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# QUANTIFYING THE EFFECTS OF JOB MATCHING THROUGH SOCIAL NETWORKS

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The recent literature explains the theoretical implications of the matching of workers to jobs through social networks. These insights are obtained for extremely simplified economies or rely on unrealistically simple social networks. Therefore, it is difficult to obtain a sense for the quantitative importance of effects generated by real life social networks. In this paper, I augment a labor market matching model to allow for information transmission through social networks. I illustrate the effects of social networks and I use simulations to quantify the predictions of the model for complex and realistic social networks. Information transmission through social contacts reduces the steady state unemployment rate from a hypothetical 6.5% to 5%. Social referrals can explain 1/5th of the observed duration dependence of unemployment. They cannot explain much of the variation in wages of otherwise homogeneous workers and do not substantially influence aggregate outcomes over the business cycle.

*JEL classification codes*: J64, J31, E24
*Key words*: job search, matching, social networks, information transmission

## I. Introduction

Many workers use the help of friends or relatives when searching for jobs. Survey evidence suggests that half of all employed workers found their jobs through social contacts (Rees 1966, Granovetter 1973, Bewley 1999, and Pellizarri 2004). The recent literature has improved our understanding of the theoretical implications of social referrals for labor market outcomes.[1] These advances rely on simplifications

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[1] Calvo-Armengol and Jackson (2004 and 2007) show that information transmission through social networks can result in a positive correlation of employment status and wages across agents and time. It can generate duration dependence of the probability of leaving unemployment, as well as, wage inequality

to reduce the complexity generated by the introduction of information transmission through social networks. One approach (see Montgomery 1991, Calvo-Armengol and Jackson 2004 and 2007, or Fontaine 2008) is to assume a very simple structure of the networks. An alternative is to assume that networks are constantly dissolved and reformed randomly (see Calvo-Armengol and Zenou 2005, or Ioannides and Soetevent 2006). The need to rely on these assumptions makes it difficult to obtain a sense for the magnitude of the effects generated by real life social networks.

In this paper, I assess these magnitudes by simulating a labor market matching model with social networks. I augment a simple matching model similar to the urn-ball model of Blanchard and Diamond (1994) to allow for information transmission through social networks. I use numerical simulations to solve the model. This makes it possible to consider more realistic – and complex – network structures and quantify the effects of information transmission through these social networks on labor market outcomes.[2]

I consider a social network that exhibits well documented, common characteristics of social networks, like clusteredness and a right skewed distribution of the number of connections.[3] To illustrate the mechanisms through which social networks affect labor market outcomes I also consider simpler structures of social networks.

In my model, information transmission through social networks increases the probability that a worker finds a vacancy and thus improves the matching of workers to vacancies. My simulation results suggest that this reduces the unemployment rate from a hypothetical 6.5% without information from social contacts to an observed 5%. The presence of social networks does not substantially affect differences of the steady state values of aggregate variables, such as the unemployment rate or movements in and out of unemployment, at different points in the business cycle.

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between different sub-groups. This last point is also made by Arrow and Borzekowski (2004), who provide quantitative results by based on simulations. Calvo-Armengol and Jackson (2009) show that intergenerational persistence in labor market outcomes can be generated though inheritance of social ties. Buhai and van der Leij (2008) present a model where social ties lead to inbreeding in occupational categories. Fontaine (2008) studies effects of differences in unemployment rates between otherwise identical social networks. Calvo-Armengol and Zenou (2005) and Ioannides and Soetevent (2006) analyze the properties of a job matching function with social referrals.

[2] This paper (and most of the papers cited above) studies the spread of information about vacancies among workers. I do not consider the effects of the transmission of information about worker characteristics to potential employers. Montgomery (1991) and Arrow and Borzekowski (2004) investigate this mechanism.

[3] See Jackson (2006), Newman (2003), and Mayer and Puller (2008).

I find that differences in the social networks of individuals can generate substantial variation in the length of unemployment spells and the probability of being employed. The probability of employment is increasing at a decreasing rate in the number of social connections of a worker. Social referrals can generate some (up to 20%) of the observed duration dependence of unemployment, but other sources – such as heterogeneity in worker characteristics – seem to be more important.

Differences in the expected duration of unemployment can affect wages through the bargaining process. Using a standard Nash bargaining framework, I find that the resulting wage differences are only minor. Information transmission through social networks cannot explain the variation in wages of otherwise homogeneous workers.

I present the matching model in Section II and discuss the characteristics of social networks in Section III. In section IV, I characterize the resulting economy and illustrate the effects of social networks. The quantitative results of simulations of the model are presented in Section V. The effect of social referrals on wages is analyzed in Section VI. Section VII concludes.

## II. Matching model

I use a labor market matching model similar to Blanchard and Diamond (1994). My model differs from the common modeling approach exemplified by Pissarides (2000) in two ways. First, the matching function is not a black box. The matching of job seekers and vacancies is modeled explicitly. This makes it possible to explicitly model the effects of social referrals, as well. The second difference is that the number of productive jobs is exogenous. This feature greatly simplifies the simulation of the model.

There are $N$ workers in the economy. Workers can be employed or unemployed. The stocks of employed and unemployed workers are denoted by $E$ and $U$. Consequently, $N=E+U$. There are $K$ jobs in the economy. A job can be productive or unproductive. If a productive job is matched to a worker it produces an output of $y$. The number of filled jobs equals the number of employed workers and is given by $E$. The number of vacancies, productive but unfilled jobs, is given by $V$. $W$ gives the number of unproductive jobs. An unproductive job does not produce any output and will not be matched to a worker. The total number jobs is given by:

$$K = E + V + W. \tag{1}$$

Time is discrete. Each period is divided into $K$ sub-periods, one for each job. All jobs are identical; therefore the order of the sub-periods does not matter. In its sub-period a job can receive a productivity shock. The probability that a previously productive job stays productive is given by $\pi_{11}$. A productive job turns unproductive with probability $1-\pi_{11}$. If a filled job becomes unproductive the match is destroyed, the respective worker looses her job and is unemployed. The probability that a previously unproductive job becomes productive is given by $\pi_{01}$. If a job becomes productive a vacancy appears. A vacancy is filled when it is seen by an unemployed worker. An unfilled vacancy reappears in the next period.

