The Facts About Referrals: Toward an Understanding of Employee Referral Networks*

Stephen Burks† Bo Cowgill‡ Mitchell Hoffman§ Michael Housman¶

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Abstract

Using unique personnel data from nine large firms in three industries, we document five consistent facts about hiring through employee referral networks. First, referred applicants have similar skill characteristics to non-referred applicants, both observable-to-the-firm (e.g., schooling) and unobservable-to-the-firm (e.g., cognitive and non-cognitive ability), but are more likely to be hired, more likely to accept job offers, and have higher pre-job assessment scores. Second, referred workers have similar skill characteristics to non-referred workers. Third, referred workers are less likely to quit and are more productive, but only on rare high-impact performance metrics; on most standard non-rare performance metrics, referred and non-referred workers perform similarly. Fourth, referred workers have slightly higher wages, but yield substantially higher profits per worker. Fifth, workers who make referrals have higher productivity than others, are less likely to quit after making a referral, and refer those like themselves on particular productivity metrics. Differences between referred and non-referred workers tend to be larger at low-tenure levels; for young, Black, and Hispanic workers; and in strong labor markets. No leading class of theories can alone account for all or most of these results, leading us to suggest several theoretical extensions.

JEL Classifications: J24, M51, J30, O32, J63

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†University of Minnesota, Morris

‡UC Berkeley Haas School of Business

§University of Toronto Rotman School of Management; mitchell.hoffman@rotman.utoronto.ca

¶Evolv, Inc.

1 Introduction

Firms often use referrals from existing employees to hire new workers: about 50% of US jobs are found through informal networks and about 70% of firms have programs encouraging referral-based hiring.[1] A large and growing theoretical literature seeks to understand hiring through referrals, as well as drawing 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 also a rapidly growing empirical literature on employee referrals (see e.g., Ioannides and Loury (2004) and Topa (2012) for excellent reviews), there remain important challenges in bringing the theory to the data. On the most basic level, employee referrals are difficult to measure and observe. In addition, many of the main implications of theory concern worker productivity and "unobserved ability," but direct data on these are rare.

In this paper, we overcome these challenges by combining 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. These data provide a unique opportunity to document facts about referrals, which we hope future theory will grapple with. Our exercise is in the style of papers such as Baker et al. (1994a,b) (who documented facts about internal labor markets instead of referrals). We list our five main facts, as well as related sub-findings:

1. **Applicant quality and hiring.** Referred applicants are more likely to be hired, and conditional on receiving a job offer, they are more likely to accept it. Compared to non-referred applicants, referred applicants do not have higher levels of skill characteristics, both observable-to-the-firm (e.g., schooling) or unobservable-to-the-firm (e.g., cognitive and non-cognitive ability); they do, however, score higher on job tests used to measure their likely performance on the job. Referral differences in hiring are largest in strong labor markets and for applicants with high job test scores.

[1] Granovetter (1974) showed that roughly 50% of workers are referred to their jobs by social contacts, a finding which has been confirmed in more recent data (Topa, 2012). A leading online job site, CareerBuilder, estimates that 69% of firms on CareerBuilder have a formal employee referral program in which referrals from existing employees are explicitly encouraged, often in the form of monetary bonuses for when referred candidates get hired. See CareerBuilder's publication "Referral Madness." With increased unemployment in the aftermath of the Great Recession, popular interest in referrals has continued to grow, with some commentators arguing that referral networks are becoming increasingly important to workers. See, e.g., "Employers Increasingly Rely on Internal Referrals in Hiring – In Hiring, a Friend in Need is a Prospect, Indeed," *New York Times*, 1/27/2013, and "How Social Networks Drive Black Unemployment," *New York Times*, 5/5/2013.

[2] Montgomery (1991) and Calvo-Armengol and Jackson (2004), 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 referral networks 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).

2. **Worker quality.** Focusing on workers instead of applicants, we find that, compared to non-referred workers, referred workers do not have higher levels of schooling, cognitive ability, or non-cognitive ability, nor do they score differently in terms of experimental measures of their preferences (e.g., risk aversion, patience, or altruism).

3. **Turnover and productivity.** Compared to non-referred workers, referred workers have lower turnover. Referred workers have similar performance on most non-rare everyday productivity metrics (e.g, sales conversion rates in call-centers and number of computer code reviews performed in high-tech), but substantially higher performance on rare high-impact metrics (e.g., avoiding trucking accidents and inventing patents). Referral differences in turnover and productivity tend to decline with tenure. For trucking accidents, referral differences are greatest in strong labor markets.

4. **Wages and profits.** Referred workers earn higher wages than non-referred workers in only one industry (high-tech), but produce substantially higher profits per worker. The variance of wages is similar between referred and non-referred workers, both initially and over time, and the wages of referred and non-referred workers are not differentially related to worker productivity. In trucking, where we have the data to examine race and earnings, Whites earn more than Blacks among non-referred workers, but not among referred workers.

5. **Referrers.** People making referrals ("referrers") tend to refer those with similar characteristics and productivity. Referrers have higher productivity than non-referrers. Larger referral bonuses are associated with more referrals and people are less likely to quit after making a referral.

After documenting these facts, we then discuss them in light of existing theories. At a broad level, theories of referrals can be clustered into three main classes: (1) learning theories (Simon and Warner, 1992; Dustmann et al., 2012; Brown et al., 2013; Galenianos, 2013), where referrals reduce uncertainty about applicant match quality; (2) homophily theories (Montgomery, 1991; Casella and Hanaki, 2008; Galenianos, 2012), where workers refer people like themselves and this enables firms to hire better workers; and (3) peer benefit theories (Kugler, 2003; Castilla, 2005; Heath, 2013), where referrals improve monitoring and coaching of new workers. None of the three classes of theories on its own can account for all or most of our results.

Most related to our paper is a small, but growing economics literature on why firms use referrals.[3] In a complementary approach to our paper, Beaman and Magruder (2012) and Pallais and Sands (2013) conduct field experiments using Indian and Filipino workers, respectively, to study whether and why referred workers are more productive. While these papers have the virtue of exploiting exogenous variation in key economics features (including referrers' incentives and information, and

[3]The literature on referrals was pioneered by sociologists, particularly Granovetter (1973, 1974). There is also substantial more recent work by sociologists, e.g, Fernandez et al. (2000) and Castilla (2005), who analyze differences between referred and non-referred workers at one call-center plant. 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 (2012) for surveys, as well as Kramarz and Skans (2013) and Schmutte (2013) for noteworthy recent examples. This literature is connected to, but, we believe, conceptually separate, from work on theories of referral-based hiring by firms.

whether referrers and referrals work together), our paper has the strength of analyzing referrals using a broad range of natural work environments. Turning to non-experimental studies, recent contributions include Dustmann et al. (2012), Heath (2013), and Hensvik and Skans (2013).[4] Most similar to our paper in using direct measures of referral status and developed country workers is Brown et al. (2013), who use personnel data from one US firm to provide a rich analysis of wages, turnover, and hiring. Relative to Brown et al. (2013), we use a much larger sample over nine firms, direct measures of productivity, and detailed data on applicant and worker skill characteristics.

We make several contributions to what is known about referrals. Past work has focused primarily (but certainly not exclusively) on wages and turnover. Using our large dataset over nine firms, we confirm past findings that referred workers have lower turnover, but find that referred workers only have higher wages in high-tech, where wage differences are modestly sized and do not decline with tenure. Because of our rich data on skill characteristics, we can examine to what extent differences in hiring, wages, and turnover reflect differences in skill characteristics. We find that referred and non-referred workers do not differ in terms of most observable- and unobservable-to-the-firm characteristics, and that controlling for these characteristics generally has small impacts on estimates of referral differences in hiring, wages, and turnover.

Although we find modest differences between referred and non-referred workers in wages, we find substantial differences in productivity, both in dynamics (referral differences in productivity decline with tenure) and levels. With only data on wages (that is, without productivity data), referral differences by tenure would seem inconsistent with learning theories, whereas referral differences by tenure in actual productivity data support learning theories. Existing theories and evidence on referrals focus on a single dimension of "productivity." However, our results suggest that the benefits of referrals accrue quite differently across standard everyday vs. rare high-impact dimensions of productivity, and we provide several pieces of evidence that referrals and non-referrals may differ in their non-pecuniary value for the job. We believe that future theory may benefit from considering these different dimensions.

Our data were deliberately chosen to span a broad range of worker types and skill groups.[5] When researchers use individual-level productivity data (be it to study referrals or other topics), they often use it from one plant or one firm, given that individual-level productivity data are scarce. While powerful insights can still be drawn, there is often a question of whether the results generalize to other workers and firms in the economy. In our study, 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. From

[4] Dustmann et al. (2012) develop a dynamic search model of learning through referrals, which they test using co-ethnic 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 co-worker linkages between entering and incumbent workers using matched employer-employee data from Sweden.

[5] Call-center work is a relatively low-skill job, long-haul trucking is a moderate-skill job, and high-tech work requires advanced skills. Having a broad range of skills groups in the data is quite useful, as the value of referral-based hiring may be thought to vary based on the type of job.

a larger set of firms we considered for this project, we chose nine for our dataset where we had strong institutional knowledge and which shared several common data elements: high-frequency individual productivity data across multiple dimensions, as well as demographics, cognitive skills, non-cognitive skills, and work friendships. Taking advantage of our very large sample to explore interaction effects, we show that some referral differences tend to be larger among young, Black, and Hispanic workers, and among workers hired in strong local labor markets.

In addition to its importance for theory, understanding which theories of referrals are most supported by the facts also likely has policy implications. For example, in homophily theories of referrals, referral status serves as a signal of unobserved ability. Thus, public policies aimed at expanding labor networks for disadvantaged workers may have immediate informational benefits, which would not be present under, say, peer benefit theories of referrals. Under peer benefit theories, the productivity benefit of referrals may depend on whether referring and referred workers are co-located, which would not be relevant for other theories.[6]

Section 2 describes the three leading classes of theories of employee referrals: learning, homophily, and peer benefit. Section 3 describes the data. Sections 4-8 provide key facts about referral networks. For ease of exposition, we organize each fact and related sub-findings into 1-4 "results." Section 9 discusses the implications of our facts for theory. Section 10 concludes.

2 Theories of Employee Referrals

In *learning theories* of employee referrals, referrals reduce uncertainty about applicant match quality. Simon and Warner (1992), as well as Dustmann et al. (2012) and Brown et al. (2013) in important extensions, posit that referral relationships provide signals of greater precision compared with those on other workers. Building on Jovanovic's (1979) seminal model of employee learning, workers are heterogeneous in their match quality, but this match quality is initially unknown. By providing better initial information, referrals aid employers in learning about their workers. This informational advantage leads those hired through referral to be better matched for the job than non-referred workers, making referred workers both more productive and less likely to quit. Since there is less variation in match quality among referred workers (and thus less option value from future revelation of ability), referred workers will use a higher reservation wage policy and will have higher initial wages. As tenure increases and greater information is observed about workers, differences between referred and non-referred workers in wages, retention, and productivity will dissipate.[7]

[6]Examples of policies aimed at expanding labor networks may include internship and mentor programs; networking events; and helping people use network-enhancing technologies (see, e.g., Newman, 1999). In a concrete recent example, the senior citizen organization, AARP, has worked on developing senior-friendly online social networking tools, thereby helping seniors stay in touch with more contacts, and hopefully increasing the probability of referrals among older workers (see, e.g., "AARP has new help for older workers," *USA Today*, 7/31/2012). The underlying theory of referrals may be relevant for many questions of optimal design for a system to connect older workers, e.g., should a referral still be encouraged if the referrer elder is likely to leave a company shortly after the referred worker would arrive? In peer benefit theories, the answer may be Yes, whereas in learning and homophily theories, the answer may be No.

[7]Although learning theories concerns job-specific match, one can also imagine theories where referrals reduce uncertainty about occupation-specific match or overall ability. While learning models do not generally predict lower wage variance for referrals, this prediction is delivered by Datcher (1983). Dustmann et al. (2012) and Brown et al. (2013)

In *homophily theories* of referrals, referrals are valuable because referred workers tend to be similar to the person referring them in unobserved ability. In a pathbreaking paper, Montgomery (1991) presents a model of referrals and wage determination under *homophily*, the pervasive sociological phenomena of people to associate with those like themselves (McPherson et al., 2001). Ability, which is general, is unobserved until after production, and workers tend to be connected with those of similar ability. Aware of homophily in ability, firms only hire through referrals from incumbent workers revealed to have high ability. Thus, although the underlying mechanism is different from learning models, homophily models also imply that referred workers will be advantageously selected relative to non-referred workers. Referrals have higher average ability, are more likely to be hired, more productive, and earn higher wages. Unlike in learning models, there is no prediction that differences between referred and non-referred workers will fade (Brown et al., 2013).[8]

Peer benefit theories focus on the social interactions that may be part of referral relationships. In his study of call-center workers in the sociology literature, Castilla (2005) provides qualitative interview evidence that referrers and referrals are often in "buddy" relationships at work. Referrals may help to reduce moral hazard problems more generally, reducing the costs of monitoring and helping solve limited liability problems, as well as providing other benefits such as mentoring or coaching (Kugler, 2003; Heath, 2013), or the enjoyment of getting to work with a social tie. Because of these forces, referred workers exert more effort than non-referred workers, thereby achieving higher productivity (conditional on observables), and also making referred applicants more desirable for firms and thus more likely to be hired. Opposite from learning theories, gaps in wages between referred and non-referred workers may increase with tenure, provided that wages are based on past performance. In addition, firms may even tie future wage increases for referrers to the performance of those they refer, leading to higher wage variance for referrers compared to non-referrers.[9]

Besides the three leading models, it could also be the case that referrals reflect favoritism. 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.[10]

find support for different predictions of learning theories. We note that, even if referrals reduce uncertainty about match quality, referral differences may not decline with tenure if firms invest more in training for referred compared to non-referred workers; see Altonji and Pierret (2001) for a related point in the context of statistical discrimination.

[8] Galenianos (2012) incorporates homophily into a search-theoretic model of referrals. Hensvik and Skans (2013) find support for several predictions of homophily models.

[9] As discussed in Brown et al. (2013), peer benefit theories do not make clear predictions about initial wages. Referred workers will exert higher effort, but may be hired even if they have lower observables. We interpret peer benefit theories as predicting that, conditional on observables, referred workers are more productive than non-referred workers. Heath's (2013) model also predicts that differences in wage *variance* between referred and non-referred workers will increase with tenure. Within what we call peer benefits from referrals, Pallais and Sands (2013) distinguish between team production benefits, which depend on the referrer and referral working together, and peer influence benefits, which do not. Pallais and Sands (2013) find evidence for the former, but not the latter.

[10] Firms may also use referrals for the simple reason of reducing recruiting costs; we return to this later in our analysis of profits from referral hiring in Result 10. In addition to the models discussed above, there is a separate strand of literature analyzing how properties of social networks affect job-finding (e.g., Calvo-Armengol and Jackson, 2004). In these models, the focus is on the impact of the properties of worker networks as opposed to firm hiring decisions. The facts we document are less relevant for network architecture models, and so they are not the focus of our paper.

3 Data

For each of the 3 industries, we discuss (1) the nature of the data; (2) how productivity is measured and what survey data were collected; and (3) how referrals are 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. Table C1 summarizes the data elements and Table C2 provides means.

Call-centers. The call-center data are from seven large firms in the call-center industry. We obtained the data from a human resources (HR) analytics firm called Evolv, which provides the call-center firms with job testing software.[11] The data have about 375,000 applicants and about 75,000 employees, containing all applicants and hires over 2009-(July) 2013. The vast majority of the workers (about 85%) are located in different parts of the US, with a small number from the Philippines, India, and Mexico. Each of the seven call-center firms operates about 10-20 call-center locations ("plants") and provides service to large end-user companies, e.g. large credit card or cellphone companies. Within each location, workers work for different end-user companies.

In the call-centers, the production process consists of in-bound and out-bound calls, with workers doing primarily customer service or sales work. Performance is measured using five industry-standard productivity measures. The three objective productivity measures are: schedule adherence, measuring the share of work time a worker spends performing calls; 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: the share of time that a manager listens in and judges the service to be high quality (quality assurance); and the customer satisfaction score. Workers are 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 is available from applicant job tests, including numerous questions on cognitive and non-cognitive ability.

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 around $50-$150. The applicant must be hired for a referrer to be paid, and in some locations, the referral must stay 30 or 90 days to yield a bonus.

Trucking. The data are from a very large US trucking firm, covering all driver applicants and hires over the period 2002-2009. 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 after hire for a subset of 900 new drivers who received training starting in late 2005 and 2006. Data collected include cognitive and non-cognitive ability, experimental preferences (collected through incentivized lab experiments), and more detailed information on worker background, all data which were not observed by the firm at time of hire.[12]

[11] One of the paper's authors, Michael Housman, is the current Vice President of Analytics for Evolv, Inc.

[12] See Burks et al. (2008) and Appendix B for more on the collection of the data.

The production process consists of delivering loads between locations. Drivers are paid almost exclusively by the mile (a piece rate), are non-union, 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 the same number of hours (60 hrs/week, which is the federal legal limit), 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, not getting lost, and coordinating with people to unload the truck. A rare, high-impact performance metric in trucking is accidents. Turnover is high, both in quits and fires, though quits outnumber fires by 3 to 1. Workers who have poor performance, either in miles or accidents, risk getting fired.

Referral status for truckers is measured using both 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 Appendix B.1). Only for the trucking firm do we have matched data on who referred whom, and we only have the match for the period 2007-2009. For referring an inexperienced driver who is hired, an incumbent worker receives \$500. For referring an experienced driver, an incumbent worker receives \$500 when the driver is hired and \$500 if the referred driver stays at least 6 months.

High-tech. We use data from a large high-tech firm. The data have about 25,000 employees and 1.4 million applicants. For 2003-2008, we have data on all new hires and all applicants that are interviewed. In addition, for 2008-2011, we have data on all applicants who apply (instead of just those interviewed) for engineer and computer programmer positions.

Most of the high-tech workers are high-skill individuals with advanced education. The largest share are engineers and computer programmers. In addition, some workers are in sales and customer support. Our non-rare productivity measures are subjective performance reviews (by the employee's supervisor) and detailed objective measures of employee behavior, including hours worked and the number of times one reviewed or debugged other people's code, built new code, or contributed to the firm's code library. We also have data on worker innovation, a rare, but high-impact aspect of performance in many high-tech fields. Worker innovation is measured using patent applications since getting hired and using contributions to the firm's internal ideas board.[13] 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; this provides us with data on personality traits and work friendships which are not directly observed by the firm at time of hire.

Referral status at the high-tech firm is measured using administrative data from the company's employee referral program (i.e. a current employee forwarded an applicant's resume to the HR department). Referral bonuses have varied over time, but are usually a few thousand dollars, and

[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 data analysis in the paper, 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, though the two are highly correlated). Second, it allows us to compare referred and non-referred workers 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.

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.

4 Applicant quality and hiring

Result 1 *Referred applicants are substantially more likely to be hired. Referral differences in hiring are greater for high-ability workers and in strong labor markets. The largest association between referral status and hiring process advancement comes in terms of "getting looked at."*

Table 1 analyzes linear probability models of being hired on referral status and observables. Throughout the paper, standard errors are clustered at the applicant or worker level (depending on whether we are analyzing applicants or workers).[14] In call-centers, referred applicants are 5.9 percentage points more likely to be hired (up from a base of 18% for non-referred applicants), and falling to 5.1 percentage points once demographics and job test scores are controlled for. In trucking, referred applicants are 10 percentage points more likely to be hired up from a base of 17%. In high-tech, referred applicants are 0.27 percentage points 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 referred workers may be better along unobserved dimensions.

While it is well-known that referred applicants are more likely to be hired,[15] our data yield three additional novel results on referrals and hiring. First, referral differences in hiring are greater for applicants with higher pre-job assessment scores (which we analyze in call-centers and high-tech, where we have pre-job assessment data). In trucking, there are no pre-job assessment data, but the data include job openings all over the US over an 8-year time-frame, which we do not have for the other industries. Thus, second, in trucking, not only are referred applicants more likely to be hired, but the difference is significantly greater where the state unemployment rate is lower.[16] We defer discussing why referral differences may vary with labor market conditions until Section 9.1. Finally, we take advantage of having applicant tracking data for the high-tech firm to look at different stages of the hiring process. Hence, third, in high-tech, Table C3 shows that the largest association between referral status and hiring process advancement comes in whether an applicant is "pre-screened," that is, in whether their materials are actually closely examined by a recruiter.

Result 2 *Conditional on receiving a job offer, referred applicants are more likely to accept than non-referred applicants. Referral differences in offer acceptance are greater in strong labor markets.*

[14] 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 will also show results clustering by state.

[15] For example, Brown et al. (2013) find that referred applicants are 2.4 percentage points more likely to receive an offer (the sample mean is 0.6%). In sociology, see, among others, Fernandez and Weinberg (1997); Castilla (2005).

