The Heterogeneous Impact of Referrals on Labor Market Outcomes[*†]

Benjamin Lester
Federal Reserve Bank of Philadelphia

David A. Rivers
University of Western Ontario

Giorgio Topa
Federal Reserve Bank of New York and IZA

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Abstract

We study the impact of referrals on labor market outcomes. First, we document a new set of facts exploiting data that allow us to distinguish directly between different types of referrals—those from family and friends and those from business contacts—and different types of jobs, as measured by the skill requirements of the occupation. We then develop a structural framework to interpret these facts and quantify the effects of social and business networks on employment, earnings, output, and inequality. Referrals from family and friends generate good jobs for all workers but are relied upon by those who struggle to generate offers through other channels. Referrals from business contacts are used predominantly by more productive workers who receive offers through other channels relatively frequently. An important implication is that referrals from business contacts exacerbate earnings inequality, while referrals from family and friends actually reduce inequality.

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1 Introduction

How do workers and firms form matches? Answering this question is not only crucial for explaining aggregate labor market outcomes, such as unemployment rates and output, but also for understanding the sources of inequality across individual labor market outcomes. Economists have explored a number of observable worker characteristics that are potential sources of inequality—including education, race, gender, family income, and geographic location—but much less attention has been paid to heterogeneity in workers' "job-finding capital," i.e., the resources and/or ability they have available to help them find a job. And yet, it is well documented that a worker's network of family, friends, and business associates is a crucial input into forming a match: according to surveys of workers and firms, approximately half of all jobs report using a *referral* somewhere in the hiring process.[1]

But what do referrals actually do? How do matches formed through a referral differ in terms of productivity, wages, and tenure? Do referrals help workers who otherwise struggle to find jobs through formal channels, and thus reduce inequality? Or do they help the well connected get even further ahead, and thus exacerbate inequality? Unfortunately, identifying the role that referrals play in the hiring process and quantifying their effect on labor market outcomes has faced two important challenges. First, there are few *representative* datasets that contain *direct information* about whether a referral was used to form a match. Second, even when referrals are observed in the data, the set of workers who use referrals is likely to be a *selected sample*. Given these challenges, it is perhaps not surprising that the empirical literature has found mixed evidence regarding even basic facts about referrals, such as the types of workers that use referrals most frequently or the effects of a referral on a worker's subsequent wages and tenure at the firm.[2] Without a clear understanding of the role that referrals play in matching workers and firms—or the quantitative effect on employment, wages, productivity, and output—it is difficult to design policies aimed at improving labor market efficiency and/or reducing inequality.[3]

[1]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).

[2]For example, examining the relationship between the use of a referral and match quality (typically measured using wages), Corcoran et al. (1980), Datcher (1983), Simon and Warner (1992), Marmaros and Sacerdote (2002), Kugler (2003), Bayer et al. (2008), and Dustmann et al. (2016) find a positive relationship; Pistaferri (1999), Mouw (2003), and Bentolila et al. (2010) find a negative relationship; and Marsden and Gorman (2001), Loury (2006), and Pellizzari (2010) report mixed results.

[3]As Bolte et al. (2020) argue, "[u]nderstanding the common sources of inequality and immobility is essential to designing policies that deal not only with their symptoms but also their causes." Heath (2018) offers several concrete examples of how policy should depend on the friction that referrals help overcome. For instance,

In this paper, we overcome the challenges cited above in two steps. First, we present new empirical findings using a representative survey of workers that contains direction information about whether a worker used a referral to find her current job, along with details about the nature of the relationship between the employee and the individual who provided the referral. Our main finding is that clear patterns in the data emerge only after distinguishing between *different types of jobs*, as measured by the skill requirements of the occupation, and *different types of referrals*—namely, those from a worker's social network (a family member or friend) and those from her network of business contacts. Second, to interpret these empirical findings and shed light on the underlying mechanisms, we construct a structural model of on-the-job search in which heterogeneous workers contact firms through different channels, including the two distinct types of referrals described above. Calibrating the model's parameters to match key moments from the data reveals new insights about the qualitative role of referrals in the hiring process and the quantitative implications for employment, wages, productivity, and inequality.

Qualitatively, we find that different theories are required to understand jobs formed through a referral from a worker's business network and those from a worker's social network. In particular, our results suggest that referrals from business contacts primarily screen workers based on their expected productivity—that is, they help firms find *ex ante* good worker types—as in theories in which referrals ameliorate asymmetric information about workers' productivity.[4] In contrast, referrals from family and friends generate good matches for all worker types, as in theories in which referrals improve match quality *ex post* by resolving symmetric uncertainty about match productivity or by easing inefficiencies associated with moral hazard. Quantitatively, we find that referrals from family and friends provide a key source of earnings for workers at the lower end of the income distribution, particularly in low skill markets, and thus tend to reduce earnings inequality. In contrast, referrals from business contacts primarily help high productivity workers with high incomes, particularly in high skill occupations, and thus exacerbate earnings inequality. Hence, while both types of referrals are an important source of new and better matches, the oft-discussed trade-off between output and inequality applies only to referrals from business contacts in our calibrated model.

We now describe in greater detail the data we use and the empirical facts we uncover, the model we construct to interpret these facts, and the main qualitative and quantitative insights that emerge from calibrating this model and using it to perform counterfactual exercises. Then, we explain how these results help to resolve some of the conflicting results in the existing literature, provide new insights into the role of referrals in the hiring process, and contribute to our understanding of inequality in labor market outcomes.

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she writes, "if referrals reduce search costs, companies could be required to publicize job openings," while "if referrals help companies select good workers, policy makers could offer skills certifications."

[4]We discuss existing theories about the role of referrals in more detail in Section 1.1.

Empirical Findings. We use data from the Job Search supplement to the Survey of Consumer Expectations (SCE), which is administered by the Federal Reserve Bank of New York. This dataset is particularly well-suited to our objectives in several dimensions. First, as noted above, the survey asks a broad range of questions regarding how employed workers found their current job, including whether they used a referral and the identity of the referrer. We group the responses into two classifications— "family and friends" and "business contacts"—which allows us to distinguish between referrals drawn from a worker's social and professional networks, respectively. Second, it asks about many characteristics of the job including wages, benefits, job tenure, job satisfaction, and on-the-job search behavior. In addition to detailed information about the current job, the survey also contains information about respondents' previous work experience, providing us with some scope for controlling for unobserved worker heterogeneity. Finally, since the SCE is meant to capture a representative sample of the US population, the dataset covers workers across a wide range of individual characteristics and occupations.

Our main empirical finding is that a referral from a worker's social network (friends and relatives) and a referral from her business network are completely different, and distinguishing between them is crucial for understanding the role of referrals in the labor market. To start, the two types of referrals appear to be used more frequently in different markets: referrals from family and friends are used most frequently to form matches in low skill occupations, whereas referrals from business contacts are used more intensely in high skill labor markets. Moreover, the correlations between the use of these two types of referrals and various labor market outcomes are opposites: workers who used a referral from a business contact tend to earn higher starting wages than non-referred workers but experience shorter job tenures, whereas 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 but experience less job turnover. Digging deeper, we find that the most likely explanation for these patterns derives from selection on unobserved heterogeneity. In particular, we document that the workers who got their current job using a business referral tend to meet firms at a relatively high rate—while unemployed and employed—whereas workers who got their current job through their network of family and friends generate contacts with firms at a relatively low rate.

Hence, the first part of the paper establishes that clear empirical relationships between referrals and labor market outcomes emerge once we distinguish along two relatively unexplored dimensions of the data: the source of the referral, and the type of job or occupation. These results are important for at least two reasons. First, they help explain why previous studies—which could not make the same distinctions—found mixed or conflicting results. Second, and perhaps more importantly, the patterns we document are informative about the key ingredients that a theoretical model of referrals should contain; they provide clear guideposts for the qualitative relationships that should (endogenously) emerge from such a model; and they serve as natural targets to calibrate the model and quantify the effects of these two types of referrals on labor market outcomes.

Model. Motivated by the empirical patterns we observe in the data, we construct a model with three key ingredients. First, given the clear correlations we find between various labor market outcomes and the channel through which a worker found a job, we allow for different technologies for initiating contact between workers and firms: formal search methods, referrals from business contacts, and 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 the worker draws 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.

Given these ingredients, our model can be seen as a natural extension of the workhorse models of on-the-job search with unobserved worker heterogeneity (Postel-Vinay and Robin, 2002; Cahuc et al., 2006), modified to allow for a worker's unobserved type to affect both the frequency and quality of matches formed through multiple job search channels. The model is intentionally constructed to be rich enough to confront our empirical findings, yet equally as tractable as its predecessors. We exploit this tractability to derive closed-form expressions for the new, key moments we identify from our micro-data, which allows us to calibrate a large number of parameters with minimal computational burden.

Calibration. We calibrate the model via indirect inference, which reveals the values of the structural parameters required to generate the patterns we observe in the data. In particular, interpreting the data through the lens of our model reveals the underlying relationships between a worker's unobserved type, the frequency with which the worker meets firms through different job search channels, the quality of these potential matches, and the implications for labor market outcomes. This exercise produces both qualitative and quantitative insights into the effects of referrals on labor market outcomes.

First, we find that a significant amount of the heterogeneity in employment and earnings is driven by the fact that some types of workers meet firms through business referrals much more frequently than other types. The fact that business referrals are highly sensitive to a worker's unobserved type—and, thus, the worker's *ex ante* expected productivity—suggests that referrals from business contacts are used primarily to screen workers. Hence, we find that business referrals are best described by theories which ascribe a central role to a referrer's ability to convey otherwise-private information about the job candidate, as in models based on adverse selection and homophily (e.g., Montgomery, 1991).

Referrals from family and friends are consistent with entirely different theories. In particular, we find that referrals from family and friends are used more uniformly across worker types and generate relatively high productivity matches, on average, conditional on a worker's type. Hence, these types of referrals are better described by theories in which a referral improves match quality *ex post*—for example, by reducing symmetric uncertainty about idiosyncratic match quality (as in, e.g., Simon and Warner, 1992) or easing inefficiencies that derive from moral hazard (as in, e.g., Heath, 2018).

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, earnings, inequality, and output 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 certain workers that struggle to generate offers and matches through more traditional channels. For example, in the low-skill labor market, we find that denying a "low ability" worker referrals from family and friends would reduce the worker's earnings by more than 11% and increase the worker's likelihood of unemployment by 6 percentage points. Hence, despite concerns that referrals based on nepotism may 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, in contrast, are used more frequently by high ability workers—who also receive offers through other channels at a high frequency—and their contribution to earnings is more pronounced in high skill occupations. Again, these results highlight the importance of interpreting our data through the lens of a model. The positive relationship between the use of a business referral and wages alone might have suggested that referrals from business contacts create high quality, productive matches. However, our model reveals that an important aspect of business referrals is that they increase the wages of workers who have relatively good employment prospects to begin with. Hence, the use of business referrals, which is typically encouraged by firms, increases output but also exacerbates earnings inequality.

These findings suggest that the implications of referrals may be more nuanced than they appear at first glance, and speak to the ongoing debate about the sources of economic inequality and the design of policies aimed at mitigating any unintended, adverse effects.[5] For one, our

[5] See Topa (2019) and Hellerstein and Neumark (2020) for additional discussion on the implications of referrals for inequality.

results indicate that identifying the source of a referral is crucial for achieving different policy objectives; a law or an employer referral program that treats all types of referrals with the same broad brush will almost surely have unintended consequences. If the source of the referral cannot be distinguished (or verified), one should at least allow their policy prescriptions to vary across occupations with different skill requirements.

Our results also shed new light on the unseen, heterogeneous costs associated with worker mobility. For example, if moving away from home reduces the value of a worker's social network in finding a job, then workers in low-skill occupations will naturally face higher moving costs. In contrast, if changing occupation reduces the value of a worker's existing network of business contacts, then the cost of occupational mobility would be relatively large for the high skilled. We expand on the connections between our results and the broader discussion of mobility and inequality in the literature review below.

1.1 Related literature

Our paper contributes to the large (and growing) literature that studies the effects of referrals on labor market outcomes.[6] Most early attempts to quantify the impact of finding a job through a referral focused primarily on deriving empirical estimates of the productivity, wages, and turnover of referred workers, relative to non-referred workers; see, for instance, the seminal work by Datcher (1983), as well as Corcoran et al. (1980), Green et al. (1995), and Korenman and Turner (1996). However, since referrals are typically not randomly assigned, these estimates are potentially driven by selection and unobserved heterogeneity, as opposed to capturing the direct effects of referrals. Broadly speaking, the literature has pursued two different approaches to overcome this challenge. First, a number of recent papers have exploited the availability of panel data and more sophisticated identification strategies to estimate the direct effects of referrals, including Bayer et al. (2008), Kramarz and Skans (2014), Schmutte (2015), Dustmann et al. (2016), Gee et al. (2017), and Heath (2018). Alternatively, a number of papers have used experimental settings to generate exogenous variation in the use of referrals; see, e.g., Bandiera et al. (2009), Beaman and Magruder (2012), Pallais and Sands (2016), and Friebel et al. (2023).

Our paper complements these strands of the literature in several important ways. The first derives from the unique nature of our data, which are drawn from a wide array of workers and occupations and contain detailed information about the job search process, including direct information about the use of different types of referrals. In contrast, most existing studies rely on data that either contain detailed information about job search methods *or* contain a representative sample of workers and/or occupations.[7] Using these data, we document a

[6]For a broad overview of this literature, we refer the reader to the surveys by Ioannides and Loury (2004) and Topa (2011), and concentrate here on those studies most related to our work.

[7]For example, the data used by Brown et al. (2016), Burks et al. (2015), Castilla (2005), Heath (2018), and

new set of stylized facts that highlight the heterogeneous impacts of referrals, and provide a novel explanation for conflicting results in earlier studies. Second, we account for the role of unobserved worker heterogeneity and selection by interpreting the relationships we observe in the data through the lens of a model. Targeting a large number of moments from the data allows us to recover key model parameters, which reveal new qualitative insights into the role of (different types of) referrals in the matching process, along with quantitative estimates of the contribution of (different types of) referrals to employment, earnings, inequality, and output.

