# REFERRAL-NETWORKS IN FRICTIONAL LABOR MARKETS

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# ABSTRACT

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This dissertation is composed of three essays using labor search models to explore the role of referral-networks in the labor market. The first, "**The Stabilizing Effect of Referral-Networks on the Labor Market**," examines how the use of informal connections (i.e. referral-networks) affects the severity and duration of recessions. To do so, I develop a search-and-matching model in which there are two hiring methods, formal channels and informal channels, and workers endogenously adjust their network of informal contacts in response to shocks and government policy. I show referral-networks have a stabilizing effect on the labor market, reducing the severity of adverse economic shocks and accelerating post-recession recovery. Counterfactuals demonstrate the government must exercise caution when enacting policies intended to expedite economic recovery. Policies that generically improve worker-firm matching prolong recovery by 8 months, as they facilitate relatively more matches between workers and low-productivity firms during recessions. In contrast, policies aimed at reducing the costs of network-formation or increasing referral-network prevalence facilitate more matches between workers and high-productivity firms, expediting recovery by 3-6 months.

The second chapter, "**The Impact of Referral-Networks on Sectoral Reallocation**," investigates a new explanation for the long-run decline in sectoral switching– the increased prevalence of referral-networks. Using data from the Current Population Survey (CPS), I first document empirically significant increase in the use of referral-networks in the job-search process by the unemployed. Moreover, this increase is concurrent with the decline in sectoral switching. The CPS is then used

to estimate the effect of using referral-networks on the likelihood of an individual switching sectors at a various levels of industry classifications. For all aggregations, using referral-networks significantly reduces the probability a worker switches sectors. After controlling for demographics, these estimates imply an increase in the prevalence of referral-network use could explain as much as 5% to 40% of the decline in sectoral switching.

To better illustrate the policy implications of this finding, a discrete time sectoral-switching model is constructed using a search and matching framework with labor market referrals. The estimated model estimates a referral-switching elasticity of about -.12, which is within the empirically estimated range of -.05 to -.22 for the 2-sector industry aggregation, demonstrating that the increased of the prevalence of referrals overtime can explain about 20% of the decline in US sectoral switching. Welfare results indicate that referrals are a "benign" cause of the decline, i.e. welfare declines upon effectively banning the use of referral-networks. These results have important implications for policymakers. They suggest that the cause of the decline in sectoral switching (and more generally job-changing) is the result of improved matching efficiency over time rather than market inefficiency.

The third chapter, "**Does Job-Finding Using Informal Connections Reduce Mismatch?**," presents evidence that nonpecuniary benefits of a job, such as hours, commute time, and work environment, are a salient factor in a worker's decision to either accept or reject the offer. Using data form the Survey of Consumer Expectations (SCE), I document three empirical facts on the use of referral-networks and mismatch. First, not all referrals reduce perceived mismatch as reported by workers. For high-skill workers, referrals from former coworkers tend to reduce perceived nonpecuniary-mismatch. For low-skill workers, referrals from friends and family tend to increase perceived non-pecuniary mismatch.

Given these empirical facts, I construct a search-and-matching model of the labor market similar to Buhrmann [2018a] where workers and firms are given types on a unit interval and suffer increasingly greater productivity losses depending on distance between the firm's type and the worker's type. I augment this baseline model with mismatch along two dimensions – skill and nonpecuniary preferences– and calibrate it to the US economy. Results show nonpecuniary preferences can generate more dispersion in skill-mismatch for very low-skill workers and very high-skill workers. Moreover, while referral-networks generally improve aggregate mismatch, they have a heterogeneous affect on nonpecuniary mismatch by type. For low-skill (high-skill) workers, referral-networks increase (decrease) nonpecuniary mismatch.

Overall, the results from this dissertation serve as a guide for policymakers. While government intervention may be deemed necessary in recessions, it is vital to understand the role specific matching channels serve in the economy in order for a policy to achieve the desired result. Understanding that referrals generate more high-productivity matches suggests policymakers should investigate policies aimed at improving network formation and functionality. Similarly, distinguishing between formal and informal methods of job finding are key to understanding recent labor market phenomenon. The second chapter shows informal channels have become more ubiquitous in order to facilitate matching. While this change creates patterns in the data that seem concerning, a closer investigation reveals this seems to be a result of the market simply adapting to be more efficient. Finally, understanding why people use formal and informal channels is vital to understanding worker-firm mismatch on a micro-level. While high-skill workers use informal channels to find better matches, low-skill seem to use them to find any match faster. In essence, the findings of this dissertation emphasize the need for policymakers to understand the nuanced behavior of job seekers and the differing goals of various job-finding methods. One cannot simply treat all job-finding as the same, especially if a particular method is widely used and leads to significantly different outcomes, and expect to implement efficient policy. Thus, it is important to understand how certain job-finding methods differ on a micro level and apply these finding to macro policy.

# 1. THE STABILIZING EFFECTS OF REFERRAL-NETWORKS ON THE LABOR MARKET

## 1.1 Introduction

The use of informal connections is a pervasive feature of the labor market (Topa 2011; Granovetter 1995). An estimated 85% of workers have attempted to use their network of contacts to find a job, and about 50% of all currently existing jobs were formed through the use of referral-networks (Ionnides and Loury 2004). For workers, using this network of informal connections to find a job leads to lower expected unemployment durations, higher wages (Igarashi 2016), and faster job-to-job transitions (Arbex, O'Dea, and Wiczer 2017). Hiring through referrals is beneficial from a firm's perspective as well, resulting in better matches as measured by productivity (Castilla 2005) and longer expected employment tenure (Brown et al. 2016 and Burks et al. 2015). Hiring through referrals also significantly improves worker-firm matching; Galenianos [2014] finds most of the differences in worker-firm matching efficiency across industries can be explained by differences in referral-network use. Recent evidence presented by Hellerstein et al. [2015] also suggests local economies with greater referral-network prevalence enjoy higher job-finding probabilities for displaced workers. Moreover, the authors find little evidence the effectiveness of referrals declined during the Great Recession.

This paper investigates how referral-network use impacts both the severity and length of recessions. Moreover, it examines the effectiveness of policies aimed to promote the use of informal connections relative to more traditional methods such as applying online or contacting employers directly. Since the Great Recession, there has been a renewed focus on programs and policies that seek to curb and shorten periods of economic downturn, and one feature common to these policies is the development of employment services meant to train individuals and expedite job-finding.[1] However, a recent study commissioned by the Department of Labor conducted by McConnell et al. [2016] calls into question the effectiveness of these programs in matching unemployed workers with quality jobs. Thus, while these policies may increase the matching rate between workers and firms, the added labor market congestion they generate in the process makes their aggregate impact unclear. Conversely, theoretical and empirical evidence suggests hiring through informal channels generates higher quality matches, but are policies designed to impact the use of informal channels more or less effective than traditional employment services?[2]

To answer these question, this paper uses a version of Galenianos' [2014] random search and matching model with hiring through both a costly formal channel and a less costly informal channel meant to capture the use of referrals. Two additional features are added to this framework in order to analyze post-recession economic recovery. First, we introduce firm heterogeneity and on-the-job search similar to Pissarides [1994] and Gautier [2002], creating an economy with "good jobs" and "bad jobs," distinguished by productivity. While all workers would like to have a "good job," search frictions may induce job seekers to settle for a "bad job" initially but continue to search on-the-job for better employment opportunities. Hence, policies can affect job creation along two margins: the total number of jobs and the number of high productivity jobs. Second, endogenous network formation allows workers to create a network of informal contacts (a referral-network) that varies by employment status and adjusts dynamically in response to shocks and policy.[3] This component

[1]For example Workforce Innovation and Opportunity Act (WIOA) of 2014 and the newly proposed ELEVATE Act of 2019 both highlight the role of their job search services.

[2]Rees [1996] notes referrals can act as an effective screening process since the referring individual's reputation and credibility are at stake. Empirically, Castilla [2005] find workers hired through informal channels are more productive while Brown et al. [2016] and Burks et al [2015] find referred workers have longer expected tenures.

[3]While most models of unemployment which include referrals assume networks are static or fixed, empirical evidence suggests referral-networks do evolve. Caria and Hassen [2013] find in a lab setting that individuals act strategically when forming their network. Conte et al. [2009] similarly find in a lab setting that individuals update their networks consistently given new information, even dropping links that are no longer beneficial.

better captures the general equilibrium effects of proposed policies. In the model, the economy is comprised of two markets that open sequentially –the labor market and the connections market. In the labor market, workers and firms seek to be matched subject to frictions. A worker can influence how quickly she finds a job and/or climbs the job ladder by building her referral-network in the connections market. In this market, workers take the aggregates of the labor market as given and seek to be matched with middlemen known as networkers. These networkers comprise the worker's referral-network and are interpreted as social connections such as friends and relatives,[4] and these informal connections can potentially help the worker match with a firm in the labor market.

A unique equilibrium exists given a few conditions. The model is then calibrated to the U.S. economy, and a recessionary shock is simulated. Notably, economies in which referral-networks are more widely used experience shorter and less severe recessions, as the prevalence of these informal connections mitigate the sullying effects documented by Barlevy [2002]. That is, referral-networks make it relatively less costly for high-productivity firms to remain in the market, causing fewer "good jobs" to exit and fewer "bad jobs" to enter during a recession. Thus, the peak unemployment rate is lower and the economy recovers faster, as fewer "good jobs" disappear after the initial recessionary shock. Policy counterfactuals demonstrate government officials must be careful when enacting labor market policy intended to curb the effects of recessionary shocks. Policies that generically improve worker-firm matching prolong recovery by as much as 8 months, as they facilitate relatively more matches between workers and low-productivity firms (i.e. they increase the so-called sullying effects of recessions).[5] In contrast, policies aimed at reducing the costs of network-formation or increasing referral-network prevalence facilitate matches between workers and high-productivity firms, expediting recovery by 3-6 months.

[4]If one assumes workers cannot observe each other's labor market status as in Arbex, O'Dea, and Wiczer [2017], then networkers can be interpreted as other workers. This alternative interpretation does not change any results.

[5]The sullying effect refers to the empirical phenomenon of less productive and more temporary jobs being created during recessions. This was documented in Barlevy [2002]

Papers that model informal connections, such as Galenianos [2014] and Igarashi [2016], typically augment the standard matching function found in Pissarides [2000], distinguishing between the costly formal and less costly informal channels of job-finding. Some models, such as Galeotti and Merlino [2014] and Schmutte [2016], incorporate endogenous referral use on the *intensive margin*, allowing for workers to endogenously choose the intensity with which they use their referral-network. The closest model to the current work is Galenianos [2016]. In this model, high-skilled and low-skilled workers meet and form links with one another to create an endogenous network. Galenianos then uses the model to demonstrate how endogenous network formation can lead to labor market inequality. The present paper adds to this existing literature by both allowing workers to dynamically adjust their network in response to shocks and to create a portfolio of connections that varies by employment status. While the impact of referral-networks on the labor market has been widely studied, few have investigated its aggregate impact during recessions. Hellerstein et al. [2015] in a reduced-form framework find neighborhood level evidence that the effectiveness of referral-networks does not diminished during recessions. This paper extends this analysis to the aggregate economy while also examining various labor market policies.

The chapter is organized as follows. Section 2 presents the environment. Section 3 performs a quantitative analysis, first estimating the model and then highlighting the effects of referral-networks on the severity and duration of recessions. Section 4 discusses policy implications using dynamic counterfactuals to study the effects of policies aimed to curb the impact of recessions. Section 5 concludes.

## 1.2 Model

The model is a discrete time version of Galenianos [2014] with two additions: heterogeneous firms (which generates on-the-job search) and endogenous network formation.

### 1.2.1 Firms, Workers, and Networkers

Time is discrete and the horizon is infinite. All agents are risk neutral and take the interest rate $r$ as given, implying each period is discounted by $\Delta = 1/(1+r)$. There are three different types of agents- firms, workers, and networkers- interact in two distinct submarkets. The first submarket is the *labor market*, in which workers and single-worker firms seek to be matched subject to search frictions. In the second submarket, referred to as the *connections market*, workers attempt to match with networkers who then serve as informal references in the labor market.[6]

Firms are active in the labor market and are either vacant and searching for a worker or filled and producing. Firms can only employ one worker, so this paper uses the terms *firm* and *job* interchangeably. These firms pay some vacancy cost while searching and produce a numeraire good when filled. There are two firm types that differ in both their productivity and vacancy costs. Specifically, a firm is either "good" and possesses high-productivity $y_{LG}$ and high vacancy costs $k_{LG}$ (G-firms) or "bad" and possesses low-productivity $y_{LB}$ and low vacancy costs $k_{LB}$ (B-Firms).[7]

Workers are homogeneous and are active in both the labor market and connections market. In the labor market, workers can either be unemployed, employed by a B-firm, or employed by a G-firm. When unemployed, workers receive some unemployment benefits $z_L > 0$ and seek to be matched with either firm type. Search frictions may induce workers to settle initially for a job at a B-firm. However, since G-firms are more productive than B-firms, they will also pay higher wages. Thus, a worker employed at a B-firm will still actively engage in on-the-job search (OTJS). A worker at a G-firm does not search on the job, as no firms offer a wage higher than a G-firm. In the connections market, workers search to be matched with networkers subject to frictions. Each worker will form informal connections with a measure of

[6] It is useful to view the present framework as a "Day-Night" model. During the day, workers work or seek to be matched with firms. At night, workers socialize and develop informal connections.

[7] Following Pissarides [1994] and Gautier [2002], vacancy creation is more expensive for a G-firm than for a B-firm. A G-firm must have both higher productivity and a higher vacancy cost than a B-firm in order for there to be an equilibrium.

networkers to create a referral-network. These connections can help the worker find a job in the labor market by recommending them to a firm. One should view referral-networks as an intermediate good since workers use them to either find employment or move up the job ladder. Networks depreciate at a rate $\delta_C$.[8] Consequently, workers must continuously engage in costly search to maintain (or possibly expand) their referral-network. This feature can represent the time costs associated with attending conferences or professional events.

Networkers operate in the connections market and can be either active or inactive. When inactive, networkers receive some outside option $z_C$ and seek to be matched with workers. When active, networkers receive some fee for agreeing to serve as a reference for the worker in the labor market. The networking fee paid to networkers could theoretically be a literal cost paid to some professional service that specializes in matching workers with jobs.[9] More generally, one could interpret this fee as some time cost associated with maintaining the network, such as taking the time to keep up with your contacts or performing *quid pro quo* favors for networkers. Networkers are divided into three types: those who assist unemployed workers, those who assist workers employed at B-firms, and those who assist workers employed at G-firms.[10]

Figure 1.1 provides a visual depiction of the timing of events. At the start of every period, shocks occur. There are then two successive sub-periods corresponding to the two submarkets. First, the events of the labor market occur. In this submarket, wages are paid to employed workers and production occurs, followed by hiring. With some probability worker-firm matches are then exogenously terminated, signaling the close of the labor market in period $t$. The connections market then opens. In this market, fees are first paid to active networkers, inactive networkers seek to match with workers, and finally a portion of the matches between workers and networkers

[8] This feature captures that contacts vary in usefulness over time. For example, a close professional contact could move or retire, rendering them unable to recommend you for a job.

[9] With very few changes necessary, this framework could be adapted to study headhunting services or online social networks such as LinkedIn.

[10] For now, it is assumed there is an equal measure of each type of networker.

are terminated. Importantly, agents operating in each submarket *takes the current aggregate variables of the other submarket as given.*

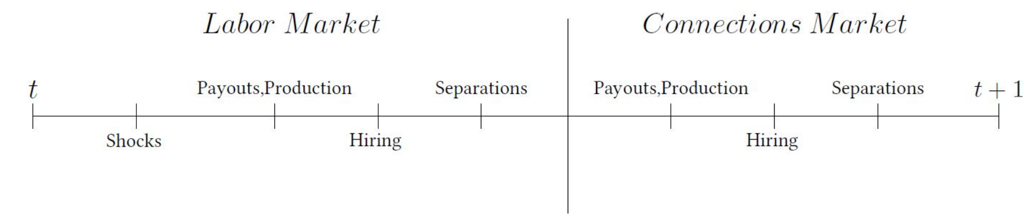


Fig. 1.1. Timing of Events

### 1.2.2 Matching Technology

In the labor market, there are two channels through which firms and workers match–formal and informal. Existing matches are exogenously destroyed with probability $\delta_L$. In the connections market, workers and networkers have one method of matching and existing matches are exogenously terminated with probability $\delta_C$.

In the labor market, matching through formal channels is modeled using a standard matching function as in Pissarides (2000). Let $v_{Li}$ and $n_{Li}$ denote the measure of posting firms and measure of workers employed by firms of type $i = B, G$. Define market tightness for B-firms as $\theta_{LB} = v_{LB}/u_L$ and for G-firms as $\theta_{LG} = v_{LG}/(u_L + n_{LB})$, where $u_L = 1 - n_{LB} - n_{LG}$ is aggregate unemployment in the labor market. The matching function generates $\mathcal{M}_{\mathcal{L}}(s_{Li}, v_{Li}) = s_{Li}v_{Li}/((s_{Li}^{\mu_L} + v_{Li}^{\mu_L})^{1/\mu_L})$,[11] matches per period where $\mu_L$ is a matching efficiency parameter and $s_{Li}$ denotes the number of workers searching to be matched with firm type $i$. This implies $s_{LB} = u_L$ and $s_{LG} = u_L + n_{LB}$, as workers currently employed by a B-firm would rather be employed at a G-firm and thus search on-the-job. The probability a worker matches with a firm using for-

[11]This matching function is the same as is used in den Hann et al. [2000] and has the convenient property for empirical analysis of being bounded between zero and one, unlike the Cobb-Douglas matching function. Petrosky-Nadeau and Wasmer [2017] note this particular function produces business cycle moments comparable to models that use the Cobb-Douglas functional form. See Petrongolo and Pissarides [2001] for further discussion of alternative matching functions.

mal channels is $\mathcal{M}_{\mathcal{L}}(s_{Li}, v_{Li})/s_{Li}$=$\theta_{Li}q(\theta_{Li})$ and the probability a firm matches with a worker via formal channels is $\mathcal{M}_{\mathcal{L}}(s_{Li}, v_{Li})/v_{Li}$=$q(\theta_{Li})$.

Workers and firms can also be matched through informal channels. The matching technology is similar to Galenianos [2014], in which a worker's informal connections can refer the worker to a firm. A meeting through a referral occurs when an operating firm of either type identifies an opportunity for expansion. The firm then asks its current employee to refer someone for the open position. The employee contacts her referral-network and asks if they know of a suitable candidate. The networkers who comprise her network act as middlemen, talking to other networkers who are connected to workers seeking to be matched with firms. This feature is consistent with Granovetter [1973] who finds more distant or "weak ties" are more productive. With some probability, the process is successful in hiring a worker for the newly created position. If a worker is successfully hired via referral, the firm immediately sells off the position to an entrepreneur and takes as payment a fraction of the surplus from the newly created job.[12] For a worker, let $i = U, B$ denote the worker's current employment status and $j = B, G$ denote future potential employment states. The probability of matching with a firm via informal channels depends on a referral efficiency parameter $\rho_{ij}$, the measure of firms of type $j$ currently filled and producing, and the measure of networkers the worker is connected to $N_{Ci}$. Then $\mathcal{R}_{ij}(n_{Lj}, N_{Ci}) = n_{Lj}\rho_{ij}N_{Ci}^{\alpha}$, for $\alpha \in (0, 1)$,[13] gives the probability of a worker matching with a firm through informal channels. For firm type $k = B, G$, the probability depends on the number of workers than could be referred $s_{Lk}$ and the number of connections their employee possesses $N_{Ck}$. Thus the probability of a firm hiring a worker through a referral has a similar functional form: $\mathcal{H}_k(s_{Lk}, N_{Ck}) = s_{Lk}\rho_k N_{Ck}^{\alpha}$.

[12] This surplus sharing process is identical to what is presented in Galenianos [2014] and Igarashi [2016]. This paper will assume the firm makes a take-it-or-leave it offer to the entrepreneur who accepts the deal.

[13] This assumption is motivated by Calvo-Armengol and Zenou [2005], Beaman [2011], and Wabha and Zenou [2005] who argue large networks theoretically can and empirically do suffer from congestion externalities.

In the connections market, the matching technology is analogous to matching through formal channels in the labor market with one minor difference. In this submarket, search is directed instead of random, meaning workers search for the three different types of networkers separately.[14] Let $v_{Ci}$ be the number of vacancies posted by workers, where $i = U, B, G$ denotes vacancies for networkers who assist unemployed workers, workers employed at a B-firm, and workers employed at a G-firm, respectively. Here, vacancies are interpreted more generally as open positions in a worker's referral-network. In addition, let $I_{Ci}$ denote the measure of inactive networkers in the connections market of type $i$ and define market tightness as $\theta_{Ci}{=}I_{Ci}/u_{Ci}$. Similar to the labor market, the matching function in the connections market is defined as $\mathcal{M}_C(I_{Ci}, v_{Ci}){=}I_{Ci}v_{Ci}/(I_{Ci}^{\mu_C} + v_{Ci}^{\mu_C})^{1/\mu_C}$, where $\mu_C$ is a matching efficiency parameter. The probability of an inactive networker matching with a worker is $\mathcal{M}_C(I_{Ci}, v_{Ci})/u_{Ci}{=}\theta_{Ci}q(\theta_{Ci})$ and the probability of a worker matching with an inactive networker is $\mathcal{M}_C(I_{Ci}, v_{Ci})/v_{Ci}{=}q(\theta_{Ci})$. Importantly this framework implies both employed and unemployed workers are always updating referral-network for every possible labor market status they could experience.[15]

### 1.2.3 Wages and Value Functions

#### Labor Market

The value function and wages of the labor market are first described. Let $\mathcal{U}_L$ be the value of unemployment for workers in the labor market. When unemployed, a worker receives her outside option $z_L$ and finds a job at a B-firm with probability $p_{UB}{=}(\theta_{LB}q(\theta_{LB}){+}n_{LB}\rho_{UB}N_{CU}^{\alpha})$ and a job at a G-firm with probability $p_{UG}{=}(\theta_{LG}q(\theta_{LG})$

[14] Intuitively, this captures that certain connections may be better at helping workers exit unemployment while others may specialize at helping workers up the job ladder.

[15] This is a necessary simplifying assumption to keep the model tractable. If workers only searched for networkers to assist them based on their current labor market status, there would be a distribution of referral-networks by labor market status due to the network adjustment process which would take place each time a worker's labor market status changed. Simplifying assumptions of this nature are often necessary in network models. See Fontaine [2008] and Calvo-Armengol and Zenou [2005] for other examples.

$+n_{LG}\rho_{UG}N_{CU}^{\alpha}$). However, with probability $\delta_L$, a worker that found employment this period is separated from her job. Letting $h_L$=$(1-\delta_L)(p_{UB}+p_{UG})$, the resulting value function is:

$$\mathcal{U}_L = z_L + (1-\delta_L)p_{UB}\Delta\mathbb{E}[\mathcal{W}'_{LB}] + (1-\delta_L)p_{UG}\Delta\mathbb{E}[\mathcal{W}'_{LG}] + (1-h_L)\Delta\mathbb{E}[\mathcal{U}'_L] \quad (1.1)$$

where $\mathbb{E}$ is the expectations operator at time $t$ and $W_{Li}$ is the value of employment at firm $i$=$B, G$. For notational convenience, the $t$ subscripts are dropped and the $t+1$ variables are indicated by an apostrophe (i.e. $\mathcal{W}_{LB,t+1} = \mathcal{W}'_{LB}$). When employed at a B-firm, workers earn wage $w_{LB}$. Since wages are higher at G-firms, agents search on the job, accepting offers from G-firms and rejecting offers from other B-firms. With probability $p_{BG}$=$(\theta_{LG}q(\theta_{LG})+n_{LG}\rho_{BG}N_{CB}^{\alpha})$, a worker at a B-firm meets and accepts an offer from a G-firm. Regardless of whether on-the-job search is successful, there is again a $\delta_L$ probability of the job being exogenously destroyed that period and the worker entering unemployment. The value function is:

$$\mathcal{W}_{LB} = w_{LB} + p_{BG}\Delta\mathbb{E}[(1-\delta_L)\mathcal{W}'_{LG} + \delta_L\mathcal{U}'_L] + (1-p_{BG})\Delta\mathbb{E}[(1-\delta_L)\mathcal{W}'_{LB} + \delta_L\mathcal{U}'_L] \quad (1.2)$$

When a worker is employed at a G-firm, there is no longer an incentive to search on-the-job. As such, she earns wage $w_{LG}$ and with probability $\delta_L$ is separated from her job and enters unemployment:

$$\mathcal{W}_{LG} = w_{LG} + \Delta\mathbb{E}[(1-\delta_L)\mathcal{W}'_{LG} + \delta_L\mathcal{U}'_L] \quad (1.3)$$

Let $\mathcal{V}_{Li}$ denote the value function of a firm of type $i = B, G$ posting a vacancy. A firm posting a vacancy incurs a cost $k_{Li}$ per period, and a successful match is formed and not subsequently dissolved that same period with probability $(1-\delta_L)q(\theta_{Li})$. If a vacant firm successfully finds and retains a match, it gets the expected discounted value of a filled job. The value function is:

$$\mathcal{V}_{Li} = -k_{Li} + (1-\delta_L)q(\theta_{Li})\Delta\mathbb{E}[\mathcal{J}'_{Li}] + (1-(1-\delta_L)q(\theta_{Li}))\Delta\mathbb{E}[\mathcal{V}'_{Li}] \quad (1.4)$$

where $\mathcal{J}_{Li}$ denotes the value function of a firm with a filled position. A B-firm that currently employs a worker produces $y_{LB}$ and pays a wage $w_{LB}$. With some probability $H_B$, the firm identifies an opportunity for expansion, asks its employee for a referral, and is successful in hiring a worker. The newly created position is sold off to an entrepreneur. The firm receives a fraction $\gamma$ of the expected surplus from the newly created position ($\gamma \mathcal{J}'_{LB}$). However, regardless of whether the firm successfully expands, there is a chance its current employee may receive an offer from a G-firm. If this occurs, the employee will choose to leave, and the B-firm will have a vacancy next period plus the value it gained from the sold-off position, for a total value of $\gamma \mathcal{J}'_{LB} + \mathcal{V}'_{LB}$. If the firm does not lose its current employee to on-the-job search, the job is still destroyed with probability $\delta_L$. Thus, with probability $(1 - p_{BG})(1 - \delta_L)$, the B-firm gets the value from selling off the newly created position plus the value of operating next period ($(1 + \gamma)J'_{LB}$). Otherwise, the firm only receives the fraction of the surplus from the newly created position plus the value of a vacancy next period. With probability $1 - H_B$, the firm is unsuccessful in hiring a new worker through a referral. Thus, if its worker receives an offer from a G-firm, she leaves and the B-firm receives the value of a vacancy next period $\mathcal{V}'_{LB}$. If the worker does not find a job at a G-firm and is not exogenously separated from her job with probability $(1 - p_{BG})(1 - \delta_L)$, then the B-firm receives the value of a filled job next period $J'_{LB}$. Otherwise, it receives the value of a vacancy next period. The value of a filled position is similar for a G-firm with only one notable difference–there is no threat of losing an employee to on-the-job search. Recall $H_G$ is the probability a G-firm successfully expands via referral. The value functions for a filled B-firm and G-firm respectively are:

$$\begin{aligned}\mathcal{J}_{LB} = y_{LB} - w_{LB} + H_B \Delta \mathbb{E}[p_{BG}(\gamma \mathcal{J}'_{LB} + \mathcal{V}'_{LB}) + (1-p_{BG})((1-\delta_L)(1+\gamma)J'_{LB}+ \\ \delta_L(\gamma \mathcal{J}'_{LB} + \mathcal{V}'_{LB}))] + (1-H_B)\Delta \mathbb{E}[p_{BG}V'_{LB} + (1-p_{BG})((1-\delta_L)J'_{LB} + \delta_L V'_{LB})]\end{aligned} \tag{1.5}$$

$$\begin{aligned}\mathcal{J}_{LG} = y_{LG} - w_{LG} + H_G \Delta \mathbb{E}[(1-\delta_L)(1+\gamma)\mathcal{J}'_{LG} + \delta_L(\gamma J'_{LG} + V'_{LG})] \\ + (1-H_G)\Delta \mathbb{E}[(1-\delta_L)J'_{LG} + \delta_L V'_{LG}]\end{aligned} \tag{1.6}$$

A free entry condition is imposed, which assumes firms of both types continue post vacancies in the labor market until $\mathcal{V}_{Li,t}$=0 $\forall t$ for $i = B, G$. Applying this condition to (1.4), (1.5), (1.6) and combining gives the vacancy supply conditions for each firm type:

$$\frac{k_{LB}}{(1-\delta_L)q(\theta_{LB})} = \Delta E\left[y'_{LB} - w'_{LB} + \frac{k_{LB}}{(1-\delta_L)q(\theta'_{LB})}(H'_B\gamma + (1-p'_{BG})(1-\delta_L))\right] \tag{1.7}$$

$$\frac{k_{LG}}{(1-\delta_L)q(\theta_{LG})} = \Delta E\left[y'_{LG} - w'_{LG} + \frac{k_{LG}}{(1-\delta_L)q(\theta'_{LG})}(H'_G\gamma + (1-\delta_L))\right] \tag{1.8}$$

When a match occurs, wages are determined through Nash bargaining, in which the wage is selected to maximize the weighted geometric surplus of the worker and the firm. To keep the model tractable, wages are also assumed to be renegotiation-proof as in Pissarides [1994] and Gautier [2002]. As such, the outside option for all workers is unemployment regardless of their previous labor market status.[16] Nash Bargaining implies:

$$\mathcal{W}_{Li} - \mathcal{U}_L = \frac{1-\beta_L}{\beta_L}\mathcal{J}_{Li} \tag{1.9}$$

[16]Initially, a worker leaving a B-firm for a G-firm has a higher outside option than a worker joining a G-firm from unemployment. Thus, this would lead to G-firms offering two different wages. However, as soon as the worker joins the G-firm, the firm would want to renegotiate wages and would be successful in doing so as the outside option for the worker would now be unemployment.

Where $\beta_L \in (0,1)$ is the bargaining parameter common to all workers. Substituting (1.1), (1.2), and (1.5) into (1.9) and (1.1), (1.3), and (1.6) into (1.9):

$$w_{LB} = (1-\beta_L)z_L + \beta_L y_{LB} + \beta_L \left[\frac{H_B\gamma}{(1-\delta_L)q(\theta_{LB})}k_{LB} + \frac{p_{UB}}{q(\theta_{LB})}k_{LB} + \frac{(p_{UG}-p_{BG})}{q(\theta_{LG})}k_{LG}\right] \tag{1.10}$$

$$w_{LG} = (1-\beta_L)z_L + \beta_L y_{LG} + \beta_L \left[\frac{H_G\gamma}{(1-\delta_L)q(\theta_{LG})}k_{LG} + \frac{p_{UG}}{q(\theta_{LG})}k_{LG} + \frac{p_{UB}}{q(\theta_{LB})}k_{LB}\right] \tag{1.11}$$

Finally, we have the inflow-equal-outflow conditions:

$$n'_{LB} = (1-\delta_L)[(1-p_{BG})n_{LB} + p_{UB}(1-n_{LG}-n_{LB})] \tag{1.12}$$

$$n'_{LG} = (1-\delta_L)[n_{LG} + p_{BG}n_{LB} + p_{UG}(1-n_{LG}-n_{LB})] \tag{1.13}$$

In steady state, note that all $t$ variables are equal to their $t-1$ values (i.e. $n'_{LB} = n_{LB}$). The labor market framework is only different from Galenianos in that time is discrete and there is on-the-job search, meaning workers employed at a B-firm leave to go work at a G-firm with probability $p_{BG}$.

**Proposition 1.** *In the labor market, a steady state equilibrium is* $(\theta_{Lj}, n_{Lj}, w_{Lj})_{j=B,G}$ *that satisfy (1.7), (1.8), and (1.10)-(1.13). Given the aggregates of the connections market, there exists a unique steady state equilibrium in the labor market.*

The proof of existence is shown in the Appendix. The local stability of this steady state is also checked numerically using the macroeconomic modeling program Dynare, which is freely available and compatible with Matlab.

### Connections Market

The value functions and fees are now described for the connections market. Taking market aggregates as given, workers post vacancies and choose the number of networkers of each type to employ in the next period to maximize their discounted expected utility in the *labor market* for each labor market status, subject to vacancy costs and networking fees. In other words, workers pick $v_{CU}$ and $N'_{CU}$ to maximize the value of being unemployed (1.1), $v_{CB}$ and $N'_{CB}$ to maximize the value of being employed at a B-firm (1.2), as well as $v_{CG}$ and $N'_{CG}$ to maximize the value of being employed by a G-firm (1.3) each period regardless of their current labor market status. Algebra shows this is equivalent to maximizing for unemployed workers, B-firm workers, and G-firm workers respectively:[17]

$$Q_{LU}N_{CU}^{\alpha} + \Delta\mathbb{E}[\mathcal{U}'_L]$$
$$Q_{LB}N_{CB}^{\alpha} + \Delta\mathbb{E}[\mathcal{W}'_{LB}]$$
$$Q_{LG}N_{CG}^{\alpha} + \Delta\mathbb{E}[\mathcal{W}'_{LG}]$$

where $Q_{Li}$ for a worker with labor market status $i = U, B, G$ is a combination of labor market aggregates and parameters outside the control of the worker. Their values are:

$$Q_{LU} = \left(\rho_{UB}n_{LB}\left[\frac{\beta_L k_{LB}}{(1-\beta_L)(q(\theta_{LB}))}\right] + \rho_{UG}n_{LG}\left[\frac{\beta_L k_{LG}}{(1-\beta_L)(q(\theta_{LG}))}\right]\right)$$
$$Q_{LB} = \left[\beta_L u_L \rho_B \gamma \frac{k_{LB}}{(1-\delta_L)q(\theta_{LB})} - \beta_L \rho_{BG} n_{LG} \frac{k_{LG}}{q(\theta_{LG})} + n_{LG}\rho_{BG}\left[\frac{\beta_L}{(1-\beta_L)}\left(\frac{k_{LG}}{q(\theta_{LG})} - \frac{k_{LB}}{q(\theta_{LB})}\right)\right]\right]$$
$$Q_{LG} = [\gamma \frac{k_{LG}}{(1-\delta_L)q(\theta_{LG})}(u_L\rho_G + n_{LB}\rho_{BG})]$$

The $Q_{Li}$ should be thought of as a productivity parameters that determine how effective additional connections are at maximizing expected utility given the current state of the labor market. For example, $Q_{LU}$ increases with employment of both firm types $(n_{LB}, n_{LG})$ and vacancy costs $(k_{LB}, k_{LG})$. That is, as vacancy costs increase, firms will post fewer vacancies and choose to rely relatively more on matching through informal channels, making informal contacts more productive.

