Job referrals and labor market outcomes:
It’s not who you know, it’s how you know them*†

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Abstract

Though referrals are ubiquitous in the hiring process, it remains unclear exactly what they do. We exploit a novel data set to shed light on this question. Importantly, the data enables us to distinguish between different types of referrals—namely, those from family and friends and those from business contacts—and different types of jobs, as measured by the skill requirements of the occupation. Using these distinctions, we document clear patterns with respect to the frequency with which different types of referrals are used by workers in different occupations and subsequent labor market outcomes. Then we develop a structural framework to interpret our empirical findings and quantify the effects of social and business networks on employment rates, earnings, and job turnover across workers with different skills. For example, we find that referrals from family and friends contribute up to 20% of earnings for a subset of workers who struggle to generate offers through more traditional channels, and hence this type of referral is an important force for reducing earnings inequality. Referrals from business contacts, in contrast, have a more muted impact on earnings, as such referrals are most commonly used by workers who generate offers from other sources more readily.

Keywords: Labor Markets, Referrals, Networks, Search Theory, Asymmetric Information

JEL Classification: E42, E43, E44, E52, E58

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1 Introduction

According to surveys of workers and firms, a referral is used somewhere in the hiring process for approximately half of all jobs.\footnote{Topa (2011) provides an extensive review of usage rates across surveys of both workers and firms. Most surveys of job seekers find between 50 and 60 percent of workers report using a referral to find employment (Corcoran et al., 1980 Lin et al., 1981 Bridges and Villemez, 1986 Granovetter, 1995), though others find even higher usage rates (Holzer, 1987b; Elliott, 1999). Similar rates have also been documented in other countries (Gregg and Wadsworth, 1996; Alon and Stier, 2019; Wahba and Zenou, 2005). Surveys of firms also indicate widespread use of referrals or word-of-mouth techniques, though results vary from just under 40 percent of hires using a referral (Holzer, 1987a; Marsden, 2017) to significantly more than 50 percent (Neckerman and Kirschenman, 1991; Miller and Rosenbaum, 1997).} Given its prevalence, this feature of job search is presumably an important channel for connecting workers with firms, and for transmitting information that is valuable for forming good matches. Moreover, as access to (and reliance on) referral networks tends to be heterogeneous across segments of the labor force, the use of referrals has the potential to generate (or ameliorate) economic inequality.\footnote{See, e.g., the influential work of Calvo-Armengol and Jackson (2004), Ioannides and Datcher Loury (2004) provide an extensive overview of the relationship between networks and inequality.}

However, despite the prevalence of referrals, and their potentially important implications for labor market outcomes, it remains unclear exactly what (if anything) referrals actually do. While the theoretical literature has proposed a variety of channels through which a referral could play an important role in the match formation process, understanding and quantifying the effects of referrals has proven difficult, in large part because there are few representative data sets containing detailed information regarding the job search and/or hiring processes. Indeed, the existing empirical literature has found conflicting evidence regarding some of the most elementary facts about referrals, such as the types of workers that use referrals most frequently, and the effects of using a referral on, e.g., a worker’s starting wage.

The goal of this paper is to gain a better understanding of how referrals are used in the hiring process, and the quantitative implications for labor market outcomes, both at the individual level and in the aggregate. We proceed in three steps. First, we exploit a novel data set to establish a new set of facts about workers who used a referral in the process of forming their current match, paying particular attention to the wages they earn, their average job tenure, and the frequency with which they receive offers for new jobs, relative to the non-referred. Then, motivated by these facts, we develop a structural model that allows us to interpret our empirical findings and assess whether various theories of referrals are qualitatively consistent with the data. Finally, we combine our theoretical framework
with a variety of key moments from the data to calibrate the model and quantify the contribution of referrals to employment rates, wages, turnover, earnings inequality, and total output. We now describe each of these steps in greater detail.

**Facts.** As a first step, we document a number of new facts about the types of workers and occupations that tend to use referrals, and the characteristics of matches formed through a referral (relative to those formed through other channels). Our data, which comes from a supplement to the Survey of Consumer Expectations, has a number of unique features that make it well-suited to study these issues: the survey draws from a wide range of demographic groups, industries, and occupations; it contains a rich set of information describing the job characteristics of currently employed workers; and, most importantly, it paints a highly descriptive picture of the job search process that generated the current job (as well as other offers), including *direct information about the use of referrals*.

One particularly important aspect of the data is that it allows us to distinguish between *different types of referrals*—namely, those from family and friends and those from sources we call “business contacts.” We find that the extent to which these two types of referrals are used differs substantially across occupations: referrals from family and friends are used relatively more frequently to find low-skill jobs, whereas referrals from business contacts are used relatively more frequently to find high-skill jobs. This suggests that the two types of referrals could be playing very different roles, and hence have different effects on observable outcomes.

In fact, we find that the two types of referrals have *opposing* relationships with labor market outcomes. In particular, we document that workers who used a referral from a business contact tend to earn higher starting wages than non-referred workers, but experience shorter job tenures. Digging deeper, we find that this occurs because workers who got their current job using a business referral continue to meet other firms at a relatively high rate. Alternatively, workers who used a referral from a friend or relative to get their current job tend to have lower starting wages than non-referred workers and experience less job turnover, because they receive offers at a relatively low rate.

Hence, the first part of the paper establishes that clear relationships emerge once we distinguish along two relatively unexplored dimensions of the data: the source of the referral, and the type of referrals. We are not the first to speculate that referrals can play multiple roles; for example, Loury (2006) makes the distinction between theories of referrals based on “good matches” vs. “limited choices.” Instead, a key part of our contribution is confirming that different types of referrals play different roles, identifying these different types of referrals in the data, and quantifying their effects on labor market outcomes.
job or occupation. These relationships are not only suggestive about the different roles that the two
types of referrals play in the hiring process, but they also help explain why previous studies—which
could not make the same distinctions in the data—found mixed/conflicting results. However, these
empirical findings alone are insufficient to make substantive statements about the role of referrals in
shaping labor market outcomes.

Consider, for example, the positive relationship between the use of a business referral and a
worker’s starting wage. Studying this bivariate relationship alone, one might be tempted to con-
clude that matches formed through business referrals are more productive, perhaps because referrals
are an efficient technology for sharing information and creating good matches. However, an equally
plausible explanation is that (ex ante) more productive workers tend to use business referrals to find
a job, perhaps because reputation concerns ensure that business contacts only refer “good” workers.
Yet another possibility is that matches formed through business referrals are no more productive than
matches formed through other channels, but instead workers who tend to use business referrals have
better outside options (perhaps because they have larger networks of business contacts) and hence
negotiate higher wages.

Distinguishing between these explanations is crucial for understanding both the qualitative role
that these two types of referrals are playing in the search process and the quantitative contribution
of each type of referral to observable outcomes, including employment rates, inequality, and total
output. Therefore, in order to account for the endogenous nature of the empirical relationships we
uncover, and to leverage the multiple, inter-related moments from the data, we construct a theoretical
framework to interpret our empirical results.

Model. The key ingredients of the model are motivated by the patterns we observe in the data. First,
given the clear correlations we find between various labor market outcomes and the channel through
which a worker found a job, we assume different technologies can initiate contact between workers
and firms. In particular, we assume these contacts may arrive through formal search methods, through
referrals from business contacts, or through referrals from family and friends. Moreover, we allow
the quality of the match—i.e., the match-specific productivity of a worker-firm pair—to depend on
the channel through which the contact was initiated.

Second, since some workers appear to generate offers through different channels at different rates,
even after controlling for a variety of observable characteristics, we allow for worker heterogeneity along some intrinsic type or “ability.” We allow a worker’s ability to affect both the (exogenous) rate at which the worker meets firms through different channels, along with the match-specific productivity they draw conditional on meeting a firm through a specific channel.

Finally, since a worker’s ability (or proclivity) to contact firms and generate offers does not evaporate after forming a match—but rather seems to be an important feature of understanding heterogeneity in wages and turnover—we assume that workers search when both unemployed and employed. In particular, our model builds off of the workhorse on-the-job search models developed by Burdett and Mortensen (1998), Postel-Vinay and Robin (2002), and, in particular, Cahuc et al. (2006).

Within this framework, we provide a complete analytical characterization of the equilibrium. Moreover, we exploit the model’s tractability to derive closed-form expressions for a number of key moments that we will later target in the data, including the fraction of currently employed workers who used each job search channel to get their current job, and the average wage and tenure of currently employed workers conditional on the job search channel they used to form their current match. To the best of our knowledge, these derivations are new to the literature.

**Quantitative.** Armed with a new set of moments from the data, and a model built to interpret these moments, we perform a calibration which produces two sets of insights. First, the calibrated parameter values reveal the relationships between a worker’s type, the frequency with which she matches with firms through different channels, and the quality of those matches that are required to fit the various targets in the data. These relationships, in turn, are informative about which theories can potentially explain the primary role of referrals from business contacts and the (potentially different) role of referrals from family and friends.

More specifically, we find that matching the patterns in the data requires significant heterogeneity in the rate at which workers contact firms: “high ability” workers simply generate offers much more frequently than “low ability” workers. However, this heterogeneity is largely driven by differential rates in which workers meet firms through business referrals and other, formal channels of search. Referrals from family and friends, in contrast, appear to arrive at more uniform rates across workers, but tend to result in highly productive matches. Hence, any theory of referrals must imply that meetings generated through business contacts are highly sensitive to a worker’s underlying type, as in
theories based on adverse selection\textsuperscript{4}, whereas referrals from family and friends generate good matches independently of a worker’s underlying type, as in theories based on symmetric uncertainty or moral hazard\textsuperscript{5}.

In addition to revealing qualitative insights into the role of referrals in the labor market, the calibrated model allows us to quantify the extent to which (different types of) referrals affect employment and earnings across workers in high- and low-skill labor markets. Interestingly, though referrals from family and friends have a negative correlation with wages in our regression analysis, we find that they are a crucial source of jobs for a certain subset of workers that struggle to generate offers and matches through more traditional channels. For example, in the low-skill labor market, we find that referrals from family and friends account for more than 20\% of earnings and a 4\% reduction in the unemployment rate of “low ability” workers. Hence, despite concerns that referrals based on nepotism would exacerbate earnings inequality, our findings suggest that referrals from friends and relatives are, in fact, an important force for reducing earnings inequality.

Referrals from business contacts have a more muted impact on employment rates and earnings, and the impact is more equal across different types of workers. Again, these results highlight the importance of interpreting our data through the lens of a structural model: whereas our regression results alone might suggest that referrals from business contacts have a significant, positive effect on wages, the model reveals that workers who tend to use this channel—in particular high ability workers in high-skill markets—tend to generate offers through other channels relatively frequently as well. Hence, our findings suggest that business referrals do not produce significantly better matches, but are rather used by workers who generate offers relatively frequently through multiple job search channels.