Our paper also complements the large theoretical literature that studies how referrals ease certain frictions in the matching process, and the subsequent implications for labor market outcomes. For example, some theories posit that referrals reduce adverse selection, since a current employee can provide information about a prospective worker's unobserved productivity (Montgomery, 1991; Casella and Hanaki, 2008; Galenianos, 2014; Bolte et al., 2020). Other theories conjecture that referrals create good matches by reducing symmetric uncertainty regarding idiosyncratic match quality (Simon and Warner, 1992; Dustmann et al., 2016; Brown et al., 2016; Galenianos, 2013). Still others propose that referred workers are more productive *ex post* because the referrer can monitor or mentor the new worker (Kugler, 2003; Castilla, 2005; Beaman and Magruder, 2012; Heath, 2018). Finally, some models attribute the primary role of referrals to reducing search frictions by making workers better aware of existing vacancies (Holzer, 1988; Topa, 2001; Galeotti and Merlino, 2014; Galenianos, 2014; Schmutte, 2015).

In contrast to these papers, we use a model that does not derive explicit microfoundations for a particular theory of referrals. Rather, we adopt a more flexible, parsimonious approach, and let the data dictate the relationship between, e.g., a worker's underlying type, the rate at which the worker meets firms through different channels, the quality of the matches generated through each channel, and the subsequent effects on wages and turnover. By being ex ante agnostic about the specific mechanisms, the model remains rich enough to accommodate and identify the distinct properties of referrals from different sources. As a result, our paper sheds light on *which* of the theories cited above are most consistent with the empirical evidence regarding the relationship between different types of referrals and labor market outcomes across occupations.

Our work is also closely related to several recent papers that study the impact of referrals by combining theoretical models of referrals with data containing information on workers' job search methods. Perhaps most closely related to our work is Arbex et al. (2019) and the

Marmaros and Sacerdote (2002) contains direct evidence of whether a referral was used but are drawn from workers in specific occupations, industries, or demographic groups. Data collected from a more representative sample rarely contains information about how a worker-firm match was formed, forcing researchers to use proxies that are likely to be correlated with (specific types of) referrals: for example, Bayer et al. (2008) and Schmutte (2015) use geographic clustering, Dustmann et al. (2016) use ethnicity, Gee et al. (2017) use social media connections, Hensvik and Skans (2016) exploit overlap at a previous employer, and Kramarz and Skans (2014) use family relationships. However, unlike several of the datasets cited above, our data does not contain detailed information about firms, which limits our ability to control for firm fixed effects.

contemporaneous paper by Moon (2023), both of which construct on-the-job search models and calibrate these models to data from the SCE. Despite these broad similarities, the focus of these two papers is much different from our own. Arbex et al. (2019) develop a model with a rich network structure, and focus exclusively on heterogeneity in workers' access to business referrals. Like us, they find that this unobserved heterogeneity across workers is an important source of dispersion in employment status and earnings. However, their focus is more on the impact of network structure and connectedness, while we focus more on the distinct qualitative and quantitative effects of referrals from different sources across different occupations. Moon (2023) concentrates on developing explicit microfoundations for one particular theory of referrals—namely, he models the strategic incentives of a referrer to provide firms with an accurate signal of match-specific productivity. Consistent with our findings, his model predicts that referrals from business contacts should be associated with higher wages.[8]

In addition to the literature that studies referrals explicity, our findings contribute to the broader discussion on the sources of inequality, in the sense that they uncover new channels for understanding heterogeneity in workers' job-finding rates and productivity, and the subsequent implications for mobility across time, space, and occupations. To start, many papers have documented the importance of unobserved worker characteristics in driving heterogeneity in labor market outcomes; see Bowlus (1997), Fontaine (2008), and Gregory et al. (2024) for specific examples that highlight heterogeneity in the rate at which workers receive opportunities to form new matches. Our results shed new light on how this heterogeneity in workers' "job-finding capital" can be explained through differences in their ability to find new jobs through their network of contacts—which is typically unobserved in the data—and the subsequent effects on employment, earnings, and inequality.[9]

Quantifying the contribution of business and social networks to the process of job formation is also informative about the costs of network destruction. In particular, since relocating often severs a worker's connections to friends and family, while changing occupations often renders a worker's business network less valuable, our results provide new insights into the (often difficult to measure) costs and/or barriers to geographic and occupational mobility. For example, our finding that social networks are particularly important for workers in low-skill occupations is consistent with the literature that has pointed to large moving costs in order to rationalize

[8]Another recent, related paper is by Caldwell and Harmon (2019), who estimate a structural on-the-job search model using matched employer-employee data from Denmark. In contrast to our paper, they use a worker's network of contacts as a source of variation in outside options to study the relationship between bargaining power and wages. They find that an increase in information about job openings–coming from closely connected former co-workers employed in other firms–leads to higher mobility and wage growth.

[9]In this context, our findings also contribute to the literature that studies the sources of frictions in the matching process between workers and firms, and the various technologies through which workers and firms meet and match; see, for example, Coles and Smith (1998), Lagos (2000), Calvó-Armengol and Zenou (2005), and Stevens (2007).

limited mobility patterns in the data, especially among low-skill workers; see, e.g., Topel (1986), Greenwood (1997), Chiquiar and Hanson (2005), Diamond (2016), and Kaplan and Schulhofer-Wohl (2017). Over time, the differential costs of mobility across geographic locations can contribute to earnings inequality, as lower-skilled workers, who tend to have lower earnings, are less likely to migrate in response to negative local economic shocks (Bound and Holzer, 2000).

2 Data and Construction of Key Variables

As noted above, we use data from a supplement to the Survey of Consumer Expectations (SCE), which is a nationally representative, monthly online survey of a rotating panel of about 1,300 household heads. New respondents are drawn each month 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.[10] Our analysis focuses on non-self-employed individuals aged 18–64, which leaves us with a sample of about 5,000 observations covering 2013–2018. 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* used, we rely on a question from the survey that asks currently employed workers "How did you learn about your current job".[11] Using the worker's response to this question, we construct binary indicators for two types of referrals: (i) family or 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 friends equal to 1, and to 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.[12]

[10] The survey was designed by Jason Faberman, Andreas Mueller, Ayşegül Şahin, and Giorgio Topa. See Faberman et al. (2022) for a more detailed description of the survey and associated dataset, and see Appendix A for additional details about how we generate some of our variables and arrive at our final estimation sample.

[11] We provide the full text of the survey question in Appendix A.

[12] Using this method of classification, about 8% of referred workers have both referrals indicators equal to

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.[13] 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.[14] The version we use comes from 2016 and is based on data from the American Community Surveys from 2010-2012, accessible via IPUMS.[15]

To give the reader a sense of the NPB occupational index, Table 9 in Appendix A provides a list of NPB scores assigned to various occupations, aggregated at the 2-digit occupation level for the sake of presentation. 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.

3 Empirical Results

In this section, we present a series of empirical results. In Section 3.1, we study the types of occupations in which workers in our survey report using a referral from a friend or relative or a referral from a business contact to find their current job. Exploring the usage of these two distinct types of job search channels across occupations is a natural starting point; after all, a kind word from an applicant's relative is obviously not the same as a letter from her former supervisor, and the value of these two types of referrals is presumably different for a hiring manager at a fast food chain and a company searching for a general counsel. Our results confirm that the usage patterns are, indeed, quite different: referrals from friends and relatives are used more frequently to form matches in low skill occupations, whereas referrals from

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.

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

[14] We have also produced results using an alternative occupation index constructed using O*NET data. Specifically, the index is constructed by calculating the fraction of jobs within an occupation code that require a bachelor's degree, which generates a score ranging from 0 to 100. The results are qualitatively and quantitiatvely similar using this alternative measure, and are available upon request.

[15] The NPB scores are available for download at http://www.npb-ses.info/.

business contacts are used relatively more frequently to form matches in high skill occupations.

The fact that these two types of referrals are being used to find different types of jobs suggests that they are playing distinct roles—or easing different frictions—and thus could be associated with different labor market outcomes. In Sections 3.2 and 3.3, we explore whether referrals are associated with higher or lower starting wages and longer or shorter job tenures *controlling for* the nature of the referrer and the skill requirements of the job. We show that clear, and opposite, patterns emerge in the data: referrals from business contacts are associated with higher starting wages but shorter tenures, whereas referrals from friends and relatives are associated with lower starting wages but longer tenures. Interestingly, when we attempt to control for unobserved worker heterogeneity (using workers' previous wages), we find that our wage results weaken, suggesting that selection may be playing an important role; for example, a referral from a friend or relative may not be *causing* the worker to receive a low starting wage, but rather workers who need help from their social network to find a job might have other, unobservable characteristics that are associated with lower starting wages.

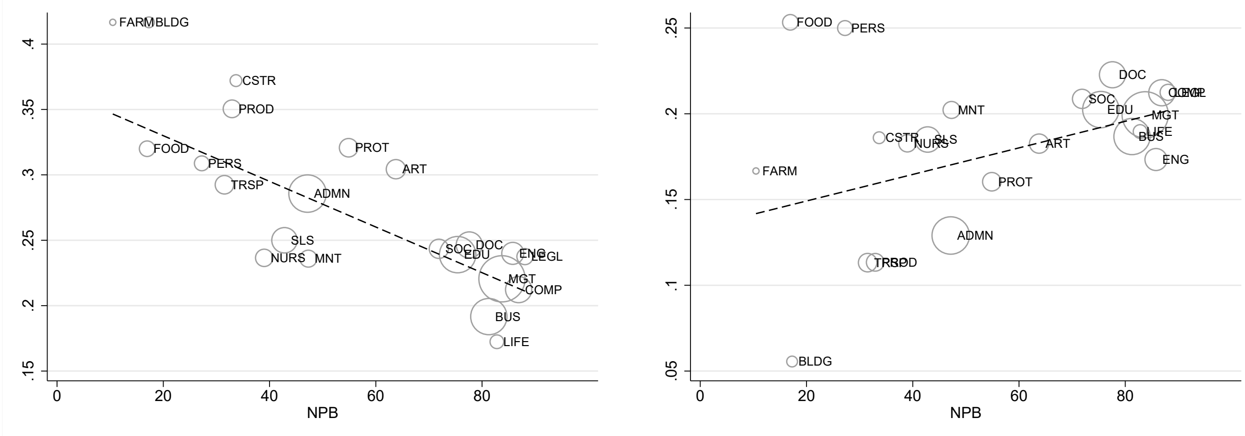
In Section 3.4, we leverage another unique feature of the data to help paint a more complete picture. In particular, using information about how often a worker is in contact with new firms—even when employed—we document that those workers who got their current job using a referral from a friend or relative meet new firms infrequently, relative to non-referred workers, whereas workers who got their current job using a referral from a business contact meet new firms at a relatively rapid rate. This finding suggests that an important dimension of unobserved heterogeneity reflects differences in workers' ability (or the resources they have available) to generate contacts with firms, or what we call "job-finding capital."

Taken together, these results are important for several reasons, which we discuss in detail in Section 3.5. First, they can help us resolve a number of puzzles in the existing empirical literature. Second, and perhaps more importantly, these results highlight the importance of going beyond simple regression analysis to explore the role of referrals within the context of an equilibrium model; they inform our choice of the key model ingredients to include; and they provide natural targets for our calibration exercise, which allows us to uncover new qualitative and quantitative insights into the role of (different types of) referrals in the labor market.

3.1 Usage of Referrals Across Occupations

Figure 1a plots the fraction of currently employed workers who report using a referral from a friend or relative in the process of being hired at their current job (y-axis) against NPB scores (x-axis) for each 2-digit occupation code, which proxy for the job's skill requirements. 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.

Figure 1: The Use of Referrals Across Occupations



(a) Referrals from Family and Friends

(b) Referrals from Business Contacts

Notes: This figure plots the fraction of individuals within each 2-digit occupation that found their current job through a referral from family and friends (a) and from a business contact (b) against the skill content of the job (NPB score). The size of each dot is proportional to the number of individuals within each occupation. Overall, the fraction of individuals that found their job through a referral is 25.0% for family/friends and 18.5% for business.

Of course, these patterns could reflect differences in the characteristics of the workers in these occupations, and not necessarily differences in the occupations themselves. 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 and geographic region fixed effects, and a rich set of worker characteristics.[16] These characteristics include age, gender, race, marital status, number of children under the age of 6, and home ownership status.[17] Table 1 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. To interpret these results, comparing a worker in “Retail Sales” (NPB score of about 26) with a worker in “Media and Communication” (NPB score of about 76), our results imply that the “Media and Communication” worker is 3pp (18%) more likely to use a business referral and 10pp (39%) less likely to use a family/friends referral.

[16] While we employ a linear probability model for all of our binary outcomes, for ease of exposition, our results are very similar using a logit or probit specification. In addition, while we use the skill index for the more detailed 3-digit occupation code in all of the regressions, the results remain similar if we use the more aggregated 2-digit occupation code, as in Figures 1a and 1b.

[17] While we observe detailed information in our data about workers, we observe little information about employers. Specifically, we observe whether the employer has multiple establishements, the employer type (government, private-sector, non-profit, or family business), industry, and a coarse measure of the number of employees. All of our result are robust to including these variables as controls.

Table 1: Referral Usage and Skill Index

	Type of Referral			
	Business	Family/Friends	Business	Family/Friends
Skill Index	0.0008***	-0.0018***	0.0006**	-0.0020***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Time and Region FE			✓	✓
Individual Controls			✓	✓
N	3779	3779	3779	3779

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 patterns we document in Figure 1 and Table 1 suggest that referrals from family and friends and referrals from business contacts might be playing different roles (or helping to overcome different frictions) in the matching process, in which case one might naturally expect them to be associated with different labor market outcomes. In the next two sections, we examine the relationship between the use of referrals and two standard measures of labor market outcomes—wages and tenure—and show that clear and opposing relationships emerge after distinguishing between different types of referrals and different types of occupations.