[16] If a driver's home state unemployment rate were 5%, the difference between referred and non-referred workers in the chance of getting hired would be 10.1 percentage points. If instead the unemployment rate were 10%, the difference would be 8.8 percentage points. Thus, referred/non-referred differences in hiring are 13% smaller in a state with 10% unemployment compared to one with 5% unemployment, which seems, to us, to be a small to moderate-sized difference.

Table 1 also shows that referred applicants are more likely to accept offers. We estimate as in Result 1 restricting to applicants receiving offers. In baseline specifications without demographics or pre-job assessment controls, referred applicants are 5.0, 7.3, and 2.7 percentage points more likely to accept an offer in call-centers, trucking, and high-tech, respectively (relative to an acceptance base of 54%, 80%, and 75% for non-referred applicants). Results are similar after controls are added.[17] The result seems unsupportive of homophily models. In Montgomery's (1991) homophily model, referred applicants sometimes receive multiple job offers and should be *less* likely to accept an offer than non-referred applicants, whereas we find the opposite. Not only are referred applicants more likely to accept offers, but this difference is larger when the unemployment rate is lower. For non-referred applicants, the offer acceptance rate is higher where unemployment is higher, whereas for referred applicants, the offer acceptance rate is more acyclic.[18]

Result 3 *Referred applicants do not look better than non-referred applicants in terms of schooling, cognitive ability, and non-cognitive ability. (If anything, they look slightly worse.)*

Data on applicant cognitive and non-cognitive ability are only available for call-centers, and data on applicant schooling are only available for call-centers and high-tech. With this data, Table 2 compares referred and non-referred applicants on a quality metric that is observed by firms, namely schooling, and on quality metrics that are not observed by firms at time of hire, namely cognitive and non-cognitive ability. Analyzing unobserved-to-the-firm dimensions of quality is especially useful given that "unobserved ability" is a central feature of homophily and learning models.[19] Column 1 shows that, in call-centers, referred applicants have 0.09 fewer years of schooling, which is statistically significant 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 0.006 standard deviations (σ) lower in intelligence, and 0.01σ lower on the Big 5 Personality Index, our measure of non-cognitive ability, which is equal to the mean of the normalized Big 5 personality characteristics. Referred applicants are less conscientious, less agreeable, and less open, but are more extraverted.[20] In high-tech, referred applicants also have slightly less schooling. We are not aware of prior work on applicant skills. Homophily models (and learning models) predict that referred applicants should be superior in terms of hard-to-observe aspects of ability; thus, Result 3 seems unsupportive of these models.

[17] The only work we are aware of on this result is by Yakubovich and Lup (2006) in the sociology literature. Using a much smaller sample than ours, they find that referred applicants are more likely to accept offers.

[18] With 5% unemployment, the referred/non-referred gap in the offer acceptance rate is 8.4 percentage points, whereas at 12% unemployment, there is no referred/non-referred gap in offer acceptance.

[19] With the exception of SAT scores in high-tech, our data on cognitive skills, non-cognitive skills, and experimental preferences were *not observed by firms* at time of hire. In the call-centers, data on cognitive and non-cognitive skills, as well as substantial other information about work-relevant skills and job fit, are collected by the job testing company, Evolv; only a final job test score is 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 non-cognitive skills were collected in a survey of existing workers by HR. Of course, firms may receive partial information about cognitive/non-cognitive skills during recruitment, so it is more correct to think of such as variables as not easily observed instead of unobserved (Altonji and Pierret, 2001).

[20] Of the Big 5, conscientiousness, agreeableness, extraversion, and openness are usually considered desirable, whereas neuroticism is usually considered undesirable, e.g., Dal Bo et al. (2013). See Borghans et al. (2008) for an excellent survey on non-cognitive skills. For an example of a recent paper looking at cognitive and non-cognitive skills as important measures of general worker ability, see Dal Bo et al. (2013).

Result 4 *Referred applicants achieve higher pre-job assessment scores.*

For many jobs, workers participate in pre-work tests that measure their performance or quality. In call-centers, applicants complete "job tests" that measure their likely performance as future employees. In high-tech, applicants do interviews with current workers.[21] Panels B and C of Table 2 show that referred call-center and high-tech applicants score 0.10σ and 0.16σ higher, respectively, on pre-job assessments. We are not aware of prior work on referrals and job testing. If job tests uncover a typically unobserved dimension of worker quality, Result 4 supports learning and homophily theories. An important confound to interpreting Result 4 as evidence in favor of learning or homophily theories would be if referrers could coach referred applicants in preparation for assessments. However, our discussions with managers indicate that possible coaching is unlikely to explain our results.[22]

5 Worker quality

Result 5 *Referred workers look similar to non-referred workers in terms of most characteristics, including schooling, work experience, cognitive and non-cognitive ability, and experimental preferences.*

Table 3 performs analysis similar to Table 2, using workers instead of applicants. Panel A shows that referred call-center and trucking workers have slightly *fewer* years of schooling, whereas referred high-tech workers have slightly more. Referred workers have similar GPA (high-tech) and years of related experience (trucking & high-tech). Panel B shows that referred and non-referred workers have similar levels of cognitive ability. Referred truckers score 0.12σ lower on an IQ test and referred high-tech workers score 11 points higher on the SAT test (neither difference is statistically significant). In Panel C, there are a few interesting patterns in personality—referred workers tend to be slightly less agreeable and slightly more extraverted. However, on the overall Big 5 Index, differences are slight in all three industries. While referred workers do not have higher levels of human capital and ability in Panels A-C, it could be they differ in terms of certain preferences, which we measure for truckers using lab experiments; e.g., referred workers might be less likely to quit because they are more patient, have a greater risk tolerance for weekly swings in trucker income, or are more altruistic. Panel D does not support this. The one significant difference is that referred workers are somewhat less trusting. Homophily (and learning) theories of referrals predict that referred workers will look better on hard-to-observe characteristics; thus, Result 5 seems unsupportive of these theories.[23]

[21] It is important to note that referral status is not directly factored into either pre-job assessment. That is, referral status is not incorporated into the scoring of the call-center job test, and high-tech interviewers are not informed beforehand whether an applicant was referred. See Autor and Scarborough (2008) for more background on job testing.

[22] For call-centers, managers we interviewed thought it was very unlikely that referrers were preparing referred applicants for job tests. For high-tech, the interviews are unstructured. Interviewers are encouraged to evaluate the candidate from his or her own unique perspective, thereby making it difficult for a referrer to prep an applicant. The assessments are relatively brief, and the scores likely reflect an applicant's skills instead of their effort. The high-tech firm uses most of its employees to conduct interviews and interviewers are assigned to applicants in a quasi-random fashion; thus, applicants are unlikely to come across a referrer or other friends in interviews.

[23] Hensvik and Skans (2013) find that Swedish workers who have linked work histories with an incumbent employee, in the sense that both workers worked at a plant at the same time in the past, tend to have higher cognitive and non-cognitive skills; theirs is the only other work we are aware of on whether referred workers have superior cognitive

6 Turnover and productivity

Result 6 *Despite similarities in observable characteristics, referred workers are substantially less likely to quit than non-referred workers. Differences in quitting decline with tenure.*

Table 4 estimates Cox Proportional Hazard models. In call-centers, referred workers are 13% less likely to quit. In trucking, referred workers are about 11% less likely to quit. Given the coefficient on driver home state unemployment rate of -0.06, the reduction in quitting among referred workers is of the same magnitude impact as that from a 2 percentage point increase in the driver's home state unemployment rate. In high-tech, referred workers are around 23% less likely to quit. The coefficients remain large after controlling for demographics, job test scores, and measures of average productivity to date (measured using average handle time, miles, and subjective performance in call-centers, trucking, and high-tech, respectively). While several papers find that referred workers have lower turnover, a fact supporting all three leading models, there is much less evidence on how these differences change with tenure. Dustmann et al. (2012) find that differences decline with tenure, whereas Brown et al. (2013) do not. In all three industries we study, the magnitude of referred/non-referred quitting differences declines with tenure, which supports learning theories.

An alternative explanation for why referred workers are less likely to quit is the referral bonus. For some of the referred workers we study, namely, experienced truckers and workers at some of the call-center firms, part of the referrer's bonus is contingent on the referred worker staying for some period of time. In our earlier IZA working paper (Burks et al., 2013), we show using a regression discontinuity design that the referral bonuses appear to have little impact on quitting around the bonus tenure threshold; that is, referred workers are not willing to stay an extra day or extra week so the referrer can receive a bonus, and the "zero effect" is precisely estimated. In addition, the largest quitting differences we observe are for the high-tech firm (Panel C of Table 4), where referral bonuses are paid solely for the referred worker getting hired. These two pieces of evidence 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 much more common than fires in all three industries, referred workers are also less likely to be fired.[24]

Result 7 *Referred and non-referred workers have similar productivity on most non-rare metrics. In high-tech, referred workers score higher on subjective performance reviews.*

Table 5 regresses non-rare productivity on referral status. We normalize the productivity variables to ease comparisons across performance measures and industries. In call-centers, there are no

and non-cognitive skills. Our results may differ for several reasons, including one, we use different measures of a referral, or two, US and Swedish labor markets may differ. Whereas we find consistent results of no difference across low- and high-skill jobs, Hensvik and Skans (2013) find that referrals select on cognitive ability for high-skill jobs and on non-cognitive ability for low-skill jobs.

[24] In all three industries, we can distinguish quits and fires in the data. Referred workers are 3%, 13%, and 36% less likely to be fired in call-centers, trucking, and high-tech, respectively. The difference is highly statistically significant for trucking, but not quite statistically significant for call-centers and high-tech, reflecting that fires are much less common than quits.

statistically significant differences between referred and non-referred workers on 4 of 5 productivity measures, and on schedule adherence, referred workers are slightly less productive (by 0.03σ). In trucking, the coefficient on referral is essentially 0, with a standard error of 0.01σ. In high-tech, referred workers have slightly higher subjective performance scores (by 0.04σ),[25] arguably the most important performance metric, but score no better on most objective performance measures. Of the 7 objective performance measure coefficients, 2 are statistically significant from 0 (1 negative, 1 positive), but all are small. The difference in subjective performance decreases with tenure in column 3. In Castilla's (2005) study of one call-center, referred workers have 3.5% more phone calls per hour than non-referred workers. Using a much larger sample, our 95% confidence interval for the performance advantage of referred workers is $[-1.80\%, 0.24\%]$, meaning we can rule out differences 10 times smaller than those in Castilla (2005).[26]

One potential concern in estimating the relationship between referral status and productivity (or wages) is differential attrition based on productivity or wages. Among non-referred workers, the "bad apples" might get "weeded out" after some period of time, whereas both low-ability and high-ability referred workers may stick with the job. However, as noted also by Brown et al. (2013), learning theories are predicated on differential attrition; thus, given our focus on documenting facts as they relate to equilibrium predictions of theory, results without corrections for differential attrition may be the main ones of interest. Still, 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 Table C5, our productivity results are relatively similar as in the baseline.[27]

Result 8 *Referred workers have superior performance on rare high-impact metrics, namely innovation and avoiding work accidents. Differences fade with tenure, significantly so for work accidents and moderately so for innovation.*

In the trucking industry, although standard non-rare productivity is measured in miles per week, an extremely important measure of performance is driver accidents, both from a business and policy point of view. Using a linear probability model in Panel A of Table 6, we estimate that referred workers have a weekly accident probability that is about 0.11 percentage points below that of non-referred workers. Given a baseline accident probability of about 1.8% per week, referred workers have roughly a 6 percent lower risk of having an accident each week. An alternative explanation for why referred drivers have fewer accidents, which is unrelated to the three leading theories of referrals

[25] To put the 0.04σ magnitude into perspective, we re-did the regression in column 1 of Panel C of Table 5, using the logarithm of the performance rating instead of standardized performance. The coefficient on referral is 0.0037 (se=0.0011), indicating that referred workers have 0.4% higher subjective performance, which is an order of magnitude less than the referral differences in rare high-impact outcomes in Table 6.

[26] Our 95% confidence interval for referral differences is $[-0.149, 0.020]$ calls/hour, off a base of 8.25 calls/hour. Castilla (2005) finds that referred workers have 0.7 more calls/hour (off a base of 20). Holzer (1987a) and Pinkston (2012) show that referred workers have higher subjective productivity ratings, using data from the Employment Opportunity Protection Project. Pallais and Sands (2013) show that referred workers have higher productivity on oDesk.

[27] We repeat these tests for wages in Table C6. Heath (2013) and Brown et al. (2013) also provide similar robustness checks. Other approaches to address differential attrition would be to estimate a simultaneous equation model of productivity and retention with a common latent factor, or to estimate a structural dynamic model of productivity and retention (Hoffman and Burks, 2012), though doing either would require relatively strong assumptions.

but potentially related to favoritism, is that referred workers may be assigned different roles in a firm than non-referred workers. Although we have rich controls for the type of work that different drivers are doing, it might be possible that referred workers 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 "non-preventable," accidents the driver could not control. Referred drivers are 10% less likely to have preventable accidents (column 3), which is substantial, but only 2% less likely to have non-preventable accidents (column 8). Referral differences in accident risk are sharpest early on and fade with tenure, consistent with learning theories. Referred workers are initially 20% less likely to have an preventable accident (column 4), a difference which is eliminated after 2.75 years. In addition, referral differences in accident rates are larger for drivers hired in booms, proxied by if the driver's home state unemployment rate at year-of-hire is low.[28]

Panels B and C of Table 6 shows that referred high-tech workers are also more innovative than non-referred workers. Panel B shows that referred workers are significantly more likely to file patent applications. Patents are a standard measure of idea production 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. Referred workers produce 28% more patents than non-referred workers in the baseline, and 25% more once we control for demographics and interview score.[29] To account for patent quality, we study citation-weighted patents in columns 7-12. Referred workers achieve 27-31% more citation-weighted patents than non-referred workers. For both the baseline and citation-weighted patent analysis, referral effects fade somewhat with tenure; while the coefficient on Referral X Tenure is not statistically different from 0, the coefficient in column 10 indicates that the difference in citation-weighted patents by referral status fades by about one third after two years.

Panel C shows that referred workers also are more innovative in terms of the number of ideas they contribute to the firm idea board. The high-tech firm has a structured online forum for proposing new business and technology ideas, to which all employees at the firm can contribute. Ideas are visible to all workers, who can choose to assign a subjective rating to an idea. Though many ideas are never implemented, several of the firm's most successful projects were proposed on the idea board. To account for idea quality, we analyze ideas weighted by the average rating they receive. Referred workers produce 14-15% more rating-weighted ideas. See Appendix A.9 for more discussion.

Why might referred workers be less likely to have accidents and more likely to develop patents and other new ideas? Why couldn't the trucking firm use past accidents to predict new accidents, and why couldn't the high-tech firm just use past measures of a person's innovation (e.g., 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

[28] Column 7 indicates that for drivers hired when the state unemployment rate is 4%, referred drivers have an 18% (40-4*5.6) lower accident risk. For drivers hired when the state unemployment rate is 7%, there is no difference between referred and non-referred workers. See Appendix A.7 for more.

[29] The overdispersion parameter, α, is 21.0 (se=1.86) in column 1, indicating a highly significant degree of overdispersion, suggesting use of a negative binomial instead of a poisson model (Cameron and Trivedi, 2005).

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 or other innovative outcomes is 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 starting right out of college or graduate school; most of these workers have no patenting history before joining the high-tech firm.[30] Panel B column 6 shows that among workers over 27, referrals develop 11% more patents than non-referrals, whereas among workers 27 or younger, referrals develop 49% more patents. For older workers, information about past innovation may leak out during the hiring process, so there is less further information to know, whereas there may be little past information for younger workers, for whom referrals may provide substantial additional information.[31]

7 Wages and profits

Result 9 *Referred workers earn similar wages in call-centers and trucking, and earn slightly higher wages in high-tech. Where observed, differences in wages do not decline with tenure. Referred and non-referred workers also do not appear to differ in the variance of wages, either in levels or in trends. In trucking, although referred workers do not earn more than non-referred workers overall, they do earn more among Black and Hispanic workers.*

To compare the earnings of referred and non-referred workers, Table 7 presents estimates:

$$log(w_{it\tau}) = \alpha + \beta * REF_i + f(t) + \gamma_\tau + X_i\Gamma + \epsilon_{it\tau} \quad (1)$$

where $w_{it\tau}$ is worker i's earnings at tenure t at time τ; REF_i is a dummy for being referred; $f(t)$ is a polynomial in worker tenure; and γ_τ is a time fixed effect. The controls, X_i, include cohort, demographics, and job test scores; thus, we can ask whether referred workers receive higher wages over what is observable to the firm at time of hire. In call-centers (Panel A), the 95% confidence interval on "referral" is [-0.0037,0.0074], meaning we can rule out that referred workers have more than 0.74% higher salary. For trucking (Panel B), earnings differences will mostly just reflect miles differences since truckers are paid primarily by piece rate. Referred truckers have 0.3% lower earnings. Once a Referral X Tenure interaction term is added in columns 3 and 4, the coefficient on referral becomes slightly positive but remains statistically insignificant, along with the coefficient on Referral X Tenure. Referred high-tech workers earn about 1.7% higher wages (Panel C). The referral coefficient is similar controlling for demographics and interview score, and referral differences do not decline with tenure. In high-tech, referred workers are paid more even conditional on their characteristics, as we would

[30] Among workers age 27 or less at hire who go on to patent at the high-tech firm, only 10% have any pre-hire patents. Among workers over 27, only 38% have any pre-hire patents. See Appendix A.8 for more on these calculations.

[31] For trucking accidents, too, we observe a sizeable interaction term on Referral X Young, though it is not statistically significant. In their analysis of neighborhood effects, Bayer et al. (2008) also find that referral differences are greater for young workers. Interestingly, if we look at wages and quitting in high-tech or trucking (instead of subjective performance, patenting, or accidents), we see no evidence of referral differences varying by age.

expect when there is an important unobservable component to match. Controlling for subjective productivity to date only modestly lowers the coefficient.

As we did 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. Table C6 shows mostly similar results. For assessing whether the Referral X Tenure coefficient may be biased by attrition, we also estimate using individual fixed effects in Table 7, finding coefficients on Referral X Tenure that are close to 0 in all three industries.[32]

The last 3 columns of each panel in Table 7 appear to show no differences in the variance of wages for referred workers relative to non-referred workers. First, we regress wages on controls. Second, we regress the squared residuals on referral status and the fitted wage from the first stage:[33]

$$\begin{aligned} log(w_{it\tau}) &= \alpha + f(t) + \gamma_\tau + X_i\Gamma + \epsilon_{it\tau} \\ \hat{\epsilon}_{it}^2 &= \beta_0 + \beta_1 * REF_i + \beta_2 * \widehat{log(w_{it})} + u_{it} \end{aligned} \tag{2}$$

There is insignificantly lower variance among referred call-center workers, whereas there is insignificantly higher variance among referred truckers and high-tech workers. Nor do differences in wage variance between referred and non-referred workers seem to change significantly with tenure.

For trucking, although there is no overall referral difference in earnings, we can examine whether there may be referral differences for workers of different races. Interestingly, for Black and Hispanic workers, as seen in column 6, referred Blacks earn 4.2% more than non-referred Blacks, and referred Hispanics earn 3.1% more than non-referred Hispanics. Showing the full specification in Table C8, we see that, among non-referred workers, Black workers earn 2.2% less than Whites (and Hispanics earn roughly the same as Whites). In contrast, among referred workers, Blacks earn 2.5% more than Whites. We discuss possible interpretations in Section 9.1 and Appendix A.2.[34]

There is also no evidence that the wages of referred and non-referred workers respond differently to past productivity. Looking at the interaction of Referral and average productivity to date in Table 7, we see that wages are slightly more responsive to productivity for referred workers in call-centers (compared to for non-referred workers), and slightly less responsive in trucking and high-tech, but none of the estimates are statistically significantly different from zero. In models of employer learning, past productivity realizations are used to predict future productivity and are thus incorporated in wages; if referrals aid firms in learning about workers, one might imagine that the wages of referred workers would be less responsive to average productivity to date, but we see no evidence of that.[35]

[32] Unlike us, Brown et al. (2013) find that referral differences in the path of wages are eliminated once they restrict to workers staying at least 5 years.

[33] Our procedure for analyzing the variance of earnings for referred vs. non-referred workers follows that in Heath (2013). By including the fitted values from the 1st stage in the 2nd stage, we account for differences in wage variance related to observables, e.g. higher skill people have greater wage variance (Juhn et al., 1993). See Appendix A.10.

[34] We can only analyze Black and Hispanic differences in trucking. For call-centers, race data are kept separate from the main data (see Section B.2), and for high-tech, we lack statistical power to do this analysis. For trucking, we also examined accidents, quitting, and firing, and found no statistically significant Race X Referral interactions. In addition, in trucking, there are only data on race for workers, not for applicants.