Define $F_{Ci}$=$Q_{Li}N_{Ci}^{\alpha}$ for $i = U, B, G$. The worker's problem is:

$$\mathcal{V}_{Ci}(N_{Ci}) = \max_{N'_{Ci}, v_{Ci}} \left\{ Q_{Li}N_{Ci}^{\alpha} - \phi_{Ci}N_{Ci} - k_C v_{Ci} + \Delta\mathbb{E}[\mathcal{V}'_{Ci}(N'_{Ci})] \right\}$$
$$s.t.\ \ N'_{Ci} = (1-\delta_C)[N_{Ci} + v_{Ci}q(\theta_{Ci})] \tag{1.14}$$

[17]For the complete derivations of these terms, see the Appendix.

for each $i$ where $v_{Ci}$ is the number of vacancies or openings a worker has in her network for networkers who can help her given her employment status $i$, $k_C$ is the cost of posting a vacancy, and $\phi_{Ci}$ is the networking fee paid to networkers. In this context, one can interpret vacancies as a measure of the intensity of network formation, as more vacancies indicate a greater desire on the part of the worker to expand her referral-network. Taking derivative and combining the two first order conditions give the Euler equation:

$$\Delta\mathbb{E}[\mathcal{J}'_{Ci}] = \frac{k_C}{(1-\delta_C)q(\theta_{Ci})} \tag{1.15}$$

where $\frac{dV'_{Ci}}{dN_{Ci}}$=$J'_{Ci}$. In this context, $J'_{Ci}$ is the marginal value of an additional networker in the next subperiod. This condition states workers will continue to look for informal contacts until the expected marginal value of a networker is equal to the discounted cost of search. Combining the envelope condition with the Euler equation gives the vacancy supply condition:

$$\frac{k_C}{(1-\delta_C)q(\theta_{CU})} = \Delta E\left[\frac{dF'_{CU}}{dN'_{CU}} - \phi'_{CU} - \frac{d\phi'_{CU}}{dN'_{CU}}N'_{CU} + \frac{k_C}{q(\theta'_{CU})}\right] \tag{1.16}$$

Networkers of all three types can either be active (A) or inactive (I). If inactive, networkers find employment in an unemployed worker's network with probability $\theta_{Ck}q(\theta_{Ck})$ where $k = U, B, G$ corresponds to the networker's type (either assisting unemployed, assisting workers at B-firms, or assisting workers at G-firms). After becoming active, there is a chance $\delta_C$ they are separated from their newly found job. When employed by a worker, networkers are paid a fee for their services. Importantly, this fee is endogenous and determined through bargaining between workers and networkers. The value functions are:

$$\mathcal{I}_{Ck} = (1-\delta_C)[\theta_{Ck}q(\theta_{Ck})\Delta\mathbb{E}[\mathcal{A}'_{Ck}] + (1-(1-\delta_C)\theta_{Ck}q(\theta_{Ck}))\Delta\mathbb{E}[\mathcal{I}_{Ck'}] \tag{1.17}$$

$$\mathcal{A}_{Ck} = \phi_{Ck} + \Delta\mathbb{E}[(1-\delta_C)A'_{Ck} + \delta_C I'_{Ck}] \tag{1.18}$$

Stole-Zwiebel [1996] intra-firm bargaining is used to derive the closed-form solution for the networking fee. As is the case with standard Nash Bargaining, the networking fee is selected to maximize the weighted geometric surplus of the worker and the networker. However, given the decreasing returns to scale (DRTS) production technology, solving for the closed-form solution of the fee paid to the networker is not straightforward. With each additional hire, the marginal productivity of *all* networkers currently employed is reduced. Consequently, the worker would like to not only negotiate a lower fee for the new hire, but also a lower fee for all the networkers currently employed in her network. Stole-Zwiebel [1996] derive the solution to this bargaining environment using a finite sequence of pairwise bargaining sessions. Intuitively, this is modeled as negotiation of wages between a firm and a union in which contracts are at will and cannot be committed to indefinitely by either side. This bargaining is modeled as a Brügemann et al. [2015] Rolodex game.[18] Nash Bargaining implies the surpluses are split according to:

$$\mathcal{A}_{Ci} - \mathcal{I}_C = \frac{(1-\beta_C)}{\beta_C}\mathcal{J}_{Ci} \tag{1.19}$$

where $\beta_C \in (0,1)$ is the bargaining power of a networker. Algebra gives the expression for the networking fee:

$$\phi_{Ci} = \beta_C \left[\frac{dF_{Ci}}{dN_{Ci}} - \frac{d\phi_{Ci}}{dN_{Ci}}N_{Ci}\right] + \beta_C k_C(\theta_{Ci})$$

As discussed, Stole and Zwiebel [1996] prove the general solution to this differential equation is:[19]

$$\phi_{Ci} = \frac{\alpha\beta_C}{1+\alpha\beta_C-\beta_C} Q_{Li} {N_{Ci}}^{\alpha-1} + \beta_C k_C(\theta_{Ci}) \tag{1.20}$$

Note this formulation also implies the fee is instantly renegotiated between the worker and *all employed networkers* when a new hire is made.[20]

[18]Traditionally, it was modeled as a Binmore, Rubinstein, Wolinsky (1986) alternating offers game played between the worker and the networker. However, Brügemann et al. [2015] show this produces inaccurate Shapely values. Using the Rolodex game produces the correct Shapely values used by Stole-Zwiebel without changing the solution.

[19]Cahuc et al. [2008] show the steps required to solve the differential equation in their appendix. Petrosky-Nadeau and Wasmer [2017] provide a condensed overview of the derivation.

[20]It is assumed the outside option of a worker is held constant *while the fee is be bargained over.* This is a standard assumption in the literature, employed by Cahuc et al [2008], Chang [2013], Mortenson [2010], Acemoglu et al. [2014], and Petrosky-Nadeau and Wasmer [2017].

The final equations necessary to close the model are the active networkers flow equations:

$$n'_{Ci} = (1 - \delta_C)[n_{Ci} + \theta_{Ci} q(\theta_{Ci})(1 - n_{Ci})] \tag{1.21}$$

**Proposition 2.** *A steady state equilibrium in the connections market is* $(\theta_{Ci}, \phi_{Ci}, n_{Ci})_{i=U,B,G}$ *that satisfy (1.16), (1.20), and (1.21). Given the aggregates of the labor market, there exists a unique steady state equilibrium in the connections market.*

The proof of this proposition is shown in the Appendix. It is a relatively simple proof, as the environment is practically identical to the standard search and matching model of a large firm. The only departure from the standard model is the directed search for different types of networkers, which is a trivial difference.

**Proposition 3.** *A steady state equilibrium is* $(\theta_{Ci}, \phi_{Ci}, n_{Ci})_{i=U,B,G}$ *that satisfy (1.16), (1.20), (1.21) and* $(\theta_{Lj}, n_{Lj}, w_{Lj})_{j=B,G}$ *that satisfy (1.7), (1.8), and (1.10)-(1.12). There exists a unique steady state equilibrium.*

This is formally shown in the Appendix, but follows directly from **Proposition 1** and **Proposition 2**.

## 1.3 Quantitative Analysis

In this section, the model is empirically estimated to match aggregate moments of the US labor market from 2010 to 2016. The effects of referral-networks on the severity and duration of recessions are then analyzed.

### 1.3.1 Estimation

In order to analyze stabilizing nature of referral-networks, the model is calibrated to the US economy from 2010 to 2016. While some common parameters are taken from the literature, the rest are estimated using generalized method of moments (GMM). Two data sources are primarily used to construct moments for the GMM estimation.

Data from the Bureau of Labor Statistics (BLS) are used to construct almost all labor market moments. However, the BLS does not ask questions concerning the method that led to an individual finding a job, either going from unemployed to employed or transitioning from one employer to another. Moreover, the BLS does not ask questions specifically related to the use of referrals. To that end, moments requiring specific information on the method of job-finding are constructed using the Survey of Consumer Expectations (SCE).[21] The SCE is a relatively new data set constructed and maintained by the New York Branch of the Federal Reserve. The nationally representative core survey consists of a 12 month panel rotation of individuals who are surveyed about their beliefs concerning future macroeconomic statistics such as unemployment and inflation as well as beliefs regarding their future personal income, employment status, etc. The SCE also conducts several supplement surveys per annum, which provide yearly cross-sectional data on a variety of topics, including the housing market, inflation expectations, student debt, and more. For this paper, the SCE Job Search Survey supplement is particularly useful as it asks about on-the-job search activities as well as the method by which individuals found their current job. These data are used primarily to constructs aggregate moments concerning referral use.[22]

The model is calibrated so one period is a month. From the literature, the discount rate $\Delta$ is chosen to be 0.9881 and the size of the labor force in the labor market is set to 1. Following Igarashi (2016), the fraction of the surplus a firm receives when selling off a newly created position to an entrepreneur ($\gamma$) is 1. Without loss of generality, the productivity of a B-firm is normalized to 1. Finally, the separation probability ($\delta_L$) is estimated using microdata from the CPS following the methods described in Shimer [2012].[23] There are a few moments not derived from the BLS or the SCE. For example, the average monthly job-finding probability is also found

[21]The data are updated frequently and are available free of charge at the New York Fed's website.

[22]Both the SCE and the BLS are nationally representative data sets, which mitigates potential concerns about comparability.

[23]For a brief overview of the method, see the data appendix. For a more detailed description, see Shimer [2012]. Estimation files are available upon request.

following Shimer [2012], and is used as a GMM target moment. In addition, the US Department of Labor states the average replacement rate from 2010 to 2016 is about 40.3%, and thus, the GMM procedure will select parameters such that an unemployed individual receives about 40.3% of the average wage in the labor market, which will pin down the value of $z_L$.[24] Using the empirical findings of Merz and Yashiv [2007], the GMM procedure selects parameters such that the cost of posting a vacancy is about 6 months of wages on average, which will inform the estimates of $k_{LB}$ and $k_{LG}$. Following the literature, the target average labor share is (2/3).[25]

The GMM targets constructed using the SCE are the fraction of jobs found via referrals, the fraction of job-to-job transitions that occur as a result of a referral, and the fraction of workers who report searching for work on-the-job. These moments are calculated as the averages of these statistics for the available 2010-2016 data and will be integral in identifying the prevalence parameters $\rho_{UG}$, $\rho_{UB}$, and $\rho_{BG}$. The fraction of workers in the SCE who report looking for work on-the-job is 16%. This moment is used as a target to help pin down the equilibrium distribution of firm types. Since workers can only engage in on-the-job search while employed at B-firms, the GMM procedure will target a distribution in which 16% of all producing firms are B-firms.

Using BLS data from 2010-2016, the average labor market tightness is .455 and the average unemployment rate is .0718. These two moments will help in identifying the bargaining power of labor market workers ($\beta_L$) as well as the matching efficiency parameter ($\mu_L$). The remaining parameters to be estimated are all related to the network formation process in the connections market. As theses parameters describe an unobservable process, it is critical to select observable labor market moments driven by these underlying network activities. Intuitively, since referrals are so critical in the job-finding process, moments related to employment transitions will be helpful in

[24] Mulligan [2012] estimates the benefits for the non-employed is about 63% when considering all US programs. Hall and Milgrom [2008] calculate the value of leisure to be closer to 71%. Changing the targeted value to either of these estimates does not significantly change results.

[25] While this target is chosen to be consistent with the rest of the search and matching literature, new research by Karabarbounis and Neiman (2018) demonstrate this may be too low of a target. For a more detailed explanation of this topic as well as the construction of these moments and all other moments, see the data appendix.

determining the latent parameter values for the network-formation process. Consequently, the remaining moments are related to labor market worker flows, such as the number of separations resulting from on-the-job transitions as a fraction of all separations. This moment will help determine $\alpha$, as it provides further information on the relative effectiveness of networkers in on-the-job search. Similarly, the ratio of job to job (JtJ) transitions relative to employment to unemployment (EU) transitions, EU flows as a fraction of the total number of employed,[26] and the fraction of separations due to job to job transitions are informative moments which will determine $\beta_C$, $k_C$, $\delta_C$.

While these moments are informative, they are not all straightforward to calculate. EU as a fraction of unemployment are available using the BLS labor force tables. However, the fraction of separations due to JJ transitions as well as the ratio of JJ transitions to unemployment must be estimated empirically. Fallick and Fleischmann (2004) (henceforth FF) proposed an empirical methodology to measure these labor market flows. Exploiting the 1994 CPS redesign, they are able to determine whether an interviewed individual is working for the same employer she worked for in the previous interview month. This paper uses their estimates for the years 2010-2016 to obtain the desired moments.[27] Table 1.1 summarizes the moments, the sources for the moments, and the resulting estimates from the GMM procedure. In general, the model is able to match the data well. The resulting parameter estimates are reported in Table 1.2.

### 1.3.2 Robustness Checks

The predictions of the model are compared to available empirical benchmarks to alleviate concerns of overfitting. The first robustness check compares model pre-

[26] In the current framework, workers cannot enter non-employment, so this moment does not include workers who transition from employment to not in the labor force. The model could easily be extended to accommodate this additional feature.

[27] Both their estimates using historical data and estimates using the most recent data available can be found online.

Table 1.1.
Overview of Moments and Estimates

| Moment Description | Source | Target | Estimate |
|---|---|---|---|
| Labor Market Tightness | BLS Average 2010-2016 | 0.4550 | 0.5781 |
| Labor Market Unemployment Rate | BLS Average 2010-2016 | 0.0718 | 0.0639 |
| Replacement Rate | US Labor Department Average 2010-2016 | 0.4030 | 0.5054 |
| Fraction of Jobs Found via Referral | SCE 2014-2016 Average | 0.4084 | 0.4209 |
| Fraction of Jobs Found via Referral OTJS | SCE 2014-2016 Average | 0.4421 | 0.4369 |
| Fraction of Jobs Found via Referral from U | SCE 2014-2016 Average | 0.3791 | 0.3866 |
| Average Job-Finding Probability (U) | BLS CPS 2010-2016 Average (Shimer) | 0.2800 | 0.3525 |
| Labor Share | Literature | 0.6667 | 0.8772 |
| OTJ Transitions as a Fraction of Employment | BLS CPS Average 2010-2016 (F&F) | 0.0129 | 0.0154 |
| Average Vacancy Cost to Wage Ratio | Merz and Yashiv (2007) | 6.000 | 3.380 |
| Ratio of EE to EU Transitions | BLS CPS Average 2010-2016 (F&F) | 1.2600 | 0.6415 |
| Flows EU as a Fraction of Employment | BLS JOLTS Average 2010-2016 | 0.0121 | 0.0241 |
| Fraction of Workers Searching OTJ | SCE 2014-2016 Average | 0.1600 | 0.1461 |
| Fraction of Separations from JtJ Transitions | BLS CPS Average 2010-2016 (F&F) | 0.2900 | 0.3137 |

dictions to three untargeted empirical moments: the average vacancy duration, the average unemployment duration, and the average tenure spent with an employer. All three of these moments are critical to the functioning of the labor market and therefore will serve as good barometers of the model's performance. Table 1.3 summarizes results. From 2010-2016, the BLS reports an average unemployment duration of about 8.52 months (34 weeks). The model predicts an average unemployment duration of about 8.48 months. Data for employee tenure is also derived from the BLS. Every two years, the BLS conducts a survey in which they ask employed workers how long they have worked for their current employer. The median employer tenure reported from 2010-2016 is 4.45 years. Accounting for both endogenous separations resulting from on-the-job search and exogenous separations, the model predicts an average tenure of 37.5 months or about 3.12 years. The final moment used for comparison is the average time it takes a firm to fill an open vacancy. For this statistic, the Society for Human Resource Management (SHRM) estimates that it takes on average 1.38 months. The model predicts an average time to fill of 1.51 months.

Table 1.2.
Model Parameters

| Parameter | Description | Value | Source |
|---|---|---|---|
| $\Delta$ | Discount Rate | 0.9881 | Literature |
| $L$ | Labor Force | 1 | Literature |
| $y_{LB}$ | "Bad" Job Productivity | 1 | Normalization |
| $\gamma$ | Expansion Surplus Fraction | 1 | Igarashi (2016) |
| $\delta_L$ | LM Separation Probability | 0.0235 | Estimated (Shimer 2012) |
| $z_L$ | LM Outside Option | 0.6113 | GMM |
| $\delta_C$ | CM Separation Probability | 0.0343 | GMM |
| $k_C$ | CM Vacancy Cost | 4.992 | GMM |
| $k_{LG}$ | "Good" Job Vacancy Cost | 4.811 | GMM |
| $k_{LB}$ | "Bad" Job Vacancy Cost | 0.7120 | GMM |
| $y_{LG}$ | "Good" Job Productivity | 1.479 | GMM |
| $\beta_L$ | LM Bargaining Power | 0.3758 | GMM |
| $\beta_C$ | CM Bargaining Power | 0.8959 | GMM |
| $\alpha$ | Referral Match Exponent | 0.5717 | GMM |
| $\rho_{UB}$ | Referral Efficiency B-firm from U | 4.641 | GMM |
| $\rho_{UG}$ | Referral Efficiency G-firm from U | 0.1009 | GMM |
| $\rho_{BG}$ | Referral Efficiency G-firm from B-firm | 0.5707 | GMM |
| $\mu_L$ | LM Matching Efficiency Parameter | 0.5911 | GMM |
| $\mu_C$ | NM Matching Efficiency Parameter | 0.6232 | GMM |

Table 1.3.
Robustness Check: Additional Labor Market Moments

| Moment | Data | Model | Source |
|---|---|---|---|
| Average Unemployment Duration (months) | 8.52 | 8.48 | BLS 2010-2016 |
| Average Employee Tenure (years) | 4.45 | 3.12 | BLS 2010-2016 |
| Average Time to Fill Vacancy (months) | 1.38 | 1.51 | SHRM |

Two additional robustness checks are performed to compare the qualitative predictions of the model to empirical observations of the use of referral-networks in the labor market. Using data from the United Kingdom, Galeotti and Merlino [2014] document an inverted "U-shaped" relationship between separation rate and the referral job-finding probability. Specifically, the fraction of jobs found using referrals should initially increase as the separation probability increases for low values of $\delta_L$, but then begin to decrease with the separation probability for high values of $\delta_L$. The model replicates this empirical result well, as shown in the left panel of Figure 1.2.

In addition, Hellerstein et al. [2015] find reduced-form empirical evidence that labor markets in which networks are more prevalent should have higher job-finding probabilities for unemployed workers during recessions. In order to compare the model's prediction to this finding, a recession is simulated[28] and the predicted job-finding probabilities of the unemployed in economies with varying degrees of referral prevalence, $\rho_{ij}$, are shown in the right panel of Figure 1.2. During the recession (i.e. the first two quarters), the job-finding probability is higher for workers in economies with higher referral prevalences. This result is also true for the post-recession recovery period.

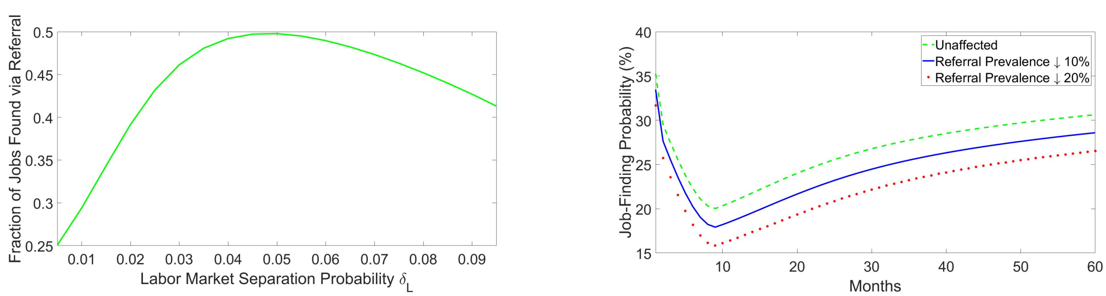


Fig. 1.2. Robustness Check Figures: Inverted-U and Job-Finding Probability

### 1.3.3 The Stabilizing Effects of Referral-Networks

The paper now analyzes how referrals impact a variety of macro-aggregates both during recessions and during post-recession recovery period. Hellerstein et al. [2015] find networks are linked to faster re-employment for displaced workers during re-

[28]See Section 1.3.3 for details.

cessions. In addition, authors find little evidence to support the idea that referral-network effectiveness fell during the Great Recession. Both these facts are consistent with the current framework and suggest referral-networks should play an important role in economic recoveries.

In order to study post-recession recoveries, it is necessary to specify an auto-regressive process for an aggregate productivity shock. To that end, let $\chi$ be a multiplicative shock applied to $y_{LB}$ and $y_{LG}$. The log of this shock is assumed to follow an AR(1) process of the form $\log(\chi_t)=\omega \log(\chi_{t-1})+ \epsilon_t$, where $\omega \in (0,1)$ is a persistence parameter and $\epsilon_t \sim N(0,\sigma)$. Following Petrosky-Nadeau (2017), the persistence parameter is set to .983. The parameter $\sigma$ is chosen so that a simulated recession produces[29] a peak unemployment rate reaches 10%, consistent with the peak rate observed during the Great Recession. This results in a value of $\sigma = .046$. With the auto-regressive process fully specified, two questions are now addressed. First, how do referral-networks impact the severity of recessions? Second, how do referral-networks affect the recovery speed of macro-aggregates?

Define output, consumption, and welfare as:

$$\begin{aligned}
\text{Output} &= n_{LB}y_{LB} + n_{LG}y_{LG} \\
\text{Consumption} &= n_{LB}w_{LB} + n_{LG}w_{LG} + u_L z_L - k_C(v_{CU} + v_{CB} + v_{CG}) \\
\text{Welfare} &= n_{LB}y_{LB} + n_{LG}y_{LG} - k_{LB}v_{LB} - k_{LG}v_{LG} - k_C(v_{CU} + v_{CB} + v_{CG})
\end{aligned}$$

Here, output is simply the number of workers employed at both types of firms multiplied by each firm type's productivity parameters $y_{Li}$. Welfare is total output plus consumption from unemployment benefits ($u_L z_L$) minus the costs incurred by firms to post vacancies ($-k_{LB}v_{LB} - k_{LG}v_{LG}$) minus the costs of forming all types of connections $-k_C(v_{CU} + v_{CB} + v_{CG})$. Compared to an economy without referral-networks (i.e. $\rho_{UB}, \rho_{UG}, \rho_{BG}$=0), economies with referral-networks experience less severe recessions. Table 1.4 shows the peak effect of recessions on the unemployment

[29] The shock is modeled as being unanticipated to mirror the Great Recession. Since the model is calibrated on a monthly basis, a negative shock is applied for 8 periods to simulate 2 quarters of negative economic growth.

rate, output, and expected unemployment duration (U-Duration). During the trough of the recession, the unemployment rate is more than 10 percentage points higher for economies without referral-networks, and the expected unemployment duration is almost a year longer. Moreover, aggregate output is almost 10% lower at the nadir of the recession. While referral-networks do lead to lower peak unemployment rates, peak expected unemployment durations, and higher peak output, the relative fluctuations are also lessened. In an economy without referrals, the unemployment rate rises by almost 12 percentage points compared to only 3.6 percentage points for an economy with referrals. Similarly, the fluctuation in expected unemployment duration is almost six times as severe and the fall in output 10% more severe for an economy without referrals. Though the effect is smaller, aggregate welfare is similarly affected. In total, the fluctuation of aggregate welfare is about 1% less over the course of the recession.

A similar trend is observed for economies with various degrees of referral-network prevalence. A 20% decrease in the prevalence of referrals results in a 35% increase in the fluctuation of the unemployment rate and a month longer expected unemployment duration in the trough of the recession. In addition, both the nadir and fluctuation in output decline with referral prevalence. Thus, even relatively minor differences in the prevalence of referral-networks can lead to pronounced differences in the volatility experienced in the post-recession recovery period. These results highlight one aspect of the stabilizing effect of referral-networks on the labor market during recessions. That is, economies with higher degrees of referral prevalence will experience less severe fluctuations in aggregate variables.

Less fluctuation in expected U-duration obviously implies reduced volatility in the job-finding probabilities for the unemployed. It should be noted, however, this increased referral probability also has a significant impact on the probability of transitioning from a B-firm to a G-firm (BG transition). In an economy without referrals, the trough BG transition probability is 2.73% compare to 6.43% in an economy with referrals. In addition, the fluctuation from the start of the recession to the trough in

Table 1.4.
Fluctuation of Labor Market Aggregates in Response to a Recession

| | Unemployment Rate | |
|---|---|---|
| | Trough | Fluctuation |
| Baseline | 10% | 3.63% |
| Referral-Networks ↓ 10% | 10.9% | 4.21% |
| Referral-Networks ↓ 20% | 12% | 4.91% |
| No Referrals | 21.1% | 11.71% |
| | Expected U-Duration | |
| | Trough | Fluctuation |
| Baseline | 4.99 months | 2.16 months |
| Referral-Networks ↓ 10% | 5.58 months | 2.59 months |
| Referral-Networks ↓ 20% | 6.31 months | 3.15 months |
| No Referrals | 16.8 months | 12.5 months |
| | Output | |
| | Trough | Fluctuation |
| Baseline | 0.8926 | 0.4277 |
| Referral-Networks ↓ 10% | 0.8829 | 0.4299 |
| Referral-Networks ↓ 20% | 0.8731 | 0.4324 |
| No Referrals | 0.8039 | 0.4620 |

the BG transition probability is reduced by almost 9%. Thus, referral-networks not only have a stabilizing influence on employment probabilities but also on the probability of moving up the job ladder during recessions, mitigating the reduced upward mobility that accompanies a recession. This result extends the findings of Arbex et al. [2018], demonstrating referrals help workers climb the job ladder faster even during times of economic downturn.

These results are due to the key mechanisms through which referrals operate. Figure 1.3 shows the dynamic response of the composition of firms in response to a recession for varying degrees of referral-network prevalence. The lower costs associated with hiring through referrals reduces the total number of firms that exit the market in response to a recession, resulting in a lower unemployment rate. This is driven by fewer G-firms exiting the market, as referrals provide them with a more cost-effective hiring method. Moreover, the increased matching rate associated with more prevalent referral-networks results in a lower expected U-duration during both the recession and post-recession recovery period. Both of these mechanism reduce the so-called sullying effects of a recession. Barlevy [2002] documents job quality is procyclical and shows the procyclicality of job quality can largely be explained by the entry of less productive firms during recessions. When a recession occurs, it becomes relatively more costly (less profitable) for G-Firms to remain in the market. This results in a net loss of G-firms in response to the shock. The fall in the measure of G-firms incentivizes the entry of relatively more B-firms for two reasons. First, the exit of G-firms reduces competition for labor, making it easier for B-firms to hire workers from unemployment. Second, the reduced number of G-firms in the market reduces the probability of labor turnover, i.e. a worker leaving a B-firm for a G-firm as a result of on-the-job search. With a fall in the number of G-firms and a rise in the number of B-firms, the fraction of low-productivity firms in the economy increases as shown in the rightmost panel of Figure 1.3.[30]

Notably, the degree of the fluctuation is greater when referral prevalence is lower. An economy without referrals experiences a 72.1% greater reduction in the number of high-productivity firms and an 86.4% increase in the number of low-productivity firms in response to a recession. Even a 10% reduction in referral prevalence results in 4.4% more B-Firms entering and 8.7% more G-firms exiting the labor market. These results highlight the impact of referral-networks on the sullying effects associated with recessions. Since referrals provide an alternative, and more cost-effective, method of hiring to G-firms, fewer are forced to exit the market in the aggregate. This stabilizing effect is then further propagated by the increased matching rate referrals

[30]In the economy without referrals, there is initially a drop in the number of B-Firms. This is due to the fact that there are no referrals to offset the initial shock. Thus, B-firms exit the market until market conditions are improved by the continual exit of G-Firms. This additional fluctuation results in a higher degree of volatility following a recession.

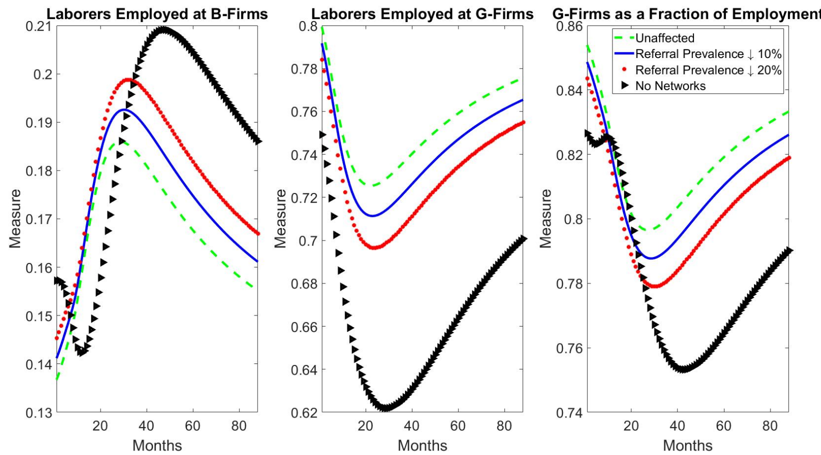


Fig. 1.3. Dynamic Adjustment of Firm Composition in Response to a Recession

provide, which allows additional G-firms to enter the market. In response, the entry of B-firms is reduced due to the greater number of G-firms who find it profitable to remain in the labor market. Hence, referral-networks have a stabilizing effect on the distribution of firms in the economy, reducing the exit of high-productivity firms and the creation of more temporary, low-paying jobs. Thus, by reducing the sullying effects, referral-networks mitigate the distortions caused by recessions.

In addition to decreasing volatility, referrals also expedite post-recession recovery of important macroeconomic aggregates.[31] Table 1.5 shows the additional time in months it takes various labor market aggregates to recover from the recession relative to the calibrated model for varying degrees of referral prevalence. For example, consider the bottom-rightmost entry of 47. This value means it takes 47 months longer for the unexpected unemployment duration to recovery after a recession in an economy without referrals relative to the estimated baseline model (i.e. the model in which referral prevalence is unaffected).

[31] As is the case for many models that simulate dynamic adjustments (see for example Phelan and Trejos [2000]), it takes quite some time for an economy to return to steady-state following a shock. To that end, this paper considers a macroeconomic variable to have recovered from the recession when it is withing 3% of its original steady-state value. Using a different recovery threshold does not significantly affect results.

In an economy without referrals, it takes consumption, output, and welfare almost an additional year to recover. The results are similar for the wage earned at G-firms as well as the average wage. Wages earned at B-firms are comparatively less affected, a result related to the cost-saving nature of referrals. Since vacancy costs are higher for G-firms, the availability of a more cost-effective hiring channel aides their recovery to a greater degree. This naturally extends to the wages paid by G-firms also recovering relatively more quickly in an economy with greater referral prevalence. The recovery of the job-finding probability for the unemployed (UE JFP) and employed (EE JFP) about 4 and 2 additional years to recover, respectively. This extra recovery time results in expected unemployment duration and the unemployment rate taking close to 4 years to completely stabilize. The qualitative results hold even across economies that vary less severely in terms of referral prevalence. In an economy in which referrals are 20% less prevalent, it takes output, consumption, and welfare an additional two months to stabilize. Even reducing the prevalence of referrals by 10% increases the recovery time of expected unemployment duration by seven months.

All these results demonstrate referral-networks accelerate the stabilization of an economy post-recession. This feature is primarily driven by the increased matching rate facilitated by referral-networks. As discussed, referrals increase (reduce) the number of matches between workers and G-firms (B-firms). Consequently, relatively fewer G-firms exit and relatively fewer B-firms enter the market in response to a recession in an economy with high referral prevalence. Moreover, this increased matching rate further expedites the entry of additional high-productivity firms during the post-recession recovery period, thereby quicken the recovery of the job-finding probability, output, and welfare. Thus, referral-networks not only reduce the volatility of market aggregates during recessions but also hasten the stabilization of the economy.

Table 1.5.
Post-Recession Recovery Time for Macro Aggregates Relative to Estimated Model

| | Consumption | Output | Welfare |
|---|---|---|---|
| Referral-Networks ↓ 10% | 1 | 1 | 1 |
| Referral-Networks ↓ 20% | 2 | 2 | 2 |
| No Referrals | 11 | 9 | 8 |
| | Bad Firms | Good Firms | Unemployment Rate |
| Referral-Networks ↓ 10% | 3 | 6 | 6 |
| Referral-Networks ↓ 20% | 5 | 12 | 13 |
| No Referrals | 13 | 40 | 46 |
| | Wage Bad Firms | Wage Good Firms | Average Wage |
| Referral-Networks ↓ 10% | 1 | 1 | 1 |
| Referral-Networks ↓ 20% | 1 | 2 | 3 |
| No Referrals | 5 | 11 | 10 |
| | UE JFP | EE JFP | U-Duration |
| Referral-Networks ↓ 10% | 6 | 3 | 7 |
| Referral-Networks ↓ 20% | 12 | 7 | 14 |
| No Referrals | 46 | 25 | 47 |

## 1.4 Policy Implications

The previous section demonstrates economies with less effective referral-networks experience slower recovery after recessions. This is particularly true for the unemployment rate, job-finding probability, and expected unemployment duration. Research demonstrates that extended periods of unemployment lead to wage scarring effects in both the short-term and long-term. Hyatt and McEntarfer [2012] find a worker who is unemployed two to three quarters experiences a 4-6% decrease in wages at her next job. Moreover, workers who are unemployed for over six months experience lower earnings for the next 30-45 years [Cooper 2013], which also can contribute to lower earnings for the children of the affected workers (Oreopolis, Page, Stevens 2008). There are also increased physical (Strully 2009) and mental (Classen and Dunn 2012) health risks associated with extend periods of unemployment. To that end, policies aimed at improving various aspects of referral-network formation and effectiveness have significant welfare implications.

Four model parameters are varied that correspond to different government policies. The first policy seeks to improve the efficiency of matching through referrals, which corresponds to increasing the referral-network prevalence parameters ($\rho_{ij}$). Many companies offer bonuses to employees who refer a qualified candidate who is then hired by the firm. If the government were to provide funding to increase the saliency of these incentives, this would improve the rate at which a job is filled through a referral. More generally, this policy could be accomplished by publicizing to firms the benefits of an employee referral program or even incentivizing the firms themselves to have one in place. The next policy seeks to improve the matching rate between workers and networkers (i.e. increase $\mu_C$). This corresponds to expanding (and perhaps mandating) job club events and networking directories offered to job-seekers, similar to the directory of clubs offered currently by the Minnesota Department of Employment and Economic Development (DEED). The government could also lower the costs of referral-network formation ($k_C$) by subsidizing networking events for workers. While there is interest in such an event,[32] they are expensive to host. Increased government funding can improve the regularity of these events and decrease the cost of finding good connections. As a final policy experiment, this paper also analyzes the impact of increasing generic job-finding efficiency ($\mu_L$).

Table 1.6 details the impact of each policy on recession volatility. All of the proposed policies result in reduced volatility relative to the baseline model, except for increasing the general matching rate $\mu_L$. This is due to the increased entry of B-firms during recessions facilitated by this change. Recall, the parameter $\mu_L$ determines the efficiency of a worker matching with *any* firm. Thus, while increasing $\mu_L$ makes matching between workers and G-firms more efficient, it also makes matching be-

[32]For example "The 3 Driving Components of the Workforce Development" organized and paid for by the Walworth County Economic Development Alliance in Wisconsin

tween workers and B-firms more efficient. Since recessions make it relatively more costly for G-firms to enter the market, the increased matching efficiency facilitates relatively more matches between workers and B-firms during times of economic downturn. This leads to a 3.84% increasing in the sullying effects of recessions, increasing the fluctuation the economy experiences.