3.2 Referrals and Starting Wages

We first study workers' starting wages. In column (1) of Table 2, we report the 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. We find that workers referred to their current job by a business contact have starting wages that are approximately 16% higher than those of non-referred workers, while those referred by family and friends have starting wages that are approximately 9% lower than those of non-referred workers. In column (2), we control for the skill index of the worker's occupation.[18] 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

[18] Overall our regression results are similar if, instead of conditioning on the skill index measure of occupations (NPB score), we use 3-digit occupation dummy variables.

Table 2: Starting Wages and Referrals

	Log Real Starting Wage					
	(1)	(2)	(3)	(4)	(5)	(6)
Business Referral	0.161***	0.148***	0.085***			
	(0.025)	(0.023)	(0.022)			
Family/Friends Referral	-0.093***	-0.046**	-0.024			
	(0.023)	(0.021)	(0.020)			
Any Referral				0.005	0.028	0.017
				(0.020)	(0.019)	(0.017)
Skill Index		0.010***	0.005***		0.010***	0.005***
		(0.000)	(0.000)		(0.000)	(0.000)
Log Previous Wage			0.530***			0.535***
			(0.014)			(0.014)
Time and Region FE	✓	✓	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓	✓	✓
N	3317	3317	2311	3317	3317	2311

Notes: Estimates are from regressions of 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.

at the previous job and the starting wage at the current job. Moreover, while the coefficient on business referrals remains positive and statistically significant, the coefficient on referrals from family and friends becomes small and insignificant. As we discuss in more detail below, these findings are consistent with a selection effect; 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, for reasons that can't be observed by the econometrician, and hence receive lower wages.

Columns (4)–(6) 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 value 1 if the worker used *any* type of referral. The relationship between the use of a referral and starting wages disappears. As we discuss in more detail in Section 3.5, the fact that referrals from business contacts and family/friends are associated with opposing, offsetting effects on starting wages can potentially 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. We measure the job tenure of all currently employed workers at the time of the survey using data on the start date of each worker's current job. 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.[19] However, despite the potential limitations of our stock-sampled measure of job tenure, the results based on this measure reveal crucial information about the relative tenure of workers across job search methods and occupations. For one, it is well known that data of this nature—which is left-truncated and right-censored—suffers from competing biases that, under certain assumptions, cancel each other out.[20] Moreover, even if they do not offset each other exactly, our focus on *relative tenure*—and the large differences we find between the relative tenure of workers who used business referrals and those who used referrals from family and friends—would likely dominate any biases due to stock sampling. Finally, as a robustness check, we use our quantitative model to directly compare stock-sampled spells to completed spells, and we find that the two measures deliver almost identical results regarding the differences in tenure across job search method.

In Table 3, we regress our measure of job tenure on the dummy variables for referrals, using the same set of controls described above. Columns (1)–(3) show that workers who were referred by business contacts have significantly shorter job durations than non-referred workers, while those who were referred by family and friends have significantly longer durations. Columns (4)–(6) illustrate, again, the importance of distinguishing between the two types of referrals: we find a small positive (although not precisely estimated) relationship between the use of *any* referral and job tenure in our data. Hence, much like our results on wages and referral usage, treating all referrals the same masks stark differences between the effects of referrals from business contacts and those from family and friends.

3.4 Contact Rates and Job Search Channels

To summarize, workers who used a referral from a business contact to find their current job have higher starting wages and shorter tenure, on average, while workers who used a referral from a friend or relative have lower starting wages and stay longer at the job. Note that, on their own, these results are surprising within the context of standard models: while higher wages are

[19]Since workers are only tracked for one year in the SCE, we observe very few completed job spells.

[20]On the one hand, since our sample is left-truncated, workers with shorter spells are less likely to be sampled, which leads to overestimating the average length of employment 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.

Table 3: Job Tenure and Referrals

	Log Job Duration					
	(1)	(2)	(3)	(4)	(5)	(6)
Business Referral	-0.185***	-0.195***	-0.172***			
	(0.055)	(0.054)	(0.065)			
Family/Friends Referral	0.216***	0.246***	0.229***			
	(0.049)	(0.049)	(0.060)			
Any Referral				0.070	0.084*	0.087*
				(0.043)	(0.043)	(0.052)
Skill Index		0.007***	0.007***		0.006***	0.007***
		(0.001)	(0.001)		(0.001)	(0.001)
Log Previous Wage			-0.142***			-0.157***
			(0.036)			(0.036)
Time and Region FE	✓	✓	✓	✓	✓	✓
Individual Controls	✓	✓	✓	✓	✓	✓
N	3779	3779	2476	3779	3779	2476

Notes: Estimates are from regressions of 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 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 and 2) are similar when using this more restricted sample.

typically associated with draws from a "better" distribution of match-specific productivity (in, e.g., Mortensen and Pissarides, 1994), shorter tenures are typically associated with draws from a "worse" distribution (in, e.g., Jovanovic, 1979; Burdett and Mortensen, 1998; Postel-Vinay and Robin, 2002). In this section, we show that one can resolve this tension by studying the characteristics of the workers who use different job search channels. Specifically, we explore the relationship between the channel that a worker used to find his current job and the rate at which the worker contacts new firms while employed.

In particular, Table 4 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, which is potentially consistent with both higher wages but also shorter tenure. In contrast, workers hired through a referral from a family member or friend are significantly less likely to have had contact with a new firm in the past four weeks, which is potentially consistent with lower wages and longer tenure.[21] Importantly, our results indicate that the channel through which a worker found her current job reflects certain characteristics of

[21]We test other horizons as well and find similar results.

the worker, which are not captured by our individual controls, but have significant implications for the rate at which a worker generates contacts with new firms.[22]

Table 4: Contact Rates and Referrals

	Probability of Contact (Last 4 Weeks)		
	(1)	(2)	(3)
Business Referral	0.050***	0.048***	0.037*
	(0.018)	(0.018)	(0.023)
Family/Friends Referral	-0.043***	-0.037**	-0.050**
	(0.016)	(0.016)	(0.021)
Skill Index		0.001***	0.001
		(0.000)	(0.000)
Log Previous Wage			0.047***
			(0.013)
Time and Region FE	✓	✓	✓
Individual Controls	✓	✓	✓
N	3779	3779	2476

Notes: Estimates are from regressions of 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 and 2) are similar when using this more restricted sample.

3.5 Discussion of Empirical Results

The results presented above are valuable for at least two reasons. First, they help us to resolve conflicting evidence in the existing empirical literature. Second, they illustrate the importance of using a model to uncover the role referrals in the labor market; they inform the choice of the main ingredients to include in such a model; and they provide key targets for our calibration exercise. We expand on each of these important points below.

[22]Note that an alternative explanation for our results is that distinct job search channels generate different non-wage benefits. For example, if friends and relatives have superior knowledge about a worker's preferences or personal circumstances, then matches formed through family and friends could be "better" 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 earn seemingly low wages but 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 of their job than non-referred workers.

Relationship to existing results. Recognizing that referrals from contacts in a workers' business and social networks are used more frequently at different types of occupations—and are associated with opposing effects on starting wages—can potentially resolve some of the puzzles in the literature studying the role of referrals in shaping labor market outcomes. For example, several studies that use representative worker surveys (see, e.g., Pellizzari, 2010) find an ambiguous relationship between using (any type of) referral and starting wages. As Table 2 illustrates, this null result can be understood as masking the opposing effects of these two, distinct types of referrals. Other studies use matched employer-employee (MEE) data and infer the incidence of a referral by identifying co-worker networks; see, e.g., Hensvik and Skans (2016) and Glitz and Vejlin (2021). These studies largely find a positive wage effect of referrals, which is also consistent with our results since, by definition, co-workers are characterized as business contacts. Interestingly, Dustmann et al. (2016) use MEE data but identify referrals by matching on ethnic background, which is more likely to reflect referrals from family and friends. They find that referrals are associated with lower wages (before controlling for firm fixed effects), as our results would anticipate. Finally, several narrow surveys draw from a single occupation, which our results indicate could be dominated by one specific type of referral. For example, Simon and Warner (1992) use a sample that only includes scientists and engineers—which likely oversamples business referrals—and find a positive wage effect.[23] Of course, we do not claim that our results explain all of the previous results in the existing literature; instead, we view a key contribution as demonstrating that the referrer's identity is an important distinguishing feature of a referral, which sheds new light on many, seemingly puzzling results and opens up a number of new questions for future research.

Motivating the model exercise. Much of the empirical literature has attempted to interpret the role of referrals in the labor market by comparing stylized predictions from a specific theoretical model to observational outcomes derived from relatively narrow regressions. However, the results above highlight the challenges associated with this approach, along with the benefits of studying the role of referrals within the context of a structural model.

Consider, for example, the positive relationship between using a business referral and starting wages. Studying this bivariate relationship alone, one might be tempted to conclude that matches formed through business referrals are more productive, perhaps because referrals provide an efficient technology for sharing information about idiosyncratic match quality, which is realized after the match has been formed. However, an equally plausible explanation is that workers who are *ex ante* more productive tend to use business referrals to find a job, perhaps because reputation concerns ensure that business contacts only refer "good" workers. Yet an-

[23] We thank an anonymous referee for pointing out the relationship between several of these results in the existing literature and the patterns we document.

other 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 candidate explanations is crucial for understanding the role of business referrals in the job-finding process and the subsequent implications for labor market outcomes, both at the individual level and in the aggregate.

While all three of these stories could qualitatively fit a subset of the empirical patterns we document, an equilibrium model allows us to identify and test various mechanisms across multiple, inter-related dimensions. Continuing with the example above, while it may be straightforward to identify a mechanism that generates a wage premium for workers hired through a business referral, it is considerably more challenging to require that the candidate mechanism also explains why this channel is used more frequently at high skill jobs, why these workers leave their jobs more quickly, and why workers who use this channel seem to generate contact with other firms at a relatively high rate even after controlling for observable characteristics. The challenge compounds after recognizing that many jobs are also filled using a referral from family and friends, even though this job search channel generates entirely different patterns altogether.

To face this challenge, in the next section we use the facts derived above 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 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 do not vanish after forming a match, we assume that workers search both off and *on the job.*

Importantly, in addition to informing our choice of model ingredients, the results above also provide targets for our quantitative analysis. As we show in Section 5, these moments allow us to identify the value of key structural parameters, revealing both qualitative and quantitative insights into the impact of referrals on labor market outcomes.

4 Model

We incorporate multiple job search channels into the workhorse model of on-the-job search with unobserved worker heterogeneity, as formulated by Postel-Vinay and Robin (2002) and Cahuc et al. (2006). In fact, as we establish below, if one aggregates these multiple channels into a single matching technology, the characterization of many standard equilibrium objects is essentially the same as in Cahuc et al. (2006). For this reason, we keep the characterization of these objects brief (though sufficiently detailed to remain self-contained), and instead focus on deriving the novel predictions that emerge from our framework—namely, the endogenously-generated relationships between the channel through which a worker found her current job, the arrival rate and quality of new job opportunities, and the subsequent implications for her wage and tenure. In particular, we are able to derive analytical expressions from our model corresponding to all key moments from the data (channel-specific and otherwise). Hence, despite a seemingly minimal departure from a well-known benchmark, our model is rich enough to confront the new facts that we uncovered in Section 3, with essentially no loss in tractability.

4.1 Environment

We consider a continuous time, infinite horizon environment. 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 an unobserved attribute or "ability" $a \in \mathcal{A} \equiv \{a_1, ..., a_N\}$ for some $N \in \mathbb{N}$. We let π_i denote the fraction of workers with ability a_i, with $\sum_{i=1}^{N} \pi_i = 1$. As we discuss below, a worker's ability a_i should not be confused with their skill or occupation: when we take the model to the 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*.[24]

There is 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 $x \in [\underline{x}, \overline{x}]$. 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 δ.

Meetings. The first departure from the existing literature is that we assume contacts or "meetings" between workers and firms occur through one of three channels: a referral from a friend or relative; a referral from a business contact; or formal ("other") channels. We denote these by F, B, and O, respectively, and denote the set of possible channels by $\mathcal{C} \equiv \{F, B, O\}$.

[24] For example, our model could be interpreted as the market for lawyers, and a_i distinguishes the unobserved ability *across* lawyers.

The second 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 $\lambda_j^e(a_i)$ and $\lambda_j^u(a_i)$, respectively. Conditional on meeting, a match-specific productivity is then drawn from a distribution with cdf $H_j(x|a_i)$. It will be convenient to define

$$\Gamma_j^k(x|a_i) = \lambda_j^k(a_i)\bar{H}_j(x|a_i)$$

for $j \in \mathcal{C}$ and $k \in \{e, u\}$, where $\bar{H}_j(x|a_i) \equiv 1 - H_j(x|a_i)$. In words, $\Gamma_j^e(x|a_i)$ is the arrival rate of meetings for an employed worker of ability a_i through channel j with a match-specific productivity that exceeds x. We define the arrival rate of such meetings through *any* channel by

$$\Gamma^k(x|a_i) = \sum_{j \in \mathcal{C}} \Gamma_j^k(x|a_i), \quad k \in \{e, u\}.$$

This specification allows a worker's type to affect both the arrival rate of meetings and the idiosyncratic quality of the match. This modeling choice, while stylized, is meant to encapsulate a variety of micro-founded theories of job referrals (discussed in the literature review), as some theories focus on the role of referrals in generating meetings for (at least some types of) workers, while other theories focus on the quality of matches formed through referrals.[25]

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 β 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 at the incumbent firm (x), the worker moves to the poaching firm. The worker and the poaching firm bargain over the wage, where 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. Specifically, if the expected value of remaining at the incumbent firm at wage w is less than the outside option of moving to the poaching firm at the maximum wage $f(x')$, the worker remains at the incumbent firm but renegotiates his wage using the outside option of the poaching firm.

[25] The distinction between referrals' effect on meetings and match quality is also present in a recent working paper by San (2021).

Otherwise, the worker remains at the incumbent firm and his wage is unchanged.

4.2 Key Equilibrium Objects

In this section, we define the key objects that make up a steady-state equilibrium in the model described above. Proposition 1, below, provides a complete characterization. As the derivation is relatively close to that in Cahuc et al. (2006), it is relegated to Appendix C.