2 Data

We use data from a supplement to the Survey of Consumer Expectations (SCE), which is administered by the Federal Reserve Bank of New York. The SCE is a nationally representative, monthly online survey of a rotating panel of about 1,300 household heads. New respondents are drawn each month

\textsuperscript{4}See, e.g., Montgomery (1991), Casella and Hanaki (2008), and Galenianos (2014).

\textsuperscript{5}For theories based on learning and symmetric uncertainty, in the spirit of Jovanovic (1979), see, e.g., Simon and Warner (1992), Galenianos (2013), Dustmann et al. (2015), and Brown et al. (2016). For theories that posit referrals generate peer effects or reduce moral hazard, see, e.g., Kugler (2003), Castilla (2005), Beaman and Magruder (2012), and Heath (2018).
to match various demographic targets from the American Community Survey (ACS), and they stay on the panel for up to twelve months. The supplement we use, called the Job Search Survey, has been administered annually since 2013.\footnote{The survey was designed by Jason Faberman, Andreas Mueller, Aysegul Sahin, and Giorgio Topa. See Faberman et al. (2017) for a more detailed description.}

This dataset is particularly well-suited to our objectives in several dimensions. First, the survey asks a broad range of questions regarding how employed workers found their current job. Second, it asks about many different characteristics of the job including wages, benefits, job tenure, job satisfaction, and job search behavior. Third, since it is a representative survey it covers workers across a wide range of individual characteristics and occupations. In addition to detailed information about the current job of the worker, our data also contains information about respondents’ previous work experience, along with all of the usual demographic information contained in the SCE data.

Our analysis focuses on non-self-employed individuals aged 18 – 64. This leaves us with a sample of about 5,000 observations covering the years 2013-2018. See Appendix A for additional details about how we generate some of our variables and arrive at our final estimation sample.

2.1 Construction of key variables

Before presenting our empirical results, we describe how we construct two key variables related to the source of the referral (business versus family/friends) and the skill content of the job.

First, to determine whether a worker used a referral, and the type of the referral, we rely on a question from the survey that asks currently employed workers how they “learned about their current job.” Using the workers’ response to this question, we construct binary indicators for two types of referrals: (i) family and friend, and (ii) business contact. Since individuals are allowed to give multiple responses to this question, these measures are not mutually exclusive. For those that indicated they were “referred by a friend or relative,” we set the indicator for referral from family and friend equal to 1, and 0 otherwise. For referral from business contacts, we set the indicator equal to 1 if the individual responded that they were “referred by a former co-worker, supervisor, business associate”. We also set the business contacts indicator equal to 1 if they reported being “referred by a current employee at the company,” as long as they did not also indicate that they were referred by a friend or relative. In other words, if a worker who indicated that they were referred by a friend or relative also indicated that they were referred by a current employee at the company, we classify this as a referral from a
family member or friend, as it seems most likely that the two answers correspond to the same referrer. However, if the worker responded that they were referred by a current employee at the firm but not by a friend or relative, we classify the referrer as a business contact.  

Second, to classify different types of jobs, we measure the skill content of each (employed) worker’s reported occupation using the Nam-Powers-Boyd (NPB) occupational index. This index ranks occupations (at the 3-digit occupation level) based on the earnings and educational levels of the workers in each occupation. To do so, one first calculates the median education level and median earnings of individuals in each occupation. Then, these values are weighted by the number of people in each occupation to create a percentile measure of the position of each occupation in both the education and earnings distributions. Finally, these two percentiles are averaged to generate the index. Scores can range from 0 to 100. The version we use comes from 2016 and is based on data from the American Community Surveys from 2010-2012, accessible via IPUMS.

To give the reader a sense of the NPB occupational index, Table 1 provides a list of NPB scores assigned to various occupations, aggregated at the 2-digit occupation level for the sake of presentation. One can see that scores range from 0 to 100, with “Food Preparation and Serving Related Occupations” (FOOD) at the bottom and “Legal Occupations” (LEGL) at the top. Note that each of these groups is a weighted average of scores at the 3-digit occupation level; for example, FOOD contains both “chefs and head cooks” (NPB score of 40) and “dishwashers” (NPB score of 1), while LEGL contains both “lawyers, judges, and related workers” (NPB score of 99) and “paralegals and legal assistants” (NPB score of 70). For all of our regression analysis, below, we use the finer, 3-digit occupation scores.

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7 Using this method of classification, about 8% of referred workers have both referrals indicators equal to 1. We experimented with several ways of dealing with the overlap between the two measures, including fully partitioning the three responses related to referrals, and our empirical results did not change significantly.

8 Occupations in the SCE are categorized using the Standard Occupational Classification System (SOC) from the Bureau of Labor Statistics (BLS).

9 We also experimented with an alternative occupation index constructed using O*NET data. Specifically the measure was computed as the fraction of jobs within an occupation code that require a bachelor’s degree, which generated scores that also ranged from 0 to 100. Results were qualitatively similar using this alternative measure.

10 The NPB scores are available for download at http://www.npb-ses.info.
Table 1: Nam-Powers-Boyd Index (2-Digit Occupation Level)

<table>
<thead>
<tr>
<th>Occupation</th>
<th>NPB Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food Preparation and Serving Related Occupations (FOOD)</td>
<td>17</td>
</tr>
<tr>
<td>Building and Grounds Cleaning and Maintenance Occupations (BLDG)</td>
<td>17</td>
</tr>
<tr>
<td>Personal Care and Service Occupations (PERS)</td>
<td>27</td>
</tr>
<tr>
<td>Transportation and Material Moving Occupations (TRSP)</td>
<td>32</td>
</tr>
<tr>
<td>Production Occupations (PROD)</td>
<td>33</td>
</tr>
<tr>
<td>Construction and Extraction Occupations (CSTR)</td>
<td>34</td>
</tr>
<tr>
<td>Healthcare Support Occupations (NURS)</td>
<td>39</td>
</tr>
<tr>
<td>Sales and Related Occupations (SLS)</td>
<td>43</td>
</tr>
<tr>
<td>Office and Administrative Support Occupations (ADMN)</td>
<td>47</td>
</tr>
<tr>
<td>Installation, Maintenance, and Repair Occupations (MNT)</td>
<td>47</td>
</tr>
<tr>
<td>Protective Service Occupations (PROT)</td>
<td>55</td>
</tr>
<tr>
<td>Arts, Design, Entertainment, Sports, and Media Occupations (ART)</td>
<td>64</td>
</tr>
<tr>
<td>Community and Social Service Occupations (SOC)</td>
<td>72</td>
</tr>
<tr>
<td>Education, Training, and Library Occupations (EDU)</td>
<td>75</td>
</tr>
<tr>
<td>Healthcare Practitioners and Technical Occupations (DOC)</td>
<td>78</td>
</tr>
<tr>
<td>Business and Financial Operations Occupations (BUS)</td>
<td>81</td>
</tr>
<tr>
<td>Life, Physical, and Social Science Occupations (LIFE)</td>
<td>83</td>
</tr>
<tr>
<td>Management Occupations (MGT)</td>
<td>84</td>
</tr>
<tr>
<td>Architecture and Engineering Occupations (ENG)</td>
<td>86</td>
</tr>
<tr>
<td>Computer and Mathematical Occupations (COMP)</td>
<td>87</td>
</tr>
<tr>
<td>Legal Occupations (LEGL)</td>
<td>88</td>
</tr>
</tbody>
</table>

Notes: This table provides the Nam-Powers-Boyd (NPB) occupational index score aggregated to the 2-digit occupation level.
3 Empirical Results

In this section, we examine the frequency with which the two different types of referrals are used across occupations, and the characteristics of matches formed using each type of referral. Since our indicators of usage are derived from currently employed workers, our estimates in this section are based on the sample of workers who were currently employed at the time of the survey. Note that in Section 5, when we calibrate our model to a larger set of moments, we will use the full sample of employed and unemployed workers.

3.1 Usage of Referrals Across Occupations

We first examine the relationship between the usage of the two types of referrals and the skill requirements of different occupations. As a first step, Figure 1a plots, for each two-digit occupation code, the percentage of currently employed workers who report having used a referral from a family member or friend in the process of being hired at their current job. Figure 1b plots the corresponding relationship for business referrals.

The figures suggest that referrals from family and friends are used more often in the formation of low-skill jobs, while referrals from business contacts are used relatively more often in the formation of high-skill jobs. Of course, these patterns could reflect differences in the characteristics of the workers in these occupations, and not necessarily differences in the occupations themselves.

Therefore, to establish that this relationship is not just capturing worker characteristics, we run
a linear regression on a dummy variable for referral usage (for each type of referral) against the skill index of the occupation, time fixed effects, and a rich set of worker characteristics. These characteristics include age, gender, race, marital status, number of children under the age of 6, home ownership status, and year and geographic region fixed effects. Table 2 confirms that there is a positive relationship between the use of business referrals and occupational skill, and a (stronger) negative relationship between the use of referrals from family and friends and occupational skill.

Table 2: Referral Usage and Skill Index

<table>
<thead>
<tr>
<th>Type of Referral</th>
<th>Skill Index</th>
<th>Time and Region FE</th>
<th>Individual Controls</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Business</td>
<td>Family/Friends</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Skill Index</td>
<td>0.0008***</td>
<td>-0.0018***</td>
<td></td>
<td>3779</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time and Region FE</td>
<td>✓</td>
<td>✓</td>
<td></td>
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<tr>
<td>Individual Controls</td>
<td>✓</td>
<td>✓</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Estimates are from regressions in which the outcome is whether an individual used either a business or family/friend referral to find their current job. Individual controls include age, gender, race, marital status, number of children under the age of 6, and home ownership status. Standard errors are presented in parentheses below the point estimates. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level.

The fact that referrals from family and friends appear relatively more useful at low skill jobs, while referrals from business contacts appear relatively more useful at high skill jobs, suggests that the two types of referrals are playing different roles (or helping to overcome different frictions) in the matching process. This observation prompts two conjectures. First, if the two types of referrals are playing different roles, then one might naturally expect them to be associated with different labor market outcomes. Second, if the mix of referrals from family and friends and business contacts varies across occupations—and referrals from these two sources have different effects on labor market outcomes—then one would also expect that two studies focusing on different occupations or sectors may find conflicting results regarding the relationship between labor market outcomes and the use of any type of referral.

11 For ease in interpretation we employ a linear probability model for all of our binary outcomes. However, results are very similar using a logit or probit specification.  
12 In the regressions, we use the skill index for the more detailed 3-digit occupation code. However, the results remain similar if we use the more aggregated 2-digit occupation code, as in Figures 1a and 1b above.
We now explore these conjectures in the data. In particular, we examine the relationship between the use of referrals and two standard measures of labor market outcomes: wages and tenure. We show that clear and opposing relationships emerge only after conditioning on the two types of heterogeneity highlighted above—namely, different types of referrals and different types of occupations.

