

USING ANALYTICS TO MEASURE THE VALUE OF EMPLOYEE REFERRAL PROGRAMS

Evolv Study: The benefits of an employee referral program significantly outweigh the costs



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RESEARCH INSIGHT

Organizations without an employee referral program would be well-advised to implement one immediately and those with a program should look favorably on referred applicants.

EXECUTIVE SUMMARY

65% of companies report having an employee referral program and 36% filled their last opening through an employee referral.



Yet very little is known about the efficacy of these programs. Do referred applicants make better employees than their non-referred counterparts? If so, what's the reason why? Using data from seven contact centers and a large firm in the trucking industry, we quantified the differences between referred and non-referred employees across measures of retention and productivity. Through the use of advanced econometric techniques, we found that referred employees have 10% longer tenure than non-referred employees and demonstrate approximately equal performance. Taken together, the benefits of a referral program appear to outweigh the costs by a factor of 2 to 7.5.

Employees hired through an employee referral program stay 10% longer

INTRODUCTION

We live in a time when the saying “It’s not what you know but who you know” really shapes the way people look for jobs.

Family, friends and acquaintances often play a tremendously important role in helping someone find a new job. 50% of job seekers report having found a job with the help of a friend or family member¹. This process is vitally important to businesses as a way of sourcing new talent. The success of a company’s employee referral program largely determines its ability to harness the hiring potential of current employees’ ‘social networks’.

Referral programs are widely used - 36% of companies filled their last opening through an employee referral - but are not without their costs². Other methods of sourcing job candidates, such as online job boards, help wanted signs, and cold calling, can be up to 40% less expensive than sourcing through referrals. So we asked the central question: is a referred employee a better employee? We divided this question into two parts: do referred employees stay longer and are referred employees more productive?

Surprisingly, there is little economics literature exploring these questions. Recent research has revolved around comparing wage growth between referred and non-referred workers. But, from the perspective of an hourly employer with high turnover, the costs of wage growth are small compared to the costs of hiring candidates and are dwarfed entirely by the cost of a trained employee leaving before costs are recouped³. Our research shows that the benefit of hiring a referred worker is 2-7.5 times greater than the costs and provides quantitative evidence that referral programs are an excellent way to hire.

This research is the result of a collaboration between Evolv and the Yale School of Management. More technical results than those that appear in this white paper can be found in an academic working paper co-authored by Evolv’s Vice President of Analytics, Dr. Michael Housman⁴.

BACKGROUND

Referral based hiring has its rewards but also its risks. Hiring by referrals can be detrimental to your business if workers refer close friends and family regardless of whether they are a good fit for the job.



On the other hand, social networks may provide a myriad of hiring benefits, such as a greater means of monitoring employee work habits and better sourcing information on job candidates. Using this knowledge wisely can translate into increased employee retention and the hiring of more productive employees. Any impact found behind referral-based hiring could stem from two effects:

- The Selection Effect: Existing employees may be more likely to refer applicants that they think will do well in the role and those applicants may have a greater opportunity to learn more about the job. The result is an employee who is a better fit for the job.
- The Treatment Effect: Referred employees may stay longer and be more productive because they find it more enjoyable to work with their friends. They may also find opportunities for coaching and mentoring that might not exist otherwise.

Using the methods outlined below, we quantified the impact of referral-based hiring and determined whether it stems primarily from the selection effect or the treatment effect.

METHODS AND DATA

In order to investigate the differences between referred and non-referred workers we used three different econometric methods: survival curves and Cox proportional hazard models to study employee tenure and ordinary least squares (OLS) regressions to study employee performance.

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We obtained data from seven firms in the call-center industry and a large firm in the trucking industry. The call-center data follows tens of thousands of hourly wage workers and includes information on work history, daily performance and productivity. The data from the trucking industry also has millions of observations on key performance metrics across referred and non-referred employees. Additionally, for both industries we supplemented this historical data with survey data on worker friendships and social networks. Much of this survey data was collected from the Evolv platform. This data set is ideal for not only discerning the impacts of referrals on hiring and performance across industries, but also in determining if the reason for the observed differences between referred and non-referred workers is due to the selection or treatment effect.

DESCRIPTIVE STATISTICS:

For both industries the share of referred employees falls in the 20-40% range.