Value Functions and Wage Functions Let $V^u(a_i)$ denote the expected discounted value of an unemployed worker with ability a_i, 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. Since a firm generates zero output when unmatched, the expected surplus created by forming a match with productivity x is $V^e(a_i, x, f(x)) - V^u(a_i)$, i.e., the worker's value of being employed at a wage equal to the total output of the match, $f(x)$, less the worker's value of being unemployed. Hence, it is straightforward to establish that an unemployed worker with ability a_i will form a match with a new firm if, and only if, the match-specific productivity $x \geq x^\star(a_i) \equiv x_i^\star$, where $x_i^\star$ satisfies

$$V^u(a_i) = V^e\left(a_i, x_i^\star, f\left(x_i^\star\right)\right), \qquad i \in \{1, ..., N\}. \tag{1}$$

Following Cahuc et al. (2006), the worker will earn a wage $w^u(a_i, x)$ that satisfies

$$V^e(a_i, x, w^u(a_i, x)) = V^u(a_i) + \beta\left[V^e(a_i, x, f(x)) - V^u(a_i)\right]. \tag{2}$$

Intuitively, $w^u(a_i, x)$ yields the worker an expected utility equal to his outside option of unemployment plus a share β of the match surplus.

Now consider an employed worker with ability a_i, productivity x, and wage w who contacts a new firm and draws match-specific productivity x'. If $x' > x$, the worker moves to the new firm at a wage $w^e(a_i, x, x')$ satisfying

$$V^e(a_i, x', w^e(a_i, x, x')) = V^e(a_i, x, f(x)) + \beta\left[V^e(a_i, x', f(x')) - V^e(a_i, x, f(x))\right]. \tag{3}$$

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 β 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 will use the threat of leaving to renegotiate his current wage if x is sufficiently high. In particular, let $\widehat{x}(a, x, w)$ denote the value of x' such that a currently employed worker of ability a with match-specific productivity $x > x'$ would renegotiate her wage to exactly w, i.e.,

$$w = w^e\left(a_i, \widehat{x}(a, x, w), x\right), \tag{4}$$

so that $w^e(a_i, x', x) \leq w$ if $x' \leq \widehat{x}(a, x, w)$. Then the worker renegotiates her wage to $w^e(a_i, x', x)$ if $x' \geq \widehat{x}(a_i, x, w)$, and otherwise her wage remains w.

Distribution of Workers Unemployed workers of ability a_i exit unemployment when they meet a firm and draw match-specific productivity $x \geq x_i^\star$. Once employed, a worker moves only when he meets a new firm with a higher match-specific productivity. In this section, we use these 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 currently employed at a job with match-specific productivity x. It will be convenient to define the *cumulative measure* of employed workers with ability a_i and match-specific productivity $x' \leq x$ by $\Phi^e(x|a_i) \equiv \int_{\underline{x}}^{x} \phi^e(a_i, x')dx'$. These equilibrium objects are characterized by three sets of conditions:

$$\pi_i = \phi^u(a_i) + \Phi^e(\overline{x}|a_i) \tag{5}$$

$$\dot{\phi}^u(a_i) = \delta\Phi^e(\overline{x}|a_i) - \phi^u(a_i)\Gamma^u(x_i^\star|a_i) = 0 \tag{6}$$

$$\dot{\Phi}^e(x|a_i) = -\Phi^e(x|a_i)\left[\delta + \Gamma^e(x|a_i)\right] + \phi^u(a_i)\left[\Gamma^u(x_i^\star|a_i) - \Gamma^u(x|a_i)\right] = 0 \tag{7}$$

for all $i \in \{1, ..., N\}$ and $x \in [x_i^\star, \overline{x}]$. Condition (5) simply requires that summing the measures of unemployed and employed workers with ability a_i yields the (exogenously specified) aggregate measure of workers with ability a_i. Conditions (6) and (7) are steady-state conditions, equating the inflow and outflow of workers into every possible state.[26] For example, in equation (7), workers with ability a_i and current productivity $x' \leq x$ exit when their match is destroyed, which occurs at rate δ, or when they find a better match with productivity $x'' > x$, which occurs at rate $\Gamma^e(x|a_i)$. Meanwhile, unemployed workers with ability a_i enter this state by meeting a firm and drawing productivity $x' \in [x_i^\star, x]$, which occurs at rate $\Gamma^u(x_i^\star|a_i) - \Gamma^u(x|a_i)$.

4.3 Equilibrium

A steady-state equilibrium is characterized by thresholds $x^\star(a)$ and $\widehat{x}(a, x, w)$, 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)–(7).[27] The following proposition provides a closed-form

[26] Note that, e.g., $\dot{\phi}^u(a_i)$ denotes the rate of change in the measure of unemployed workers of type a_i.

[27] Recall that, for ease of exposition, we denote $x^\star(a_i)$ by $x_i^\star$.

characterization of the equilibrium objects that are key to our analysis.[28]

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

$$w^e(a_i, x, x') = f(x') - p(1-\beta) \int_x^{x'} \frac{r + \delta + \Gamma^e(x''|a_i)}{r + \delta + \beta\Gamma^e(x''|a_i)} dx'', \tag{8}$$

for $x' > x \geq x_i^\star$, *and*

$$w^u(a_i, x) = w^e(a_i, x_i^\star, x), \tag{9}$$

for $x \geq x_i^\star$, *where* $x_i^\star$ *satisfies*

$$f(x_i^\star) = b + p\beta \int_{x_i^\star}^{\overline{x}} \frac{[\Gamma^u(x|a_i) - \Gamma^e(x|a_i)]}{r + \delta + \beta\Gamma^e(x|a_i)} dx \tag{10}$$

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

$$\phi^u(a_i) = \frac{\delta\pi_i}{\delta + \Gamma^u(x_i^\star|a_i)} \quad \textit{for all } i \in \{1, ..., N\}, \tag{11}$$

and

$$\Phi^e(x|a_i) = \frac{\delta\pi_i \left[\Gamma^u(x_i^\star|a_i) - \Gamma^u(x|a_i)\right]}{\left[\delta + \Gamma^u(x_i^\star|a_i)\right]\left[\delta + \Gamma^e(x|a_i)\right]} \quad \textit{for all } x \geq x_i^\star \textit{ and } i \in \{1, ..., N\}. \tag{12}$$

In what follows, it will be helpful to derive the (unconditional) distribution of wages across workers, which we do in the Lemma below.

Lemma 1. *For any wage* $w \in [w^u(a_i, x), w^e(a_i, x, x)]$, *the fraction of workers of type* a_i *employed at a firm with productivity* $x \geq x_i^\star$ *that earn a wage* $w' \leq w$ *is given by*

$$G(w|a_i, x) = -\frac{\phi^u(a_i) d\Gamma^u(x|a_i) + \Phi^e\left(\widehat{x}(a_i, x, w)|a_i\right) d\Gamma^e(x|a_i)}{\phi^e(a_i, x)\left[\delta + \Gamma^e\left(\widehat{x}(a_i, x, w)|a_i\right)\right]}. \tag{13}$$

4.4 Key Model-Implied Moments

We now show how the framework developed above can be used to analyze and interpret the empirical regularities documented in Section 3. As a first step, we derive the joint distribution of employed workers' unobserved types, their match-specific productivities, and the channel through which they found their job. Then we use this distribution to derive analytical expressions for several key model-implied moments, including the fraction of workers that used each job search channel, and the relationship between a worker's job search channel, wage, and expected tenure. In Section 5, we use these expressions—which, to the best of our knowledge,

[28]Given these expressions, the remaining equilibrium objects can be easily constructed. The proof is in Appendix C.

are new to the literature—to derive quantitative estimates of the model's structural parameters from key moments in the data, without resorting to costly simulations.

As a first step, since workers' future labor market transitions do not depend on the channel through which they formed their current match, the probability that a worker of type a_i currently employed with productivity x received her job through channel $j \in \{B, F, O\}$ is

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

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.

Using this expression, we can define the measure of workers of type a_i currently employed with productivity x that got their job through channel j as

$$\phi^e_j(a_i, x) = \Lambda_j(a_i, x)\phi^e(a_i, x). \tag{14}$$

Integrating and summing $\phi^e_j(a_i, x)$ reveals that the fraction of currently employed workers who used channel j to find their current job is

$$\frac{1}{1-u}\sum_i \int_{x^\star_i}^{\overline{x}} \phi^e_j(a_i, x)dx, \tag{15}$$

where $u = \sum_i \phi^u(a_i)$ denotes the measure of unemployed workers.[29]

Since the distribution of wages across workers, conditional on a_i and current productivity x, is the same for all $j \in \{B, F, O\}$,[30] the average wage of currently employed workers who got their job through channel j is thus[31]

$$\frac{\sum_i \int_{x^\star_i} \mathbb{E}\left[w \mid a_i, x\right] \phi^e_j(a_i, x)dx}{\sum_i \int_{x^\star_i} \phi^e_j(a_i, x)dx}, \tag{16}$$

[29] Since the measure of workers is normalized to one, note that u is also equal to the unemployment rate.

[30] 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 $x' = x^\star$ 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.

[31] 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).

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

$$\mathbb{E}\left[w \ |a_i, x\right] = \underline{w}G(\underline{w}|a_i, x) + \int_{\underline{w}}^{\overline{w}} wdG(w|a_i, x) = \overline{w}(a_i, x) - \int_{\underline{w}}^{\overline{w}} G(w|a_i, x)dw. \tag{17}$$

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 currently employed workers who got their job through channel j is equal to

$$\frac{\sum_i \int_{x_i^\star} \tau(x, a_i)\phi_j^e(a_i, x)dx}{\sum_i \int_{x_i^\star} \phi_j^e(a_i, x)dx}. \tag{18}$$

5 Quantitative Exercise

In this section, we calibrate the model to key moments in our data. This exercise generates new qualitative insights into the role of referrals in the labor market, along with new quantitative insights into how much they contribute to employment, earnings, inequality, and output. Importantly, for both sets of insights, we find that the distinction between referrals from business contacts and those from family and friends is crucial.

5.1 Parameters, Target Moments, and Identification

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 bachelor's degree or more (whom we refer to as "high skill"), and those with some college or less (whom we refer to as "low skill").[32] 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 of 95%. We also assume, in both markets, that there are two types of unobserved ability, $a \in \{a_1, a_2\}$.[33] Finally, we choose functional forms for the production and matching technologies: we assume that the production technology is linear, $f(x) = px + c$, while the matching

[32] 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 a key parameter of this model across education groups. In addition, since the model contains both employed and unemployed workers, segmenting the market by educational attainment makes it easier to map the model to the data, since a worker's educational attainment is invariant to employment status, while their NPB score is not.

[33] We also experimented with versions of the model with more than two types, but our calibration results loaded most of the weight on just two types.

technologies are given by $\Gamma_j^u(x|a) = \lambda_j^u(a)\,[1 - H_j(x|a)]$ and $\Gamma_j^e(a) = \theta\Gamma_j^u(a)$ for $j \in \{B, F, O\}$, so that θ captures the differential arrival rates between searching on and off the job.[34]

We assume that the rate at which workers of ability a_i meet firms through channel j satisfies

$$\lambda_j^u(a) = \begin{cases} \kappa_j & \text{if } a = a_1 \\ \kappa_j + \alpha_j & \text{if } a = a_2, \end{cases}$$

so that κ_j captures level differences in meeting rates across channels, while α_j captures differences in meeting rates across types within each channel. We assume that the distribution of match-specific productivity, $H_j(x|a_i)$, is defined by a beta distribution with shape parameters $\xi_j(a)$ and $\eta_j(a)$. To reduce the number of parameters we need to calibrate, we assume $\xi_j(a_2) = 2\xi_j(a_1)$ and $\eta_j(a_i) = \eta$ for $j \in \{B, F, O\}$ and $i \in \{1, 2\}$. Given this assumption, the parameters ξ_j and η jointly determine the mean and variance of the distribution of match-specific productivity draws through each channel j, along with the sensitivity of these moments to workers' ability a_i.[35]

Calibration strategy. In each market (low and high skill), we set the bargaining power, β, using an estimate from outside of our sample. In particular, within the context of a model also based on Cahuc et al. (2006), Lise et al. (2016) use data from the NLSY to estimate the surplus-sharing parameter β across the same two education groups that we study. We use their estimates of $\beta = 0.188$ and $\beta = 0.272$ for the low and high skill markets, respectively.

Sixteen parameters remain for each market. To calibrate these parameter values, we calculate a vector of sixteen moments from the data, $\widehat{m}$, and then derive the counterparts of these moments (using our analytical results) in the model, $\widetilde{m}(\chi)$, for a particular vector of parameter values, χ. We then iterate over χ to minimize the loss function

$$L(\chi) = -\frac{1}{2}\left(\widehat{m} - \widetilde{m}(\chi)\right)^T \widehat{W}^{-1}\left(\widehat{m} - \widetilde{m}(\chi)\right),$$

where $\widehat{W}$ is the diagonal of the covariance matrix of $\widehat{m}$, estimated via the nonparametric bootstrap.[36] While the sixteen internally calibrated parameters are interdependent and, hence, jointly estimated, there are certain moments that are particularly informative about the value of specific parameters. Below we provide an intuitive discussion. In Appendix D we provide

[34]Note that we are assuming that arrival rates across channels scale up proportionally for employed and unemployed workers. In separate calculations, available upon request, we find that we cannot reject the null hypothesis that the relative contact rates (of employed/unemployed workers) are the same across search channels.

[35]Given our parameterization, the mean of each distribution is $\frac{\xi_j a}{\xi_j a + \eta}$ and the variance is $\frac{\xi_j a \eta}{(\xi_j a + \eta)^2 (1 + \xi_j a + \eta)}$.

[36]Appendix D provides a more detailed description of the construction of the empirical targets and the derivation of their model counterparts.

some more formal results regarding the identification of our model.