Table 1.6.
Policies and Fluctuation of Labor Market Aggregates in Response to a Recession

| | Unemployment Rate | |
|---|---|---|
| | Trough | Fluctuation |
| Baseline | 10% | 3.63% |
| Referral Matching ($\rho_{ij}$) $\uparrow$ 10% | 9.26% | 3.15% |
| Network Costs ($k_C$) $\downarrow$ 10% | 9.58% | 3.35% |
| Networker Matching ($\mu_C$) $\uparrow$ 10% | 9.96% | 3.60% |
| Standard Matching ($\mu_L$) $\uparrow$ 10% | 10.1% | 3.94% |
| | Expected U-Duration | |
| | Trough | Fluctuation |
| Baseline | 4.99 months | 2.16 months |
| Referral Matching ($\rho_{ij}$) $\uparrow$ 10% | 4.52 months | 1.82 months |
| Network Costs ($k_C$) $\downarrow$ 10% | 4.72 months | 1.96 months |
| Networker Matching ($\mu_C$) $\uparrow$ 10% | 4.954 months | 2.13 months |
| Standard Matching ($\mu_L$) $\uparrow$ 10% | 5.096 months | 2.377 months |
| | Output | |
| | Trough | Fluctuation |
| Baseline | 0.8926 | 0.4277 |
| Referral Matching ($\rho_{ij}$) $\uparrow$ 10% | 0.9155 | 0.4105 |
| Network Costs ($k_C$) $\downarrow$ 10% | 0.8966 | 0.4267 |
| Networker Matching ($\mu_C$) $\uparrow$ 10% | 0.8926 | 0.4277 |
| Standard Matching ($\mu_L$) $\uparrow$ 10% | 0.8947 | 0.4329 |

Table 1.7 shows the reduced recovery time in months for each proposed policy. Thus, one should interpret a negative number in the table as the policy resulting

Table 1.7.
Reduced Recovery Time in Months Relative to Calibrated Model

| | Consumption | Output | Welfare |
|---|---|---|---|
| Referral Matching ($\rho_{ij}$) $\uparrow$ 10% | 1 | 1 | 1 |
| Network Costs ($k_C$) $\downarrow$ 10% | 0 | 0 | 1 |
| Networker Matching ($\mu_C$) $\uparrow$ 10% | 0 | 0 | 0 |
| Standard Matching ($\mu_L$) $\uparrow$ 10% | -1 | 0 | -1 |
| | Bad Firms | Good Firms | Unemployment Rate |
| Referral Matching ($\rho_{ij}$) $\uparrow$ 10% | 3 | 5 | 6 |
| Network Costs ($k_C$) $\downarrow$ 10% | 2 | 3 | 3 |
| Networker Matching ($\mu_C$) $\uparrow$ 10% | 0 | 0 | 1 |
| Standard Matching ($\mu_L$) $\uparrow$ 10% | -4 | -1 | -8 |
| | UE JFP | EE JFP | U-Duration |
| Referral Matching ($\rho_{ij}$) $\uparrow$ 10% | 6 | 4 | 5 |
| Network Costs ($k_C$) $\downarrow$ 10% | 3 | 2 | 3 |
| Networker Matching ($\mu_C$) $\uparrow$ 10% | 2 | 1 | 1 |
| Standard Matching ($\mu_L$) $\uparrow$ 10% | -8 | -4 | -8 |

in a longer recovery time relative to the baseline model. In general, the policies have little effect on the recovery of output and consumption,[33] but network-centric policies do expedite the recovery of the unemployment rate, job-finding probabilities, and expected unemployment duration. However, the effect increasing the matching efficiency between workers and networkers (increasing $\mu_C$) is relatively weaker than improving referral-network matching or reducing network-formation costs. The latter two policies can accelerate the recovery of the unemployment rate by 3-6 months and expected unemployment duration by 3-5 months. As was the case with recession volatility, post-recession recovery is hindered by improving matching efficiency in general. This policy exacerbates the sullying effects, causing more G-firms to exit and relatively more B-firms to enter the labor market. This significantly delays the

[33]These variables are primarily driven by the recovery of aggregate productivity, which is common in this class of model.

recovery of the job-finding probability for both employed and unemployed workers, thereby delaying the recovery of the unemployment rate by 8 months.

These results emphasize that it is important to understand what channels facilitate recovery. That is, policies that seek to create any type of job, whether it be high- or low-productivity, can exacerbate the effects of a recession. Conversely, policies that facilitate matching between workers and high-productivity jobs can significantly hasten post-recession recovery, as they reduce distortions caused by sullying effects. This current framework demonstrates that policies aimed at improving network-formation and referral prevalence operate precisely through this desired channel, significantly accelerating recovery. This serves as a guide to policymakers concerned with the wage scarring effects associated with extended periods of unemployment.

In a more general context, these results suggest local policymakers working in labor markets in which referrals are less prevalent could allocate more funds to networking events as a preventative measure. This could make their local economy less vulnerable to the negative effects of prolonged unemployment caused by recessions. At the federal level, the findings of this paper inform efficient discretionary spending during a recession. That is, these results must be considered when deciding which labor markets needs the most assistance in the wake of a recession.

## 1.5 Conclusion

This paper introduces a search and matching model of the labor market that incorporates hiring through referrals as well as endogenous network formation. Within this framework, I demonstrate referral-networks have a stabilizing effect on the economy, reducing the severity of adverse shocks and accelerating post-recession recovery. Plausible differences in referral-network prevalence can expedite economic recovery of the unemployment rate and job-finding probability by six months to a year. This has significant welfare implications considering the wage scarring effects associated with extended periods of unemployment.

Under the lens of the model, more productive firms have higher job-creation costs, which makes them relatively more susceptible to negative productivity shocks. Since referral-networks especially facilitate matching between workers and high-productivity firms, they mitigate the sullying effects of recessions documented by Barlevy [2002]. Since networks result in fewer low-productivity firms entering and fewer high-productivity firms leaving in response to a negative economic shock, labor market aggregates fluctuate less and stabilize more quickly. Counter-factual exercises demonstrate government policies such as subsidizing networking events and employee referral programs can significantly expedite post-recession recovery.

At the macro level, the model suggests the government must be cautious when enacting policies intended to curb the effects of recessions. Policies that improve matching through formal channels can exacerbate the sullying effects of recessions, lengthening recovery time instead of shortening it. This model demonstrates focusing efforts on improving referral matching avoids this potential pitfall, as referrals lead to the creation of more productive jobs. These results are consistent with Hellerstein et al. [2015] who find workers who find employment using referrals during recessions tend to have higher earnings and job-tenure.

# 2. THE IMPACT OF REFERRAL-NETWORKS ON SECTORAL REALLOCATION

## 2.1 Introduction

Sectoral switching in the United States has declined significantly since 1970, and the underlying catalyst has remained elusive to researchers. While the literature has explored several hypotheses– from changing skill requirements across industries (Molloy et al. 2016) to increased geographical homogeneity (Kaplan and Schulhofer-Wohl 2017)– many of these explanations are at odds with the microdata, as shown by Molloy et al. [2016].[1] Currently, the main consensus is that a change in the *returns to switching jobs* is responsible for the decline, but the underlying mechanisms are prompting this change are not well understood. For policymakers, the primary concern is whether or not this decline is a symptom of a more serious problem in the labor market. If so, understanding the cause can inform labor market policy intended to correct this inefficiency. If not, understanding the cause alleviates concern for workers' economic well-being.

This paper focuses on a new explanation for the the decline in sectoral switching– referral-networks. Figure 2.1 demonstrates the decline in sectoral switching has been accompanied by a marked increase in the use of referral-networks in the job-finding process. Specifically, Figure 2.1 shows the fraction of unemployed workers who report contacting friends and family when looking for work as well as the fraction of individuals who switch industries each year at different industry aggregations.[2] The use of referral-networks among the unemployed has doubled since the 1970s, which

[1]See Molloy et al [2014, 2016, 2017] and Kaplan Schulhofer-Wohl [2017] for extensive analyses. In general, they find that none of the explanations provided here can simultaneously explain the long run decline in geographical migration, sectoral switching, or job-to-job transitions.

[2]See Data Appendix for more information on the various levels of industry/sectoral aggregations and for details on the construction of the industry switching data series.

is suggestive of a fundamental change in the nature of job-finding. Moreover, while the use of personal contacts in job finding has substantially increased since 1968, the use of other search methods has either declined or remained fairly stable as shown in Figure 2.2.

This evidence motivates the three main questions addressed by this paper. First, how do differences in sector-specific referral-networks influence switching decisions? Second, to what extent can increased reliance on referral-networks in the job-finding process explain the decline in sectoral switching seen in the data? Finally, given the relationship between sectoral switching and referrals, what are the implications for policy and welfare? The concern is that the lack of sectoral switching could be a symptom of a more problematic issue. This type of result leaves room for government intervention, possibly in the form of switching subsidies and re-training. However, it could also be the case that workers switch less due to increased market efficiency. That is, the underlying catalyst behind the decline in sectoral switching could be *improving* the quality of matches between workers and firms, thereby reducing the need for sectoral switching. In either case, understanding the underlying mechanism causing the decline is essential for crafting policy.

To answer these questions, this paper develops a search-and-matching model that incorporates referrals similar to Galenianos [2014] where there is hiring through both a formal costly channel and a less costly informal channel meant to capture the use of referrals. The economy consists of two sectors a la Chang [2013], and in each sector, workers and firms seek to be matched subject to search frictions. Workers also decide when to switch sectors in response to sector-specific productivity shocks. Workers are endowed with connections (i.e. a referral-network), but the size and effectiveness of this network is asymmetric across sectors. This environment effectively allows one to study the trade-offs an individual faces when deciding to switch sectors. On the one hand, referrals increase the overall job-finding probability for an unemployed worker. Hence, a worker with comparatively good connections in a particular sector will naturally be more drawn to this sector. On the other hand, sector-specific shocks

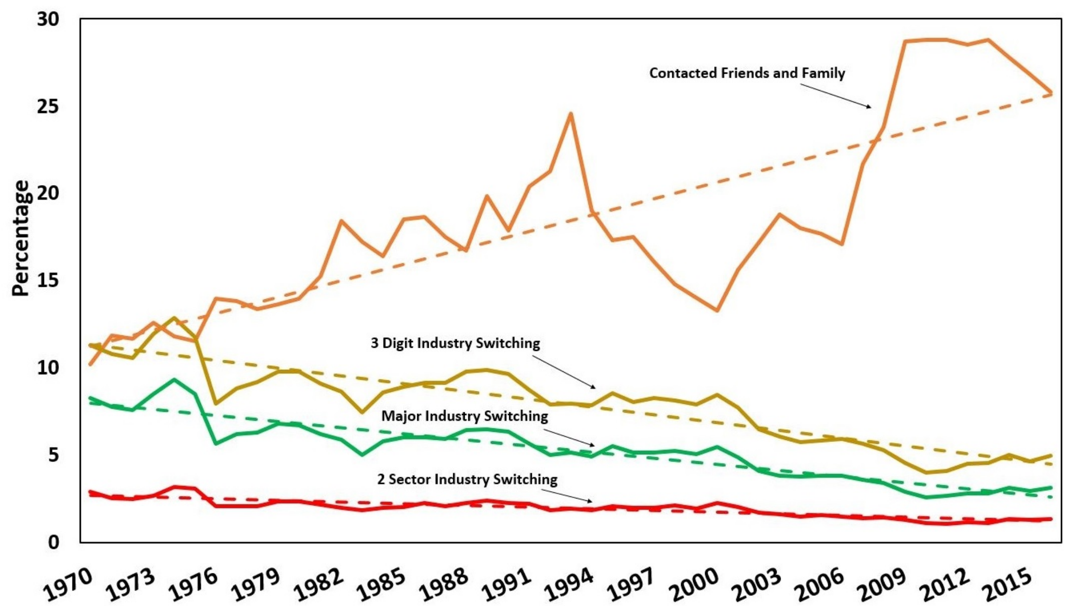


Fig. 2.1. Sectoral Switching and Intensity of Referral-Network Use of Unemployed

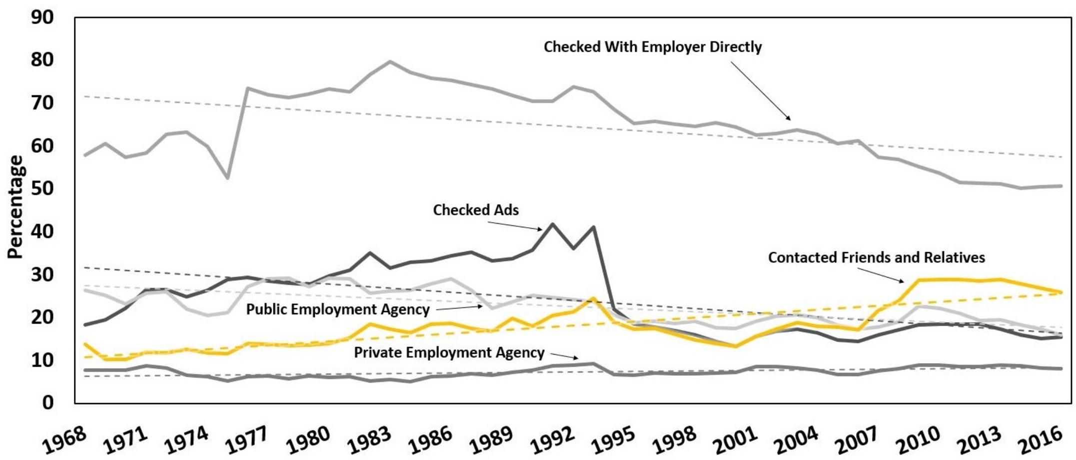


Fig. 2.2. Percentage of Unemployed Workers Who Use Certain Search Methods

make certain sectors more productive. This difference in productivity could be salient enough to entice the worker to switch to a sector in which she does not benefit as much from her referral-network. Thus, though the sector a worker is currently in may become relatively less productive, she may choose to remain in the sector due to the strength of her referral network (i.e. increased job-finding probability). Modeling this tension enables analysis of how workers value matching efficiency relative to a higher expected wage conditional on finding a match in another sector. Similarly, the search frictions allow us to study the value of referrals from the firm's perspective. In this environment, a firm possesses two methods of hiring workers. First, it can post multiple vacancies, each at a cost $k$. Second, it can rely on referrals from its current employees. As in Galenianos (2014), these referrals are costless, allowing for the firms to save on recruiting costs and decrease the expected search time. This is reflected in the wage of employed connected workers, as firms value the increased matching efficiency these referrals provide.

In general, the rate at which the firm is able to hire through referrals is non-monotonic, as it depends on the level of employment and unemployment.[3] The effectiveness of referrals also depends on the level of employment and the prevalence of referrals in a particular sector. Thus, when employment is high, a connected individual has a much higher probability of being hired via referral. Importantly, the model predicts that the prevalence of referrals can distort switching decisions. That is, workers are more drawn to the sector that offers a higher chance of employment via referrals. Moreover, since the effectiveness of referrals depends on the size of the labor force in a sector, the more workers who choose to locate in a sector, the more valuable connections and referrals become. This is the so-called "attraction effect," in which individuals choose to locate where the referral rate is higher. This effect can make workers less sensitive to sectoral shocks, as an increase in the prevalence of referrals in a sector can offset the negative effects of a sector-specific productivity

[3]Intuitively, more workers who can provide referrals means more referrals are possible, but there must also be unemployed workers that can be referred, causing the non-monotonic relationship.

shock. This effect is potentially problematic from an efficiency standpoint if too few workers are switching to the relatively more productive sector.

The model is calibrated to a two sector version of the US economy. Simulated Method of Moments (SMM) is used to match key moments in the data, focusing on the period from 2000-2010. The remaining moments are derived from surveys and empirical studies involving the prevalence of referrals networks and sectoral switching. That is, averages of important aggregate moments (i.e. average aggregate employment, average unemployment duration, etc.) are targeted. The calibrated model generates a referral-switching elasticity of about -0.12, which is in line with the range of estimates from the microdata. This implies that the increase in reliance on referral-networks can account for about 20% of the decline in sectoral switching at the 2-sector aggregation.[4] A welfare analysis is conducted to assess the efficiency of the labor force allocation across sectors in the presence of referrals and the attraction effect. If referral-networks are eliminated from the model, welfare decreases by 5%. Thus, though referral-networks can explain the decline in sectoral switching, the increased matching efficiency they provide outweighs the negative effects they cause by reducing the switching rate.

The results of this exercise are consistent with what Molloy et al. [2016] refer to as a "benign cause of the decline in job changing." That is, these results suggest that matching efficiency improvements provided by referrals dominate any potential negative attraction effects. From a policy perspective, these results suggest that the decline in sectoral switching (and more generally job changing) is indicative of markets evolving to become more efficient based on the current needs of all economic agents and should not be viewed as a problem to be fixed per se. These findings are broadly consistent with a recent hypothesis put forth by Molloy et al [2016], who find that states with lower levels of "social trust" also experience few job and industry switches. The results here imply that this lack of social trust generates a greater need for a mechanism that reduces information asymmetries, leading to the rise in

[4]See section 2.2 for discussion regarding finer aggregations.

the prevalence of referrals, the subsequent fall in sectoral switching, and the improved matching efficiency.

The rest of the paper is organized as follows: Section 2 presents stylized facts, Section 3 develops the model, Section 4 calibrates and estimates parameters in the model and performs a welfare analysis, and Section 5 concludes.

### 2.1.1 Related Literature

Rees [1966] and Granovetter [1974] were among the first to discuss the effects of labor market connections seen in the data, and Montgomery [1991] was the first to present a formal model in which workers used labor market connections. Since then, the literature has looked at the impact of labor market connections on a variety of economic outcomes such as inequality (Calvo-Armengol and Jackson [2004], [2007]), inter-industry matching efficiency (Galenianos [2014]), reducing information asymmetries and outcomes for firms (Galenianos [2013], Dustmann [2012], Beaman & Magruder [2012], Castilla [2005]), wages and social welfare (Zaharieva [2015], Igarashi [2016], Calvo-Armengol and Jackson [2007]), and unemployment duration (Calvo-Armengol [2004] and Fontaine [2008b]). Some papers have even tried to eliminate the "black box" of the matching function by creating micro-founded matching functions that incorporate referrals (Calvo-Armengol [2005] and Fontaine [2007]). This paper builds on the existing literature by taking the impact of connections in a single location as given and studies the relative value agents place on sectors that differ in referral effectiveness.

Theoretical models of labor switching were first developed by Lucas & Prescott [1974] and Rogerson [1987] with later models incorporating an infinite horizon (Phelan and Trejos [2000]) and implementing random migration in a search framework (Shimer [2007] and Mortenson [2009]). Chang [2011] adds to this work by fully endogenizing movement decisions in a search setting with decreasing returns to scale production (DRTS) and Stole-Zwiebel bargaining. The current paper builds on the previous literature by blending Chang's fully endogenous migration model with labor market connections modeled in a fashion similar to Galenianos [2014] and Igarashi [2016] in a discrete time framework.

There is a rich literature on potential causes of the decline in sectoral switching in the United States. Kaplan and Schulhofer-Wohl [2013[] argue that much of of the decline is attributable to a reduction in the geographic specificity of returns to different occupations coupled with agents' increased understanding of the benefits of living elsewhere. Molloy et al. [2014, 2017] perform an extensive reduced form empirical analysis that suggests fundamental changes in the labor market that are responsible for the decline in geographical migration as well as sectoral switching. As part of their analysis, they conclude that Kaplan and Schulhofer-Wohl's findings could perhaps explain geographical migration patters, but not the simultaneous decline in geographical and job switching in the data.

Both parties agree that the data fail to support a number of alternative potential explanations for the decline such as: the change in the share of the population between the ages of 20 and 34, changes in educational attainment, changes in the skill distribution of occupations, increased health care costs, rising share of dual earner households, and many other demographic and socio-economic changes. Ultimately, Molloy et al. [2014,2017] argue that the decline has something to do with the change in the labor market. Specifically something has changed the outside option of a worker, making her less likely to switch jobs. This paper argues that an increase in the prevalence of referrals specific to a sector can account for this fact, as it changes the returns to switching jobs.

There are a few reasons for this observed increase in the prevalence of referral-networks.

## 2.2 Stylized Facts

**Fact 1:** *The decline in sectoral switching coincides with an increase in the prevalence of referrals.*

As discussed, there has not only been a rise in the prevalence of referrals, but also a rise in the use of networks in job finding relative to other methods (See Figure 2.1 and Figure 2.2 above). One potential reason for this increased reliance on referral-networks could be a rise in perceived asymmetric information between workers and firms. Figure 2.3 shows the fraction of individuals who responded "Yes" to the question "Can people be trusted" in the General Social Survey. The dashed-trendline in the figure shows there has been a marked decline in social trust since the early 1970s.[5] As firms become increasingly less trusting, they will feel compelled to either screen applicants more thoroughly or find alternative hiring methods that produce better potential matches. Empirically, workers tend to refer individuals like themselves (Castilla [2005]). Consequently, the best way to find the appropriate candidate may be to ask current employees for recommendations to reduce information asymmetries (Galenianos [2013]).

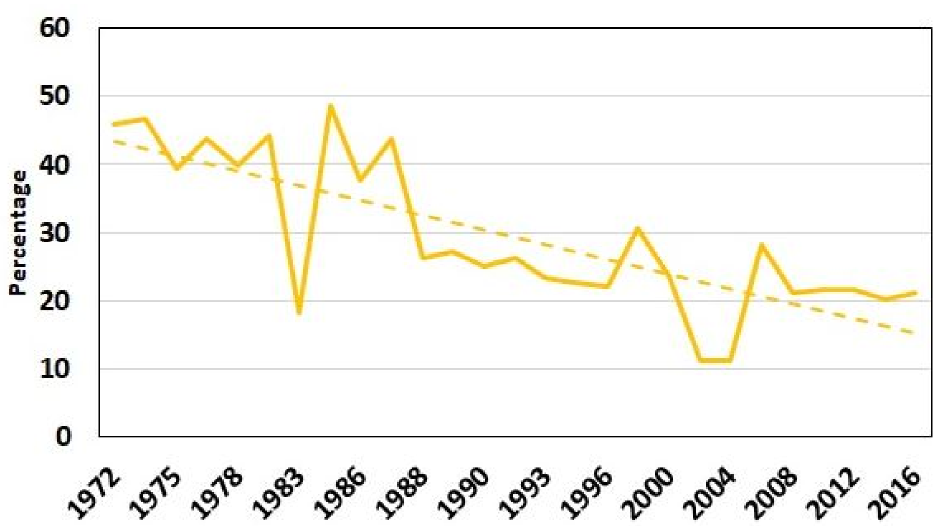


Fig. 2.3. Fraction Who Say Others are Trustworthy

[5]This same general trend is also common across industries and geographical regions as well.

**Fact 2:** *There has bee a decline in job changing, sectoral switching, and geographical migration.*

Figure 2.1 demonstrates that this decline in sectoral switching occurs at a variety of aggregations. In their analysis, Molloy et al. [2017] demonstrates that the same underlying mechanism is causing all three declines. Nevertheless, the direction of causality is not immediately intuitive. One could imagine a reverse causality story here. Agents could be moving less overtime, and *as a result*, they could be switching industries less frequently and using referrals more often. That being said, Molloy et al. [2017] argue that it is the change in job and sectoral switching that is causing the decline in migration, as job and industry switching have also declined among people who have never moved. Moreover Molloy et al. [2017] argue the switching flows are not large enough to explain the differences in job changing. All this evidence indicates a change in the labor market is responsible for the decline and not vice versa.

The literature agrees that a certain fraction of the decline can be explained by demographic changes over time, which should be taken into account when analyzing the incremental affect of referral-networks. To do this, I use the Current Population Survey Annual Social and Economic Supplement. In addition to providing basic demographic information, the survey also asks respondents about their current industry. Since the CPS is a rotating panel, there are some individuals who take the ASEC twice. That is, there are individuals who complete the ASEC the first month they enter the CPS and also then complete the ASEC in the last month they are in the ASEC. Thus, I observe whether an individual with certain demographic characteristics switches sectors that year. Moreover, I can observe the switching and demographic changes overtime. I follow the procedure of Molloy et al. [2017]. First, I run the following regression:

$$y_{it} = \beta_0 + X_{it}\beta_k + \theta_t + \epsilon_{it}$$

where $X_{it}$ is a set of demographic controls (age, homeownership, race, gender, etc.) and $\theta_t$ are the year fixed effects. Here, $\theta_t$ is interpreted as the average change in sectoral switching fluidity in a given year after controlling for these demographics. After estimating $\theta_t \forall t$, the series is normalized such that $\theta_t = 0$ for the first year in the series. This procedure creates a series of the deviations in sectoral switching fluidity overtime. The resulting series is shown below in Figure 2.4. Empirically, this paper focuses on the years 2000-2001. During this time about 28%-50% of the decline can be explained by changes in demographics. Thus, the aim of this paper will be to determine how much of the remaining decline can be attributed to an increase in the prevalence of referral-networks.

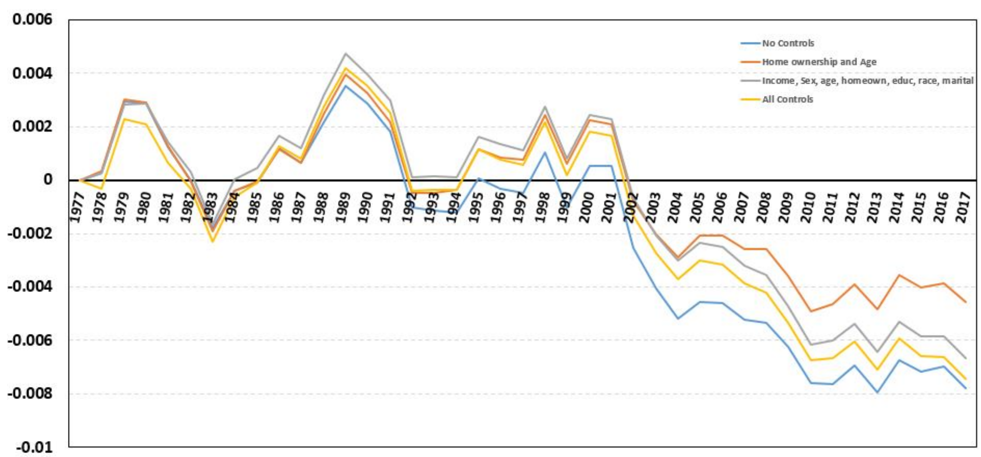


Fig. 2.4. Average Sectoral Switching Fluidity Controlling for Demographics

**Fact 3:** *Using referral-networks to find a job reduces the probability of switching sectors.*

Referral-networks are widely used, and an estimated 50% of all worker-firm matches currently in existence were formed through the use of these informal connections.[6] Empirically, it is evident that firms are also making use of their employees' connections, as Mardsen [2001] estimates that between 37% and 53% of firms obtain

[6]See Ioannides and Loury [2004] and Topa [2011] for overviews of the empirical studies of the use of connections and networks in the labor market. For the use of referrals across industries see Galenianos [2014].

new hires through their employees' networks. From a firm's perspective, there are a variety of benefits associated with the use of referrals. A firm that makes use of networks saves on time, recruiting costs, and could have better quality matches,[7] and higher productivity (Castilla [2005]). From a worker's perspective, using labor market connections is potentially beneficial along several dimensions. A worker's unemployment duration is dependent on her network, and can differ by orders of magnitude depending on the size and status of her network.[8]

In terms of wages, the Survey of Consumer Expectations (SCE) finds that a worker who found her job via labor market connections has an average wage that is 6% higher than a worker who found her job through formal search channels,[9] which implies that connected workers will have higher wages than unconnected workers. Given this evidence, the pecuniary benefits of connections appear to be significant enough influence workers' switching decisions. In other words, if a worker has a referral-network specific to an industry, it will take a comparatively larger average earnings difference in another sector to induce switching than it would for workers without referral-networks.[10]

I estimate the effect of network use on the likelihood a job-seeker switches sectors using the CPS ASEC. To estimate the long-run effect, I make use of CPS ASEC data from 1970 to the present. In addition to demographic and switching information, the CPS also asks unemployed individuals what search methods they are using to look

[7]While there is agreement in the literature that employed workers who refer unemployed workers to the firm can effectively screen for quality, there appears to be conflicting evidence for when this occurs. Dustmann [2012] argues that this happens in general as it reflects poorly if a worker refers a less-than-desirable friend. Moreover, he shows that workers tend to refer people like themselves, which implies that the referred worker is naturally more likely to meet the companies' screening standards. However, using data from a natural experiment in India, Beaman and Magruder [2012] argue that while workers can screen well, they require proper incentives to do so.

[8]See Fontaine [2008b], Calvo-Armengol & Jackson [2005], [2007].

[9]The SCE estimate is from a 2013 survey. Using earlier data, Korenman and Turner [1996] find a 20% premium for workers who used social connections in a survey of youth in Boston and a 7% premium for males living in cities from the 1982 NLSY. More recently, Igarashi [2016] estimates the wage premium to be abut 8%.

[10]Munshi [2003] demonstrates that Mexican immigrants, especially less educated immigrants, are more likely to move to a city that has a well known labor network comprised of other Mexican immigrants.

Table 2.1.
Probability Model: Switching and Referral Use

| | (1) 3-Digit | (2) 2-Digit NAICS | (3) 2-Digit Major | (4) 2 Sector |
|---|---|---|---|---|
| network | -0.0324*** | -0.0288*** | -0.0125 | -0.0136* |
| | (0.001) | (0.007) | (0.251) | (0.092) |
| nummethods | 0.0164*** | 0.0128*** | 0.0146*** | 0.0142*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| black | -0.00676 | -0.00651 | 0.00320 | 0.0215** |
| | (0.512) | (0.549) | (0.777) | (0.013) |
| asian | -0.0209 | -0.0421* | -0.0298 | -0.0208 |
| | (0.358) | (0.074) | (0.209) | (0.203) |
| married | -0.0216** | -0.0288*** | -0.0113 | -0.0187*** |
| | (0.016) | (0.002) | (0.242) | (0.010) |
| children | -0.00214 | -0.00291 | 0.00623* | 0.00675** |
| | (0.543) | (0.432) | (0.099) | (0.019) |
| age | -0.00331*** | -0.00347*** | -0.000515 | 0.0000192 |
| | (0.000) | (0.000) | (0.110) | (0.936) |
| homeown | 0.0284*** | 0.0232*** | 0.0146* | 0.00502 |
| | (0.000) | (0.005) | (0.091) | (0.428) |
| college | -0.104* | -0.168*** | -0.0997* | -0.0291 |
| | (0.061) | (0.002) | (0.059) | (0.433) |
| _cons | 0.836*** | 0.778*** | 0.504*** | 0.138*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| $N$ | 15222 | 15222 | 15222 | 15222 |
| Year FE | Yes | Yes | Yes | Yes |

$p$-values in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

for work. The respondents can indicate any number of activities, one of which is "Contacted friends and family," which this paper interprets as using their referral-network. Thus, I am able to run a pooled regression to assess the impact of using referral-networks on the probability a worker switches sectors by the time of the second ASEC survey. The results are shown in Table 2.1.[11]

Here, **network** is an indicator variable, taking a value of 1 if an individual reports contacting friends and family as a job-search method. The variable **nummethods**

[11]See the Data Appendix for more details on the construction of the data set. The appendix also reports the marginal effects from a probit regression that produce nearly identical results.

proxies for search intensity and represents the number of search methods listed by the individual.[12] The regression also controls for Year fixed effects and basic demographics such as marital status, race, home ownership, education, etc. The independent variables are various sectoral-switching indicator variables that take a value of 1 if an individual switch sectors. Four sectoral switching aggregations are examined. The variable **3-Digit** takes a value of 1 if an individual switches industries according to the CPS ind1990 3-digit industry classification codes. Similarly, **2-Digit NAICS** indicates switches made at the 2-digit NAICS code level, **2-Digit Major** indicates switches made at the 2-digit major industry level, and **2 Sector** indicates switches at a 2-sector economy aggregation.[13]

Using a referral-network has a negative and significant affect on the probability an individual job-seeker switches sectors, ranging from a 1.36% to a 3.24% decrease depending on the sectoral aggregation. Combining these results with the fraction of the decline explained by demographics, I can place bounds on the faction of the decline attributable to the increased prevalence of referral-network use.[14] These bounds are reported in Table 2.2. In the quantitative section of the paper, these bounds will be used as barometer by which one can judge the efficacy of the model.

Table 2.2.
Fraction of Decline Explained by Referral-Networks by Industry Aggregation

| 3-Digit | 2-Digit NAICS | 2-Digit Major | 2 Sector |
|---|---|---|---|
| 6.18%-19.39% | 4.65%-19.21% | 0%-19.21% | 4.82%-39.76% |

[12]In the appendix, I report alternative estimates using CPS Time Use data to control for search intensity. Unfortunately, many observations are lost in the merging process and the results are no longer significant. However, the coefficient estimations for network use are almost identical for the 3-digit and 2-Digit NAICS aggregations. The qualitative and quantitative results are also robust to controlling for unemployment duration.

[13]See Data Appendix for more details.

[14]See appendix for details.

## 2.3 Environment

This environment is a combination of a few papers. The switching aspect of the model is essentially identical to Chang [2013]. The wage derivation for multiple worker types in a decreasing returns to scale setting (DTRS) is described in detail in Cahuc et al. [2008]. The way referrals are modeled in the labor market are identical to the methods used in Galenianos [2014] and Igarashi [2016]. Finally, the discrete time version of the intra-firm bargaining comes from Krause and Lubik [2013].

### 2.3.1 Firms and Workers

Time is discrete and agents take the interest rate $r$ as given and discount each period by $\Delta = \frac{1}{1+r}$. There are two distinct labor sectors $S_{i=1,2}$. In each sector, there is a mass of risk-neutral firms, which will be determined by a free-entry condition. Across sectors, there is a measure $L$ of risk-neutral, infinitely lived workers who can choose to switch sectors.

Workers are identical in productivity but differ in their connectivity. There are two types of workers– workers whose home sector is S1 ($HS_1$ workers) and workers whose home sector is S2 ($HS_2$ workers). A worker whose home sector is S1 has a stronger referral-network in S1 relative to S2. Similarly, a worker whose home sector is S2 has a stronger referral-network in S2 relative to S1. Workers are endowed with connections and cannot change their status. Workers can either be unemployed and searching or employed and working. When unemployed, workers receive their outside option $z$, which can be interpreted as unemployment benefits. At the end of a period, a worker can also decide whether or not to pay some cost $c$ and switch sectors.

In each sector, there exists an endogenous mass of firms. While firms are homogeneous within a sector, they are heterogeneous across sector, differing in their production technology. Let the subscript $i$=1,2 refer to the sector and the subscript $j$=a,h refer to the worker type. Firms have production function $A_iF(N_{ih}, N_{ia})$, where $N_{ih}, N_{ia}$ are the measure of $HS_i$ workers and the measure of $HS_{\sim i}$ workers respectively, who are currently employed by a firm in sector $i$. Importantly, the production function F exhibits decreasing returns to scale, taking the form $F(N_{ih}, N_{ia}) = {N_{ih}}^{\alpha_i} + {N_{ia}}^{\alpha_i}$, with $\alpha \in (0,1)$. In order for a steady state equilibrium to exist without the two sectors collapsing into one sector, there must be some sort of diminishing returns to changing sectors, which is accomplished with this assumption.[15] To post a vacancy a firm much incur a cost $k_{i=1,2}$, which can be sector-specific. Firms can perfectly identify the type of a worker, and thus, post type-specific vacancies.

The timing of events in this model is now described. Figure 1.1 provides a visual representation of the timing of events. At the start of period $t$, all productivity shocks in each sector occur. After the shocks, all unemployment benefits and wages are paid out and production for that period occurs in each sector. Next, both hiring via standard search and hiring via referrals happen simultaneously. Subsequently, firing and separations then occur. Finally, after separations occur, agents of both types make their sectoral switching decisions.