3.2 Referrals and Starting Wages

The first labor market outcome we study is workers’ starting wages. In column (1) of Table 3, we report results of a regression of log (real) starting wages on dummy variables that indicate whether the worker used a referral from a business contact or family/friend in the hiring process. Again, we control for time and region fixed effects, as well as observable worker characteristics. This regression suggests that workers who were referred to their current job by a business contact tend to have starting wages that are approximately 16% higher than non-referred workers, while those who were referred by family and friends tend to have starting wages that are approximately 9% lower than the non-referred. In column (2), we control for the skill index of the worker’s occupation. Note that the coefficient on business referrals is essentially unchanged, while the coefficient on referrals from family and friends decreases in absolute value, but remains negative and statistically significant.

In column (3), we also control for the previous wage in an attempt to control for unobserved worker heterogeneity. Not surprisingly, there is a strong positive relationship between the wage at the previous job and the starting wage at the current job. Moreover, while the coefficient on business referrals remains positive and statistically significant when controlling for previous wages, the coefficient on referrals from family and friends becomes small and insignificant. As we discuss in more detail below, these findings are consistent with an environment in which referrals from family and friends do not necessarily reduce wages, but rather tend to be used by workers who ultimately earn lower starting wages (because of characteristics not easily observed by the econometrician). For example, the results in column (3) are consistent with an environment in which workers who use referrals from family and friends have fewer outside options than otherwise similar workers, and hence receive lower wages.

In columns (4)–(6), we report results for the same regressions without distinguishing between the two types of referrals, i.e., we regress starting wages on a dummy variable that takes on the value 1 if the worker used any type of referral. We find that the relationship between the use of a referral and
Table 3: Starting Wages and Referrals

<table>
<thead>
<tr>
<th></th>
<th>Log Real Starting Wage</th>
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<th></th>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
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<td>Any Referral</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>N</td>
<td>3317</td>
<td>3317</td>
<td>2311</td>
<td>3317</td>
<td>3317</td>
<td>2311</td>
</tr>
</tbody>
</table>

Notes: Estimates are from regressions on the log of the real starting wage for the worker’s current job. Individual controls include age, gender, race, marital status, number of children under the age of 6, and home ownership status. Standard errors are presented in parentheses below the point estimates. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level. There are 462 observations for which we do not observe the starting wage. We lose 1006 observations when adding previous wage as a control due to missing data on previous wage. Results for the specifications without previous wage as a control (columns 1, 2, 4, and 5) are similar when using this more restricted sample.

starting wages disappears. This insight—that referrals from business contacts and family/friends are associated with opposing effects on starting wages—may help to explain why the existing literature has found mixed evidence regarding the relationship between wages and referrals.

3.3 Referrals and Job Tenure

We now analyze the relationship between the use of referrals and job tenure. Ideally one would like to analyze the duration of completed employment spells, but this is not possible given the repeated, cross-sectional nature of our data. Instead, we construct the job tenure of all currently employed workers at the time of the survey. Despite the potential limitations of our stock-sampled measure of job tenure, we believe that results based on this measure are still informative about the relative tenures across different types of referrals and occupations. Moreover, since we can calculate both measures

---

13Workers are only tracked for a period of one year in the SCE, and thus we observe very few completed job spells.
14As is well known, data like ours—which is left-truncated and right-censored—suffers from competing biases. On the one hand, since it is left-truncated, workers with shorter spells are less likely to be sampled. Hence, our measure of
of tenure in our quantitative model below, we can directly control for the stock-sampling of tenure and measure the difference in means between the two measures.

In Table 4 we regress this measure of job tenure on the dummy variables for referrals, using the same set of controls described above. As in much of the previous literature, columns (4)–(6) suggest that there is a positive (although not precisely estimated) relationship between referrals and job tenure in our data. However, as in our results above on wages and usage of referrals, these regressions mask stark differences between the effects of referrals from business contacts and those from family and friends. In particular, columns (1)–(3) illustrate that workers who were referred by business contacts have significantly shorter job durations than the non-referred, while those who were referred by family and friends have longer durations.

Table 4: Job Tenure and Referrals

<table>
<thead>
<tr>
<th></th>
<th>Log Job Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Business Referral</td>
<td>-0.185***</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
</tr>
<tr>
<td>Family/Friends Referral</td>
<td>0.216***</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
</tr>
<tr>
<td>Any Referral</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Skill Index</td>
<td>0.007***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>Log Previous Wage</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Time and Region FE</td>
<td>✓</td>
</tr>
<tr>
<td>Individual Controls</td>
<td>✓</td>
</tr>
<tr>
<td>N</td>
<td>3779</td>
</tr>
</tbody>
</table>

Notes: Estimates are from regressions on the log of the duration of the current job. Individual controls include age, gender, race, marital status, number of children under the age of 6, and home ownership status. Standard errors are presented in parentheses below the point estimates. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level. We lose 1298 observations when adding previous wage as a control due to missing data on previous wage. Results for the specifications without previous wage as a control (columns 1, 2, 4, and 5) are similar when using this more restricted sample.

average tenure overestimates the average tenure of length spells. On the other hand, since it is right-censored, our measure of average tenure underestimates the average length of completed spells. Under certain assumptions (see, e.g., Heckman and Singer [1984]), these biases cancel and the average job duration that we observe is a consistent estimate of the true, uncensored duration.
**What generates these opposite patterns?** There are several reasons why matches formed through different channels may last for longer or shorter periods of time. For example, if a worker’s relatives and friends have superior knowledge about the worker’s preferences or personal circumstances, than matches formed through family and friends could be “better” matches along non-pecuniary dimensions, such as flexible hours, non-wage benefits, or the potential for faster advancement, which would explain why workers who match through this channel tend to stay at their job longer. However, we do not find any evidence suggesting a relationship between the use of referrals and job satisfaction or “fit.” In particular, in Appendix A we exploit several questions from the survey on job satisfaction to document that workers hired through either type of referral are no more or less satisfied with various aspects their job than non-referred workers. Consistent with this evidence, we also show that workers hired through either type of referral are no more or less likely to be currently looking for a new job, relative to non-referred workers. Finally, we document that wage growth among workers that got their current job through either type of referral does not appear significantly different than that among non-referred workers.

Instead, the difference in job tenure appears to be driven by different arrival rates of outside offers after being hired into their current job. Table 5 reports the output of a linear regression model where the dependent variable is an indicator for whether a currently employed worker has had at least one contact with another firm in the last four weeks. As is evident, workers who got their current job through a business contact are significantly more likely to make contact with additional firms than non-referred workers, whereas those who were hired through a referral from a family or friend are significantly less likely to have generated new contacts in the past four weeks.

**3.4 Summary of Facts and Key Ingredients for a Model**

In this section, we have established that the frequency with which different job search channels are used varies systematically across occupations, and that worker-firm matches formed through different job search channels are associated with significant differences in labor market outcomes. In particular, business referrals are used relatively more frequently at high skill jobs, and they are associated with higher starting wages but shorter tenures, as workers hired through business referrals continued to

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15 As we discuss in detail in the Appendix, workers are asked about their overall satisfaction, their satisfaction with their compensation, the “fit” of the job, the opportunities for promotions or other career progression, and their satisfaction with other, non-wage aspects of the job.

16 We test other horizons as well, and find similar results.
### Table 5: Contact Rates and Referrals

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Business Referral</td>
<td>0.050***</td>
<td>0.048***</td>
<td>0.037*</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Family/Friends Referral</td>
<td>-0.043***</td>
<td>-0.037**</td>
<td>-0.050**</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.016)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Skill Index</td>
<td>0.001***</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>Log Previous Wage</td>
<td></td>
<td></td>
<td>0.047***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.013)</td>
</tr>
<tr>
<td>Time and Region FE</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Individual Controls</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>N</td>
<td>3779</td>
<td>3779</td>
<td>2476</td>
</tr>
</tbody>
</table>

Notes: Estimates are from regressions on an indicator for whether or not an individual had contact with at least one potential employer in the last four weeks. Individual controls include age, gender, race, marital status, number of children under the age of 6, and home ownership status. Standard errors are presented in parentheses below the point estimates. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level. We lose 1303 observations when adding previous wage as a control due to missing data on previous wage. Results for the specifications without previous wage as a control (columns 1, 2, 4, and 5) are similar when using this more restricted sample.

receive offers at a high rate after forming a match. In contrast, matches formed with the help of family and friends occur relatively more frequently at low skill jobs, and they are associated with lower starting wages, though this difference vanishes when controlling for worker fixed effects (through previous wages). Still, despite earning relatively low wages, workers who are hired through family and friends tend to stay longer at their job, as they receive new opportunities less frequently than others.

In the next section, we use these facts to guide the construction of a structural model of the labor market. The model has three key ingredients. First, we assume that matches between workers and firms can be formed through three distinct channels: a referral from family and friends, a referral from a business contact, or other (formal) job search channels. Second, since workers in our data appear to generate offers through these different channels at (persistently) different rates, even after controlling for a variety of observable characteristics, we introduce unobserved worker heterogeneity. Importantly, we allow the rate at which workers meet firms through the different job search channels
and the quality of the matches they form to depend on their unobserved type or “ability.” Third, since workers’ (heterogeneous) abilities to generate offers does not vanish after forming a match, we assume that workers search both off and on the job.

4 Model

4.1 Environment

The model builds off of the job ladder models of Postel-Vinay and Robin (2002) and Cahuc et al. (2006). We consider a continuous time, infinite horizon environment in which all agents are risk neutral and discount the future at rate $r > 0$. There is a measure 1 of workers who are heterogeneous with respect to their ability, which we denote by $a \in A \equiv \{a_1, ..., a_N\}$ for some $N \in \mathbb{N}$. We let $\pi_i$ denote the fraction of workers with ability $a_i$, with $\sum_{i=1}^{N} \pi_i = 1$. As we discuss in more detail below, a worker’s ability $a_i$ should not be confused with their skill or occupation: when we take the model to data, we interpret each occupation or skill level as a separate labor market, and interpret $a_i$ as the unobservable ability of workers within that market.

There is also a large measure of firms that operate a constant returns to scale production technology. When a worker meets a firm, the pair draws a match-specific productivity $x \in [\underline{x}, \bar{x}]$. If they choose to form a match, the worker and firm jointly produce a flow amount $f(x) = px - c$ for some $p \in \mathbb{R}_+$ and $c \in \mathbb{R}$. An unmatched (unemployed) worker consumes a flow amount $b$, while an unmatched vacancy at a firm produces 0. Worker-firm matches are exogenously destroyed at rate $\delta$.

Meetings. The first key point of departure from the existing literature is that we assume contacts or “meetings” between a worker and a firm are initiated through one of three channels: a referral from a family member or friend; a referral from a business contact; or formal (what we call “other”) channels. We denote these three channels by $F$, $B$, and $O$, respectively, and denote the set of possible channels by $\mathcal{C} = \{F, B, O\}$.