Identification. The first five parameters, which are not specific to the different job-finding channels, are most informed by relatively standard aggregate moments. The job destruction rate, δ, and the relative efficiency of on-the-job search, θ, are informed by the job-destruction (EU) and job-to-job (EE) transition rates in the data, respectively. The flow value of unemployment, b, plays a key role in determining whether workers accept job offers, and thus will be informed by the unemployment rate in each sub-sample. Lastly, aggregate wage dispersion is highly informative about the variance of match-specific productivities, which is determined in large part by the parameter η and the distribution over ability types, summarized by π_1.[37] Hence, to ensure that the model-generated distribution of wages matches the corresponding measure in the data, we calculate the distribution of wages in each sub-sample (high and low skill markets) after controlling for observable characteristics, and then calculate the fraction of workers in the model earning less than the wages that lie at the 25th and 75th percentiles of the empirical distribution.[38] The targets, of course, are 0.25 and 0.75, respectively.

The remaining eleven parameters must be discussed within the context of the different job-finding channels. To start, the regression results in Section 3 provide evidence consistent with lower ability workers being more likely to use F referrals and higher ability workers being more likely to use B referrals. Therefore, the average productivity of jobs found through channel F is likely to be lower, and thus the average wage of these jobs is likely to be informative about the intercept of the production technology, c. Similarly, since the average productivity of jobs found through B is likely higher, the average wage of jobs found through B is informative about how output increases with the match-specific productivity, p.

The parameters $\{\kappa_B, \kappa_F, \kappa_O\}$ determine level differences in the rate at which workers contact firms through each of the three channels. As a result, κ_B and κ_F are informed by the fraction of currently employed workers who found their job through channel B and F, respectively. Since the majority of jobs are found through other channels, κ_O is most informed by the overall rate at which unemployed workers contact firms (through any channel).

The parameters $\{\alpha_B, \alpha_F, \alpha_O\}$ determine the rate at which high ability (a_2) workers contact firms through the various channels, relative to low ability (a_1) workers. Since type a_2 workers are more likely to be employed and, again, the majority of contacts occur through channel O, α_O is informed by the average contact rate of employed workers. A key mechanism in our model implies a connection between the channel that workers use to find their job and their place in the wage distribution: as we discuss in greater detail below, type a_2 workers earn higher

[37] Since π_1 determines the extent of unobserved worker heterogeneity in the model, it is important in driving many of the moments in the calibrated model.

[38] Specifically, we use the same set of variables used in the regressions in Section 3: individual controls, time and region fixed effects, and the NPB score.

wages and are more likely to use channel B, while type a_1 workers earn lower wages and are more likely to use channel F. Hence, following the logic in Arbex et al. (2019), we target two additional moments that capture how the fractions of employed workers who used channels B and F change with wages. In particular, for $j \in \{B, F\}$, we target the difference in the fraction of workers in the top wage quartile that used channel j to find their job and the fraction of workers in the bottom wage quartile that used channel j to find their job. These moments inform the parameter values of α_B and α_F.

Finally, given η, the average productivity of matches formed through channel O is determined by ξ_O, which is most informed by the average wage of workers hired through channel O. In addition to driving average wages, match-specific productivities also affect tenure, as workers with higher productivity are less likely to separate. Therefore, ξ_B and ξ_F inform the average tenure of jobs found through channels B and F, respectively, relative to those found through O.

Model fit. Table 5 reports the model fit for both high and low skill markets. As one can see, the model is able to match the targeted moments quite well overall.[39] In Appendix F, we provide further evidence that the model is capable of replicating the empirical patterns in the data that we document in Section 3, including untargeted moments not used in the model calibration. In particular, we show that data simulated from our calibrated model generates similar relationships between the usage of referrals, the skill content of the occupation, starting wages, job tenure, and contact rates. Importantly, while some of these relationships are closely related to targeted moments (usage and tenure), the results on starting wages and contact rates by channel are not, and thus provide additional empirical support for our model.

5.2 Qualitative Insights from Calibration

Table 5 also summarizes the parameter values identified by the calibration. Some of these values are easy to interpret directly, and have close counterparts in related job search models. For example, the job destruction rate (δ) and the relative arrival rate of meetings for employed workers (θ) are both roughly in line with existing estimates in the literature.[40] The flow value

[39]The model struggles slightly to fit the EU and EE rates in the low skill market. However, moments involving transitions between employment states are noisy in our data since we observe workers for only a year.

[40]Cairó and Cajner (2018) provide estimates of separation rates across educational attainment levels. Our estimate of δ for workers with a college degree is slightly higher than theirs, while our estimate for workers with some college or less lies in between their (separate) estimates for workers with some college and those with only a high school degree. Similarly, the average of our estimates of θ in low and high skill markets falls within the range of recent estimates; see, e.g., Elsby and Gottfries (2022), Bilal et al. (2022), Moscarini and Postel-Vinay (2023), and Elsby et al. (2022), whose estimates of the relative intensity of on-the-job search (for all workers) lie between 0.15 and 0.2. Lise et al. (2016) arrive at estimates in a similar range as well, but interestingly find that on-the-job search is relatively more efficient for workers with less education.

Table 5: Parameter Values and Target Moments from Calibration

Parameter	High Skill Value	Low Skill Value	Closest Target	High Skill Model	High Skill Data	Low Skill Model	Low Skill Data
δ	0.017	0.018	Job destruction (EU) rate	0.015	0.015	0.016	0.013
θ	0.248	0.121	Job transition (EE) rate	0.021	0.023	0.022	0.031
b	3.132	11.910	Unemployment rate	0.053	0.053	0.075	0.075
π_1	0.766	0.307	Fraction wages $\leq w_{25}$	0.249	0.250	0.247	0.250
η	108.536	96.141	Fraction wages $\leq w_{75}$	0.749	0.750	0.750	0.750
α_O	0.905	4.074	Contact rate employed	0.128	0.128	0.126	0.123
κ_O	0.165	0.245	Contact rate unemployed	0.258	0.244	0.348	0.350
ξ_O	9.590	41.113	Avg wage (O)	32.929	33.234	20.133	20.114
p	244.418	58.741	Avg wage (B)	36.885	36.571	21.341	21.739
c	8.263	-7.379	Avg wage (F)	32.950	32.937	20.343	20.624
α_B	1.503	1.712	Usage differential (B)	0.106	0.117	0.050	0.042
κ_B	0.051	0.036	Fraction employed (B)	0.188	0.187	0.140	0.140
α_F	0.044	0.157	Usage differential (F)	-0.026	-0.020	0.058	0.049
κ_F	0.042	0.035	Fraction employed (F)	0.204	0.204	0.273	0.274
ξ_B	8.472	40.019	Avg tenure B/O	0.853	0.853	0.887	0.887
ξ_F	11.188	50.886	Avg tenure F/O	1.158	1.158	1.298	1.305

Notes: This table reports the values of the 16 parameters that are calibrated internally, along with the values of our 16 targeted moments in the data and as computed analytically in our model, separately for the high skill and low skill markets. Most of these moments are self-explanatory. "Fraction wages $\leq w_x$" denotes the fraction of employed workers earning less than the wages at the $x \in \{25^{th}, 75^{th}\}$ percentiles in the data, respectively. "Usage differential (j)" refers to the difference in the fraction of workers in the top wage quartile that used channel $j \in \{B, F\}$ to find their job and the fraction of workers in the bottom wage quartile that used channel j to find their job. "Fraction employed (j)" denotes the fraction of employed workers who found their job using channel $j \in \{B, F\}$.

of unemployment (or home production), b, is a controversial parameter in the literature, with values of this "replacement rate" ranging from 0% (Moscarini and Postel-Vinay, 2023) to 95% (Hagedorn and Manovskii, 2008) of the surplus generated from a match. Our estimates are qualitatively similar to those in Lise et al. (2016), in that we also find less educated workers value leisure (or home production) more than highly educated workers.

The remaining parameters determine the properties of the channel-specific matching and production technologies—i.e., the relationships between workers' unobserved types, the frequency with which they contact firms through different channels, and the output generated by these potential matches—that are necessary to generate the empirical patterns we observe in the data. Given the large number of these parameters, and the myriad ways they interact with one another, it is difficult to interpret these values independently. In what follows, we highlight the main qualitative properties of these technologies implied by the calibrated parameter values, explain how these properties enable the model to match the target moments in the data, and discuss the relationship between these properties and existing theories of referrals.

Key properties of the matching and production technologies. Table 6 reports a few summary statistics that reveal several key properties of the calibrated model environment. First, matching the data through the lens of our model requires significant heterogeneity in the rate at which otherwise similar workers receive offers (through any channel), both when they are unemployed and when they are employed. For example, in both the high and low skill markets, the overall rate at which unemployed workers of type a_2 match with firms, $\Gamma^u(x_2^\star|a_2)$, is more than ten times larger than the matching rate of type a_1 unemployed workers.[41]

The second key insight is that this heterogeneity stems mostly from differences in the arrival rate of offers through business referrals and, to a lesser extent, other (formal) channels. For example, in the high skill market, the rate at which type a_2 workers match with firms through a business referral, $\Gamma_B^u(x_2^\star|a_2)$, is approximately thirty times larger than the corresponding matching rate of type a_1 workers. Offers that arrive through referrals from family and friends, in contrast, are significantly less sensitive to a worker's unobserved type.

The third key insight is that there are important differences in expected output across channels. In both markets, F referrals create the best matches, conditional on worker type. For example, in the high skill market, the expected output for a type a_2 worker from a match formed through channel F is approximately 21% (11%) higher than the expected output from a match formed through channel B (O). This result highlights the benefits of interpreting data through the lens of a model: though one might be tempted to conclude that B referrals generate the best matches, since they are associated with higher productivity *unconditionally*, in fact F referrals generate higher productivity matches *conditional* on ability (which cannot be observed directly in the data).

Finally, while we observe similar qualitative patterns in both high and low skill markets, there are important quantitative differences. For example, while high ability workers are more likely to use B relative to F in both markets, the difference is more pronounced in the high skill market. In addition, the fraction of all meetings initiated through other channels (O) is significantly larger in the low skill market than in the high skill market. We discuss the implications of these differences in more detail below.

Model mechanism. We now discuss how the properties of the channel-specific matching technologies identified in the calibration generate equilibrium outcomes that are consistent with the wide range of patterns we document in the data, both within and across markets.

Recall that our empirical analysis revealed clear relationships between the job search channel a worker used and her wage, tenure, and frequency of contact with firms. Specifically, workers who found their current job through a business referral earn higher wages but experience shorter

[41] Recall that the arrival rates of offers for employed workers are simply scaled by θ, so that the statements above regarding arrival rates apply equally well to employed and unemployed workers.

Table 6: Summary Statistics from Calibrated Model

Name	Notation	High Skill a_2	High Skill a_1	High Skill Ratio $\left(\frac{a_2}{a_1}\right)$	Low Skill a_2	Low Skill a_1	Low Skill Ratio $\left(\frac{a_2}{a_1}\right)$
Arrival rate overall	$\lambda^u(a_i)$	2.709	0.258	10.517	6.258	0.316	19.826
Arrival rate through B	$\lambda^u_B(a_i)$	1.554	0.051	30.249	1.748	0.036	48.183
Arrival rate through F	$\lambda^u_F(a_i)$	0.085	0.042	2.053	0.191	0.035	5.511
Arrival rate through O	$\lambda^u_O(a_i)$	1.069	0.165	6.498	4.319	0.245	17.654
Expected output through B	$\int f(x)dH_B(x\|a_i)$	41.269	25.961	1.590	19.307	9.886	1.953
Expected output through F	$\int f(x)dH_F(x\|a_i)$	50.040	31.104	1.609	22.827	12.951	1.763
Expected output through O	$\int f(x)dH_O(x\|a_i)$	44.970	28.107	1.600	19.700	10.216	1.928

Notes: This table reports several summary statistics using the calibrated parameter values. The arrival rate is the rate of contacts with an employer. Expected output is measured as expected hourly output.

tenure because—for reasons unexplained by observable characteristics—these workers generate contacts with firms at a relatively high rate. In contrast, workers who found their current job through their social network earn lower wages and experience longer tenures because, for these workers, new opportunities arrive relatively infrequently.

In the model, these patterns emerge in equilibrium through the endogenous sorting of unobservable types (a_1 and a_2) across different states (employment status, productivity, and wage) through different channels (B, F, and O). To see why, first note that type a_2 workers meet firms through all channels more frequently than type a_1 workers, but the difference in the arrival rate of meetings through channel B across abilities is much more pronounced than the difference in the arrival rate through channel F, i.e., $\lambda_B(a_2)/\lambda_B(a_1) > \lambda_F(a_2)/\lambda_F(a_1)$. As a result, a randomly selected employed worker who got her job through channel B is more likely to be of type a_2, while a worker who got his job through channel F is more likely to be of type a_1. Moreover, note that the expected productivity in any match is higher for a_2 workers than a_1 workers for all three channels. Hence, the expected wage of type a_2 workers is relatively high, in equilibrium, for multiple reasons: their expected productivity is higher than a_1 workers in every match; they draw new match-specific productivities more frequently; and they have a better outside option when bargaining with the firm. Together these findings imply that a randomly selected worker who got her job through channel B (F) will have a relatively high (low) wage.

Endogenous sorting on workers' unobserved types also helps rationalize the observed relationships between job search channel and tenure. For example, since a randomly selected worker who found their job through channel B is likely to be a type a_2 worker—and type a_2 workers contact new firms relatively frequently—it follows that workers who found their job through channel B will experience shorter tenures. However, differential arrival rates alone are not sufficient to match the large quantitative differences in tenure across job search channels, while still matching other key moments such as usage rates across channels. Matching all of the targets of our calibration reveals that matches formed through channel B (F) have relatively low (high) productivity, conditional on the worker's type. Intuitively, to generate the relatively long tenure of matches formed through channel F, it must be that type a_1 workers meet firms relatively infrequently *and* that matches formed through channel F are sufficiently productive that future contacts are unlikely to produce a better match.

Finally, the results in Table 6 are also helpful for understanding how the model generates differential usage rates of channels B and F across markets. For example, in the high skill market, meetings occur relatively frequently through B, compared to the overall meeting rate, whereas meetings through B are a smaller proportion of meetings in the low skill market.