Workers are connected through an exogenously given social network. I refer to connected workers as 'friends'. The vacancy-worker matching mechanism allows for the referral of vacancies by employed workers to their unemployed friends. In the next section, I describe these social networks.

Each worker hears with probability $a$ about each vacancy. Both employed and unemployed workers hear about a vacancy with the same probability. If an unemployed worker hears about a vacancy she applies for the job. If an employed worker hears about a vacancy she tells one of her unemployed friends about it. I allow for the possibility that jobs obtained through referrals are no match for the characteristics of the job seeker. This feature makes the model flexible enough to capture a high or low number of friends while simultaneously matching the empirical importance of social referrals. The probability that a referred job is suitable for the job seeker is given by $q$. With $0 < q \leq 1$. If a job is suitable the unemployed friend applies to the job. An employed worker who has no unemployed friends does not transmit information about the vacancy. If more than one worker hears about the vacancy – directly or indirectly – one of the applicants is picked at random. If no worker applies for the vacancy the vacancy remains unfilled and the sub-period ends. An unemployed worker always accepts the job offer and is immediately employed.

The filling of vacancies, the opening of new vacancies and the disappearance of productive jobs is characterized by the following system of equations:

$$E_t = \pi_{11} E_{t-1} + \theta_t \pi_{11} V_{t-1} + \theta_t \pi_{01} W_{t-1}, \tag{2}$$

$$V_t = \left(1-\theta_t\right)\pi_{11} V_{t-1} + \left(1-\theta_t\right)\pi_{01} W_{t-1}, \tag{3}$$

$$W_t = \left(1-\pi_{11}\right) E_{t-1} + \left(1-\pi_{11}\right) V_{t-1} + \left(1-\pi_{01}\right) W_{t-1}. \tag{4}$$

The matching rate $\theta_t$ is the probability that a vacancy is filled in a given period. It depends on the probability that information about the vacancy reaches at least one unemployed worker and hence on information transmission through social networks.

## III. Networks

As mentioned above, I consider an economy with $N$ workers – or in the terminology of network analysis, a network with $N$ nodes.[4] Workers $i$ and $j$ can be friends with each other, in this case the nodes $i$ and $j$ are linked – or connected. This relationship is symmetric; if worker $i$ is a friend of worker $j$, then worker $j$ is also a friend of worker $i$. The friendships between workers are recorded in the symmetric $n^*n$ matrix $g$. If worker $i$ and worker $j$ are friends, the corresponding elements of the friendship-matrix $g$ are equal to one, $g(i,j) = 1$ and $g(j,i) = 1$. Otherwise, the elements of $g$ are equal to zero.

The number of connections (friends) of an individual is referred to as the number of *degrees* of a node. The *cluster coefficient* measures the cliquishness of a network. It captures the fraction of the friends of a given individual who are friends with each other. The literature considers different ways of calculating this measure. I follow Jackson and Rogers (2005) and define the *cluster coefficient* as:

$$C = \frac{\sum_{i:j\neq i,k\neq j,i} g_{ij}g_{jk}g_{ik}}{\sum_{i:j\neq i,k\neq j,i} g_{ij}g_{jk}}.$$

According to Jackson (2006) and Newman (2003), social networks are characterized by a number of common characteristics. The degree distribution (the distribution of the number of friends) is right skewed and has fat tails. Social networks tend to be cliquish and exhibit a cluster coefficient that cannot be explained by random formation of links. In a randomly generated network with many nodes and few connections, the cluster coefficient equals the probability that two nodes are connected and is close to zero. Mayer and Puller (2008) find cluster coefficients between.17 and.27 for large friendship networks on university campuses. Newman (2003) and Jackson (2006) report cluster coefficients ranging from.09 to.45 for co-authorship networks in different academic disciplines; Goyal et al. (2006) report cluster coefficients from.16 to.20 among co-authors in economics. Newman (2003)

[4] The notation here is based on Jackson (2006).

also reports a cluster coefficient of.2 for a network of actors, where a link is established when 2 actors co-star in the same movie.

To study the role of the network structure in the job search process, I consider 4 different kinds of networks. First, as a benchmark, I examine an economy without referrals through social connections. Second, I consider a network that consists out of pairs. Each worker shares information with exactly one other worker. I use this simple case to illustrate the effect of social referrals. The third case is a network where each pair of workers has an equal probability of being linked. This network results in a unique social environment for each worker, but does not exhibit the classic characteristics of social networks, like clusteredness. The number of links of individuals is binomially distributed. This kind of network is also called 'random graph'. The forth – and most realistic case – is a network with the classic characteristics of social networks. I simulate a network that exhibits characteristics like clusteredness and skewness of the degree distribution. Comparing the results to the results for the random network reveals the importance of the network structure.

## IV. Effects of social networks

In this section, I describe the steady state equilibrium of the economy.[5] I illustrate effects of referrals through social networks on aggregate and individual level effects. In Section V, I use simulations to quantify the magnitude of these effects.

### A. Aggregate effects

I denote steady state outcomes with subscript *s*. The steady state level of employment depends on the exogenously determined parameters ($\pi_{11}$, $\pi_{01}$, and $a$) and on the matching rate ($\theta_s$), which is determined endogenously and depends on the structure of the referral networks. Social referrals influence the steady state through their effect on the matching rate, $\theta_s$. $\theta_s$ depends on the number of job seekers and how they obtain information. The transition probabilities $\pi_{11}$ and $\pi_{01}$ determine the steady state level of productive jobs:

$$E_s + V_s = \frac{\pi_{01}}{1 - \pi_{11} + \pi_{01}} K. \tag{5}$$

[5] Note that the steady state applies for each sub-period. The sequence in which each job is hit by the productivity job and is filled does not matter.