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We found that roughly 37% of call center employees and 20% of trucking employees were hired by referral. More importantly, we found that referred and non-referred employees are slightly different across observed characteristics, suggesting that there are differences in these groups that can affect employment and productivity outcomes. For example, in trucking 46% of referred workers had completed high school and only 36% of non-referred workers had done so. Interestingly, among call center workers we found that 23% of non-referred workers had more than a high school education whereas only

16% of referred workers did. A selection of call center summary statistics is listed below.

TABLE 1: CALL CENTER SUMMARY STATISTICS

Demographics	No Referral	Referral
> High School Education	23%	16%
Female	66%	58%

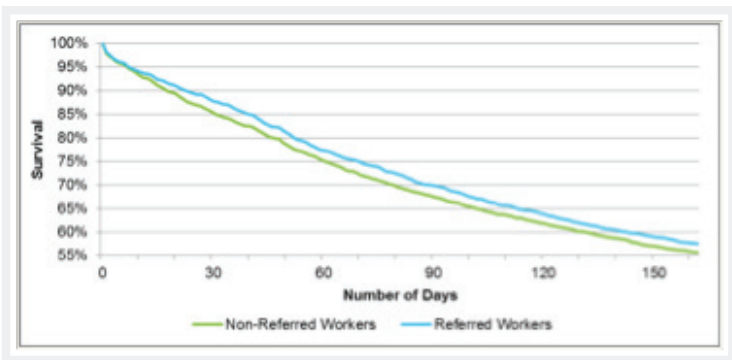
RESULTS

Employee Survival:

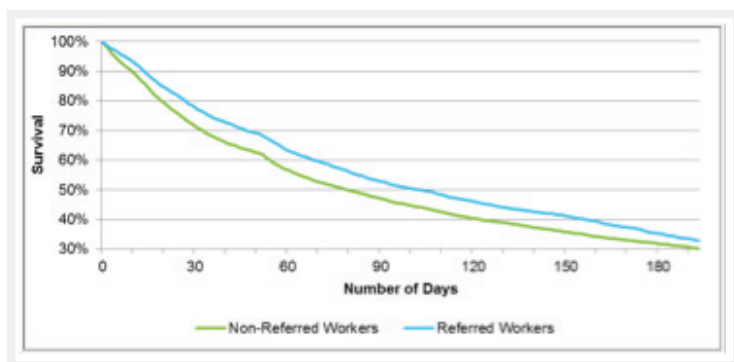
In order to determine whether referred workers are retained longer than non-referred workers, we used survival models. We chose survival because it allowed us to avoid the instability associated with turnover as well as the censoring issues one encounters when working with attrition. Furthermore, analyzing survival allowed us to engage in more complex modeling than would have been possible using turnover or attrition⁵. Figure 1 displays survival curves representing employees that were and were not referred among the trucking and call center employees⁶.

FIGURE 1: SURVIVAL CURVES

Call Center Survival by Referral Status



Trucking Survival by Referral Status



These survival curves indicate that referred employees stay longer than non-referred employees by about 10% of median tenure for both the trucking and call center data. The impact of this result on profitability is enormous because it gives a simple tool for making decisions that lead to a fully trained and more productive workforce compared to a workforce with lower median tenure that is newly trained and less productive.

Because referred workers do stay longer, we used Cox proportional hazard models to find whether these differences are due to treatment effects, selection effects or both. We chose to use Cox proportional hazard models because - unlike accelerated failure time models - it avoids the need to choose a functional form. By including a dummy variable representing whether an employee was referred, the Cox proportional hazard model produces odds ratios that can be interpreted as the hazard rate - the instantaneous probability of attrition - for referred and non-referred employees. After controlling for site and program specific effects, we divided these odds ratios and were able to calculate that a referred call-center worker is 13% less likely to quit than a non-referred worker. To test for the presence of the treatment effect, we included control variables representing the number of friends at the company the employee has and the number of people at the company an employee knows. The results of this Cox proportional hazard model maintained that a referral had a significant negative impact on quitting, but the coefficients on the variables measuring the size of an employee's social network were statistically zero. Table 2 presents the results of running this model on the data for call center agents.

TABLE 2: COX PROPORTIONAL HAZARD MODEL RESULTS

Variables	Model 1	Model 2
Referral	-0.13***	-0.07**
	[0.03]	[0.03]
Friends at company		-0.02
		[0.02]
Number of people known at company		-0.03
		[0.02]
Observations	20,040	17,941

*** Significant at 1% level

** Significant at 5% level

We also ran similar models from our trucking data while including controls for the state unemployment rate, the driver's average productivity to date, driver tenure, demographic controls and fixed effects for time and driver's school.

