Labor Markets with Endogenous Job Referral Networks: Theory and Empirical Evidence

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Abstract

This paper develops a model of frictional job search in which job referral networks evolve endogenously in response to local labor market conditions. An intuitive "Network Balance" condition characterizes the equilibrium density of the job referral network. The model helps explain observed counter-cyclical movements in referral-based search, and shows that endogenous referral networks may amplify labor market shocks. It also implies that the use of referrals by others limits the effectiveness of referral-based search. I find support for this prediction using data from the Cornell National Social Survey. The data show workers are less likely to find jobs through referral in markets where referrals are more widely used.

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1 Introduction

Economists have long recognized the substantial role of job referrals as a form of search (Rees 1966; Ioannides and Loury 2004). The spread of communication technology seems to have strengthened, rather than weakened, local social networks (Mok et al. 2009), reinforcing their role as intermediaries of labor market information. A growing literature demonstrates empirically that job referrals and local social interactions matter, both for finding a job, and in terms of what happens on the job (Loury 2006; Bayer et al. 2008; Hellerstein et al. 2011; Goel and Lang 2009; Beaman and Magruder 2012; Dustmann et al. 2011; Schmutte 2015). Incorporating job referrals and social interactions should be a fruitful approach to improving the explanatory power of labor market models.

This paper makes two contributions to our understanding of the relationship between job referral networks and local labor markets. First, I develop a dynamic model of job search in which the density of the referral network is determined jointly with unemployment, vacancies, and the wage rate. Very few papers attempt to make referral networks endogenous, and this is the first to do so in a dynamic labor market model. I closely follow the model of Calvó-Armengol and Zenou (2005), in which workers respond to labor market conditions by varying the intensity with which they search for employment by seeking referrals. I introduce "Network Balance" as a condition determining the equilibrium density of the job referral network. The Network Balance condition requires that the amount of job information flowing to workers seeking referral be equal to the amount of job information flowing from workers giving referral. By adding this condition, the density of the referral network is a well-defined equilibrium outcome of individual decisions about referral-seeking effort.

Data from the Current Population Survey and Quarterly Workforce Indicators (QWI) show (i) a strong countercyclical relationship between referral-seeking and unemployment, (ii) a non-monotonic relationship between referral-seeking and labor market tightness. Both of these empirical features are new to the literature and consistent with the model. In this empirically relevant case, the model suggests movements in referral network density may amplify labor market shocks.

The paper's second contribution is to evaluate the relationship between local labor market conditions and referral-based hiring using new individual-level from the Cornell National Social Survey (CNSS). The CNSS data record whether workers found their most recent job through a referral. I combine these data with local labor market conditions, including unemployment, job flow rates, population density, and the CPS measure of referral use among the unemployed. The analysis shows that local labor market conditions explain more of the variation in referral-based hiring than do individual demographic characteristics. The data also support a key counterintuitive prediction of the job search model: the probability of being hired through referral is decreasing in the use of referrals by other workers. Because data on referral-based hiring is quite scarce, I also report basic facts from the the CNSS regarding variation in referral-based hiring across demographic and skill groups as well as across industries.

Altogether, this paper combines two basic insights. The first is that a referral network, as an informal labor market intermediary, emerges endogenously in response to labor market conditions. Workers use referrals more when jobs are hard to find through other means. The underlying ebb and flow of job information through referral networks is therefore an emergent outcome of the choices of individual workers deciding how to participate in job search. The second insight is that the endogenous evolution of this intermediation service can exacerbate variation across time and space in aggregate labor market outcomes. Together, the model in this paper explains how social institutions interact with labor market conditions, and how variability in labor market conditions can be driven by social institutions.

In Section 2, I describe the contribution of this paper. Section 3 introduces the model, focusing on the role of information transmission through referrals and its testable implications. In Section 3, I introduce the Network Balance condition and prove the existence of equilibrium in the density of the job referral network. 5 completes the full general equilibrium model, assessing its implications in light of the aggregate data. Section 6 tests the behavioral predictions from Section 3 and reports basic facts on referral hiring from the CNSS. Section 7 concludes with possible avenues for future work.

2 Related Literature

The present paper joins a broad theoretical literature that focuses on referral networks as conduits for information about employment opportunities. Arrow and Borzekowski (2004) and Calvo-Armengol and Jackson (2004) use partial equilibrium models to show that the structure of social networks can generate persistent differences in employment and earnings across groups of workers. Calvó-Armengol and Zenou (2005) and Fontaine (2008), push the same intuition into a general equilibrium framework in which it is possible to ask whether the partial equilibrium outcomes hold up and also how exogenous referral network structures affect the aggregate labor market. Galenianos (2011) considers a similar model, but allows for heterogeneous agents and the possibility that referrals assist with screening.

The challenge of endogenizing job referral networks has been addressed in a closely related paper. Galeotti and Merlino (forthcoming) build a static labor market model with endogenous job contact networks. Their paper provides a clear microfoundation of the network formation process as a strategic game played in advance of labor market matching. My approach to making referral networks endogenous is simpler. I introduce the concept of "Network Balance" as an equilibrium condition to endogenize referral network structure. This condition provides an explicit link between individual choices and the aggregate outcomes that are the focus of the model. Furthermore, as I demonstrate in the text, and exploit empirically, this formulation links the structure of the referral network to a measurable moment in aggregate data from the Current Population Survey (CPS). I trade off the clear, explicit, microfoundations of Galeotti and Merlino (forthcoming) against the ability to complete a dynamic general equilibrium model in which referral network density is endogenously determined along with unemployment, vacancies, and wages. One key theoretical result, that referral network density is non-monotonic with respect to labor market tightness, is common across both papers. That these two complementary approaches arrive at similar conclusions reflects the strength of the underlying idea. The two approaches provide different options for future research that extends the applications of endogenous referral networks.

This paper also contributes to a group of microeconometric studies of the link between local labor market conditions and the productivity of referrals. Galeotti and Merlino (forthcoming) also use data from the UK to find that productivity of referral is nonlinear in the regional separation rate. I add to this literature by documenting that referral productivity is also decreasing in the intensity of referral use. My model also predicts a non-linearity in the formal offer arrival rate, which I cannot directly measure. My estimates of the effect of the hiring rate, which is strongly positively correlated with the separation rate, are positive, but imprecisely estimated.

Wahba and Zenou (2005), using Egyptian data, find support for the prediction in Calvó-Armengol and Zenou (2005), that the probability of being hired through referral should be 'hump-shaped' in referral network density. In their model, referral networks are exogenous. Unlike their paper, I use reported referral use to measure referral network density rather than population density. In the empirical work, I draw on Wahba and Zenou (2005) by including a quadratic term in population density as an additional control for the cost of search through referral. Further progress in this area relies on finding sources of data that are both geographically detailed and include information on referral use.

3 Individual Referral-Seeking and Equilibrium Network Density

The model is an extension of Calvó-Armengol and Zenou (2005) that allows for endogenous density of the job referral network. Interest centers on the steady-state equilibrium of a matching model augmented with endogenous job referral networks. Making the structure of the referral network endogenous requires an additional equilibrium condition, for which I introduce the concept of Network Balance. Network Balance requires that the net intensity of requests for information within the network is balanced with the flow of information provided by the network. The equilibrium referral network responds to the extent of information flowing through the labor market, which is then determined by the optimizing behavior of firms maximizing the present value of vacancies. The model works through endogenous spillovers across the choice of referral-seeking intensity on the part of workers, and, in particular, that job-finding through referral is negatively related to the intensity of referral use in one's local labor market. I provide novel evidence in support of these implications in Section 6.

3.1 Model Setup

Workers begin each period either employed or unemployed, and choose a contact intensity that determines the amount of effort put into seeking referrals. Firms then decide whether or not to open new vacancies. Once vacancies are created, employers issue job offers at random to workers.

Search is undirected. Firms can not discriminate between employed and unemployed workers in making job offers. Workers who are unemployed and receive an offer retain it and become employed. Workers who are already employed and receive an outside offer are able to pass a job offer on to an unemployed worker requesting information from her – to make a referral. If there is more than one unemployed person requesting information, she chooses someone at random. At the end of this transfer stage, all unemployed workers with at least one job offer become employed, and all job offers that have not been transferred by employed workers expire.

Time is discrete and workers and firms are infinitely lived. There is a continuum of measure μ of identical workers, a fraction of whom begin the period employed. Workers discount the future at rate ρ, maximize wealth, and receive utility b when unemployed. There is a continuum of measure 1 of identical firms. The unemployment rate at the beginning of any period t is u_{t-1}. Employers open a total of V_t vacancies. $v_t = V_t/\mu$, the expected number of offers per worker, is the formal recruiting intensity on the part of employers. As is common in matching models, we assume the number of offers received by any worker is a Poisson random variable with expectation v_t. Thus, an individual worker hears about at least one vacancy through the formal market with probability $\lambda_t = (1 - e^{-v_t})$. Each filled vacancy produces y_0 units of output when initially occupied, and $y_1 \geq y_0$ in each subsequent period that the position is filled.

Workers also search for jobs through referral by asking other workers for job information. Each worker, i, chooses a contact intensity, γ_i, that determines how many workers he will query for a job offer. The number of workers contacted follows a Poisson distribution with mean γ_i. By assumption, workers do not discriminate between unemployed and employed workers when looking for referrals.[1] Workers also do not know how many other workers are asking any given contact for a referral. They must predict the expected number of competitors for information.