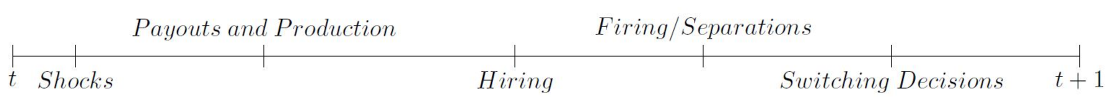


Fig. 2.5. Timing of Events

### 2.3.2 Matching Technology

There are two channels through which firms and workers match–formal and informal. Existing matches are exogenously destroyed with probability $\delta$. Matching through formal channels is modeled using a standard matching function a la Pissarides [2000]. Let $v_{ij}$ and $u_{ij}$ denote the measure of vacancies posted by firms in sector $i$ for worker type $j$ and measure of unemployed workers in sector $i$ of type $j$,

[15]For further discussion on the assumption of decreasing returns to scale, see the appendix.

respectively. Define market tightness as $\theta_{ij} = \frac{v_{ij}}{u_{ij}}$. The matching function generates $m(u_{ij}, v_{ij}) = \mu\frac{u_{ij}v_{ij}}{u_{ij}+v_{ij}}$, where $\mu_i$ is a sector-specific matching-efficiency parameter.[16] This function possess all the characteristics of a standard matching function: constant returns to scale, increasing in both inputs, $m(u_{ij}, 0) = m(0, v_{ij}) = 0$, and $m \leq min\{u_{ij}, v_{ij}\}$. The probability of an unemployed agent finding a job through formal channels is thus $\frac{m(u_{ij},v_{ij})}{u_{ij}} = \theta_{ij}q(\theta_{ij})$ and the probability of a firm hiring an unemployed worker through formal channels is $\frac{m(u_{ij},v_{ij})}{v_{ij}} = q(\theta_{ij})$. In standard Mortenson-Pissarides models, referrals are not modeled explicitly, and the matching function acts as a black box that dictates the rates or probabilities with which jobs are found or workers hired using *all* search methods, including referrals. This paper emphasizes that referrals are important enough in the labor market to merit being explicitly modeled apart from the matching function. Consequently, in this setting, one should think of the matching function as capturing the effectiveness of other standard job finding methods in producing a match between employers and agents, such as looking through ads, applying for jobs online, etc.[17]

Workers and firms can also be matched through informal channels. The matching technology is similar to Galenianos [2014], in which a worker's informal connections can refer the worker to a firm. In this model, I assume a worker of a particular type is connected to all other workers of the same type for simplicity, though this need not be the case. A meeting through a referral occurs when an operating firm identifies an opportunity for expansion. The firm then asks its current employee to refer someone for the open position. The employee contacts her referral-network and asks if they know of a suitable candidate. With some probability, the process is successful in hiring a worker for the newly created position. For a given worker type, the probability of matching with a firm via informal channels depends on a sector-

[16]This matching function is the same as is used in den Hann et al. [2000] and has the convenient property for empirical analysis of being bounded between zero and one, unlike the Cobb-Douglas matching function. Petrosky-Nadeau and Wasmer [2017] note this particular function produces business cycle moments comparable to models that use the Cobb-Douglas functional form. See Petrongolo and Pissarides [2001] for further discussion of alternative matching functions.

[17]For a good overview of matching functions, see Petrongolo and Pissarides [2001].

specific ($i = 1, 2$) referral efficiency parameter $\rho_i$[18] and the measure workers of the same type currently employed ($n_{ij}$). Then $\mathcal{R}_{ij}(n_{ij}) = \psi_j \rho_{ij} n_{ij}$ gives the probability of a worker matching with a firm through informal channels, where $\psi_a \in [0, 1]$ and $\psi_h = 1$. The parameter $\psi_j$ determines how effective referral-networks are for a worker not in her home sector. When an $HS_1$ worker is looking for work in S1, this term is 1 (i.e. $\psi_h = 1$). Conversely, when an $HS_1$ worker is looking for work in S2, $\psi_a \in (0, 1)$ and reduces the effectiveness of referral-networks.[19] Similarly, the probability an employed worker in sector $i$ of type $j$ is able to refer a worker their employer depends on the referral-network efficiency parameter $\rho_i$ and the measure workers of the same type currently searching for employment in sector $i$ ($u_{ij}$). Thus the probability of a firm hiring a worker through informal channels is $\mathcal{H}_{ij}(u_{ij}) = \rho_i u_{ij}$. The total job finding probability for a worker in sector $i$ of type $j$ is thus $\mathcal{R}_{ij} + \theta_{ij} q(\theta_{ij})$.

### 2.3.3 Equilibrium

For notational convenience, the time subscripts are dropped and the $t+1$ variables are denoted by an apostrophe (i.e. $\mathcal{V}_1' = \mathcal{V}_{1,t+1}$). Firms in each sector are competitive and take labor market aggregates as given. A firm that employs $N_{ih}$ $HS_i$ workers ($N_{ia}$ $HS_{\sim i}$ workers) in sector $i$ has a $\psi_h \rho_i N_{1h} u_{1h}$ ($\psi_a \rho_i N_{1a} u_{1a}$) probability of hiring a $HS_i$ ($HS_{\sim i}$) worker via a referral. Consequently, a firm in sector 1 solves the following problem:

$$V_1 = \max_{N_{1h}', N_{1a}', v_{1h}, v_{1a}} \Big\{ A_1(N_{1h}^{\alpha} + N_{1a}^{\alpha}) - N_{1h} w_{1h} - N_{1a} w_{1a} - k_1(v_{1h} + v_{1a}) + E_t \Delta [V_1'(A_1', N_{1h}', N_{1a}')] \Big\} \tag{2.1}$$

$$s.t. \quad N_{1h}' = (1 - \delta)[N_{1h} + v_{1h} q(\theta_{1h}) + \rho_1 N_{1h} u_{1h}] \quad (\mu)$$

$$s.t. \quad N_{1a}' = (1 - \delta)[N_{1a} + v_{1a} q(\theta_{1a}) + \rho_1 N_{1a} u_{1a}] \quad (\lambda)$$

[18] Alternatively, this parameter could also be interpreted as the prevalence of referrals in a given sector.
[19] An equally value interpretation is that this parameter reduces the size of the referral network.

where $w_{1j}$ represents the wage received by worker type $j = h, a$. $E$ is the expectations operator evaluated at time period $t$. Taking and combining first order conditions gives the two Euler equations:

$$E_t[J'_{1h}] = \frac{k_1}{\Delta(1-\delta)q(\theta_{1h})} \tag{2.2}$$

$$E_t[J'_{1a}] = \frac{k_1}{\Delta(1-\delta)q(\theta_{1a})} \tag{2.3}$$

where $J'_{1j}$=$V_1{}'_{N_j}(A'_1, n'_{1h}, n'_{1a})$. In this context, $J'_{1j}$ is the expected marginal value of an additional worker of type $j$ next period for a firm in sector 1. These are the free entry conditions for firms that dictate the number of vacancies. That is, firms will post vacancies for each type until the expected marginal value is equal to the discounted costs of the vacancy. Combining the envelope conditions with the Euler equations gives:

$$\frac{k_1}{q(\theta_{1h})} = (1-\delta)E_t\Delta[\alpha A'_1 N_{1h}^{\alpha-1} - w'_{1h} - \frac{\partial w'_{1h}}{\partial N'_{1h}}N'_{1h} - \frac{\partial w'_{1a}}{\partial N'_{1h}}N'_{1a} + \frac{k_1(1+\rho_1 u_{1h})}{\Delta q(\theta_{1h})}] \tag{2.4}$$

$$\frac{k_1}{q(\theta_{1a})} = (1-\delta)E_t\Delta[\alpha A'_1 N_{1a}^{\alpha-1} - w'_{1a} - \frac{\partial w'_{1a}}{\partial N'_{1a}}N'_{1a} - \frac{\partial w'_{1h}}{\partial N'_{1a}}N'_{1h} + \frac{k_1(1+\psi_a\rho_1 u_{1a})}{\Delta q(\theta_{1a})}] \tag{2.5}$$

These are analogous to the vacancy supply conditions found in standard search and matching models without intra-firm bargaining. That is, the expected marginal benefit a worker provides a firm must be equal to the discounted value of the posted vacancy.[20] The derivations for firms in sector 2 follow an identical procedure.

For agents in sector 1, let $\mathcal{U}_{1j}$ and $\mathcal{W}_{1j}$ be the value of unemployment and employment respectively for worker types $j = h, a$. An unemployed $HS_2$ worker maximizes the value of unemployment by choosing effort level $e_{1a}$, where the choice of effort determines the likelihood of switching sectors. After this choice, she receives her outside option $z$. With probability $(1-\delta)(\mathcal{R}_{1a} + \theta_{1a}q(\theta_{1a}))$, she finds a job and is not

[20]This vacancy supply condition reduces to the standard Mortenson-Pissarides condition if $\alpha = 1$. With CRS production, wages are no long dependent on the number of workers hired, and one is left with the expected cost of a vacancy equal to output minus the wage, plus the additional benefit gained from closing the current vacancy.

subsequently separated from that job in the same period. Otherwise, she pays the switching cost based on the effort level chosen, and switches sectors with a probability that equals her chosen effort level. If the switch is successful, she enjoys the discounted expected value of unemployment in the other sector. If the switch is unsuccessful, she receives the discount expected value of unemployment in her current sector. An unemployed $HS_1$ worker faces a nearly identical problem. The only difference is that the probability of finding job and not subsequently being separated from that job in the same period is $(1-\delta)(\mathcal{R}_{1h}+\theta_{1h}q(\theta_{1h}))$. For notational convenience, denote $p_{1h}$=$(1-\delta)(\mathcal{R}_{1h}+\theta_{1h}q(\theta_{1h}))$ and $p_{1a}$=$(1-\delta)(\mathcal{R}_{1h}+\theta_{1h}q(\theta_{1h}))$.

An employed worker of type $j=a,h$ selects $e_{1j}$ to maximize the value of employment. Next, she receives her wage, and with probability $\delta$, she is separated from her job. If separated, she pays the cost associated with her switching effort choice. Thus, with probability $e_{1j}$ she then enjoys the discounted expected value of employment in the other sector. Otherwise, she remains in the current sector. There is no on-the-job search for employed agents of either type. The resulting value functions are:

$$\mathcal{U}_{1c}=\max_{e_{1c}\geq 0}\Big\{z_1+h_{1c}\Delta E[\mathcal{W}'_{1c}]+(1-h_{1c})(-C(e_{1c})+e_{1c}\Delta E[\mathcal{U}'_{2c}]+(1-e_{1c})\Delta E[\mathcal{U}'_{1c}])\Big\} \tag{2.6}$$

$$\mathcal{U}_{1d}=\max_{e_{1d}\geq 0}\Big\{z_1+h_{1d}\Delta E[\mathcal{W}'_{1d}]+(1-h_{1d})(-C(e_{1d})+e_{1d}\Delta E[\mathcal{U}'_{2d}]+(1-e_{1d})\Delta E[\mathcal{U}'_{1d}])\Big\} \tag{2.7}$$

$$\mathcal{W}_{1c}=\max_{e_{1c}\geq 0}\Big\{w_{1c}+(1-\delta_c)\Delta E[\mathcal{W}'_{1c}]+\delta_c(-C(e_{1c})+e_{1c}\Delta E[\mathcal{U}'_{2c}]+(1-e_{1c})\Delta E[\mathcal{U}'_{1c}])\Big\} \tag{2.8}$$

$$\mathcal{W}_{1d}=\max_{e_{1d}\geq 0}\Big\{w_{1d}+(1-\delta_d)\Delta E[\mathcal{W}'_{1d}]+\delta_d(-C(e_{1d})+e_{1d}\Delta E[\mathcal{U}'_{2d}]+(1-e_{1d})\Delta E[\mathcal{U}'_{1d}])\Big\} \tag{2.9}$$

In order to capture the idea that switching sectors may be costly, agents must pay a cost that is a function of the effort they choose. The function $C(e_{ij})$ is assumed to be increasing with effort and strictly convex with $C(0) = 0$. Taking first order conditions of equations (2.6) and (2.7):[21]

$$C_{e_{1h}}(e_{1h}) = \Delta E[\mathcal{U}'_{2a} - \mathcal{U}'_{1h}] \tag{2.10}$$

$$C_{e_{1a}}(e_{1a}) = \Delta E[\mathcal{U}'_{2h} - \mathcal{U}'_{1a}] \tag{2.11}$$

In words, agents select a level of effort such that the marginal cost of their effort is equal to the expected discounted difference that would be obtained by successfully switching sectors. The value functions for agents in sector 2 are virtually identical.

### 2.3.4 Wage Determination and Intra-firm Bargaining

Due to the decreasing returns to scale, Stole-Zwiebel [1996] intra-firm bargaining is used to derive the closed-form solutions for the wages. As is the case with standard Nash Bargaining, wages for each worker type are selected to maximize the weighted geometric surplus of a match between the worker and the firm. However, even though the same equation used in typical Nash Bargaining is also used in Stole-Zwiebel bargaining, the DRTS production technology makes solving for the closed-form solution of the wage more difficult (i.e. one must now solve a differential equation). This occurs. This is due to the fact that each additional hire reduces the marginal productivity of *all* workers currently employed at the firm. Consequently, the firm would like to not only negotiate a lower wage for the new hire, but also a lower fee for all the networkers currently employed in her network. Stole-Zwiebel [1996] derive the solution to this differential equation using a finite sequence of pairwise bargaining sessions. Within each bargaining session, a Brügemann et al. [2015] Rolodex game if played between workers and the firm.[22] The essence of this bargaining game is that neither

[21] Note that is unnecessary to take the first order conditions of the employment value functions, as these are identical to the conditions obtained from the unemployment value functions. Since migration decisions occur after hiring and firing, workers who were employed but are separated from their jobs make exactly the same choices and unemployed workers.

[22] Traditionally, it was modeled as a Binmore, Rubinstein, Wolinsky [1986] alternating offers game played between the worker and the networker. However, Brügemann et al. [2015] show this produces inaccurate Shapely values. Using the Rolodex game produces the correct Shapely values used by Stole-Zwiebel without changing the solution.

firms nor workers can indefinitely commit to the contracts proposed. Contracts are at will, but negotiated for all workers simultaneously (much like unions engaging in collective bargaining). As a result, firms strategically over-employ workers, ensuring future production is not seriously disrupted and simultaneously driving down equilibrium wages. The equilibrium results of this game are used using a standard Nash Bargaining framework, one obtains the familiar bargaining condition:

$$W_{ij} - U_{ij} = \frac{\beta}{(1-\beta)} J_{ij} \tag{2.12}$$

where $\beta \in (0,1)$ is the bargaining power of all worker types. For a connected worker in sector 1, the left hand side of (2.12) can be rewritten using (2.6) and (2.8) as:

$$W_{1h} - U_{1h} = w_{1h} - z - M_{1h} + \frac{\beta}{(1-\beta)} \frac{k_1}{q(\theta_{1h})} \Big[ 1 - (\theta_{1h} q(\theta_{1h}) + \rho_1 n_{1h}) \Big] \tag{2.13}$$

where $M_{1h}$=$[\delta - (1-h_{1h})](-C(e_{1h}) + e_{1h}\Delta E[\mathcal{U}'_{2a} - \mathcal{U}'_{1h}])$. Recall that $J_{1h} = V_{1_{N_{1h}}}$. Combining (2.12) and (2.13):

$$\begin{aligned} &w_{1h} = (1-\beta)(z_1 + M_{1h}) + \\ &\beta \left[ \alpha A_1 N_{1h}^{\alpha-1} - w_{1h} - \frac{\partial w_{1h}}{\partial n_{1h}} n_{1h} - \frac{\partial w_{1a}}{\partial n_{1h}} n_{1a} + k_1 \Big( \theta_{1h} + \frac{\rho_1 L_{1h}}{q(\theta_{1h})} \Big) \right] \end{aligned} \tag{2.14}$$

where $L_{1h}$ is the measure of $HS_1$ workers currently in S1. Thus, the wages for the agents are a convex combination of their outside option and their marginal value of production. This result is somewhat problematic, as it implies that this differential equation must be solved in order to obtain a closed form solution for the wage. As discussed, Stole and Zwiebel [1996] proved that the general solution to these differential equations are:[23]

$$w_{1h} = (1-\beta)(z_1 + M_{1h}) + \beta k_1 \left( \theta_{1h} + \frac{\rho_1 L_{1h}}{q(\theta_{1h})} \right) + \beta \frac{\alpha_1 A_1 N_{1h}^{\alpha_1 - 1}}{1 + \alpha_1 \beta - \beta} \tag{2.15}$$

$$w_{1a} = (1-\beta)(z_1 + M_{1a}) + \beta k_1 \left( \theta_{1a} + \frac{\psi_a \rho_1 L_{1a}}{q(\theta_{1a})} \right) + \beta \frac{\alpha_1 A_1 N_{1a}^{\alpha_1 - 1}}{1 + \alpha_1 \beta - \beta} \tag{2.16}$$

The derivatives of (2.15) and (2.16) with respect to the number of workers are both less than zero as expected. The functional form of the wage for both worker

[23]Cahuc et al. [2008] show the steps required to solve the differential equations in their appendix.

types is nearly identical. The difference stems from the relative difference in ability of the worker types to provide referrals. The firm recognizes that these referrals result in savings in terms of vacancy postings. Thus, the firm pays these workers an additional amount that reflects the prevalence of referrals times the number of employed and unemployed individuals in the sector. Substituting (2.15) and (2.16) into (2.4) and (2.5) respectively gives complete versions of the vacancy-supply conditions:

$$\frac{k_1}{q(\theta_{1h})} = (1-\delta)\Delta E\Big[\frac{\alpha_1(1-\beta)}{1+\alpha_1\beta-\beta}A_1' {N_{1h}'}^{\alpha_1-1} - \Big((1-\beta)(z_1+M_{1h}') + \beta k_1\theta_{1a}' + \frac{\beta k_1\rho_1 L_{1h}'}{q(\theta_{1h}')}\Big)+ \Big(\frac{k_1(1+\rho_1 u_{1h}')}{q(\theta_{1h}')}\Big)\Big] \tag{2.17}$$

$$\frac{k_1}{q(\theta_{1a})} = (1-\delta)\Delta E\Big[\frac{\alpha_1(1-\beta)}{1+\alpha_1\beta-\beta}A_1' {N_{1a}'}^{\alpha_1-1} - \Big((1-\beta)(z_1+M_{1a}') + \beta k_1\theta_{1h}' + \frac{\beta k_1\psi_a\rho_1 L_{1a}'}{q(\theta_{1a}')}\Big)+ \Big(\frac{k_1(1+\psi_a\rho_1 u_{1a}')}{q(\theta_{1a}')}\Big)\Big] \tag{2.18}$$

The equations for sector 2 are similarly derived.

### 2.3.5 Labor Flow Equations

There are two kinds of flows possible in this model–flows in and out of unemployment and flows across sectors. For sector 1, the labor flows must be:

$$n_{1h}' = (1-\delta)[n_{1h} + (\theta_{1h}q(\theta_{1h}) + \rho_1 n_{1h})(L_{1h} - n_{1h})] \tag{2.19}$$

$$n_{1a}' = (1-\delta)[n_{1a} + (\theta_{1a}q(\theta_{1a}) + \psi_a\rho_1 n_{1a})(L_{1a} - n_{1a})] \tag{2.20}$$

In words, the stock of employed individuals in the next period is equal to the stock of employed workers in the current period not separated from their jobs plus any new hires that are not separated from their job in this current period. For labor flows across sectors, it must be:

$$
\begin{aligned}
L'_{1h} = L_{1h} + e_{2a}\Big[&(1-h_{2a})[L - L_{1h} - n_{2a}] + \delta[n_{2a} + (\theta_{2a}q(\theta_{2a}) + \psi_a\rho_2 n_{2a}) \\
&\cdot (L - L_{1h} - n_{2a})]\Big] - e_{1h}\Big[(1-h_{1h})[L_{1h} - n_{1h}] + \\
&\delta[n_{1h} + (\theta_{1h}q(\theta_{1h}) + \rho_1 n_{1h})(L_{1h} - n_{1h})]\Big] \qquad (2.21)
\end{aligned}
$$

$$
\begin{aligned}
L'_{1a} = L_{1a} + e_{2h}\Big[&(1-h_{2h})[L - L_{1a} - n_{2h}] + \delta[n_{2h} + (\theta_{2h}q(\theta_{2h}) + \rho_2 n_{2h}) \\
&(L - L_{1a} - n_{2h})]\Big] - e_{1a}\Big[(1-h_{1a})[L_{1a} - n_{1a}] + \\
&\delta[n_{1a} + (\theta_{1a}q(\theta_{1a}) + \psi_a\rho_1 n_{1a})(L_{1a} - n_{1a})]\Big] \qquad (2.22)
\end{aligned}
$$

That is, the stock of labor in sector 1 of type $j$ in the next period is equal to the stock the current period plus the fraction of the unemployed labor force from sector 2 that switches to sector 1, minus the fraction of the unemployed labor force that switches from sector 1 to sector 2. Notice, that the two terms that comprise the measure of agents that could possibly move are unemployed workers who failed to find a job and workers who were separated from their job. Also note that one does not explicitly need to write out equations governing the law of motion for $L'_{2c}, L'_{2d}$. Since the exogenous fraction of connected individuals as well as the total size of the labor force is known, those can be derived using (2.21) and (2.22).

Steady state equilibrium can now be discussed. In a steady state equilibrium, there is no switching as agents are indifferent between sectors. Hence, $e_{ij} = 0$ for all $i$ and $j$. Moreover, one can take as given that $U_{ij}$=$U'_{ij}$, $W_{ij}$=$W'_{ij}$, etc. Using these facts, the number of equilibrium equations is greatly reduced. There will be two vacancy supply conditions in each sector, two labor flows conditions in each sector, and two cross-sector equilibrium conditions. Thus a steady-state equilibrium is given by $L_{1c}, L_{1d}, n_{1c}$,$n_{1d}, n_{2c}, n_{2d}, \theta_{1c}, \theta_{1d}, \theta_{2c}, \theta_{2d}$ that solve the the vacancy supply equations for both types in both sectors, the labor flow conditions for both types in both sectors, as well as two additional equations:

$$z_2 - z_1 = \frac{\beta}{1-\beta}\left[k_1\Big(\theta_{1h} - \theta_{2a}\Big) + k_2\left(\frac{\rho_1 n_{1h}}{q(\theta_{1h})} - \frac{\psi_a\rho_2 n_{2a}}{q(\theta_{2a})}\right)\right] \qquad (2.23)$$

$$z_2 - z_1 = \frac{\beta}{1-\beta}\left[k_1\Big(\theta_{1a} - \theta_{2h}\Big) + k_2\left(\frac{\psi_a\rho_1 n_{1a}}{q(\theta_{1a})} - \frac{\rho_2 n_{2h}}{q(\theta_{2h})}\right)\right] \qquad (2.24)$$

where these two equations are obtained by setting $\mathcal{U}_{1h} = \mathcal{U}_{2a}$ and $\mathcal{U}_{1a} = \mathcal{U}_{2h}$. Note that one can always rewrite the variable $u_{ij}$ in terms of $L_{ij}$ and $n_{ij}$. Given that the equations are nonlinear in nature, the existence and uniqueness of equilibrium must be proved.

**Proposition 4.** *Given the steady state equations, there exists a unique steady state equilibrium.*

## 2.4 Quantitative Analysis

This section discusses the data, calibration strategy, and estimation of the 2-sector model to a quarterly time-frame using US data. The two sectors are called S1 and S2. The aggregation S1 consists of Agriculture, Mining, Utilities, Transportation, Manufacturing, Wholesale Trade, Retail Trade, Construction, and Other Services. The aggregation S2, which consists of Business and Professional Services, Leisure and Hospitality, Education, Health, Information, FIRE, and Government. The data for the calibration are aggregated by these industry specifications. With a few exceptions, the data used is restricted to 2000-2010. For the calibration exercise, some parameters are taken from the literature while others are estimated using a Simulated Method of Moments (SMM) procedure. Finally, the estimated parameters are used to conduct a welfare analysis.

### 2.4.1 Data

The sectoral switching rates are obtained using IPUMS CPS ASEC microdata while the data concerning the rise in the prevalence of referrals overtime come from IPUMS CPS and the BLS CPS tables.[24] To compute the referral-switching elasticity and average sectoral switching flows within the model, it is necessary to obtain the

[24] See appendix for details on the dataset construction procedure.

distribution of the productivity shocks, which this paper estimates outside the model and then targets as a moment (see section 6.2 below). More precisely, the distribution of the *quarterly difference in productivity ratios* between two sectors is estimated. As is standard, productivity in industry $i$ ($p_i$) is defined as:

$$p_i = \frac{output_i}{total\ labor\ hours_i}$$

Thus, in order to calculate productivity for each industry $i$, as well as the productivity for aggregations of these industries, quarterly measures of output and labor hours are required.[25] For total labor hours, this paper primarily makes use of the Bureau of Labor Statistic's (BLS) seasonally adjusted Nonfarm Quarterly Total Hours of Wage and Salary Workers by Sector, which is available by the NAICS definition of major industries through the first quarter of 2017. This data is supplemented with data from the IPUMS CPS monthly data to obtain hours estimates for workers in the agriculture, forestry, and fishing industries.[26]

The data for output by industry come from the Bureau of Economic Analysis (BEA), which provides quarterly estimates of real value added by major industry from the first quarter of 2005 to the fourth quarter of 2016 adjusted for inflation using 2009 chain-weighted dollars. Given that value added data are only available starting in 2005, the final data series used span quarterly from 2005 through 2016, which provides a time series dataset of productivity by industry that is 48 quarters long. Define the quarterly difference in productivity ratios between industry $i$ and industry $j$ at time $t$ ($DRatio_{i,j,t}$) as:

$$DRatio_{i,j,t} = \frac{p_{i,t}}{p_{j,t}} - \frac{p_{i,t-1}}{p_{j,t-1}}$$

This definition creates a final data series that is 47 quarters in length. For the purposes of this paper, the 2-sector aggregation of industries into S1 and S2 (as described in

[25] Though there are estimates for both labor and multi-factor productivity by sector available from the BLS KLEMS, these estimates are not comparable, as they are reported as ratios indexed by a specific year. That is, these productivity estimates only allow the researcher to effectively compare productivity overtime within a sector. In light of this fact, it is necessary to construct an alternative data set that would allow comparisons across sectors.

[26] See Data Appendix for a discussion on the construction of the IMPUMS CPS monthly hours data.

Section 2.4.2) is used, and the data series constructed using the above definition. Using this dataset, the distribution of the difference in productivity ratios overtime is estimated in section 6.2.

### 2.4.2 Estimation

**Calibration.** The model is calibrated to a quarterly basis. The total measure of the labor force is normalized to 1 (L=2). Following Shimer [2005], the quarterly interest rate $r$ is set to .012, which implies a discount rate $\Delta$=.9881. The separation probability is taken as the average over this period as documented by the BLS, which gives $\delta = .0316$. The functional form for the cost of switching sectors is $C(e_{ij}) = .5{e_{ij}}^2$.

**Productivity Estimation.** To estimate the mean productivity ratio difference moment, Maximum Likelihood is used to fit the data to a normal distribution with mean $\mu$ and variance $\sigma^2$. Given a sample size of 50, one might worry about the asymptotic consistency of the estimates. Moreover, there is evidence that the standard errors obtained using the information matrix with small samples sizes can be quite inaccurate. To alleviate these concerns, two steps are taken. First, the standard errors from the information matrix are discarded in favor of bootstrapped standard errors. Second, Monte Carlo simulations are performed that instill confidence in the accuracy of these estimates. Table 2.3 below reports parameter estimates. The .0004 estimate for the mean is used as a target moment for the estimation procedure. One may think that the data may better be described using an AR(1) specification. In general, there is little empirical support for this alternative specification.[27]

**SMM Estimation.**There are 15 parameters left to be estimated: the outside option for unemployed workers ($z_1 = z_2 = z$), the prevalence of referrals in both sectors, the referral penalty parameter $\psi_a$, the fraction of $HS_1$ workers $\gamma_{1h}$, worker bargaining power $\beta$, the cost of a vacancy ($k_1 = k_2 = k$), the matching efficiency parameter in

[27]See Data Appendix for the Monte Carlo results and a discussion of an Alternative AR(1) specification.

Table 2.3.
MLE Estimates of $N \sim (\mu, \sigma^2)$ for the productivity ratio $\frac{S1}{S2}$

| $\hat{\mu}$ | $\hat{\sigma^2}$ |
|---|---|
| .0004$^{***}$ | .0001$^{***}$ |
| (1.548e-16) | (9.69e-16) |

Standard errors in parentheses are obtained

using 10,000 bootstrap replications

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

each sector, two parameters that govern the production functions $(\alpha_1, \alpha_2)$, and four parameters that govern the productivity shocks for each sector– $\mu_{A_1}, \mu_{A_2}, \sigma_{A_1}, \sigma_{A_2}$. These remaining parameters are estimated using Simulated Method of Moments (SMM). For this procedure, target moments from the data that correspond output produced by the model are selected. Then, a grid-search is performed over a parameter space to minimize the sum of squared residuals of the differences between the moments simulated by the model and the moments from the data (i.e. minimize the squared distance between the model's simulated unemployment rate and the unemployment rate found in the data).

For the sake of parsimony, almost all targets are constructed using data from 2000-2010, with only two exceptions. First, the mean of the productivity ratio difference of .0004 reported in 2.3 is estimated using data spanning 2005-2017 to obtain a more consistent estimate. Second, the targets for the fractions of jobs found via referrals in each sector uses data constructed by Galenianos (2014), who uses the 1994 wave of the NLSY, as these are the only known estimates of referral use by industry.

The average market tightness moment is take from Hall [2005], and the switching rate target is calculated by dividing the IPUMS ASEC yearly average switching rate from 2000-2010 by four, which gives a quarterly target. The remaining moments are all derived from the BLS. The replacement rate, the job-separation rates, and the job-finding probabilities were calculated by Shimer[2005,2012] using data from the BLS.[28] The total employment share of S2 (i.e. the fraction of the labor force in S2), the median unemployment duration, and the labor share of output are all calculated using BLS data. The average unemployment duration in each sector is calculated as the average across all industries within the corresponding aggregate sector from 2000-2010. The unemployment rate in each sector as well as the aggregate rate targeted are BLS averages over the specified years.

In the model, the switching-referral elasticity is calculated using the following metric:

$$Elasticity = \frac{\%\Delta Switches}{\%\Delta\rho}$$

In words, the switching-referral elasticity is the percent change in the total number of switches given productivity shocks divided by the percent change in the prevalence of referrals $\rho$. In practice, this is calculated by applying a productivity shock to the economy in steady state and then applying the same shock to the same initial steady state while also changing the prevalence parameter in the sector workers are leaving as a result of the shock. This is done for discretized grids of the productivity shock distributions, and the probability weights from the estimated normal distributions are used to obtain an average elasticity. A similar procedure is used to calculate the average quarterly switching rates. See the Table 2.4 for a summary of targets, the values chosen, and the fit of the model using the SMM procedure. The values for all estimated and calibrated parameters are reported below in Table 2.5.

The model predicts a referral-switching elasticity of -.129, which is in the empirically estimated range for the 2-sector aggregation. This suggests the change in the prevalence of referrals can explain about 20% of the decline in sectoral switching at the 2-sector aggregation. The difference in referral rates across sectors effective creates an additional cost. That is, since referrals are more common in sector 2, an

[28]This data was constructed by Robert Shimer. For additional details, and Shimer [2005].The aggregate job-finding and job-separations probabilities are only available through 2007, and the average of each series from 2000-2007 is used as the target.

Table 2.4.
SMM Targets, Estimates, and Sources

| Description | Estimate | Target | Source |
|---|---|---|---|
| Market Tightness | .5118 | .5390 | Hall (2005) |
| Aggregate Unemployment | .0619 | .0590 | BLS |
| Agg Job-Finding Probability | .4573 | .4189 | Shimer (2012)/ BLS |
| Unemployment S1 | .0687 | .0724 | BLS Average 2002-2016 |
| Unemployment S2 | .0555 | .0570 | BLS Average 2002-2016 |
| Fraction of Jobs Found via Referral S1 | .3706 | .3369 | Galenianos (2014) |
| Fraction of Jobs Found via Referral S2 | .2874 | .2707 | Galenianos (2014) |
| Replacement Rate | .3563 | .4000 | Shimer (2005,2012)/ BLS |
| Agg Switching Rate | .0040 | .0040 | CPS Implied Quarterly Average 2005-2016 |
| Employment Fraction S2 | .5206 | .5230 | BLS |
| Labor Share of Output | .8503 | .6000 | BLS |
| Expected Difference Mean Ratio | .0009 | .0004 | MLE Estimate of Productivity Data |
| Average Unemployment Duration S1 | 2.3346 | 1.730 | BLS |
| Average Unemployment Duration S2 | 2.0336 | 1.810 | BLS |

Table 2.5.
Parameter Values

| Parameter | Value | Source | Parameter | Value | Source |
|---|---|---|---|---|---|
| $z$ | 1.17 | SMM | $\alpha_1$ | .7876 | SMM |
| $\rho_1$ | 1.32 | SMM | $\alpha_2$ | .7073 | SMM |
| $\rho_2$ | .6483 | SMM | $\mu_{A_1}$ | 3.1 | SMM |
| $\beta$ | .5644 | SMM | $\mu_{A_2}$ | 3.3 | SMM |
| $k$ | 1.9573 | SMM | $\sigma_{A_1}$ | .0919 | SMM |
| $\mu_1$ | .9450 | SMM | $\sigma_{A_2}$ | .0269 | SMM |
| $\mu_2$ | 1.0183 | SMM | $L$ | 2 | Normalized |
| $\psi_a$ | .0904 | SMM | $\delta$ | .0316 | Literature |
| $\Delta$ | .9881 | $\frac{1}{1+r}$ | $r$ | .012 | Literature |
| $\gamma_{1h}$ | .4532 | SMM | | | |

agent who switching to sector 1 must be compensated accordingly. This additional cost to switching changes the outside option of agents, changes the switching rate, and is vital to the operation of the labor market. Consequently, it fulfills all of the requirements Molloy et al. [2014] expect the mechanism causing the decline in US sectoral switching to have.

### 2.4.3 Welfare Analysis

Economists are chiefly interested in explaining the decline in sectoral switching only insofar as it relates to an underlying problem that requires policy intervention. For example, if the fixed costs of switching sectors has increased overtime, the government may be able to improve welfare by providing switching subsidies. That being said, it could also be the case that the decline in sectoral switching (and more generally job changing) is not a symptom of an underlying problem. Rather, it could be a result of markets evolving based on the needs of workers and firms.

The theoretical and quantitative results of the model demonstrate that a rise in the prevalence of referrals can explain the decline in sectoral switching. Whether or not this labor market phenomenon requires policy intervention is now explored. If the attraction effect dominates any gains in matching efficiency that accompany referrals, then eliminating referrals from the model should cause welfare to rise. This result would suggest that policy intervention in the form of switching subsidies could be employed to improve market outcomes. Conversely, if eliminating referrals results in a decrease in welfare, this suggests that the matching efficiency gains dominate the negative attraction effect. This finding would suggest that the empirical decline in sectoral switching is not a problem to be remedied per se.

To eliminates referrals, one simply sets $\rho_1 = \rho_2 = 0$. In order to accurately calculate the welfare gains or losses, a dynamic analysis is performed in which the referral channels are close and the economy adjusts to the new steady state. One should think of the "banning" of networks as the passing of anti-nepotism laws.[29] The mere presence of a distortion, however, does not guarantee removing referrals will increase welfare. Define aggregate welfare as:

$$\sum_{t=1}^{\infty} \Delta^t [z(u_{1c,t} + u_{2c,t} + u_{1d,t} + u_{2d,t}) + F_{1,t}(n_{1c,t}, n_{1d,t}) + F_{2,t}(n_{2c,t}, n_{2d,t}) \\ - k(v_{1c,t} + v_{1d,t} + v_{2c,t} + v_{2d,t})]$$

[29] Igarashi [2016] conducts a similar exercise to answer a different question in a single sector economy.

That is, total welfare is the infinite, discounted sum of payments made out to unemployed individuals and production from firms minus the costs of posting vacancies for each worker type in each sector. Table 2.6 shows the results of the policy experiment.

