge. A significant limitation is that personnel policies are rarely randomized by firms.[37] Further empirical research on referrals using natural or randomized experiments is also sorely needed and should be complementary to our article.

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Supplementary Material

An Online Appendix for this article can be found at QJE online (qje.oxfordjournal.org).

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