For a given worker, j, who is contacted by i for a referral, let X_j be the number of requests for referrals. X_j is Poisson with $E(X_j) = s$. All workers are homogeneous, so $E(X_j) = E(X_k) = s$. Note that the referral network at t is completely characterized by the single parameter s. Call s the 'density' of the referral network. In simple random graphs, this is the characteristic feature of the network in the sense that the average degree of nodes in a simple random graph is a sufficient statistic for the graph structure.

Once all job offers have been transferred to their final destinations, unemployed workers become employed if they receive at least one offer and begin to produce. In the first period of employment, they earn the 'training' wage, w_0, and earn w_1 in subsequent periods.

The present model abstracts away from on-the-job search, as does the Calvó-Armengol and Zenou (2005) model it extends. A large empirical literature documents that many new jobs are associated with job-to-job transitions. This raises the question of when an employed worker will keep a new job offer rather than pass it on. Incorporating on-the-

[1] The latter assumption may seem counterintuitive, since workers should know who is employed and therefore be able to direct their search for referrals. This assumption is not essential for the results, but makes the problem simpler to set up.

job search in a meaningful way would require a model in which jobs differ on the basis of some characteristic – most likely the wage – about which workers care. Such models have been partially developed in Mortensen and Vishwanath (1994) and Schmutte (2015). A full treatment of these issues is beyond the scope of this paper, but it should be possible to incorporate the network balance condition into a model with wage posting and on-the-job search.

3.2 The Within-Period Flow of Job Information

I next focus on how job information moves through the labor market within each period. Workers are small relative to the market, and so do not take account of how their choices affect aggregate outcomes. Taking the unemployment rate, vacancy rate, and referral network density as fixed at their steady-state values, workers choose a referral contact intensity, γ_i, to maximize the present value of lifetime utility. When the economy is in steady-state, there is no inter-temporal dimension to this choice. For the rest of this section, I suppress time subscripts.

The decision to use referrals is determined by how productive they are in generating offers. When a worker requests a referral, what is the probability that he receives one? It is the probability of the joint event that his contact is employed, is holding a job offer, and chooses to give him the offer from among all the other people asking for a referral. Assume the worker contacted for a referral is worker j. Since the process of contacting workers for referral is undirected, the probability that worker j is employed is simply $1-u$. Since the formal job search process is also undirected, given the Poisson assumption, the probability that j holds at least one job offer is $\lambda = (1 - e^{-v})$.

The probability that worker j chooses to give worker i the offer from among all people asking her for a referral is $\mathrm{E}[\frac{1}{k+1}]$ where k is the number of competing referral requests.[2] The number of competitors for referral, k, is also Poisson with parameter s, and $\mathrm{E}[\frac{1}{k+1}] = \frac{(1-e^{-s})}{s}$ (see Appendix A). To highlight the economic intuition, observe that the probability limit of receiving an offer as the expected number of competitors, s, goes to zero, is one. Likewise, as s goes to infinity, the probability of getting an offer through referral goes to zero. Also, it is easy to show that this probability is always decreasing in s, since $s > 0$ always.

[2] Technically, an employed worker can receive more than one job offer, as can an unemployed worker. It is possible to assume contacts distribute all unused offers – see Appendix B. One advantage of such an extension is that unemployed workers can also provide referrals if they receive multiple offers. This extension adds some complexity to the model without changing its qualitative implications.

The probability that a worker who was asked for a referral actually provides one is:

$$\pi(u, v, s) = \frac{(1-u)(1-e^{-v})(1-e^{-s})}{s} \tag{1}$$

This expression has a number of intuitively appealing properties. If $u = 1$, so that all workers are unemployed, the probability of getting an offer through referral is 0. Likewise, if there are no jobs coming from employers, $v = 0$ and $\pi(u, 0, s) = 0$. An immediate implication is that the number of productive requests for job information is distributed Poisson with parameter $\gamma_i \pi(u, v, s)$. Let $P(u, v, s, \gamma_i)$ be the probability of getting at least one offer through referral. Then

$$P(u, v, s, \gamma_i) = 1 - \exp[-\gamma_i \pi(u, v, s)]. \tag{2}$$

Using the properties of Poisson random variables again, the number of job offers a worker receives from all sources is Poisson distributed with rate parameter $v + \gamma_i \pi(u, v, s)$. So, the probability that an unemployed worker finds at least one job offer and gets hired is

$$h(u, v, s, \gamma_i) = 1 - \exp[-(v + \gamma_i \pi(u, v, s))]. \tag{3}$$

3.3 The Effort Put into Seeking a Referral

As in Holzer (1988), the intensity of referral search is chosen to maximize individual utility, given the expected productivity of their use. Referral productivity depends on local labor market conditions and the extent of competition for referrals. It may also depend on individual characteristics that influence the cost of using referrals and the benefits of finding work. Let K_i denote the value to worker i of obtaining employment, and let c_i denote the constant marginal cost of intensifying the search for a referral.[3]

The worker's intra-period choice problem is to choose the referral contact intensity to maximize:

$$\max_{\gamma_i \geq 0} (h(u, v, s, \gamma_i))K_i - c_i \gamma_i. \tag{4}$$

[3] The constant marginal cost assumption is made for convenience of exposition, but is not required for the model's predictions.

The contact intensity, γ_i, is the solution to the Kuhn-Tucker condition:

$$\gamma_i \left[\frac{\partial h}{\partial \gamma_i} K_i - c_i \right] = 0 \quad (5)$$

$$\gamma_i \geq 0. \quad (6)$$

At an interior solution, the marginal increase in the probability of being hired associated with increasing search effort is equated with the cost-benefit ratio:

$$\frac{\partial h}{\partial \gamma_i} = \frac{c_i}{K_i} \quad (7)$$

$$\pi(u, v, s) \left[1 - h(u, v, s, \gamma_i)\right] = \frac{c_i}{K_i} \quad (8)$$

$$\pi(u, v, s) \left[\exp(-(v + \gamma_i \pi(u, v, s)))\right] = \frac{c_i}{K_i}. \quad (9)$$

Equation (8) shows that the marginal benefit of increasing contact intensity on the probability of being hired is increasing in referral productivity, π, and decreasing in the hiring probability. It is the probability a worker gets a referral in the case he would not have otherwise been hired. The marginal benefit of increasing γ_i is the expected increase in probability of getting an offer through referral conditional on not receiving an offer otherwise.

The third equation can be solved for γ_i at an interior solution:

$$\gamma_i^* = \frac{\ln \pi(u, v, s) - v - \ln \frac{c_i}{K_i}}{\pi(u, v, s)}. \quad (10)$$

Increases in the productivity of referrals through π have opposing effects on contact intensity. At the intensive margin, an increase in π means that any person contacted for referral is more likely to be provide one. At the extensive margin, for any given number of referral contacts, a larger fraction of them are expected to be productive.

These two effects create opposing incentives for the choice of contact intensity. The relationship between γ_i^* and the arrival rate of offers, v, is non-monotonic, increasing when v is low, suggesting that at low levels, increases in v will push more workers to use referrals because they are more productive. As the arrival rate of formal offers increases, workers are increasingly likely to find employment through formal means, making the cost of referrals less attractive.

3.4 Implications

This model of individual choice yields several implications for the relationship between local labor market conditions and the probability of being hired through referral. Notably, the probability a worker is hired through referral is decreasing in the intensity of referral use by other workers. Section 6 provides evidence consistent with this prediction using individual-level data from the Cornell National Social Survey (CNSS) that record whether individuals were hired to their current job through referral.

Substituting the solution for the optimal referral-use intensity, γ_i^*, from Equation 10, into the equation for the probability of obtaining a referral, $P(u, v, s)$, Equation 2, yields

$$P^*(u, v, s) = 1 - \frac{c_i e^v}{K_i \pi(u, v, s)}. \tag{11}$$

Recall that u and v are the unemployment rate and formal offer arrival intensity. The variable s is the density of the referral network, c_i is the marginal cost of search through referral, and K_i is the value of employment. It follows that the unconditional probability of being hired through referral is

$$R^*(u, v, s, K_i, c_i; q) = (q + (1-q)e^{-v})P^*(u, v, s), \tag{12}$$

where q is the probability that a worker takes a referral when one is available.

The model delivers the following comparative static predictions, which are proven in the Appendix:

Claim 1. $\frac{\partial R}{\partial \gamma^*} < 0$. *The probability of being hired through referral is strictly decreasing in referral network density.*

Claim 2. $\frac{\partial R}{\partial u} < 0$. *The probability of being hired through referral is strictly decreasing in the unemployment rate.*

Claim 3. *There exists a* v^* *such that* $\frac{\partial R}{\partial v} > 0$ *when* $v < v^*$ *and* $\frac{\partial R}{\partial v} < 0$ *when* $v \geq v^*$.

Intuitively, $\frac{\partial R}{\partial \gamma^*} < 0$ reflects congestion. Increases in referral-seeking on the part of unemployed workers unambiguously makes referrals less productive, and therefore makes workers less likely to seek them. Similarly, $\frac{\partial R}{\partial u} < 0$ because higher rates of unemployment also increase the competition for referrals and make them less productive.

Increases in the offer arrival rate, v, have two offsetting effects. The direct effect of a higher offer rate is to increase the probability that a worker gets an offer directly, and so does not need referral. The indirect effect is that referrals, when used, are more likely to be productive. The indirect effect dominates the direct effect when the offer rate is very low.