The total number of new job-worker matches in each period is given by:

$$M(U_s,V_s)=\theta_s\left[\pi_{11}V_s+\pi_{01}W_s\right].$$

In the steady state, the total matches per period equals the total number of destroyed matches, $M(U_s, V_s)=(1-\pi_{11})E$. The steady state employment level is determined by $\theta_s$, $\pi_{11}$, and $\pi_{01}$:

$$E_s=\frac{\theta_S}{(1-\pi_{11})}(\pi_{11}V_s+\pi_{01}W). \tag{6}$$

**No network**

As a benchmark, I derive the matching rate $\theta_s^{NO}$ without information transmission through social networks.[6] The superscript *NO* indicates the absence of social referrals. The probability that a vacancy receives no application is given by: $(1-a)^{U_s}$. The steady state matching probability is:

$$\theta_S^{NO}=\left[1-(1-a)^{U_S}\right]. \tag{7}$$

Given $a$, $\pi_{11}$, and $\pi_{01}$ equations (5), (6), and (7) describe the steady state level of employment. It is also possible to derive the effects of changes in the exogenous variables on the steady state outcome. The reaction of $\theta_s^{NO}$ to a change in the employment level is given by:

$$\frac{d\theta_S^{NO}}{dE_S}=(1-a)^{(1-E_S)}\ln(1-a)<0. \tag{8}$$

An increase in the employment rate decreases the matching rate.

**Network of pairs**

Now, I consider a very simple network structure to highlight some of the mechanisms of information transmission through social contacts. I use the superscript *PAIR* to

[6] The resulting matching process is equivalent to an urn-ball matching process, see Blanchard and Diamond (1994).

indicate social referrals through a network of pairs. Each worker is connected to one other worker. Workers can be part of a fully employed pair, a partially employed pair, or an unemployed pair. The stock of these pairs is given by $Q_s^2$, $Q_s^1$, and $Q_s^0$. The total number of workers is $N = 2(Q_s^0 + Q_s^1 + Q_s^2)$. The number of employed workers is given by $E = Q_s^1 + 2Q_s^2$. A vacancy is filled if it is seen by an unemployed worker or an employed worker with an unemployed partner. Holding the value of $a$ fixed, social referrals increase the probability that a vacancy is filled from

$$\theta_S^{NO} = \left[1-(1-a)^{2Q_S^0+Q_S^1}\right]$$

to

$$\theta_S^{PAIR} = \left[1-(1-a)^{2Q_S^0+Q_S^1}(1-qa)^{Q_S^1}\right].$$

The magnitude of the difference between $\theta_s^{NO}$ and $\theta_s^{PAIR}$ depends on the values of $q$. A larger value of $q$ makes referrals more useful and leads to a bigger difference between $\theta_s^{NO}$ and $\theta_s^{PAIR}$.

The model with social referrals generates the matching probability implied by the data with a lower value of $a$, $\overline{\theta}_S = \theta_s^{NO} = \theta_S^{PAIR} \Rightarrow a^{PAIR} < a^{NO}$.

The reaction of $\theta_s^{PAIR}$ to a change in the aggregate employment level is more complex than without social referrals. It depends on the employment status of the workers connected to newly employed or unemployed workers:

$$\left.\frac{d\theta_s^{PAIR}}{dQ_S^2}\right|_{\overline{Q_S^0}} \neq \left.\frac{d\theta_s^{PAIR}}{dQ_S^1}\right|_{\overline{Q_S^2}}.$$

Similar to the case without referrals, $\theta_s^{PAIR}$ decreases, if a worker with an employed partner finds a job:

$$\left.\frac{d\theta_s^{Pair}}{dQ_S^2}\right|_{\overline{Q_S^0}} = (1-a)^{2Q_S^0}(1-qa)^{Q_S^1}\ln(1-a)+(1-a)^{2Q_S^0+Q_S^1}(1-qa)\ln(1-qa)<0.$$

If a worker from a pair with two unemployed workers finds a job the change in $\theta_s^{PAIR}$ is between 0 (for $q$=1) and $\theta_s^{NO} < 0$ (for $q$=0).

The aggregate unemployment rate is not sufficient to determine the matching probability. The position of the employed and unemployed workers in the social network can affect the probability that a vacancy is matched to a worker. This illustrates that different network structures can result in difference in steady state outcomes.

**Complex networks**

It is not possible to derive a closed form expression for $\theta_s$ for more realistic and complex network structures. Workers have different numbers of friends and friends of friends. Each individual has a unique position in the network associated with a unique state dependent probability of seeing a job. The probability that a worker finds a job through a referral depends on her social network, on the employment status of the members of her social network, and on $q$. A large number of employed friends can provide more information about job openings. Friends of friends increase the probability of employment of friends, but at the same time they also compete for information.

**Targeted information dispersal**

If firms are aware of the social connections of individuals it may be beneficial for them to target individuals with a lot of social contacts. I explore this possibility by allowing the probability of seeing a vacancy to depend on the number of friends of an individual, $a = a(\#\text{ of friends})$, with $\frac{da(\#\text{ of friends})}{d\#\text{ of friends}} > 0$.

In this setup an individuals' benefits from a lot of social connections are magnified. More social connections can provide more information about job openings through referrals and in addition they are associated with a higher probability of observing a vacancy directly.

For the simulation exercise I use the function form $a_i = a(friends_i) = \left[k + (1-k)\Theta\left(friends_i - \overline{friends}\right)\right]a^*$, where $\Theta(.)$ is the cdf of the standard normal distribution. The value $a^*$ is calibrated to obtain a referral ratio of one. The exogenously given constant $k$ reflects the importance of the targeted information dispersal. The case without targeted information dispersal is results from $k=0$. The results presented in the paper where obtained for $k = \frac{4}{5}$.

**Endogenous vacancies**

In this paper the number of productive jobs is determined exogenously. In models with endogenous determination of productive jobs (or vacancies) the number of vacancies is determined by equating the cost of posting a vacancy and the expected value of a vacancy. The productivity of a filled vacancy and the probability of filling a vacancy determine of the value of a vacancy. The probability of filling a vacancy depends positively on the ratio of unemployed workers to vacancies. Adding information transmission through social networks leads to a connection between the probability of filling a vacancy and the structure of the social network.