Table 3 presents the results of these Cox proportional hazard models:

TABLE 3: COX PROPORTIONAL HAZARD MODEL RESULTS, TRUCKING

Variables	Model 1	Model 2
Referral	-0.132***	-0.134***
	[0.022]	[0.022]
State Unemployment Rate		-0.045***
		[0.011]

*** Significant at 1% level

We see similar outcomes between the trucking and call center data, specifically the positive impact referrals have on worker retention. Our analyses show that referred drivers are about 13% less likely to quit at any given time than non-referred drivers. In other words, the effect of a referred driver on retention is the same as a 2-3 percentage point increase in the driver's home state unemployment rate.

EMPLOYEE PRODUCTIVITY

In order to investigate the effects of referrals on worker productivity we ran OLS regressions on truck driver and call-center worker productivity. The results are in tables 4 and 5 below.

TABLE 4: PRODUCTIVITY REGRESSION RESULTS, CALL CENTER⁷

	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
Dependent Variable	Schedule Adherence	Worker Performance	Sales Conversion Rate	Quality Assurance	Customer Satisfaction
Referral	-0.021 [0.013]	-0.000 [0.010]	-0.027 [0.015]	0 [0]	0.003 [0.003]
Observations	152,683	749,848	134,386	31,908	603,860
Clusters	3136	12,497	3,192	2,864	11,859
R-squared	0.119	0.559	0.655	0.178	0.033

TABLE 5: PRODUCTIVITY REGRESSION RESULTS, TRUCKING⁸

Dependent Variable	All Weeks		Exclude 0 Mile Weeks		Trim 5/95%	
	Regression n1	Regression n2	Regression n3	Regression n4	Regression n5	Regression n6
Referral	-30.78*** [10.75]	-25.28** [11.44]	-3.98 [8.17]	-1.08 [8.61]	-3.23 [7.80]	-0.67 [8.21]
Demographic Controls	No	Yes	No	Yes	No	Yes
Mean of Dependent Variable	1,659	1,677	1,926	1,919	1,927	1,918
R-squared	0.19	0.17	0.08	0.09	0.08	0.08

*** Significant at 1% level

** Significant at 5% level

To measure trucking productivity we ran 6 different regressions. They all measure the effect of a referral on the average number of miles a trucker drives per week, the trucking industry's standard measure of worker productivity. The first two regressions include all observed weeks, with the second regression including controls for worker demographics. We also ran regressions that dropped all weeks where drivers drove zero miles and regressions that dropped the largest and smallest 5% of observations for number of miles driven (also excluding zero mile weeks). We chose to drop zero mile weeks because workers are not working those weeks, causing these values to not measure what we consider to be worker productivity.

In both the call-center and trucking industries there is relatively little evidence that referred workers are more productive than non-referred workers. In the call-center data, the differences between referred and non-referred workers on all five of the productivity measures are not statistically significant. In trucking, when all the data is used, it also appears that referred workers are slightly less productive, by around 25-30 miles per week, which is about 1.5% to 2% of total productivity. However, once the zero mile weeks are eliminated, the productivity differences between referred and non-referred workers are all but eliminated.

CONCLUSION AND INTERPRETATION

Referred workers are significantly less likely to quit than non-referred workers. There is no evidence, however, that referred workers are more productive.

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While our analysis proves that referred workers are by some measures better employees than non-referred workers, it is interesting that there is little to no difference in productivity between these two groups. This suggests that the power of using employee social networks lies in finding workers who are a better fit for a job, not in finding workers who are more productive overall. In order to capitalize on this 'selection effect' we advocate using interview questions that explore a candidate's fit in a particular position.

Referrals can have a powerful effect on your bottom line. We found that referred workers stay 10% longer than non-referred workers, meaning that, in terms of worker tenure, hiring 10 referred workers is the equivalent of getting an 11th free. In call-center work, it costs \$600-800 to source, screen and hire a new employee and as much as \$2,400 more to train the new hire. . This translates into a savings of \$300-320 per referral⁹. With call-center referral bonuses for hourly wage workers often ranging from \$40-150, this means that a referral can be 2 to 7.5 times more valuable than what is typically paid for them. For the trucking data we computed the profits per referred worker to be 28% higher than profits per non-referred worker¹⁰. We also found that the profitability of workers who were referred by an employee with productivity above the median was 5 times higher than the profitability of workers who were referred by an employee with productivity below the median¹¹ .