Table 2.6.
Welfare Results After Setting $\rho_1, \rho_2 = 0$

| | Pre-policy | Post-Policy | Change (%) |
|---|---|---|---|
| Welfare | 7.2132 | 6.8327 | -5.4 |
| Output | 7.2103 | 6.9002 | -4.3 |
| Posted Vacancies | .0705 | .1208 | 71.3 |
| Vacancy Costs | .1380 | .2363 | 71.2 |
| Time to Hire | 1.5798 | 1.9554 | 23.8 |

Closing the referral channel causes a 5.4% decrease in aggregate welfare, which is primarily driven by a 4.3% fall in total output. This fall in output is a result of increased matching frictions, which significantly delay worker-firm matching. With hiring through referrals no longer an option, firms are forced to exert more effort searching for potential workers through formal channels. Thus, the number of posted vacancies increases by 71%, increasing expenditures on hiring by the same amount. Despite this increase in vacancies, however, the expected time to hire sill increases by almost 24% for firms. This delay in the expected hiring time reduces the level of labor a firm has employed, thereby reducing output in the aggregate.

These results imply researchers should not view the decline in sectoral switching as a symptom of an underlying problem. On the contrary, though referrals may appear to "distort" sectoral labor allocations, the benefits they provide in terms of matching efficiency outweigh the inefficiencies created by this distortion. Referral-networks significantly reduce the cost of search for a firm. This reduction in search frictions can be interpreted as a reduction in information asymmetries a referral offers to the firm. Thus, there does not appear to be a need for policy intervention.

## 2.5 Conclusion

This paper investigates a new possible explanation for the long-run decline in sectoral switching–the increased prevalence of referral-networks. Using data from the CPS, I first document empirically the significant increase in the use of referral-networks in the job-search process by the unemployed. Moreover, the paper shows this increase is concurrent with the decline in sectoral switching. Using data from the CPS, I am able to estimate the effect of using referral-networks on the likelihood of an individual switching sectors at a various levels of industry classifications. For all aggregations, using referral-networks significantly reduces the probability a worker switches sectors. After controlling for demographics, these estimates imply an increase in the prevalence of referral-network use could explain as much as 40% of the decline in sectoral switching.

To better understand the policy implications of this finding, a discrete time sectoral-switching model is constructed using a search and matching framework with labor market referrals explicitly modeled. The estimated model estimates a referral-switching elasticity of about -.12, which is within the empirically estimated range for the 2-sector industry aggregation, demonstrating that the increased of the prevalence of referrals overtime can explain about 20% of the decline in US sectoral switching. Welfare results indicate that referrals are a “benign” cause of the decline, as a counter-factual policy experiment demonstrates that welfare declines upon effectively banning the use of referral-networks.

These results have important implications for policymakers. They suggest that the cause of the decline in sectoral switching (and more generally job-changing) is the result of improved matching efficiency over time rather than some market inefficiency. These results are consistent with findings by Molloy et al. [2016] who find that states with less “social trust” tend to have lower job-changing and sectoral switching rates. Firms seem to have become more cautious about who they hire due to some increase in information asymmetries. As such, they have become increasingly reliant on referrals to reduce search costs, and workers have responded in kind by increasingly using their referral-network to find a job. Thus, the rise in the prevalence of referrals seems to be a result of markets evolving to meet the needs of workers and firms, and the decline in sectoral switching attributable referral-networks appears to be a natural symptom of this phenomenon.

# 3. DOES JOB-FINDING USING INFORMAL CONNECTIONS REDUCE MISMATCH?: THE ROLE OF NONPECUNIARY BENEFITS

## 3.1 Introduction

Mismatch arises between workers and firms when the characteristics or preferences of the worker do not align with those of the firm. The most common form of mismatch studied in the literature is *skill-mismatch*, which occurs when the skills of the worker do not match the skill requirements of the firm. However, this is not the only dimension along which a firm and a worker can be poorly matched. For example, a worker may be working longer hours than she desires, or the firm may not have certain amenities the worker would like to have available. In both of these cases, there is *nonpecuniary-mismatch* between the worker and firm. That is, there are characteristics of the firm other than skill requirements that do not perfectly align with the worker's preferences.

Studies show skill-mismatch is costly. Gautier and Teulings [2015] estimate that skill-mismatch reduces output by as much as 11%, and Lise and Postel-Vinay [2015] show mismatched workers tend to experience lower wages and shorter employment durations. However, evidence suggests nonpecuniary-mismatch is costly from both a monetary perspective and a welfare perspective as well. Gallen and Winston [2018] show extended vehicle travel times due to construction significantly reduce the effectiveness of government spending on infrastructure, which suggests commute times have a significant impact on welfare. Mas and Pallais [2017] find workers are willing to incur a 20% wage decrease to avoid a schedule created on short notice by the firm and an 8% decrease to have the option to work from home. Data from the Survey of

Consumer Expectations[1] show 47.7% (74.8%) of respondents reject (accept) job offers for reasons related to nonpecuniary benefits, compared to only 40.2% (60%) citing the wage and 9% (65.2%) citing the skill requirements of the job as a determining factor.

Given how costly mismatch is for both workers and firms, job-finding/vacancy-filling channels that reduce search frictions caused by asymmetric information are critical. Notably, job-finding through informal contacts (referral-networks) has been shown to reduce these exact frictions. Using informal connections to find a job leads to workers experiencing shorter durations of unemployment, higher wages [Igarashi 2016], and faster job-to-job transitions (Arbex, O'Dea, and Wiczer [2017]). Moreover, studies show matches formed using referral-networks are more productive. Castilla [2005] finds in a field experiment study of telemarketers that workers tended to refer prospective employees who were more productive. Similarly, empirical firm-level studies by Brown et al. [2016] and Burks et al. [2015] find referred employees generally experience longer tenures and tend to be similar in quality to the person who referred them. These empirical studies regarding productivity, however, tend to focus on the benefits the firm enjoys by hiring through referrals and do not fully explore why workers value referral-networks.

The present work studies how referral-networks affect aggregate worker-firm mismatch. Three stylized facts concerning referral-networks and mismatch are first discussed. Perceived mismatch by workers is obtained using data from the Survey of Consumer Expectations' Job Search Survey. Workers rate how satisfied they are with their jobs on a variety of dimensions, including compensation, skill, opportunities for promotion, and non-wage benefits. Moreover, the survey provides data concerning the method by which a worker found her current job, allowing me to compare differ-

[1]Some [All] survey questions were taken or adapted from the Survey of Consumer Expectations, 2013-2019 Federal Reserve Bank of New York (FRBNY). The SCE questions are available without charge at http://www.newyorkfed.org/microeconomics/sce and may be used subject to license terms posted there. FRBNY did not participate in or endorse [identify users survey], and FRBNY disclaims any responsibility or legal liability for the administration of the survey and the analysis and interpretation of data collected.

ences in satisfaction along these dimensions conditional on the job-finding method as well as other worker characteristics. The empirics show referrals do not generically reduce perceived mismatch along any observable dimension. In fact, only referrals from former co-workers reduce perceived nonpecuniary-mismatch, and they only do so for high-skilled workers. No referral methods significantly reduce skill-mismatch for any skill type.

Using these facts as a guide, I create a search-and-matching model of the US labor market in which firms and workers seek to be matched subject to search frictions. The base model is derived from McCall [1970] and is augmented in a fashion very similar to Buhrmann [2018] with two exceptions. First, workers can receive job offers through two channels–formal and informal. Formal channels represent job-finding methods such as applying online, contacting the employer directly, using a public employment agency, etc while informal channels represent job search using informal connections. The second difference is the introduction of an additional dimension of mismatch, namely nonpecuniary-mismatch. A worker's skill type $s$ and nonpecuniary type $\gamma$ are distributed independently along unit intervals.[2] Along the skill dimension, workers are vertically differentiated with more highly skilled workers possessing a higher value of $s$. In general, high-skilled workers enjoy higher wages, which is consistent with this vertical differentiation. Conversely, although workers' nonpecuniary type is distributed along a unit interval, there is no inherent vertical differentiation along this dimension. Non pecuniary mismatch is treated more similarly to a preference, with no value being superior.

The model restricts its focus to the worker's problem. Workers engage in random search and receive job offers that follow one of two Poisson arrival rates, representing job finding through formal or informal methods. An offer consists of a "wage-fit" draw determined by the skill type of the worker, the skill requirements of the job, the nonpecuniary preferences of the worker, and the nonpecuniary benefits provided by

[2] In principle, there could be a correlation between skill type and preferences for non-wage amenities. This author is unaware of any such studies.

the firm. This "wage-fit" draw determines the flow utility a worker would enjoy should she accept the job. A worker's only choice is whether or not to accept the current offer and leave unemployment or reject the offer and continue searching. Since offers are drawn from a continuous distribution, workers will not wait for a perfect match along either dimension. Workers will, therefore, tolerate some degree of mismatch, selecting jobs that provide some reservation value. The degree of mismatch accepted is a function of this reservation value, as a specific worker type accepts relatively more mismatch if they have a lower reservation value.

To assess both the affects of nonpecuniary preferences and referral-networks on aggregate mismatch. The model is calibrated to the US economy. Empirical findings are twofold. First, preferences for nonpecuniary benefits increases mismatch along the skill dimension *ceteris paribus.* Second, while referrals reduce mismatch along the nonpecuniary dimension, they increase mismatch along the skill dimension in terms of dispersion within skill types while still reducing mismatch on average. The implications of these results are important to consider when crafting efficient labor market policy. If workers are selecting jobs along multiple dimensions, not all of which may be beneficial to productivity or output, the estimated detrimental effects of skill-mismatch are likely over-stated. Moreover, since skill-mismatch is partially preference induced, it is unclear how policymakers should view the empirically documented persistence in skill-mismatch documented by Guvenen et al. [2015].

The remainder of this paper is organized as follow. Section 2 presents the stylized facts concerning referral-network use and its effect on mismatch. Section 3 constructs an augmented McCall model similar to Buhrmann [2017] which incorporates nonpecuniary-mismatch as well as job-finding through informal connections. Section 4 performs a quantitative analysis, calibrating the model to the US labor market and conducting counterfactuals. Section 5 concludes.

### 3.1.1 Related Literature

The use of informal connections in job-finding is an integral component of the labor market (Topa [2011] and Granovetter [1995]). An estimated 85% of workers have attempted to use their network of contacts to find a job, and about 50% of all currently existing jobs were formed through the use of referral-networks (Ionnides and Loury [2004]). For workers, using this network of informal connections to find a job leads to lower expected unemployment durations, higher wages (Igarashi [2016]), and faster job-to-job transitions (Arbex, O'Dea, and Wiczer [2017]). Hiring through referrals is beneficial from a firm's perspective as well, resulting in better matches as measured by productivity (Castilla [2005]) and longer expected employment tenure (Brown et al. [2016] and Burks et al. [2015]). Hiring through referrals also significantly improves worker-firm matching; Galenianos [2014] finds most of the differences in worker-firm matching efficiency across industries can be explained by differences in referral-network use. The current paper adds to this literature by studying the impact of referral-networks on mismatch.

The present mismatch literature primarily focuses on cognitive skill-mismatch. Buhrmann [2018] constructs an augmented McCall model with vertically differentiated skill types and shows changes in aggregate mismatch can explain why the average wage is uncorrelated with market tightness. Guvenen et al. [2015] and Lindenlaub [2017] both create models of multi-dimensional skill-mismatch allowing for worker-firm mismatch along the verbal, cognitive, and non-cognitive (social skills) domains. Some studies have developed models with a hierarchy of types (Shimer and Smith [2000]) while others have developed two-sided search models with skill-mismatch (Teulings and Gautier [2004], Lise and Robin [2017]). This paper expands on the current literature by developing a model in which mismatch can exist between a worker and a firm on a dimension entirely separate from skill.

## 3.2 Referral-Network Use and Mismatch

This section introduces the data from the Survey of Consumer Expectations and presents three facts regarding how job-finding through informal channels affects mismatch along the skill and nonpecuniary dimensions.

### 3.2.1 Data

The primary data source used in this paper is the 2014-2017 Survey of Consumer Expectations (SCE). The SCE is a relatively new microdata set constructed and maintained by the New York Branch of the Federal Reserve. The nationally representative core survey consists of a 12 month panel rotation of individuals who are asked question regarding their beliefs about future macroeconomic statistics such as unemployment and inflation as well as beliefs regarding their future personal income, employment status, etc. The SCE also conducts several supplement surveys per annum, which provide yearly cross-sectional data on a variety of topics, including the housing market, inflation expectations, student debt, and more. For this paper, the SCE supplementary Job Search Survey is particularly useful. This survey ask questions concerning the method by which individuals found their current job, about the characteristics of their current job, and how satisfied they are with their current job along 5 different dimensions. Additionally, each respondent is provided a unique identification number, enabling researchers to merge individual data across various SCE surveys. This feature conveniently allows one to merge the SCE Job Search Survey with the SCE Core Survey. Doing so allows me to observe basic individual demographic information in addition to specific job-search methods and match satisfaction data.

The primary data of interest concern job-finding through referrals and match satisfaction responses. The SCE Labor Market Survey asks individuals how they found their current position, allowing them to select from a variety of options.[3] Of these options, three are different referral methods. Individuals can indicate they found their job through a referral from a friend or relative, a former coworker/business associate, or a current employee at the company. While any of these three responses will be counted as using informal connections to find a job, the distinction between the three channels is important and is discussed in detail in 3.2.2.

The SCE Labor Market Survey also asks individuals how satisfied they are with their current job on a scale. [4] These include questions regarding: how well the job fits their skills/experience (SKILLFIT), how satisfied they are with the wage (WAGE), how satisfied they are with opportunities for career advancement (PROMOTION), how satisfied they are with the nonpecuniary aspects of the job (NONWAGE), and finally how satisfied are they with the overall fit (OVERALL). These responses paired with the job-finding data allow me to identify how the perceived mismatch of the worker varies with referral use.

### 3.2.2 Stylized Facts

Given the categorical nature of the satisfaction data, this paper uses ordered logits to estimate the effect of referral use on job satisfaction.[5] In general, ordered logits control for year fixed-effects, worker demographics,[6] some firm characteristics,[7] and other variables that could affect satisfaction. These include whether or not the job is part time (PARTTIME) or temporary (TEMPORARY), a proxy for the worker's cog-

[3]These include but are not limited to: "Found through the employer's website," "Found job opening through other means, including help wanted ads," "Found through union/professional registers."

[4]This is either a scale of 1-5 or a scale of 1-7. In practice, these responses are grouped together into coarser categories to ensure the proportional odds assumption for ordered logits is satisfied and to facilitate robustness checks using generalized ordered logits that do not require the proportional odds assumption.

[5]See appendix for robustness checks performed using generalized ordered logits that do not rely on the parallel trends assumption. Allowing for this more general specification does not affect the main results.

[6]These include age, income, race, marital status, sex, education, and the presence of children.

[7]These include firm size and whether or not the firm is a government organization.

nitive ability (ABILITY), indicators for being at the firm for over a year (TENURE) or working more than 40 hours a week (HOURS40+), being in a union (UNION), a proxy for job security (JOBSECURITY), whether or not there has been a recent wage reduction (WAGEREDUCT), and the length of unemployment duration experienced before their present employment (UGAP).[8] REFERRAL is an indicator variable, taking a value of one if a worker indicates she was matched with her current employer via referral. PREVEMP is an indicator variable, which takes a value of one if a worker indicates she was matched with a previous employer. These variables are used to obtain three stylized, empirical facts.

**Fact 1**: *Referrals do not generically reduce perceived mismatch.*

Results from an ordered logit regression are reported in Table 3.1. In general, coefficients have the expected sign with respondents generally being less satisfied at part time and temporary jobs. Interestingly however, job finding through referrals does not seem to generically improve perceived mismatch from a workers perspective. Rather, the signs indicate referrals decrease satisfaction with overall fit, nonpecuniary benefits, and the wage albeit the effects are not significant. It is important to note this result is not necessarily at odds with the existing literature concerning referral use. While it could be the case that our measures of match quality are flawed, the worker's perceptions may not be entirely reflective of reality. Regardless, worker's perceptions will affect their choices, making this an intriguing result. Investigating further by controlling for referral heterogeneity yields the second stylized fact.

**Fact 2**: *The type of referral matters when assessing the affect of informal connections on perceived mismatch.*

[8]ABILITY is constructed using the number of correct answers provided to a set of math questions in the SCE core survey. JOBSECURITY is derived from respondents' answer to the question "How likely is it that you will be employed in 6 months?"

Table 3.1.
How Referrals Affect Perceived Mismatch

| | (1) OVERALL | (2) NONWAGE | (3) SKILLFIT | (4) WAGE | (5) PROMOTION |
|---|---|---|---|---|---|
| REFERRAL | -0.0216 | -0.0833 | 0.0308 | -0.109 | 0.0145 |
| | (0.869) | (0.420) | (0.781) | (0.280) | (0.867) |
| PREVEMP | 0.370 | -0.304 | 0.505 | -0.0558 | 0.0852 |
| | (0.308) | (0.223) | (0.101) | (0.831) | (0.686) |
| PARTTIME | -0.209 | -0.413*** | -0.365** | -0.127 | -0.0979 |
| | (0.268) | (0.005) | (0.021) | (0.394) | (0.456) |
| ABILITY | -0.127* | 0.115** | -0.0297 | 0.0363 | -0.110** |
| | (0.069) | (0.023) | (0.599) | (0.475) | (0.014) |
| HOURS40+ | 0.169 | -0.251** | 0.341*** | -0.162 | 0.238** |
| | (0.245) | (0.029) | (0.007) | (0.155) | (0.011) |
| UNION | -0.0960 | -0.0677 | -0.0325 | -0.0753 | -0.110 |
| | (0.570) | (0.628) | (0.829) | (0.578) | (0.331) |
| TEMPORARY | -0.748*** | -0.706*** | -0.537** | -0.450** | -0.642*** |
| | (0.004) | (0.001) | (0.020) | (0.035) | (0.002) |
| COMMUTE | 0.000344 | 0.000334 | 0.000393 | 0.000197 | 0.0000265 |
| | (0.585) | (0.511) | (0.488) | (0.658) | (0.933) |
| WAGEREDUCT | -0.440*** | -0.684*** | -0.807*** | -0.692*** | -0.660*** |
| | (0.008) | (0.000) | (0.000) | (0.000) | (0.000) |
| UGAP | -0.00196 | 0.0000716 | -0.00371*** | -0.00118 | -0.00132 |
| | (0.106) | (0.954) | (0.002) | (0.366) | (0.294) |
| JOBSECURITY | 0.547** | 0.273 | 0.515*** | 0.506*** | 0.435*** |
| | (0.025) | (0.107) | (0.008) | (0.004) | (0.003) |
| TENURE | -0.191 | 0.159 | 0.104 | -0.0388 | -0.412*** |
| | (0.259) | (0.213) | (0.446) | (0.762) | (0.000) |
| *N* | 1254 | 1767 | 1766 | 1767 | 1767 |
| Demographics | Yes | Yes | Yes | Yes | Yes |
| Firm Traits | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |

*p*-values in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 3.2 demonstrates the heterogeneous affects different types of referrals have on perceived match quality. While referrals from former coworkers (REFCOWORKER) improve worker satisfaction with nonpecuniary benefits, referrals from friends and family members (REFFF) decreases worker satisfaction. In theory, a former coworker knows the skills and preferences of the worker being referred. A former coworker is likely able to provide inside informal regarding the tangible and intangible nonpecuniary benefits of the position, effectively helping the job-seeker determine whether the current offer is a good fit. Homophily effects could also partially explain this result. If workers tend to form connections with similar individuals, it is likely their preferences for nonpecuniary amenities are also similar. Thus, the presence of an informal connection at a firm is itself a signal the firm could be a good fit.

Referrals made by family and friends being detrimental to match quality is consistent with Loury [2005] and Cappallari et al. [2015]. Loury argues workers experiencing little success in job search will eventually settle for any job they or their friends can find. Moreover, since time may be of the essence, the jobs friends and family can find on short notice are likely of lower quality. It is also possible psychological factors of failing to find a job and being forced to turn to family members could be driving this result. Alternatively, it could be the job a family member finds requires the worker to work for that family member specifically, which could be viewed as a detrimental feature of the job. In either case, this distinction prompts further investigation into the interactive effects between referral heterogeneity and worker heterogeneity

**Fact 3**: *Referrals affect satisfaction along the nonpecuniary dimension differently for low-skill and high-skill workers.*

Table 3.3 and 3.4 show the heterogeneous effect of referral channels for high-skill and low-skill workers respectively.[9] For high-skill workers, we see REFCOWORKER still has a positive and significant effect while the effect of REFFF is not significant. The converse is true for low-skill workers. REFFF not only has a significant negative effect on perceived nonpecuniary-mismatch but also causes a significant decrease in the overall satisfaction of the worker at the job. REFFF also negatively impacts perceived skill-mismatch, satisfaction with the wage, and satisfaction with promotion opportunities though these results are not significant.

[9] High-skill workers are considered have completed a bachelor's degree, an associate degree, or a more advanced degree.

Table 3.2.
Heterogeneous Affect of Referrals on Perceived Mismatch

| | (1) OVERALL | (2) NONWAGE | (3) SKILLFIT | (4) WAGE | (5) PROMOTION |
|---|---|---|---|---|---|
| REFFF | -0.118 | -0.199* | -0.0303 | -0.192* | -0.0869 |
| | (0.421) | (0.086) | (0.810) | (0.091) | (0.413) |
| REFCOWORKER | -0.136 | 0.306* | 0.0702 | 0.0137 | -0.0513 |
| | (0.469) | (0.052) | (0.672) | (0.928) | (0.712) |
| REFCUREMP | -0.00399 | -0.118 | 0.205 | -0.125 | 0.198 |
| | (0.985) | (0.464) | (0.254) | (0.421) | (0.177) |
| PREV EMP | 0.346 | -0.292 | 0.495 | -0.0617 | 0.202 |
| | (0.338) | (0.239) | (0.108) | (0.812) | (0.382) |
| PARTTIME | -0.226 | -0.425*** | -0.374** | -0.135 | -0.0779 |
| | (0.231) | (0.004) | (0.018) | (0.367) | (0.585) |
| ABILITY | -0.129* | 0.106** | -0.0366 | 0.0349 | -0.138*** |
| | (0.066) | (0.038) | (0.519) | (0.493) | (0.004) |
| HOURS40+ | 0.142 | -0.259** | 0.336*** | -0.168 | 0.195* |
| | (0.326) | (0.024) | (0.008) | (0.139) | (0.052) |
| UNION | -0.0828 | -0.0562 | -0.0268 | -0.0639 | -0.104 |
| | (0.625) | (0.687) | (0.859) | (0.637) | (0.394) |
| TEMPORARY | -0.736*** | -0.714*** | -0.543** | -0.462** | -0.627*** |
| | (0.004) | (0.001) | (0.018) | (0.030) | (0.005) |
| COMMUTE | 0.000304 | 0.000282 | 0.000361 | 0.000156 | -0.000177 |
| | (0.635) | (0.576) | (0.516) | (0.724) | (0.609) |
| WAGEREDUCT | -0.480*** | -0.721*** | -0.820*** | -0.723*** | -0.660*** |
| | (0.004) | (0.000) | (0.000) | (0.000) | (0.000) |
| UGAP | -0.00207* | 0.0000845 | -0.00370*** | -0.00124 | -0.00120 |
| | (0.090) | (0.946) | (0.002) | (0.342) | (0.353) |
| JOBSECURITY | 0.399* | 0.156 | 0.451** | 0.414** | 0.312** |
| | (0.093) | (0.338) | (0.015) | (0.013) | (0.032) |
| TENURE | -0.167 | 0.201 | 0.117 | -0.0166 | -0.407*** |
| | (0.324) | (0.114) | (0.392) | (0.897) | (0.001) |
| *N* | 1254 | 1767 | 1766 | 1767 | 1767 |
| Demographics | Yes | Yes | Yes | Yes | Yes |
| Firm Traits | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |

*p*-values in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Once again, these results are consistent with Loury (2005). Low-skill workers have a more difficult time finding jobs compared to high-skill workers. Left with no alternative recourse, these workers reach out to friends and family members for help. While these informal connections are productive and do lead to employment, they are not ideal fits. Conversely, high-skill individuals use their informal connections to improve match quality.

Table 3.3.
High Skill: Heterogeneous Affect of Referrals on Perceived Mismatch

| | (1) OVERALL | (2) NONWAGE | (3) SKILLFIT | (4) WAGE | (5) PROMOTION |
|---|---|---|---|---|---|
| REFF | 0.125 | -0.103 | 0.159 | -0.246 | -0.0761 |
| | (0.543) | (0.523) | (0.362) | (0.120) | (0.596) |
| REFCOWORKER | -0.0775 | 0.342* | 0.166 | 0.0806 | 0.0753 |
| | (0.740) | (0.081) | (0.421) | (0.675) | (0.661) |
| REFCUREMP | -0.0365 | -0.311 | 0.262 | -0.0101 | 0.127 |
| | (0.894) | (0.125) | (0.252) | (0.961) | (0.489) |
| PREVEMP | 0.741 | 0.0325 | 0.460 | 0.0924 | 0.0117 |
| | (0.117) | (0.922) | (0.240) | (0.793) | (0.968) |
| PARTTIME | -0.412 | -0.546*** | -0.228 | -0.344 | -0.0282 |
| | (0.133) | (0.009) | (0.315) | (0.114) | (0.891) |
| ABILITY | -0.249** | 0.110 | -0.101 | -0.0116 | -0.158** |
| | (0.020) | (0.141) | (0.218) | (0.878) | (0.021) |
| HOURS40+ | 0.111 | -0.270* | 0.264 | -0.449*** | 0.0286 |
| | (0.562) | (0.077) | (0.100) | (0.003) | (0.825) |
| UNION | -0.373* | -0.169 | -0.0787 | -0.237 | -0.0656 |
| | (0.092) | (0.357) | (0.687) | (0.192) | (0.678) |
| TEMPORARY | -0.542 | -0.837*** | -0.545* | -0.561** | -0.686** |
| | (0.109) | (0.003) | (0.071) | (0.049) | (0.019) |
| COMMUTE | -0.00234 | -0.00239 | -0.00223 | -0.00345** | -0.00340** |
| | (0.219) | (0.137) | (0.185) | (0.031) | (0.015) |
| WAGEREDUCT | -0.600*** | -0.849*** | -0.759*** | -0.653*** | -0.750*** |
| | (0.010) | (0.000) | (0.000) | (0.001) | (0.000) |
| UGAP | -0.00779** | -0.00282 | -0.00866*** | -0.00552** | -0.00587** |
| | (0.018) | (0.216) | (0.001) | (0.019) | (0.014) |
| JOBSECURITY | 0.883** | 0.410* | 0.106 | 0.499** | 0.189 |
| | (0.019) | (0.081) | (0.671) | (0.042) | (0.341) |
| TENURE | -0.310 | 0.153 | 0.0296 | -0.182 | -0.560*** |
| | (0.176) | (0.372) | (0.870) | (0.295) | (0.000) |
| *N* | 749 | 1069 | 1068 | 1069 | 1069 |
| Demographics | Yes | Yes | Yes | Yes | Yes |
| Firm Traits | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |

*p*-values in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 3.4.
Low Skill: Heterogeneous Affect of Referrals on Perceived Mismatch

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | OVERALL | NONWAGE | SKILLFIT | WAGE | PROMOTION |
| REFFF | -0.425* | -0.302* | -0.233 | -0.138 | -0.119 |
| | (0.053) | (0.079) | (0.220) | (0.416) | (0.460) |
| REFCOWORKER | -0.372 | 0.204 | -0.265 | -0.308 | -0.350 |
| | (0.268) | (0.458) | (0.364) | (0.235) | (0.157) |
| REFCUREMP | 0.0676 | 0.126 | 0.0426 | -0.380 | 0.250 |
| | (0.846) | (0.648) | (0.889) | (0.139) | (0.321) |
| PREVEMP | -0.200 | -0.709* | 0.474 | -0.343 | 0.481 |
| | (0.748) | (0.081) | (0.368) | (0.419) | (0.217) |
| PARTTIME | 0.0909 | -0.271 | -0.474** | 0.125 | -0.0248 |
| | (0.739) | (0.198) | (0.036) | (0.554) | (0.903) |
| ABILITY | -0.00892 | 0.112 | 0.0642 | 0.0788 | -0.108 |
| | (0.926) | (0.116) | (0.429) | (0.268) | (0.113) |
| HOURS40+ | 0.125 | -0.363** | 0.351 | -0.0131 | 0.299* |
| | (0.601) | (0.050) | (0.100) | (0.942) | (0.075) |
| UNION | 0.320 | 0.140 | 0.00982 | 0.122 | -0.130 |
| | (0.264) | (0.538) | (0.968) | (0.576) | (0.516) |
| TEMPORARY | -1.086** | -0.700** | -0.395 | -0.325 | -0.489 |
| | (0.012) | (0.043) | (0.288) | (0.344) | (0.162) |
| COMMUTE | 0.000612 | 0.000823 | 0.00110 | 0.000482 | -0.00000951 |
| | (0.684) | (0.556) | (0.549) | (0.591) | (0.978) |
| WAGEREDUCT | -0.304 | -0.532*** | -0.989*** | -0.769*** | -0.565*** |
| | (0.221) | (0.006) | (0.000) | (0.000) | (0.003) |
| UGAP | -0.00179 | 0.00182 | -0.00188 | 0.000780 | 0.000387 |
| | (0.158) | (0.410) | (0.168) | (0.640) | (0.757) |
| JOBSECURITY | -0.0755 | -0.115 | 0.935*** | 0.307 | 0.445** |
| | (0.814) | (0.623) | (0.002) | (0.196) | (0.045) |
| TENURE | -0.0396 | 0.250 | 0.141 | 0.161 | -0.318* |
| | (0.885) | (0.216) | (0.529) | (0.418) | (0.093) |
| *N* | 505 | 698 | 698 | 698 | 698 |
| Demographics | Yes | Yes | Yes | Yes | Yes |
| Firm Traits | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |

*p*-values in parentheses
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

## 3.3 A Model of Job Search and Heterogeneous Mismatch

Empirical results demonstrate high- and low-skill workers use referrals for different reasons. Low-skill workers view referral-networks as safety nets to be used when job search goes poorly. Conversely, high-skill workers use referrals to find a better nonpecuniary fit. It is not clear, however, how mismatch along the nonpecuniary dimension affects aggregate productivity. Moreover, it is not clear the degree to which skill-mismatch can be attributed to preferences for nonpecuniary benefits.

To better understand the relevant implications for policymakers, I construct a theoretical model of the labor market. The model is very similar to Buhrmann [2018], which augments a standard McCall model to allow for a continuum of worker and firm types. Time is continuous. Agents are risk-neutral, infinitely lived, and discount the future at a rate $r$. There are only two states a worker can potentially experience– employment or unemployment. Firms can have at most one opening and are either vacant and searching or filled.

Workers and firms seek to be matched subject to search frictions. These frictions represent the costly nature of search and are meant to capture the difficulty of finding a job. Workers search randomly and receive job offers from firms. These offers will have a certain value that depends on the wage and the nonpecuniary benefits the firm would provide as well as the worker's skill type and preferences. Once a worker receives an offer, she must either accept or reject it. This decisions will depend on the expectation of the value of future offers the worker could receive. That is, conditional on a worker's type and the distribution of firm types, a worker must decide whether it is better to wait for future offers or accept the current offer.

**Worker and Firm Heterogeneity.** Workers are heterogeneous in both skills, indexed by type $x \in [0, 1]$, and nonpecuniary preference, indexed by $j \in [0, 1]$. Thus a worker's type is completely described by the pair $(x, j)$. Importantly, skill is vertically differentiated, with a higher $x$ indicating a higher skilled worker. Conversely, nonpecuniary preferences are not treated as being vertically differentiated, which is discussed in detail below. For the purposes of this paper, workers with $x \geq .5$ are considered to be high-skilled. Firms are also heterogeneous in skill requirements $y \in [0, 1]$ and in nonpecuniary amenities $k \in [0, 1]$. For workers, skill types $x$ are distributed according the the cdf $Q$ with corresponding pdf $q(x)$ while nonpecuniary preferences $j$ are distributed according to the cdf $P$ with corresponding pdf $p(j)$. Similarly, firm skill requirements $y$ are distributed according to the cdf $G$ with corresponding pdf $g(y)$ while nonpecuniary amenities $k$ are distributed according to the cdf $A$ with corresponding pdf $a(k)$. The firm type distributions $G$ and $A$ only include vacant firms and do not vary as a result of worker behavior.

**Job Search.** Workers encounter job offers at a Poisson rate, but the rate varies by skill type and by the method of job search. Workers will have two channels through which they can receive offers–formal and informal. While informal channels represent job-finding through referrals, formal channels represent job search using traditional methods. Let $\lambda_h$ and $\rho_h$ be the Poisson rates of offers received by high-skill workers through form and informal channels, respectively. Similarly, let $\lambda_\ell$ and $\rho_\ell$ be the Poisson rates of offers received by low-skill workers through form and informal channels, respectively. Search through formal methods is random, meaning the probability of meeting a firm with characteristics $(y, k)$ is independent of the worker's own type $(x, j)$. Search through informal methods, however, is not necessarily random. Consistent with empirical evidence, search through informal methods will be partially targeted for high-skill workers along the nonpecuniary dimension.[10] This means when a worker receives an informal offer, the nonpecuniary distribution faced by the worker will be better tailored to the worker's nonpecuniary preferences $j$. Call this cdf $A_h$ with corresponding pdf $a_h(k)$. For low-skill workers, informal offers are drawn from a less suitable distribution to be consistent with the observed stylized facts. Call this cdf $A_\ell$ with corresponding pdf $a_\ell(k)$. Unemployed workers who receive a job

[10]See Buhrmann [2018b] and Cheremukhin [2016] for more examples of papers with targeted search.

offer must decide whether to accept or reject the offer. Matches between workers and firms are exogenously destroyed at a Poisson rate $s$.

**Utility and Wages.** Utility obtained through consumption and nonpecuniary benefits. Unemployed workers received a flow of benefits $b(x) \geq 0$. Employed workers get utility from wages $w(x, y)$ and nonpecuniary benefits $\phi(j, k)$. Thus, the total utility enjoyed by an employed worker is $\psi(x, y, j, k) = \Delta w(x, y) + (1 - \Delta)\phi(j, k)$ where $\Delta \in (0, 1)$ determines the weight the worker places on the wage relative to nonpecuniary benefits. Define skill-mismatch $\mu_{skill} = |x - y|$ and non-pecuniary mismatch $\mu_{nonp} = |j - k|$ between a worker-firm pair. Following Buhrmann [2018], let the wage function be:

$$w(x, y) = w_b + x - \delta_{skill}(x - y)^2 \tag{3.1}$$

where $\delta_{skill} > 0$ governs the severity of the penalty for skill-mismatch and $w_b$ is a base value for the wage common across skill types. This functional form ensures that the minimum wage is zero and ensures that the wage is quasiconcave in $y$. Quasiconcavity guarantees match sets along the skill dimension are convex. Thus, conditional on a worker's nonpecuniary preferences $j$ and the firm's nonpecuniary amenities $k$, if worker with skill type $x$ accepts $y_1$ and $y_2$, she will accept $y \in (y_1, y_2)$. Let the function governing nonpecuniary benefits be:

$$\phi(x, y) = \phi_b + \delta_{nonp}(j - k)^2 \tag{3.2}$$

where $\delta_{nonp} > 0$ governs the severity of the penalty for nonpecuniary-mismatch and $\phi_b$ is a base value for nonpecuniary fit common across all types of nonpecuniary preferences. The slight difference in the functional form between the wage and the nonpecuniary value is important. The wage function assumes high-skill workers are paid more than their low-skill counterpart conditional on the degree of skill-mismatch. This is consistent with the empirical findings of Buhrmann [2018]. The function form assumed for the value of nonpecuniary benefits does not assume some preferences are better than others. In this way, nonpecuniary preferences are not vertically differentiated.