The second key important departure from the existing literature is that we assume a worker’s type can affect the rate at which he meets firms through the various channels. In particular, we assume that employed and unemployed workers of ability $a_i$ generate meetings through channel $j \in \mathcal{C}$ at rate

\footnote{In other words, our model could be interpreted as the market for high skill workers—say, doctors—and ability $a_i$ distinguishes good from bad doctors.}
\( \lambda_j^e(a_i) \) and \( \lambda_j^u(a_i) \), respectively. Conditional on meeting, the potential match-specific productivity is then drawn from a distribution with cdf \( H_j(x|a_i) \). It will be convenient to define

\[
\Gamma^k_j(x|a_i) = \lambda^k_j(a_i) \tilde{H}_j(x|a_i)
\]

for \( j \in C \) and \( k \in \{e, u\} \), where we use the notation \( \tilde{H}_j(x|a_i) = 1 - H_j(x|a_i) \). In words, \( \Gamma^j_j(x|a_i) \) is the arrival rate of offers for an employed worker of ability \( a_i \) through channel \( j \) with a match-specific productivity that exceeds \( x \). It will also be convenient to define the arrival rate of such contacts through any channel by

\[
\Gamma^k(x|a_i) = \sum_{j \in C} \Gamma^k_j(x|a_i), \quad k \in \{e, u\}.
\]

Note that this specification, though clearly reduced-form, allows a worker’s type to affect both the arrival rate of meetings and the idiosyncratic quality of the match. This modeling choice was meant to encapsulate a variety of micro-founded theories of job referrals, as some (e.g., search-based) theories focus on the role of referrals in generating meetings between workers and firms, while other (e.g., information-based) theories focus on the quality of matches formed through referrals.

**Wage Determination.** To close the model, we assume that wages are determined by the strategic wage bargaining protocol described in Cahuc et al. (2006). According to this protocol, when an unemployed worker meets a firm and there are gains from trade, the firm and the worker bargain over the wage as in standard models (e.g., Mortensen and Pissarides, 1994). We let \( \beta \) denote the share of the surplus that the worker receives, or the worker’s “bargaining power.”

When an employed worker meets a new firm, a three-player bargaining game ensues. If the match-specific productivity at the poaching firm \( (x') \) is greater than the match-specific productivity at the incumbent firm \( (x) \), then the worker moves to the poaching firm and the two parties determine the wage by bargaining over the match surplus, where again \( \beta \) denotes the worker’s bargaining power. To derive this match surplus, we define the worker’s outside option (of not moving to the poaching firm) as remaining employed at the incumbent firm at a wage equal to his marginal productivity, \( f(x) \), which is the maximum that the incumbent firm would agree to pay him.

If \( x' < x \), however, the worker remains at the incumbent firm but his wage might be adjusted. In particular, the worker’s new outside option is moving to the poaching firm and earning a wage \( f(x') \). If the expected value of remaining at the incumbent firm at his current wage \( w \) is less than
this outside option, then the worker remains at the incumbent firm but renegotiates his wage using the outside option of the poaching firm. Otherwise, the worker remains at the incumbent firm and his wage remains unchanged.

4.2 Value Functions and Wage Functions

We restrict our analysis to steady-state equilibria. Let $V^u(a_i)$ denote the expected discounted value of a worker with ability $a_i$ who is currently unemployed, and let $V^e(a_i, x, w)$ denote the expected discounted value of a worker with ability $a_i$ who is currently employed at a firm with match-specific productivity $x$ earning a wage $w$.

Consider first an unemployed worker with ability $a_i$ who meets a firm and draws match-specific productivity $x$. It is straightforward to establish that there exists a threshold $x^*_i$ such that the surplus from the match is positive if, and only if, $x \geq x^*_i$, where $x^*_i$ satisfies

$$V^u(a_i) = V^e(a_i, x^*_i, f(x^*_i)), \quad i \in \{1, \ldots, N\}. \quad (1)$$

Let $w^u(a_i, x)$ denote the outcome of the wage bargaining game when an unemployed worker with ability $a_i$ meets a firm and draws match-specific productivity $x \in [x^*_i, \bar{x}]$. Following Cahuc et al. (2006), this worker will negotiate a wage $w^u(a_i, x)$ that satisfies

$$V^e(a_i, x, w^u(a_i, x)) = V^u(a_i) + \beta [V^e(a_i, x, f(x)) - V^u(a_i)]. \quad (2)$$

Intuitively, $w^u(a_i, x)$ yields the worker an expected utility equal to his outside option of unemployment, $V^u(a_i)$, plus a share $\beta$ of the surplus created by forming the match, $V^e(a_i, x, f(x)) - V^u(a_i)$.

Next, consider an employed worker with ability $a_i$, current productivity $x$, and wage $w$ who is contacted by a new firm and draws match-specific productivity $x'$. If $x' > x$, the worker will move to the new firm at a wage $w^e(a_i, x, x')$ that satisfies

$$V^e(a_i, x', w^e(a_i, x, x')) = V^e(a_i, x, f(x)) + \beta [V^e(a_i, x', f(x')) - V^e(a_i, x, f(x))]. \quad (3)$$

Intuitively, $w^e(a_i, x, x')$ yields the worker an expected utility equal to his outside option of remaining at the incumbent firm at the highest wage they are willing to pay, $V^e(a_i, x, f(x))$, plus a share $\beta$ of the surplus created by moving to the more productive match, $V^e(a_i, x', f(x')) - V^e(a_i, x, f(x))$.

Alternatively, if $x' \leq x$, the worker will remain at his current job, though he might use the threat
of leaving to renegotiate his current wage\footnote{We assume, without loss of generality, that a worker who is indifferent between moving and staying will stay at the incumbent firm.} In particular, let \( \hat{x}(a, x, w) \) satisfy
\[
    w = w^e(a_i, \hat{x}(a, x, w), x),
\]
so that \( w^e(a_i, x', x) \leq w \) if \( x' \leq \hat{x}(a, x, w) \). In words, a contact with a new firm will only trigger renegotiation if the match-specific productivity \( x' \geq \hat{x}(a, x, w) \). Hence, when a worker meets a new firm and draws match-specific \( x' \leq x \), he remains at the incumbent firm and his wage is \( w(a_i, x', x) \) if \( x' \geq \hat{x}(a_i, x, w) \), and \( w \) otherwise.

Using the thresholds described above, we can write the flow Bellman equation characterizing the value of unemployment for a worker with ability \( a_i \) as
\[
    rV^u(a_i) = b + \sum_{j \in C} \Gamma^u_j(x^*_i|a_i)E_x[V^e(a_i, x, w^u(a_i, x)) - V^u(a_i)|a, j, x \geq x^*_i].
\]
Since
\[
    d\Gamma^u(x|a_i) = -\sum_{j \in C} \lambda^u_j(a_i)dH_j(x|a_i) < 0,
\]
this expression simplifies to
\[
    \left[r + \Gamma^u(x^*_i|a_i)\right]V^u(a_i) = b - \int_{x^*_i}^{\pi} V^e(a_i, x, w^u(a_i, x))d\Gamma^u(x|a_i).
\] (5)
In words, as in standard job search models, the value of unemployment is equal to the flow output, \( b \), plus the option value of finding a job out of unemployment. Following similar steps reveals that
\[
    \left[r + \delta + \Gamma^e(\hat{x}|a_i)\right]V^e(a_i, x, w) = w + \delta V^u(a_i) - \int_{\hat{x}}^{\pi} V^e(a_i, x, w^e(a_i, x', x))d\Gamma^e(x'|a_i)
    - \int_{\hat{x}}^{\pi} V^e(a_i, x', w^e(a_i, x, x'))d\Gamma^e(x'|a_i),
\] (6)
where we’ve used \( \hat{x} \equiv \hat{x}(a_i, x, w) \) to economize on notation. Equation (6) illustrates that the expected utility of a worker of ability \( a_i \) who is currently employed at a firm with match-specific productivity \( x \) earning wage \( w \) takes into account the possibility of losing his job, the possibility of an outside offer that raises his wage at his current employer, and the possibility of moving to a new job.
4.3 Distribution of Workers

Unemployed workers of ability $a_i$ exit unemployment when they meet a firm and draw match-specific productivity $x \geq x_i^*$. Once employed, such a worker moves only when it meets a new firm with a higher match-specific productivity. In this section, we use these simple transition rules to derive the distribution of workers across possible states.

To do so, let $\phi^u(a_i)$ denote the measure of unemployed workers with ability $a_i$, and let $\phi^e(a_i, x)$ denote the measure of workers with ability $a_i$ who are currently employed at a job with match-specific productivity $x$. As we establish below, it will be convenient to define $\Phi^e(x|a_i) = \int_x^{x^*} \phi^e(a_i, x')dx'$, which represents the cumulative measure of workers with ability $a_i$ that are employed at a job with match-specific productivity $x' \leq x$.

These equilibrium objects can be characterized using three sets of conditions. First, we must have

$$\pi_i = \phi^u(a_i) + \Phi^e(x|a_i)$$

for all $i \in \{1, \ldots, N\}$, i.e., summing the measure of unemployed and employed workers with ability $a_i$ must yield the (exogenously specified) aggregate measure of workers with ability $a_i$. Second, the steady-state distribution of unemployed workers with ability $a_i$ must satisfy

$$\dot{\phi}^u(a_i) = \delta \Phi^e(x|a_i) - \phi^u(a_i) \Gamma^u(x^*|a_i) = 0$$

for all $i \in \{1, \ldots, N\}$. The condition in equation (8) requires that the inflow of workers with ability $a_i$ into unemployment is equal to the outflow of workers with ability $a_i$ into employment. The former is simply the product of the mass of employed workers with ability $a_i$, $\Phi^e(x|a_i)$, and the exogenous destruction rate $\delta$. The latter is simply the product of the mass of unemployed workers with ability $a_i$, $\phi^u(a_i)$, and the rate at which they find jobs with positive surplus, $\Gamma^u(x^*|a_i)$.

Lastly, the steady-state distribution of employed workers with ability $a_i$ and productivity $x' \leq x$ must satisfy

$$\dot{\Phi}^e(x|a_i) = -\Phi^e(x|a_i) [\delta + \Gamma^e(x|a_i)] + \phi^u(a_i) [\Gamma^u(x^*|a_i) - \Gamma^u(x|a_i)] = 0$$

for $x \in [x_i^*, \overline{x}]$. Again, equation (9) requires that the outflow of workers in this particular state is equal to the inflow. On the one hand, workers with ability $a_i$ and current match-specific productivity $x' \leq x$ leave this state either because their match is destroyed, which occurs at rate $\delta$, or because they find a
better match with productivity $x'' > x$, which occurs at rate $\Gamma^e(x|a_i)$. On the other hand, unemployed workers with ability $a_i$ enter this state by meeting a firm and drawing match-specific productivity $x' \in [x^*_i, x]$, which occurs at rate $\Gamma^u(x^*_i|a_i) - \Gamma^u(x|a_i)$.