In order to use employees' social networks for hiring needs, about 65% of hourly wage companies use formal or informal employee referral programs, though companies don't always have referral programs in place at all their locations¹². Because referrals are such an effective means for recruiting employees who will stay for longer periods of time, the 35% of employers with no referral program should consider implementing one to improve workforce selection. For those that already have referral programs, expanding them to all possible locations and examining the impact that the size and structure of the referral bonus can have on the number of referred candidates can greatly increase the profit making potential of your program.

REPORT AUTHORS

Michael Housman is the Vice President of Workforce Analytics at Evolv. Dr. Housman has over ten years of experience engaging in econometric research and working directly with stakeholders to interpret and use the findings of rigorous analysis.

Dr. Housman has consulted previously for PricewaterhouseCoopers and helped to develop a SaaS platform at Pascal Metrics, a leading provider patient safety and risk management services to hospitals and healthcare

systems worldwide. Dr. Housman received his A.M. and Ph.D. in Applied Economics and Managerial Science from The Wharton School of the University of Pennsylvania and his A.B. from Harvard University.

Will Kuffel is the Analytics Intern at Evolv. Will has helped conduct research on the positive effect of overconfidence on worker productivity and tenure, and has also researched the profitability of training contracts. He will be graduating from the University of California, Berkeley in the spring of 2013 with B.A.s in Applied Mathematics and Economics.

The Yale School of Management attracts broadminded, intellectually curious students and faculty. An integrated curriculum, close ties to Yale University, and an active connection to the Global Network for Advanced Management ensure that Yale MBAs not only acquire crucial technical skills but also develop a genuine understanding of an increasingly complex global context. Yale MBAs assimilate information and ideas from multiple sources, functional areas, and points of view to lead effectively in all regions and sectors. Yale SOM offers a full-time MBA program, an MBA for Executives program tailored to healthcare professionals, a Master of Advanced Management, a PhD, and executive programs.

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3 Brown, Meta, Elizabeth Setren, and Giorgio Topa, "Do Informal Referrals Lead to Better Matches? Evidence from a Firm's Employee Referral System," 2012. Mimeo.

4 Burks, Stephen, Bo Cowgill, Mitchell Hoffman and Michael Housman "The Value of Hiring Through Referrals" Working Paper, 2013

5 Survival curves calculate the probability that an employee stays for a given tenure (e.g. 60 days) as a function of the conditional probability that they survived all previous intervals (e.g. 0-30 days, 30-60 days) and present this as a continuous function over time.

6 For more information on survival curves see Allison, P.D. 1995. Survival Analysis Using the SAS System: A Practical Guide. Cary, NC: SAS Institute

7 Each regression includes controls for worker tenure, location, client and the number of times each outcome was measured to compute the dependent variable.

8 Each regression includes time fixed effects, cohort fixed effects, tenure fixed effects, work type controls and the annual state unemployment rate.

9 $(\$600 + \$2,400)/10$ thru $(\$800 + \$2,400)/10$

10 We compute profits per truck using the following equation:

Profits per worker = Trucking Profits + Training Contract Penalties – Training Costs

$$= \sum \delta^{t-1} (1 - Q_t) ((P - w_t - mc) y_t - FC) + \sum \delta^{t-1} \theta_k t q_t - TC$$

Where δ is the discount factor, Q_t is a dummy variable for the driver having quit by week t , P is the price the firm charges per mile, w_t the driver's wage per mile, mc the nonwage marginal cost per mile, y_t the amount of miles driven in a week and FC the fixed cost of a truck per week. $\sum \delta^{t-1} \theta_k t q_t$ represents the discounted revenues from training contract penalties and TC is a general term capturing training costs.

Using this model we were able to compute profits per referred driver to be \$3,619 and profits per non-referred driver to be \$2,822

11 Using the model described in footnote 9 we computed the profit of referred workers whose referring employee had productivity above the median to be \$6,547 while referred workers whose referring employee had productivity below the median to be \$1,371.

ABOUT EVOLV

Evolv is a big data company that helps solve workforce performance issues for the C-suite by using a configurable cloud services platform. Evolv's patent-pending technology platform unifies and supplements existing data from current systems, then uses that dataset to identify factbased workforce insights that drive measurable ROI. By using objective, data-driven methodology, Evolv helps companies uncover the core reasons behind workforce performance, enabling executives to make better operational business decisions that generally result in tens of millions of dollars in measurable value per year. For more, visit: www.evolvondemand.com, follow @EvolvOnDemand and connect on LinkedIn.