With endogenously determined vacancies the number of vacancies adjusts to changes in the economic environment. For example, the counterfactual experiment of shutting down social referrals – to determine the role of social connections for the matching process – would lead to a higher unemployment rate, this in turn increases the probability that vacancies are filled, thus makes vacancies more valuable and leads to more vacancies. Consequently a model with endogenously determined vacancies might suggest a smaller effect of referrals on the employment rate than obtained from a model with exogenous vacancies. Similar effects might arise as a response to business cycle fluctuations. These differences are most likely quantitatively small, given that the structure of the social network has only small effects on aggregate outcomes.

**B. Individual level effects**

The probability, $p_i$, that an unemployed worker, $i$, finds a job during a given time period depends on the social network of worker $i$. The probability that she is hired depends on the number of other workers applying for the same job. It is given by:

$$p_i = \Pr(\text{Hired}|\text{See\_Vacancy})\Pr(\text{See\_Vacancy})$$
$$= \Pr(\text{See\_Vacancy})\left(\Pr(other=0)+\Pr(other=1)\frac{1}{2}+\ldots+\Pr(other=l)\frac{1}{l+1}\right),$$

where Pr(*other* = 1) gives the probability that $l$ other unemployed workers hear about the vacancy.

Without social referrals this probability is identical for all workers $p_i = \overline{p}$. The probability that a worker hears about a specific vacancy is given by $a$ and the number of workers that hear about a vacancy is distributed binomial. Therefore,

$$p_i = \overline{p} = \left[1-(1-\phi)^{\pi_{11}V_s+\pi_{01}W_s}\right], \text{ with } \phi = a\sum_{k=0}^{U-1}\frac{1}{1+k}\binom{U-1}{k}a^k(1-a)^{U-k}.$$

When considering a network of pairs, the probability that an unemployed worker with an unemployed partner hears about a given vacancy is $a$. The probability that a worker with an employed partner hears about a vacancy is $a+qa$. This introduces heterogeneity in employment probabilities. The distribution of the number of other workers hearing about the vacancy is no longer binomial. More complex networks lead to different probabilities of seeing a job for each worker. In the next section, I use simulations to get a sense for the distribution of individual job-finding probabilities.

Heterogeneity in the probability of finding a job due to social referrals can lead to duration dependence. To see how, consider a simple example with two types of workers. One type, $H$, has a high probability of finding employment, $\Pr_H$. The other type, $L$, has a lower probability of finding employment, $\Pr_L < \Pr_H$.[7] The number of newly unemployed workers of each of the two types is given by $D_0^L$ and $D_0^H$. One period later type $H$ workers are more likely reemployed and the ratio of high and low type workers who have been unemployed for one period is given by:

$$\frac{D_1^H}{D_1^L} = \frac{D_0^H\left(1-\Pr_H\right)}{D_0^L\left(1-\Pr_L\right)} < \frac{D_0^H}{D_0^L}.$$

A higher share of type $L$ workers decreases the average probability of finding employment. The average job finding probability of workers who are newly unemployed is higher than that of workers who have been unemployed for one (or more) periods:

$$\frac{\Pr_H D_1^H + \Pr_L D_1^L}{D_1^H + D_1^L} = \frac{\Pr_H D_0^H\left(1-\Pr_H\right) + \Pr_L D_0^L\left(1-\Pr_L\right)}{D_0^H\left(1-\Pr_H\right) + D_0^L\left(1-\Pr_L\right)} < \frac{\Pr_H D_0^H + \Pr_L D_0^L}{D_0^H + D_0^L}.$$

Consequently, we observe duration dependence of unemployment. Note that, more conventional explanations of duration dependence are based on the same logic, but assume unobserved worker characteristics as the reason for differences in the probability of finding employment.

## V. Quantitative results

It is not possible to solve the matching model with referrals through social networks analytically. Therefore, I simulate the model.[8] Table 1 displays the parameters used for the simulations. I use the parameter values of Blanchard and Diamond (1994) where possible. The unit period is one week. The ratio of total jobs, $K$, to the number

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[7] In these case with a network of pairs these types would be unemployed workers with an employed partner ($H$) and unemployed workers with an unemployed partner ($L$).

[8] I simulate an economy with $N$=2000 for 5000 periods. The first 100 periods are discarded and the remaining 4900 are used to calculate the steady state results. I also simulate the random and the clustered social networks.

of workers, $N$, is 1.05. The probability that a productive job remains productive in the next period is.982. The probability of that an unproductive job becomes productive is.22. Like Blanchard and Diamond, I consider a different set of values to describe the economy during a recession, $\pi_{11}$=.981 and $\pi_{01}$=.129. As additional robustness checks, I also consider the scenarios of a boom (with $\pi_{11}$=.983 and $\pi_{01}$=.3) and an extreme recession (with $\pi_{11}$=.975 and $\pi_{01}$=.075).

I consider two values of $q$. First $q$=1, i.e. the probability that a referred job matches the worker characteristics is equal to the probability that a self discovered job is a good match. Then I set $q$=.1 the probability that a referred job matches the worker characteristics is one tenth of the probability that a self discovered job is a good match.

I calibrate the probability that an individual sees a job, $a$, to generate the unemployment rate of 5% obtained by Blanchard and Diamond (1994). The value depends on the subsequent information transmission through social networks.

I consider four different network structures: no network, a network of pairs, a random network, and a clustered and skewed network. For the random network and the clustered network, I select the network density, i.e. the average number of friends, to produce the stylized fact that 50% of all jobs are obtained through referrals. The required network density depends on the structure of the network. The characteristics of the resulting networks are displayed are in Table 2.

**Table 1. Parameters for simulation**

| | | $\pi_{11}$ | $\pi_{01}$ | $\pi_{11}$ | $\pi_{01}$ | Source |
|---|---|---|---|---|---|---|
| | | Normal | | Recession | | |
| Transition probabilities | | 0.982 | 0.220 | 0.981 | 0.129 | Blanchard & Diamond (94) |
| | | Boom | | Extreme Recession | | |
| Transition probabilities | | 0.983 | 0.300 | 0.975 | 0.075 | Blanchard & Diamond (94) |
| | | No network | Pairs | Random | Clustered | Source |
| $a$ (probability of seeing vacancy) | $q$ =1 | 0.006 | 0.003 | 0.003 | 0.003 | Calibrated to generate unemployment rate of 5% |
| | $q$ =.1 | 0.006 | 0.006 | 0.030 | 0.030 | |
| Average number of friends | $q$ =1 | 0 | 1 | 1.63 | 2.29 | Calibrated to generate referral ratio of one |
| | $q$ =.1 | 0 | 1 | 15.6 | 46.3 | |

Note: Time periods $T$=5000 (the first 100 periods are not used). Number of workers $N$=2000. Number of total jobs $K$=2100 (Blanchard and Diamond 1994).