Relationship to existing theories. By imposing flexible, reduced-form relationships between workers' unobserved types, the arrival rates of meetings, and the distributions of productivity across search channels, the parameter values that emerge from our calibration exercise help us understand the distinct roles that referrals from business contacts and family/friends play in the match formation process. In this section, we discuss how the properties of these matching technologies that we've uncovered relate to existing theories of referrals. Note that our goal in this section is not to derive explicit, micro-founded theories, but rather to lay out, for the first time, the properties of these two types of referrals that a successful theory must match in order to be consistent with the data.

On the one hand, as we discussed above, a worker's tendency to meet a firm through a business referral is highly sensitive to the worker's *ex ante* type, a_i. As a result, business referrals frequently initiate contact for type a_2 workers who are likely to have high match-specific productivity at a firm, and are rarely used to initiate contact for type a_1 workers who are typically less productive. Hence, business referrals appear most consistent with theories that rely on a referrer's ability to *screen* workers based on their expected productivity at the firm, as conjectured by Montgomery (1991) and others.[42]

On the other hand, referrals from family and friends appear to generate relatively high productivity matches independently of a worker's underlying type. This property is consistent with theories that ascribe a central role to the ability of referrals to generate good matches *ex post*. One such theory, put forward by Simon and Warner (1992), among others, postulates that referrals improve workers' and firms' ability to overcome *symmetric uncertainty* by learning

[42]For instance, a model in which reputation concerns provide business contacts with incentive to only refer workers with high expected productivity could generate this outcome. Alternatively, a model in which business networks featured a greater degree of homophily regarding workers' productivity (relative to social networks) could also generate the desired result. In either case, type a_2 workers would meet firms through channel B more frequently than type a_1 workers, after which information would be revealed and the match formation decision could occur.

about their match-specific productivity more efficiently. An alternative theory, which is also consistent with the properties of $\Gamma_F(\cdot)$ revealed by our calibration exercise, is that referrals from family and friends help overcome *moral hazard*. According to this theory (put forward by, e.g., Heath, 2018), a worker referred by a family or friend has more incentive to work hard and less incentive to shirk.

The finding that low types (a_1) rely much more heavily on referrals from friends and family is consistent with the idea that referrals can act as a "last resort" for individuals with few outside options, as espoused by Loury (2006). However, note that our findings are *not* consistent with theories of referrals based on nepotism or other forms of favoritism, in which referred workers are, on average, less productive than workers hired through more formal channels (see, e.g., Bandiera et al., 2009; Fafchamps and Moradi, 2015).

5.3 Quantitative Insights from Calibration

In this section, we use the calibrated model to explore the quantitative effects of referrals from business contacts and family and friends on employment, earnings, output, 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, and follow them for a period of ten years.[43] Then, we repeat the simulation but shut down referrals from business contacts, by setting $\Gamma_B(x|a) = 0$, and evaluate the labor market outcomes 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.[44]

The contribution of referrals to earnings. Table 7 reports the average annual earnings, the average employment rate, and the average wage (conditional on being employed) of workers during their first ten years in the labor market.[45] Several interesting insights emerge.

First, and perhaps most striking, is the extent to which low ability workers depend on referrals from family and friends. For instance, our simulations suggest that more than 11% (7%) of earnings of low ability workers in low (high) skill occupations can be attributed to referrals from family and friends. Intuitively, referrals from family and friends are critically

[43]The results reported below are similar at 20 and 30 year horizons, as well.

[44]Note that, in these quantitative exercises, we assume that shutting down one channel has no effect on the arrival rate or quality of matches generated by other channels. This allows for a clean decomposition of the relative contribution of each channel to labor market outcomes. Moreover, existing evidence shows that workers already exploit available job search channels, with plenty of time to spare; see, e.g., Mukoyama et al. (2018). This suggests that workers without access to one particular job search channel may not be able to easily increase the arrival rate and/or quality of matches through an alternative channel.

[45]Note that the average employment rate reported in Table 7 is lower than in the steady state because, in the simulation, each individual starts off unemployed.

Table 7: Contribution of Referrals to Earnings and Employment

Outcome	Exercise	High Skill: Low Ability	High Skill: High Ability	High Skill: Overall	Low Skill: Low Ability	Low Skill: High Ability	Low Skill: Overall
Annual Earnings	Benchmark	\$45,196	\$100,460	\$58,244	\$18,348	\$45,650	\$37,207
	Shut down B Referrals	-5.4%	-5.0%	-5.3%	-2.0%	-1.1%	-1.0%
	Shut down F Referrals	-7.4%	-0.8%	-4.9%	-11.2%	-1.2%	-2.6%
Employment Rate	Benchmark	0.89	0.97	0.91	0.67	0.96	0.87
	Shut down B Referrals	-2.1%	-0.9%	-1.8%	-2.0%	-0.2%	-0.5%
	Shut down F Referrals	-1.4%	0.0%	-1.1%	-9.2%	0.2%	-1.9%
Wage	Benchmark	\$24.21	\$49.79	\$30.25	\$13.17	\$22.74	\$19.79
	Shut down B Referrals	-3.5%	-4.1%	-3.8%	0.1%	-0.9%	-0.5%
	Shut down F Referrals	-6.2%	-0.8%	-4.3%	-2.2%	-1.4%	-1.4%

Notes: This table reports estimates from a simulation of our calibrated model in which a cohort of 30,000 workers enters the market unemployed. We follow this cohort for a period of 10 years. The top panel reports average annual earnings over these 10 years in both markets (high and low skill) for low and high ability workers (a_1 and a_2, respectively). The middle panel reports the average employment rates for each of these groups, and the bottom panel reports average hourly wages of employed workers. In each panel, the top row reports results from our benchmark model, while the second and third rows report how the baseline results change when we shut down referrals from business contacts and family/friends, respectively.

important to this subset of workers for two reasons: first, because they struggle to contact firms through other channels (O or B); and second, because matches formed through family and friends tend to be high quality matches (for all abilities). Second, while our calibration suggests that low ability workers depend heavily on referrals from family and friends, high ability workers do not: in both low and high skill markets, high ability workers match with firms through channels B and O sufficiently frequently that shutting down channel F has very modest effects on earnings and, in fact, no effect on employment.

The effects of referrals from business contacts are quite different: while the contribution of channel B to labor market outcomes is more even across workers' abilities, our calibration suggests that workers' networks of business contacts are considerably more important in high skill occupations than in low skill occupations. For example, shutting down channel B reduces earnings by about 5% in the former, and only about 1% in the latter. Intuitively, there are several reasons why the effects of business referrals are more pronounced in high skill occupations. For one, referrals from business contacts are used more frequently in the high skill market, especially among high ability workers who have higher average match-specific productivity. Moreover, since the calibrated production function is steeper in the high skill market, a reduction in average match quality translates into a larger loss in output.[46]

[46] In general, shutting down any channel $j \in \{B, F, O\}$ has three effects: workers spend more time in unemployment; they have lower match-specific productivity, on average, when matched; and they receive a smaller share of the surplus, since outside offers arrive more slowly. In most cases, the reduction in earnings associated with shutting down job search channels is driven predominantly by a reduction in the wages of employed workers–both because they have lower match-specific productivity and because they get fewer outside offers. However, in the case of low ability workers in the low skill market, it is the opposite–the effect is mainly caused

Finally, since the quantitative effect of referrals differs significantly both across B and F, and across low and high skill occupations, Table 7 illustrates again the importance of distinguishing between different types of referrals and the different types of occupations in which they are used. Importantly, these results also highlight the advantage of interpreting the data through the lens of a model. For instance, the regression results in Table 2, 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 workers' wages, while referrals from family and friends have modest, negative effects 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 reveals that referrals from family and friends have a large, positive effect on workers' wages, but they tend to be used by workers who otherwise struggle to find jobs (and hence earn, on average, lower wages).[47]

Referrals, output, and inequality. While referrals are widely regarded as an important channel for matching workers and firms, a central, yet open question is whether referrals mitigate or exacerbate earnings inequality. More specifically, do referrals primarily help workers with dim employment prospects to find good-paying jobs? Or, instead, do they mostly help relatively well-connected, high-wage workers to earn even more? The answers to these questions are key for assessing the implications of referrals on earnings inequality and evaluating an explicit role for referrals in the context of labor market policies.

Table 8 reports the change in total output and inequality (as measured by the standard deviation of earnings) in the simulations described above, in which we separately shut down B and F in low and high skill labor markets. The table reveals that the relationship between referrals and inequality again relies on the crucial distinction between referrals from different sources. In particular, the simulations reveal that referrals from business contacts increase earnings inequality, particularly in high skill occupations, by increasing the wages of high ability workers, who are already well-paid. Referrals from family and friends, however, do the exact opposite: they reduce earnings inequality, particularly in low skill occupations, by increasing employment and wages among low ability workers (while doing very little for high ability, high-wage workers).

by lower levels of employment. This is driven by the fact that low ability workers, in particular in the low skill market, have a much harder time meeting firms than do high skill workers.

[47] Our results are also informative about *firms'* incentives to hire through different channels. For instance, the greater usage rates of business referrals in high skill markets could be an indication that firms value the screening role of referrals when hiring in high skill occupations, which makes sense because output in these markets is highly sensitive to productivity (i.e., the value of p in the high skill market is much larger). In contrast, the frequent use of referrals from friends and relatives in low skill markets could be an indication that a friction like moral hazard—i.e., ensuring workers show up and work hard—is the more relevant friction when hiring in low skill occupations.

Table 8: Contribution of Referrals to Output and Inequality

	Total Output		St. Dev. of Earnings	
Exercise	**High Skill**	**Low Skill**	**High Skill**	**Low Skill**
Benchmark	\$70,695	\$38,469	\$25,319	\$13,103
Shut down B Referrals	-2.9%	-0.7%	-2.7%	-0.5%
Shut down F Referrals	-3.8%	-2.8%	3.8%	5.3%

Notes: This table reports estimates from a simulation of our calibrated model in which a cohort of 30,000 workers enters the market unemployed. We follow this cohort for a period of 10 years. The left panel measures average (hourly) output over these 10 years, and the right panel measures the standard deviation in earnings across workers. 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 referrals from business contacts and family/friends, respectively.

Hence, the central question of whether referrals generate a trade-off between output and inequality depends crucially on the distinction between these two types of referrals. For example, employers almost always allow—and sometimes encourage—their employees to refer candidates from their network of business contacts. Our results offer a natural explanation of why this is optimal, as a candidate referred through an employee's business network is likely to be a productive (high ability) worker. However, from a policy point of view, there is a trade-off: since business referrals increase the contact rate of high ability workers, they increase the likelihood that these workers are matched (which increases total output), but also increase their bargaining power through repeated outside offers (which increases wage inequality). In contrast, out of concerns for nepotism, some employers do *not* allow current employees to refer their relatives. Our results suggest that these types of concerns may be misplaced: since referrals from friends and relatives create good matches for all worker types, prohibiting this form of job search can generate less output and greater inequality. Moreover, since referrals from family and friends are used most intensely by workers in low skill markets who struggle to find work through other channels, restricting employees from referring their relatives can ultimately harm those workers at the bottom of the income distribution the most.

6 Concluding Remarks

A longstanding challenge in labor economics is understanding the channels through which workers and firms form productive matches, and the implications for labor market outcomes. In surveys of both workers and firms, referrals are often cited as a key input into the match formation process. However, while there may be a consensus that referrals are widely used, there is far less agreement about *who* uses them most frequently, *why* they are valuable, or *how* they ultimately affect match quality, wages, turnover, inequality, and output.

In this paper, we try to make progress on these important questions. Our contribution can be broken down into three parts. First, leveraging a relatively new dataset, we show that clear patterns emerge from the data only after distinguishing between different types of referrals and different types of jobs. Second, by interpreting these patterns through the lens of a model, we are able to assess various theories of referrals and explore which mechanisms are (or are not) consistent with the patterns we find in the data. Lastly, by further exploiting our calibration results, we are able to derive quantitative estimates of the contribution of referrals from different sources in low- and high-skill labor markets.

We find that referrals from friends and family are a crucial source of jobs for a subset of workers that struggle to generate offers and matches through more traditional channels. Indeed, this type of referral improves earnings and employment outcomes, and represents an important force for reducing earnings inequality. In contrast, business referrals tend to increase the wages of workers who have relatively good employment prospects to begin with. Hence, the use of business referrals, which is typically encouraged by firms, increases output but also exacerbates earnings inequality. These findings are important in assessing the impact of referrals in the labor market and in evaluating their role within the broader context of labor market policies.

Our results open up a number of avenues for future research. Having established the crucial distinction between referrals from business and social contacts—and laying out the equilibrium relationships between workers' types, the arrival rate of meetings, and the distribution of productivity draws that must prevail for each job search channel—the obvious next step is to explore the deeper microfoundations of how and why workers develop their business and social networks, along with the incentives of contacts within these different types of networks to provide a referral. For example, our findings that business referrals are highly sensitive to workers' ex ante types while referrals from family and friends are not suggests that a business contact's willingness to refer a worker is more motivated by the private benefits of doing so (e.g., the reputational reward from finding a good worker) whereas a social contact's payoffs from referring a friend or relative likely contain an altruistic component.[48] By uncovering the differential incentives of business and social contacts, along with the heterogeneous value of these contacts across occupations, our results are also informative about some of the relevant tradeoffs that workers face when they are *forming* their business and social networks.