The critical value, v^*, is the formal offer rate at which the direct effect begins to dominate. The extent to which workers prefer offers obtained through referral to offers obtained directly, measured by the variable q, affects the critical value. Specifically, if $q = 1$, then $v^* > 0$. Increases in q decrease v^*, and there are parameterizations of the model with $q \in (0, 1)$ where $v^* = 0$. That is, if workers always take referrals over direct offers, then increases in the formal offer rate unambiguously decreases the probability of being hired through referral.

When evaluating these predictions in Section 6, there are two interpretive issues to consider. First, we can not tell whether workers who do not report finding their current job through referral tried unsuccessfully to get a referral or if they did not try to get a referral at all. Note, for instance, that corner solutions are possible. $\gamma_i > 0$ requires

$$\pi(u, v, s)e^{-v} > \frac{c_i}{Ki}. \tag{13}$$

This result implies that there could be selection to referral use on the basis of variation in $\frac{c_i}{K_i}$ for workers in the same labor market. For developing the general equilibrium model, I assume all workers are homogeneous and therefore choose the same level of referral-seeking. The interpretation of the results in Table 4 does not depend crucially on this assumption. See Appendix B.2 for a full discussion of these points.

A second interpretive issue arises from the fact that the analysis of the relationship between local labor market conditions and referral in the CNSS is restricted to workers who recently changed jobs. As a result, the analysis is restricted to employed workers. This restriction is needed to match the state of the labor market at the time when a worker was hired through referral. The relevant comparative static predictions are, therefore, for the probability that a currently-employed worker was hired through referral. The key predictions remain the same. See Section 6.2.2 for details.

4 The Equilibrium Network Density

I now describe how equilibrium referral network density is determined by individual contact intensities. Workers respond to expected competition for job information from each worker they contact. Thinking in terms of a referral network, where requests for job information are directed edges, the number of people requesting information from worker j is the 'in-degree' of j. A form of balance must obtain in such a network. All of the 'incoming' requests for information received by workers are also 'outgoing' requests for information sent by workers. This provides a balancing condition: the expected number of incoming requests for job information must equal the expected number of outgoing requests.

In the steady-state equilibrium of the model it is clearly the case that workers only use referrals when unemployed. Furthermore, following Calvó-Armengol and Zenou (2005), I assume workers are homogeneous for characterizing the model's equilibrium. It follows that:

Claim 4. *Network Balance*

$$s = \gamma^* u,$$

where γ^* is the common choice of γ among unemployed workers.

(Proof in Appendix)

Since γ^* is a function of s determined as the solution to the worker's within-period choice problem, we have

$$s = \gamma^*(u, v, s)u. \tag{14}$$

We define the equilibrium network density s^* as the fixed point in s, if one exists, to the above expression.

Claim 5. *s^* exists and is unique.*

(Proof in Appendix)

Section 5 incorporates this network balance condition into a general equilibrium matching model and illustrates the equilibrium network balance relationship.

5 Labor Market Equilibrium

To complete the model, I embed the Network Balance condition into the dynamic labor market equilibrium that matches firms and workers. The model delivers the usual steady-state equilibrium quantities: unemployment, vacancies, and wages (u^*, v^*, w_1^*). The referral search intensity, γ^*), which is equivalently the referral network density, is endogenously determined with these other four outcomes.

The Worker's problem

$I_{E,t}$ is the present value of the utility stream associated with being employed

$$I_{E,t} = w_1 + \frac{1}{1+\rho}\left[(1-\delta)\, I_{E,t} + \delta I_{U,t}\right]. \tag{15}$$

$I_{U,t}$ is the present value of the utility stream associated with being unemployed:

$$I_{U,t} = \max_{\gamma_t}\left\{b - c(\gamma_t) + h(u_{t-1}, v_t, \gamma_t, s_t)\left[w_0 + \frac{1}{1+\rho}\left((1-\delta)\, I_{E,t} + \delta I_{U,t}\right)\right]\right\}. \tag{16}$$

I already showed in Section 3.3 how the worker chooses γ_t for given $(u_{t-1}, v_t, w_{1,t})$ along with the constant K, which we now see includes the present discounted value of future earnings streams associated with being employed. In steady-state equilibrium, the choice of $\gamma_{i,t}$ only affects this through the hiring probability h.

I proceed by substituting into Equation (16) the within-period solution γ_t that satisfies the Kuhn-Tucker condition and network equilibrium, $s_t = \gamma_t u_{t-1}$, so that

$$I_{U,t} = b - c(\gamma_t) + h(u_{t-1}, v_t, \gamma_t)\left[w_0 + \frac{1}{1+\rho}\left((1-\delta)\, I_{E,t} + \delta I_{U,t}\right)\right]. \tag{17}$$

I follow the literature in assuming that the outside option, $b = 0$, and competitive pressure dictates $w_0 = b = 0$. It follows that the steady state increment to utility associated with finding a job is

$$I_E - I_U = \frac{1+\rho}{\rho + \delta + (1-\delta)h(u, v, \gamma)}\left(w_1 - c(\gamma)\right). \tag{18}$$

The Employer's Problem

Firms open vacancies according to a free entry condition: the expected profit stream associated with the marginal vacancy is 0. Vacancies cost κ per period to keep open. A given vacancy is filled with probability $f(u_{t-1}, v_t, s_t)$.

The number of new job matches in the economy in period t is

$$u_{t-1}\mu h(u_{t-1}, v_t, \gamma_t), \tag{19}$$

so the rate at which vacancies are matched to unemployed workers must be

$$m(u_{t-1}, v_t, \gamma_t) = u_{t-1} h(u_{t-1}, v_t, \gamma_t). \tag{20}$$

Hence, the probability that a particular vacancy is filled is equal to

$$f(u_{t-1}, v_t, s_t) = \frac{m(u_{t-1}, v_t, \gamma_t)}{v_t}. \tag{21}$$

This implies

$$\frac{f(u_{t-1}, v_t, s_t)}{h(u_{t-1}, v_t, \gamma_t)} = \frac{u_{t-1}}{v_t}. \tag{22}$$

Here, as in Calvó-Armengol and Zenou (2005), because the matching function is not homogeneous of degree 1, the v/u ratio is not a sufficient statistic to characterize tightness.

The present value of the profit stream associated with a filled vacancy is

$$I_{F,t} = y_1 - w_1 + \frac{1}{1+\rho}\left[(1-\delta)\, I_{F,t} + \delta I_{V,t}\right]. \tag{23}$$

The present value of the profit stream associated with an unfilled vacancy is

$$I_{V,t} = -\kappa + \frac{1}{1+\rho}\left\{(1 - f(u_{t-1}, v_t, s_t))\, I_{V,t} + f(u_{t-1}, v_t, s_t)\left[(1-\delta)\, I_{F,t} + \delta I_{V,t}\right]\right\}. \tag{24}$$

Free entry implies $I_{V,t} = 0$. Invoking the steady state assumption and rearranging terms yields

$$I_F = \left(\frac{1+\rho}{1-\delta}\right) \frac{\kappa}{f(u, v, s)} \tag{25}$$

and the "labor demand curve"

$$\frac{y_1 - w_1}{\rho + \delta} = \left(\frac{1}{1-\delta}\right) \frac{\kappa}{f(u, v, s)}. \tag{26}$$

Wages

Workers and firms bargain over the surplus associated with the match. The wage, w_1 acts to transfer the surplus wealth from the firm to the worker. The bargaining solution is determined as the solution to the cooperative Nash problem

$$w_1 = \arg\max \left(I_E - I_U\right)^{\beta} \left(I_F - I_v\right)^{(1-\beta)}. \tag{27}$$

The new parameter, $0 \leq \beta \leq 1$ is the worker's bargaining power. Solving this problem yields:

$$w_1 = \beta\left(y_1 + \kappa \frac{v}{u}\right) + (1-\beta) c(\gamma). \tag{28}$$

5.1 Steady State Labor Market Equilibrium

The steady state equilibrium is defined as a tuple $(u^*, v^*, w_1^*, \gamma^*)$ of unemployment rate, vacancy rate, wage, and referral network density that jointly satisfy the four equilibrium conditions:

Beveridge Curve

$$(1-\delta)m(u,v,s) = \delta(1-u) \tag{29}$$

Labor Demand

$$\frac{y_1 - w_1}{\rho + \delta} = \left(\frac{1}{1-\delta}\right)\frac{\kappa}{f(u,v,s)} \tag{30}$$

Wage Setting

$$w_1 = \beta\left(y_1 + \kappa\frac{v}{u}\right) + (1-\beta)c(\gamma) \tag{31}$$

Network Balance

$$s = \gamma^* u,$$

where γ^* is the common choice of γ among unemployed workers.

The evolution of unemployment over time is given by the difference between the flow into unemployment and the flow out of unemployment

$$u_t - u_{t-1} = \delta(1-u_{t-1}) - (1-\delta)u_{t-1}h(u_{t-1}, v_t, \gamma_t) \tag{32}$$

In steady state,

$$(1-\delta)m(u,v,s) = \delta(1-u). \tag{33}$$

5.2 The Empirical Relationship between Aggregate Referral Use, Unemployment, and Labor Market Tightness

Figure 1 plots, for the period 1998–2010, the monthly unemployment rate and share of unemployed workers who report asking friends and neighbors for information as part of their job search. The correlation between the referral share and the unemployment rate is 0.85. Altogether, the data indicate that the use of referrals in job search strongly counter-cyclical.[4]. Figure 1 is consistent with the general equilibrium model characterized in Section 5.