### 4.4 Equilibrium

Given the derivations above, a steady-state equilibrium is characterized by thresholds $\{x^*_i\}_{i=1,...,N}$ and $\hat{x}(a, x, w)$, value functions $V^u(a)$ and $V^e(a, x, w)$, wage functions $w^u(a, x)$ and $w^e(a, x, x')$, and distribution functions $\phi^u(a)$ and $\Phi^e(x|a)$ satisfying equations (1)–(9). The following proposition provides a closed-form characterization of the equilibrium objects that are key to our analysis. The proof is in Appendix C.

**Proposition 1.** In a steady-state equilibrium, the wage functions described above are given by

$$w^e(a_i, x, x') = f(x') - p(1 - \beta) \int_x^{x'} \frac{r + \delta + \Gamma^e(x''|a_i)}{r + \delta + \beta \Gamma^e(x''|a_i)} dx'', \quad (10)$$

for $x' > x \geq x^*_i$, and

$$w^u(a_i, x) = w^e(a_i, x^*_i, x), \quad (11)$$

for $x \geq x^*_i$, where $x^*_i$ satisfies

$$f(x^*_i) = b + p\beta \int_{x^*_i}^{x} \frac{[\Gamma^u(x|a_i) - \Gamma^e(x|a_i)]}{r + \delta + \beta \Gamma^e(x|a_i)} dx \quad (12)$$

for $i \in \{1, 2, ..., N\}$. The distribution functions are given by

$$\phi^u(a_i) = \frac{\delta \pi_i}{\delta + \Gamma^u(x^*_i|a_i)} \quad \text{for all } i \in \{1, ..., N\}, \quad (13)$$

and

$$\Phi^e(x|a_i) = \frac{\delta \pi_i [\Gamma^u(x^*_i|a_i) - \Gamma^u(x|a_i)]}{[\delta + \Gamma^u(x^*_i|a_i)] [\delta + \Gamma^e(x|a_i)]} \quad \text{for all } x \geq x^*_i \text{ and } i \in \{1, ..., N\}. \quad (14)$$

### 4.5 Key Model-Implied Moments

The model studied above is, in many ways, a minimal departure from the standard job ladder models of Postel-Vinay and Robin (2002) and Cahuc et al. (2006). However, by incorporating different job search methods in a simple, tractable manner, our model generates a rich set of testable implications

\footnote{Given these expressions, the remaining equilibrium objects can be easily constructed.}
regarding the relationship between a worker’s current labor market status and the channel through which they found their job. In particular, before proceeding to our quantitative analysis, we now derive the joint distribution of employed workers’ types, their match-specific productivities, and the channel through which they found their job. This allows us to provide analytical expressions for several key model-implied moments corresponding to the empirical patterns described in Section 3. We will use these expressions later, when we calibrate the model in Section 5, to help explain how the model’s structural parameters are identified from these target moments. As an aside, these derivations are also helpful in that they allow us to calibrate the model without resorting to costly simulations.

**Joint Distribution and Usage of Referrals.** Consider a worker of type $a_i$ currently employed with productivity $x$. Since the rate at which such a worker exits this state is independent of the channel through which she formed the match, the probability that such a worker received her job through channel $j \in \{B, F, O\}$ is

$$\Lambda_j(x|a_i) = \frac{\phi^u(a_i) d \Gamma_j^u(x|a_i) + \Phi^e(x|a_i) d \Gamma_j^e(x|a_i)}{\sum_{j \in \{B,F,O\}} \phi^u(a_i) d \Gamma_j^u(x|a_i) + \Phi^e(x|a_i) d \Gamma_j^e(x|a_i)}.\$$

To see why, note that the numerator represents the flow of (unemployed and employed) type $a_i$ workers into matches of quality $x$ through channel $j$, while the denominator represents the flow of type $a_i$ workers into matches of quality $x$ through any channel. Therefore, we can define the measure of workers of type $a_i$ currently employed with productivity $x$ that got their job through channel $j$ as

$$\phi_j^e(x|a_i) = \Lambda_j(x|a_i) d \Phi^e(x|a_i).\tag{15}$$

Integrating and summing across the working population reveals that the fraction of currently employed workers who got their job through channel $j$ is

$$\frac{1}{1 - u} \sum_i \int_{x_i}^\infty \phi_j^e(x|a_i) dx\tag{16}$$

where

$$u = \sum_i \phi^u(a_i)$$

\[20\] For the sake of presentation, we will relegate the derivation of certain standard moments, such as the job-to-job transition rate, to Appendix D.
denotes the measure of unemployed workers or, equivalently, the unemployment rate (since the measure of workers is normalized to one).

**Wages, Tenure, and Job Search Channel.** To calculate average wages of workers who acquired their job through a specific job search channel, the following lemma is useful.\(^{21}\)

**Lemma 1.** The fraction of workers of type \(a_i\) employed at a firm with productivity \(x \geq x^*_i\) that earn a wage \(w' \leq w\) is given by

\[
G(w|a_i, x) = -\frac{\phi^u(a_i) d\Gamma^u(x|a_i) + \Phi^e(\hat{x}(a_i, x, w)|a_i) d\Gamma^e(x|a_i)}{\phi^e(a_i, x) [\delta + \Gamma^e(\hat{x}(a_i, x, w))]},
\]

for all wages \(w \in [w^u(a_i, x), w^e(a_i, x, x)]\).

To calculate the expected wage of a currently employed worker of type \(a_i\) with productivity \(x\) who got their job through channel \(j\), note that the distribution of wages across workers, conditional on \(a_i\) and current productivity \(x\), is the same for all \(j \in \{B, F, O\}\).\(^{22}\) Hence, the average wage of currently employed workers who got their job through channel \(j\) is

\[
\sum_i \int_{x^*_i}^{x} \mathbb{E}[w|a_i, x] \phi^e_j(x|a_i) dx \over \sum_i \int_{x^*_i}^{x} \phi^e_j(x|a_i) dx ,
\]

where, letting \(\underline{w} \equiv w^u(a_i, x)\) and \(\bar{w} \equiv w^e(a_i, x, x)\),

\[
\mathbb{E}[w|a_i, x] = \underline{w} G(\underline{w}|a_i, x) + \int_{w^u}^{\bar{w}} w dG(w|a_i, x) = \bar{w}(a_i, x) - \int_{w}^{\bar{w}} G_j(w|a_i, x) dw .
\]

Similarly, since the expected tenure of a worker of type \(a_i\) who is currently employed at a firm with productivity \(x\),

\[
\tau(x, a_i) = \frac{1}{\delta + \Gamma^e(x|a_i)},
\]

is also independent of the channel through which the worker got the job, the expected tenure of

\(^{21}\)Note that we derive and target average wages instead of average starting wages. This is because, as is well known, the strategic wage protocol of Postel-Vinay and Robin (2002) and Cahuc et al. (2006) can often produce counterfactual starting wages for those workers hired out of unemployment. Indeed, if the option value of starting to climb the job ladder is sufficiently high, these models can even predict that workers accept negative wages early in their careers, which clearly violates constraints outside of the model (such as the minimum wage).

\(^{22}\)To see why, note that the current wage of a type \(a_i\) worker with productivity \(x\), \(w^e(a_i, x', x)\), only depends on the value \(x' < x\) of either his last job or his last offer (with \(x' = x^*\) if he was last unemployed). Given the nature of Poisson arrivals, \(x'\) does not depend on the channel through which the worker got his current job.
currently employed workers who got their job through channel \( j \) is equal to
\[
\frac{\sum_i \int_{x_i^*} \tau(x, a_i) \phi_j^i(x|a_i) dx}{\sum_i \int_{x_i^*} \phi_j^i(x|a_i) dx}.
\] (20)

5 Quantitative Exercise

In this section, we calibrate the model to key moments in our data. This exercise produces two sets of insights. First, the calibrated parameter values reveal the properties of the matching technologies—i.e., \( \Gamma_j(x|a) \) for \( j \in \{B, F, O\} \)—that are required to match the empirical patterns we observe in high- and low-skill markets. In other words, interpreting the data through the lens of our model reveals the underlying relationships between the job search channels that a worker uses, his unobserved type, and his labor market outcomes. These relationships, in turn, are informative about which theories can potentially explain the primary role of referrals from family and friends, which theories are consistent with the patterns we observe among workers who use referrals from business contacts, and which theories are inconsistent with our empirical findings.

Second, the calibrated model allows us to quantify the extent to which (different types of) referrals affect employment and earnings across workers in high- and low-skill labor markets. In particular, we find that referrals from family and friends are a crucial channel of job search for low ability workers, particularly in low skill jobs. Referrals from business contacts, which also contribute to reduced unemployment and higher earnings, have a more muted impact, as workers who use these referrals most tend to generate offers through other channels relatively frequently as well.

5.1 Maintained Assumptions

We calibrate the model at a monthly frequency. Since our empirical results highlight the differential role of referrals across high- and low-skill jobs, we split our data into two sub-samples: those workers with a bachelors degree or more (whom we refer to as “high skill”), and those with some college or less (whom we refer to as “low skill”).\(^\text{23}\) We think of the two markets as distinct labor markets, and hence calibrate the model separately for each skill group.

In both markets, the discount factor, \( r \), is chosen to yield an annual discount rate equal to 95%. We

\(^{23}\text{As we explain below, we choose to distinguish these two markets by education, as opposed to the NPB score of the occupation, to leverage existing estimates of several key parameters of this model across education groups.}\)
also assume, in both markets, that there are two types of unobserved ability, and normalize \( a_1 = 1 \) and \( a_2 = 2 \). Finally, we choose functional forms for the production and matching technologies that are common across both markets. In particular, we assume a linear production technology, \( f(x) = px + c \), and a matching technology that satisfies

\[
\Gamma_j^u(x|a) = \left( \alpha_j a + \kappa_j \right) \left[ 1 - x^{1+\xi_j a} \right],
\]

for \( j \in \{B, F, O\} \), with \( \Gamma_j^u(x|a) = \theta \Gamma_j^u(x|a) \). According to this functional form, \( \alpha_j \) captures the effect of a worker’s ability on the rate at which she meets firms through channel \( j \), while \( \xi_j \) captures the effect of her ability on the quality of matches that she forms with a firm through channel \( j \). The parameter \( \kappa_j \) captures a level effect of meeting rates across channels—allowing, e.g., meetings through formal (or “other”) channels to occur more frequently for all workers—while \( \theta \) represents the relative efficiency of searching on the job.

### 5.2 Parameters and Targets in High- and Low-Skill Markets

In each market (high and low skill), we set several parameter values outside of the calibration. First, we set \( \delta \) to match the job-destruction rate directly observed in our data. Second, using data from the NLSY, Lise et al. (2016) estimate the value of the bargaining power parameter, \( \beta \), and the relative efficiency of on-the-job search, \( \theta \), across education groups within the context of a model also based on Cahuc et al. (2006). We use their estimates. Finally, we set the flow value of unemployment, \( b \), equal to 25 percent of the average wage of employed workers in each skill group.