**Table 2. Charactersitics of the simulated networks**

| | | $q$=1 | | | $q$=.1 | |
|---|---|---|---|---|---|---|
| | Pairs | Random | Clustered | Pairs | Random | Clustered |
| Average number friends | 1 | 1.63 | 2.29 | 1 | 15.61 | 46.34 |
| Variance of number of friends | - | 1.27 | 2.32 | - | 3.93 | 50.59 |
| Skewness of number of friends | - | 0.80 | 1.29 | - | 0.30 | 1.60 |
| Cluster coefficient | - | 0.00 | 0.36 | - | 0.01 | 0.36 |

Note: I simulate the random and clustered networks. The network size is 2000.

## A. Aggregate results

Table 3 describes the aggregate variables of the economy for the 4 different network structures and the two different values of $q$. Column 1 displays the result for the case without social referrals. Columns 2 through 4 show the results for $q$=1 and a network of pairs, a random network, and a clustered network. Columns 2 through 4 show the results for $q$=.1 and the three network types. Rows 1 through 3 present the results for "normal" economic conditions. The unemployment rate is displayed in row one. All models are calibrated to generate a 5% unemployment rate. Row 2 displays the probability of moving from unemployment to employment. All values a very similar for the different types of networks and for both values of $q$. The clustered network results in a slightly lower probability of moving from unemployment to employment. Well connected workers find reemployment in the period of their job loss and never appear as unemployed. Row 3 displays the ratio of workers who find their jobs through referrals to workers who find their job directly without referrals. The random and clustered networks are calibrated to a ratio of one. A network of pairs leads to a lower share of workers who found their jobs through referrals. For $q$=1, referred jobs are equally good fits as self observed vacancies and the referral ratio is close to one (.91). If referred jobs are less likely to be a good fit for a worker, i.e. $q$=.1, the referral ratio drops accordingly to.09.

I investigate the importance of referrals for these aggregate variables. I do this by simulating the model with the same set parameters used for the baseline simulations but suppress referrals. I "turn off" information transmission through social networks. Unemployed workers are less likely to see a vacancy and leave unemployment (Row 5 vs. Row 2). If half of all jobs are obtained through referrals (columns 3, 4, 6, and 7), this leads to an increase of the unemployment rate to about 6.5% (Row 3 vs. Row 1). In other words, information transmission through social networks reduces the unemployment rate from 6.5% to 5%. The network structure and the value of $q$ have almost no effect for any of these comparisons.

Table 3. Aggregate results

| Row # | | | | | $q$=1 | | | $q$=.1 | |
|---|---|---|---|---|---|---|---|---|---|
| | | | No network | Pairs | Random | Clustered | Pairs | Random | Clustered |
| | | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| 1 | Baseline | Unemployment rate | 0.050 | 0.050 | 0.050 | 0.050 | 0.050 | 0.050 | 0.050 |
| 2 | | Transition to employment | 0.290 | 0.291 | 0.279 | 0.271 | 0.290 | 0.289 | 0.270 |
| 3 | | Ratio referred / direct | 0.000 | 0.906 | 1.002 | 0.998 | 0.094 | 0.998 | 1.000 |
| 4 | Turn off referrals | Unemployment rate | 0.050 | 0.063 | 0.065 | 0.064 | 0.052 | 0.065 | 0.065 |
| 5 | | Transition to employment | 0.290 | 0.235 | 0.229 | 0.232 | 0.281 | 0.229 | 0.229 |
| 6 | | Ratio referred / direct | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| 7 | Recession | Unemployment rate | 0.093 | 0.094 | 0.093 | 0.093 | 0.093 | 0.095 | 0.097 |
| 8 | | Transition to employment | 0.170 | 0.168 | 0.165 | 0.162 | 0.169 | 0.166 | 0.161 |
| 9 | | Ratio referred / direct | 0.000 | 0.829 | 0.958 | 0.983 | 0.090 | 0.722 | 0.633 |
| 10 | Boom | Unemployment rate | 0.036 | 0.036 | 0.036 | 0.036 | 0.036 | 0.035 | 0.035 |
| 11 | | Transition to employment | 0.364 | 0.366 | 0.347 | 0.335 | 0.364 | 0.373 | 0.335 |
| 12 | | Ratio referred / direct | 0.000 | 0.925 | 0.984 | 1.003 | 0.097 | 1.125 | 1.136 |
| 13 | Extreme recession | Unemployment rate | 0.214 | 0.216 | 0.215 | 0.215 | 0.215 | 0.216 | 0.217 |
| 14 | | Transition to employment | 0.088 | 0.087 | 0.087 | 0.086 | 0.088 | 0.087 | 0.086 |
| 15 | | Ratio referred / direct | 0.000 | 0.683 | 0.829 | 0.900 | 0.078 | 0.341 | 0.276 |

Note: Based on simulations over 5000 periods. The first 100 periods are not considered in the calculations.

Next, I examine whether the different network structures affect the employment response to business cycle fluctuations. I simulate the models again now using, $\pi_{11}$=.981 and $\pi_{01}$=.129. The new steady state variables are described in rows 7 to 9. The reactions to changes in the economic environment are very similar for all the network structures considered.[9] For $q$=1, the unemployment increases to about 9.3% for all 4 models (Row 7 vs. Row 1).

The probability of transitioning from unemployment increases by similar amounts. Moreover, the vacancy to unemployment ratio changes to by similar degree for all models. For $q$=.1, economies with a random or clustered network experience a slightly more severe recession. The unemployment rate rises to 9.5% and 9.7% respectively. Unemployed workers do not pass along information about vacancies but utilize the information for their own benefit. Hence a higher unemployment rate decreases the probability of referrals; accordingly row 9 reveals a drop in the referral ratio during recessions. This effect is sensitive to the choice of $q$ and is most pronounced for a clustered network with a low value of $q$.