[4]Note that the denominator for the share of workers that use referral is the number of unemployed workers, which is the numerator of the unemployment rate. If anything, this mechanical relationship should induce a negative correlation between the two time series. Indeed, the correlation between the referral share and the employment-population ratio, which should be free of this form of bias, is -0.9.

The model also characterizes the relationship between the vacancy rate and referral network density. However, there is no state-level source of information on vacancies for the period of study. Instead, I consider a proxy for labor market tightness that is available from the QWI – the average number of periods of non-employment for newly hired workers. This QWI variable measures, for all newly hired workers, the number of quarters (up to a maximum of 4) they were not observed in employment. Intuitively, small values for this variable are associated with markets in which unemployed workers are hired quickly, and high values are associated with markets where they are not.[5]

Figure 2 displays a scatter plot of state-year averages of the two variables. The source data are state-level summaries of referral use from the CPS, and average non-employment duration for new hires from QWI, over the period 1998–2010. On the horizontal axis is the state-year average number of periods of non-employment for newly hired workers. On the vertical axis is the state-year share of unemployed workers who used referral as part of job search. The figure also includes a second-order polynomial trend line. The figure indicates that the referral share is non-monotonic in the average non-employment duration. This feature of the data is consistent with the basic comparative static predictions of the model, and anticipates the general equilibrium model in Section 5.

5.3 Model Implications

The nature of the equilibrium relationships is illustrated in Figure 3. The figure is plotted in the (u, v) domain to highlight the similarity with a conventional matching model. The Beveridge Curve and Job Creation locus retain their conventional shape. In addition to u and v, we add the equilibrium referral network density parameter, γ.

Note that the Network Balance locus is 'hump-shaped' in (u, v). Any unemployment rate can support two different vacancy rates at a particular level of referral use. The intuition behind this result is related to the reason the probability of finding a job through referral is non-monotonic in the offer arrival rate. When the vacancy rate is low, increases in the vacancy rate tend to drive workers to seek referrals, because they are more productive. To offset this effect, unemployment must rise. Eventually, the vacancy rate becomes high enough that further increases drive workers away from referrals, because they are unnecessary. At that point, the unemployment rate must decrease to draw workers back

[5] Consistent with this intuition, and the idea of using this variable as a proxy for the vacancy rate, I note the correlation between unemployment and the average non-employment duration is positive, at 0.2279, as in an inverse Beveridge curve.

to referral use.[6]

The movement of network density over the business cycle is theoretically ambiguous. Equilibrium density, γ, is increasing within the region bounded by the Network Balance curve. An inward shift of the Job Creation curve reduces vacancies, increases unemployment, and increases referral density. More plainly, a demand-driven recession increases referral network density. By contrast, an outward shift of the Beveridge Curve should increase vacancies, increase unemployment, and reduce referral density. Thus a recession associated with structural changes in the rate of job matching will reduce referral use. The results in Figure 1 show that, empirically, referral network density is highly counter-cyclical.

The model also predicts that reservation wages, and hence bargained wages, will change over the business cycle. It therefore provides an alternate, potentially complementary, explanation for the Shimer puzzle. Shimer (2005) shows that the benchmark equilibrium matching model on which this paper builds, predicts counter-factually small labor supply fluctuations in response to productivity shocks that affect job creation. In the example from Figure 3, a negative productivity shock that reduces employment will also increase the referral network density. As a result, the downward pressure on wages from reduced productivity is compensated by upward pressure that arises because the cost of search through referral increases (see Equation 31). The counter-cyclical movements of referral network density illustrated in Figure 1 serve to amplify the effects of productivity shocks on unemployment relative to a case with a constant outside option.

Note that referrals are generally thought to be a relatively inexpensive form of search, so this mechanism is unlikely to explain a substantial portion of excess volatility in unemployment. Even less is known about the relative costs of search through different channels than is known about the presence of referrals. One study, Caliendo et al. (2010), finds that reservation wages are increasing in the size of the individuals referral network, albeit in a different context.

[6] The non-monotonicity in the Network Balance equation is consistent with a similar finding by Galeotti and Merlino (forthcoming). Using a static model and a different mechanism for making referrals endogenous, they show that referral use is non-monotonic in the economy's separation rate. The same kind of congestion-driven relationship also appears in a different form in Calvó-Armengol and Zenou (2005) and Wahba and Zenou (2005).

6 Does Network Congestion Matter?

The model motivates an exploration of the relationship between local labor market conditions and the productivity of job referral. In the steady-state equilibrium, the model makes strong comparative static predictions based on the assumption that there are endogenous spillovers in referral use. These spillovers imply that the probability that a worker is hired through referral is negatively related to the density of the local referral network. In this section, I use novel data from the Cornell National Social Survey, together with data on local labor market conditions, to provide evidence in support of this model feature. I use data on the aggregate referral-seeking intensity of the unemployed collected in the Current Population Survey (CPS), and show how this data moment can be used to measure the density of the referral network. Along the way, I provide new descriptive evidence on the use and productivity of referrals.

6.1 Data

Cornell National Social Survey

The 2008 Cornell National Social Survey (CNSS) was a random digit dial survey collected by the Survey Research Institute at Cornell University in November and December 2008.[7] The sample was meant to be representative of the total U.S. population. The survey asked respondents to report whether they obtained their most recent job through the referral of a friend or relative who already worked for the same employer. In addition, the survey collected a range of demographic, work history, and opinion questions.[8] Equally important for studying the relationship between job referrals and local labor market conditions is that that data have geographic detail that extends to the level of the Census block group. I use the geo-codes on the CNSS to merge data on local labor market conditions confronting each individual.

To measure local labor market conditions at the time of referral, I need to know when the referral occurred and where the worker was searching for work at that time. The job referral question in the CNSS applies to a worker's most recent job. To determine when they were searching for that job, I use information from another question on completed

[7] Data from the CNSS are available at `https://cisermgmt.cornell.edu/cnss/`.

[8] In addition to a battery of standard demographic questions, the CNSS allowed various researchers from Cornell University to submit questions that would be administered as part of the survey. The crucial question used in this paper on referral behavior was sponsored by Brian Rubineau. I also use some of the work history questions sponsored by Yael Levitte and Matthew Freedman. I am indebted to all three for their generosity in letting me use these data for this analysis

tenure, which is available only for currently employed workers. The tenure question is only sufficiently finely-grained for workers who obtained their most recent job within the last two years. For those workers, I can observe whether they have moved since starting their job. Imposing these restrictions leaves a sample of 168 workers. Complete data on all local labor market characteristics are available for 142 of these. The small sample size limits the power of my statistical tests. Given the data, my finding that the effect of referral network density decreases the productivity of referrals is strong and robust, and, as I will argue, difficult to explain on the basis of alternative mechanisms.

Data on Local Labor Market Conditions

The local labor market variables include measures of unemployment, job accession and separation rates, and the use of personal contacts to search for work. County-level unemployment rate data come from the Local Area Unemployment Statistics (LAUS) of the BLS. Data on the rate of hiring, and the duration of non-employment for newly hired workers are from the Quarterly Workforce Indicators (QWI) developed by the Longitudinal Employer and Household Dynamics (LEHD) program of the U.S. Census Bureau and are also included as county level aggregates[9]. Finally, data on referral use as a form of search are collected in the Basic Current Population Survey. In all cases, I use the values of local labor market conditions in 2007 to correspond as closely as possible to the conditions that prevailed when they found their current job.

Referral Network Density

I transform the share of unemployed workers that report using referrals as part of job search from the CPS to measure the referral network density. Let p_k^{ref} be the fraction of unemployed workers in state k who contacted at least one friend as measured in the CPS. From this, I can back out $\bar{\gamma}$ as

$$\bar{\gamma_k} = -\log(1 - p_k^{ref}), \tag{34}$$

which follows from the fact that the probability of contacting at least one friend, given a referral search intensity of γ_k^*, is $1 - e^{-\gamma_k^*}$.[10]

[9]This paper uses the R2012Q1 version of the public use QWI. The raw data are available for download from http://www.vrdc.cornell.edu/news/data/qwi-public-use-data/ For a comprehensive overview of the LEHD data and production of the QWI, see Abowd et al. (2009).

[10]The empirical results are qualitatively the same whether I use p_k^{ref} directly or the transformation to γ^*. I report my results using γ^* to maintain consistency with the model.

6.2 Results: The Probability of Being Hired Through Referral

Table 1 presents summary statistics for the full CNSS and the final sample. The sample is, as expected, younger, but otherwise demographically similar to, the full population. About 30 percent of workers report being referred for their current job, which is consistent with the fraction reported in the survey in Ioannides and Loury (2004). The table also reports the sample mean of the local labor market variables across CNSS workers. The average worker confronts a market in which 22 percent of unemployed workers report using personal contacts to find work.

6.2.1 Who Gets Referred?

Because data on referral use is fairly uncommon, there is value in reporting basic descriptive statistics on who is hired through referral, and in what parts of the economy they work. The CNSS collects information on basic demographic and human capital characteristics making it straightforward to document how referrals affect different groups of workers. The 2008 CNSS included a question about the industry in which a worker is employed, but is otherwise somewhat limited in the information it collects on job characteristics.