Twelve parameters remain for each market: \( \{\alpha_j, \kappa_j, \xi_j\}_{j \in \{B, F, O\}} \) govern the job matching process through the three different channels; \( \{p, c\} \) determine the production technology; and \( \pi_1 \) determines the distribution of unobserved heterogeneity (or ability). We calibrate these parameters to match twelve moments in our data. The first two moments are standard: for each skill group, we target the aggregate unemployment rate and job-to-job (EE) transition rate. Leveraging the detailed description of workers’ job search experience available in our data, the third moment we target is the rate at which

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24We also experimented with versions of the model with more than two types. However, under these specifications, our calibration results tended to load most of the weight on two types.

25Since we are also calibrating the constant \( c \) in the production function \( f(x) = px + c \), the flow value of unemployment does not take on the crucial role that it plays in many search models of the labor market. For robustness, we consider alternative specifications and the main results below are essentially unchanged.
employed workers contact other firms each month.\textsuperscript{26}

The nine remaining moments are specific to the relationship between job search channels and labor market outcomes. To start, using the expression derived in (16), we target the fraction of all employed workers that used a business referral ($j = B$) to find their current job, and the fraction that used a referral from family or friends ($j = F$). Second, using the expression derived in (18), we target the average (log) wage of currently employed workers who got their job through channel $j \in \{B, F, O\}$.\textsuperscript{27} For the next two moments, we use the expression derived in (20) to target the average tenure of workers who got their job through channel $j \in \{B, F\}$, relative to the average tenure of the non-referred.\textsuperscript{28}

Finally, as we discuss in greater detail below, a key mechanism in our model implies a connection between the channel that a worker uses and their place in the wage distribution. In particular, we show that type $a_2$ workers earn higher wages and are more likely to use channel $B$. Hence, following Arbex et al. (2018), we target two additional moments that capture how the fractions of employed workers who used channel $B$ and $F$ change with wages. In particular, in Appendix \textbf{D} we derive an object we denote $\Omega_j(w)$, which represents the fraction of employed workers earning less than wage $w$ who found their job through channel $j \in \{B, F, O\}$. Then, for channels $j = B$ and $j = F$, we target $\Omega_j(w_{75}) - \Omega_j(w_{25})$, where $w_{75}$ and $w_{25}$ denote the wages at the $75^{th}$ and the $25^{th}$ percentiles of the wage distribution, respectively.

Table \textbf{6} reports the model fit for each of the two sub-samples. As one can see, the model is able to match the data well. Table \textbf{10} in Appendix \textbf{D} reports the parameter values that emerge from the calibration.

**Key properties of matching patterns.** To illustrate the key properties of the matching technology required to fit the data, we first plot $\Gamma_j(x|a)$ for $j \in \{B, F, O\}$ corresponding to our estimates from the high skill market; we discuss our estimates from the low skill market below. Two key properties emerge from Figures \textbf{2} and \textbf{3}.

First, matching the data through the lens of our model requires significant heterogeneity in the rate

\textsuperscript{26}We derive explicit expressions for the contact rate and the job-to-job transition rate in Appendix \textbf{D}.

\textsuperscript{27}Note that calculating log wage requires a slight modification to the expressions in (18) and (20).

\textsuperscript{28}As noted earlier in the text, in our data we observe tenure up to the sampling date, and not the total tenure of a completed employment spell. Taking this into account, we only target the difference in observed tenures across job search channels here, and not the levels. Later, when we simulate the model, we compare the two objects—total tenure, and tenure up to a sampling date—using model-generated data to check that they are similar. We find that they are.
Table 6: Moments from Calibrated Model and Data

<table>
<thead>
<tr>
<th>Target</th>
<th>High Skill Model</th>
<th>High Skill Data</th>
<th>Low Skill Model</th>
<th>Low Skill Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment rate</td>
<td>0.052</td>
<td>0.053</td>
<td>0.075</td>
<td>0.075</td>
</tr>
<tr>
<td>Contact rate (employed)</td>
<td>0.125</td>
<td>0.124</td>
<td>0.116</td>
<td>0.115</td>
</tr>
<tr>
<td>EE rate</td>
<td>0.016</td>
<td>0.020</td>
<td>0.018</td>
<td>0.024</td>
</tr>
<tr>
<td>Fraction hired through B referral</td>
<td>0.187</td>
<td>0.187</td>
<td>0.140</td>
<td>0.140</td>
</tr>
<tr>
<td>Fraction hired through F referral</td>
<td>0.204</td>
<td>0.204</td>
<td>0.274</td>
<td>0.274</td>
</tr>
<tr>
<td>Average tenure hired through B relative to non-referral</td>
<td>0.882</td>
<td>0.851</td>
<td>0.884</td>
<td>0.885</td>
</tr>
<tr>
<td>Average tenure hired through F relative to non-referral</td>
<td>1.157</td>
<td>1.161</td>
<td>1.312</td>
<td>1.310</td>
</tr>
<tr>
<td>Average (log) wage non-refferred workers</td>
<td>3.359</td>
<td>3.355</td>
<td>2.894</td>
<td>2.893</td>
</tr>
<tr>
<td>Average (log) wage workers hired though B</td>
<td>3.379</td>
<td>3.412</td>
<td>2.940</td>
<td>2.942</td>
</tr>
<tr>
<td>Average (log) wage workers hired though F</td>
<td>3.352</td>
<td>3.331</td>
<td>2.904</td>
<td>2.904</td>
</tr>
<tr>
<td>Differential usage of B across wage distribution (75/25)</td>
<td>0.035</td>
<td>0.030</td>
<td>0.003</td>
<td>-0.002</td>
</tr>
<tr>
<td>Differential usage of F across wage distribution (75/25)</td>
<td>-0.021</td>
<td>-0.020</td>
<td>0.012</td>
<td>0.006</td>
</tr>
</tbody>
</table>

Notes: This table reports the values of our 12 targeted moments in the data and as computed analytically in our model, separately for the high skill and low skill markets.

at which workers receive offers through any channel. More specifically, the figures make it clear that the arrival rate of all offers for low ability workers, $\Gamma_u(x|a_1)$, is significantly smaller than the arrival rate of offers for high ability workers, $\Gamma_u(x|a_2)$.\(^{29}\) Hence, our calibration suggests that a potentially important source of heterogeneity—which is not present in standard on-the-job search models—lies in the ability of workers to generate offers.

Second, this heterogeneity stems mostly from differences in the arrival rate of offers through business referrals and other (formal) channels, and less so from differences in the arrival rate of offers generated by referrals from family and friends. That is, $\Gamma_B$ and $\Gamma_O$ are more sensitive to $a$ than $\Gamma_F$. Hence, whatever makes different workers more or less able to generate offers manifests itself through more formal methods of job search—referrals from business contacts or other channels—whereas more informal channels (like referrals from family and friends) are more equally effective across all workers.

Lastly, turning to the difference across markets, Figure\(^{[4]}\) illustrates that the basic matching patterns across workers and channels are similar in low- and high-skill markets. However, the heterogeneity discussed above—i.e., the difference in arrival rates across workers of type $a_1$ and $a_2$—is less pronounced in low-skill markets.

\(^{29}\)Recall that the arrival rate of offers for employed workers are simply scaled by $\theta$—i.e., $\Gamma^e(x|a) = \theta \Gamma_u(x|a)$—so that the statements above regarding arrival rates apply equally well to employed and unemployed workers.
Figure 2: Matching technology across workers and channels

Figure 3: Matching technology across workers and channels
Figure 4: Matching technology across high- and low-skill markets
How do these properties generate the patterns we observe in the data? The three properties highlighted above generate the basic patterns we document in the data in a natural way. In particular, the second property implies that a randomly selected employed worker who got her job through channel $B$ is more likely to be type of $a_2$, while a worker who got his job through channel $F$ is more likely to be type $a_1$. Moreover, from the first property above, type $a_2$ workers receive offers more frequently than type $a_1$ workers. Taken together, these properties imply that a worker who got her current job through channel $B$ will continue to get good offers at a high rate after matching, generating a relatively high wage but a relatively short tenure. Alternatively, a worker who got his current job through channel $F$ will receive fewer offers in the future, which implies that he will experience lower wage growth but stay at the firm for a longer tenure. Finally, since these properties are less pronounced in the low-skill labor market, this selection effect is weakened, and the relationship between, e.g., wages and job search method becomes less significant, as in the data.

5.3 The contribution of referrals to labor market outcomes

In this section, we quantify the effect of referrals from business contacts and family and friends on employment, earnings, and inequality. To do so, we simulate the labor market experience of a cohort of workers who enter the market unemployed at $t = 0$, assuming they have access to all three job search channels. Then, we repeat the simulation but shut down referrals from business contacts—i.e., we set $\Gamma_B(x|\alpha) = 0$—and evaluate the earnings of different types of workers ($a_1$ and $a_2$) across low- and high-skill labor markets. Finally, we repeat the exercise but shut down referrals from family and friends, while restoring a worker’s ability to meet firms through business contacts. Table 7 reports the employment status of all workers after ten years ($t = 120$ months), as well as the average earnings of each type of worker over the first ten years of their career.

As one can see, low ability workers rely quite heavily on referrals from family and friends. In the high skill market, for example, the earnings of type $a_1$ workers decrease more than 11% when we shut down referrals from family and friends, while their unemployment rate increases 2.6%. These effects are even stronger in the low skill market, where referrals from family and friends account for more than 20% of earnings and a 4% reduction in the unemployment rate of type $a_1$ workers. In contrast, as type $a_2$ workers use referrals from business contacts and other, formal channels relatively more frequently, shutting down contacts from family and friends has only a minor impact on their labor
Table 7: Contribution of Referrals to Earnings and Employment

<table>
<thead>
<tr>
<th>Exercise</th>
<th>Average Annual Earnings</th>
<th>Unemployment Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High Skill Low Skill</td>
<td>High Skill Low Skill</td>
</tr>
<tr>
<td>Benchmark</td>
<td>$39,455 $64,519</td>
<td>11.40% 1.70%</td>
</tr>
<tr>
<td></td>
<td>$21,045 $42,555</td>
<td>14.20% 3.20%</td>
</tr>
<tr>
<td>Shut down B</td>
<td>-4.5% -2.3%</td>
<td>+0.84 pp +0.48 pp</td>
</tr>
<tr>
<td></td>
<td>-4.7% -6.6%</td>
<td>+1.2 pp +1.1 pp</td>
</tr>
<tr>
<td>Shut down F</td>
<td>-11.1% -0.6%</td>
<td>+2.6 pp +0.02pp</td>
</tr>
<tr>
<td></td>
<td>-21.1% -1.4%</td>
<td>+4.1pp +0.2 pp</td>
</tr>
</tbody>
</table>

Notes: This table reports estimates from a simulation of our calibrated model in which workers enter the market in unemployment and then follows them for a period of 10 years. The left panel measures average annual earnings over these 10 years, and the right panel measures the unemployment rate in the last period. In the first row we report these measures separately by market and by ability type. In the second and third rows we report how these baseline results change when we shut down business and family/friends referrals in the model.