I also simulate a boom ($\pi_{11}$=.983 and $\pi_{01}$=.3) and an extreme recession ($\pi_{11}$=.975 and $\pi_{01}$=.075). The results are displayed in columns 10 through 12 and 13 through 15. Overall the differences in aggregate employment outcomes are very similar for all network types. The negative relationship between the overall employment rate and the referral rate is again apparent and most pronounced for a clustered network with a low value of $q$.

Table 4 displays the results when allowing for targeted information dispersal. I set $q$=.1 and let $a$ depend on the number of friends of an individual. I pick the average number of friends to obtain a referral ratio of one. For the random network the average value of $a$ is equal to.004 and for the clustered network it is.007. The standard deviation is.002 and.005 respectively. The aggregate employment results for the different states of the business cycle are very similar to the previous specifications. However, it can be seen that the referral ratio stays closer to one across the different economic environments. Moreover, turning off referrals leads to a smaller increase in the unemployment rate than above. In other words, social referrals with targeted information transmission – as modeled here – have a smaller effect on aggregate employment. Targeting well connected individuals is not necessarily the best strategy to fill a vacancy. If all employers target these individuals they and their friends are most likely employed. It is possible that employers update

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[9] I also considered more extreme changes to the economic environment the differences induced by different networks are still minor.

**Table 4. Targeted information dispersal**

| | | Baseline | | Turn off referrals | | Recession | | Boom | | Extreme recession | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Random | Clustered | Random | Clustered | Random | Clustered | Random | Clustered | Random | Clustered |
| Aggregate results | Unemployment rate ($u$) | 0.050 | 0.050 | 0.058 | 0.049 | 0.095 | 0.093 | 0.036 | 0.039 | 0.215 | 0.215 |
| | Prob. vacancy filled, $\theta$ | 0.451 | 0.454 | 0.370 | 0.473 | 0.641 | 0.673 | 0.357 | 0.371 | 0.850 | 0.914 |
| | Transition to employment | 0.279 | 0.214 | 0.254 | 0.295 | 0.163 | 0.138 | 0.350 | 0.258 | 0.086 | 0.081 |
| | Ratio referred / direct | 0.998 | 1.002 | 0.000 | 0.000 | 0.795 | 0.926 | 1.067 | 1.004 | 0.452 | 0.619 |
| Individual results | Standard deviation of $u$ relative to baseline no_network | 3.413 | 6.205 | 1.100 | 0.978 | 6.238 | 10.732 | 2.523 | 4.855 | 12.833 | 19.694 |
| | Persistence of employment | 0.706 | 0.775 | 0.730 | 0.689 | 0.820 | 0.847 | 0.636 | 0.731 | 0.891 | 0.897 |
| | Duration dependence | 1.076 | 1.272 | 0.999 | 0.996 | 1.051 | 1.269 | 1.092 | 1.248 | 1.028 | 1.144 |

| | | Random | Clustered |
|---|---|---|---|
| Wage results | Mean wage | 0.478 | 0.478 |
| | Standard deviation wage | 0.008 | 0.015 |
| | 10th percentile | 0.468 | 0.460 |
| | 90th precentile | 0.488 | 0.494 |

Note: Probability see job: (i) Random: average $a$ is 0.004, with standard deviation of 0.002 (ii) Clustered: average $a$ is 0.007, with standard deviation of 0.005.

their priors and adjust the rate at which they contact better connected individuals. Deriving the resulting equilibrium is beyond the scope of this paper.

**B. Individual level results**

The simulations results in Table 5 describe the effect of referrals through social networks on individual workers. Row 1 displays the standard deviation of the average time unemployed relative to the baseline economy with no social referrals. More complex networks introduce heterogeneity among workers; some workers are better connected than others. This leads to variation in the average time unemployed. The variation in the model with a random network is smaller than with the clustered and skewed network. This is due to the fact that in the latter case the variation in the number of friends is higher. A lower value of $q$ reduces the impact of the variation in the number of friends.

Row 2 shows that the persistence of the employment status as measured by the first order autocorrelation of the employment status. The information transmission through social networks has basically no effect on this persistence.

Row 3 displays the duration dependence of exiting unemployment, as measured by the ratio of the probability of finding a job in the first week of unemployment divided by the probability of finding a job after two weeks of unemployment. Without the information transmission through social networks all unemployed workers are identical and there is no duration dependence. In the presence of social referrals, workers with good connections are more likely to find employment quickly. Workers with bad connections are unemployed for longer periods of time and less likely to find a job in a given period. The clustered and skewed network with $q$=1 generates the highest duration dependence (a ratio of 1.14). Lynch (1989) investigates duration dependence using NLSY data, the comparable ratio reported by her is 1.75.[10] While social referrals can explain part of the observed duration dependence, other sources of heterogeneity seem to be more important.

In Rows 4, 5, and 6, I report the results for simulations for an economy in a recession. The standard deviation of the average unemployment probability increases, as unemployment becomes more likely. Consistent with the above observation that referrals play a lesser role when more workers are unemployed the social network induced duration dependence decreases during recessions. This is not consistent with Shimer (2008) who finds – using CPS data – that the effect of unemployment

[10] Based on CPS data Shimer (2008) reports a similar level of duration dependence.