[35] It is important to note that learning is match-specific in Simon and Warner's (1992) learning model of referrals, but is general in employer learning models such as Altonji and Pierret (2001) and Kahn and Lange (2013). However, if firms set wages equal to the expectation of match quality given past productivity signals, as is assumed in Simon and Warner (1992), then match-specific learning models will also predict that wages should be less responsive to average

Identifying employer learning is empirically challenging, let alone identifying whether employer learning may occur differently for referred vs. non-referred workers, particularly as there are often alternative hypotheses. For example, it may be the case that there is no learning (thus, wages equal productivity), but that productivity is evolving idiosyncratically. To distinguish learning from idiosyncratic productivity evolution, we follow Kahn and Lange (2013) and compare leads and lags of residualized productivity with respect to residualized wages in Table C9. When employer learning is occurring, wages are more highly correlated with past productivity than with future productivity, which we find evidence for in Table C9. However, it is not the case that there are smaller lead/lag differences for referred workers compared to non-referred workers, thereby providing no evidence that more has already been learned about the productivity of referred workers.

Result 10 *Referred workers produce substantially higher profits per worker. This difference is driven by referrals from high-productivity workers.*

We focus our profits analysis on trucking and call-centers because the production process is relatively simple. (Given the complex nature of high-tech production, it would be difficult to calculate profits per worker.) Profits per worker is calculated using the average discounted profit stream from a worker, accounting for referral bonuses, training costs, and recruiting costs (see Section B.6 for details). Panel D of Table 8 shows that referred truckers yield average discounted profits of \$2,201 whereas non-referred truckers yield \$1,756. In addition, we see that truckers referred by above-median productivity drivers yield \$4,190 in average profits, whereas referrals from below-median productivity workers yield \$1,063, which is below average profits from non-referred workers. Referred workers also produce higher profits per worker in call-centers. This fact is consistent with Montgomery's (1991) homophily model, but is not a prediction from learning or peer benefit theories. We are not aware of prior work comparing profits from referred and non-referred workers.

8 Referrers

Result 11 *Referred workers tend to have similar characteristics to their referrer. They also have similar performance on particular productivity metrics.*

We focus on trucking where we know who referred whom. Panel A of Table 8 regresses characteristics of a referred worker on a vector of characteristics of the referrer, as well as the referrer's 3-digit zip-code. We see strong evidence of "like referring like," e.g., for a referrer living in a given 3-digit zip code, if he is Black, his referrals are more likely to be Black by 45 percentage points. Panels B and C show that homophily extends to productivity: if a referrer performs well on a performance metric, all else equal, his referrals are more likely to perform well on that metric. We estimate:

$$y_{i_r t\tau} = \alpha + \gamma \overline{y}_r + X_r\beta_1 + X_i\beta_2 + f(t) + \theta_\tau + \epsilon_{i_r t\tau} \quad (3)$$

where $y_{i_r t\tau}$ is a behavior of worker i referred by r at tenure t at time τ; $\overline{y}_r$ is the average behavior of worker r; X_r and X_i are vectors of characteristics for r and i; $f(t)$ is a polynomial in tenure; and

productivity to date for referred workers (compared to non-referred workers).

θ_τ is a time fixed effect. Panel B shows that if a referrer's average lifetime productivity is 100 miles per week above the mean, the person they refer is on average 33 miles per week above the mean. Panel C shows that if the referrer has an accident at some point, the person they refer is 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 analyzing various geographic controls for both referrers and referrals, showing that our estimates are robust.[36] We are not aware of prior research on referrer-referral correlations in productivity; our finding is one of the main predictions of homophily theories.[37]

Result 12 *Higher ability employees are more likely to make referrals. In high-tech, referrers have higher wages than non-referrers, but there are no differences between the groups in wage variance.*

Table 9 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 week (Panel B). In homophily models of referrals, ability is correlated within networks, so firms optimally accept referrals only from current high-ability workers. That high-ability workers make more referrals is consistent with homophily models. It is also consistent with Heath (2013), where firms prefer referrals from high-ability workers because there is greater scope to punish them. One alternative explanation for higher ability people making more referrals is that higher ability workers are more sociable or have wider social networks. While we do not have measures of a worker's entire social network, we have the number of friends that the high-tech workers report having at work. Another measure of how connected a person is is whether they were referred themselves. Controlling for having more friends and being referred (both of which are positively associated with making referrals), high productivity workers remain significantly more likely to make referrals.[38]

Table C10 shows that high-tech referrers tend to have higher earnings than non-referrers, but have similar wage variance. To analyze wage variance, we use the same estimation procedure used in equation (2). This finding differs from that in Heath (2013), who finds in Bangladesh that referrers tend to have higher wage variance than non-referrers. Thus, Result 12 is only partially supportive of peer benefit theories, which posit that referrers may have higher wage variance due to firms tying the referrer's future wage increases to the performance of the referred worker.

Result 13 ***Motivations of referrers:*** *Higher referral bonuses are associated with a greater share of applicants who are referred. Compared to workers of similar productivity and tenure, workers are less likely to quit after making referrals.*

[36] In the first 3 columns of Panel B, and the first 2 columns of Panel C, we include state fixed effects for both the referring and referred worker. In column 4 of Panel B and column 3 of Panel C, we include 3-digit zip code for the referrer. For further discussion, see Appendix A.12.

[37] In contemporaneous work, Pallais and Sands (2013) also find a correlation between the productivity of referrers and referrals. Although our finding seems most suggestive to us of homophily models, it could also possibly be reconciled with learning models: If high-productivity referrers have more precise signals about applicants, this would cause those referred by high-productivity referrers to have higher productivity, an interpretation evidenced by Beaman and Magruder (2012). Our finding does not seem consistent with basic versions of peer benefit theories.

[38] Hensvik and Skans (2013) show that higher ability workers are more likely to have been co-workers in the past with new workers entering the firm, compared to lower ability workers.

In Panel A of Table 10, we regress the share of applicants in call-centers who are referred on the log of the referral bonus. Information about the levels of referral bonuses is only available for some of the call-centers and the variation in referral bonuses is purely observational. With these important caveats in mind, Table 10 shows that a 100% increase in the referral bonus is associated with a 7-11 percentage point increase that an applicant is referred. We are not aware of prior work relating the level of referral bonuses to the share of applicants who are referred.[39]

Panel B of Table 10 shows that workers who make a referral for the first time are less likely to quit after doing so than workers with similar productivity and tenure. After making their first referral, truckers and high-tech workers are roughly 16% and 30% less likely to quit, respectively. We know of no prior work on this fact and discuss several interpretations in Section 9.1.

9 Discussion: From Facts Back to Theories

We now discuss to what extent our facts are consistent with learning, homophily, and peer benefit theories of referrals, as well as with theories based on favoritism.

9.1 Interpreting the Facts

Applicant quality and hiring. We find that referred applicants are more likely to be hired, which is consistent with past work, and a prediction of both homophily and peer benefit theories; differences in hiring probabilities hold in the baseline and conditional on demographic controls and pre-job assessment scores. Referred applicants look similar in terms of schooling, cognitive ability, and non-cognitive ability, but score higher on pre-job assessments predicting their job performance. Contrary to homophily theories, where referred applicants have more options due to having higher average ability, we find that referred applicants are more likely to accept job offers. Overall, none of the three leading theories appears to predict well the results on applicant quality and hiring.

Why are referred applicants more likely to accept offers? This could reflect referred applicants having greater non-pecuniary taste for the job, a hypothesis we return to in Section 9.2. Alternatively, if having offers rejected is costly, it may reflect reputational concerns of the referrer. The referrer may choose to refer people they believe are likely to accept offers or may try to convince a referred worker to accept an offer.

Worker quality. A large advantage of our data is that it contains worker quality characteristics that are observable to firms at time of hire, as well as characteristics which are unobservable to firms at time of hire but are observed later by the researcher (e.g., through surveys shortly after hire in trucking). With a few exceptions, referred workers look similar on observable characteristics such as schooling and worker experience, as well as on unobservable (to the firm) characteristics of cognitive ability, non-cognitive ability, and experimental preferences. That is, contrary to homophily and

[39] Beaman and Magruder (2012) and Beaman et al. (2013) conduct field experiments where subjects are asked to make a referral, showing that randomly assigned larger bonuses cause subjects to be more likely to make a referral. However, in Beaman and Magruder (2012) and Beaman et al. (2013), the applicants (outside the initial subjects) are *all* referred, so our result on the share of the applicant pool is conceptually distinct.

learning theories, referred workers do not have superior characteristics. Favoritism theories would predict that referred workers would actually have worse characteristics, and this is true for a few characteristics, but on most characteristics, referred and non-referred workers are similar.

Turnover and productivity. Referred workers have similar productivity on most non-rare everyday productivity metrics. (One important exception is that referred high-tech workers have higher subjective performance reviews.) Similar levels of non-rare everyday productivity are inconsistent with all three leading models, as well as with favoritism, which may predict that referred workers have lower productivity. However, referred workers have superior performance on rare high-impact measures, as well as lower turnover; referral differences in turnover and rare high-impact productivity tend to decrease with tenure, consistent with learning theories.

Why is it that referred workers appear to perform better on rare high-impact performance metrics, but not on most non-rare metrics? In learning models, such a fact could occur if referrers have superior information over the firm about referred workers' likely performance on rare high-impact metrics, but not about non-rare metrics.[40] In homophily models, such a fact could reflect that people are more likely to be socially connected with those of similar ability on rare high-impact metrics as opposed to everyday metrics. Although it is hard to say with any certainty, the additional fact that differences are concentrated among young workers seems to suggest a learning story, where less information is available to firms about the high-impact performance of young workers. In addition, Table 8 shows correlations in outcomes between referrers and referrals for both miles and accidents, so it is not the case that there are only referrer-referral correlations for rare high-impact outcomes.

Wages and profits. In call-centers and trucking, referred and non-referred workers earn similar wages, whereas in high-tech, referred workers earn 1.7% more, a difference which remains even after many controls are added (including average subjective performance to date). Homophily and learning theories predict that referred workers earn higher initial wages. In wage regressions for all three industries, the interaction of referral and tenure is not statistically significantly different from zero either in the baseline or when individual fixed effects are added; thus, there is no evidence that differences in wages *decrease* with tenure, as predicted in learning theories, or that differences *increase* with tenure, as would be predicted in Heath's (2013) moral hazard model (but not in all peer benefit models). Referred workers producing higher profits is consistent with homophily theories.

We believe that institutional differences in pay-setting across industries may be important for our results. Managers from call-centers and trucking informed us that pay-setting is somewhat formulaic, at least initially; over time, pay increases account for tenure and performance, but initial pay is largely centrally determined, factoring in past working experience (if any). If most people in a given cohort have the same pay, it is unlikely there will be a referral wage premium. In higher-skill firms, such as our high-tech firm, or the firms studied in Baker et al. (1994a,b) or Brown et al. (2013), firms may have more latitude in setting pay. Further, for trucking, because workers are paid by piece rate, effort levels may already be high; thus, there may be less scope for any peer benefits

[40] There may be something about the nature of rare events, where referrers are likely to have useful information. A friend may remember the time three years ago when Johnny almost had an accident, but swerved out of the way at the last second. Such information may be difficult to uncover during an interview.

from referrals to further increase effort and lead to referral differences in wages.[41]

In trucking, although referred workers do not earn more than non-referred workers *overall*, referrals do earn more than non-referrals among Blacks and Hispanics. In learning models, one interpretation is that firms may have less precise information about minority applicants than White applicants (as in Phelps (1972) and many subsequent models). If referrals lower the variance of applicant match quality to the same level for minorities and Whites, then this may erase gaps between the two groups in productivity. One difficulty with a learning model explanation is that among referred workers, we actually see that Blacks earn slightly more than Whites. A second interpretation is that referrers may be slightly "choosier" when deciding to refer minority candidates (though we note, also, that Black and Hispanic workers are equally likely to be referred as White workers, see Table C7). Appendix A.2 provides further discussion.

Referrers. People tend to refer people like themselves, both in characteristics and in specific behaviors, e.g., drivers with trucking accidents tend to refer other drivers who later have accidents, supportive of the "like-referring-like" assumption in homophily theories. While peer benefit theories predict a referrer-referral correlation in wages (Heath, 2013), i.e. because the firm may condition a referrer's future wage increases on the referral's performance, it is not clear that they would predict a correlation in productivity. In support of a different key implication of homophily theories, that firms prefer referrals from high ability workers, we find that high ability workers are much more likely to make referrals. We discuss further in Appendix A.5.

One intriguing new fact is that workers who make a referral are subsequently less likely to quit, conditional on their characteristics and productivity. Provided that workers who are less likely to quit are those that like their jobs or companies, the fact may reflect that workers prefer to make referrals for jobs or companies they think are good (or that they think their friend will like, if their friend has similar tastes). We think that this may be the simplest interpretation. There are clearly a number of alternative interpretations, though they seem less compelling to us for various reasons.[42] The idea of workers making referrals because they think the job or company is good (and because they are altrustic toward their friend), or of workers making more referrals when the bonus is higher,

[41] Although piece rates may help solve the "effort problem," selecting good drivers is still very important, given large persistent productivity differences across workers. Thus, even under piece rate pay, learning and homophily models still likely predict that referred workers will have higher wages. We believe that further analysis on how social networks interact with performance pay (e.g., Bandiera et al., 2010) represents an important direction for future work.

[42] We briefly address three alternative explanations. First, it could be that a referrer gets utility from working with their friend or social contact. For trucking, such an explanation may be less plausible, given the solitary nature of production. For high-tech, although the firm we study is quite large, it is possible that a referrer and referral could still work together; though we cannot address directly (because we do not see if the referral and referrer are working together), using data on worker friendships, we observe that workers with many friends are no less likely to quit than workers with fewer friends (see column 3 of Table 10). Although work friends are not randomly assigned, and referral relationships could be different than that from other work friends, column 3 Table 10 provides no evidence that having more friends is associated with less quitting. Second, making a referral might *cause* a worker to become less likely to quit, e.g. because the firm treats the referrer favorably after making a referral or because the referrer becomes more productive. Our results hold controlling for average productivity to date and job rank, thus helping rule out that the difference is due to workers becoming observably better, though it is conceivable that making a referral could cause workers to become more empowered or committed on an unobserved dimension. Third, it could be that the referrer is more likely to stay because of a referral bonus. However, for high-tech, the bonus is paid upon the referred worker getting hired, and thus should not affect long-term job retention.

lie outside the three leading classes of theories, which do not model the decision of referrers.

Differences by Labor Market Conditions. For trucking, the data contain workers living all over the US over an 8-year time-frame, allowing us to examine referral differences in varied labor market conditions. 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 hire. Likewise, for trucking accidents, non-referred worker performance is negatively correlated with unemployment at time of hire, whereas for referred workers, there is less cyclical correlation. For non-referred workers, the 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.[43] 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. And, if firms anticipate these differences in match quality, referred applicants may be differentially more likely to be hired in booms. We underscore, though, that our result on referrals and labor market conditions are only available for one firm. Further research is clearly called for here.[44]

Summary. Table 11 summarizes our results, previous research (if any) on each result, and predictions of the leading theories.[45] While it is clearly unreasonable to imagine that a parsimonious economic theory could predict all results, the leading theories fail to explain a significant number of the results, in some cases making oppositely signed predictions.[46] In terms of what the theories predict correctly, we note that learning theories predict most of the results on turnover and productivity, whereas homophily theories predict many of the results on wages and profits, and on referrers. Peer benefit models fare less well, appearing to make no unique predictions which are confirmed in the data.

9.2 Extensions to Theory

We discuss ways by which theory can be extended to be consistent with our facts. The parsimony of existing theories is primarily a virtue, not a vice, and we can recognize that many theories can

[43] Kahn (2008) finds that without accounting for firm fixed effects, workers starting jobs during booms tend to have higher match quality. However, once firm identity is controlled for, as occurs implicitly in our study of particular firms, workers hired during booms tend to have lower match quality.

[44] Although managers focused on reputational concerns as constraining whether referral quality varies with labor market conditions, there are potentially other explanations. For example, Schmeider (2013) documents substantial differences in earnings changes for job-to-job vs. unemployment-to-job transitions. It could be that referred and non-referred applicants may be more likely to come from unemployed applicants vs. applicants with jobs, but we are unable to evaluate this explanation as we do not observe past work histories in our personnel data.

[45] Brown et al. (2013) and Heath (2013) also provide tables summarizing predictions on theories of employee referrals. Table 11 builds on these efforts, while adding a large number of new results.

[46] If we do a very crude counting up of results predicted by the theory, we calculate that learning theories predict 32% (7/22) of results, homophily theories predict 45% (10/22) of results, and peer benefit theories predict 18% (4/22) of results.

be modified in different ways to deliver different results. However, our facts suggest a few main modifications to theory, one of which, allowing for referred and non-referred workers to differ in non-pecuniary taste for the job, can help rationalize a number of results at once.

Three dimensions of match quality: non-pecuniary taste, everyday productivity, and high-impact productivity. To our knowledge, all existing models of referrals analyze a single dimension of match quality, which is then a simple function of worker productivity. However, our facts seem to suggest that referrals may operate very differently across different dimensions. Suppose match quality can be divided into non-pecuniary taste for the job, productivity on everyday tasks, and productivity on rare high-impact tasks. If referrals have a higher non-pecuniary taste for the job, this alone may help reconcile three of the facts that are not well-predicted by the leading three classes of models. It can explain: (1) our fact that referred applicants are more likely to accept offers conditional on receiving them; (2) why referred workers are substantially less likely to quit, even conditional on actual productivity; (3) via the theory of compensating differentials why we found only modest differences in wages between referred and non-referred workers. If firms recognize that referred workers tend to have a higher taste for the job, then the difference in wages may be smaller than the difference in average productivity between referred and non-referred workers.[47]

To further test whether referred and non-referred workers may differ in non-pecuniary taste for the job, we analyze survey data that we collected on truckers. We asked drivers questions about very specific aspects of the job, such as how much they minded being away from home. As seen in Table C11, referred workers reported greater satisfaction with different non-pecuniary aspects of the job.

Allowing for two dimensions of productivity can help account for our result that referral differences in productivity are found for rare high-impact outcomes, but not for everyday productivity outcomes.

We refer to dimensions of "match" because some facts seem to suggest that theories of referrals should focus on "match," likely at the occupation or industry level instead of job-specific match. Referred applicants and workers do not have superior levels of schooling, experience, cognitive ability, non-cognitive ability, or experimental preferences, attributes which past research has shown are useful in many different occupations and jobs, and which are likely important elements of a person's "overall ability." However, referred applicants and workers do score higher on tests designed to predict job performance. We suggest focus on occupation- or industry-specific match instead of job-specific match due to our result that some referral differences are largest for younger workers, suggesting that the benefit of referrals could depend on information about a person's work history.

Learning <u>and</u> homophily. Some of our facts are predicted by learning models of referrals, whereas others are predicted by homophily models. We, thus, believe it may be useful to consider models featuring both learning <u>and</u> homophily. Learning models can rationalize most of the findings in our third fact, e.g., that the magnitude of referral differences in turnover and productivity tend to shrink with tenure. Homophily can rationalize many of the findings in our fourth and fifth facts, e.g., that people refer those like themselves, and that high-ability people make more referrals (which

[47] Although our data suggest that differences in productivity are larger than differences in wages, it is difficult for us to claim this with certainty.

is what firms encourage in homophily models).

Incentives of referrers. With the exception of two noteworthy recent field experiments in the developing world by Beaman and Magruder (2012) and Beaman et al. (2013), existing theory and empirical work on referrals do not consider the incentives or motivations of *referrers*. Our findings, that higher bonuses are associated with more referrals and that referrals seem to be made by people who enjoy their jobs more (as measured by whether these workers later quit), suggest the importance of analyzing the incentives of referrers. While arguably the simplest interpretation of another fact, that referred applicants are more likely to accept offers, is that they have greater non-pecuniary taste for the job, this could also potentially reflect the incentives of referrers. If having an offer rejected is embarrassing for the referrer, referrers will be more likely to refer those they think will accept.

10 Conclusion

A central question in social science is what do social networks do and who benefits from them? We shed a little light on this question by documenting facts about one specific but very common form of network, employee referral networks, which are believed to be of consequence for many aspects of the labor market. Are referred workers more "productive," and, if so, who benefits from this? Under which conditions and for which types of referrals and referrers are these differences largest?

We find that referred workers and applicants are more "productive" than non-referred workers and applicants, but not in terms of observable-to-the-firm skills (such as schooling), unobservable-to-the-firm skills (such as cognitive and non-cognitive ability), or performance on standard non-rare productivity metrics. However, referrals are more likely to accept job offers, less likely to quit, and are more productive on rare high-impact outcomes: all else equal, referred workers have 10% fewer preventable accidents, invent 25-30% more patents, and provide 15% more idea board ideas. Firms earn substantially higher profits per worker from referred workers. While referred workers earn only modestly higher wages, they likely receive greater non-pecuniary utility from the job than non-referred workers. Referral differences are greater at low-tenure levels and for younger workers, which is consistent with learning models, and firms tend to favor referrals from their highest ability workers, which is consistent with homophily models. Peer benefit theories predict few results, though we cannot rule out peer benefits may be present here or may be first-order in other work settings.