Table 2 reports the share of workers who report having obtained their most recent job through referral. Table 3 restricts the analysis to the main analysis sample of employed workers who recently changed jobs. The former results draw on a larger sample size; the latter should better capture the role of referral in the labor market. The overall share of workers hired through referral is 28.03 percent in the full sample and 29.76 percent among workers who recently changed jobs. Both figures are at the bottom of the range of estimates reported in U.S. survey data (Bewley 1999).

Focusing on the overall sample in Table 2, the data indicate very little variation across demographic groups in the probability of being hired through referral. These findings are consistent with Holzer (1988) and other research summarized in Ioannides and Loury (2004). Black workers are slightly less likely to have been hired through referral than white workers, and Hispanic workers are slightly less likely than non-Hispanic workers. At 16.67 percent, only the share of non-native workers hired through referral is considerably smaller than the overall employed population. The table also shows that college-educated workers are roughly 20 percent less likely to have been hired through referral than non-college educated workers. On the demand side, I also report the shares disaggregated by sector. Consistent with evidence from the NLSY reported by Kugler (2003), the share of referred workers is highest in the goods-producing sectors (34.02 percent) and the service sector (30.11 percent). The share is lowest in public administration (21.74 percent).

Among the sample of recent job changers in Table 3, some of these patterns change. Among this subsample, black and Hispanic workers are slightly more likely to have been hired through referral than are white or non-Hispanic workers. Furthermore, non-native workers are no less likely to have been referred than natives. High school-educated workers remain considerably more likely to have been referred than college educated-workers. Likewise, the pattern of referral use across sectors is qualitatively identical, but the differences are much larger in magnitude – 47.83 percent of workers in the goods-producing sector found their job through referral. Because of the small sample sizes, some caution is required when interpreting these latter results. Overall, these descriptive statistics indicate that very little of the variation in hiring through referral is associated with observable individual characteristics.

6.2.2 Does Network Congestion Matter?

Table 4 presents results of probit models that predict whether CNSS workers obtained their current job through referral. Of primary interest is the effect of other workers' decisions to use referral in job search on the probability of being hired through referral. From Claim 1, the model predicts the probability of being hired through referral is decreasing in the density of the referral network. The parameter on the state referral network density, γ, measures this effect.[11]

The data consistently show a strong negative correlation between referral network density and the probability of being hired through referral. In all specifications, the marginal effect of referral network density is around -1.1. At face value, this implies a one standard deviation increase in referral network density is associated with a five percentage point decrease in the probability of being hired through referral. Since the baseline probability of being hired through referral is about 30 percent, this is a large estimate.

The models in column (1) and column (2) compare the explanatory power of individual characteristics and local labor market conditions. Local labor market conditions

[11] Technically, Claim 1 is a statement about the unconditional probability of being hired through referral. The CNSS data condition on employment, so the relevant prediction is that the probability that an employed worker was hired through referral is decreasing in the referral network density. A proof of this prediction appears as Claim 6 in Appendix .

are at least as good at predicting variation in the productivity of referral as individual demographic and human capital characteristics. The reader might be surprised by the statistical and economic insignificance of individual characteristics in the probability of being hired through referral. This is consistent with Holzer (1988), who finds finds that individual characteristics do not explain cross-sectional variation in the probability of a job offer in data from the Youth Cohort of the National Longitudinal Survey.

Of course there is concern that these models are plagued by self-selection and omitted variables. The measure of referral network density could simply be absorbing omitted factors that make the probability of being hired through referral less likely. If so, then controlling for factors that directly affect the probability of being hired through referral should attenuate the omitted variable bias.

Columns (3), (4) and (5) attempt to control for factors that influence the costs and benefits of search through referral. Population density was suggested by Wahba and Zenou (2005) as a proxy for network density. I use tract-level population density as a proxy for the cost of contact. Workers in higher density tracts will find it easier to search through referral, all else the same. The coefficient on density is positive, although imprecisely estimated, and the quadratic term is negative, as in Wahba and Zenou (2005). In column (5), I reintroduce individual-level observables correlated with referral use and productivity. This attenuates the estimate of γ, but only modestly.

To understand the significance of this finding, note that unless there are spillovers or general equilibrium effects, models with homophily and correlated shocks predict that workers in states with high levels of referral use will also use referrals a lot. The persistent negative correlation between referral network density and referral productivity supports the importance of spillovers in general, as is consistent with the model proposed in this paper. Of course, other models are consistent with this finding. For instance, if employers are less likely to hire through referral when the number of people seeking referrals is high, we would see the same negative correlation. The challenge of distinguishing different equilibrium models of referral use is left to future work.

Note also that the results do not uphold the other comparative static predictions. In the model, the unemployment rate is predicted to decrease the probability of being hired through referral. In the data, however, there is essentially no relationship between county-level unemployment and being hired through referral. We do not have a good proxy for the vacancy rate nor for the formal offer arrival rate. The county-level hiring rate is a potential proxy for the overall rate of recruiting intensity. This has a positive but statistically insignificant point estimate. Since the rates of hiring and separation tend to move together, this finding is somewhat at odds with Galeotti and Merlino (forthcoming) who find a negative relationship between the separation rate and hiring through referral.

7 Conclusion

I have presented a frictional matching model with an endogenous job referral network. The key structural feature of the referral network determined in the model is its steady-state density. Workers adjust their referral-seeking behavior in response to local labor market conditions, including an endogenous spillover mediated through the referral network density. In equilibrium, referral network density increases when markets are slack, consistent with the intuition that referral networks as a social institution emerge endogenously to facilitate exchange.

As a check of the modeling assumptions, I have also provided new information on the link between referral productivity and aggregate referral use. The data provide consistent evidence that referral productivity is negatively correlated with aggregate referral use. This stylized fact is consistent with the model, and should be of interest to those studying the microeconomic determinants of referral use and productivity.

The theoretical model in this paper is very simple, and there is more work to do on a full characterization of the steady-state equilibrium and its implications for cross-sectional variation in employment and earnings. Also, the model does not incorporate heterogeneity among workers, in terms of the returns to search, the cost of search, or opportunities for referral. Finally, I have not yet considered how, if at all, the presence of endogenous referral networks affects labor market policy. All of these extensions are feasible within the current modeling framework.

Empirical work in this area is compromised by the lack of data that combine good geographic detail with information on referral use. Nevertheless, it should be possible to use the existing theoretical framework with aggregate data on referral use from the CPS to evaluate the model across variation in employment conditions and referral use across states. The implications of this model for explaining local labor market variability and volatility, and the effects of social networks on the efficacy of labor market policy, are topics for future research.

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Figures and Tables

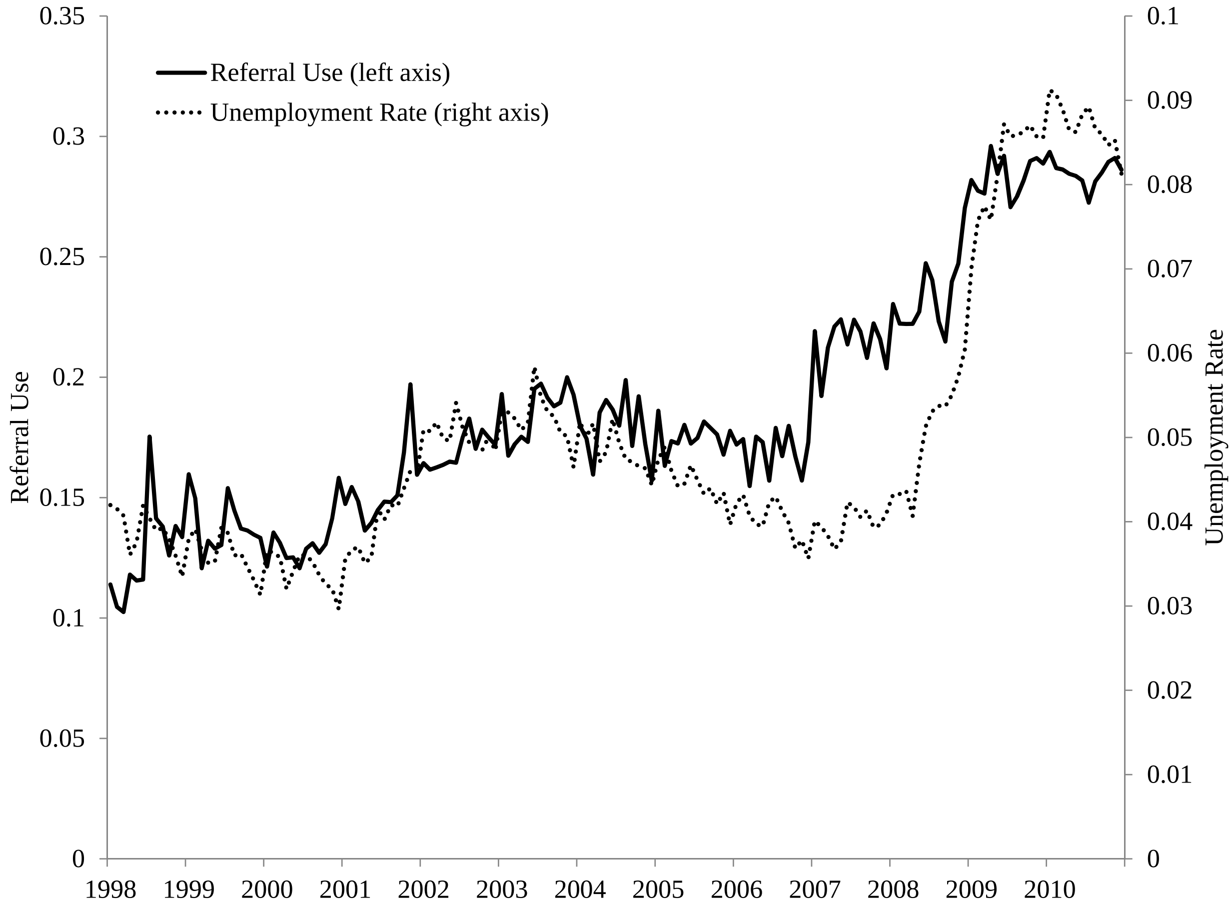

Figure 1: SOURCE: CPS Basic Monthly. The figure plots the monthly unemployment rate and the share of unemployed workers who report using friends and neighbors as part of their job search.