In addition to providing new insights into network formation, our results are also informative

[48]Note that these incentives also have important ramifications for the implied composition of a worker's business and social networks. For example, if business referrals are motivated by an individual's private payoffs, then all of a type a_2 worker's contacts would be willing to make a referral, regardless of their own type. Under this interpretation, the large discrepancy in arrival rates through channel B does not require that the worker's business network consist of mostly a_2 workers; that is, the network would not need to exhibit a high degree of homophily to match the data, as in, e.g., Montgomery (1991).

about the costs of network destruction. For example, consider the literature that studies worker mobility across geographic locations. Within this literature, one key finding is that substantial moving costs are needed to rationalize the internal migration patterns observed in the data, particularly for low-skill workers (Kennan and Walker, 2011; Diamond, 2016; Piyapromdee, 2021).[49] In addition, the literature studying the Moving to Opportunity programs has found that, despite previous research documenting the importance of neighborhoods for economic outcomes, moving families from high-poverty to low-poverty neighborhoods has no significant effect on earnings or employment (Katz et al., 2001; Chetty et al., 2016). Our results provide a natural explanation for—and a bridge between—these two important findings. Specifically, since low-skill workers rely heavily on referrals from friends and relatives, and relocating often severs a worker's connections to many contacts in his social network, perhaps relocating low-skill workers to a low-poverty neighborhood embodies a (previously undocumented) cost—namely, the loss of job-finding capital associated with one's social network. Thus, by offering a deeper explanation of the *sources* of migration costs, our findings have potentially important implications for the design of social programs aimed at improving labor market outcomes by promoting migration. Analogously, our results on referrals from business contacts could provide new insights into the costs associated with occupational mobility, as changing occupations may significantly alter the structure of one's business network.

Finally, our results also shed new light on firms' incentives to use different channels to hire workers. For example, to fill a position in which output is highly sensitive to the worker's idiosyncratic productivity, a firm may require a referral from a business contact, since this channel is effective in locating high ability workers. The cost, however, is that such workers tend to receive frequent offers once employed. In contrast, a firm that is trying to fill a vacancy that does not require a high ability worker—or a vacancy in which turnover is particularly costly—may prefer to hire through their existing workers' social network. We leave exploring these interesting questions for future work.

[49]Indeed, Zerecero (2021) documents particularly high migration costs away from one's birthplace.

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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. We also provide a list of 2-digit occupation codes and their corresponding NPB scores, as well the text of the survey question we use to construct our measures of business and family/friends referrals.

Our data set combines the annual Job Search supplement 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.[50] 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.

[50]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.

Table 9: Nam-Powers-Boyd Index (2-Digit Occupation Level)

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

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

Table 10: SCE Survey Question on Referrals

How did you learn about your current job? [check all that apply]

- ☐ Found through the employer‘s website (1)
- ☐ Inquired with the employer directly through other means, including in-person (2)
- ☐ Found through an employment agency (including the conversion from temporary to permanent work) (3)
- ☐ Referred by a friend or relative (4)
- ☐ Referred by a former co-worker, supervisor, teacher, business associate (5)
- ☐ Referred by a current employee at the company (6)
- ☐ Found through a school/university/government employment or career center (7)
- ☐ Found through an online job search engine (8)
- ☐ Found job opening through other means, including help wanted ads (9)
- ☐ Found through union/professional registers (10)
- ☐ Contacted by potential employer (11)
- ☐ Temporary or part-time job converted into full-time job (12)
- ☐ Within-company promotion or transfer (13)
- ☐ Returned to a previous employer, including one where I had a previous internship or something similar (14)
- ☐ Began work in the family business (15)
- ☐ Don‘t remember (17)

Notes: This is the text of the survey question JH1 from the SCE Job Search Survey. Individuals that answered "Referred by a friend or relative (4)" are coded as a family/friends referral and individuals that answered "Referred by a former co-worker, supervisor, teacher, business associate (5)" or "Referred by a current employee at the company (6)" are coded as a business referral.

B Additional Empirical Results

Job Satisfaction and Referrals

Table 11 reports results from linear regressions 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 satisfied would you say you are with other aspects of the job, such as benefits, maternity/paternity leaves, flexibility in work hours, etc?"

4. "How well do you think this job fits your experience and skills?"

5. "How would you rate the opportunities for a promotion or other career progression with your current employer, over the next three years?"

For the first three measures respondents are asked to respond on a scale from 1-5 capturing "very dissatisfied" to "very satisfied". For the last two, they are asked to respond on a scale from 1-7 ranging from "very poor" to "very good". As the results indicate, there are no systematic differences in job satisfaction across job search method.

Table 11: Job Satisfaction and Referrals

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

Notes: Estimates are from regressions 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 three of the measures, there is one individual for whom we do not observe answers regarding job satisfaction.

Search Behavior of Employed Workers and Referrals

Table 12 reports results from regressions 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 weak evidence that business referred workers search more in terms of hours, but not in terms of overall probability.

Table 12: On-the-Job Search and Referrals

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

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.

C Omitted Proofs

Proof of Proposition 1

Using the thresholds described in the text, we can write the flow Bellman equation characterizing the value of unemployment for a worker with ability a_i as

$$rV^u(a_i) = b + \sum_{j \in \mathcal{C}} \lambda_j^u(a_i) \int_{x_i^\star}^{\overline{x}} \left[V^e(a_i, x, w^u(a_i, x)) - V^u(a_i)\right] dH_j(x|a_i).$$

Since $d\Gamma^u(x|a_i) = -\sum_{j\in\mathcal{C}} \lambda_j^u(a_i) dH_j(x|a_i) < 0$, this expression simplifies to

$$\left[r + \Gamma^u\left(x_i^\star|a_i\right)\right] V^u(a_i) = b - \int_{x_i^\star}^{\overline{x}} V^e(a_i, x, w^u(a_i, x)) d\Gamma^u(x|a_i). \tag{19}$$

In words, as in standard job search models, the value of unemployment is equal to the flow value of unemployment, b, plus the option value of finding a job out of unemployment.

Following similar steps for employed workers reveals that

$$\begin{aligned}[r+\delta+\Gamma^e(\widehat{x}|a_i)]\,V^e(a_i,x,w) =& w+\delta V^u(a_i)-\int_{\widehat{x}}^{x} V^e(a_i,x,w^e(a_i,x',x))d\Gamma^e(x'|a_i)\\ &-\int_{x}^{\overline{x}} V^e(a_i,x',w^e(a_i,x,x'))d\Gamma^e(x'|a_i),\end{aligned} \tag{20}$$

where $\widehat{x}\equiv\widehat{x}(a_i,x,w)$.

By construction, the $\widehat{x}(a,x,f(x))$ threshold has the following properties, which are useful later:

$$x=\widehat{x}(a,x,f(x)) \tag{21}$$

$$V^e(a_i,x,w)=V^e(a_i,\widehat{x}(a_i,x,w),f(\widehat{x}(a,x,w)))\,. \tag{22}$$

Now, by substituting (8), equation (20) can be written

$$\begin{aligned}[r+\delta+\Gamma^e(\widehat{x})]\,V^e(a_i,x,w) = & w+\delta V^u(a_i)+V^e(a_i,x,f(x))\left[\beta\left[\Gamma^e(\widehat{x}|a_i)-\Gamma^e(x|a_i)\right]+(1-\beta)\Gamma^e(x|a_i)\right]\\ &-(1-\beta)\int_{\widehat{x}}^{x} V^e(a_i,x',f(x'))d\Gamma^e(x'|a_i)-\beta\int_{x}^{\overline{x}} V^e(a_i,x',f(x'))d\Gamma^e(x'|a_i),\end{aligned}$$

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

Setting the wage $w=f(x)$, substituting (21), and simplifying yields

$$[r+\delta+\beta\Gamma^e(x)]\,V^e(a_i,x,f(x))=f(x)+\delta V^u(a_i)-\beta\int_{x}^{\overline{x}} V^e(a_i,x',f(x'))d\Gamma^e(x'|a_i).$$

Differentiating with respect to x then yields

$$\frac{\partial V^e(a_i,x,f(x))}{\partial x}=\frac{p}{r+\delta+\beta\Gamma^e(x|a_i)}. \tag{23}$$

Using this relationship in the expression for $V^e(a_i,x,w)$ above, integrating by parts, using (20), and simplifying yields

$$\begin{aligned}(r+\delta)V^e(a_i,x,w) =& w+\delta V^u(a_i)\\ &+p\left[(1-\beta)\int_{\widehat{x}}^{x}\frac{\Gamma^e(x'|a_i)}{r+\delta+\beta\Gamma^e(x'a|a_i)}dx'+\beta\int_{x}^{\overline{x}}\frac{\Gamma^e(x'|a_i)}{r+\delta+\beta\Gamma^e(x'a|a_i)}dx'\right].\end{aligned} \tag{24}$$

Plugging in $w=w^e(a_i,x,x')$, subtracting $(r+\delta)V^e(a_i,x,f(x))$, and using (20) yields

$$\begin{aligned}&(r+\delta)\left[V^e(a_i,x',f(x'))-V^e(a_i,x,f(x))\right]=\\ &w^e(a_i,x,x')-f(x)+p\left[(1-\beta)\int_{x}^{x'}\frac{\Gamma^e(x''|a_i)}{r+\delta+\beta\Gamma^e(x''a|a_i)}dx''-\beta\int_{x}^{x'}\frac{\Gamma^e(x''|a_i)}{r+\delta+\beta\Gamma^e(x''a|a_i)}dx''\right]\end{aligned}$$

since $\widehat{x}\left(a_i, x, w^e(a_i, x, x')\right) = x$. Using (23) yields

$$w^e(a_i, x, x') =$$
$$(r+\delta)\beta \int_x^{x'} \frac{p}{r+\delta+\beta\Gamma^e(x''|a_i)} dx'' + f(x) - p(1-2\beta) \int_x^{x'} \frac{\Gamma^e(x''|a_i)}{r+\delta+\beta\Gamma^e(x''a|a_i)} dx''.$$

Straightforward algebra then yields the expression in (8).

Next, to characterize $x_i^\star$, note that we can use (2) and (23) to get that

$$\begin{aligned} rV^u(a_i) &= b - \int_{x_i^\star}^{\overline{x}} \left[V^e(a_i, x, w^u(a_i, x)) - V^u(a_i)\right] d\Gamma^u(x|a_i) \\ &= b - \beta \int_{x_i^\star}^{\overline{x}} \left[V^e(a_i, x, f(x)) - V^u(a_i)\right] d\Gamma^u(x|a_i) \\ &= b + \beta \int_{x_i^\star}^{\overline{x}} \frac{p\Gamma^u(x|a_i)}{r+\delta+\Gamma^e(x|a_i)} dx, \end{aligned} \tag{25}$$

where the last equality follows from integration by parts. We can also use (1) and (24) to write

$$\begin{aligned} rV^e(a_i, x_i^\star, f(x_i^\star)) &= f(x_i^\star) + \delta V^u(a_i) + \beta \int_{x_i^\star}^{\overline{x}} \frac{p\Gamma^e(x|a_i)}{r+\delta+\Gamma^e(x|a_i)} dx \\ \Rightarrow rV^u(a_i) &= f(x_i^\star) + \beta \int_{x_i^\star}^{\overline{x}} \frac{p\Gamma^e(x|a_i)}{r+\delta+\Gamma^e(x|a_i)} dx. \end{aligned} \tag{26}$$

Equating (25) and (26) yields (10).

Finally, to characterize the equilibrium distributions, note that substituting (5) into (6) yields (11), and substituting (11) into (7) then yields (12).

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 $w' \le w$. In a steady-state equilibrium, the outflow of such workers is

$$G(w|a_i, x)\phi^e(a_i, x)\left[\delta + \Gamma^e\left(\widehat{x}(a_i, x, w)|a_i\right)\right]. \tag{27}$$

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 $w' \le w$. 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 $x' > \widehat{x}(a_i, x, w)$.

The inflow of workers into this set can be written

$$\phi^u(a_i) \sum_j \lambda_j^u(a_i) h_j(x|a_i) + \Phi^e\left(\widehat{x}(a_i, x, w)|a_i\right) \sum_j \lambda_j^e(a_i) h_j(x|a_i). \tag{28}$$

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

$$\sum_j \lambda_j^k(a_i)h_j(x|a_i) = -d\Gamma^k(x|a_i).$$

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 $x' \leq \widehat{x}(a_i, x, w)$. Equating the outflow and inflow in equations (27) and (28) 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 (13) yields

$$g(w|a_i, x) = -\frac{\partial \widehat{x}}{\partial w}\left\{\frac{\phi^e\left(\widehat{x}|a_i\right)d\Gamma^e(x|a_i)\left[\delta + \Gamma^e\left(\widehat{x}\right)\right] - \left[\phi^u(a_i)d\Gamma^u(x|a_i) + \Phi^e\left(\widehat{x}|a_i\right)d\Gamma^e(x|a_i)\right]d\Gamma^e\left(\widehat{x}\right)}{\phi^e(a_i, x)\left[\delta + \Gamma^e\left(\widehat{x}\right)\right]^2}\right\},$$

where

$$\frac{\partial \widehat{x}}{\partial w} = \frac{r + \delta + \beta\Gamma^e(\widehat{x}|a_i)}{p(1-\beta)\left[r + \delta + \Gamma^e(\widehat{x}|a_i)\right]}.$$

D Quantitative Exercise

Moments used in the calibration

Here we provide a more detailed description of the sixteen moments we use to calibrate the model.

Unemployment rate. The unemployment rate implied by the model is $u = \sum_i \phi^u(a_i)$, where $\phi^u(a_i)$ is characterized in equation (11).