Interestingly, however, shutting down referrals from business contacts has only a modest effect on earnings, particularly for type $a_2$ workers in the high skill market. Intuitively, while these workers generate offers through channel $B$ at a high frequency, and thus use this channel to get jobs fairly often, they generate offers through channel $O$ at a high rate, too. Hence, they climb the job ladder fairly quickly with or without referrals from business contacts. In the low skill market, however, type $a_2$ workers generate offers significantly less frequently, through all three channels, and hence climb the job ladder considerably more slowly. As a result, the marginal contribution of additional offers is much higher, so that shutting down contacts through business referrals has a more sizeable impact on earnings.

Discussion. The results in Table 7 suggest that referrals play an important role in generating matches between workers and firms, and in generating offers that can be used by workers to increase their wages. Of course, these results are vulnerable to the standard Lucas et al. (1976) critique, as workers could potentially respond to losing access to one job search channel by expending more energy pursuing contacts through other sources. However, existing evidence (Mukoyama et al., 2018) suggests that workers already exploit available job search channels—with plenty of time to spare—which suggests that it might not be so easy, e.g., to find a substitute for job opportunities that arise through one’s network of family and friends.

In this case, our results suggest that referrals from friends and relatives are crucial for a subset of workers that struggle to generate offers and matches through other, more traditional channels.
Therefore, an important takeaway from our analysis is that referrals from family and friends play a key role in reducing inequality by supporting the earnings of workers who fall in the left tail of the distribution. Interestingly, the large contribution of referrals from family and friends to the earnings prospects of low ability workers also has meaningful implications for their mobility patterns: if a worker’s network of family and friends is specific to a particular geographic location (such as their hometown), then the results in Table 7 could help explain why studies of geographical mobility seem to impute large, yet difficult to explain moving costs.

Notice that the results in Table 7 also highlight the importance of interpreting the data through the lens of a model. For instance, the regression results in Table 3, which report the correlation between the use of these two types of referrals and wages, might lead one to believe that referrals from business networks have a large, positive effect on worker’s wages, while referrals from family and friends have a smaller, negative effect on wages. However, by allowing for unobserved heterogeneity and accounting for selection effects, our modeling exercise illustrates that this conclusion would be erroneous. Instead, our calibration suggests that referrals from family and friends play a crucial role in the job search process for large segments of the labor market.
A Data Description

In this appendix we describe how we arrive at our final estimation sample and provide additional details regarding the construction of our wage and tenure variables.

Our data set combines the cross-sectional surveys of the SCE from 2013-2018. We keep individuals that are of working age (18 to 64) and that are not self-employed, for a total of 5,099 observations. After excluding individuals who work in military occupations and dropping a small number of observations with missing demographic data or inconsistent wage data, we are left with a final sample of 5,062 observations.

All three wage measures (current, starting, previous) are reported as either hourly, weekly, or annual. Survey respondents are also asked to report their usual hours spent at their job per week for both their current job and their previous job. We divide weekly wages by usual hours and annual wages by usual hours and by 52 to convert everything to hourly wages. We then deflate all three nominal wage measures using the relevant CPI index obtained from the BLS.

For job tenure, the SCE survey asks workers the month and year in which they started their current job. We use this information to compute the duration of the worker’s current job at the time of the survey.

\[\text{For the 2013 data, survey respondents were not directly asked the usual hours on their previous job, and instead were asked how much their hours increased or decreased from their previous job. We use this change and the reported usual hours at the current job to construct previous hours.}\]
B Additional Empirical Results

Job Satisfaction and Referrals

Table 8 reports results from a regression relating the job search method used to find a worker’s current job and their reported satisfaction with that job in response to the following questions:

1. “Taking everything into consideration, how satisfied would you say you are, overall, in your current job?”
2. “How satisfied would you say you are with your level of compensation at your current job?”
3. “How well do you think this job fits your experience and skills?”
4. “How would you rate the opportunities for a promotion or other career progression with your current employer, over the next three years?”
5. “How satisfied would you say you are with other aspects of the job, such as benefits, maternity/paternity leaves, flexibility in work hours, etc?”

To construct the dependent variable, a response of “very satisfied” or “somewhat satisfied” is assigned a value 1, and a response of “very dissatisfied,” “somewhat dissatisfied,” or “indifferent” is assigned a value 0. As the results indicate, there are no systematic differences in job satisfaction on across job search method.

Search Behavior of Employed Workers and Referrals

Table 9 reports results from a regression relating four measures of on-the-job search to the method used to find a worker’s current job. The measures we use are number of job applications sent out in the past 4 weeks, whether any job search was performed over the past weeks as well as the past 12 months, and the number of hours of job search over the past 4 weeks. Overall there do not seem to be any large differences in on-the-job search based across job finding method. There is some weak evidence that individuals who found their job via family/friends referral are slightly less likely to have searched over the past 12 months, although not over the past 4 weeks. There is also some evidence that business referred workers search more in terms of hours, but not in terms of overall probability.
Table 8: Job Satisfaction and Referrals

<table>
<thead>
<tr>
<th></th>
<th>Overall</th>
<th>Compensation</th>
<th>Fit</th>
<th>Promotion</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>Business Referral</td>
<td>0.080</td>
<td>0.069</td>
<td>0.069</td>
<td>0.132</td>
<td>0.093*</td>
</tr>
<tr>
<td>(0.051)</td>
<td>(0.054)</td>
<td>(0.059)</td>
<td>(0.089)</td>
<td>(0.053)</td>
<td></td>
</tr>
<tr>
<td>Family/Friends Referral</td>
<td>0.019</td>
<td>0.013</td>
<td>0.013</td>
<td>-0.050</td>
<td>-0.032</td>
</tr>
<tr>
<td>(0.045)</td>
<td>(0.048)</td>
<td>(0.052)</td>
<td>(0.080)</td>
<td>(0.048)</td>
<td></td>
</tr>
<tr>
<td>Skill Index</td>
<td>0.004***</td>
<td>0.005***</td>
<td>0.007***</td>
<td>0.005***</td>
<td>0.006***</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Time and Region FE</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Individual Controls</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>N</td>
<td>3068</td>
<td>3067</td>
<td>3067</td>
<td>3068</td>
<td>3067</td>
</tr>
</tbody>
</table>

Notes: Estimates are from regressions based on indicator variables constructed from categorical responses regarding five different measures of job satisfaction. Individual controls include age, gender, race, marital status, number of children under the age of 6, and home ownership status. Standard errors are presented in parentheses below the point estimates. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level. These questions were not asked in 2013, which reduces the number of observations by 711. For 3 of the measures we do not observe satisfaction for 1 individual.

C Omitted Proofs

Proof of Proposition 1

First, note that, by construction, the $\hat{x}(a, x, f(x))$ threshold has the following properties, which are useful later:

$$x = \hat{x}(a, x, f(x))$$  \hspace{1cm} (22)

$$V^e(a_i, x, w) = V^e(a_i, \hat{x}(a_i, x, w), f(\hat{x}(a_i, x, w))).$$  \hspace{1cm} (23)

Now, by substituting (10), equation (6) can be written

$$[r + \delta + \Gamma^e(\hat{x})] V^e(a_i, x, w) = w + \delta V^u(a_i) + V^e(a_i, x, f(x)) [\beta [\Gamma^e(\hat{x}|a_i) - \Gamma^e(x|a_i)] + (1 - \beta)\Gamma^e(x|a_i)]$$

$$- (1 - \beta) \int_\hat{x}^x V^e(a_i, x', f(x')) d\Gamma^e(x'|a_i) - \beta \int_\hat{x}^x V^e(a_i, x', f(x')) d\Gamma^e(x'|a_i),$$

where, again, we’ve used $\hat{x} \equiv \hat{x}(a_i, x, w)$ to economize on notation.

Setting the wage $w = f(x)$, substituting (22), and simplifying yields

$$[r + \delta + \beta \Gamma^e(x)] V^e(a_i, x, f(x)) = f(x) + \delta V^u(a_i) - \beta \int_x^\pi V^e(a_i, x', f(x')) d\Gamma^e(x'|a_i).$$
Table 9: On-the-Job Search and Referrals

<table>
<thead>
<tr>
<th></th>
<th># of Applications (Last 4 Weeks)</th>
<th>Any Search (Last 4 Weeks)</th>
<th>Any Search (Last 12 Months)</th>
<th>Search Hours (Last 4 Weeks)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Business Referral</td>
<td>-0.028</td>
<td>0.020</td>
<td>0.005</td>
<td>0.252*</td>
</tr>
<tr>
<td></td>
<td>(0.217)</td>
<td>(0.018)</td>
<td>(0.022)</td>
<td>(0.149)</td>
</tr>
<tr>
<td>Family/Friends Referral</td>
<td>-0.190</td>
<td>0.010</td>
<td>-0.036*</td>
<td>0.148</td>
</tr>
<tr>
<td></td>
<td>(0.195)</td>
<td>(0.016)</td>
<td>(0.020)</td>
<td>(0.134)</td>
</tr>
<tr>
<td>Skill Index</td>
<td>-0.012***</td>
<td>-0.001**</td>
<td>-0.000</td>
<td>-0.010***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Time and Region FE</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Individual Controls</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>N</td>
<td>3779</td>
<td>3765</td>
<td>3118</td>
<td>3779</td>
</tr>
</tbody>
</table>

Notes: Estimates are from regressions on the total number of applications sent in the past 4 weeks, indicators for whether individuals have searched at all for a job over the past 4 weeks and past 12 months, and the total number of job search hours over the past 4 weeks. Individual controls include age, gender, race, marital status, number of children under the age of 6, and home ownership status. Standard errors are presented in parentheses below the point estimates. *** denotes significance at the 1% level, ** denotes significance at the 5% level, and * denotes significance at the 10% level. There are 14 observations for which we do not observe search behavior over the past 4 weeks. For search behavior over the past 12 months we exclude observations for which individuals have a tenure of less than 12 months, since we cannot determine whether they were searching on or off the job.