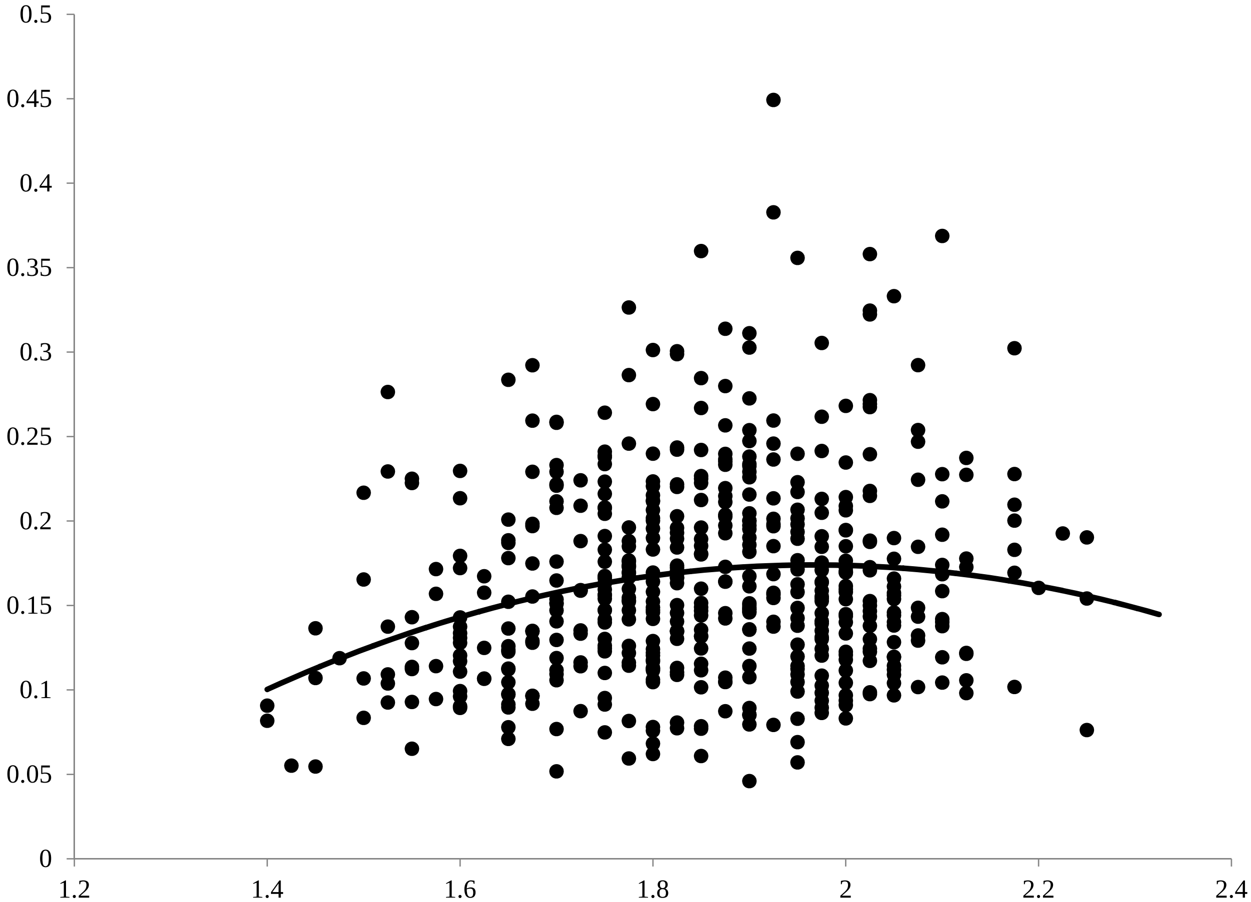

Figure 2: The figure plots state-year aggregates from the monthly CPS of the share the share of unemployed workers who report using friends and neighbors as part of their job search against state-year aggregate measures from the QWI of the number of periods of non-employment for newly-hired workers.

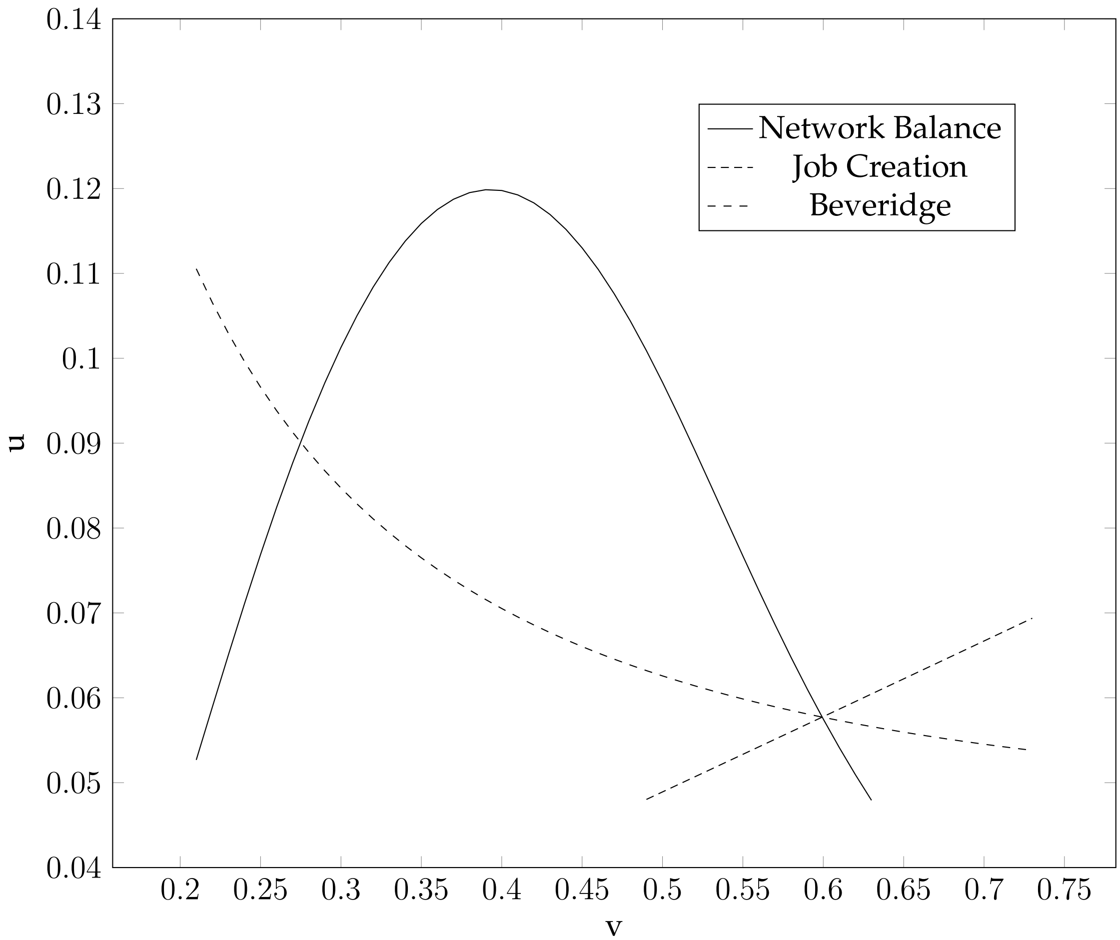

Figure 3: Simulated Equilibrium Relationships. $\gamma = 2.1$ in this equilibrium. The simulated equilibrium uses the parameter values $\delta = 0.05, r = 0.05, c = 1, \kappa = 1, \beta = 0.5,$ and $y1 = 15$

Table 1: Sample Averages

	All	Recent Job Change	Analysis Sample
Referred to current job	0.285	0.311	0.322
White	0.806	0.770	0.776
Male	0.457	0.491	0.487
Less than High School	0.050	0.043	0.039
High School Graduate	0.196	0.205	0.211
Some College	0.293	0.292	0.298
College	0.262	0.248	0.243
Post Graduate	0.198	0.211	0.217
Age in 2000	42.15	35.01	34.98
Married	0.604	0.547	0.546
Native-born	0.920	0.889	0.901
In Labor Force	0.695	1	1
Employed	0.637	1	1
Changed Jobs in last 2 yrs.	0.189	1	1
Accession Rate			0.963
Separation Rate			0.928
Tract Pop. Density per KM			1.453
County Unemployment Rate			4.611
Share Seeking Referral			0.221
Num. Obs.	852	161	152

SOURCE: 2008 CNSS, QWI, and CPS data. author's calculations.
NOTE: Sample averages of the variables used to analyze individual-level probability of being hired through referral. The first column describes the full sample from the Cornell National Social Survey. The second column restricts attention to employed individuals who report having obtained their most recent job within the last two years. The third column further restricts to individuals for whom data on all variables are available. The panel on the right describes the sample used in the final analysis. The final sample is restricted to employed individuals who reported starting their most recent job within two years of their interview. All variables are from the CNSS except those describing local economic conditions, which are linked from other sources described in the text. 'Asked Friends' is the fraction of unemployed workers in the state who reported in the Current Population Survey asking friends and neighbors as part of their job search.