Beyond their relevance for theories of referrals, our findings may allow some broader speculation about the importance of referral networks. Theoretical work (e.g., Jackson, 2008) and numerical simulations (e.g., Arrow and Borzekowski, 2004) suggest that referral networks could play a significant role in contributing to wage inequality. However, we find only modest differences in earnings between referred and non-referred workers, though we strongly emphasize that these are *within-firm* comparisons. A number of our facts, though, suggest that referred workers may receive greater non-pecuniary utility from their jobs than non-referred workers. Thus, even if it were to hold that referrals play only a modest role in contributing to within-firm wage inequality, our results suggest that referrals could still play a much larger role in contributing to within-firm inequality in worker utility, if referrals lead to significant compensating differentials.[48]

Methodologically, we illustrate both the promise and limitations in combining large personnel datasets. Personnel data can provide large-scale, inside-the-firm information, which may be valuable for bringing theory to the data on a whole host of 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,[49] 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. Our facts speak largely to equilibrium predictions of theory, as opposed to facts based on quasi-randomized or randomized variation.[50] Further empirical research on referrals using natural or randomized experiments is also sorely needed, and should be complementary to our paper.

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[48] Or consider another new result, that referred workers developed 25-30% more patents than non-referred workers and that differences are greatest among young workers. Although the result is correlational, it suggests that referrals could play a useful role in discovering young talent in scientific production.

[49] This may especially be the case for our findings which can only be analyzed in one industry. Our approach is no substitute for the large value gained in using comprehensive administrative data or representative surveys.

[50] For field experimental research on referrals, see Beaman and Magruder (2012), Beaman et al. (2013), and Pallais and Sands (2013), as well as work in progress by Abaluck et al. (2013).

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Table 1: Referred Applicants are More Likely to be Hired and More Likely to Accept Job Offers

Panel A: Call-center	(1) Hired	(2) Hired	(3) Hired	(4) Hired	(5) Accept offer	(6) Accept offer	(7) Accept offer
Referral	0.059***	0.056***	0.051***	0.051***	0.050**	0.049**	0.049**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.025)	(0.025)	(0.025)
Job test score (normalized)			0.077***	0.069***			0.002
			(0.001)	(0.001)			(0.017)
Referral X Job test score				0.030***			
				(0.002)			
Demographic controls	No	Yes	Yes	Yes	No	Yes	Yes
Observations	375,777	375,777	375,777	375,777	2,417	2,417	2,417
R-squared	0.081	0.085	0.112	0.113	0.238	0.239	0.239
Mean dep var if ref=0	0.18	0.18	0.18	0.18	0.54	0.54	0.54

Panel B: Trucking	(1) Hired	(2) Hired	(3) Hired	(4) Accept offer	(5) Accept offer	(6) Accept offer
Referral	0.101***	0.098***	0.115***	0.073***	0.073***	0.145***
	(0.002)	(0.002)	(0.008)	(0.003)	(0.003)	(0.011)
			[0.010]			[0.008]
Referral X State unemp			-0.0027**			-0.012***
			(0.0012)			(0.0018)
			[0.0013]			[0.0014]
State unemployment rate			0.0009			0.013***
			(0.001)			(0.002)
			[0.004]			[0.005]
Demographic controls	No	Yes	Yes	No	Yes	Yes
Observations	A	A	A	$0.23A$	$0.23A$	$0.23A$
R-squared	0.067	0.068	0.068	0.070	0.071	0.072
Mean dep var if ref=0	0.17	0.17	0.17	0.80	0.80	0.80

Panel C: High-tech	(1) Hired	(2) Hired	(3) Accept offer	(4) Accept offer	(5) Hired	(6) Hired	(7) Hired	(8) Accept offer	(9) Accept offer
Referral	0.0027***	0.0027***	0.027**	0.026**	0.057***	0.033***	0.025***	0.018***	0.017***
	(0.0003)	(0.0003)	(0.011)	(0.011)	(0.002)	(0.002)	(0.001)	(0.006)	(0.006)
Interview Score						0.101***	0.089***		0.068***
						(0.001)	(0.001)		(0.009)
Ref X Int score							0.056***		
							(0.002)		
Demog controls	No	Yes	No	Yes	Not available	Not available	Not available	Not available	Not available
Observations	1,175,016	1,175,016	5,738	5,738	240,304	240,304	240,304	29,269	29,269
R-squared	0.586	0.586	0.597	0.598	0.157	0.255	0.261	0.556	0.558
Mean dv if ref=0	0.0028	0.0028	0.74	0.74	0.07	0.07	0.07	0.67	0.67

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. * significant at 10%; ** significant at 5%; *** significant at 1%

In Panel A, all regressions include month-year of application dummies and location fixed effects. In columns 1-4, demographic controls are race, age, gender, and years of schooling. For columns 5-7, the only available demographic control is years of schooling. The job test is an applicant's normalized test score.

In Panel B, all regressions include work type controls, month-year of application dummies, and state fixed effects. Demographic controls are age and gender. Standard errors clustered by state in brackets. The exact number of applicants, A, is withheld to protect firm confidentiality, $A >> 100,000$.

In Panel C, all columns include job position ID dummies, month-year of application fixed effects, and office location dummies. Demographic controls are race and gender. Columns 1-5 are based on applicants from 2008-2011. Columns 6-9 are based on applicants from 2003-2008 who make it to the interview stage. Applicant demographic data are only available for the sample in columns 1-5, whereas applicant interview scores are only available for the sample in columns 6-9.

Table 2: Referred Applicants Have No Better Characteristics (Schooling, Cognitive Ability, and Non-cognitive Ability), but Perform Better in Pre-job Assessments (Job Tests or Interviews)

Panel A: Call-Center Chars	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep var:	Schooling in years (mean dv =12.61)	Intelligence (normalized)	Big 5 index (normalized)	Conscien-tiousness (normalized)	Neuroticism (normalized)	Agree-ableness (normalized)	Extra-version (normalized)	Openness (normalized)
Referral	-0.092***	-0.006	-0.014***	-0.078***	0.000	-0.019***	0.064***	-0.037***
	(0.012)	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Obs	49,463	325,882	363,160	370,307	368,716	370,220	370,220	370,220
R-squared	0.105	0.027	0.082	0.082	0.022	0.027	0.118	0.069

Panel B: Call-center Job Tests	(1) Job Test Score (normalized)	(2) Job Test Score (normalized)
Referral	0.1031***	0.0950***
	(0.0042)	(0.0042)
Demographic controls	No	Yes
Observations	286,017	286,017
R-squared	0.0281	0.0353

Panel C: High-tech Schooling and Interview Scores	(1) Schooling in years (mean dv=16.55)	(2) Interview score (normalized)
Referral	-0.120**	0.163***
	(0.055)	(0.004)
Observations	4,464	641,043
Clusters	4,464	239,110
R-squared	0.0581	0.157

Notes: This table presents regressions of various characteristics and pre-job assessment scores on whether an applicant was referred and controls. Standard errors clustered by applicant in parentheses. For an explanation of how the different variables are measured and defined, see Appendix B. * significant at 10%; ** significant at 5%; *** significant at 1%

In Panel A, an observation is an applicant. All regressions include month-year of application dummies, location dummies, and controls for race, age, and gender.

In Panel B, an observation is an applicant. The regressions include month-year of application dummies and location dummies. Demographic controls are race, age, gender, and years of schooling.

In Panel C, an observation is an applicant-interview. Getting hired at the firm generally requires multiple interviews, so there are multiple interviews per applicant. Regressions include job type dummies, month-year of application, interview type dummies. Demographic data are not available for these applicants.

Table 3: Do Referred Workers Have More Desirable Characteristics? Schooling & Work Experience, Cognitive Ability, Non-cognitive Ability, and Experimental Preferences

Panel A: Schooling & Work Exp Dep var:	(1) Schooling in years	(2) Schooling in years	(3) Schooling in years	(4) Undergrad GPA (normed)	(5) Grad school GPA (normed)	(6) Related experience in years	(7) Related experience in years	(8) Number of jobs in last 2 years	(9) Max years at a prev job
Sample:	Call-center	Trucking	High-tech	High-tech	High-tech	Trucking	High-tech	Trucking	Trucking
Referral	-0.078***	-0.209	0.038	0.033	0.059	-0.002	0.005	0.119	-0.156
	(0.025)	(0.134)	(0.027)	(0.051)	(0.071)	(0.117)	(0.165)	(0.101)	(0.585)
Observations	10,179	894	10,890	1,623	793	894	1,817	893	517
R-squared	0.103	0.0467	0.1559	0.1348	0.2310	0.0796	0.7520	0.0577	0.401
Mean dep var	12.86	12.85	16.97	0	0	1.170	5.842	1.601	8.044

Panel B: Cognitive Ability Dep var:	(1) Intelligence (normalized)	(2) IQ (normalized)	(3) SAT total score (mean dv=1401)
Sample:	Call-center	Trucking	High-tech
Referral	0.016**	-0.120	11.09
	(0.003)	(0.099)	(9.54)
Observations	64,223	849	899
R-squared	0.049	0.078	0.216

Panel C: Personality Dep var:	(1) Big 5 index (normalized)	(2) Conscientiousness (normalized)	(3) Neuroticism (normalized)	(4) Agreeableness (normalized)	(5) Extraversion (normalized)	(6) Openness (normalized)
Call-centers:						
Referral	-0.012***	-0.074***	-0.018**	-0.012	0.058***	-0.050***
	(0.003)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
Observations	75,341	75,548	75,465	75,543	75,543	75,543
R-squared	0.093	0.129	0.043	0.035	0.187	0.085
Trucking:						
Referral	-0.033	-0.044	0.055	-0.169*	0.102	NA
	(0.049)	(0.092)	(0.091)	(0.099)	(0.092)	
Observations	895	895	895	895	895	
R-squared	0.029	0.019	0.015	0.061	0.029	
High-tech:						
Referred	0.017	0.067	-0.080	-0.153***	0.089*	0.006
	(0.026)	(0.050)	(0.049)	(0.049)	(0.049)	(0.050)
Observations	1,853	1,853	1,855	1,855	1,854	1,854
R-squared	0.039	0.044	0.049	0.035	0.033	0.034

Panel D: Experimental Preferences Dep var:	(1) CRRA risk aversion	(2) Patient options chosen	(3) Beta in HD model	(4) Delta in HD model	(5) Trust	(6) Altruism V1	(7) Altruism V2
Sample:	Trucking	Trucking	Trucking	Trucking	Trucking	Trucking	Trucking
Referral	-0.021	-0.025	-0.015	-0.006	-0.536**	-0.018	-0.251
	(0.157)	(0.157)	(0.018)	(0.012)	(0.226)	(0.185)	(0.187)
Observations	894	894	894	872	894	894	894
R-squared	0.021	0.053	0.019	0.006	0.035	0.044	0.016
Mean dep var	0.503	0.597	0.841	0.974	3.367	1.659	3.641

Notes: This table presents regressions of various outcomes on whether a worker was referred and controls. An observation is a worker, with robust standard errors in parentheses. For an explanation of how the different variables are measured and defined, see Appendix B. For the call-centers, the regressions include month-year of hire dummies, location dummies, client dummies, and controls for race, age, and gender. For trucking, the regressions include work type controls, race, age, gender, and marital status; the drivers here are from the same training school and were hired in late 2005 or 2006 (results are similar if we control for month-year of hire dummies and state dummies). For high-tech, the regressions include race, age, gender, month-year of hire dummies, job category dummies, job rank dummies, and office location dummies. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Referrals and Quitting

Panel A: Call-center workers	(1)	(2)	(3)	(4)	(5)
Referral	-0.135***	-0.129***	-0.118***	-0.200***	-0.198***
	(0.027)	(0.027)	(0.028)	(0.039)	(0.039)
Average handle time to date			0.000153		
			(0.000146)		
Referral X Tenure (days)				0.00115**	0.00114**
				(0.00052)	(0.00052)
Job Test Score Controls	No	Yes	Yes	No	Yes
Observations	1,178,019	1,178,019	1,178,019	1,178,019	1,178,019

Panel B: Truckers	(1)	(2)	(3)	(4)	(5)	(6)
Referral	-0.114***	-0.104***	-0.105***	-0.105***	-0.164***	-0.140***
	(0.022)	(0.022)	(0.023)	(0.023)	(0.029)	(0.028)
Average miles to date			-0.019***	-0.019***		
			(0.0023)	(0.0023)		
Current state unemployment rate				-0.061***		
				(0.018)		
Referral X Tenure (weeks)					0.0012***	0.00085**
					(0.00042)	(0.00043)
Demographic controls	No	Yes	Yes	Yes	No	Yes
Observations	0.94M	0.94M	0.94M	0.94M	0.94M	0.94M

Panel C: High-tech Workers	(1)	(2)	(3)	(4)	(5)	(6)
Referral	-0.230***	-0.236***	-0.223***	-0.217***	-0.399***	-0.387***
	(0.061)	(0.061)	(0.062)	(0.060)	(0.105)	(0.106)
Interview Score			-0.123***	-0.103***		
			(0.029)	(0.029)		
Average subjective performance to date				-0.314***		
				(0.025)		
Referral X Tenure (months)					0.0101**	0.0090*
					(0.0051)	(0.0051)
Demographic controls	No	Yes	Yes	Yes	No	Yes
Observations	301,272	301,272	301,272	301,272	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. * significant at 10%; ** significant at 5%; *** significant at 1%

In Panel A, an observation is a worker-day. All regressions 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.

In Panel B, an observation is a worker-week. All regressions include month-year of hire dummies, month-year dummies, driver training contracts, work type controls, and state dummies. Demographic controls are gender, race, marital status, and age. The exact sample size is withheld to protect firm confidentiality, $M >> 100,000$, $N >> 10,000$.

In Panel C, an observation is a worker-month. All regressions include month-year of hire dummies, job category dummies, job rank dummies, and office location dummies. Demographic controls are race, age, gender, and education.

Table 5: Referrals and Non-rare Productivity Measures (Normalized)

Panel A: Call-center Workers Dep var:	(1) Adherence share	(2) Average handle time	(3) Sales conversion rate	(4) Quality assurance	(5) Customer satisfaction
Referral	-0.0271**	0.0011	-0.0137	0.0160	0.0027
	(0.0124)	(0.0104)	(0.0083)	(0.0172)	(0.0034)
Observations	152,683	749,848	134,386	31,908	603,860
Clusters	3,136	12,497	3,192	2,864	11,859
R-squared	0.1418	0.5631	0.7254	0.1755	0.0337

Panel B: Truckers Dep var = Miles per Week	(1)	(2)	(3)	(4)
Referral	-0.00004	-0.00049	0.00297	0.00231
	(0.01018)	(0.01005)	(0.01001)	(0.00987)
Demographic controls	No	Yes	No	Yes
Miles sample	Baseline	Baseline	Trim 5/95	Trim 5/95
Observations	$0.86M$	$0.86M$	$0.78M$	$0.78M$
Clusters	$0.85N$	$0.85N$	$0.84N$	$0.84N$
R-squared	0.0767	0.0811	0.0626	0.0664

Panel C: High-Tech Dep var:	(1) Subj perf	(2) Subj perf	(3) Subj perf	(4) Hours worked	(5) Code reviews	(6) Bug actions	(7) Builds	(8) P4Calls	(9) Wiki edits	(10) Views
Referral	0.037***	0.040***	0.064***	-0.023*	-0.012	0.003	0.038***	-0.001	0.018	0.005
	(0.012)	(0.012)	(0.015)	(0.013)	(0.011)	(0.015)	(0.010)	(0.010)	(0.015)	(0.013)
Referral X Tenure (quarters)			-0.0052*							
			(0.0027)							
Demographic controls	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	104,255	104,255	104,255	250,980	289,689	289,689	289,689	289,689	289,689	289,689
Clusters	16,546	16,546	16,546	11,066	11,123	11,123	11,123	11,123	11,123	11,123
R-squared	0.084	0.093	0.084	0.139	0.269	0.048	0.193	0.008	0.059	0.100

Notes: This table examines whether a worker's referral status predicts productivity. All specifications are OLS regressions with standard errors clustered by worker in parentheses. Each productivity measure has been normalized so that the coefficients are all in standard deviation units. The non-rare productivity metrics are described further in Appendix B. * significant at 10%; ** significant at 5%; *** significant at 1%

In Panel A, productivity is measured using one of 5 different 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, productivity is measured in miles and then normalized. 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, state dummies, and the annual state unemployment rate. Demographic controls are gender, race, marital status, and age. In regards to sample restrictions, "Baseline" refers to the sample excluding 0 mile weeks. "Trim 5/95%" refers to trimming the lowest 5% and highest 5% of the miles observations (after excluding 0 mile weeks). The exact sample size is withheld to protect firm confidentiality, $M >> 100,000$, $N >> 10,000$.

In Panel C, productivity is measured in terms of a subjective performance rating or objective performance measure. An observation is a worker-quarter in columns 1-3 and a worker-month in columns 4-10. Columns 1-3 include quarter-year of hire dummies, quarter-year dummies, a fifth-order polynomial in tenure, job category dummies, job rank dummies, and office location dummies. Columns 4-10 have the same controls except they use month-year of hire dummies (instead of quarter-year of hire dummies) and they use month-year dummies (instead of quarter-year dummies). Demographic controls are race, age, gender, and education.

Table 6: Referrals and Rare High-Impact Productivity: Trucking Accidents and Innovation

Panel A: Truck Accidents	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent var (0-1):	Accident	Accident	Preventable accident	Preventable accident	Preventable accident	Preventable accident	Preventable accident	Non-preventable accident (placebo test)
(all coefs multiplied by 100)								
Referral	-0.11***	-0.11***	-0.08***	-0.16***		-0.09***	-0.40***	-0.02
	(0.03)	(0.03)	(0.02)	(0.03)		(0.02)	(0.10)	(0.02)
							[0.11]	
Referral X Young						-0.10		
						(0.06)		
Referral X Tenure (weeks)				0.0011***	0.00084***			
				(0.00021)	(0.00025)			
Ref X Unemp rate at hire							0.056***	
							(0.017)	
							[0.018]	
State unemp rate at hire							-0.063***	
							(0.012)	
							[0.013]	
Mean dep var X 100	1.79	1.79	0.82	0.82	0.82	0.82	0.82	0.66
% reduction for referred drivers	6%	6%	10%	20%	NA	11%	49%	3%
Demographic controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Worker FE	No	No	No	No	Yes	No	No	No
R-squared	0.0076	0.0077	0.0056	0.0056	0.038	0.0056	0.0056	0.0024

Panel B: Patents	DV=Num patents						DV=Citation-weighted patents					
Neg bin models	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Referral	0.28***	0.25***	0.25***	0.30*		0.11	0.31***	0.27***	0.27***	0.43**		0.02
	(0.08)	(0.08)	(0.08)	(0.17)		(0.16)	(0.09)	(0.09)	(0.09)	(0.21)		(0.18)
Ref X Ten(months)				-0.001	-0.004					-0.006	-0.003	
				(0.007)	(0.005)					(0.008)	(0.004)	
Referral X Young						0.38*						0.63*
						(0.23)						(0.32)
Demog controls	No	Yes	Yes	Yes	No	Yes	No	Yes	Yes	No	No	Yes
Interview Scores	No	No	Yes	No	No	No	No	No	Yes	No	No	No
Worker FE	No	No	No	No	Yes	No	No	No	No	No	Yes	No
Mean dep var	0.0047	0.0047	0.0047	0.0047	0.0047	0.0047	0.0067	0.0067	0.0067	0.0067	0.0067	0.0067

Panel C: Ideas on Idea Board	DV=Rating-weighted ideas				
Neg bin models	(1)	(2)	(3)	(4)	(5)
Referral	0.15**	0.14**	0.14**	0.22**	
	(0.07)	(0.07)	(0.07)	(0.08)	
Referral x Tenure (months)				-0.0057	0.0055**
				(0.0046)	(0.0022)
Demographic controls	No	Yes	Yes	Yes	No
Interview Scores	No	No	Yes	No	No
Worker FE	No	No	No	No	Yes
Mean Dep Var	0.108	0.108	0.108	0.108	0.108

Notes: This table examines whether a worker's referral status predicts rare high-impact productivity. Panel A analyzes employee trucking accidents, whereas Panels B and C analyze innovation in the high-tech firm. Standard errors clustered by worker. * significant at 10%; ** significant at 5%; *** significant at 1%.