Differentiating with respect to $x$ then yields

$$
\frac{\partial V^e(a_i, x, f(x))}{\partial x} = \frac{p}{r + \delta + \beta \Gamma^e(x|a_i)}.
$$

(24)

Using this relationship in the expression for $V^e(a_i, x, w)$ above, integrating by parts, using (6), and simplifying yields

$$(r + \delta)V^e(a_i, x, w) = w + \delta V^u(a_i)$$

(25)

$$+ p \left[ (1 - \beta) \int_x^x \frac{\Gamma^e(x'|a_i)}{r + \delta + \beta \Gamma^e(x'|a_i)} dx' + \beta \int_x^{x'} \frac{\Gamma^e(x'|a_i)}{r + \delta + \beta \Gamma^e(x'|a_i)} dx' \right].$$

Plugging in $w = w^e(a_i, x, x')$, subtracting $(r + \delta)V^e(a_i, x, f(x))$, and using (6) yields

$$(r + \delta) [V^e(a_i, x', f(x')) - V^e(a_i, x, f(x))] =$$

$$w^e(a_i, x, x') - f(x) + p \left[ (1 - \beta) \int_x^{x'} \frac{\Gamma^e(x''|a_i)}{r + \delta + \beta \Gamma^e(x''|a_i)} dx'' - \beta \int_x^{x'} \frac{\Gamma^e(x''|a_i)}{r + \delta + \beta \Gamma^e(x''|a_i)} dx'' \right].$$

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since \( \hat{x}(a_i, x, \omega_e(a_i, x, x')) = x \). Using (24) yields

\[
\begin{align*}
\omega_e(a_i, x, x') &= (r + \delta)\beta \int_x^{x'} \frac{p}{r + \delta + \beta \Gamma_e(x''|a_i)} dx'' + f(x) - p(1 - 2\beta) \int_x^{x'} \frac{\Gamma_e(x''|a_i)}{r + \delta + \beta \Gamma_e(x''a_i)} dx''.
\end{align*}
\]

Straightforward algebra then yields the expression in (10).

Next, to characterize \( x_i^\star \), note that we can use (2) and (24) to get that

\[
\begin{align*}
rV^u(a_i) &= b - \int_{x_i^\star}^{\Gamma} [V^e(a_i, x, \omega^u(a_i, x)) - V^u(a_i)] d\Gamma^u(x|a_i) \\
&= b - \beta \int_{x_i^\star}^{\Gamma} [V^e(a_i, x, f(x)) - V^u(a_i)] d\Gamma^u(x|a_i) \\
&= b + \beta \int_{x_i^\star}^{\Gamma} \frac{p\Gamma^u(x|a_i)}{r + \delta + \Gamma_e(x|a_i)} dx,
\end{align*}
\]

where the last equality follows from integration by parts. We can also use (1) and (25) to write

\[
\begin{align*}
rV^e(a_i, x_i^\star, f(x_i^\star)) &= f(x_i^\star) + \delta V^u(a_i) + \beta \int_{x_i^\star}^{\Gamma} \frac{p\Gamma^e(x|a_i)}{r + \delta + \Gamma_e(x|a_i)} dx \\
\Rightarrow rV^u(a_i) &= f(x_i^\star) + \beta \int_{x_i^\star}^{\Gamma} \frac{p\Gamma^e(x|a_i)}{r + \delta + \Gamma_e(x|a_i)} dx.
\end{align*}
\]

Equating (26) and (27) yields (12).

Finally, to characterize the equilibrium distributions, note that substituting (7) into (8) yields (13), and substituting (13) into (9) then yields (14).

**Proof of Lemma 1**

Let \( G(w|a_i, x) \) denote the fraction of type \( a_i \) workers currently employed at a firm with productivity \( x \) that earn a wage \( w' \leq w \). In a steady-state equilibrium, the outflow of such workers is

\[
G(w|a_i, x)\phi^e(a_i, x) [\delta + \Gamma^e(x|a_i)].
\]

Intuitively, the product of the first two terms yields the measure of workers of type \( a_i \) employed at a firm with productivity \( x \) that earn a wage \( w' \leq w \). The third term yields the rate at which these workers exit the set, either because the job is destroyed or because they contact a new firm with productivity \( x' > \hat{x}(a_i, x, w) \).
The inflow of workers into this set can be written

\[ \phi^u(a_i) \sum_j \lambda^u_j(a_i) h_j(x|a_i) + \Phi^e(\hat{x}(a_i, x, w)|a_i) \sum_j \lambda^e_j(a_i) h_j(x|a_i). \]  

(29)

Intuitively, type \( a_i \) individuals in employment state \( k \in \{e, u\} \) receive opportunities to be employed at firms of type \( x \) through channel \( j \) at rate

\[ \sum_j \lambda^k_j(a_i) h_j(x|a_i) = -d\Gamma^k(x|a_i). \]

However, they will only accept and earn a wage \( w' \leq w \) if (i) they are hired from unemployment, or (ii) they were employed at a firm of type \( x' < x \) such that \( w^e(a_i, x', x) \leq w \) or, equivalently, a firm of type \( x' \leq \hat{x}(a_i, x, w) \). Equating the outflow and inflow in equations (28) and (29) yields the result.

For the sake of completeness, here we derive \( g(w|a_i, x) = dG(w|a_i, x) \), the density of wages across workers of ability \( a_i \) currently employed at productivity \( x \). Differentiating (17) yields

\[
g(w|a_i, x) = -\frac{\partial \hat{x}}{\partial w} \left\{ \phi^e(\hat{x}|a_i) d\Gamma^e(x|a_i) \left[ \delta + \Gamma^e(\hat{x}) \right] - \left[ \phi^u(a_i) d\Gamma^u(x|a_i) + \Phi^e(\hat{x}|a_i) d\Gamma^e(x|a_i) \right] d\Gamma^e(\hat{x}) \right\},
\]

where

\[
\frac{\partial \hat{x}}{\partial w} = \frac{r + \delta + \beta \Gamma^e(\hat{x}|a_i)}{p(1 - \beta) [r + \delta + \Gamma^e(\hat{x}|a_i)]}.
\]
Additional Results from Quantitative Exercise

Additional moments used in the calibration

Here we derive analytical expressions for several additional moments used in the calibration.

**Offer rate for employed workers.** The model is silent on whether a firm “makes an offer” to a worker when the surplus of the match is negative, i.e., when \( x < x^*_i \). We adopt the convention that offers are only extended when there is a positive surplus to the match. Hence, the arrival rate of offers for employed workers is

\[
\sum_i \frac{\Phi^e(1|a_i)}{1-u} \left[ 1 - e^{-\Gamma^e(x^*_i|a_i)} \right].
\]

(30)

**Job-to-job transition rate** Since a worker currently matched at a type \( x \) job moves if and only if he contacts a firm and draws \( x' > x \), the job-to-job transition rate is:

\[
\sum_i \frac{\Phi^e(1|a_i)}{1-u} \int_{x^*_i}^{\pi} \left[ 1 - e^{-\Gamma^e(x|a_i)} \right] \frac{d\Phi^e(x|a_i)}{\Phi^e(1|a_i)} = \frac{1}{1-u} \sum_i \int_{x^*_i}^{\pi} \left[ 1 - e^{-\Gamma^e(x|a_i)} \right] d\Phi^e(x|a_i). \]

(31)

**Use of referrals across wages.** Let \( \omega_j(a, x|w) \) denote the cumulative measure of workers of type \( a \) who are matched at a firm with productivity \( x \) that got their job through channel \( j \in \{B, F, O\} \) and currently earn wage \( w' \leq w \). In a stationary equilibrium we must have

\[
\dot{\omega}_j(a, x|w) = \Phi^e(\tilde{x}(a, x, w)|a) d\Gamma^e_j(x|a) + \phi^u(a) d\Gamma^u_j(x|a) \mathbb{I}_{\{w \geq w^u(x, a)\}}
\]

\[
- \omega_j(a, x|w) \left[ \delta + \Gamma^e(\tilde{x}(a, x, w)|a) \right] = 0.
\]

The first line in the expression above captures the inflow of workers into the set. First, a mass \( \Phi^e(\tilde{x}(a, x, w)|a) d\Gamma^e_j(x|a) \) of type \( a \) workers accept offers that arrived through channel \( j \) at a job with match-specific productivity \( x \) and earn a wage less than or equal to \( w \). Second, a mass \( \phi^u(a) d\Gamma^u_j(x|a) \) of type \( a \) unemployed workers accept an offer that arrived through channel \( j \) at a job with match-specific productivity \( x \), and hence enter the set if \( w \geq w^u(a, x) \). The second line in the expression captures the outflow of workers, who exit either because the match is destroyed or because an offer arrives that increases their current wage above \( w \) (either at the incumbent or the poaching firm).
Solving yields
\[ \omega_j(a, x|w) = \frac{\Phi^e(\hat{x}(a, x, w)|a) d\Gamma^e_j(x|a) + \phi^u(a) d\Gamma^u_j(x|a) \mathbb{1}_{\{w \geq w^u(x, a)\}}}{\delta + \Gamma^e(\hat{x}(a, x, w)|a)}. \]

Using this, the measure of workers earning wage \( w' \leq w \) that got their job through channel \( j \) is:
\[ \Omega_j(w) = \sum_i \int \omega_j(a_i, x|w) dx. \]

Then the fraction of workers earning \( w' \leq w \) that got their job through channel \( j \) is:
\[ \frac{\Omega_j(w)}{\sum_j \Omega_j(w)}. \]

**Parameter Values from Calibration.**

Table 10 reports the parameter values from the calibration.
Table 10: Parameter Values from Calibration

<table>
<thead>
<tr>
<th>Parameter</th>
<th>High Skill</th>
<th>Low Skill</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\xi_B$</td>
<td>7.48</td>
<td>2.85</td>
</tr>
<tr>
<td>$\alpha_B$</td>
<td>0.76</td>
<td>0.30</td>
</tr>
<tr>
<td>$\kappa_O$</td>
<td>-0.74</td>
<td>-0.29</td>
</tr>
<tr>
<td>$\xi_F$</td>
<td>45.08</td>
<td>55.81</td>
</tr>
<tr>
<td>$\alpha_F$</td>
<td>0.08</td>
<td>0.00</td>
</tr>
<tr>
<td>$\kappa_O$</td>
<td>-0.06</td>
<td>0.02</td>
</tr>
<tr>
<td>$\xi_O$</td>
<td>19.48</td>
<td>9.81</td>
</tr>
<tr>
<td>$\alpha_O$</td>
<td>0.82</td>
<td>0.34</td>
</tr>
<tr>
<td>$\kappa_O$</td>
<td>-0.76</td>
<td>-0.29</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.16</td>
<td>0.33</td>
</tr>
<tr>
<td>$p$</td>
<td>74.62</td>
<td>74.59</td>
</tr>
<tr>
<td>$c$</td>
<td>-40.96</td>
<td>-46.73</td>
</tr>
<tr>
<td>$b$</td>
<td>7.21</td>
<td>4.56</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.27</td>
<td>0.19</td>
</tr>
<tr>
<td>$\pi_1$</td>
<td>0.47</td>
<td>0.45</td>
</tr>
</tbody>
</table>

Notes: This table presents our calibrated parameter values, separately for the high skill and low skill markets. The $\xi$ parameters capture the effect of ability on the distribution of match-specific productivity. The $\alpha$ parameters capture the effect of worker ability on the arrival rate of offers. The $\kappa$ parameters capture the level differences in arrival rates across channels. $\delta$ is the exogenous job destruction rate. $\theta$ is the relative efficiency of searching on the job. $p$ and $c$ are the production function parameters. $b$ is the flow value of unemployment. $\beta$ is the bargaining power parameter. $\pi_1$ is the probability of low ability types.
References