### 3.3.1 Equilibrium

The equilibrium strategy for a worker of type $(x, j)$ is to choose a reservation utility value, $\psi^*(x, j)$, accepting all offers from firm types $(j, k)$ that generate a value greater than or equal to $\psi^*(x, j)$ and rejecting all other offers. The reservation utility will depend on the worker's type $(x, j)$. An equilibrium for the model is characterized by the set of reservation values $\{\psi^*(x, j)\}_{(x,j)\in[0,1]\times[0,1]}$.

**Value Functions.** Let $E(x, y, i, j)$ be the value of employment for a worker of type $(x, j)$ employed by a firm $(y, k)$. The employed worker gets flow utility $\psi(x, y, j, k)$ from the current match. At a Poisson rate $s$, the match is exogenously terminated and the worker receives the continuation value $U(x, j)$. Otherwise, she receives the continuation value $E(x, y, j, k)$. In equilibrium, there will be a convex subset of firm types $(y, k) \in [0, 1] \times [0, 1]$ whose offers the worker will accept. However, the worker only cares about the total utility associated with an offer (i.e. the weighted sum of the wage and nonpecuniary fit). Consequently, the problem is equivalent to writing the worker's problem in terms of the utility of the offer $\psi$. The value of employment for a worker skill category $i = h, \ell$ (high-skill or low-skill) is:

$$E_i(x, j, \psi) = \frac{\psi + s \cdot U_i(x, j)}{r + s} \tag{3.3}$$

Unemployed workers receives flow utility $b(x) \geq 0$. If no offer arrives, the continuation value is $U(x, j)$. For high-skill workers, an offer of flow value $\psi$ arrives from formal channels at a rate $\lambda_h$ and from informal channels at a rate $\rho_h$. For low-skill workers, an offer of flow value $\psi$ arrives from formal channels at a rate $\lambda_\ell$ and from informal channels at a rate $\rho_\ell$. The flow value of unemployment for high-skill workers is:

$$\begin{aligned} rU_h(x,j) = b(x) &+ \lambda_h \int_{\underline{\psi}}^{\bar{\psi}} \max\{E_h(x,j,\psi) - U_h(x,j), 0\} d\tilde{G}_{fh}(\psi|x,j) \\ &+ \rho_h \int_{\underline{\psi}}^{\bar{\psi}} \max\{E_h(x,j,\psi) - U_h(x,j), 0\} d\tilde{G}_{nh}(\psi|x,j) \end{aligned} \tag{3.4}$$

where $\tilde{G}_{fh}$ and $\tilde{G}_{nh}$ is the distribution of wage offers conditional of the worker's type from formal and informal channels respectively. Similarly, the flow value of unemployment for low-skill workers is:

$$\begin{aligned} rU_\ell(x,j) = b(x) &+ \lambda_\ell \int_{\underline{\psi}}^{\bar{\psi}} \max\{E_\ell(x,j,\psi) - U_\ell(x,j), 0\} d\tilde{G}_{f\ell}(\psi|x,j) \\ &+ \rho_\ell \int_{\underline{\psi}}^{\bar{\psi}} \max\{E_\ell(x,j,\psi) - U_\ell(x,j), 0\} d\tilde{G}_{n\ell}(\psi|x,j) \end{aligned} \tag{3.5}$$

where $\tilde{G}_{f\ell}$ and $\tilde{G}_{n\ell}$ is the distribution of wage offers conditional of the worker's type from formal and informal channels respectively.

**Reservation Utility.** A worker will accept all offers that satisfy $E_i(x,j,\psi) \geq U_i(x,j)$. Given this, the lowest utility value a worker accepts is the one that makes her indifferent between employment and unemployment. This cut-off value is the reservation utility, $\psi^*(x,j)$, and a worker will reject all offers that provide utility less than $\psi^*(x,j)$ and accept otherwise. Then:

$$\begin{aligned} \frac{\psi^*(x,j) + sU_i(x,j)}{r+s} &= U_i(x,j) \\ \implies \psi^*(x,j) &= rU_i(x,j) \end{aligned}$$

Without loss of generality, substituting this expression into 3.4 gives:

$$\begin{aligned} \psi^*(x,j) = b(x) &+ \lambda_h \int_{\underline{\psi}}^{\bar{\psi}} \max\{E_h(x,j,\psi) - U_h(x,j), 0\} d\tilde{G}_{fh}(\psi|x,j) \\ &+ \rho_h \int_{\underline{\psi}}^{\bar{\psi}} \max\{E_h(x,j,\psi) - U_h(x,j), 0\} d\tilde{G}_{nh}(\psi|x,j) \end{aligned} \tag{3.6}$$

**Proposition 5.** *The strategy of a worker type (x,j) is to accept an offer of a firm iff the utility value it provides is greater than $\psi^*(x,j)$ defined by:*

$$\psi^*(x,j) = b(x) + \frac{\lambda_h}{r+s}\left[\int_{\psi^*(x,j)}^{\bar{\psi}} 1 - \tilde{G}_{fh}(\psi|x,j)d\psi\right] + \frac{\rho_h}{r+s}\left[\int_{\psi^*(x,j)}^{\bar{\psi}} 1 - \tilde{G}_{nh}(\psi|x,j)d\psi\right] \tag{3.7}$$

*Furthermore, solution to this equation exists and is unique.*

From equation 3.7, one can obtain the reservation utility for all worker types condition on model primitives. Since the reservation utility completely defines a worker's equilibrium strategy, we therefore know whether a worker of type $(x,j)$ will accept or reject any offer. Define the offer acceptance indicator function $\mathbb{1}(x,y,j,k)$ as:

$$\mathbb{1}(x,y,j,k) = \begin{cases} 1 & \psi(x,y,j,k) \geq \psi^*(x,j) \\ 0 & \text{otherwise} \end{cases} \tag{3.8}$$

With this indicator function, we can define statistics of interest very similarly to Buhrmann [2018]. The expected wage of an employed worker will skill designation $i = h, \ell$ is:[11]

$$\bar{w}_i(x,j) = \left(\frac{\lambda}{\lambda+\rho}\right)\frac{\int_0^1\int_0^1 w(x,y)\mathbb{1}(x,y,j,k)g(y)h(k)dy\,dk}{\int_0^1\int_0^1 \mathbb{1}(x,y,j,k)g(y)h(k)dy\,dk} + \left(\frac{\rho}{\lambda+\rho}\right)\frac{\int_0^1\int_0^1 w(x,y)\mathbb{1}(x,y,j,k)g(y)a_i(k)dy\,dk}{\int_0^1\int_0^1 \mathbb{1}(x,y,j,k)g(y)a_i(k)dy\,dk} \tag{3.9}$$

[11]Given the reservation utility values, it is convenient to write expressions as a double integral rather than a single integral.

That is, the expected wage is the average accepted wage is the average of the accepted wage through formal channels and informal channels. The expected utility of an employed worker is:

$$\bar{\psi}(x,j) = \left(\frac{\lambda}{\lambda+\rho}\right) \frac{\int_0^1 \int_0^1 [\Delta w(x,y) + (1-\Delta)\phi(j,k)] \mathbb{1}(x,y,j,k) g(y) h(k) dy\, dk}{\int_0^1 \int_0^1 \mathbb{1}(x,y,j,k) g(y) h(k) dy\, dk} + \left(\frac{\rho}{\lambda+\rho}\right) \frac{\int_0^1 \int_0^1 [\Delta w(x,y) + (1-\Delta)\phi(j,k)] \mathbb{1}(x,y,j,k) g(y) a_i(k) dy\, dk}{\int_0^1 \int_0^1 \mathbb{1}(x,y,j,k) g(y) a_i(k) dy\, dk} \tag{3.10}$$

The expected nonpecuniary penalty of an employed worker is:

$$\bar{\phi}_i(j,k) = \left(\frac{\lambda}{\lambda+\rho}\right) \frac{\int_0^1 \int_0^1 \phi(j,k) \mathbb{1}(x,y,j,k) g(y) h(k) dy\, dk}{\int_0^1 \int_0^1 \mathbb{1}(x,y,j,k) g(y) h(k) dy\, dk} + \left(\frac{\rho}{\lambda+\rho}\right) \frac{\int_0^1 \int_0^1 \phi(j,k) \mathbb{1}(x,y,j,k) g(y) a_i(k) dy\, dk}{\int_0^1 \int_0^1 \mathbb{1}(x,y,j,k) g(y) a_i(k) dy\, dk} \tag{3.11}$$

The expected accepted skill-mismatch penalty of an employed worker is:

$$\bar{\mu}_{iskill}(x,j) = \left(\frac{\lambda}{\lambda+\rho}\right) \frac{\int_0^1 \int_0^1 |x-y| \mathbb{1}(x,y,j,k) g(y) h(k) dy\, dk}{\int_0^1 \int_0^1 \mathbb{1}(x,y,j,k) g(y) h(k) dy\, dk} + \left(\frac{\rho}{\lambda+\rho}\right) \frac{\int_0^1 \int_0^1 |x-y| \mathbb{1}(x,y,j,k) g(y) a_i(k) dy\, dk}{\int_0^1 \int_0^1 \mathbb{1}(x,y,j,k) g(y) a_i(k) dy\, dk} \tag{3.12}$$

The expected accepted skill-mismatch penalty of an employed worker is:

$$\bar{\mu}_{inonp}(x,j) = \left(\frac{\lambda}{\lambda+\rho}\right) \frac{\int_0^1 \int_0^1 |j-k| \mathbb{1}(x,y,j,k) g(y) h(k) dy\, dk}{\int_0^1 \int_0^1 \mathbb{1}(x,y,j,k) g(y) h(k) dy\, dk} + \left(\frac{\rho}{\lambda+\rho}\right) \frac{\int_0^1 \int_0^1 |x-y| \mathbb{1}(x,y,j,k) g(y) a_i(k) dy\, dk}{\int_0^1 \int_0^1 \mathbb{1}(x,y,j,k) g(y) a_i(k) dy\, dk} \tag{3.13}$$

Define the hazard rate as the rate at which an acceptable offer arrives, and consequently, a worker transitions from unemployment to employment. This is equal to the Poisson arrival rate multiplied by the probability the offer is accepted added together for all job offer channels. Without loss of generality, the value for a high-skill worker is:

$$\begin{aligned}\mathcal{H}_i(x,j) &= \lambda_h[1-\tilde{G}_{fh}(\psi^*(x,j)|x,j)] + \rho_h[1-\tilde{G}_{nh}(\psi^*(x,j)|x,j)] \\ &= \lambda \int_0^1 \int_0^1 \mathbb{1}(x,y,j,k)g(y)h(k)dy\,dk + \rho \int_0^1 \int_0^1 \mathbb{1}(x,y,j,k)g(y)a_i(k)dy\,dk\end{aligned} \tag{3.14}$$

Define $u(x,j)$ as the unemployment rate for workers with type $(x,j)$. The equilibrium unemployment rate for a given type is determined using a steady-state condition. If we assume there is a constant level of unemployment over time:

$$\begin{aligned}u_i(x,j)\mathcal{H}_i(x,j) &= s(1-u_i(x,j)) \\ \implies u_i(x,j) &= \frac{s}{s+\mathcal{H}_i(x,j)}\end{aligned} \tag{3.15}$$

That is, we obtain equation 3.15 by setting flows into unemployment equal to flows out of unemployment. This implies an aggregate employment rate of $\bar{u} = \int_0^1 \int_0^1 u(x,j)dx\,dj$.

### 3.4 Quantitative Analysis

The model is now calibrated in order to investigate the effect of referrals and preferences for non-pecuniary benefits on mismatch. Following the literature, I assume workers and firm are uniformly distributed on (0,1), and I use the wage function $w(x,y) = x - \delta_{skill}(x-y)^2$, as in Buhrmann [2018]. Buhrmann notes this functional form implies high skill workers have the ability to earn more than their low-skill counterparts, *ceteris paribus*. Consequently, there is true vertical differentiation along the skill dimension. The nonpecuniary benefits function is $\phi(j,k) = \delta_{nonp}(j-k)^2$. Importantly, this functional form implies there is no vertical differentiation on the nonpecuniary preferences dimension. That is, there isn't a preference that is considered "superior." These functional forms ensure the model is consistent with the empirical and theoretical predictions of the literature.[12] The unemployment benefit function takes the form $b(x) = b_1 x$, where $b_1 > 0$.[13]

Job-finding through formal channels assumes that draws come from firm types $(y, k)$ where both $y$ and $k$ are uniformly distribution along the unit interval. This implies $\tilde{G}_{f\ell}(\psi|x, j) = \tilde{G}_{fh}(\psi|x, j)$. To be consistent with empirical evidence from the SCE, I assume the offer distribution workers experience using informal connections is both different from the formal offer distribution and heterogeneous by worker skill category (high-skill and low-skill). High-skill workers who receive an offer via informal channels meet a firm with characteristics $(y, k)$ where $y$ is drawn from a uniform distribution on the unit interval. However, $k$ is drawn from the half of the unit interval containing the worker's own skill type. For example, a worker with $j$=.6 who receives a referral encounters firms uniformly distributed on the interval $(.5, 1)$. This captures the nonpecuniary targeting seen empirically for high-skill workers. Low-skill workers experience the converse. That is, when a low-skill individual receives an offer via informal channels, she encounters firm types $(y, k)$ where $y$ is distributed uniformly on the unit interval and $k$ is distributed uniformly on the half of the unit interval that does not contain the worker's nonpecuniary preference type $j$. This captures the nonpecuniary penalty low-skill workers experience when using informal connections.

The model is calibrated in order to assess the effects of referrals and nonpecuniary preferences on mismatch and welfare. The model is calibrated at the monthly frequency. The calibrated parameters are shown in Table 3.5. Most of the parameters are taken from Buhrmann (2018a).

### 3.4.1 Results

Figure 3.1 shows the upper- and lower-bounds of the firm skill requirement types $y$ accepted by worker of skill type $x$. The resulting match acceptance sets are shown

[12]See Guvenen et al. [2015] as well as Eeckhout and Kircher [2011] for details.

[13]Lise et al. [2016], Buhrmann[2018], and Buhrmann [2018b] also make use of this functional form.

Table 3.5.
Calibrated Parameters

| Parameter | Value | Source |
|---|---|---|
| $b_1$ | .4 | Buhrmann (2018a) |
| $r$ | .001 | Buhrmann (2018a) |
| $s$ | .2 | Unemployment Rates |
| $\lambda$ | 1.25 | Unemployment Rate |
| $\rho$ | .1667 | Fraction of Informal Offers |
| $\delta_s$ | .1003 | Buhrmann (2018a) |
| $\delta_p$ | .1003 | Buhrmann (2018a) |

for the baseline calibrated economy as well as an economy without referrals and an economy in which workers do not care about nonpecuniary preferences. The figure demonstrates nonpecuniary preferences have a significant impact on workers' decisions along the skill dimension. That is, nonpecuniary preferences induce workers to be less picky along the skill dimension, as evidenced by workers unwillingness to accept greater skill mismatch when these preferences are ignored. This result it true for both low-skill and high-skill workers.

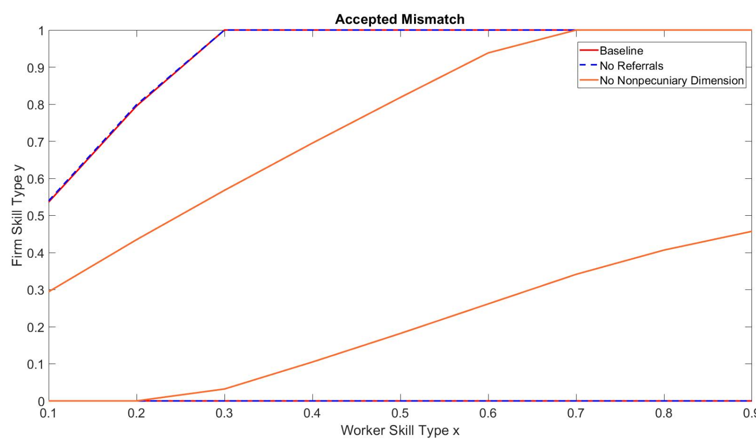


Fig. 3.1. Counterfactual: Acceptance Bounds

Figure 3.2 demonstrates the effects of nonpecuniary preferences on mismatch along both the skill and nonpecuniary dimension. The solid lines represent the average nonpecuniary mismatch across worker skill types while the shaded region denotes the highest and the lowest average mismatch accepted by worker skill type. The left panel demonstrates how the range of mismatch accepted by skill type changes as increasingly more weight is placed on nonpecuniary fit. Two characteristics are especially noteworthy. First, as more weight is placed on nonpecuniary fit, skill mismatch is both higher on average and more dispersed. Thus, the model is able to capture the dispersion Buhrmann (2018) finds in the data within workers of the same skill type. Second, nonpecuniary preferences seem to better replicate the improved positive sorting of high-skill workers relative to the base model. As greater weight is placed on nonpecuniary fit, the relative accepted mismatch between low-skill and high-skill workers decreases. Moreover, we see the dispersion within skill types is smaller for high-skill workers than for low-skill workers. These results suggest within-type skill dispersion can be explained by nonpecuniary preferences. That is, high-skill workers can match with firm on an entirely separate dimension, making them more or less willing to accept various degrees of skill-mismatch.

The right panel shows nonpecuniary mismatch by skill type. As increasing importance is placed on nonpecuniary fit, both the average and the dispersion of nonpecuniary mismatch falls. Interestingly, the decrease is not linear. There is a much greater fall in the average accepted nonpecuniary mismatch (in terms of both the average and dispersion) going from 15% to 30% compared to 30% to 45%, despite utility being linear. This is a result of the vertical differentiation of wage offers by skill type, which interacts with nonpecuniary preferences nonlinearly.

The effect of referrals on mismatch is shown in Figure 3.3. The top two panels show the effect of referral-networks on skill-mismatch while the bottom two panels show the effect on nonpecuniary mismatch. The top-left panel shows the effect of eliminating referral-networks completely. Eliminating referrals increases skill-mismatch on average. However, it does not have a homogeneous effect on the dispersion. While removing referrals increases dispersion for low-skill types, it decreases dispersion for some high skill types (.8 and .9 types) by 7%-27%. Without this channel, these high-

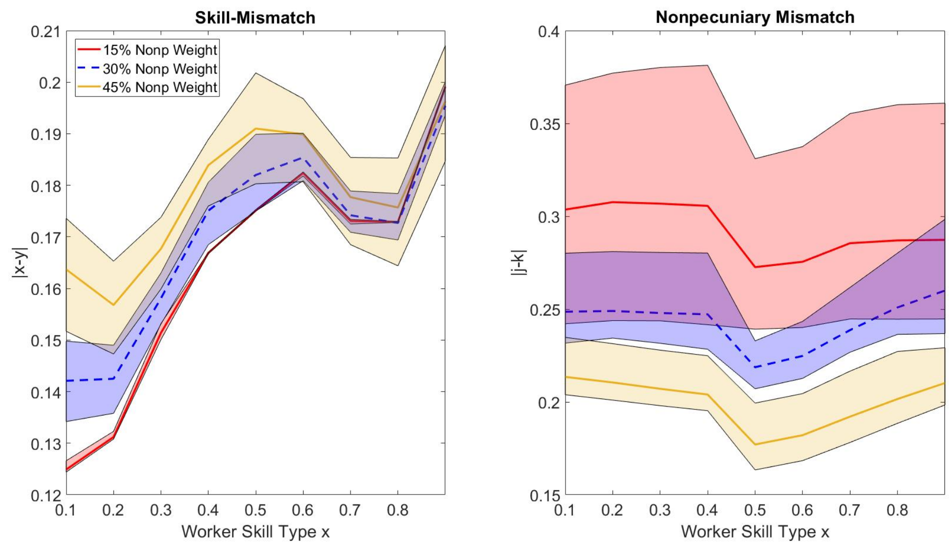


Fig. 3.2. Counterfactual: Nonpecuniary-Mismatch by Worker Skill Type

skill workers cannot wait as long as they could in the baseline model for a better nonpecuniary fit. Thus, they trade-off by being more choosy regarding their skill fit, leading to less dispersion.

In the context of the model, we can discern how much of the change in the average and the dispersion are attributable to how referrals affect matching on the nonpecuniary dimension. To do this, the referral channel is eliminated, but the rate at which standard offers are received is adjusted such that there is no change in the effective offer rate relative to the baseline. For skill-mismatch, the result of this experiment is shown in the top-right panel. High-skill workers no longer have greater dispersion in this scenario, as the rate of offer arrivals is sufficiently high. In general, the improved matching along the pecuniary dimension seems to reduce skill-mismatch for high-skill workers uniformly. However, this is not the case for low-skill workers. Around skill type x=1.5, we can see referral-networks appear to create more skill-mismatch dispersion while still lowering average skill-mismatch. Thus, while referral-networks seem to reduce skill-mismatch on average, they have a heterogeneous effect on the dispersion of skill-mismatch by high- and low-skill.

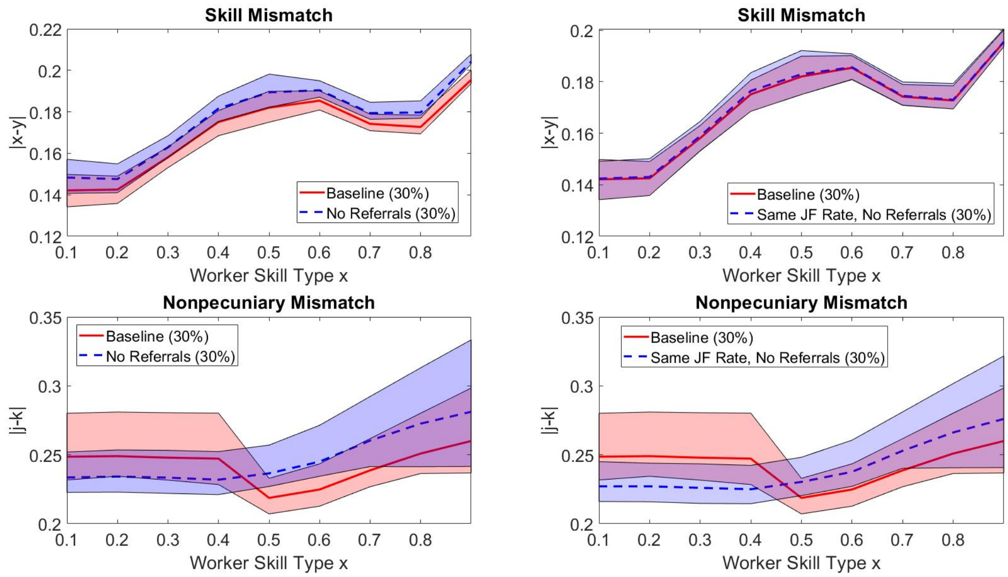


Fig. 3.3. Counterfactual: Referrals and Mismatch by Worker Skill Type

The bottom two panels of Figure 3.3 show the effects of referrals on nonpecuniary-mismatch. Unsurprisingly, referral-networks reduce (increase) mismatch along this dimension for high-skill (low-skill) workers, even controlling for the decreased rate of job offers (the bottom-right panel). While this is expected, the model is able to parse the effects by the rate of matching and by the change in offer distribution. For low-skill workers, the change in the offer distribution (rate) encountered when using referrals explains 1%-10% (90%-99%) of the change in dispersion. For high-skill workers, the change in the offer distribution (rate) encountered when using referrals explains 9%-20% (80%-91%) of the change in dispersion.

### 3.5 Conclusion

In this paper, I present evidence that nonpecuniary benefits of a job are a salient factor in a worker's decision to either accept or reject the offer. Using data form the SCE, I provide evidence of three empirical facts regarding the use of referral-networks and mismatch. I show empirically referrals do not generically reduce perceived mismatch, and the type of referral matters. For high-skill workers, referrals from former coworkers tend to reduce perceived nonpecuniary-mismatch. For low-skill workers, referrals from friends and family tend to increase perceived non-pecuniary mismatch.

Given these empirical facts, I construct a search-and-matching model of the labor market similar to Buhrmann [2018a]. I augment this baseline model with mismatch along two dimensions – skill and nonpecuniary preferences– and calibrate it to the US economy. Results show nonpecuniary preferences can generate more dispersion in skill-mismatch for very low-skill workers and very high-skill workers. Moreover, while referral-networks generally improve aggregate mismatch, they have a heterogeneous affect on nonpecuniary mismatch by type. For low-skill (high-skill) workers, referral-networks increase (decrease) nonpecuniary mismatch.

In its current form, this paper assumes perceived nonpecuniary-mismatch is in agreement with reality. The extent to which a worker's perception of fit is reflective of reality is not addressed and is an area for future study. Importantly, this paper shows mismatch along the skill dimension can be heavily influenced by preferences along the nonpecuniary dimension. This calls into question the extent to which skill-mismatch should be viewed as a problem to be fixed or a result of worker preferences.

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# APPENDICES

# A. APPENDIX: THE STABILIZING EFFECTS OF REFERRAL-NETWORKS ON THE LABOR MARKET

## A.1 Derivations of $Q_{Li}$

This section derives the values of $Q_{Li}$. These values should be thought of as the productivity of referral-networks, which depends on labor market aggregates. The term $Q_{LU}$ is first derived. Recall, letting $h_L$=$(1-\delta_L)(p_{UB}+p_{UG})$, the resulting value of unemployment is (1.1). Choosing $N_{CU}, v_{CU}$ to maximize $U_L$ subject to costs (which are omitted initially notational convenience) gives the following equivalent expressions:

$$\begin{aligned}
&\max_{N_{CU}\geq 0, v_{CU}\geq 0}\Big\{\mathcal{U}_L\Big\}\\
&\equiv \max_{N_{CU}\geq 0, v_{CU}\geq 0}\Big\{z_L+(1-\delta_L)p_{UB}\Delta\mathbb{E}[\mathcal{W}'_{LB}]+(1-\delta_L)p_{UG}\Delta\mathbb{E}[\mathcal{W}'_{LG}]+(1-h_L)\Delta\mathbb{E}[\mathcal{U}'_L]\Big\}\\
&\equiv \max_{N_{CU}\geq 0, v_{CU}\geq 0}\Big\{z_L+(1-\delta_L)p_{UB}\Delta\mathbb{E}[\mathcal{W}'_{LB}-\mathcal{U}'_L]+(1-\delta_L)p_{UG}\Delta\mathbb{E}[\mathcal{W}'_{LG}-\mathcal{U}'_L]+\Delta\mathbb{E}[\mathcal{U}'_L]\Big\}\\
&\equiv \max_{N_{CU}\geq 0, v_{CU}\geq 0}\Big\{z_L+p_{UB}\left[\frac{\beta_L k_{LB}}{(1-\beta_L)(q(\theta_{LB}))}\right]+p_{UG}\left[\frac{\beta_L k_{LG}}{(1-\beta_L)(q(\theta_{LG}))}\right]+\Delta\mathbb{E}[\mathcal{U}'_L]\Big\}
\end{aligned} \tag{A.1}$$

Here, $z_L$ is a constant, and can therefore be dropped from the maximization problem without loss of generality. Recall $p_{UB}$ ($p_{UG}$) is the sum of the probability of finding a job at a B-firm (G-firm) using both standard methods and referrals. Since workers take the market aggregates of the labor market as given, this implies the referral probabilities are the only ones of interest when forming networks. Thus, the maximization problem (A.1) can be rewritten as (dropping the max operator for notational convenience):

$$\Big\{\rho_{UB}n_{LB}N_{CU}^{\alpha}\left[\frac{\beta_L k_{LB}}{(1-\beta_L)(q(\theta_{LB}))}\right]+\rho_{UG}n_{LG}N_{CU}^{\alpha}\left[\frac{\beta_L k_{LG}}{(1-\beta_L)(q(\theta_{LG}))}\right]+\Delta\mathbb{E}[\mathcal{U}_L']\Big\}$$
$$\equiv\Big\{\Big(\rho_{UB}n_{LB}\left[\frac{\beta_L k_{LB}}{(1-\beta_L)(q(\theta_{LB}))}\right]+\rho_{UG}n_{LG}\left[\frac{\beta_L k_{LG}}{(1-\beta_L)(q(\theta_{LG}))}\right]\Big)N_{CU}^{\alpha}$$
$$-\phi_{CU}N_{CU}-k_C v_{CU}+\Delta\mathbb{E}[\mathcal{U}_L']\Big\}$$

where $Q_{LU}{=}\Big(\rho_{UB}n_{LB}\left[\frac{\beta_L k_{LB}}{(1-\beta_L)(q(\theta_{LB}))}\right]+\rho_{UG}n_{LG}\left[\frac{\beta_L k_{LG}}{(1-\beta_L)(q(\theta_{LG}))}\right]\Big)$. In a similar manner, $Q_{LB}$ can be derived. Though the max operator and cost expressions are dropped for notational convenience, the state $\mathcal{W}_{LB}$ is still maximized by choosing $N_{CB}, v_{CB}$. As before, labor market aggregates are taken as given. Thus terms that are constant or that do not contain $N_{CB}$ can be dropped without loss of generality in determining the maximization problem. The max operator is again dropped for notational convenience. The following are equivalent maximization problems:

$$\Big\{\mathcal{W}_{LB}\Big\}$$
$$\equiv\Big\{w_{LB}+p_{BG}\Delta\mathbb{E}[(1-\delta_L)\mathcal{W}_{LG}'+\delta_L\mathcal{U}_L']+(1-p_{BG})\Delta\mathbb{E}[(1-\delta_L)\mathcal{W}_{LB}'+\delta_L\mathcal{U}_L']\Big\}$$
$$\equiv\Big\{w_{LB}+p_{BG}\Delta\mathbb{E}[(1-\delta_L)(\mathcal{W}_{LG}'-\mathcal{W}_{LB}')]+\delta_L\Delta\mathbb{E}[\mathcal{W}_{LB}'-\mathcal{U}_L']+\Delta\mathbb{E}[\mathcal{W}_{LB}']$$
$$\equiv\Big\{w_{LB}+p_{BG}\left[\frac{\beta_L}{(1-\beta_L)}\left(\frac{k_{LG}}{q(\theta_{LG})}-\frac{k_{LB}}{q(\theta_{LB})}\right)\right]+\Delta\mathbb{E}[\mathcal{W}_{LB}']\Big\}$$
$$\equiv\Big\{\beta_L u_L\rho_B\gamma N_{CB}^{\alpha}\frac{k_{LB}}{(1-\delta_L)q(\theta_{LB})}-\beta_L\rho_{BG}N_{LG}N_{CB}^{\alpha}\frac{k_{LG}}{q(\theta_{LG})}$$
$$+p_{BG}\Big[\frac{\beta_L}{(1-\beta_L)}\Big(\frac{k_{LG}}{q(\theta_{LG})}-\frac{k_{LB}}{q(\theta_{LB})}\Big)\Big]+\Delta\mathbb{E}[\mathcal{W}_{LB}']\Big\}$$
$$\equiv\Big\{\Big[\beta_L u_L\rho_B\gamma\frac{k_{LB}}{(1-\delta_L)q(\theta_{LB})}-\beta_L\rho_{BG}n_{LG}\frac{k_{LG}}{q(\theta_{LG})}$$
$$+n_{LG}\rho_{BG}\Big[\frac{\beta_L}{(1-\beta_L)}\Big(\frac{k_{LG}}{q(\theta_{LG})}-\frac{k_{LB}}{q(\theta_{LB})}\Big)\Big]\Big]N_{CB}^{\alpha}$$
$$-\phi_{CB}N_{CB}-k_C v_{CB}+\Delta\mathbb{E}[\mathcal{W}_{LB}']\Big\}$$

Where:

$$Q_{LB} = \Big[\beta_L u_L \rho_B \gamma \frac{k_{LB}}{(1-\delta_L)q(\theta_{LB})} - \beta_L \rho_{BG} n_{LG} \frac{k_{LG}}{q(\theta_{LG})} + n_{LG}\rho_{BG}\Big[\frac{\beta_L}{(1-\beta_L)}\Big(\frac{k_{LG}}{q(\theta_{LG})} - \frac{k_{LB}}{q(\theta_{LB})}\Big)\Big]\Big].$$

Note, that this formulation is only sensible when this value is positive. Thus, this is restricted to be the case in the GMM algorithm, which is discussed below. Using the same notational conveniences, the maximization problem for a worker at a G-firm can be written as:

$$\begin{aligned}
&\Big\{\mathcal{W}_{LG}\Big\}\\
&\equiv \Big\{w_{LG} + \Delta\mathbb{E}[(1-\delta_L)\mathcal{W}'_{LG} + \delta_L \mathcal{U}'_L]\Big\}\\
&\equiv \Big\{w_{LG} + \Delta\mathbb{E}[\mathcal{W}'_{LG}]\Big\}\\
&\equiv \Big\{[\gamma\frac{k_{LG}}{(1-\delta_L)q(\theta_{LG})}(u_L\rho_G + n_{LB}\rho_{BG})]N^{\alpha}_{CG} - \phi_{CG}N_{CG} - k_C v_{CG} + \Delta\mathbb{E}[\mathcal{W}'_{LG}]\Big\}
\end{aligned}$$

Where $Q_{LG}$=$[\gamma\frac{k_{LG}}{(1-\delta_L)q(\theta_{LG})}(u_L\rho_{UG} + n_{LB}\rho_{BG})]$.

## A.2 Proofs

The existence of a unique steady-state equilibrium is now shown. First Proposition 1 and Proposition 2 are proven. Then the existence of a unique steady-state equilibrium is proven. Proposition 2 is first proved.

**Proposition 2**. *Suppose that $Q_{Li} > 0$ for $i = U, B, G$. Further, assume $L_C/3, \delta_C$ $, \theta_{CU}q(\theta_{CU}), q(\theta_{CU}) \in (0,1)$. Then given the aggregates of the labor market, there exists a unique steady-state equilibrium in the connections market, provided $k_C, \delta_C$ are not too large.*

Without loss of generality, the existence of equilibrium is shown for networkers employed by workers to assist transitioning from unemployment to employment. Given labor market aggregates, $Q_{LU}$ can be treated as a parameter, which is positive by assumption. Substituting (1.20) into (1.16) and rearranging terms:

$$\frac{\delta_C k_C}{(1-\delta_C)q(\theta_{CU})} + \beta_C k_C \theta_{CU} = \frac{(1-\beta_C)\alpha}{1+\beta_C\alpha-\beta_C} Q_{CU} N_{CU}^{\alpha-1} \tag{A.2}$$

Thus, (A.2) and (1.21) determine an equilibrium. Suppose $n_{CU} \in (0,1)$. The value of the right-hand side of (A.2) must be positive or else the current level of employment would be unsustainable. Also note that the left-hand side of (A.2) is strictly increasing in $\theta_{CU}$. As $\theta_{CU}$ tends to infinity, the left-hand side of (A.2) goes to infinity. As $\theta_{CU}$ tends to zero, the left-hand side of (A.2) goes to $\delta_C k_C/(1-\delta_C)$ since the hiring probability $q(\theta_{CU}) \in (0,1)$ and is strictly decreasing in $\theta_{CU}$. Thus, one sees that for a given $n_{CU} \in (0,1)$, $\exists$ a unique $\theta_{CU}$ that satisfies (A.2) provided the cost of searching for connection $k_C$ and the separation rate $\delta_C$ are not so high that the market does not operate.

Now suppose we have $\theta_{CU} > 0$. One can rewrite (1.21) as:

$$n_{CU} = \frac{(1-\delta_C)\theta_{CU}q(\theta_{CU})\frac{L_C}{3}}{\delta_C + (1-\delta_C)\theta_{CU}q(\theta_{CU})} \tag{A.3}$$

Since $L_C/3, \delta_C, \theta_{CU}q(\theta_{CU}) \in (0,1)$, it is evident that for any given $\theta_{CU} > 0$, $\exists$ a unique $n_{CU}$ s.t. (A.3) is satisfied. Thus, given $\theta_{CU}$ one can always find a unique $n_{CU}$ to satisfy (A.3). Furthermore, given $n_{CU}$ one can always find a unique $\theta_{CU}$ to satisfy (A.2), given that $k_C, \delta_C$ are not too large. Thus, a unique steady-state equilibrium exists for networkers who help with U to E transitions. The proofs follow similarly for the equations governing other networker types.