**Table 5. Individual level results**

| Row # | | | No network | Pairs | $q$=1 Random | Clustered | Pairs | $q$=.1 Random | Clustered |
|---|---|---|---|---|---|---|---|---|---|
| | | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| 1 | Baseline | Standard deviation of time unemployed relative to baseline (no network) | 1.00 | 0.97 | 3.42 | 4.21 | 0.98 | 1.27 | 3.86 |
| 2 | | Persistence of employment | 0.69 | 0.69 | 0.71 | 0.71 | 0.69 | 0.70 | 0.72 |
| 3 | | Duration dependence | 1.00 | 1.01 | 1.07 | 1.14 | 1.00 | 1.01 | 1.11 |
| 4 | Recession | Standard deviation of time unemployed relative to baseline (no network) | 1.70 | 1.76 | 5.69 | 7.20 | 1.72 | 2.19 | 4.98 |
| 5 | | Persistence of employment | 0.81 | 0.81 | 0.82 | 0.82 | 0.81 | 0.82 | 0.82 |
| 6 | | Duration dependence | 1.00 | 1.01 | 1.04 | 1.08 | 1.00 | 1.00 | 1.04 |
| 7 | Boom | Standard deviation of time unemployed relative to baseline (no network) | 0.73 | 0.72 | 2.54 | 3.12 | 0.73 | 0.93 | 3.12 |
| 8 | | Persistence of employment | 0.62 | 0.62 | 0.64 | 0.65 | 0.62 | 0.61 | 0.65 |
| 9 | | Duration dependence | 1.00 | 1.01 | 1.09 | 1.16 | 1.00 | 1.01 | 1.16 |
| 10 | Extreme recession | Standard deviation of time unemployed relative to baseline (no network) | 3.17 | 3.37 | 9.89 | 12.57 | 3.22 | 3.59 | 5.37 |
| 11 | | Persistence of employment | 0.89 | 0.89 | 0.89 | 0.89 | 0.89 | 0.89 | 0.89 |
| 12 | | Duration dependence | 1.00 | 1.01 | 1.02 | 1.04 | 1.00 | 1.00 | 1.00 |

Note: Based on simulations over 5000 periods. The first 100 periods are not considered in the calculations.

duration on the job finding probability is not affected by the business cycle. In Rows 7 though 9, and 10 through 12, I display the results for a boom economy and an extreme recession. The results reinforce the previous findings. More unemployment leads to a higher variation in employment probability across individuals and to less duration dependence. Lower values of $q$ lead to less variance in the quality of individuals networks and reduce the impact of the variation in the number of friends especially in the case of an extreme recession.

Table 4 displays the individual level results with targeted information dispersal. The individual differences in the probability of finding employment are magnified. Workers with more friends have potentially more access to referrals and they are more likely to directly obtain information about vacancies. Hence the standard deviation of employment status and the duration dependence increases relative to the case without targeted information dispersal.

Workers with a high number of friends have a high probability of receiving a referral and are less likely unemployed. Table 6 shows the results of regressions of the probability of being employed on the number of friends and the number of friends of friends. For both the random network and the clustered network, additional friends increase the probability of employment at a decreasing rate. For the clustered network the number of friends of friends is negatively related to employment after controlling for the number of friends. The reason for this relationship is a competition for information. If my friends have a lot of friends they are less likely to share information with me.

**Table 6. The role of connections and the probability of employment**

| Independent variables | $q$=1 | | | | $q$=.1 | | | |
|---|---|---|---|---|---|---|---|---|
| | Random network | | Clustered network | | Random network | | Clustered network | |
| # of friends | 0.052 | 0.050 | 0.036 | 0.045 | 0.0043 | 0.0036 | 0.0015 | 0.0770 |
| # of friends squared | -0.013 | -0.012 | -0.005 | -0.007 | -0.0001 | -0.0001 | 0.0000 | -0.0006 |
| # of friends cubed | 0.001 | 0.001 | 0.000 | 0.000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| # of friends of friends | | 0.001 | | -0.002 | | 0.0000 | | -0.0005 |
| # fr. of fr. squared | | 0.000 | | 0.000 | | 0.0000 | | 0.0000 |
| # fr. of fr. Cubed | | 0.000 | | 0.000 | | 0.0000 | | 0.0000 |

Note: Linear regression of probability of employment (dependent variable) on number of friends and friends of friends. The average number of friends in the random network is 1.63. In the clustered network it is 2.29.

## VI. Wage determination through bargaining

Mortensen (2003, p.1) writes "Observable worker characteristics that are supposed to account for productivity differences typically explain no more than 30 percent in the variation in compensation." In this section, I quantify the wage dispersion that can be generated by introducing social referrals into a standard wage bargaining model. Social contacts determine the job finding probabilities of workers and therefore the outside options during the wage bargaining process between workers and firms. Consequently, information transmission through social networks can lead to wage differences among otherwise homogeneous workers.

I assume that there are no binding long-term contracts and wages are renegotiated each period. Both firms and workers have perfect information about the expected referrals through the social network of workers.

When a worker and a firm with a vacancy meet they can gain from forming a connection and filling the vacancy. Let $\beta$ be the discount rate. Let $V_E(i)$ and $V_U(i)$ express how valuable the states of employment and unemployment are to worker $i$. These values depend on the individual specific wage rate, $w_i$, the monetized utility of unemployment, $z$, and the job finding probability, $p_i$:

$$V_E(i) = w_i + \beta\left\{\pi_{11}V_E(i) + (1-\pi_{11})V_U(i)\right\}, \tag{9}$$

$$V_U(i) = z + \beta\left\{p_i V_E(i) + (1-p_i)V_U(i)\right\}. \tag{10}$$

The gain of accepting a job with a wage rate $w_i$ is:

$$G_A(w_i, p_i) = V_E(i) - V_U(i) = \frac{w_i - z}{1-\beta(\pi_{11} - p_i)}.$$

$V_F(i)$ is the value of filled job for a firm, $V_V$ the value of a vacancy, and $V_I$ the value of an idle job. Note that $V_V$ and $V_I$ do not depend on the specific worker that is interacting with the firm. Let $\overline{V}_F$ represent the expected value of $V_F(i)$, then:

$$V_F(i) = y - w_i + \beta\left\{\pi_{11}V_F(i) + (1-\pi_{11})V_I\right\}, \tag{11}$$

$$V_V = \beta\left\{\pi_{11}\theta_S\overline{V}_F + \pi_{11}(1-\theta_S)V_V + (1-\pi_{11})V_I\right\}, \tag{12}$$

$$V_I = \beta\left\{\pi_{01}\theta_S\overline{V}_F + \pi_{01}(1-\theta_S)V_V + (1-\pi_{01})V_I\right\}. \tag{13}$$

For the firm the gain of filling the vacancy is given by:

$$G_B(w_i) = V_F(w_i) - V_V.$$

The total surplus of filling the vacancy is split between the worker and the firm. The share each side receives depends on $\alpha$, the bargaining power of workers:

$$(1-\alpha)G_A(i) = \alpha G_B(i), \tag{14}$$

or, using equations (9) through (12),

$$\underbrace{(1-\alpha)\frac{w_i - z}{1-\beta\pi_{11}+\beta p_i}}_{(1-\alpha)G_A(i)} = \underbrace{\alpha\frac{y-w_i}{(1-\beta\pi_{11})}+\alpha Q}_{\alpha G_B(i)}, \text{ with } Q = \left[\frac{(\beta-\beta\pi_{11})V_I}{(1-\beta\pi_{11})} - V_V\right]. \tag{15}$$

The term $Q$ captures the value of an idle job and the outside option of the firm. It does not vary across workers.