In Panel A, an observation is a worker-week. All regressions are linear probability models which include month-year of hire dummies, month-year dummies, a fifth-order polynomial in tenure, driver training contracts, work type controls, state dummies, and the annual state unemployment rate. Demographic controls are gender, race, marital status, and age. In column 6, Young is defined as age less than or equal to 25. The unreported coefficient on the Young dummy variable in column 6 is 0.21(0.04). Standard errors clustered by state in brackets. The sample size is M observations with N workers. The exact sample size is withheld to protect firm confidentiality, $M >> 100,000$, $N >> 10,000$.

In Panels B and C, an observation is a worker-month. All specifications are negative binomial models, where the dependent variable is the number of patents in a month (Panel B) or number of rating-weighted ideas on the firm idea board in a month (Panel C). All regressions include month-year of hire dummies, a 5th-order polynomial in week of tenure, job category dummies, job rank dummies, and office location dummies. Demographic controls are race, age, gender, and education. In columns 6 and 12, Young is defined as age of hire less than or equal to 27. The unreported coefficients on the Young dummy variable are -0.21(0.21) and -0.20(0.28) in columns 6 and 12, respectively. Regressions with Worker FE are fixed-effect negative binomial models. In Panel B, there are 333,545 observations and 17,191 workers. In Panel C, there are 325,403 observations and 16,639 workers.

Table 7: Comparing the Mean and Variance of Wages for Referred vs. Non-referred Workers

Panel A: Call-centers	DV=Log(Salary)						DV=(Log(Salary) Residual)^2		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Referral	0.0019	0.0012	0.0027	0.0067		0.0041	-0.0018	-0.0019	-0.0043
	(0.0029)	(0.0028)	(0.0026)	(0.0043)		(0.0031)	(0.0015)	(0.0015)	(0.0029)
Average handle time to date			-0.0146***			-0.0111**			
			(0.0038)			(0.0049)			
Referral X Average handle time to date						-0.0093			
						(0.0057)			
Referral X Tenure (months)				-0.0005	0.0000				0.0002
				(0.0004)	(0.0003)				(0.0002)
Job Test Score Controls	No	Yes	Yes	No	No	Yes	No	1st stg	No
Individual FE	No	No	No	No	Yes	No	No	No	No
R-squared	0.1944	0.2088	0.2310	0.1945	0.4827	0.2311	0.0015	0.0016	0.0016

Panel B: Truckers	DV=Log(Salary)						DV=(Log(Salary) Residual)^2		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Referral	-0.0026	-0.0028	0.0041		0.0091	-0.0089*	0.0454	0.0470	0.0329
	(0.0046)	(0.0046)	(0.0048)		(0.0289)	(0.0051)	(0.0312)	(0.0312)	(0.0380)
Referral X Avg miles to date					-0.00054				
					(0.00138)				
Avg miles to date					0.0196***				
					(0.00065)				
Referral X Tenure (months)			-0.00039	-0.00010					0.00070
			(0.00027)	(0.00025)					(0.00100)
Referral X Black						0.0418***			
						(0.0127)			
Referral X Hispanic						0.0312*			
						(0.0177)			
Demog Controls	No	Yes	Yes	No	Yes	Yes	No	1st stg	No
Individual FE	No	No	No	Yes	No	No	No	No	No
R-squared	0.0610	0.0631	0.0631	0.1986	0.0834	0.0632	0.00006	0.00007	0.00006

Panel C: Hi-tech	DV=Log(Salary)								DV=(Log(Salary) Residual)^2		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Referral	0.017**	0.017***	0.018***	0.017***	0.019***	0.010	0.011		0.020	0.019	0.024
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.009)	(0.009)		(0.015)	(0.015)	(0.019)
Average subjective performance to date				0.034***	0.040***						
				(0.005)	(0.005)						
Ref X Avg subject performance to date					-0.016						
					(0.010)						
Ref X Ten (months)						4.9e-4	4.2e-4	-6.9e-5			-3.5e-4
						(4.1e-4)	(4.1e-4)	(2.0e-4)			(5.2e-4)
Demog Controls	No	Yes	Yes	Yes	Yes	No	Yes	No	No	1st stg	No
Interview Scores	No	No	Yes	Yes	No	No	No	No	No	No	No
Individual FEs	No	No	No	No	No	No	No	Yes	No	No	No
R-squared	0.518	0.524	0.526	0.529	0.529	0.518	0.524	0.903	0.008	0.007	0.008

Notes: This table examines whether referred workers earn higher salaries, and whether there is more or less variance in salaries among referred workers. Standard errors clustered by worker in parentheses. All the productivity variables have been standardized, so that they can be interpreted in terms of standard deviations.

In Panel A, 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, and client dummies. The sample size is 634,153 observations with 11,174 workers.

In Panel B, 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, and state dummies. Demographic controls are gender, race, marital status, and age. The sample size is $0.71M$ observations with $0.74N$ workers. The exact sample size is withheld to protect firm confidentiality, $M >> 100,000$, $N >> 10,000$.

In Panel C, an observation is a worker-month. All regressions 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. Demographic controls are race, age, gender, and education. The sample size is 245,270 observations with 10,655 workers.

Table 8: Homophily in Truckdriver Referrals and Implications for Profits per Worker

Panel A: Homophily in Characteristics	(1) Smoker	(2) Black	(3) Hispanic	(4) Female	(5) Married	(6) Age
Referring Driver Has Characteristic	0.20***	0.42***	0.42***	0.08	0.08	0.29***
	(0.06)	(0.07)	(0.12)	(0.08)	(0.06)	(0.07)
Observations	1,113	1,113	1,113	1,113	1,113	1,106
R-squared	0.59	0.68	0.72	0.59	0.53	0.58
Mean dep var	0.256	0.160	0.0547	0.132	0.437	39.96

Panel B: Homophily in Productivity	(1)	(2)	(3)	(4)
Sample	All	All	Miles>0	Miles>0
Avg miles per week (productivity) of referring driver	0.330***	0.348***	0.356***	0.310***
	(0.0400)	(0.0401)	(0.0367)	(0.0363)
Location dummies for referring worker	State	State	State	3-digit zip
Observations	40,875	40,875	36,597	36,597
Demographic controls	No	Yes	Yes	Yes
R-squared	0.205	0.209	0.190	0.233
Mean dep var	1685	1685	1882	1882

Panel C: Homophily in Accidents	(1)	(2)	(3)
Referring driver ever had an accident	0.0033*	0.0035*	0.0042
	(0.0020)	(0.0020)	(0.0029)
Mean dep var	0.0202	0.0202	0.0202
Location dummies for referring worker	State	State	3-digit zip
Observations	41,670	41,670	41,670
Demographic controls	No	Yes	Yes
R-squared	0.016	0.017	0.025

Panel D: Profits per Worker	Profits per Worker	Profits per Worker
Industry	Trucking	Call-centers
Referred (overall)	\$2,201	\$1,134
Non-referred (overall)	\$1,756	\$839
Referred (matched sample)	\$2,503	
Referred, referring worker w/ above median productivity	\$4,190	
Referred, referring worker w/ below median productivity	\$1,063	

Notes: Panels A-C of this table present OLS regressions of the characteristics and productivity of referred workers on the characteristics and productivity of referrers. Panel D compares profits between referred and non-referred workers for trucking and call-centers. For the truckers, the sample is restricted to matched referred truckers hired in 2007-2009. For the call-center workers, the sample is the same as in Table 4. * significant at 10%; ** significant at 5%; *** significant at 1%

In Panel A, an observation is a referred worker. All specifications include month-year of hire dummies and 3-digit zip code dummies, as well as six demographic variables for the referring worker (smoker, Black, Hispanic, female, married, age).

In Panel B, the dependent variable is worker productivity in miles per week. An observation is a worker-week. All regressions include month-year of hire dummies, month-year dummies, a fifth-order polynomial in tenure, work type controls, and state dummies for the *referred* driver. They also include work type dummies and tenure at date of referral for the *referring* worker. Demographic controls are gender, race, marital status, and age, and are included for both the referred and referring worker.

In Panel C, we present linear probability models where the dependent variable is whether the worker had an accident in a given week. An observation is a worker-week. The controls are the same as in Panel B.

In Panel D, we calculate accounting profits per worker for truckers and call-center workers. See Appendix B.6 for details on the calculation.

Table 9: High-Productivity Workers Are More Likely to Ever Make a Referral

Panel A: Trucking	(1)	(2)	(3)
Miles per week (normalized)	0.0047***	0.0051***	0.0051***
	(0.0013)	(0.0013)	(0.0013)
Incumbent worker was referred			0.0058
			(0.0043)
Demographic controls	No	Yes	Yes
R-squared	0.0303	0.0321	0.0322
Mean dep var	0.0382	0.0382	0.0382

Panel B: High-tech	(1)	(2)	(3)	(4)
Patents per year	0.031**	0.028**	0.028**	0.027**
	(0.015)	(0.014)	(0.014)	(0.014)
Subjective performance rating	0.029***	0.029***	0.029***	0.027***
(normalized)	(0.004)	(0.004)	(0.004)	(0.004)
Interview score			0.012***	0.011***
			(0.003)	(0.003)
Incumbent worker was referred				0.039***
				(0.006)
Friends at company				0.006***
				(0.002)
Demographic controls	No	Yes	Yes	Yes
R-squared	0.157	0.160	0.161	0.165
Mean dep var	0.173	0.173	0.173	0.173

Notes: This table presents OLS regressions on whether an employee makes a referral on the employee's average productivity. For example, inventing an extra patent per year is associated with a 17% (3 percentage point) increase in the probability of ever making a referral (column 1 of Panel B). An observation is an incumbent worker. Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

In Panel A, all regressions include work type controls, state dummies, and tenure at job controls. Demographic controls are gender, race, marital status, and age. The sample size is $0.78N$ workers. The exact sample size is withheld to protect firm confidentiality, $N >> 10,000$.

In Panel B, all regressions include month-year of hire dummies, job category dummies, job rank dummies, office location dummies, and tenure at job controls. Demographic controls are race, age, gender, and education. The sample size is 16,569 workers.

Table 10: The Motivations of *Referring Workers*: Larger Referral Bonuses are Associated with More Referrals and Workers are More Likely to Stay After Making a Referral

Panel A: Bonus Size and Referrals in Call-Centers
OLS, Dep var: Applicant was referred (0-1)

	(1)	(2)
Log Referral Bonus	0.072***	0.113**
	(0.013)	(0.052)
State FE	No	Yes
Observations	11,290	11,290
R-squared	0.0123	0.0229

Panel B: Are Incumbent Workers Less Likely to Quit After Making a Referral? Cox Models

Industry	Trucking (1)	High-tech (2)	High-tech (3)
After incumbent worker has made a referral	-0.161*	-0.262**	-0.267**
	(0.097)	(0.105)	(0.105)
Incumbent worker was referred	-0.119***	-0.270***	-0.272***
	(0.022)	(0.067)	(0.067)
Number of friends at company for the incumbent worker			0.024
(reported by other workers at the company)			(0.028)
Observations	$0.94N$	290,621	290,621

Notes: Standard errors clustered by applicant (Panel A) or worker (Panel B) in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Panel A presents OLS regressions of whether an applicant was referred (0 or 1) on the log size of the referral bonus. All data are from call-centers. An observation is an applicant. The regressions include month-year of application dummies. The sample size is small because the exact referral bonus amount is only known for some call-center locations.

Panel B presents Cox proportional hazard models of whether incumbent workers are less likely to quit after making a referral. The data are from the trucking and high-tech firms. For trucking, an observation is a worker-week, whereas for high-tech, an observation is a worker-month. For the trucking analysis, we include month-year of hire dummies, month-year dummies, driver training contracts, work type controls, state dummies, demographic controls (gender, race, marital status, age), average productivity to date (in miles), and the driver's local unemployment rate. For the high-tech analysis, we include month-year of hire dummies, job category dummies, job rank dummies, office location dummies, average productivity to date (in subjective performance ratings), and demographic controls (race, age, gender, and education). *After incumbent worker has made a referral* is a dummy equal to 1 if the worker-time period in question falls after an incumbent worker has made their first observed referral. It is 0 otherwise—it is 0 both for incumbent workers who never make referrals and for referrers who have not yet made a first referral. In defining the variable, if instead we set it equal to missing in time periods when a referrer has not yet made their first referral (and thus has a 0 probability of quitting because he/she is later observed making a referral), our estimates become slightly stronger. For trucking, we only observe referrals made during 2007-2009, but we include our full sample of drivers from 2002-2009.

Table 11: Key Facts About Employee Referral Networks

Fact	Our finding	Literature	Learning	Homophily	Peer benefits
(1) Applicant quality and hiring					
Pr(Hire)	$R > E$	$R > E^{i}$	$\sim$	$R > E$	$R > E$
Pr(Accept offer)	$R > E$	$R > E^{ii}$	$\sim$	$R < E$	$\sim$
Applicant skills (schooling, cog & non-cog ab)	$R = E$	New	$R > E$	$R > E$	$\sim$
Job test scores	$R > E$	New	$R > E$	$R > E$	$\sim$
(2) Worker quality					
Worker skills (schooling, cog & non-cog ab, expt pref)	$R = E$	New^{iii}	$R > E$	$R > E$	$\sim$
(3) Turnover and productivity					
Quitting	$R < E$	$R < E^{iv}$	$R < E$	$R < E$	$R < E$
Quitting gap with tenure	$\searrow$	$\searrow$ or flat^{v}	$\searrow$	flat	flat
Standard non-rare productivity metrics	$R = E^{*}$	$R > E^{vi}$	$R > E$	$R > E$	$R > E$
Rare high-impact productivity metrics	$R > E$	New	$R > E$	$R > E$	$R > E$
Rare high-impact productivity gap with tenure	$\searrow$	New	$\searrow$	$\sim$	$\sim$
Productivity diffs concentrated in young workers	Yes	New	Yes	$\sim$	$\sim$
(4) Wages and profits					
Initial wages	$R > E$	$R \lesseqgtr E^{vii}$	$R > E$	$R > E$	$\sim$
Wage gap with tenure	flat	$\searrow^{viii}$	$\searrow$	flat	$\nearrow$
Wage variance	$R = E$	$R \lesseqgtr E^{ix}$	$R < E$ or $\sim$	$\sim$	$\sim$
Wage variance with tenure	flat	$\searrow, \nearrow^{x}$	$\searrow$	$\sim$	$\nearrow$
Profits	$R > E$	New	$R = E$	$R > E$	$\sim$
(5) Referrers					
People refer people with similar characteristics	Yes	Yes^{xi}	$\sim$	Yes	$\sim$
People refer people with similar productivity	Yes	New^{xii}	$\sim$	Yes	$\sim$
Referrers have higher productivity	Yes	New^{xiii}	$\sim$	Yes	Yes
Referrers have higher wage variance	No	Yes^{xiv}	$\sim$	$\sim$	Yes
Larger referral bonuses correlated with more referrals	Yes	New	$\sim$	$\sim$	$\sim$
Workers are less likely to quit after making a referral	Yes	New	$\sim$	$\sim$	$\sim$

R = Referred, E = External/Non-referred, $\sim$ indicates no theoretical prediction. Results predicted by particular theories are highlighted in green.

Notes: This table summarizes the main results in the paper. Column 1 ("Our finding") lists what our paper finds. Column 2 ("Literature") lists what (if anything) other papers have found. Columns 3-5 describe the predictions of learning, homophily, and peer benefit theories. For ease of comparison, we use similar notation as in Brown et al. (2013). For example, in the first row, we list our fact that referred applicants are more likely to be hired ($R > E$). This is consistent with past literature. Our fact is predicted by homophily and peer benefit theories ($R > E$). Learning models do not make a prediction ($\sim$).

(i) Many papers, e.g., Fernandez and Weinberg (1997); Castilla (2005); Brown et al. (2013). (ii) Yakubovich and Lup (2006).
(iii) Hensvik and Skans (2013) show that new workers with prior co-worker linkages have higher cognitive skills, but lower schooling. Heath (2013) shows that referred workers have worse observables (schooling and work experience).
(iv) Many papers. (v) Dustmann et al. (2012) finds that turnover differences decline with tenure, whereas Brown et al. (2013) find that turnover differences do not decline with tenure.
(vi) Castilla (2005); Holzer (1987a); Pinkston (2012); Pallais and Sands (2013). * indicates the caveat that referrals are slightly more productive on one important non-rare productivity metric: subjective performance at the high-tech firm.
(vii) Mixed evidence. Often positive in within-firm evidence and sometimes negative in across-firm evidence. See Appendix A.10.
(viii) See Dustmann et al. (2012) and Brown et al. (2013).
(ix) Brown et al. (2013) find referrals have lower wage variance, whereas Heath (2013) finds they have higher wage variance.
(x) Brown et al. (2013) find that the variance of referred and non-referred workers' earnings converges with tenure, whereas Heath (2013) finds it diverges.
(xi) Many papers. (xii) In contemporaneous work, Pallais and Sands (2013) reach the same finding.
(xiii) In contemporaneous work, Hensvik and Skans (2013) find that referrers in co-workers linkages have higher cognitive skills.
(xiv) Heath (2013) finds referrers have higher wage variance.

Web Appendix: For Online Publication Only

A Additional Discussion and Results

In this section, we provide additional discussion of several results from the paper. We first provide discussion on the general precision of our estimates; on Race X Referral interaction terms; on referral interaction effects in general; on the relation of our productivity results to the results in Pallais and Sands (2013); and on our finding that referrers have higher productivity than non-referrers. We then move to other results, proceeding in the order in which the related result occurs in the main paper.

A.1 Precision of Estimates

For a number of our results in the paper, we find either no difference or a very small difference between referred and non-referred applicants, or between referred and non-referred workers. These include results on applicant skill characteristics, worker skill characteristics, wages in two of three industries, wage-tenure trends, wage variance (both levels and trends), non-rare productivity, and the response of wages with respect to non-rare productivity. How precisely estimated are these "zeroes?" We discuss this at different points in the main text, but provide additional discussion here.

The answer varies by result, but we would say in general that most of the relationships are precisely estimated. For differences in applicant skill characteristics and worker skill characteristics, the estimates are very precise for call-centers and moderately precise for trucking and high-tech. For example, on the overall Big 5 index among call-center applicants, the 95% confidence interval on the referral status coefficient is $[-0.018\sigma, -0.010\sigma]$, that is, between -0.02 and -0.01 standard deviations.

For wages in call-centers and trucking, where we estimate "zeroes," the estimates are precise; for both call-centers and trucking, we can rule out that referred workers have more than 0.74% higher earnings than non-referred workers. In wage regressions, the Referral X Tenure interaction terms are also relatively precisely estimated, particularly for the specifications with individual fixed effects. The standard errors are 3e-4, 2.5e-4, and 2.0e-4 for call-centers, trucking, and high-tech respectively. For example, in call-centers, the 95% confidence interval on Referral X Tenure is roughly [-6e-4,6e-4], meaning we can rule out that the difference in wages between referred and non-referred workers changes by more than about 0.2% in either direction during the first 90 days.

For comparing wage variance between referred and non-referred workers, we have somewhat less precision than for comparing wages, but estimates are still reasonably precise. For the level of wage variance, the standard errors are 13%, 9%, 14% of the sample means in call-centers, trucking, and high-tech, respectively (see Table C2 for sample means). Although all the point estimates are statistically insignificant from zero, we cannot rule out that the variance of wages for referred and non-referred workers could vary by a moderate percentage relative to the sample mean.

For analyzing whether there is differential responsiveness of wages with respect to productivity for referred vs. non-referred workers, the estimates in Table 7 are zeroes, but we cannot rule out moderate-sized differences. Looking at the Kahn and Lange (2013) correlations in Table C9, we have reasonably good precision for high-tech, though somewhat less precision for the call-centers.

For outcomes where we do find significant differences between referrals and non-referrals, it is worth noting that the estimates are also generally quite precise. For example, in trucking, we estimate that referrals are 6.7-7.9 percentage points more likely to accept an offer, 7-16% less likely to quit, 5-15% less likely to have a preventable accident in a given week.

A.2 Race X Referral Interactions for Earnings Regressions in Trucking

Although referred workers do not earn more than non-referred workers *overall* in trucking, referred workers do earn more than non-referred among Blacks and Hispanics. As seen in columns 2 and 3 of Table C8, White workers earn 1.3% more than Black workers at the firm, a difference which remains similar after controlling for referral status. As seen in columns 4 and 5, while Blacks earn 2% less than Whites among non-referred workers, they earn 2.5% more among referred workers. Recall that the truckers are paid by piece rate, and we get similar results if we analyze miles instead of earnings as the dependent variable.