Proposition 1 is now proved.

**Proposition 1**. *Suppose that it can be profitable for a firm to employ a worker, i.e.* $y_{LB} - w_{LB}, y_{LG} - w_{LG} > 0$. *Further, suppose* $p_{BU}, q(\theta_{LB}), H_B, H_G, p_{GU}, p_{BG} \in (0,1)$ *and* $(1-\delta_L)p_{GE}n_{LB} < \delta_L$. *Then given the aggregates of the connections market, there exists a unique steady-state equilibrium in the labor market, provided* $k_{LG}$ *and* $k_{LB}$ *are not too large.*

In the labor market, a $\theta_{LB} > 0, \theta_{LG} > 0, w_{LB} > 0, w_{LG} > 0, n_{LB} \in (0,1), n_{LG} \in (0,1)$ tuple that solve (1.7), (1.8), (1.10), (1.11),(1.12), (1.13) define an equilibrium. The proof proceeds by demonstrating that given any values of five of the six variables, one can always define the sixth variable on its domain using all six equations. First, the vacancy-supply conditions are analyzed. Suppose $\theta_{LG} > 0, w_{LB} > 0, w_{LG} > 0, n_{LB} \in (0,1), n_{LG} \in (0,1)$ are given. Note that (1.7) can be rewritten as:

$$(1 - \Delta[H_B\gamma + (1-p_{BG})(1-\delta_L)])\frac{k_{LB}}{(1-\delta_L)q(\theta_{LB})\Delta} = y_{LB} - w_{LB} \tag{A.4}$$

The left-hand side is positive by assumption. Note that the left-hand side is strictly increasing in $\theta_{LB}$. As $\theta_{LB}$ goes to infinity, the left-hand side also goes to infinity as $q(\theta_{LB}) \in (0,1)$ is strictly decreasing in $\theta_{LB}$ and thus tends to zero. As $\theta_{LB}$ goes to zero, the left-hand side goes to $(1-\Delta[H_B\gamma + (1-p_{BG})(1-\delta_L)])\frac{k_{LB}}{(1-\delta_L)\Delta}$, which will be less than $y_{LB} - w_{LB}$ so long as $k_{LB}$ is sufficiently small. Thus, given $\theta_{LG} > 0, w_{LB} > 0, w_{LG} > 0, n_{LB} \in (0,1), n_{LG} \in (0,1)$, $\exists$ a unique $\theta_{LB} \in (0,\infty)$ that solves (1.7), so long as the cost of posting a vacancy is not too high. The problem is similar when $\theta_{LB} > 0, w_{LG} > 0, w_{LB} > 0, n_{LB} \in (0,1), n_{LG} \in (0,1)$ are given. One can rewrite (1.8) as:

$$(1 - \Delta[H_G\gamma + (1-\delta_L)])\frac{k_{LG}}{(1-\delta_L)q(\theta_{LG})\Delta} = y_{LG} - w_{LG} \tag{A.5}$$

Using similar logic, given $\theta_{LB} > 0, \theta_{LB} > 0, w_{LB} > 0, n_{LB} \in (0,1), n_{LG} \in (0,1)$ $\exists$ a unique $\theta_{LG} \in (0,\infty)$ that solves (1.8), so long as the cost of posting a vacancy is not too high.

Now the wage equations (1.10) and (1.11) are analyzed. Since $p_{BU}, q(\theta_{LB}), H_B, p_{GU}$ $, p_{BG} \in (0,1)$, $\exists$ a unique $w_{LB}$ that solves (1.10) s.t. $\rho_G N_{CU}^{\alpha} - \rho_{BG} N_{CB}^{\alpha}$ is sufficiently large. If analysis is restricted to when this condition is satisfied, then given $\theta_{LG} > 0, \theta_{LB} > 0, w_{LG} > 0, n_{LB} \in (0,1), n_{LG} \in (0,1)$ $\exists$ a unique $w_{LB} > 0$ that solves (1.10). Similarly, given $\theta_{LG} > 0, \theta_{LB} > 0, w_{LB} > 0, n_{LB} \in (0,1), n_{LG} \in (0,1)$ $\exists$ a unique $w_{LG} > 0$ that solves (1.11), as all of the terms on the right-hand side of (1.11) are positive.

Now the labor flow equations are analyzed. Suppose $\theta_{LG} > 0, \theta_{LB} > 0, w_{LB} > 0, w_{LG} > 0, n_{LG} \in (0,1)$. One can rewrite (1.12) as:

$$n_{LB} = \frac{(1-\delta_L)p_{BU}(1-n_{LG})}{(1-(1-\delta_L)(1-p_{BG})+(1-\delta_L)p_{BU})} \tag{A.6}$$

Since $\delta_L, p_{UB}, p_{BG}, n_{LG} \in (0,1)$, it follows that $n_{LB} > 0$. Moreover, this implies that $(1-\delta_L)p_{BU}(1-n_{LG}) < (1-\delta_L)p_{BU})$, meaning $n_{LB} \in (0,1)$. Thus, given $\theta_{LG} > 0, \theta_{LB} > 0, w_{LB} > 0, n_{LG} \in (0,1)$ $\exists$ a unique $n_{LB}$ that solves (A.6). Finally, now suppose $\theta_{LG} > 0, \theta_{LB} > 0, w_{LB} > 0, w_{LG} > 0, n_{LB} \in (0,1)$. One can rewrite (1.13) as:

$$n_{LG} = \frac{(1-\delta_L)p_{GE}n_{LB} + p_{UG}(1-n_{LB})(1-\delta_L)}{\delta_L + (1-\delta_L)p_{UG}} \tag{A.7}$$

Since $n_{LB} \in (0,1)$, it must be the case that $p_{UG}(1-n_{LB})(1-\delta_L) < (1-\delta_L)p_{UG}$. Thus, given $\theta_{LG} > 0, \theta_{LB} > 0, w_{LB} > 0, n_{LB} \in (0,1)$, $\exists$ a unique $n_{LG} \in (0,1)$ that solves (A.7), so long as $(1-\delta_L)p_{GE}n_{LB} < \delta_L$.

**Proposition 3**. *Suppose the conditions of Proposition 1 and Proposition 2 are met. Then there exists a unique steady-state equilibrium.*

Suppose the conditions of Lemma 1 and Lemma 2 are satisfied. Then given the aggregates of the labor market, there exists a unique steady-state in the connections market, and given the aggregates of the connections market, there exists a unique steady-state in the labor market. This implies that there exists a unique steady-state across both markets simultaneously. Thus, a unique steady-state equilibrium exists.

## A.3 Data Appendix

### Additional Discussion of Select Empirical Moments

The average job-finding probability is constructed using methods described in Shimer (2012). Interested readers are directed there for further information on the construction of the theoretical model. Here, the empirical methodology is briefly described. In order to estimate the monthly job-finding probabilities, data on employment, unemployment, and short term unemployment are required. Short term unemployment is defined as the number of unemployed workers with zero to four weeks of being unemployed. These data series are constructed by the BLS using data from the Current Population Survey (CPS). This method works quite well, but suffers from a discontinuity that arises due to the 1994 CPS redesign, which significantly affects the short-term unemployment data series. To correct for this, Shimer uses the BLS measure from 1948 to 1993, but then uses only the short-term unemployment data for the incoming rotation groups of the CPS. This method, however, requires using the CPS microdata available on the Nation Bureau of Economic Research's (NBER's) website.[1] This paper follows this methodology since data are post the 1994 redesign. Thus, to construct this moment, the short term unemployment each month is calculated using the CPS microdata for the incoming rotation of individuals over the years 2010-2016. The series is then seasonally adjusted using the Census's X-13-ARIMA algorithm.[2] This same methodology is used to construct the monthly separation probability.

While labor share of capital is traditionally estimated to be about 2/3, recent empirical evidence suggests it is much higher after accounting for relevant factors. Karabarbounis and Neiman (2018) show that the adjusted labor share from 2010 to 2016 fluctuates between .8 and .85, which the model is able to reproduce much more closely.

## A.4 Model Formulation of Moments

The construction of moments using the model is now discussed. Aggregate market tightness is calculated as the ratio of vacancies to unemployed. Note, that this is calculated as market tightness is calculated empirically. Thus, it will not simply be a weighted average of $\theta_{LB}$ and $\theta_{LG}$. In the context of this model, this will be the the

[1] Available at urlhttp://www.nber.org/data/cps_basic.html

[2] This is publicly available at https://www.census.gov/srd/www/x13as/

total number of vacancies from both G-firms ($v_{LG}$) and B-firms ($v_{LB}$) divided by the total number of unemployed ($u_L$):

$$\frac{v_{LB} + v_{LG}}{u_L} \tag{A.8}$$

Since there is a unit measure of workers in the labor market, the unemployment rate can simply be calculated as:

$$(1 - n_{LG} - n_{LB}) \tag{A.9}$$

The average replacement rate is calculated as the average of the fraction of a B-firm wage received when unemployed ($z_L/w_{LB}$) and the fraction of the G-firm wage received when unemployed ($z_L/w_{LG}$). The weights are generated using the fraction of individuals working at each type of firm, giving:

$$\left(\frac{n_{LB}}{n_{LB} + n_{LG}}\right)\frac{z_L}{w_{LB}} + \left(\frac{n_{LG}}{n_{LB} + n_{LG}}\right)\frac{z_L}{w_{LG}} \tag{A.10}$$

The fraction of jobs found via referral is calculated as the average of the share of the job-finding rate attributable to referrals for the unemployed $(n_{LG}\rho_G N^{\alpha}_{CU} + n_{LB}\rho_B N^{\alpha}_{CU})$ $/(n_{LG}\rho_G N^{\alpha}_{CU} + \theta_{LG}q(\theta_{LG}) + n_{LB}\rho_B N^{\alpha}_{CU} + \theta_{LB}q(\theta_{LB}))$ and employed $(n_{LG}\rho_{BG}N^{\alpha}_{CB})$ / $(n_{LG}\rho_{BG}N^{\alpha}_{CB} + \theta_{LG}q(\theta_{LG}))$. If, for example, the referral probability is 50% of the entire job-finding probability, then half of the measure of individuals will find their job via referral. The weights for the average are calculated using the relative number of individuals in each labor market state. Then, the average fraction of jobs found via referral when unemployed, employed, and in total respectively are:

$$\left(\frac{n_{LG}\rho_G N^{\alpha}_{CU} + n_{LB}\rho_B N^{\alpha}_{CU}}{n_{LG}\rho_G N^{\alpha}_{CU} + \theta_{LG}q(\theta_{LG}) + n_{LB}\rho_B N^{\alpha}_{CU} + \theta_{LB}q(\theta_{LB})}\right) \tag{A.11}$$

$$\left(\frac{n_{LG}\rho_{BG}N^{\alpha}_{CB}}{n_{LG}\rho_{BG}N^{\alpha}_{CB} + \theta_{LG}q(\theta_{LG})}\right) \tag{A.12}$$

$$\begin{aligned}\frac{u_L}{u_L + n_{LB}}\left(\frac{n_{LG}\rho_G N^{\alpha}_{CU} + n_{LB}\rho_B N^{\alpha}_{CU}}{n_{LG}\rho_G N^{\alpha}_{CU} + \theta_{LG}q(\theta_{LG}) + n_{LB}\rho_B N^{\alpha}_{CU} + \theta_{LB}q(\theta_{LB})}\right) + \\ \frac{n_{LB}}{u_L + n_{LB}}\left(\frac{n_{LG}\rho_{BG}N^{\alpha}_{CB}}{n_{LG}\rho_{BG}N^{\alpha}_{CB} + \theta_{LG}q(\theta_{LG})}\right)\end{aligned} \tag{A.13}$$

The average job-finding probability is only calculated in Shimer (2012) for the unemployed, and as such, the moment is constructed in the model as the job-finding probability for the unemployed:

$$\begin{aligned} & p_{UB} + p_{UG} \\ & = n_{LG}\rho_G N_{CU}^{\alpha} + \theta_{LG} q(\theta_{LG}) + n_{LB}\rho_B N_{CU}^{\alpha} + \theta_{LB} q(\theta_{LB}) \end{aligned} \tag{A.14}$$

The labor share is calculated as the average fraction of output workers receive at B-firms ($w_{LB}/y_{LB}$) and G-firms ($w_{LG}/y_{LG}$). As before, the weights for the average are calculated by the relative number of individuals employed by each firm type:

$$\frac{w_{LB}}{y_{LB}}\left(\frac{n_{LB}}{n_{LB}+n_{LG}}\right) + \frac{w_{LG}}{y_{LG}}\left(\frac{n_{LG}}{n_{LB}+n_{LG}}\right) \tag{A.15}$$

In the present model, the fraction of employed workers searching on-the-job is equivalent to the fraction of workers employed by B-firms. This is due to the fact that a worker only searches on-the-job when employed by a B-firm. The moment is then:

$$\frac{n_{LB}}{n_{LB}+n_{LG}} \tag{A.16}$$

The ratio of vacancy costs to wages is calculated as the average expected vacancy cost ($\frac{k_{LB}}{q(\theta_{LB})}(\frac{v_{LB}}{v_{LB}+v_{LG}}) + \frac{k_{LG}}{q(\theta_{LG})}(\frac{v_{LG}}{v_{LB}+v_{LG}})$) divided by the average wage ($\frac{n_{LB}}{n_{LB}+n_{LG}} w_{LB} + \frac{n_{LG}}{n_{LB}+n_{LG}} w_{LG}$):

$$\frac{\frac{k_{LB}}{q(\theta_{LB})}(\frac{v_{LB}}{v_{LB}+v_{LG}}) + \frac{k_{LG}}{q(\theta_{LG})}(\frac{v_{LG}}{v_{LB}+v_{LG}})}{\frac{n_{LB}}{n_{LB}+n_{LG}} w_{LB} + \frac{n_{LG}}{n_{LB}+n_{LG}} w_{LG}} \tag{A.17}$$

The number of on-the-job transitions as a fraction of employment is:

$$\frac{p_{BG} n_{LB}}{n_{LB}+n_{LG}} \tag{A.18}$$

The ratio of flows from job-to-job relative to flows from employment to unemployment is:

$$\frac{p_{BG} n_{LB}}{\delta_L(n_{LB}+n_{LG}+u_L(p_{UB}+p_{UG}))} \tag{A.19}$$

The ratio of the number of separation to employment is:

$$\frac{\delta_L(n_{LB} + n_{LG} + u_L(p_{UB} + p_{UG}))}{n_{LB} + n_{LG}} \tag{A.20}$$

Finally, the number of job-to-job transitions as a fraction of all separations is:

$$\frac{p_{BG}n_{LB}}{p_{BG}n_{LB} + \delta_L(n_{LB} + n_{LG} + u_L(p_{UB} + p_{UG}))} \tag{A.21}$$

There are three additional moments used as robustness checks– average employee tenure, average hiring time, and average unemployment duration. Average employee tenure is calculated as the weighted average of the hazard rate for workers at a B-firm ($\frac{1}{(1-p_{GE})(1-\delta_L)}$) and workers at a G-firm ($\frac{1}{(1-\delta_L)}$):

$$\frac{1}{(1-p_{GE})(1-\delta_L)}\left(\frac{n_{LB}}{n_{LB}+n_{LG}}\right) + \frac{1}{(1-\delta_L)}\left(\frac{n_{LG}}{n_{LB}+n_{LG}}\right) \tag{A.22}$$

The average vacancy duration is calculated similarly:

$$\frac{1}{q(\theta_{LB})}\left(\frac{n_{LB}}{n_{LB}+n_{LG}}\right) + \frac{1}{q(\theta_{LG})}\left(\frac{n_{LG}}{n_{LB}+n_{LG}}\right) \tag{A.23}$$

The average unemployment duration is calculated as:

$$\frac{.5}{p_{UB}} + \frac{.5}{p_{UG}} \tag{A.24}$$

# B. APPENDIX: THE IMPACT OF REFERRAL-NETWORKS ON SECTORAL REALLOCATION

## B.1 Further Discussion DRTS and Stole-Zwiebel

In order for equilibrium in a two sector economy to exist, there needs to be some sort of mechanism that balances the labor force allocation across the two sectors. However, a standard Mortensen-Pissarides framework (MP) is unable to accomplish this feat due to two critical features of the model. First, as Chang (working paper) notes, any change in the productivity of a worker in a particular sector will lead to a unique labor market tightness ($\theta$), which makes an equilibrium an impossibility. This follows from the structure of a basic Pissarides model in which for each sector $i$:

$$rU_i = b + \frac{(1-\beta)k\theta}{\beta}$$

In order for there to be an equilibrium, the flow value of unemployment must be equal across sectors, which implies that $\theta_i$=$\theta_{-i}$. As discussed above, this condition is only satisfied if the productivities are equal, which means that all economic opportunities are equal and therefore, there are no interesting migration decisions to be made. The second feature of the MP model that prevents it from being used in a migrational setting is the fact that labor market outcomes are *independent* of the labor force. That is, the fraction of labor in a sector has no bearing on the equilibrium wage, unemployment, or market tightness. This, in essence, is the same problem we just discussed, but it is important for understanding what sort of features are necessary in order to equilibrate sectors. The balancing mechanism *must* depend on the labor force in a significant way if we are to have a sensible model with fairly homogeneous agents. This requirement implies that models that simply extend the MP model, such as the inclusion of connections,[1] or simply explore alternative calibrations of the standard MP model cannot equilibrate the two sector model.

Naturally, one thinks of an increasing returns to scale (IRS) matching function as a potential solution, as equilibrium outcomes will depend on the selected size of the labor force. That being said, the equilibrium does not depend of the labor force in a useful way. In other words, the labor force cannot really be used to equate the various sectors of the model. This is because changing the size of the labor force does not change the equilibrium in a smooth fashion. Trying to balance two sectors with IRS matching functions turns into a knife's edge condition that will never be met in practice.[2]

Chang comments that a formal two sector model needs to capture the effect of diminishing marginal labor across sectors, and incorporating a decreasing returns to scale (DRTS) production function is one method of doing so.[3] Yet, DTRS greatly complicates wage determination. As more workers are hired, output increases, but by an increasingly smaller magnitude, changing the surplus of all matches with each additional hire. Thus, the firm ideally wants to renegotiate wages every time it hires a new worker. This problem is never evident in the standard MP model as the surplus of a match is constant overtime, and consequently, the preferred framework adopted by economists is a one firm, one worker model.[4] Given this new difficulty, there are three options of how best to proceed. We could simply use standard Nash bargaining when every match is formed, splitting the surplus from that match at that specific time. Though simple, this solution will generate arbitrary wage dispersion which may

[1] See Galenianos (2014) and Igarashi (2016). Their formulations are independent of the size of the labor force, and thus produce a unique equilibrium given a productivity level. Thus, a two sector equilibrium version of these formulations will not exist.

[2] It is worth mentioning that as the size of the labor force approaches infinity, search frictions effectively disappear in an IRS formulation, making search obsolete, but also theoretically allowing the models to "equilibrate" artificially.

[3] There is potentially another way to capture the same movement decisions of workers by incorporating a sector specific, idiosyncratic outside options for each worker. Then the two sector model would effectively function as a Roy model with search and could have a CRS production function. However, I need to think more about this formulation before I can comment on its relative merits.

[4] This formulation is actually equivalent to a one firm, multiple workers model in the presence of CRS production.

obfuscate some of the findings of the model. The next option is to introduce Stole-Zwiebel intra-firm bargaining, which is designed especially for a situation in which the firm is bargaining with employees who are already employed.[5] This is the process we formally adopt in this paper. The third option is to have fixed exogenous wages for all workers. We explore this specification in detail in the appendix, but in general, we find that there is no significant directional differences in results whether we use the exogenous or endogenous wages.

While the DTRS assumption may invoke a bit of skepticism, it is worth noting that there are many industries in which this specification is probably more valid than CRS. Any industry that faces a scare resource constraint in terms of production (coal, natural gas, oil, agriculture) likely faces some degree of decreasing returns to scale.[6] In addition, there is evidence to suggest that massive firms may experience DRTS due to communication and oversight constraints.[7] Furthermore, we do not have hard evidence of CRS in all sectors of the economy, and in many cases we simply fail to reject CRS. Empirical evidence actually suggests that many other industries may have slightly decreasing returns to scale.[8]

[5]Note that this process derived in Stole and Zwiebel (1996) is the generalized equilibrium outcome of an extensive form game derived form Rubinstein (1982).

[6]The intuition for this is that doubling inputs will not necessary lead to doubling outputs if the output is the extraction of a natural resource. Often, expanding production means tapping into what were deemed less fruitful pockets of natural gas or using slightly worse soil, which will naturally yield less production compared to previous inputs.

[7]See Zhu (2000).

[8]See Basu and Fernald (1997).

## B.2 Proof of Steady State Equilibrium

Existence and uniqueness of equilibrium are proved form the perspective of S1. The proof for existence from the perspective of S2 is symmetric. In S1, the three relevant equations are:

$$\frac{k_1}{q(\theta_{1c})} = (1-\delta_c)\Delta[\frac{\alpha_1(1-\beta)}{1+\alpha_1\beta-\beta}A_1 p_c {N_{1c}}^{\alpha_1 - 1} - \left((1-\beta)z_1 + \beta k_1\theta_{1d} + \frac{\beta k_1 \rho_1 L_{1c}}{q(\theta_{1c})}\right) + \left(\frac{k_1(1+\rho_1 u_{1c})}{q(\theta_{1c})}\right)] \tag{A1}$$

$$n_{1c} = (1-\delta_c)[n_{1c} + (\theta_{1c}q(\theta_{1c}) + \rho_1 n_{1c})(L_{1c} - n_{1c})] \tag{A2}$$

$$z_2 - z_1 = \frac{\beta}{1-\beta}\left[k_1\left(\theta_{1c} - \theta_{2c}\right) + k_2\left(\frac{\rho_1 n_{1c}}{q(\theta_{1c})} - \frac{\rho_2 n_{2c}}{q(\theta_{2c})}\right)\right] \tag{A3}$$

Notice, one can solve for $\theta_{1c}$ using (A2) while noting $m(u,v) = \mu_1 v_{1c}^{\eta} u_{1c}^{1-\eta}$ (which implies $\theta_{1c}q(\theta_{1c}){=}\mu_1\theta_{1c}^{\eta}$ and $q(\theta_{1c}){=}\mu_1(\frac{1}{\theta_{1c}})^{1-\eta}$). This gives:

$$\theta_{1c} = (\frac{Q}{\mu_1})^{\eta}$$

where $Q = n_{1c}\left(\frac{\delta_c}{(1-\delta_c)(L_{1c}-n_{1c})} - \rho_1 n_{1c}\right)$. This effectively allows the system of thre equations to be reduced to 2.

Suppose $L_{1c}$ is fixed. Then, (A1) can be rewritten as:

$$k_1(1-(1-\delta_c)\Delta(1-\beta\rho_1 L_{1c})) = q(\theta_{1c})\Delta(1-\delta_c)\left[\frac{\alpha_1(1-\beta)}{(1+\alpha_1\beta-\beta)}A_1 p_c {n_{1c}}^{\alpha-1} - (1-\beta)z_1 - \beta k_1\theta_{1c}\right] \tag{A4}$$

As $n_{1c} \to L_{1c}$, $Q \to \infty$, $\theta_{1c} \to \infty$, $q(\theta_{1c}) \to 0$ and $\theta_{1c}q(\theta_{1c}) \to 1$. Thus the right hand side of (A4) reduced to $-\beta k_1(1-\delta_c)\Delta$. A sufficient condition for this value to be less than the left hand side of (A4) is $1 > (1-\delta_c)\Delta$, which is always true given that $\delta_c, \Delta \in (0,1)$. Note, that for the case of a disconnected worker, the $\rho_1 = 0$ no additional restrictions are required to ensure existence (the steps of the proof are identical otherwise). Conversely, as $n_{1c}$ approaches 0: $Q \to \bar{Q}$, and $\theta_{1c} \to \bar{\theta}$. However, $\frac{\alpha_1(1-\beta)}{(1+\alpha_1\beta-\beta)}A_1 p_c {n_{1c}}^{\alpha-1}$ diverges to infinity, resulting in the right hand side of (A4) diverging to infinity. Hence, since the left hand side is assumed to be positive by the previous condition, this implies that for all fixed $L_{1c}$ there exists a unique $n_{1c}$. Now $n_{1c}$ is fixed. The cross equilibrium condition can be rewritten as:

$$T = k_1(\theta_{1c} - \theta_{2c}) + k_1 \left[ \frac{\rho n_{1c}}{q(\theta_{1c})} - \frac{\rho_2 n_{2c}}{q(\theta_{2c})} \right] \tag{A5}$$

where T is a constant. As $L_{1c}$ approaches $n_{1c}$: $Q \to \infty, \theta_{1c} \to \infty, q(\theta_{1c}) \to 0, \theta_{2c} \to \bar{\theta}, q(\theta_{2c}) \to \bar{q}$, where the bars indicate constant values. Thus, the right hand side of (**??**) diverges to infinity. Conversely, as $\gamma_c L - L_{1c}$ approaches $n_{2c}$: $Q_{2c} \to \infty, \theta_{2c} \to \infty, q(\theta_{2c}) \to 0, \theta_{1c} \to \bar{\theta}, q(\theta_{1c}) \to \bar{q}$, where the bars indicate constant values and the 2c subscript indicate the equivalent function presented above, but with S2 variables. Thus, the right hand side of **??** diverges to negative infinity. Note, $\frac{\partial \theta_{1c}}{\partial L_{1c}} < 0, \frac{\partial \theta_{2c}}{\partial L_{1c}} > 0, \frac{\partial \theta_{1c}}{\partial L_{1c}} < 0, \frac{\partial q(\theta_{1c})}{\partial L_{1c}} > 0, \frac{\partial q(\theta_{2c})}{\partial L_{1c}} < 0$, which imply that the right hand side of **??** is strictly decreasing in $L_{1c}$. Since $T$ is a constant, this implies that there exists a single unique value of the labor force allocation. Thus, since there exists an unique $n_{1c}$ given a fixed $L_{1c}$ and a unique $L_{1c}$ given a fixed $n_{1c}$, the equilibrium exists and is unique for connected and disconnected workers. Note that the proof for equilibrium is almost identical for the model with two types of connected workers presented in the text.

### B.3 Data Appendix

### B.4 A More Detailed Figure 1

Note, the CPS redesign slightly changed how the question concerning asking friends and family about job opportunities was asked. The additional years come from the BLS CPS tables. Dashed lines indicated long run trend lines. The various aggregations need explaining. The 3-digit classification is the CPS ind1990 classification and the 2-digit classification is the North American Industry Classification System (NAICS). The major industry classification comes from the BLS and is exactly the classification used by Galenianos [2014] in his analysis of the by-industry use of referrals. [9] The 3-sector aggregation the the BEA combines the major industries

[9]This link describes the aggregation: $https://www.bls.gov/emp/ep_table_201.htm.$

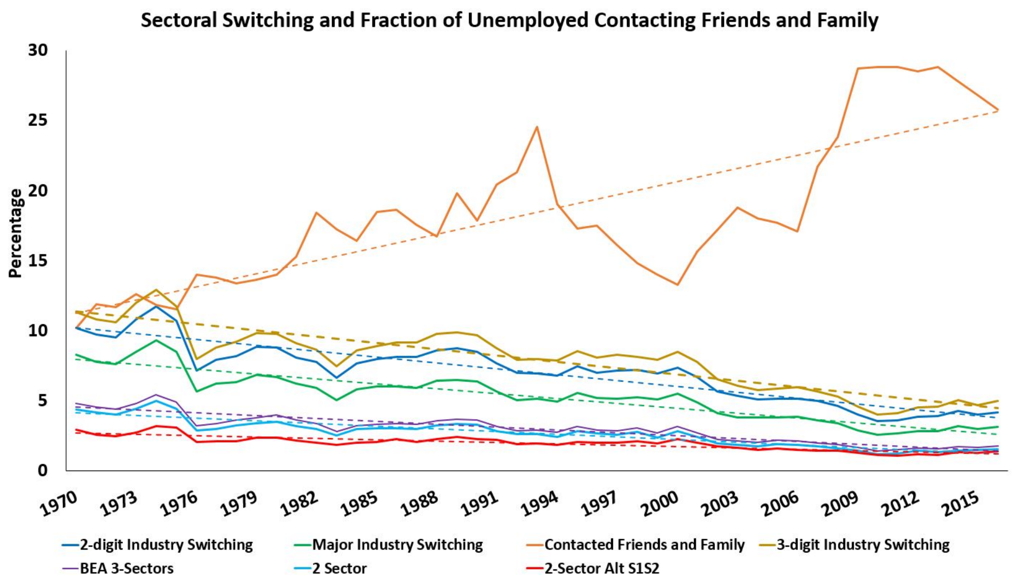


Fig. B.1. Other aggregations of the fraction of population that switch sectors and fraction of unemployed who ask friends and family about jobs.

into three broad categories–Private Goods, Private Services, and Government. There are two alternate 2-sector aggregations. The first combines the BEA 3-sector aggregation categories Private Service and Government into one sector entitled GovServe and treats Private Goods as its own sector. Finally, the other 2 sector aggregation combines Agriculture, Mining, Construction, Utilities, Transportation, Manufacturing, Wholesale Trade, Retail Trade, and Other Services into one sector called S1 and Business and Professional Services, Health, Education, Leisure and Hospitality, and Government into another sector called S2. The data for the attempted use of friends and family to find jobs as well as the sectoral switching data comes from IPUMS CPS and the National Bureau for Economic Research's (NBER) website that has the complete CPS microdata.

## B.5 Sectoral Switching and Elasticity Data

The sectoral switching rates are obtained using IPUMS CPS ASEC microdata. The CPS ASEC data are downloaded from the CPS website for the desired years.[10] Any observations that are currently unemployed or were unemployed last year are dropped. Furthermore, any observations that are imputed in any way as indicated by the downloaded data quality flags are dropped. Finally, all observations that are missing data for either the variable IND1990 or IND90LY are dropped. Thus, at any desired level of aggregation of 3-digit industries or coarser, one can compute the total number of switches per year as the number of agents for which IND1990 $\neq$ IND90LY (i.e. the number of people whose industry by the CPS 1990 classification changed from the previous year).[11]

Despite this attempt to purge the data of imputed values generated by the CPS, there is still a concern that the hot-deck allocation procedure is dramatically influencing the shape of the data. Even after dropping all observations that are imputed according to all available variables, there are still discrete jumps in the sectoral switching rates overtime. To correct for this, the procedure used by Molloy et al. (2014) is adopted.[12] In their paper, they drop any observation that has any imputed values as indicated by the variable "SUPREC" after the year 1988. However, this variable is not available on the IPUMS CPS website and is no longer available from the source used by Molloy et al. (2014).[13] Therefore, the SUPREC variable must be con-

[10]Specifically, the variables year, empstat, labforce, ind1990, ind90ly, qmigrat1g, workly, qind, qnumemps, qocc, qoccly, qmigrat1, qmigst1a, and qmigst1b are downloaded in along with the appropriate weighting variables.

[11]Note that the IPUMS CPS codes IND and INDLY are not comparable overtime while the codes ind1990, ind90ly, ind1950, and ind50ly are. Since the definitions of various industries change and new industries develop overtime, this paper elects to use the ind1990 and ind90LY variables, as these industry definitions are the closest to current definitions. A cross walk between the ind1990 CPS variable and the NAICS 3-digit industry codes can be constructed using IPUMS USA and is available upon request.

[12]In fact, the data cleaning procedure described to this point has followed exactly the procedure Molloy et al. (2014) perform in their paper.

[13]Historically, the CPS collaborated with an entity called the Unicon Research Corporation that helped compile and clean what was called the "CPS Utilities" from the CPS microdata. It is from this entity that Molloy et al. (2014) obtained the SUPREC variable. Unfortunately, Unicon shut

structed using the CPS ASEC microdata available on the Nation Bureau of Economic Research's (NBER) website.

Fortunately, sort order of the microdata on NBER and the ASEC supplement available from IPUMS CPS are the same, allowing us to easily merge the two files once the SUPREC variable is generated.[14] When working with the microdata, the variable FL_665 (sometimes FL665) is synonymous with the Unicon variable SUPREC for the years 1991-2016. This variable is not a simple indicator variable, as it describes various levels of imputation used. Consistent with the procedure described by Molloy et al. (2014), the variable SUPREC is set equal to 1 if *any* imputation procedure was used as indicated by FL_665. For the years 1988-1990, the variable FL_665 does not exist. Fortunately, a .txt file is publicly available on the US Census Bureau's website and is used to extract the value for the SUPREC variable.[15] Dropping all observations that have imputed data as indicated by the variable SUPREC corrects for the discrete jumps is switching rates overtime.

Estimates of the prevalence of referrals overtime are calculated using IPUMS CPS data from 1970 to 1993 as well as data from the BLS CPS table available from 1994-2016. This paper proxies for the prevalence of referrals using the fraction of

down in 2014, meaning much data that were previously available are no longer generally accessible to the public. It is this author's understanding that eventually all the variables generated by Unicon will be made available through either IPUMS CPS or the Minnesota Population Center. It is worth noting that some universities have access to this data in the form of CDs. That being said, the procedure described here can be used in the interim and will produce the variable SUPREC for all year up to and beyond 2014 whereas those who have access to the old Unicon data will only be have the data up to the year 2014.

[14]The exceptions are the years 2001 and 2014, which both have more observations in the CPS data than in the corresponding NBER data. In 2001, this is due to the additional SCHIP data collected that year and for 2014 this is due the the additional poverty survey information collected that year. Thus one cannot simply merge all years at once. Individual year files of the IPUMS CPS industry data and SUPREC variables must be generated, merged individually, and then appended into one complete dataset. For the years 2001 and 2014, one can match the SUPREC variable by creating and observation ID variable, creating a unique 1-1 year ID mapping for these two years.

[15]The file is available at $https://www.census.gov/housing/extract_files/toc/data/$. If the last two digits of the code are "11" this indicates that SUPREC should be set equal to 1. Data and STATA do files that generate the SUPREC variable for all available years are available upon request.

unemployed workers who report contacting friends and family for work.[16] Prior to 1994, survey respondents who were unemployed were asked "What has [this person] been doing in the last four weeks to find work?" The possible responses were checking with: friends and relatives, with a public employment agency, and private employment agency, an employer directly, placing and answering ads, other, or nothing. A respondent could check as many categories as applied. In 1994, the CPS underwent a redesign that changed the question slightly and added more possible responses.[17] This likely explains the discrete jump seen in Figure 1. That being said, even with the redesign, there is clear evidence of the prevalence of referrals increasing overtime. Moreover, it there appears to be a negative relationship between the prevalence of referrals and the sectoral switching rate.

To estimate this relationship, it is necessary to use the IPUMS data in conjunction with the CPS March Basic files from the NBER's website. The IPUMS CPS ASEC has all the necessary demographic and sectoral switching data. However, starting after 1994, the CPS website does not track questions regarding search methods used by job-seekers. Fortunately, the NBER CPS March Basic files have this information, but merging the relevant files is not straight forward. The basic procedure is now described. First, I create and merge the variable SUPREC with the IPUMS ASEC data using the procedure outlined in detail above. Then, I am able to merge the IPUMS ASEC files with the IPUMS March Basic files, matching on the YEAR and MARBASECIDP variables. Unfortunately, the MARBASECIDP was create by IPUMS separately from the survey, and therefore cannot be used to merge the NBER March Basic files with the IPUMS March Basic files. To merges these datasets, I use an

[16]Data for the years 1994, 2000, and 2001 are available upon request. The 2000 and 2001 tables were taken down from the BLS/CPS website to adjust for demographic information consistent with the 2000 Census and never re-uploaded.