Table 2: Share Referred By Demographic and Job Characteristics: All Workers

	Share Referred	Num. Obs.
All Workers	28.03	899
White	28.76	699
Black	26.47	102
Hispanic	26.98	63
Non-Hispanic	28.13	832
Male	28.19	408
Female	27.90	491
Native	29.20	815
Non-native	16.67	84
Education		898
LTHS	29.79	47
HS	30.86	175
SC	30.83	266
Coll.	23.48	230
PG	26.11	180
Sector		571
Goods	34.02	97
Service	30.11	93
Info.	26.99	289
Other	28.99	69
Pub. Admin	21.74	23

SOURCE: 2008 CNSS, author's calculations.

Table 3: Share Referred By Demographic and Job Characteristics: Workers with Recent Job Change

	Share Referred	Num. Obs.
All Workers	29.76	168
White	30.40	125
Black	25.00	25
Hispanic	33.33	12
Non-Hispanic	29.68	155
Male	28.05	82
Female	31.40	86
Native	30.14	146
Non-native	27.27	22
Education		168
LTHS	28.57	7
HS	33.33	33
SC	26.53	49
Coll.	26.19	42
PG	35.14	37
Sector		571
Goods	47.83	23
Service	32.35	34
Info.	26.83	82
Other	23.81	21
Pub. Admin	12.50	8

SOURCE: 2008 CNSS, author's calculations.

Table 4: Results

	(1)	(2)	(3)	(4)	(5)
State Referral Network Density		-3.106^{*}	-3.713^{**}	-4.081^{**}	-3.672^{*}
		(1.746)	(1.813)	(1.843)	(1.988)
County Unemployment		0.112	0.112	0.109	0.122
		(0.087)	(0.088)	(0.089)	(0.095)
County Accession Rate		0.480	0.654	0.737	0.754
		(0.488)	(0.509)	(0.519)	(0.538)
Tract Pop. Density			0.059	0.181	0.171
			(0.044)	(0.113)	(0.137)
Tract Pop. Density^2				−0.010	−0.009
				(0.008)	(0.010)
White	−0.051				0.063
	(0.275)				(0.304)
Male	−0.092				−0.117
	(0.218)				(0.233)
High School	−0.012				−0.107
	(0.584)				(0.606)
Some College	−0.125				−0.108
	(0.572)				(0.594)
College	−0.170				−0.075
	(0.586)				(0.611)
Post Graduate	0.226				0.187
	(0.586)				(0.634)
Age in 2000	−0.012				−0.011
	(0.009)				(0.009)
Married	0.108				0.153
	(0.223)				(0.236)
Native	−0.018				−0.004
	(0.708)				(0.422)
N	152	152	152	152	152
Log-likelihood	−93.679	−92.982	−92.097	−91.404	−90.042

SOURCE: 2008 CNSS, QWI, and CPS data. author's calculations.
NOTE: Probit model estimates for the CNSS sample of recent job changers. The dependent variable in each model is whether the worker was referred to their current job. The table reports coefficient estimates with standard errors in parentheses. One, two, and three stars indicate that the point estimate is significantly different from zero at the 10, 5, and 2.5 percent level of confidence.

A Theory Appendix

Claim (Poisson Lottery)**.** *Suppose you compete for an even chance at a prize with an unknown number of competitors. If the number of your competitors is a random variable with Poisson distribution and parameter s, then the probability you get the prize is $\frac{1-e^{-s}}{s}$*

Proof. The probability of this event is the expected value of $\frac{1}{k+1}$ where k is the number of other competitors for the prize. Given the assumption that the number of competitors is Poisson, we have

$$E\left[\frac{1}{k+1}\right] = \sum_{k=0}^{\infty}(\frac{1}{k+1})\frac{e^{-s}s^k}{k!} \tag{35}$$

$$= \textstyle\sum_{k=0}^{\infty} \frac{e^{-s}s^k}{k+1!} \tag{36}$$

$$= \textstyle\frac{1}{s}\sum_{k=0}^{\infty} \frac{e^{-s}s^{k+1}}{k+1!} \tag{37}$$

$$= \textstyle\frac{1}{s}\sum_{k=1}^{\infty} \frac{e^{-s}s^k}{k!} \qquad = \displaystyle\frac{1}{s}(1-e^{-s}) \tag{38}$$

∎

To prove the comparative static claims, it will be useful to have the following lemma.

Lemma 1. *At an optimal level of search intensity $\gamma_i^*(u, v, s, K_i, c_i) > 0$, the probability of receiving an offer through referral, $P^*(u, v, s, K_i, c_i)$ satisfies, (i) $P_s^* < 0$, and (ii) $P_u^* < 0$.*

Proof. By definition (11), $P^*(u, v, s, K_i, c_i) = 1 - \frac{c_i e^{-v}}{K_i \pi(u,v,s)}$. Therefore, $P_s^* = \frac{c_i e^{-v}}{K_i[\pi(u,v,s)]^2}\pi_s(u, v, s)$. Result (i) follows because $\pi_s(u, v, s) < 0$. An identical argument establishes result (ii). ∎

Proof of Claim 1.

Proof. Differentiating R with respect to γ^* yields

$$\frac{\partial R}{\partial \gamma^*} = [q + (1-q)e^v]\left(1 - \frac{c_i e^v}{K_i \pi(u, v, \gamma^* u)} \frac{\partial \pi(u, v, \gamma^* u)}{\partial \gamma^*}\right). \tag{39}$$

We need $\frac{\partial \pi}{\partial \gamma^*}$.

$$\frac{\partial \pi}{\partial \gamma^*} = \frac{(1-u)(1-e^{-v})\left[(\gamma^* u + 1)e^{-\gamma^* u} - 1\right]}{u\gamma^{*2}} \tag{40}$$

$\frac{\partial R}{\partial \gamma^*}$ shares the sign of $\frac{\partial \pi}{\partial \gamma^*}$. Suppose $\frac{\partial \pi}{\partial \gamma^*} > 0$. Then $(\gamma^* u + 1)e^{-\gamma^* u} - 1 > 0$ which requires $\gamma^* < 0$, a contradiction. ∎

Proof of Claim 2.

The proof is omitted, since it is nearly identical to the proof of Claim 1.

Proof of Claim 3.

Proof.

$$\frac{\partial R}{\partial v} = (q-1)e^{-\lambda}P + \left[q + (1-q)e^{-v}\right]\frac{\partial P}{\partial v} \tag{41}$$

$$\frac{\partial P}{\partial v} = \frac{c_i}{K_i}\left(\frac{ev(\frac{\partial \pi}{\partial v} - \pi)}{\pi^2}\right) \tag{42}$$

$$\frac{\partial \pi}{\partial v} = e^{-v}(1-u)\frac{1-e^{-\bar{\gamma}u}}{\bar{\gamma}u}. \tag{43}$$

It follows that

$$\frac{\partial \pi}{\partial v} - \pi = \left(\frac{e^{-v}}{1-e^{v}}\right)\pi. \tag{44}$$

Let $v^* = \ln 2$. It is straightforward to verify that $\frac{\partial P}{\partial v} > 0$ for $v < v^*$ and $\frac{\partial P}{\partial v} < 0$ for $v > v^*$. ∎

Proof of Claim 4:

Proof. $s = E(X)$ where X is the number of requests for referrals directed to a randomly selected worker i.

Define X_j to as the number of information requests to i that come from worker j. Recall that γ_j is the parameter on the number of information requests made by j, which is a random variable distributed as Poisson. Due to homogeneity, all unemployed workers choose the same contact intensity. Thus X_j will be distributed as Poisson with parameter $\frac{\bar{\gamma}}{\mu}$ where μ is the total measure of workers.

Finally, note that $X = \sum X_j$ so

$s = E(X) = E(\sum X_j) = \sum E(X_j) = \sum \frac{\bar{\gamma}}{\mu} = u\gamma$.

Since $\gamma_j \neq 0$ just when j is unemployed, and $\gamma_i = \gamma_{i'} = \gamma$ when i and i' are both unemployed. ∎

Proof of Claim 5:

Proof. Our task is to show there exists a unique network density, s^*, that satisfies the network balance condition, $s^* = \bar{\gamma}(u, v, s^*)u$, where

$$\bar{\gamma}(u, v, s^*) = \arg\max_{\gamma_i \geq 0} h(u.v.s.\gamma_i)K_i - c\gamma_i.$$

There are two cases of interest:

Case 1: $\frac{\partial h(u,v,0,0)}{\partial s}K_i - c_i \leq 0$. In this case, the marginal value of search through referral is exceeded by its marginal cost, even when no other unemployed workers search through referral. In this case, $\bar{\gamma}(u, v, 0) = 0 = s^*$ satisfies the network balance condition uniquely.