One possible explanation for why the Referral X Black and Referral X Hispanic interactions are positive is that, among non-referred applicants, firms may have less precise information about minority than White applicants,[1] due, for example, to cultural differences or different "discourse systems" (Morgan and Vardy, 2009). Additionally, if there is equal variance on referred applicants for Blacks and Whites, then there will have been a greater change in signal variance for referred Blacks vs. non-referred Blacks, compared to referred Whites vs. non-referred Whites. By the arguments in Simon and Warner (1992), there will be a larger difference in productivity for referred Blacks vs. non-referred Blacks, compared to referred Whites vs. non-referred Whites.[2] One potential difficulty with this explanation is that it does not account for why Blacks earn more than Whites among referred workers. In addition, if there is more being learned about Black workers, one might expect that the coefficient on Referral X Tenure will be more negative among Black workers (compared to White workers), as predicted in learning theories. However, as seen in columns 7 and 11, the coefficient on Referral X Tenure is actually slightly positive for Blacks, whereas for Whites it is slightly negative.

A second explanation for the Referral X Black and Referral X Hispanic positive interactions is that referrers may be slightly "choosier" when deciding to refer a Black or Hispanic candidate. In an influential ethnographic study in the sociology literature, Smith (2005) argues that referrals often involve significant reputational concerns for Blacks. She focuses mostly on the decisions of the referrer. If a Black worker believes their position at work is more tenuous, they may be less likely to make a referral than a non-Black, for fear of possibly compromising their reputation. One may imagine that such concerns could apply equally to referred workers, where the reputational cost of a referral who "does not work out" may be higher if the referred worker is a minority than if the referred worker is White. Such an explanation could explain why, among referred workers, Blacks seem to earn more than Whites.

Korenman and Turner (1996) is the only other paper we are aware of looking at how referral differences in earnings vary by race. Using the 1989 Study of Disadvantaged Youths and the 1982 wave of the National Longitudinal Survey of Youth (NLSY79), they find mixed results on the Referral X Black coefficient, and a negative coefficient on Referral X Hispanic. There are a number of factors that could explain our different results, including, one, our results are within one firm whereas Korenman and Turner (1996) look at workers across firms (though without controlling for firm fixed effects); two, the analysis of Korenman and Turner (1996) focuses on youths; and three, the workers we study are truckers and are paid by piece rate, whereas the sample in Korenman and Turner (1996) work in different jobs.

[1] This assumption has a long history in economics; according to Morgan and Vardy (2009), it was first employed in Phelps (1972), and has been subsequently used in Aigner and Cain (1977); Lundberg and Startz (1983); Morgan and Vardy (2009), among many others.

[2] Thus, the intuition for the positive Referral X Black interaction in learning models is somewhat different from the usual arguments about statistical discrimination. Here, non-referred Blacks will set low reservation wages because the option value from trying out the job is high. Non-referred Whites will also set a lower reservation wage than referred Whites, but not to the same extent as for Blacks; thus, the "gains" from referral status will be larger for Blacks than for Whites.

Research using different types of analysis also finds evidence that referral differences tend to be larger among minorities. Datcher (1983) finds larger referred/non-referred quitting differences for Black workers. In their analysis of neighborhood effects, Bayer et al. (2008) find that referral differences are larger for Hispanics. Topa (2001) finds that referral effects are larger among Chicago census tracts with larger minority shares. Our finding is consistent with this work.[3]

Our results on Referral X Race interactions are only from one industry (trucking). In addition, while we have described two potential mechanisms, we are unable to provide strong evidence for either one. Thus, further research is clearly needed. Still, our result is documented using a very large sample of workers doing the same sort of work and is, we believe, a contribution to the literature, suggesting that referral networks may operate differently for White vs. minority workers.

A.3 Interaction Effects of Referral Status with Labor Market Conditions and Demographics: Summary

For ease of exposition, we focused the paper's exposition of interaction effects for labor market conditions and demographics on a few statistically significant interactions. While we already mentioned most of these results in footnotes in the text, we summarize the findings here. Our data only allow us to examine interaction effects with race and labor market conditions for trucking. We observe a significant interaction of referral status and the state unemployment rate at hire for the outcomes of being hired, accepting an offer, and having an accident. There is no significant interaction for quitting or earnings. For race, we find a significant interaction for earnings. There was no statistically significant interaction for quitting or accidents (and there are no race data for applicants). For age, we observe that there are larger referral differences for young workers in trucking accidents, patents, and subjective performance. We observe no statistically significant differences for earnings or quitting in either trucking or high-tech. We are only able to analyze Referral X Age interactions for trucking and high-tech.[4]

A.4 Further Discussion of our Productivity Results and their Relation to Results in Pallais and Sands (2013)

We find that referred workers perform no better than non-referred workers on most non-rare everyday productivity measures, but have superior performance on rare high-impact outcomes. In Section 9.1, we discuss reasons from learning and homophily models why this may be the case. An additional explanation offered via the field experiments in Pallais and Sands (2013) concerns endogenous hiring. In discussing our results, Pallais and Sands (2013) observe that if firms set lower hiring standards for referred applicants, differences in productivity between referred and non-referred workers may be smaller than differences in productivity among referred and non-referred applicants. We cannot rule out the suggestion of Pallais and Sands, and it may be potentially important for understanding our results. However, we point out two concerns with their suggestion.

First, depending on the model, referral differences among applicants may be larger or smaller than referral differences among workers. For example, in Simon and Warner's (1992) learning model,

[3] Also using a different type of analysis, Holzer (1987b) finds in contrast that Black youth seem to gain less from referrals for job-finding than Whites.

[4] Beyond labor market conditions and demographics, we showed interaction effects of Referral and Interview score for hiring regressions in Table 1. We also examined Referral X Interview score interactions for other outcomes where there were significant differences between referrals and non-referrals. In high-tech, there is no significant interaction term of Referral X Interview score for quitting, patents, or subjective performance, and there is a slight negative and statistically significant relationship for salary. In call-centers, there is no statistically significant relationship for quitting.

referred and non-referred applicants have the same average match quality, and the superior productivity of referred workers relative to non-referred workers emerges *because* of endogenous hiring. Homophily models also predict that referred workers will be more productive than non-referred workers (instead of merely referred applicants being more productive than non-referred applicants). Second, simple endogenous hiring, where firms hire the best workers above some cutoff, would not explain the difference in our results across rare high-impact metrics vs. non-rare metrics.

On a slightly different note, suppose that a researcher wanted to apply the results from our paper in another industry: how could he or she define whether a productivity measure was a standard everyday measure or a rare high-impact measure? We do not have a clear objective means of assessing whether a metric is standard or high-impact. However, it seems to us that the distinction is meaningful for a number of different industries. Consider, for example, a physician. A standard non-rare measure of a physician's performance may be the number of patient referrals they receive or patient satisfaction scores. A rare high-impact measure of performance may be the number of times that the physician is sued for medical malpractice. Or, in another example, consider a supermarket cashier. A standard non-rare measure of performance may be the number of items checked per minute, whereas a rare high-impact measure may be the amount of cash stolen by the employee.

A.5 Further Discussion of Result that Higher Productivity People are More likely to be Referrers

Result 12 shows that higher productivity workers are more likely to be referrers than lower productivity workers. This is consistent with homophily theories, where firms choose to accept referrals only from high-ability workers. However, as we documented in our IZA working paper, Burks et al. (2013), none of the firms we study give different financial incentives based on the characteristics of the referring worker. In conversations, none of the managers at the different firms said that there was an advantage in the hiring process in being referred by some current employees versus others. (We cannot verify whether or not this appears to be the case in the data because, in the data, we can only link referrers to referred workers, not to referred applicants.) Rather than the referrals of high-ability incumbent workers receiving special consideration in the application process, it may simply be the case that high-ability incumbent workers make more referrals. This can occur because high-ability people naturally make more referrals or because supervisors actively encourage referrals from their highest ability workers.

A.6 From Results 3 and 5, Skill Characteristics of Applicants and of Workers

Result 3 establishes that referred applicants do not look better than non-referred applicants in terms of cognitive and non-cognitive ability. The reader may also ask whether cognitive and non-cognitive skills predict performance for the workers we study. Also using the subset of 900 workers from the trucking firm we analyze, Rustichini et al. (2012) show that cognitive and non-cognitive skills help predict worker strategies in experimental games, health behavior, worker retention, and worker accidents (they do not study referral status). Looking at our call-center and high-tech workers, we also find significant associations between cognitive and non-cognitive skills and performance, consistent with the large related literature in industrial psychology (Barrick and Mount, 1991). Results available on request. For our paper, *controlling* for cognitive and non-cognitive skills has little impact on the relationship between referral status and the various performance variables; this is unsurprising, given the very weak correlation between referral status and cognitive and non-cognitive skills.

What do learning theories predict about the skill characteristics of referred vs. non-referred applicants, and of referred vs. non-referred workers? The answer depends on whether "match" is occurring at the job or occupational level, and on to what extent various characteristics reflect aspects of a person's job or occupational match. If match is purely job-specific, and if skill characteristics measure a person's general ability, then learning theories would not seem to predict that referred applicants and workers should have higher skill characteristics. On the other hand, if learning is occupation-specific, and success in an occupation is associated with having certain characteristics, then learning theories would predict that referred workers will appear better.

A.7 From Result 8, Referrals and Accidents

As seen in Panel A of Table 6, referred drivers are 10% less likely to have preventable accidents (column 3), which is substantial, but only 2% less likely to have non-preventable accidents (column 8). The classification of preventable vs. non-preventable accidents is made by analysts at the trucking firm's insurance subsidiary and is based on federal guidelines. While the distinction is based on objective criteria, it is still imperfect, and safer drivers may also have fewer non-preventable accidents. Thus, if referred workers are safer, it is not surprising that they are also slightly less likely to have non-preventable accidents. Beyond preventable and non-preventable accidents, there are also a small share of accidents classified as "Miscellaneous" which are included in column 1 of Table 6.

As seen in Panel A of Table 6, referral differences in accident rates are larger for drivers hired in booms, proxied by if the driver's home state unemployment rate at year-of-hire is low. Column 7 indicates that for drivers hired when the state unemployment rate is 4%, referred drivers have an 18% (40-4*5.6) lower accident risk. For drivers hired when the state unemployment rate is 7%, there is no difference between referred and non-referred workers. One concern with the result is that it could potentially reflect something about economic conditions and accidents, e.g., that roads are more congested in booms than busts, or about economic conditions and trucking demand. To address this concern, we re-do the specification in column 7 adding the state unemployment rate in the *current* year, as opposed to the year of hire, as well as the interaction of referral status with current year unemployment. As seen in Table C12, the coefficient on Referral X Unemployment is statistically significant and three times larger than the statistically insignificant coefficient on Referral X Current unemployment, providing some suggestive evidence that referral differences are varying with the labor market at time of hire, as opposed to the contemporaneous labor market.

A.8 From Result 8, Referral Differences in Patent Production

Panel B of Table 6 shows that referred workers develop more patents. Our earlier IZA working paper version of the paper, Burks et al. (2013), shows that referral differences in patenting are robust, first, to using OLS instead of negative binomial models, and second, to using whether a worker ever patented instead of number of patents.

Column 6 of Panel B shows that among workers over 27, referrals develop 11% more patents than non-referrals, whereas among workers 27 or younger, referrals develop 49% more patents. The median age at hire is 27, so we defined young as a dummy for 27 or younger. If instead we define young based on 26 or younger, we obtain similar estimates. Instead of including a dummy for young vs. old, we also included an interaction of Referral X Age, yielding a coefficient of 0.63(0.46) on Referral and -0.012(0.015) on Referral X Age. Thus, across several specifications, referral differences in patenting are strongest among young workers.

As discussed in the text, relatively few workers at the firm have prior patenting records before joining the firm. Among workers age 27 or less at hire who go on to patent at the high-tech firm, only 10% have any pre-hire patents. Among workers over 27, only 38% have any pre-hire patents. These numbers are calculated by linking inventors at the firm to any prior patents using the US Patent Inventor database (Lai et al., 2010). For workers at the high-tech firm who do not patent while at the high-tech firm, we are unable to link to a past inventing history since otherwise we do not have an identifier to link them to a past patenting record.

To what extent are our patent results being driven by collaboration between the referrer and referred worker? Because we cannot link referrers and referred workers, it is difficult for us to answer this question. Although it is very indirect, one thing we can do, however, is examine whether referred workers appear to co-author with more people at the company than non-referred workers. There is no evidence that they do. Referred workers have a (statistically insignificant) 0.2 fewer co-authors per patent than non-referred workers, as well as a (statistically insignificant) 0.2 fewer co-authors total among all patents. Further, only 11% of workers who later patent at the firm had co-authored a patent with someone at the firm prior to joining.

A.9 From Result 8, Ideas on the Idea Board

Referred workers produce 14-15% more rating-weighted ideas than non-referred workers. Initially, referred workers produce 22% more rating-weighted ideas, and the difference fades with tenure. We get similar results if we analyze the number of ideas instead of rating-weighted ideas. Negative binomial models indicate substantial overdispersion for the ideas board analysis (as in the patent analysis). In Burks et al. (2013), we show that OLS models yield results of similar statistical significance, though with smaller magnitudes. Panel C of Table 6, shows that the coefficient on Referral X Tenure in months changes from -0.0057 in column 4 to 0.0055 in column 5, once individual fixed effects are controlled for in column 5. Such a large change is broadly supportive of learning theories, where the negative Referral X Tenure coefficient is predicated on differential attrition.[5]

A.10 From Result 9, Comparison of Referred and Non-referred Workers in Average Wages and Wage Variance

Throughout the paper, we use the terms earnings, wage, and salary interchangeably. Each term measures the amount of money earned by a worker at the daily, weekly, or monthly level in call-centers, trucking, and high-tech, respectively. For truckers, average earnings is determined by the number of miles driven and the level of the piece rate. We show in Table 7 that referred and non-referred truckers do not differ in overall earnings. They also do not differ in the level of the piece rate.

Past empirical research on whether referred workers have higher initial wages than non-referred workers has had mixed conclusions. On one hand, studies often find that referred workers earn higher initial wages, (e.g., Simon and Warner, 1992; Dustmann et al., 2012); this is particularly true for within-firm analyses, e.g., (e.g., Brown et al., 2013). At the same time, however, there are a number of studies that find no relationship between referral status and initial wages, including (Bridges and Villemez, 1986; Holzer, 1986; Marsden and Gorman, 2001), as well as papers finding a negative relationship between referral status and initial wages (e.g., Elliott, 1999; Green et al., 1999). Loury (2006) provides an excellent discussion. Loury (2006) argues that negative wage differences in cross-firm wage comparisons may occur if referred job-seekers have worse outside options. Alternatively, those finding jobs through referrals may have fewer offers than those finding jobs through formal means. Wage comparisons within a firm tell us about wages conditional on being hired at that firm, whereas across-firm comparisons may also reflect heterogeneity in the type of firms that hire using referrals. For comparing with our analysis, the most relevant literature comparisons on wages are probably studies conducted within firms.

[5] That the coefficient becomes positive suggests potentially another factor, e.g., differential investment over time into idea production for referred vs. non-referred production.

The last 3 columns of each panel in Table 7 appear to show no differences in the variance of wages for referred workers relative to non-referred workers. First, we regress wages on controls. Second, we regress the squared residuals on referral status and the fitted wage from the first stage. Results are similar if we add more controls to the 2nd stage; e.g., if we add the controls from column (2) of Panel (c) to the 2nd stage in columns (9) and (10), the estimates on referral status change to 0.023(standard error=0.016) and 0.019(0.015).

A.11 From Result 10, Calculation of Profits per Worker

Panel D of Table 8 shows that referred workers yield higher average profits per worker in both trucking and call-centers. What is the intuition for the result?

For both trucking and call-centers, the reductions in quitting are important. In trucking, because referred workers are less likely to quit, there is less time spent "moving up" the productivity-tenure curve and more time achieving high-level productivity. In call-centers, the initial training lasts six weeks, during which time workers produce negative profits. Because referred workers are less likely to quit, more time is spent earning positive revenues.

For trucking, we note further that the difference in profits does not capture differences in the tendency of referred and non-referred workers to *make* referrals themselves. Table 9 shows that referred workers are more likely to ever make a referral than non-referred workers. Thus, the difference we calculate may thus be an underestimate of the profit difference between referred and non-referred workers.

A.12 From Result 11, Correlation of Referrer and Referral Productivity

In Table 8, we include different geographic controls, including state and 3-digit zip code. Beyond this, we have also allowed location fixed effects to interact flexibly with the time fixed effects; this tends to have little impact on the estimates. In addition, the results in Panels A and B are robust to alternative measures of referrer behavior; instead of using the referrer's overall average productivity, results are similar if we use the referrer's productivity before the referral, meaning the results are not driven by a new shock that occurs affect the referred driver starts work. It would also be interesting to examine whether the workers referred by high-productivity and low-productivity referrers differ in terms of hard-to-observe characteristics such as cognitive and non-cognitive skills. However, because the data on cognitive and non-cognitive skills are from workers hired in 2005 and 2006, whereas the data on who refers whom is from 2007-2009, we cannot do this comparison. See Appendix B.

To gain further insight on the results in Table 8, we ran quantile regression versions of equation (3) for miles, in unreported results. We observe that the impact of higher productivity referrers tends to be similar at the 10th, 50th, and 90th quantiles, suggesting that high-productivity referrers shift the entire distribution of productivity of the workers they refer.

B Data Appendix

B.1 Reliability of Referral Measurement

Are our measures of referral status reliable? As indicated above, referral status is measured at the call-center firm by asking applicants, at the trucking firm by asking applicants and through the firm's administrative referral program, and at the high-tech company via the firm's administrative referral program. For the trucking data, self-reported referrals exceed administratively reported referrals by 24%. Of workers listed as referred in the firm's administrative program, nearly all report being referred, whereas of workers who are not listed in the firm's administrative program, some do report being referred. This difference reflects three factors: (1) Lying by applicants about their referral status, (2) Referring workers informing referred workers about the job, but who do not submit the worker's name so that they would become eligible to receive a referral bonus, and (3) Imperfect matching across datasets. Our results from the trucking firm are similar whether we use the self-reported referral definition or whether we use the administrative definition, suggesting that differences in referral status definition are unlikely to account for differences in regression results across industries.

B.2 Call-center Firms

Each call-center firm operates many locations ("plants"). In all our regressions, we include location fixed effects, which is more stringent than controlling for call-center firm fixed effects.

Evolv, the job testing firm that tracks the data from the call-center firms, keeps common demographic variables (i.e., race, gender, and age) separate from retention, wage, and productivity data. This is to ensure the non-job relevant demographics data do not influence hiring and personnel management decisions. The data provided to us do not allow us to control for gender, race, and age in retention, wage, and productivity regressions. However, controlling for these variables has little impact on estimates for both trucking and high-tech workers, suggesting that omitting them would have relatively little impact on estimates for call-center workers. We do control for race, gender, and age in Tables 1-3.

Due to data limitations, we cannot perform all analyses using all of the call-center firms. The productivity analysis is performed using data from six call-center firms. The earnings analysis is performed using data from two call-center firms. The analysis of applicant characteristics, worker characteristics, and quitting is performed using data from all of the firms. The data extends through July 2013 for all the firms, but starts at slightly different times depending on the firm (the earliest start is in 2009).

Schooling. Years of schooling, given in one of several educational categories. We use 12 years for a high-school graduate; 14 years of schooling for an Associate Degree or Technical Diploma; 16 years for a Bachelor's Degree; 18 years for a Master's Degree; and 20 years for a Doctorate. Schooling data are not currently linked with our retention, wage, or productivity data. However, as seen in Table 3, referred and non-referred workers differ by only 0.08 years of schooling, so not controlling for schooling is unlikely to significantly affect our estimates.

Intelligence. We measure intelligence using questions from applicant job tests at the seven call-center firms. The questions were developed by industrial/organizational psychologists at the job testing firm, Evolv, following appropriate validation processes. Because the job tests are proprietary and active, we cannot publish here the exact wording of the intelligence questions.

Personality. As for intelligence, we measure the Big 5 personality characteristics using questions from applicant job tests at the seven call-center firms. The questions were developed by industrial/organizational psychologists at the job testing firm, Evolv, following appropriate validation processes. The psychologists also designed the mapping from job test questions into the Big 5 characteristics. As for intelligence, because the job tests are proprietary and active, we cannot publish the exact wording of the personality questions.

Big 5 Index. An equally weighted average of the z-scores from the Big 5 personality characteristics, reversing neuroticism, as in Dal Bo et al. (2013).

Salary. Salary is measured using a worker's daily earnings. Salary data are available for two of the call-center firms.

Quitting. Worker duration is a critical outcome for many firms, and is a commonly used measure of worker performance, particularly in lower-skill high-turnover settings such as call-centers. (e.g. Autor and Scarborough, 2008)

Adherence share. Share of the time that a worker is at his or her seat working of the total amount of time they are scheduled to work. A higher number indicates higher productivity. We use the normalized version for regressions (normalized according to our data). This is one of the three objective performance measures for call-centers.

Average handle time. Average number of seconds spent by a worker on a call. A lower number indicates higher productivity. We use the normalized version for regressions (normalized according to our data). This is one of the three objective performance measures for call-centers. Average handle time to date is the running average of a worker's average handle time to date. For a worker on day t, it is the average of average handle time to date as of day $t-1$.