[17]After the redesign, the question read "What are all of the things you have done to find work during the last 4 weeks?" and the possible responses were then: contacted employer directly, interviewed with a potential employer, contacted public employment agency, contacted private employment agency, contacted friends or relatives, contacted school/university employment center, sent out resumes/filled out application, placed or answered adds, check union/professional registers, other active, looked at ads, attended job training programs/courses, and other passive.

algorithm provided to me by the IPUMS researchers.[18] Essentially, I merge the files by year, matching on the variables HRHHID, HUHHNUM, HRSAMPLE, HESERSUF, PULINENO, and GESTCEN (a variable indicating the individuals state). After merging and appending the data for all years, this generates the file I use to obtain the estimation results. Table B.1 shows the marginal effects of a probit regression on the data as a robustness check of the linear probability model.

In another robustness test, I merge the existing datafile with the IPUMS Time Use survey to get an alternate measure of search intensity for job seekers. Unfortunately, only a fraction of individuals who take the ASEC are also selected to take the TIME USE survey, which lead to a large number of observations being lost in the merge. The results from the regressions incorporating this alternative measure of search intensity are reported in Table B.2. The number of observations drop by two orders of magnitude, resulting in no significance. That being said, the coefficients for the 3-Digit aggregation as well as the 2-Digit NAICS aggregate are very similar to those estimated using nummethods as a proxy for search intensity.

## B.6 Supplement Hours Estimation Using IPUMS CPS

In order to obtain hours for workers in the agriculture, forestry and fishing industries, the quarterly number of hours is calculated from 2005-2016 using the IPUMS CPS monthly surveys.[19] The procedure is briefly described here. After the monthly CPS data for the desired years are downloaded, observations that have no observed hours worked or are constructed using imputed values are dropped. Using the NAICS major industry definitions, observations are sorted into their respective major indus-

[18] A very special thanks to Jeff Bloem who answered my many questions about this process both promptly and accurately.

[19] According to the BLS technical documentation, the Nonfarm Quarterly Total Hours of Wage and Salary Workers dataset is constructed using the CPS,CES,and NCS. Consequently, using the CPS to construct the agricultural part of the dataset is parsimonious with the BLS data. As it so happens, the fraction of the total hours this industry comprises for larger sector aggregations is fairly small, so it is highly unlikely that any difference in the calculation of the Agricultural, Forestry, and Fishing industry dramatically impact later results.

Table B.1.
Probit Marginal Effects: Switching and Referral Use

| | (1) 3-Digit | (2) 2-Digit NAICS | (3) 2-Digit Major | (4) 2 Sector |
|---|---|---|---|---|
| network | -0.0316*** | -0.0282*** | -0.0125 | -0.0138* |
| | (0.001) | (0.007) | (0.252) | (0.089) |
| nummethods | 0.0160*** | 0.0126*** | 0.0145*** | 0.0140*** |
| | (0.000) | (0.001) | (0.000) | (0.000) |
| black | -0.00678 | -0.00634 | 0.00316 | 0.0203** |
| | (0.510) | (0.559) | (0.779) | (0.012) |
| asian | -0.0191 | -0.0404* | -0.0305 | -0.0236 |
| | (0.372) | (0.076) | (0.208) | (0.210) |
| married | -0.0214** | -0.0286*** | -0.0113 | -0.0183** |
| | (0.014) | (0.002) | (0.239) | (0.011) |
| children | -0.00262 | -0.00318 | 0.00623* | 0.00662** |
| | (0.446) | (0.382) | (0.098) | (0.017) |
| age | -0.00330*** | -0.00347*** | -0.000516 | 0.00000854 |
| | (0.000) | (0.000) | (0.110) | (0.971) |
| homeown | 0.0290*** | 0.0237*** | 0.0145* | 0.00536 |
| | (0.000) | (0.005) | (0.092) | (0.399) |
| college | -0.0956** | -0.160*** | -0.102* | -0.0308 |
| | (0.049) | (0.002) | (0.071) | (0.467) |
| $N$ | 15222 | 15222 | 15222 | 15222 |
| Year FE | Yes | Yes | Yes | Yes |

$p$-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

tries.[20] Next, the months are used to create a quarter variable, and all hours within a quarter within a year are aggregated together by industry.

## B.7 Productivity Moment Estimation

Table B.2 below provides the output from the Dickey Fuller Test for stationarity, showing that the data are stationary.

```
Dickey-Fuller test for unit root                    Number of obs   =        46

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.819            -3.607            -2.941            -2.605
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

Fig. B.2. Dickey-Fuller Test Output

Since there are only about 50 observations and Maximum likelihood is known to be biased estimation procedure, a Monte Carlo procedure is conducted to gauge how accurately the procedure is able to produce the true parameters. The Monte Carlo simulation results for the mean $\mu$ and standard error $\sigma$ are presented in the tables below. For the MLE fitting of normal distribution, 90,000 simulations with a sample size of 47 were performed. In general, the simulations results shown in Table B.3 and in Table B.4 suggest that the procedure is quite accurate.

### Discussion of an Auto-Regressive Specification

Despite the first differencing of the productivity ratio data, one might suspect that the distribution could be best described as an AR(1) process. However, looking

[20] The IPUMS CPS industry codes do not correspond to the NAICS major industry codes. A cross walk between the NAICS 3-digit definitions of industries and the CPS IND variable can be created using IPUMS USA. From there, the 3-digit NAICS codes can be aggregated into the BLS definitions of major industries. This crosswalk is available upon request, as are all data construction files, in a STATA format.

at Figure B.3, there does not appear to be an obvious AR(1) pattern. The issue is further investigated using a Ljung-Box test (1978). This procedure tests whether the data are significantly different from white noise. Figure B.7 shows the results. The resulting p-value of .1090 is not significant, meaning that one cannot reject the hypothesis that this data is produced by white-noise. As such, this paper does not pursue any alternative estimation specifications.

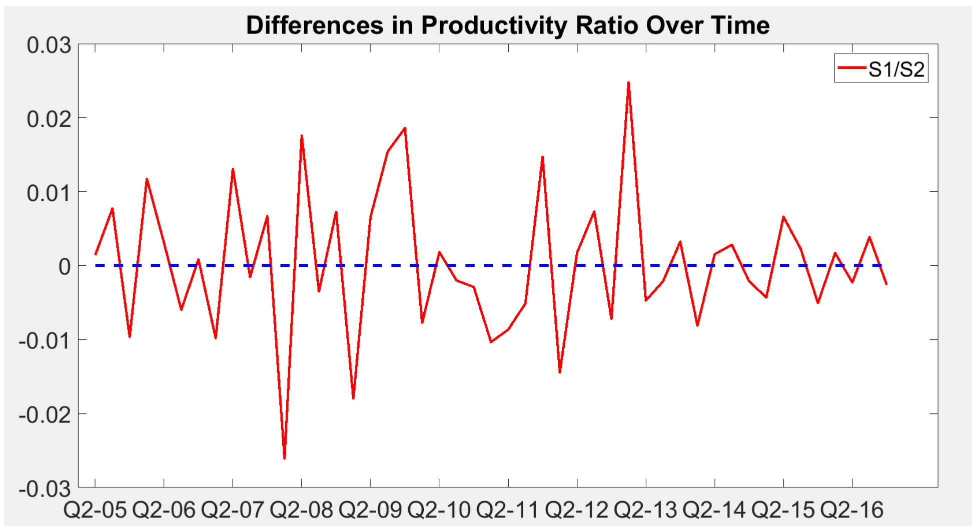


Fig. B.3. 2-Sector Productivity Ratio Difference

```
Portmanteau test for white noise
---------------------------------------
 Portmanteau (Q) statistic =    30.4045
 Prob > chi2(22)           =     0.1090
(est1 stored)
```

White Noise Test

## B.8 Estimation Details

In the SMM procedure, the weighting matrix is chosen so that all target moments are the same weight. Specifically, targets are multiplied by the appropriate factor of

10 to make the largest digit be in the 1s place. For example, the market tightness target of .63 is multiplied by 10 to make it 6.3 and the aggregate unemployment target .0735 is multiplied by 100 to make it 7.35. This prevents the solving algorithm from focusing too heavily on particular moments, and effectively weights all moments as equally important.

Table B.2.
Switching and Referral Use with IPUMS Time Use Search Intensity

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | 3-Digit | 2-Digit NAICS | 2-Digit Major | 2 Sector |
| network | -0.0293 | -0.0276 | 0.0106 | 0.0415 |
| | (0.491) | (0.535) | (0.816) | (0.278) |
| nummethods | 0.0343*** | 0.0265* | 0.0230 | 0.00740 |
| | (0.008) | (0.054) | (0.107) | (0.522) |
| intensity | -0.000507** | -0.000438* | -0.000144 | -0.0000995 |
| | (0.044) | (0.087) | (0.550) | (0.490) |
| black | -0.00678 | -0.0248 | -0.0404 | 0.0463 |
| | (0.867) | (0.555) | (0.347) | (0.167) |
| asian | 0.00535 | -0.0644 | -0.0261 | -0.0214 |
| | (0.951) | (0.489) | (0.775) | (0.768) |
| married | -0.0118 | -0.0346 | -0.0201 | -0.00896 |
| | (0.753) | (0.375) | (0.602) | (0.748) |
| children | -0.00600 | 0.00376 | 0.0270* | 0.00394 |
| | (0.708) | (0.822) | (0.096) | (0.742) |
| age | -0.00407*** | -0.00398*** | -0.000403 | -0.000886 |
| | (0.001) | (0.002) | (0.760) | (0.389) |
| homeown | 0.0487 | 0.0486 | -0.0238 | 0.0796*** |
| | (0.163) | (0.180) | (0.516) | (0.003) |
| college | -0.375** | -0.271 | -0.125 | 0.0640 |
| | (0.050) | (0.130) | (0.507) | (0.708) |
| _cons | 0.906*** | 0.812*** | 0.428*** | 0.102 |
| | (0.000) | (0.000) | (0.000) | (0.217) |
| $N$ | 877 | 877 | 877 | 877 |
| Year FE | Yes | Yes | Yes | Yes |

$p$-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3.
MLE $\mu$ Monte Carlo Simulations

| | | True $\mu$ Values | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **.0010** | **.0015** | **.0020** | **.0025** | **.0030** | **.0035** | **.0040** | **.0045** | **.0050** |
| | **.0110** | .000996 | .001500 | .001994 | .002499 | .003007 | .003506 | .004003 | .004502 | .005010 |
| | **.0125** | .000992 | .001502 | .002001 | .002499 | .003005 | .003508 | .004000 | .004508 | .005003 |
| | **.0140** | .000993 | .001499 | .001994 | .002496 | .002985 | .003494 | .004000 | .004498 | .004988 |
| | **.0155** | .000990 | .001503 | .002001 | .002501 | .003000 | .003507 | .003990 | .004492 | .004991 |
| **True $\sigma$ Values** | **.0170** | .000989 | .001500 | .002000 | .002494 | .003018 | .003500 | .003996 | .004513 | .004998 |
| | **.0185** | .001011 | .001492 | .001994 | .002518 | .002995 | .003501 | .004012 | .004509 | .005004 |
| | **.0200** | .001008 | .001498 | .002001 | .002513 | .003009 | .003499 | .003985 | .004515 | .004993 |
| | **.0215** | .000982 | .001504 | .002006 | .002509 | .002997 | .003511 | .003992 | .004488 | .005006 |
| | **.0230** | .001007 | .001515 | .001998 | .002498 | .002990 | .003508 | .004007 | .004487 | .005009 |
| | **.0245** | .001015 | .001505 | .002000 | .002517 | .002991 | .003504 | .004003 | .004493 | .004992 |
| | **.0260** | .001004 | .001495 | .002013 | .002512 | .003002 | .003501 | .003992 | .004485 | .005009 |

Table B.4.
MLE $\sigma$ Monte Carlo Simulations

| | | True $\mu$ Values | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **.0010** | **.0015** | **.0020** | **.0025** | **.0030** | **.0035** | **.0040** | **.0045** | **.0050** |
| | **.0110** | .010822 | .010819 | .010829 | .010823 | .010820 | .010827 | .010828 | .010822 | .010816 |
| | **.0125** | .012302 | .012302 | .012302 | .012302 | .012296 | .012295 | .012300 | .012304 | .012303 |
| | **.0140** | .013779 | .013771 | .013771 | .013774 | .013782 | .013774 | .013779 | .013769 | .013776 |
| | **.0155** | .015250 | .015258 | .015269 | .015250 | .015244 | .015262 | .015244 | .015241 | .015252 |
| **True $\sigma$ Values** | **.0170** | .016729 | .016723 | .016725 | .016727 | .016725 | .016727 | .016726 | .016720 | .016724 |
| | **.0185** | .018199 | .018203 | .018203 | .018201 | .018206 | .018214 | .018203 | .018208 | .018190 |
| | **.0200** | .019673 | .019676 | .019684 | .019678 | .019673 | .019686 | .019668 | .019685 | .019683 |
| | **.0215** | .021163 | .021156 | .021160 | .021165 | .021150 | .021149 | .021147 | .021169 | .021164 |
| | **.0230** | .022618 | .022636 | .022646 | .022626 | .022636 | .022626 | .022631 | .022619 | .022634 |
| | **.0245** | .024103 | .024103 | .024109 | .024105 | .024113 | .024111 | .024119 | .024123 | .024102 |
| | **.0260** | .025587 | .025574 | .025580 | .025575 | .025568 | .025586 | .025604 | .025558 | .025573 |

# C. APPENDIX: DOES JOB-FINDING USING INFORMAL CONNECTIONS REDUCE MISMATCH?: THE ROLE OF NONPECUNIARY BENEFITS

## C.1 Proof of Equilibrium

Without loss of generality, we show an equilibrium exists and is unique for high-skill workers:

$$\psi^*(x,j) = b(x) + \lambda_h \int_{\underline{\psi}}^{\bar{\psi}} \max\{E_h(x,j,\psi) - U_h(x,j), 0\} d\tilde{G}_{fh}(\psi|x,j)$$
$$+ \rho_h \int_{\underline{\psi}}^{\bar{\psi}} \max\{E_h(x,j,\psi) - U_h(x,j), 0\} d\tilde{G}_{nh}(\psi|x,j)$$
$$\psi^*(x,j) = b(x) + \frac{\lambda_h}{r+s} \int_{\underline{\psi}}^{\bar{\psi}} \max\{\psi(x,j,y,k) - rU_h(x,j), 0\} d\tilde{G}_{fh}(\psi|x,j)$$
$$+ \frac{\rho_h}{r+s} \int_{\underline{\psi}}^{\bar{\psi}} \max\{\psi(x,j,y,k) - rU_h(x,j), 0\} d\tilde{G}_{nh}(\psi|x,j)$$
$$\psi^*(x,j) = b(x) + \frac{\lambda_h}{r+s} \int_{\underline{\psi}}^{\bar{\psi}} \max\{\psi(x,j,y,k) - \psi^*(x,j), 0\} d\tilde{G}_{fh}(\psi|x,j)$$
$$+ \frac{\rho_h}{r+s} \int_{\underline{\psi}}^{\bar{\psi}} \max\{\psi(x,j,y,k) - \psi^*(x,j), 0\} d\tilde{G}_{nh}(\psi|x,j)$$
$$\psi^*(x,j) = b(x) + \frac{\lambda_h}{r+s} \left( \int_{\psi^*}^{\bar{\psi}} (\psi(x,j,y,k) - \psi^*(x,j)) d\tilde{G}_{fh}(\psi|x,j) + \int_{\underline{\psi}}^{\psi^*} 0 d\tilde{G}_{fh}(\psi|x,j) \right)$$
$$+ \frac{\rho_h}{r+s} \left( \int_{\psi^*}^{\bar{\psi}} (\psi(x,j,y,k) - \psi^*(x,j)) d\tilde{G}_{nh}(\psi|x,j) + \int_{\underline{\psi}}^{\psi^*} 0 d\tilde{G}_{nh}(\psi|x,j) \right)$$
$$\psi^*(x,j) = b(x) + \frac{\lambda_h}{r+s} \left( \int_{\psi^*}^{\bar{\psi}} (\psi(x,j,y,k) - \psi^*(x,j)) d\tilde{G}_{fh}(\psi|x,j) \right)$$
$$+ \frac{\rho_h}{r+s} \left( \int_{\psi^*}^{\bar{\psi}} (\psi(x,j,y,k) - \psi^*(x,j)) d\tilde{G}_{nh}(\psi|x,j) \right)$$

Integration by parts gives:

$$\psi^*(x,j) = b(x) + \frac{\lambda_h}{r+s}\left[\int_{\psi^*(x,j)}^{\bar{\psi}} 1 - \tilde{G}_{fh}(\psi|x,j)d\psi\right] + \frac{\rho_h}{r+s}\left[\int_{\psi^*(x,j)}^{\bar{\psi}} 1 - \tilde{G}_{nh}(\psi|x,j)d\psi\right]$$

Differentiating both sides by $\psi^*(x,j)$ and applying Leibnitz's rule:

$$\frac{\partial LHS}{\partial \psi^*(x,j)} = 1 > 0$$
$$\frac{\partial RHS}{\partial \psi^*(x,j)} = \frac{\lambda_h}{r+s}\left(\tilde{G}_{fh}(\psi^*(x,j)|x,j) - 1\right) + \frac{\rho_h}{r+s}\left(\tilde{G}_{nh}(\psi^*(x,j)|x,j) - 1\right) < 0$$

Thus there is at most one unique solution.

## C.2 Counterfactuals Concerning Total Mismatch

Figure C.1 shows the average accepted total mismatch by worker skill type. This figure is very similar to Figure 3.2, demonstrating nonpecuniary-mismatch drives total mismatch in this model.

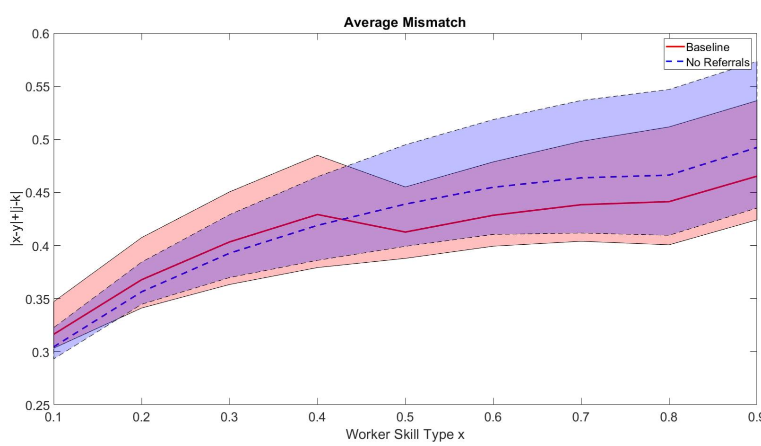


Fig. C.1. Counterfactual: Total Mismatch by Worker Skill Type

## C.3 Generalized Ordered Logits and Cut Points Estimation

This section performs robustness checks regarding the findings from the SCE. The tables show the estimation results of generalized ordered logits that do not assume the proportional odds assumption holds. Tables C.1, C.2, C.3 correspond to Tables 3.2, 3.3, 3.4 respectively. The general results still hold under these alternative specifications. High-skill workers who receive an offer through a referral tend to report a better perceived nonpecuniary match while low-skill workers report a worse perceived nonpecuniary match.

The following tables estimate the cut points for the ordered logit regressions presented above.

Table C.1.
Generalized Ordered Logit: Referrals and Perceived Mismatch

| | (1) OVERALL | (2) NONWAGE | (3) SKILLFIT | (4) WAGE | (5) PROMOTION |
|---|---|---|---|---|---|
| 1 | | | | | |
| REFFF | 0.0139 | -0.204 | -0.153 | -0.121 | -0.0909 |
| | (0.947) | (0.147) | (0.648) | (0.352) | (0.480) |
| REFCOWORKER | -0.330 | 0.619*** | -0.142 | -0.0455 | -0.188 |
| | (0.186) | (0.004) | (0.739) | (0.792) | (0.259) |
| REFCUREMP | -0.129 | 0.0226 | -0.101 | -0.0731 | 0.134 |
| | (0.661) | (0.910) | (0.829) | (0.678) | (0.457) |
| PREVEMP | 0.373 | -0.176 | 0.599 | -0.158 | 0.590* |
| | (0.461) | (0.572) | (0.565) | (0.589) | (0.063) |
| PARTTIME | -0.178 | -0.320* | 0.207 | -0.0443 | -0.0931 |
| | (0.488) | (0.075) | (0.593) | (0.796) | (0.571) |
| ABILITY | -0.191* | 0.110* | -0.212 | 0.00987 | -0.123** |
| | (0.059) | (0.072) | (0.168) | (0.866) | (0.035) |
| HOURS40+ | 0.365* | -0.518*** | -0.326 | -0.215* | 0.166 |
| | (0.088) | (0.000) | (0.377) | (0.099) | (0.186) |
| UNION | 0.0436 | -0.124 | -0.195 | -0.223 | 0.0445 |
| | (0.860) | (0.460) | (0.634) | (0.142) | (0.771) |
| TEMPORARY | -0.485 | -0.697*** | -0.379 | -0.233 | -0.707*** |
| | (0.197) | (0.006) | (0.436) | (0.344) | (0.003) |
| COMMUTE | -0.00205 | -0.000326 | 0.00451 | 0.000355 | 0.000265 |
| | (0.349) | (0.772) | (0.316) | (0.747) | (0.670) |
| WAGEREDUCT | -0.567** | -0.739*** | -0.780** | -0.629*** | -0.723*** |
| | (0.012) | (0.000) | (0.021) | (0.000) | (0.000) |
| JOBSECURITY | 0.517 | 0.241 | 0.263 | 0.286 | 0.219 |
| | (0.136) | (0.237) | (0.605) | (0.148) | (0.237) |
| 2 | | | | | |
| REFFF | -0.0915 | -0.183 | -0.0163 | -0.216* | -0.0752 |
| | (0.541) | (0.127) | (0.898) | (0.067) | (0.574) |
| REFCOWORKER | -0.0744 | 0.248 | 0.0852 | 0.0406 | 0.123 |
| | (0.698) | (0.127) | (0.611) | (0.794) | (0.467) |
| REFCUREMP | 0.0396 | -0.132 | 0.226 | -0.124 | 0.292* |
| | (0.854) | (0.428) | (0.212) | (0.444) | (0.096) |
| PREVEMP | 0.375 | -0.351 | 0.493 | 0.0321 | -0.226 |
| | (0.311) | (0.183) | (0.113) | (0.905) | (0.491) |
| PARTTIME | -0.218 | -0.467*** | -0.403** | -0.180 | -0.0454 |
| | (0.262) | (0.003) | (0.013) | (0.252) | (0.809) |
| ABILITY | -0.110 | 0.112** | -0.0242 | 0.0496 | -0.156*** |
| | (0.125) | (0.035) | (0.673) | (0.350) | (0.008) |
| HOURS40+ | 0.127 | -0.168 | 0.360*** | -0.137 | 0.243* |
| | (0.391) | (0.153) | (0.005) | (0.242) | (0.050) |
| UNION | -0.124 | -0.0424 | -0.0256 | -0.00117 | -0.295* |
| | (0.478) | (0.766) | (0.866) | (0.993) | (0.062) |
| TEMPORARY | -0.878*** | -0.766*** | -0.529** | -0.672*** | -0.483 |
| | (0.002) | (0.001) | (0.025) | (0.004) | (0.119) |
| COMMUTE | 0.000383 | 0.000367 | 0.000389 | 0.000189 | -0.00395** |
| | (0.579) | (0.494) | (0.475) | (0.671) | (0.011) |
| WAGEREDUCT | -0.421** | -0.684*** | -0.811*** | -0.757*** | -0.459** |
| | (0.014) | (0.000) | (0.000) | (0.000) | (0.012) |
| JOBSECURITY | 0.532** | 0.302* | 0.538*** | 0.591*** | 0.638*** |
| | (0.032) | (0.083) | (0.006) | (0.001) | (0.000) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes |
| *N* | 1254 | 1767 | 1766 | 1767 | 1767 |

*p*-values in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table C.2.
Generalized Ordered Logit: High-Skill Referrals and Perceived Mismatch

| | (1) OVERALL | (2) NONWAGE | (3) SKILLFIT | (4) WAGE | (5) PROMOTION |
|---|---|---|---|---|---|
| 1 | | | | | |
| REFFF | 0.461 | -0.0325 | 0.0370 | -0.236 | 0.0131 |
| | (0.154) | (0.872) | (0.937) | (0.205) | (0.942) |
| REFCOWORKER | -0.479 | 0.825*** | -0.336 | -0.0629 | -0.181 |
| | (0.166) | (0.003) | (0.544) | (0.790) | (0.388) |
| REFCUREMP | 0.275 | -0.139 | -0.486 | 0.100 | 0.0756 |
| | (0.534) | (0.599) | (0.474) | (0.680) | (0.747) |
| PREVEMP | 1.042 | 0.320 | 0.138 | -0.0583 | 0.442 |
| | (0.136) | (0.472) | (0.900) | (0.889) | (0.275) |
| PARTTIME | -0.855** | -0.504* | 0.214 | -0.319 | 0.00857 |
| | (0.030) | (0.052) | (0.695) | (0.204) | (0.972) |
| ABILITY | -0.367** | 0.0720 | -0.541** | -0.0151 | -0.194** |
| | (0.032) | (0.448) | (0.043) | (0.864) | (0.029) |
| HOURS40+ | 0.107 | -0.543*** | 0.000903 | -0.364** | -0.00133 |
| | (0.721) | (0.005) | (0.999) | (0.044) | (0.994) |
| UNION | -0.156 | -0.327 | -0.149 | -0.417* | 0.206 |
| | (0.642) | (0.155) | (0.795) | (0.065) | (0.308) |
| TEMPORARY | -0.00433 | -0.834** | -0.0117 | -0.238 | -0.669** |
| | (0.994) | (0.016) | (0.986) | (0.477) | (0.034) |
| COMMUTE | -0.00832** | -0.00277 | 0.0113* | -0.00270 | -0.00358** |
| | (0.010) | (0.155) | (0.093) | (0.152) | (0.030) |
| WAGEREDUCT | -0.859*** | -0.774*** | -0.269 | -0.668*** | -0.693*** |
| | (0.007) | (0.001) | (0.607) | (0.003) | (0.001) |
| JOBSECURITY | 0.606 | 0.524 | 0.347 | 0.0682 | 0.170 |
| | (0.342) | (0.102) | (0.591) | (0.819) | (0.509) |
| 2 | | | | | |
| REFFF | 0.149 | -0.102 | 0.172 | -0.261 | -0.0887 |
| | (0.484) | (0.539) | (0.329) | (0.114) | (0.622) |
| REFCOWORKER | -0.0193 | 0.242 | 0.205 | 0.106 | 0.321 |
| | (0.936) | (0.231) | (0.327) | (0.591) | (0.112) |
| REFCUREMP | -0.00222 | -0.343 | 0.276 | -0.0323 | 0.183 |
| | (0.994) | (0.104) | (0.232) | (0.879) | (0.403) |
| PREVEMP | 0.784 | -0.0820 | 0.447 | 0.228 | -0.475 |
| | (0.110) | (0.814) | (0.259) | (0.539) | (0.259) |
| PARTTIME | -0.326 | -0.579*** | -0.263 | -0.366 | 0.000237 |
| | (0.258) | (0.010) | (0.260) | (0.115) | (0.999) |
| ABILITY | -0.211* | 0.116 | -0.0670 | -0.0132 | -0.153* |
| | (0.054) | (0.138) | (0.419) | (0.867) | (0.063) |
| HOURS40+ | 0.131 | -0.206 | 0.279* | -0.499*** | 0.0561 |
| | (0.505) | (0.187) | (0.086) | (0.001) | (0.726) |
| UNION | -0.437* | -0.111 | -0.0618 | -0.147 | -0.348* |
| | (0.059) | (0.556) | (0.755) | (0.445) | (0.088) |
| TEMPORARY | -0.761** | -0.913*** | -0.614** | -0.873*** | -0.511 |
| | (0.040) | (0.004) | (0.048) | (0.006) | (0.217) |
| COMMUTE | -0.00191 | -0.00214 | -0.00263 | -0.00376** | -0.00429** |
| | (0.331) | (0.207) | (0.127) | (0.026) | (0.023) |
| WAGEREDUCT | -0.477* | -0.863*** | -0.783*** | -0.643*** | -0.711** |
| | (0.051) | (0.000) | (0.000) | (0.002) | (0.012) |
| JOBSECURITY | 1.110*** | 0.432* | 0.223 | 0.630** | 0.474* |
| | (0.005) | (0.084) | (0.394) | (0.016) | (0.060) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes |
| *N* | 749 | 1069 | 1068 | 1069 | 1069 |

*p*-values in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table C.3.
Generalized Ordered Logit: Low-Skill Referrals and Perceived Mismatch

| | (1) OVERALL | (2) NONWAGE | (3) SKILLFIT | (4) WAGE | (5) PROMOTION |
|---|---|---|---|---|---|
| 1 | | | | | |
| REFFF | -0.634* | -0.349* | -0.864 | -0.0263 | -0.175 |
| | (0.051) | (0.096) | (0.171) | (0.894) | (0.360) |
| REFCOWORKER | -1.026** | 0.528 | -0.496 | -0.336 | -0.357 |
| | (0.032) | (0.147) | (0.628) | (0.250) | (0.216) |
| REFCUREMP | -0.353 | 0.269 | -1.144 | -0.223 | 0.159 |
| | (0.468) | (0.438) | (0.178) | (0.451) | (0.600) |
| PREVEMP | -0.786 | -0.498 | 11.49 | -0.722 | 0.884 |
| | (0.354) | (0.292) | (0.983) | (0.137) | (0.121) |
| PARTTIME | 0.493 | 0.0410 | 0.928 | 0.556** | -0.0397 |
| | (0.235) | (0.878) | (0.253) | (0.039) | (0.867) |
| AGE | -0.00630 | 0.00285 | -0.0192 | -0.00730 | -0.0274*** |
| | (0.637) | (0.732) | (0.481) | (0.357) | (0.000) |
| HOURS40+ | 0.709* | -0.661*** | -1.459* | -0.263 | 0.211 |
| | (0.075) | (0.005) | (0.073) | (0.220) | (0.308) |
| UNION | 0.294 | 0.0162 | -0.608 | -0.0217 | -0.171 |
| | (0.511) | (0.952) | (0.460) | (0.931) | (0.487) |
| TEMPORARY | -0.584 | -0.776* | -0.676 | -0.521 | -0.568 |
| | (0.353) | (0.058) | (0.410) | (0.200) | (0.138) |
| COMMUTE | 0.00219 | 0.00270 | -0.00406 | 0.00133 | 0.00312 |
| | (0.622) | (0.189) | (0.615) | (0.465) | (0.211) |
| WAGEREDUCT | -0.463 | -0.632*** | -1.748*** | -0.700*** | -0.694*** |
| | (0.211) | (0.006) | (0.003) | (0.001) | (0.001) |
| JOBSECURITY | -0.0735 | 0.0806 | 1.552 | 0.197 | 0.241 |
| | (0.880) | (0.781) | (0.244) | (0.520) | (0.385) |
| 2 | | | | | |
| REFFF | -0.335 | -0.293 | -0.218 | -0.213 | -0.0795 |
| | (0.139) | (0.106) | (0.260) | (0.234) | (0.700) |
| REFCOWORKER | -0.145 | 0.193 | -0.233 | -0.279 | -0.375 |
| | (0.681) | (0.502) | (0.434) | (0.311) | (0.283) |
| REFCUREMP | 0.226 | 0.173 | 0.0688 | -0.377 | 0.372 |
| | (0.536) | (0.552) | (0.825) | (0.178) | (0.234) |
| PREVEMP | -0.205 | -0.836* | 0.462 | -0.225 | 0.121 |
| | (0.746) | (0.063) | (0.382) | (0.618) | (0.823) |
| PARTTIME | 0.0227 | -0.353 | -0.519** | -0.0381 | 0.0405 |
| | (0.937) | (0.121) | (0.025) | (0.869) | (0.882) |
| ABILITY | -0.0188 | 0.103 | 0.0466 | 0.132* | -0.142* |
| | (0.849) | (0.173) | (0.576) | (0.085) | (0.097) |
| HOURS40+ | 0.0506 | -0.228 | 0.441** | 0.179 | 0.400* |
| | (0.837) | (0.237) | (0.042) | (0.346) | (0.055) |
| UNION | 0.278 | 0.153 | 0.0182 | 0.163 | -0.169 |
| | (0.341) | (0.519) | (0.942) | (0.477) | (0.513) |
| TEMPORARY | -1.301*** | -0.535 | -0.260 | -0.267 | -0.458 |
| | (0.006) | (0.175) | (0.495) | (0.492) | (0.343) |
| COMMUTE | 0.000664 | 0.000839 | 0.00139 | 0.000550 | -0.00563* |
| | (0.664) | (0.503) | (0.513) | (0.495) | (0.062) |
| WAGEREDUCT | -0.228 | -0.402* | -0.909*** | -0.784*** | -0.254 |
| | (0.376) | (0.052) | (0.000) | (0.000) | (0.305) |
| JOBSECURITY | -0.000105 | 0.165 | 0.925*** | 0.754*** | 0.839*** |
| | (1.000) | (0.518) | (0.003) | (0.004) | (0.003) |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Demographics | Yes | Yes | Yes | Yes | Yes |
| *N* | 505 | 698 | 698 | 698 | 698 |

*p*-values in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table C.4.
Estimation of Cuts: Heterogeneous Referrals

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | OVERALL | NONWAGE | SKILLFIT | WAGE | PROMO |
| cut1 | -3.098*** | -1.088*** | -3.203*** | -1.089*** | -3.798*** |
| | (0.000) | (0.005) | (0.000) | (0.004) | (0.000) |
| cut2 | -2.016*** | -0.257 | -0.413 | -0.481 | -1.600*** |
| | (0.000) | (0.505) | (0.323) | (0.207) | (0.000) |
| $N$ | 1254 | 1767 | 1766 | 1767 | 1767 |

$p$-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.5.
Estimation of Cuts: Low-Skill and Referral Use

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | OVERALL | NONWAGE | SKILLFIT | WAGE | PROMO |
| cut1 | -3.915*** | -1.709*** | -2.704*** | -1.440*** | -4.275*** |
| | (0.000) | (0.001) | (0.000) | (0.007) | (0.000) |
| cut2 | -2.729*** | -0.811 | 0.116 | -0.800 | -1.991*** |
| | (0.000) | (0.129) | (0.841) | (0.136) | (0.000) |
| $N$ | 749 | 1069 | 1068 | 1069 | 1069 |

$p$-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.6.
Estimation of Cuts: High-Skill and Referral Use

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | OVERALL | NONWAGE | SKILLFIT | WAGE | PROMO |
| cut1 | -2.188*** | -0.246 | -3.608*** | -0.583 | -3.118*** |
| | (0.005) | (0.675) | (0.000) | (0.317) | (0.000) |
| cut2 | -1.197 | 0.534 | -0.760 | 0.0317 | -0.940* |
| | (0.119) | (0.364) | (0.246) | (0.957) | (0.082) |
| $N$ | 505 | 698 | 698 | 698 | 698 |

$p$-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

VITA

# VITA

Ben was born in Bloomington, IN but spent his early years in New Hampshire before moving to Louisville, KY. He attended Saint Louis University, earning BAs in both mathematics and history as well as a minor in economics. He continued onto Purdue University, earning his masters and eventually his PhD in economics. In his free time, Ben enjoys sailing, kayaking, and practically all other water-related activities. He is also a passionate supporter and fan of New England sports.