EU rate. The job destruction rate in the continuous time model is simply $1 - e^{-\delta}$. However, given the relatively high job-finding rate, Shimer (2005) argues that it's important to account for time aggregation. Hence, we adjust the separation rate to account for time aggregation as Shimer (2005) suggests in equation (2) (on page 32), so that

$$\text{separation rate} \;=\; \left(1 - e^{-\delta}\right)(1 - 0.5 \times [\text{job finding rate}])$$

where the job finding rate is determined endogenously:

$$\sum_i \frac{\Phi^u(a_i)}{u}\left[1 - e^{-\Gamma^u(x_i^\star|a_i)}\right].$$

EE rate. A worker currently matched at a type x job moves if and only if he contacts a firm and draws $x' > x$. Hence, the job-to-job transition rate is:

$$\sum_i \underbrace{\frac{\Phi^e(1|a_i)}{1-u}}_{\text{frac type } i} \underbrace{\int_{x_i^\star}^{\overline{x}} \left[1 - e^{-\Gamma^e(x|a_i)}\right] \frac{d\Phi^e(x|a_i)}{\Phi^e(1|a_i)}}_{\text{prob type } i \text{ moves}} = \frac{1}{1-u}\sum_i \int_{x_i^\star}^{\overline{x}} \left[1 - e^{-\Gamma^e(x|a_i)}\right] d\Phi^e(x|a_i).$$

Contact rates. The model is silent on whether a meeting between a worker and firm that has a negative surplus (i.e., when $x < x_i^\star$) should be counted as a "contact." We adopt the convention that unemployed workers count every meeting as a contact, and hence the average rate at which unemployed workers contact a firm is

$$\frac{\sum_i \phi^u(a_i)}{u}\left[1 - e^{-\Gamma^u(0|a_i)}\right].$$

Alternatively, we assume that an employed worker is uninterested in initiating a contact with a new firm if the surplus is negative. Hence, the arrival rate of contacts for employed workers is

$$\sum_i \frac{\Phi^e(1|a_i)}{1-u}\left[1 - e^{-\Gamma^e(x_i^\star|a_i)}\right].$$

Residual wage dispersion. Since $G(w|a_i, x)$ denotes the fraction of type a_i workers who are employed at a firm with match-specific productivity x earning a wage $w' \leq w$, the fraction of *all* workers earning $w' \leq w$ is

$$\frac{\sum_i \int_{x_i^\star}^{\overline{x}} G(w|a_i, x)\phi^e(a_i, x)dx}{1-u}.$$

Plugging in the closed form expression for $G(w|a_i, x)$ in (13) allows us to calculate the fraction of employed workers earning less than the wages that lie at the 25th and 75th percentiles of the empirical distribution.

Usage across channels. The fraction of employed workers who found their job through channel $j \in \{B, F\}$ is characterized in equation (15).

Average wages across channels. The average wage of employed workers who found their job through channel $j \in \{B, F, O\}$ is characterized in equations (16) and (17).

Average tenure across channels. The average tenure of employed workers who found their job through channel $j \in \{B, F, O\}$ is characterized in equation (18).

Differential usage of channels across the wage distribution. 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

$$\begin{aligned}\dot{\omega}_j(a, x|w) = {} & \Phi^e\left(\widehat{x}(a, x, w)|a\right) d\Gamma_j^e(x|a) + \phi^u\left(a\right) d\Gamma_j^u(x|a)\mathbf{1}_{\{w \geq w^u(x,a)\}} \\ & - \omega_j(a, x|w)\left[\delta + \Gamma^e\left(\widehat{x}(a, x, w)|a\right)\right] \quad = 0.\end{aligned}$$

The first line in the expression above captures the inflow of workers into the set. First, a mass $\Phi^e\left(\widehat{x}(a, x, w)|a\right) d\Gamma_j^e(x|a)$ 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 $\phi^u\left(a\right) d\Gamma_j^u(x|a)$ 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

$$\omega_j(a, x|w) = \frac{\Phi^e\left(\widehat{x}(a, x, w)|a\right) d\Gamma_j^e(x|a) + \phi^u\left(a\right) d\Gamma_j^u(x|a)\mathbf{1}_{\{w \geq w^u(x,a)\}}}{\delta + \Gamma^e\left(\widehat{x}(a, x, w)|a\right)}.$$

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:

$$\frac{\Omega_j(w)}{\sum_j \Omega_j(w)}. \tag{29}$$

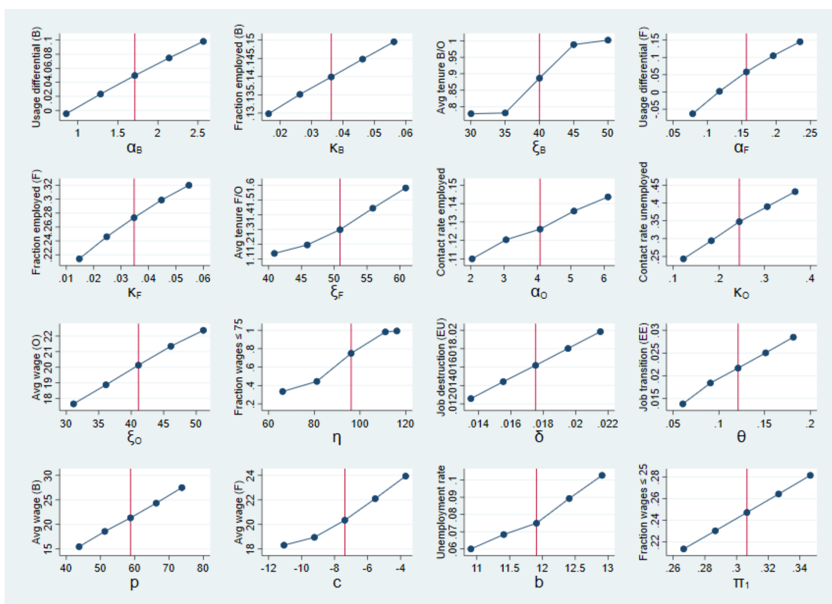
To construct the final two moments, we use (29) to calculate the fraction of workers in the top and bottom quartiles of the wage distribution that found their job through channel $j \in \{B, F\}$, and then we take the difference.

E Identification

In this Appendix we report the results of two sets of identification exercises designed to demonstrate the identification of the model's parameters. We report results corresponding to the low skill market, but we find similar results for the high skill market, and those results are available upon request.

As we discuss in the main text, we match each moment to a (unique) corresponding parameter that is particularly relevant for that moment. In our first exercise, for each moment, we vary the assigned parameter around the optimal value, while holding the other parameters fixed at their optimal values, and compute how the moment varies. Figure 2 presents the results of this exercise. As the figure demonstrates, all of the moments demonstrate significant monotonic variation with respect to their corresponding parameters.

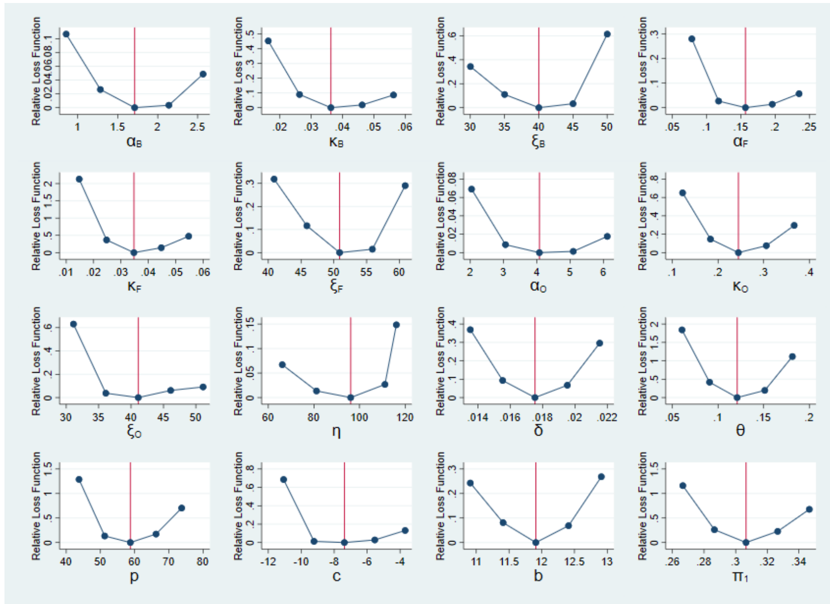
Figure 2: Moments as a Function of Assigned Parameter



Notes: For each of the parameters, we plot how each moment varies with its assigned parameter, while holding all other parameters fixed at their optimal values. The calibrated value for each parameter is indicated by the red line.

The second exercise we perform is to vary each parameter around the calibrated value, recalibrate all the other parameters, and then report the relative difference in the loss functions. The results of this exercise are reported in Figure 3. We find that the loss functions are u-shaped around the optimal values of each parameter, providing additional evidence that our model is well identified.

Figure 3: Relative Loss Function



Notes: This figure plots how the loss function changes when we fix each parameter at values around the calibrated value and re-calibrate all of the other parameters. The vertical axis plots the relative difference in the loss functions. The optimal value of the parameter is indicated by the red line.

F Regressions on Simulated Data

In this Appendix we show that our model is capable of replicating the empirical patterns we demonstrate in the SCE data in Section 3 which relate referrals usage to various labor market outcomes. In particular, we replicate the regression results in that section (see Tables 1 - 4) on our simulated data. For convenience we also report the corresponding results from Section 3.

We first examine the relationship between the usage of referrals and the skill content of the occupation. In the real data we use a continuous measure of skill, the NPB score. Since in the simulated data our measure of occupational skill is binary, we replicate the results in Table 1 using the binary measure for the skill content of the occupation as defined in Section 5. Table 13 shows that our model simulated data generates a very similar relationship as compared to the real data for both business and family/friends referrals.

Next we examine how starting wages, job tenure, and contact rates vary with the channel used to find the job. For each set of results we report regressions run on data simulated from our model as well as the SCE data. For the results using the simulated data we use our binary measure of skill. For the results using the SCE data, we use the continuous measure of skill, and thus these results are identical to those reported in Section 3, but we reproduce them again here for convenience.[51]

In Table 14 we look at the relationship between starting wages and the usage of both types of referrals. For business referrals, we find a positive and statistically significant association with starting wages that decreases in magnitude once we control for previous wages, a rough proxy

[51] We have also run these regressions in the real data using the binary measure of skill, and the estimated relationships with referrals usage are quantitatively very similar.

Table 13: Simulated Regressions Usage

	Model Type of Referral Business	Family/Friends	*Data* Type of Referral Business	Family/Friends
Skill / Market	0.051***	-0.075***	0.043***	-0.076***
	(0.012)	(0.014)	(0.013)	(0.015)

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. Results in the first set of columns correspond to estimates based on data simulated from our model. Results in the second set of columns correspond to estimates based on the SCE data. For the simulated data regressions, we draw a sample size equal to that used in the real data. We repeat this 100 times and report the means and standard deviations of those estimates. 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.

for the unobserved ability of the worker, as we find in the real data. For family/friends referrals, we find a negative relationship when not controlling for the skill content of the occupation or the previous wage, as in the real data, although the magnitude is smaller, and as a result not statistically significant. We also find that controlling for previous wage causes this estimate to increase, leading to a small and statistically insignificant relationship between family/friends referrals, as in the real data. The simulated regression results also deliver a very similar positive correlation between previous wages and starting wages.

Table 14: Simulated Regressions Starting Wages

	Model Log Real Starting Wage			*Data* Log Real Starting Wage		
	(1)	(2)	(3)	(1)	(2)	(3)
Business Referral	0.122***	0.107***	0.033**	0.161***	0.148***	0.085***
	(0.024)	(0.021)	(0.017)	(0.025)	(0.023)	(0.022)
Family/Friends Referral	-0.024	0.000	0.024*	-0.093***	-0.046**	-0.024
	(0.016)	(0.016)	(0.014)	(0.023)	(0.021)	(0.020)
Skill Index		0.266***	0.067***		0.010***	0.005***
		(0.012)	(0.009)		(0.000)	(0.000)
Log Previous Wage			0.598***			0.530***
			(0.016)			(0.014)

Notes: Estimates are from regressions of the log of the real starting wage for the worker's current job. Results in the first set of columns correspond to estimates based on data simulated from our model. Results in the second set of columns correspond to estimates based on the SCE data, as reported in Table 2. For the simulated data regressions, we draw a sample size equal to that used in the real data. We repeat this 100 times and report the means and standard deviations of those estimates. 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 results for job tenure are reported in Table 15. Overall the regressions in simulated and real data generate very similar results, both between tenure and the two types of referrals, and between tenure and previous wages.

Table 15: Simulated Regressions Tenure

	Model				*Data*		
	Log Job Duration				Log Job Duration		
	(1)	(2)	(3)		(1)	(2)	(3)
Business Referral	-0.170***	-0.170***	-0.143**		-0.185***	-0.195***	-0.172***
	(0.057)	(0.057)	(0.056)		(0.055)	(0.054)	(0.065)
Family/Friends Referral	0.226***	0.227***	0.218***		0.216***	0.246***	0.229***
	(0.045)	(0.046)	(0.046)		(0.049)	(0.049)	(0.060)
Skill Index		0.001	0.074*			0.007***	0.007***
		(0.039)	(0.040)			(0.001)	(0.001)
Log Previous Wage			-0.219***				-0.142***
			(0.050)				(0.036)

Notes: Estimates are from regressions of the log of the duration of the current job. Results in the first set of columns correspond to estimates based on data simulated from our model. Results in the second set of columns correspond to estimates based on the SCE data, as reported in Table 3. For the simulated data regressions, we draw a sample size equal to that used in the real data. We repeat this 100 times and report the means and standard deviations of those estimates. 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.

Finally we look at how contact rates are related to the usage of referrals. In both the real and simulated data we find a strong positive relationship between contact rates and business referrals, with similar magnitudes. For family/friends referrals we find a negative relationship with contract rates in both cases, although the magnitudes in the simulated data are slightly smaller.

Table 16: Simulated Regressions Contact Rates

	Model			*Data*		
	Probability of Contact (Last 4 Weeks)			Probability of Contact (Last 4 Weeks)		
	(1)	(2)	(3)	(1)	(2)	(3)
Business Referral	0.064***	0.078***	0.033*	0.050***	0.048***	0.037*
	(0.020)	(0.019)	(0.019)	(0.018)	(0.018)	(0.023)
Family/Friends Referral	-0.011	-0.031*	-0.016	-0.043***	-0.037**	-0.050**
	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.021)
Skill Index		-0.235***	-0.362***		0.001***	0.001
		(0.013)	(0.014)		(0.000)	(0.000)
Log Previous Wage			0.382***			0.047***
			(0.016)			(0.013)

Notes: Estimates are from regressions of an indicator for whether or not an individual had contact with at least one potential employer in the last four weeks. Results in the first set of columns correspond to estimates based on data simulated from our model. Results in the second set of columns correspond to estimates based on the SCE data, as reported in Table 4. For the simulated data regressions, we draw a sample size equal to that used in the real data. We repeat this 100 times and report the means and standard deviations of those estimates. 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.