Case 2: $\frac{\partial h(u,v,0,0)}{\partial s}K_i - c_i > 0$. In this case, when the network density is zero, individual workers will optimally choose a positive level of referral search intensity. The individual choice, $\bar{\gamma}(u, v, s^*)$, must satisfy the Kuhn-Tucker condition

$$\pi(u, v, s^*) \exp\left[-\left(v + \bar{\gamma}\pi(u, v, s^*)\right)\right] = \frac{c_i}{K_i}.$$

The network balance equilibrium must be individually rational when $s^* = \bar{\gamma}u$. We must show that there is a unique solution, $\bar{\gamma}$, that solves

$$\pi(u, v, \bar{\gamma}u) \exp\left[-\left(v + \bar{\gamma}\pi(u, v, \bar{\gamma}u)\right)\right] = \frac{c_i}{K_i}. \tag{45}$$

Define $b(\bar{\gamma}) = \pi(u, v, \bar{\gamma}u) \exp\left[-\left(v + \bar{\gamma}\pi(u, v, \bar{\gamma}u)\right)\right]$. It is straightforward to verify the following properties:

1. $b(0) > \frac{c_i}{K_i}$. This follows from the assumption $\frac{\partial h(u,v,0,0)}{\partial s}K_i - c_i > 0$.
2. $b'(\bar{\gamma}) < 0$.
3. $\lim_{\bar{\gamma}\to\infty} b(\bar{\gamma}) = 0$.

By the above argument, along with continuity of $b()$, $b()$ should cross $\frac{c_i}{K_i}$ somewhere on the positive line. That is, there exists $s^* = \bar{\gamma}u$ that solves Equation (45).

∎

Proof of Claim 6.

In the CNSS data, we measure the probability a worker was referred conditional on being employed. Under the assumption of a constant separation rate, the probability a currently employed worker was hired through referral is the probability that worker was hired through referral, conditional on having been hired at all. This is just the ratio

$$r^*(u, v, s, K_i, c_i; q) = \frac{R^*(u, v, s, K_i, c_i; q)}{h^*(u, v, s, K_i, c_i)}. \tag{46}$$

The denominator is the probability a worker is hired from unemployment given the optimal referral-use intensity, γ_i^*, $h(u, v, s, \bar{\gamma}) = 1 - e^{-v}(1 - P^*(u, v, s))$. Therefore, we derive the following:

Claim 6. *Conditional on being employed, the probability of being hired through referral is decreasing in the referral network density and in the unemployment rate. Formally, let* $r = \frac{R(u,v,s,K_i,c_i)}{h(u,v,s,K_i,c_i)}$. *Then*

$$\frac{\partial r}{\partial \bar{\gamma}} < 0, \tag{47}$$

and

$$\frac{\partial r}{\partial u} < 0, \tag{48}$$

Proof. To conserve notation, let $A = (q + (1 - q)e^{-v})$, $h^* \equiv h^*(u, v, s, K_i, c_i)$, and $h_s^* = \frac{\partial h^*}{\partial s}$, with similar definitions for R^*, R_s^*, P^*, and P_s^*. The partial derivative of r^* with respect to s is

$$r_s^* = \frac{R_s^* h^* - h_s^* R^*}{h^{*2}}. \tag{49}$$

Clearly, $R_s^* = AP_s^*$,and $h_s^* = e^{-\lambda}P_s^*$.Through substitution, the numerator of 49 is

$$\begin{aligned} R_s^* h^* - h_s^* R^* &= AP_s^*\left(1 - e^{-v}(1 - P^*)\right) - e^{-v}P_s^* AP^* \\ &= AP_s^*\left(1 - e^{-v}\right). \end{aligned}$$

Since $(1 - e^{-v})$ is a probability, it follows that r_s^* has the same sign as P_s^*, which is negative, according to Lemma 1. The result follows.

The proof that $r_u^* < 0$ is exactly analogous. ∎

B Implications of Key Model Assumptions – For Web Publication

Here I consider relaxations of two of the model assumptions from the main text. First, I relax the assumption that workers can only pass on one offer via referral. Second, I discuss the implications of relaxing the assumption that all workers choose a strictly positive level of referral contact intensity, γ_i.

B.1 Allowing workers to distribute multiple offers

In the model, workers – both employed and unemployed – can receive multiple offers from employers. In the main text, I assume only employed workers provide referrals, and that they can provide at most one referral. However, in the model nothing prevents any worker – employed or unemployed – from receiving multiple offers directly from employers. Here I consider an alternative model of information transmission in which all workers can transmit all of their unused offers as referrals.

The specific alternative I consider is a model of information transmission in which each worker receives requests for job offers from unemployed workers. Then, formal offers are distributed randomly at rate v to all workers, just as in the main text. Employed workers distribute all job offers at random to their contacts. Unemployed workers take the first job offer they receive, and then distribute any remaining offers to their contacts.

Consider ω_{ij}^e to be the random variable that defines the number of offers employed contact j provides to unemployed worker i. The expected number of contacts is still s. The expected number of offers j sends is equal to the number she receives: v. Assuming these offers are distributed independently at random to all her contacts, ω_{ij} is Poisson with rate parameter $\frac{v(1-e^s)}{s}$.

Unlike the model of the main text, unemployed workers can also provide referrals, but only if they have more than one offer. If X_j is the number of offers received by unemployed worker j, then the number of offers j distributes is truncated Poisson, with expectation $E(X_j|X_j > 1) = v(1 - e^{-v})$. Assuming the remaining offers are distributed at random, the number of offers passed to unemployed contact i is Poisson with rate parameter $\frac{v(1-e^s)(1-e^{-v})}{s}$.

The flow of referrals to worker i is the sum over all contacts of independent Poisson random variables. Referral offers flow at rate

$$\eta(u, v, s) \equiv \frac{[(1-u) + u(1-e^{-v})]\, v(1-e^{-s})}{s}. \quad (50)$$

At this rate, the probability any contact provides an offer is

$$\pi(u, v, s) = 1 - e^{-\eta(u,v,s)}. \quad (51)$$

It is straightforward to show the partial derivatives $\eta_u < 0$, $\eta_v > 0$ and $\eta_s < 0$. It follows immediately that $\pi_u < 0$ and $\pi_s < 0$, from which the proofs of Claims 3 and 4 follow. The non-monotonicity result follows from observing that the structure of the proof of Claim 6 will remain the same, up to equation (44). At that point, make the substitition:

$$\frac{\partial \pi}{\partial v} - \pi(u, v, s) = \eta_v e^{-\eta} - (1 - e^{-\eta}) = (1 + \eta_v)e^{-\eta} - 1. \tag{52}$$

Note $\eta_v > 0$ for all v and $e^{\eta} = 1$ when $v = 0$. Therefore, $\frac{\partial \pi}{\partial v} - \pi(u, v, s) > 0$ for v near 0. Furthermore, e^{η} is increasing and unbounded in v while η_v is decreasing and bounded in v. It follows that there exists $v^* > 0$ such that $\frac{\partial \pi}{\partial v} - \pi(u, v, s) < 0$.

As a final note, the assumption that contacts distribute offers at random and without replacement is somewhat awkward. An alternative assumption is that offers are distributed without replacement. For example, if you contact an employed worker who has received three offers, and has been contacted by 4 workers for a referral, then the probability of getting an offer is simply 3/4. While the intuition is clear, modeling this assumption involves the analytically intractable problem of computing the expectation of the ratio of Poisson distributed random variables. I conjecture that the way in which the probability that a contact is productive changes with u, v, and s remains the same in this alternative setting.

B.2 The assumption that all workers choose positive contact intensity

In modeling labor market equilibrium, I assume, following the literature, that workers are homogeneous. When workers are homogeneous, they all choose the same contact intensity, and it is innocuous, therefore, to assume they all choose a positive contact intensity. Otherwise, there is no referral network to study. The comparative static predictions in Claims 1, 2, and 3 are derived under the assumption that contact intensity is positive.

When considering the within-period model of individual behavior in Section 3, I temporarily relax the homogeneity assumption to entertain the possibility that workers may differ in the marginal cost, c_i, and the marginal benefit, K_i, of seeking referrals. I do so in anticipation of the empirical analysis in Section 6.2.2 of referral-based hiring using individual-level data from the CNSS, where I use individual-level controls as well as information on population density to control for variation across workers in the costs and benefits of referral-based search.

Given that there is a corner solution in the worker's problem, and that only 20-30 percent of workers report using referral in job search, it is worth asking what happens if the assumption that all workers seek referral is relaxed. For the empirical work, this poses a selection problem. The data record whether a worker was referred for her current job. However, the probability of being hired through referral depends on whether a worker sought a referral at all, and, conditional on seeking referral, whether the worker received a referral and used it to obtain their job. In the CNSS data, only the final outcome is observed. It is therefore very difficult to model the joint selection process, as illustrated by Abowd and Farber (1982) in the context of modeling union status.

The reduced-form estimates in Table 4 are valid under several assumptions. The first is when all workers choose positive contact intensity. Even with positive contact intensity, some workers may not contact any workers due to randomness. The second assumption is that the selection process, which is a function of the marginal cost, c_i, and the marginal benefit, K_i, is uncorrelated with the labor market characteristics of interest. Finally, note that the probability a worker seeks referral depends on the probability that contacts are productive, $\pi(u, v, s)$. The same factors that act at the intensive margin to reduce referral use also act at the extensive margin. Therefore, the reduced-form estimates in Table 4 can be interpreted as picking up the combined influence at the intensive and extensive margin.