Sales conversion rate. Share of the time that a sales call results in a sale. This number is only available for call-center workers engaged in sales. A higher number indicates higher productivity. We use the normalized version for regressions (normalized according to our data). This is one of the three objective performance measures for call-centers.

Quality assurance. Managerial rating of whether a worker was providing quality service, measured on a 0-1 scale. A higher number indicates higher productivity. We use the normalized version for regressions (normalized according to our data). This is one of the two subjective performance measures for call-centers.

Customer satisfaction. Rating from post-call customer surveys of whether customers were satisfied with the service provided, measured on a 0-1 scale. A higher number indicates higher productivity. We use the normalized version for regressions (normalized according to our data). This is one of the two subjective performance measures for call-centers.

Friends at company, People know at company. Applicants were asked the questions "How many friends do you have that work at this company?" and "How many people do you know that work at this company?" The response options for both questions were "0," "1-2," "3-4," or "5 or more." We convert "1-2" to 1.5, "3-4" to 3.5, and "5 or more" to 5 for both questions.

Job test score. An applicant's overall score on the job test. We normalize the score in-sample.

B.3 Trucking Firm

For 900 of the workers, there is extensive information about worker background, cognitive ability, non-cognitive ability, and experimental preferences. These workers were hired at one of the trucking firm's training schools in late 2005 and 2006. Most of the survey data was collected during the workers' commercial driver's license training.

Information on who referred a given worker is only available for October 1, 2007 through December 31, 2009.

Schooling. Years of schooling, given in one of several educational categories. We use 12 years for a high-school graduate; 14 years of schooling for an Associate Degree or Technical Diploma; 16 years for a Bachelor's Degree; 18 years for a Master's Degree; and 20 years for a Doctorate. There is no schooling data for our main sample of applicants and workers.

Young. A dummy for age of hire less than or equal to 25. As seen in Table C7, being in this low age range predicts whether a worker was referred at the trucking firm (where the mean age at hire is 38.8 years), while age by itself has no predictive power.

Salary. Most truckers are paid almost exclusively paid by the mile. Drivers receive small payments for other tasks (e.g., helping unload the truck), the frequency of which depends somewhat on work type. For the salary analysis in the paper, to be conservative, we eliminate workers in work types where non-mileage payments are more frequent. Results are similar whether or not those workers are included.

Related experience. Related experience is a worker's years of experience with a large on-road vehicle.

IQ. IQ is measured using the score on Raven's Progressive Matrices test. The test consists of 5 sections with 12 questions each, producing a score out of 60. We normalize the test scores in sample.

Big 5 Personality. We measure the Big 5 personality characteristics with the same measures as in Rustichini et al. (2012) using the Multidimensional Personality Questionnaire (MPQ), which consists of 154 multiple-choice questions. For all the traits, we normalize the scores in sample. Rustichini et al. (2012) note that it is difficult to use the MPQ to create a measure of Openness that is separate from cognitive ability or intelligence. Thus, following Rustichini et al. (2012), we do not define a separate measure of Openness, and focus only on 4 of the Big 5 characteristics.

Big 5 Index. An equally weighted average of the z-scores from 4 of the Big 5 personality characteristics (excluding Openness), reversing neuroticism, similar to that in Dal Bo et al. (2013).

CRRA risk aversion. (CRRA) risk aversion is measured using a task similar to that in (Holt and Laury, 2002). CRRA uses choices between (A) Getting \$2, \$3, \$4, \$5, \$6, or \$7 for sure vs. (B) A lottery with a 50% chance of getting \$10 and a 50% chance of getting \$2.

Patient options chosen. Subjects completed a time preference experiment where they chose between getting \$80 at a later date or receiving between \$45 and \$75 today, making a total of 28 choices. The later date varied was 1 day, several days, 1 week, or 4 weeks. Patient options chosen is the share of the 28 choices where the worker chose the patient option.

Beta in HD model. The time preference experiment can be used to estimate a model of hyperbolic discounting (HD) with beta-delta preferences (Laibson, 1997). A time period corresponds to 1 day, so β is the amount of present bias between today and tomorrow.

Delta in HD model. The δ implied by the present-bias experiment (Laibson, 1997).

Trust. Subjects played a Sequential Prisoner's Dilemma. In the game, Player 1 could send \$0 or \$5 to Player 2. Player 2 can respond by sending \$0, \$1, \$2, \$3, \$4, or \$5 back. Any funds sent by Player 1 or 2 are doubled by the researcher. Subjects played both roles using the Strategy Method. The variable trust is the average number of dollars sent by Player 1.

Altruism V1. The number of dollars Player 2 would send back in the Sequential Prisoner's Dilemma if Player 1 sent him or her \$0.

Altruism V2. The number of dollars Player 2 would send back in the Sequential Prisoner's Dilemma if Player 1 sent him or her \$5.

Miles. The number of miles driven by a driver each week. Even though most drivers work the same number of hours (60 hrs/week, which is the federal legal limit), there are substantial and persistent productivity differences across workers in miles per week. For example Hoffman and Burks (2012) estimate that for the trucking firm, all else equal, drivers at the 90th percentile of miles achieve almost 50% more miles per week than drivers at the 10th percentile. When asked the reason for significant cross-driver differences in average miles per week, managers at the trucking firm emphasized several factors, including speed, skill at avoiding traffic, route planning, skill at not getting lost, and coordinating with people to unload the truck. For example, drivers who arrive late to a location may have to wait long periods of time for their truck to be unloaded, which can be highly detrimental to weekly miles. Trucking loads are assigned by a central dispatching system, and are assigned primarily based on proximity and are not assigned based on driver ability. Thus, it is unlikely that there would be favoritism in load assignment based on referral status or other factors (e.g., race). See Hubbard (2003) and Hoffman and Burks (2012) for more on measuring productivity in trucking. Average miles to date is the running average of a worker's miles, measured on a weekly basis. For a worker at week of tenure t, it is the average of miles by week $t-1$.

Accident. Whether the driver has a trucking accident in any given week. The company's definition of an accident is quite broad and includes serious as well as relatively minor accidents. Our use of a weekly dummy variable for having an accident is sensible, as we observe very few weeks where drivers have multiple accidents.

Preventable accident. An accident that a driver had control over and thus is at least partially at fault. Determined to be preventable (instead of non-preventable) by analysts at the firm's insurance subsidiary, based on guidelines from the Federal Motor Carrier Safety Administration.

Non-preventable accident. An accident that the driver could not control, based on guidelines from the Federal Motor Carrier Safety Administration.

B.4 High-tech Firm

There are about 25,000 workers in the high-tech dataset. However, most data is missing for about 8,000 of these workers, leaving about 17,000 workers for most of the analysis.

Job position ID. Job position IDs are identifiers for different positions that applicants to the high-tech firm apply for. For example, a job position ID may for an entry-level programmer at one particular office.

Schooling. Years of schooling, given in one of several educational categories. We use 12 years for a high-school graduate; 14 years of schooling for an Associate Degree or Technical Diploma; 16 years for a Bachelor's Degree; 18 years for a Master's Degree; and 20 years for a Doctorate. We obtained data on applicant schooling for a small sample applying between 2008 and 2010 for lower-level jobs.

Young. A dummy for age of hire less than or equal to 27, which is the median age at hire.

SAT Total. Combined score from Math and Writing sections of the SAT. Each is out of 800 points, so the total score is out of 1600 points. We focus on the Math and Writing section scores because data on Verbal section scores are missing for almost all respondents. The SAT data are obtained from a 2006 survey of existing employees administered by the firm.

Big 5 Personality. The Big 5 Personality characteristics were measured using the Big Five Inventory Test (John et al., 1991). The data are obtained from a 2006 survey of existing employees administered by the firm. For all the 5 traits, we normalize the scores in sample.

Salary. As in Baker et al. (1994a,b), we analyze salary using regular salary, excluding bonuses. Also, since salary is given in local currency, we exclude non-US employees from the salary analysis, following Baker et al. (1994a,b).

Subjective performance. An employee's quarterly performance review score, provided by the employee's manager. It is given on a scale from 0-5. We normalize the scores in sample. Average subjective performance to date is the running average of a worker's subjective performance, measured on a quarterly basis. For a worker at quarter tenure t, it is the average of subjective performance by quarter $t-1$.

Hours worked. The data include timestamps of the most frequent activities that employees engage in, which we use to construct the average number of hours worked per day over the course of a month. Employees log an average of around 5-7 hours per day. Since employees work longer hours than this, our hours measure only captures some of the activities that employees engage in. We normalize the number of hours in-sample.

The following measures correspond to objective tasks performed at work, such as writing and reviewing computer code. The activity measures are best thought of as capturing a combination of effort and output, as opposed to output alone. For all the following measures, we winsorize high outliers, limiting activity measures for an employee*months to the 99th percentile of the distribution of all employee months with a positive amount of activity,

Code reviews. Before new code becomes part of the firm's canonical code base, it must be reviewed by one or more peers. These reviews are fairly regular; the average engineer participates in just over one per workday. We count the number of code reviews an engineer participates in as an author and the number as a reviewer. The former is a proxy for the amount of new code written, while the latter is a measure of ones helpfulness as a reviewer and the extent to which one has been assigned responsibility for maintaining an important part of the firm's codebase.

Bugs database actions (bug actions). Bugs are tracked by a database. Employees make entries as they identify, diagnose, and fix bugs. Software engineers are most likely to be involved in diagnosing and fixing bugs, while non-engineers often identify them.

Builds. Software is "built" (essentially a compilation) primarily for testing purposes, and also to use the software in an internal or external environment.

Perforce calls (P4calls). Engineers make calls to the Perforce system, a third-party software program that maintains the firm's codebase and facilitates engineers interaction, for a variety of purposes, including when they check out code for editing or viewing, or when they submit code for review.

Wiki page edits and views. The firm's code is documented in an extensive internal wiki. When significant changes are made to code, the engineer responsible often updates the wiki. Providing documentation of changes is viewed as good citizenship.

Number of Friends. Based on a 2006 survey of existing employees conducted by the firm. Employees listed other employees they said were their friends. From this, we construct both self-reported friends and other-reported friends (based on whether others report the employee as a friend). Note that only for the high-tech firm do we have data on who is friends with whom (for the call-center and trucking firms, we only have data on the number of each employee's friends).

Patents. Number of patent applications associated with an employee. 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 applications are later approved as patents, but the process usually takes several years. Throughout the paper, we measure "patents" using patents applied for. Patents with multiple employee co-authors from the high-tech firm are counted toward each employee.

Citation-weighted patents. Patent citations are the most widely used measure of patent quality (e.g. Jaffe et al., 1993). Following Trajtenberg (1990), we construct citation-weighted patents as one plus the number of citations for each patent. To limit the influence of outliers, we trim employees with citation counts above the 90th percentile in-sample.

B.5 Matching High-tech Inventors to Patent Citations

Our goal was to match inventors at the high-tech firm to patent citations of their patents. Because the data from the high-tech firm do not contain patent numbers, we matched employee names from the company database to the US Patent Inventor database (Lai et al., 2010), which lists the first and last name of each inventor on each patent (and occasionally middle name or initial). For each inventor, we attempted a variety of matches with each name in the employee names – starting with the most difficult match (full name), and proceeding until the easiest match (last name only), in the following order:

1. The inventor's full name
2. The inventor's first name and last name (middle name or initial excluded).
3. The inventor's first name, middle initial and last name.
4. The inventor's first name and last name.
5. The inventor's first initial and last name.
6. The inventor's last name.

If any of these attempts returned exactly one unique employee, we linked the patent inventor to the unique employee and discontinued further match attempts for that employee. If an inventor was matched to zero or multiple employees, we discarded the inventor and invention (thereby ensuring that each inventor is linked to either zero or one employee record). This matching technique connects 90% of the firm's inventors listed in the US Patent Inventor database. Many of the remaining 10% are non-employees who had collaborated with the firm on technological projects. To link inventors at the firm with patents before joining, we rely on the US Patent Inventor database (Lai et al., 2010).

B.6 Calculating Profits per Worker

B.6.1 Trucking

Profits per worker is defined to equal discounted revenue, minus costs from a worker having any accidents, minus the cost of training and recruiting a worker (which depends on whether the worker needs commercial driver's license training and whether they were referred), minus any referral bonuses paid, plus any training contract penalties collected when the worker quits:

$$\begin{aligned}\pi &= \text{Discounted revenue - Accident cost - Training/Recruiting cost - Referral bonus + Recovered damages} \qquad (4)\\ &= \sum_{t=1}^{\infty} \delta^{t-1} (1-Q_t) \left[y_t (P - w_t - mc) - FC - c_A A_t\right] - TC(E,r) - 500r - 500\delta^{26} rE (1-Q_{26}) + (1-E) \sum_{t=1}^{\infty} \delta^{t-1} \theta k_t q_t\end{aligned}$$

where q_t is a dummy for quitting in week t; $Q_t = \sum_{s=1}^{t} q_s$ is whether a driver has quit in the first t weeks; y_t is a driver's weekly miles; P is the price the firm charges for one mile of shipment; w_t is wage per mile; mc is the non-wage marginal cost per mile (i.e. truck wear and gas costs); FC is fixed costs per week (i.e. support for the drivers and the opportunity cost of the truck); c_A is the cost of an accident; A is a dummy for having an accident; $TC(E,r)$ is the cost of training and recruiting a worker; E is a dummy for whether the worker is experienced; r is a dummy for whether the worker was referred; k_t is the quit penalty for a worker who quits in week t; and θ is the share of the training contract penalty collected by the firm. We assume values for P, mc, FC, c_A, TC, and θ based on consultation with the trucking firm. Specifically, we assume that $P = \$1.90$ per mile, $mc = \$1.20$ per mile, $FC = \$475$ per week, $c_A = \$1,000$, $TC = \$2,500 - \$500r - \$1,750e$, and $\theta = 0.3$. The relatively small assumed accident cost of $1,000 reflects the broad definition of an accident in the data. In addition, we assume that $\delta = 0.9957$, following Hoffman and Burks (2012). Hoffman and Burks (2012) estimate a structural model of quitting using a subset of the trucking firm data; they assume a weekly discount factor of 0.9957, corresponding to a "low" annual discount factor of 0.8, finding the model works best for discount factors in that range. If instead we assume a higher δ for our profits calculation here, the level of profits slightly increases, but our conclusions are identical. For example, if we assume $\delta = 0.9990$, corresponding to an annual discount factor of 0.95, referred average profits per worker is $2,838 compared to $2,285 for non-referred workers, a difference of 24%. Profits per worker from above-median referring workers is $4,493 compared to $1,412 for below-median referring workers.

B.6.2 Call-centers

We obtained data on revenues and costs for one of the call-center firms in our data. For our profits calculation, we assume that other firms have a similar cost and revenue structure. The call-center workers are paid an hourly wage instead of a piece rate. Otherwise, the profits formula is relatively similar as in trucking. The formula is simple and is rooted closely to how (we were informed) managers in the industry sometimes calculate profits per worker:

$$\begin{aligned} \pi &= \text{Discounted revenue - Training/Recruiting cost - Referral bonus} \qquad (5) \\ &= \sum_{t=1}^{\infty} \delta^{t-1} (1 - Q_t) [(P - w_t - mc) - FC] - TC(E, r) - r * \text{Referral bonus} \end{aligned}$$

We were provided separate cost and revenue data for when the worker is in training, and for when the worker has completed training. During training, the worker produces no revenues ($P = 0$), has an average wage of $9 per hour, and there is an additional overhead of $2.25 per hour; further, the worker is trained for 8 hours a day. After six weeks of training, revenues are $P = \$26.70$ per hour, the wage is $10 per hour, and there is an additional overhead of $2.50 per hour. For the discount factor, the firm that provided the data uses a discount factor of $\delta = 1$ for its own calculations. Thus, we follow them in using $\delta = 1$. We assume that $TC(E, r) + r * \text{Referral bonus} = \$100$ for both referred and non-referred workers. Bonuses are often paid for the referred workers, whereas the baseline cost of recruiting are likely higher for the non-referred workers. In the formula, profits will solely be determined how long a worker stays with the firm, and thus abstracts from productivity along the other dimensions (such as number of call completed per hour or call quality). However, given that referred and non-referred workers did not significantly differ along those dimensions, this simplification is unlikely to affect our conclusions comparing profits from referred vs. non-referred workers.

C Additional Figures and Tables

Table C1: Summary of Data Elements

	Call-centers	Trucking	High-tech
Referral status	W,A	W,A	W,A
Productivity	W	W	W
Social network	W	W	W
Job test or interview scores	W,A		W,A
Demographics	A	W,A	W,A
Cognitive ability	W,A	W	W
Personality	W,A	W	W
Experimental games		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.

Table C2: Sample Means

	Call-center firms	**Trucking firm**	**High-tech firm**
Referred	36%	20%	33%
Years of schooling	13.0	12.9	17.0
Female	62.0%	7.8%	Confidential
Black	22.0%	15.0%	Confidential
Hispanic	22.6%	5.2%	Confidential
Age at hire	26.2	38.8	28.7
Log(Salary)	4.32	6.59	Confidential
$(\text{Log(Salary) Residual})^2$	0.0117	0.364	0.104
Accidents		0.018	
Preventable accidents		0.0082	
Patents			0.0047
Citation-weighted patents			0.0067
Rating-weighted ideas			0.108
Workers	75,993	N	25,282
Applicants	375,777	A	1,415,320

Notes: This table provides sample means. 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, $A >> 100,000$, $N >> 10,000$. Entries are blank if a variable is not applicable. Demographic data are for workers. In call-centers, the salary data mean is at the daily level. For trucking, the salary and accident data are at the weekly level. For high-tech, the innovation data are at the monthly level.

Table C3: Referral Status and Success at Different Stages of the Hiring Process at the High-tech Firm

Panel A: Success Conditional on Getting to a Stage	Was pre-screened (1)	Passed pre-screen (2)	Passed interviews (3)	Receive offer (4)	Accept offer (5)
Referred	0.43***	-0.15***	0.0059***	-0.012	0.026**
	(0.0018)	(0.0027)	(0.0015)	(0.0083)	(0.011)
Observations	1,175,016	226,629	112,678	6,301	5,738
R-squared	0.356	0.269	0.573	0.421	0.598
Mean Dep Var	0.193	0.497	0.0559	0.911	0.747
Panel B: Success in Getting to a Stage among All Applicants	Was pre-screened (1)	Passed pre-screen (2)	Passed interviews (3)	Receive offer (4)	Accept offer (5)
Referred	0.43***	0.14***	0.0044***	0.0034***	0.0027***
	(0.0018)	(0.0017)	(0.0004)	(0.0004)	(0.0003)
Observations	1,175,016	1,175,016	1,175,016	1,175,016	1,175,016
R-squared	0.356	0.203	0.501	0.536	0.586
Mean Dep Var	0.193	0.0959	0.00536	0.00488	0.00365

Notes: This table presents linear probability models analyzing whether referred applicants are more likely to be successful at different stages of the application process. An observation is an applicant. Robust standard errors in parentheses. All columns include job position ID dummies, month-year of application fixed effects, and office location dummies, as well as demographic controls (race and gender).* significant at 10%; ** significant at 5%; *** significant at 1%.

At the high-tech firm, applicants' resumes are stored in summary form. Recruiters can select candidates to examine more closely, that is, to pre-screen. An applicant's referral status is observed before a recruiter decides to pre-screen. There is no official firm policy that referred applicants must be pre-screened. Passing the pre-screen refers to whether a recruiter chooses to move a candidate to the interview stage. The interview stage consists of a number of different interviews. After the interviews, if an applicant has been successful, a formal committee makes the decision to make the offer.

As can be seen, referral is most strongly associated with success in terms of getting pre-screened. Being referred is associated with a more than tripling in one's chance of getting pre-screened. Then, among applicants who are pre-screened, referred applicants actually perform slightly worse in getting to the next stage. Referred applicants perform better in interviews. Referred applicants are slightly less likely to get approved by the formal hiring committee, though the difference is not statistically significant.

The only work we are aware of on referral differences at multiple stages of the recruitment process is the interesting study by Yakubovich and Lup (2006) in the sociology literature. Although their sample size is much smaller, Yakubovich and Lup (2006) find significant referral differences at several stages of the recruitment process. In their data, there is no initial pre-screening phase, so their is no analogue in their paper to our result on pre-screening.

Table C4: Robustness Check on Referrals and Non-rare Productivity Measures (Normalized): Interaction Effects of Referral Status and Tenure

Panel A: Call-center

	Adherence share		Average handle time		Sales conversion		Quality assurance		Customer satisfaction	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Referral	-0.027**	-0.045**	0.001	-0.006	-0.014	-0.037***	0.016	0.023	0.0027	0.0106*
	(0.012)	(0.020)	(0.010)	(0.014)	(0.008)	(0.013)	(0.017)	(0.033)	(0.0034)	(0.0060)
Referral X Tenure (months)		0.0040		0.0011		0.0045**		-0.0013		-0.0011*
		(0.0045)		(0.0018)		(0.0021)		(0.0047)		(0.0006)
Observations	152,683	152,683	749,848	749,848	134,386	134,386	31,908	31,908	603,860	603,860
Clusters	3,136	3,136	12,497	12,497	3,192	3,192	2,864	2,864	11,859	11,859
R-squared	0.1418	0.1418	0.5631	0.5631	0.7254	0.7255	0.1755	0.1755	0.0337	0.0337

Panel B: Truckers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Referral	-0.00004	-0.00049	-0.01621*	-0.01789*	0.00297	0.00231	-0.00983	-0.01133
	(0.01018)	(0.01005)	(0.00984)	(0.00977)	(0.01001)	(0.00987)	(0.00971)	(0.00964)
Referral X Tenure (weeks)			0.00022	0.00024*			0.00018	0.00019
			(0.00014)	(0.00014)			(0.00014)	(0.00014)
Demographic controls	No	Yes	No	Yes	No	Yes	No	Yes
Miles sample	Baseline	Baseline	Baseline	Baseline	Trim 5/95	Trim 5/95	Trim 5/95	Trim 5/95
Observations	0.86M	0.86M	0.86M	0.86M	0.78M	0.78M	0.78M	0.78M
Clusters	0.85N	0.85N	0.85N	0.85N	0.84N	0.84N	0.84N	0.84N
R-squared	0.07674	0.08113	0.07678	0.08118	0.06256	0.06640	0.06259	0.06643

Panel C: Hi-tech, Subj Perf	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Referral	0.037***	0.040***	0.040***	0.064***	0.058***		0.045***	-0.040
	(0.012)	(0.012)	(0.012)	(0.015)	(0.015)		(0.012)	(0.039)
Interview Score			0.033***					
			(0.0062)					
Referral X Tenure (quarter)				-0.0052*	-0.0034	-0.0027		
				(0.0027)	(0.0026)	(0.0032)		
Referral X Young								0.096*
								(0.052)
Demographic controls	No	Yes	Yes	No	Yes	No	Yes	Yes
Worker FE	No	No	No	No	No	Yes	No	No
Observations	104,255	104,255	104,255	104,255	104,255	104,255	86,815	104,255
Clusters	16,546	16,546	16,546	16,546	16,546	16,546	16,546	16,546
R-squared	0.084	0.093	0.094	0.084	0.093	0.477	0.104	0.093

Notes: This table examines whether a worker's referral status predicts productivity, providing a robustness check accompanying Table 5. All specifications are OLS regressions with standard errors clustered by worker in parentheses. Each productivity measure has been normalized so that the coefficients are all in standard deviation units. The non-rare productivity metrics are described further in Appendix B. * significant at 10%; ** significant at 5%; *** significant at 1%

In Panel A, productivity is measured using one of 5 different normalized measures. An observation is a worker-day, with the same controls as in Panel A of Table 5.

In Panel B, productivity is measured in miles and then normalized. An observation is a worker-week, with the same controls as in Panel B of Table 5. "Trim 5/95%" refers to trimming the lowest 5% and highest 5% of the miles observations (ignoring all 0 mile weeks). The exact sample size is withheld to protect firm confidentiality, $M >> 100,000$, $N >> 10,000$.

In Panel C, productivity is measured in terms of subjective performance rating. An observation is a worker-quarter, with the same controls as in columns 1-3 of Panel C of Table 5.

Table C5: Robustness Check on Referrals and Non-rare Productivity Measures (Normalized): Accounting for Differential Attrition

Panel A: Call-center

	Adherence share		Average handle time		Sales conversion		Quality assurance		Customer satisfaction	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Referral	-0.027**	-0.020	0.001	-0.011	-0.014	-0.022*	0.016	-0.021	0.0027	0.0011
	(0.012)	(0.015)	(0.010)	(0.014)	(0.008)	(0.013)	(0.017)	(0.032)	(0.0034)	(0.0079)
Attrition sample	Full	Stayers	Full	Stayers	Full	Stayers	Full	Stayers	Full	Stayers
Observations	152,683	53,089	749,848	152,080	134,386	33,592	31,908	7,512	603,860	99,758
R-squared	0.1418	0.1068	0.5631	0.6215	0.7254	0.5968	0.1755	0.1785	0.0337	0.0331
Clusters	3,136	1,965	12,497	6,048	3,192	1,512	2,864	1,839	11,859	6,687

Panel B: Truckers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Referral	-0.00004	-0.00049	-0.01084	-0.01219	0.00297	0.00231	-0.00908	-0.01053
	(0.01018)	(0.01005)	(0.00973)	(0.00965)	(0.01001)	(0.00987)	(0.00983)	(0.00975)
Demographic controls	No	Yes	No	Yes	No	Yes	No	Yes
Attrition sample	Full	Full	Stayers	Stayers	Full	Full	Stayers	Stayers
Miles sample	Baseline	Baseline	Baseline	Baseline	Trim 5/95	Trim 5/95	Trim 5/95	Trim 5/95
Observations	0.86M	0.86M	0.31M	0.31M	0.78M	0.78M	0.29M	0.29M
Clusters	0.85N	0.85N	0.37N	0.37N	0.84N	0.84N	0.56N	0.56N
R-squared	0.07674	0.08113	0.08210	0.08520	0.06256	0.06640	0.06396	0.06673

Panel C: High-Tech	(1) Subj perf	(2) Subj perf	(3) Subj perf	(4) Hours worked	(5) Code reviews	(6) Bug actions	(7) Builds	(8) P4Calls	(9) Wiki edits	(10) Views
Referral	0.025**	0.029**	0.045***	-0.027**	-0.011	0.005	0.037***	0.002	0.016	0.003
	(0.012)	(0.012)	(0.016)	(0.013)	(0.011)	(0.016)	(0.011)	(0.010)	(0.015)	(0.013)
Referral X Tenure (quarter)			-0.0038							
			(0.0027)							
Attrition sample	Stayers	Stayers	Stayers	Stayers	Stayers	Stayers	Stayers	Stayers	Stayers	Stayers
Demographic controls	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	97,433	97,433	97,433	241,893	278,624	278,624	278,624	278,624	278,624	278,624
Clusters	15202	15202	15202	10773	10829	10829	10829	10829	10829	10829
R-squared	0.0915	0.0969	0.0916	0.139	0.275	0.050	0.197	0.008	0.059	0.100

Notes: This table examines whether a worker's referral status predicts productivity, providing a robustness check accompanying Table 5. All specifications are OLS regressions with standard errors clustered by worker in parentheses. Each productivity measure has been normalized so that the coefficients are all in standard deviation units. The non-rare productivity metrics are described further in Appendix B. * significant at 10%; ** significant at 5%; *** significant at 1%

In Panel A, productivity is measured using one of 5 different normalized measures. In the Stayers regressions, we create a balanced panel by looking at the productivity in the first 90 days of workers who stay more than 90 days. An observation is a worker-day, with the same controls as in Panel A of Table 5.

In Panel B, productivity is measured in miles and then normalized. In the Stayers regressions, we create a balanced panel by looking at the productivity in the first 12 months of workers who stay more than 12 months. An observation is a worker-week, with the same controls as in Panel B of Table 5. "Trim 5/95%" refers to trimming the lowest 5% and highest 5% of the miles observations (ignoring all 0 mile weeks). The exact sample size is withheld to protect firm confidentiality, $M >> 100,000$, $N >> 10,000$.

In Panel C, productivity is measured in terms of a subjective performance rating or objective performance measure. We create a balanced panel by looking at the productivity in the first 4 years of workers who stay more than 4 years. An observation is a worker-quarter in columns 1-3 and a worker-month in columns 4-10. We use the same controls as in Panel C of Table 5.

Table C6: Robustness Check on Comparing the Mean and Variance of Wages for Referred vs. Non-referred Workers: Accounting for Differential Attrition

Panel A: Call-centers	DV=Log(Salary)						DV=(Log(Salary) Residual)^2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Referral	0.0019	0.0040	0.0012	0.0020	0.0067	0.0047	-0.0018	-0.0059*
	(0.0029)	(0.0038)	(0.0028)	(0.0036)	(0.0043)	(0.0052)	(0.0029)	(0.0034)
Referral X Tenure (months)					-0.0005	-0.0004		
					(0.0004)	(0.0018)		
Attrition sample	Full	Stayers	Full	Stayers	Full	Stayers	Full	Stayers
Job Test Score Controls	No	No	Yes	Yes	No	No	No	No
Observations	634,153	82,815	634,153	82,815	634,153	82,815	634,153	82,815
Workers	11,174	1,245	11,174	1,245	11,174	1,245	11,174	1,245
R-squared	0.1944	0.2567	0.2088	0.2567	0.1945	0.2567	0.0015	0.0020
Panel B: Trucking	DV=Log(Salary)						DV=(Log(Salary) Residual)^2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Referral	-0.0026	-0.0002	-0.0028	-0.0004	0.0041	0.0074	0.0454	0.0300
	(0.0046)	(0.0045)	(0.0046)	(0.0044)	(0.0048)	(0.0068)	(0.0312)	(0.0411)
Referral X Tenure (months)					-0.00039	-0.0011		
					(0.00027)	(0.00084)		
Attrition sample	Full	Stayers	Full	Stayers	Full	Stayers	Full	Stayers
Demographic controls	No	No	Yes	Yes	Yes	Yes	No	No
Observations	0.71M	0.26M	0.71M	0.26M	0.71M	0.26M	0.71M	0.26M
Clusters	0.74N	0.32N	0.74N	0.32N	0.74N	0.32N	0.74N	0.32N
R-squared	0.0610	0.0428	0.0631	0.0441	0.0631	0.0441	0.00006	0.00012
Panel C: High-tech	DV=Log(Salary)						DV=(Log(Salary) Residual)^2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Referral	0.017**	0.015**	0.017***	0.015**	0.011	0.0089	0.020	0.020
	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.0089)	(0.015)	(0.016)
Ref X Ten (months)					4.2e-4	4.9e-4		
					(4.1e-4)	(4.1e-4)		
Attrition sample	Full	Stayers	Full	Stayers	Full	Stayers	Full	Stayers
R-squared	0.518	0.520	0.524	0.525	0.524	0.525	0.008	0.008
Demog Controls	No	No	Yes	Yes	Yes	Yes	No	No
Observations	245,270	226,434	245,270	226,434	245,270	226,434	245,270	226,434
Workers	10,655	10,465	10,655	10,465	10,655	10,465	10,655	10,465

Notes: This table performs a robustness check accompanying Table 7. We examine whether referred workers earn higher salaries, and whether there is more or less variance in salaries among referred workers. Standard errors clustered by worker in parentheses.

In Panel A, an observation is a worker-day, with the same controls as in Panel A of Table 7. In the Stayers regressions, we create a balanced panel by looking at the first 90 days of workers who stay more than 90 days.

In Panel B, an observation is a worker-week, with the same controls as in Panel B of Table 7. In the Stayers regressions, we create a balanced panel by looking at the first year of workers who stay more than 1 year. The exact sample size is withheld to protect firm confidentiality, $M >> 100,000$, $N >> 10,000$.

In Panel C, an observation is a worker-month, with the same controls as in Panel C of Table 7. In the Stayers regressions, we create a balanced panel by looking at the first 4 years of workers who stay more than 4 years.

Table C7: Do Labor Market Conditions or Demographics Predict Referral Status? Evidence from Trucking

DV: Applicant or Worker was Referred (0 or 1)	(1)	(2)	(3)	(4)
Sample	Applicants	Workers	Workers	Workers
State unemployment rate	-0.0028	-0.0095***	-0.0096***	-0.0095***
	(0.0026)	(0.0023)	(0.0023)	(0.0023)
Black			-0.0066	-0.0069
			(0.0065)	(0.0064)
Hispanic			-0.0017	-0.0023
			(0.0104)	(0.0103)
Age			-6.94e-06	
			(2.4e-04)	
Young = (Age$\leq$25)				0.0149*
				(0.0080)
Demographic controls	No	No	Yes	Yes
Observations	A	N	N	N
R-squared	0.0230	0.0307	0.0313	0.0314
Mean dep var	0.104	0.200	0.200	0.200

Notes: This table examines correlates of whether a given applicant or worker at the trucking firm was referred using linear probability models. Robust standard errors in parentheses. All regressions include work type controls, month-year of application dummies, and state fixed effects. The state unemployment rate is the annual state unemployment rate. Beyond race and age, demographic controls are gender and marital status. The exact numbers of applicants (A) and workers (N) are withheld to protect firm confidentiality, $A >> 100,000$, $N >> 10,000$. * significant at 10%; ** significant at 5%; *** significant at 1%

Column 1 indicates a negative relationship between the state unemployment rate and whether an applicant is referred (though the coefficient is not statistically significant at conventional levels). Looking at workers instead of applicants in columns 2-4, we see that a higher unemployment rate at time of hire is negatively associated with whether a worker was referred. The results in columns 2-4 reflect both (i) that strong labor markets are associated with a somewhat higher share of applicants who are referred (as seen in column 1) and (ii) that referred applicants are differentially more likely to be hired relative to non-referred applicants in strong labor markets (as seen in Table 1).

Table C8: Examining Referred/Non-referred Differences in Earnings by Race in Trucking: Robustness Check for Table 7

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Sample of workers:	All	All	All	Non-referred	Referred	Black	Black	Hispanic	Hispanic	White	White
Referral	-0.0089*		-0.0028			0.0353***	0.0165	0.0312*	0.0155	-0.0092*	0.0001
	(0.0051)		(0.0046)			(0.0110)	(0.0121)	(0.0168)	(0.0188)	(0.0051)	(0.0053)
Referral X Black	0.0418***										
	(0.0127)										
Referral X Hispanic	0.0313*										
	(0.0177)										
Black	-0.0222***	-0.0125**	-0.0125**	-0.0217***	0.0248**						
	(0.0061)	(0.0055)	(0.0055)	(0.0061)	(0.0123)						
Hispanic	-0.0010	0.0063	0.0063	0.0016	0.0228						
	(0.0091)	(0.0080)	(0.0080)	(0.0093)	(0.0155)						
Ref X Tenure (months)							0.0012**		0.0010		-0.0005*
							(0.0005)		(0.0009)		(0.0003)
Observations	$0.71M$	$0.71M$	$0.71M$	$0.54M$	$0.17M$	$0.08M$	$0.08M$	$0.03M$	$0.03M$	$0.60M$	$0.60M$
R-squared	0.0632	0.0631	0.0631	0.0643	0.0649	0.0922	0.0923	0.0926	0.0927	0.0603	0.0603

Notes: This table examines differences across races in referred/non-referred differences in log earnings (the dependent variable). Standard errors clustered by worker in parentheses. An observation is a worker-week. Column 1 is the same as column 6 in Panel B of Table 7. Columns 6-11 examine referral differences separately for Black, Hispanic, and White drivers. In all columns, the controls are the same as in column 6 in Panel B of Table 7. The exact sample size is withheld to protect firm confidentiality, $M >> 100,000$. * significant at 10%; ** significant at 5%; *** significant at 1%

Table C9: Kahn and Lange (2013) Test: Asymmetry in Correlations Between Earnings and Performance, Comparing Referred vs. Non-referred Workers

Panel A: Call-centers	Referred workers				Non-referred workers			
Lag/Lead	1	2	3	4	1	2	3	4
Lag	0.153	0.144	0.113	0.075	0.164	0.139	0.138	0.151
Lead	0.094	0.051	0.080	-0.103	0.108	0.107	0.164	0.134
Difference	0.059	0.093	0.033	0.178	0.056	0.032	-0.026	0.017
	(0.033)	(0.055)	(0.087)	(0.173)	(0.029)	(0.039)	(0.064)	(0.136)
Panel B: High-Tech	Referred workers				Non-referred workers			
Lag/Lead	1	2	3	4	1	2	3	4
Lag	0.226	0.246	0.258	0.229	0.224	0.227	0.232	0.278
Lead	0.137	0.095	0.074	0.055	0.131	0.111	0.114	0.130
Difference	0.089	0.151	0.184	0.174	0.093	0.116	0.118	0.148
	(0.022)	(0.036)	(0.045)	(0.075)	(0.021)	(0.035)	(0.047)	(0.077)

Notes: This table examines correlations between lagged or lead productivity and contemporaneous wages. Column 1 analyzes the correlation between one period lagged productivity (productivity in $t-1$) and earnings during the current period (earnings in t), as well as the correlation between one period lead productivity (productivity in $t+1$) and earnings during the current period. Standard errors in parentheses are generated from 500 bootstrap repetitions, with sampling over workers.

In Panel A, an observation is a worker-month. Productivity is measured using the negative of a worker's average handle time. Productivity and earnings are residualized using month of hire dummies, a fifth-order polynomial in tenure, location dummies, and client dummies.

In Panel B, an observation is a worker-year. Productivity is measured using a worker's average subjective performance review. Productivity and earnings are residualized using month of hire dummies, month dummies, a fifth-order polynomial in tenure, job category dummies, office location dummies, and demographic controls (race, age, gender, and education). We do not include job rank dummies (although we include them in wage regressions) because they capture an aspect of the worker's performance. To obtain a more balanced panel, we restrict to workers who stay at least 4 years with the firm.

Table C10: Comparing the Mean and Variance of Wages for Referrers vs. Non-Referrers in High-tech

	DV=Log(Salary)								DV=(Log(Sal) Residual)^2		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Made Referral	0.03***	0.03***	0.03***	0.03***	0.03***	0.02***	0.02**		0.01	0.01	0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.01)		(0.02)	(0.02)	(0.03)
Average subjective performance to date				0.03***	0.04***						
				(0.005)	(0.004)						
Made Referral x Avg subj perf to date					-0.02						
					(0.012)						
MadeRef x Young						0.016					
						(0.011)					
MadeRef x Months							7.8e-4*	2.2e-4			5.6e-4
							(4.0e-4)	(2.2e-4)			(5.3e-4)
Demographic Controls	No	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	No
Interview Scores	No	No	Yes	Yes	Yes	Yes	No	No	No	No	No
Individual FEs	No	No	No	No	No	No	No	Yes	No	No	No
R-squared	0.526	0.531	0.533	0.536	0.536	0.533	0.526	0.903	0.008	0.007	0.008

Notes: This table analyzes the mean and variance of salary for referrers compared to non-referrers (that is, comparing workers who ever make at least one referral vs. other workers). The variable "Made Referral" is a dummy for a worker who has already made a referral. For workers who never make referrals, it is always 0, whereas for workers who make a referral, it equals 1 after the worker makes their first successful referral. An observation is a worker-month. All regressions include month of hire dummies, month dummies, a fifth-order polynomial in tenure, job category dummies, job rank dummies, and office location dummies. Demographic controls are race, age, gender, and education. The sample size is 242,222 worker-months, with 10,367 workers. * significant at 10%; ** significant at 5%; *** significant at 1%

Table C11: Using Surveys to Examine Whether Referred Truckers Have Greater Non-pecuniary Taste for the Job

	(1) Feel bothered when receive unexpectedly low paycheck (normalized)	(2) Demands of the job interfered with family life (normalized)	(3) Acceptable number of times at home per month (normalized)
Referral	-0.457**	-0.299*	0.310*
	(0.197)	(0.176)	(0.173)
Observations	223	215	226
R-squared	0.07	0.05	0.04

Notes: This table examines whether a worker's referral status predicts survey measures satisfaction with particular aspects of the job. The models are OLS regressions, with robust standard errors in parentheses. All drivers are from the same training school and were hired in late 2005 or 2006 (results are similar if we control for month-year of hire dummies and state dummies). The survey was administered by mail to drivers in summer 2006, for drivers who had been working for several months. The survey questions are asked on a 5-point scale from Strongly Disagree (-2) to Strongly Agree (+2), and then normalized in-sample. Controls for age, gender, race, and marital status in all regressions. * significant at 10%; ** significant at 5%; *** significant at 1%

Table C12: Robustness Check on How Referred/Non-referred Differences in Accident Risk Vary With the Business Cycle: Evidence from Trucking

	(1) Preventable Accidents
Referral	-0.42***
	(0.10)
	[0.10]
Referral X Current state unemployment	0.014
	(0.010)
	[0.008]
Current state unemployment	0.016
	(0.013)
	[0.016]
Referral X Unemployment at hire	0.043**
	(0.019)
	[0.023]
Unemployment at hire	-0.066***
	(0.012)
	[0.013]
Mean dep var	0.82
Observations	M
R-squared	0.0056

Notes: This table provides a robustness check on referred workers have fewer accidents. Standard errors clustered by worker in parentheses. Standard errors clustered by state in brackets. An observation is a worker-week. The regression is a linear probability model, with the same controls as in column 7 of Panel A of Table 6. The exact sample size is withheld to protect firm confidentiality, $M >> 100,000$, $N >> 10,000$.

Appendix References

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