Without social referrals all workers have the same probability of finding a job and thus the same wage.[11] With social referrals, the connections of a worker affect the probability of finding a job, $p_i$. A higher probability implies a higher outside option for the worker and decreases the gain from a contract for a given wage:

$$\left.\frac{\partial G_A}{\partial p_i}\right|_{w_i} < 0.$$

The job finding probability of a specific worker does not affect the outside option of the firms. Consequently equation (14) implies that a high value of $p_i$ will lead to a high value of $w_i$. Some of the surplus of the firm is transferred to the worker.

Equation (14) can be solved to obtain an expression for the wage as a function of $p_i$, the exogenously given parameters ($\pi_{11}$ and $\pi_{01}$) and an expression capturing the expected values of a vacancy and an idle job:

$$w_i = \frac{(1-\beta\pi_{11}+\beta p_i)\alpha y + (1-\beta\pi_{11})(1-\alpha)z}{(1-\beta\pi_{11}+\alpha\beta p_i)} + \frac{(1-\beta\pi_{11}+\beta p_i)(1-\beta\pi_{11})}{(1-\beta\pi_{11}+\alpha\beta p_i)}\alpha Q. \tag{16}$$

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[11] See Appendix for the closed form expression of the wage.

To get a sense for the magnitude of the variation in wages due to social referrals I parameterize the values in equation (16). I pick the period discount rate $\beta = .999062$. This corresponds to a yearly interest rate of 5%. I normalize $y = 1$ and pick $z = .15$. The values $\pi_{11} = .982$ and $\theta_{11} = .45$ are obtained from Table 2. I approximate $Q$ by calculating its value for the case of homogeneous workers with a job finding probability that equal is to the average job finding probability for heterogeneous workers (see Appendix).

Table 7 presents the resulting wage distribution for the different network types and different values for $\alpha$ and $q$.[12] Without social referrals (or with a network of pairs) all workers earn the same wage. The two other network structures introduce very little heterogeneity in wages. With the bargaining process assumed here, social

**Table 7. Effect on wages**

| Bargaining power of workers ($\alpha$) | | $q$=1 | | | $q$=.1 | | |
|---|---|---|---|---|---|---|---|
| | No network | Pairs | Random | Clustered | Pairs | Random | Clustered |
| $\alpha$ =.5 | | | | | | | |
| Mean wage | 0.48 | 0.48 | 0.48 | 0.48 | 0.48 | 0.48 | 0.48 |
| Standard deviation wage | - | - | 0.01 | 0.01 | 0.00 | 0.00 | 0.01 |
| 10th percentile | 0.48 | 0.48 | 0.47 | 0.46 | 0.48 | 0.48 | 0.47 |
| Median wage | 0.48 | 0.48 | 0.48 | 0.48 | 0.48 | 0.48 | 0.48 |
| 90th precentile | 0.48 | 0.48 | 0.49 | 0.49 | 0.48 | 0.48 | 0.49 |
| $\alpha$ =.1 | | | | | | | |
| Mean wage | 0.21 | 0.21 | 0.21 | 0.21 | 0.21 | 0.21 | 0.21 |
| Standard deviation wage | - | - | 0.01 | 0.01 | 0.00 | 0.00 | 0.01 |
| 10th percentile | 0.21 | 0.21 | 0.20 | 0.19 | 0.20 | 0.20 | 0.19 |
| Median wage | 0.21 | 0.21 | 0.21 | 0.21 | 0.21 | 0.21 | 0.21 |
| 90th precentile | 0.21 | 0.21 | 0.22 | 0.22 | 0.21 | 0.21 | 0.22 |
| $\alpha$ =.9 | | | | | | | |
| Mean wage | 0.87 | 0.87 | 0.87 | 0.87 | 0.87 | 0.87 | 0.87 |
| Standard deviation wage | - | - | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 10th percentile | 0.87 | 0.87 | 0.87 | 0.87 | 0.87 | 0.87 | 0.87 |
| Median wage | 0.87 | 0.87 | 0.87 | 0.87 | 0.87 | 0.87 | 0.87 |
| 90th precentile | 0.87 | 0.87 | 0.87 | 0.88 | 0.87 | 0.87 | 0.88 |

Note: See Tables 1 and 2 for parameters used for simulations. Additional parameters for the bargaining process: period discount rate $\beta$ = .999062.

[12] I obtained similar results when considering an economy in recession, boom, or extreme recession.

referrals contribute very little to the wage variation of otherwise homogeneous workers. Targeted information dispersal leads to magnified difference in employment probabilities. As seen in the bottom of Table 7, this is reflected in some wage dispersion. Nevertheless even in this extreme setting the resulting wage variation is relatively minor. The wages at the 90th percentile of the wage distribution are 7% higher than at the 10th percentile.

## VII. Conclusion

I augment a labor market matching model by incorporating information transmission through social networks. I simulate the resulting economy. I find that without social referrals the steady state unemployment rate would be 6.5% instead of 5%. The predictions for aggregate outcomes of a matching model with social networks and a standard model without social networks are quantitatively very similar. Social referrals generate heterogeneity in unemployment duration and can explain at most 1/5th of the observed duration dependence of unemployment. They cannot explain the variation in wages of otherwise homogeneous workers.

This paper quantifies the effects of the sharing of information about vacancies among workers. I do not take into account some other mechanisms through which social networks might affect labor market outcomes. For example, social networks might be used to transmit information about worker characteristics to potential employers.

Moreover, to isolate the effects of social networks, I assume homogeneous workers that differ only in their position in the network. I do not consider the effects of membership in different social networks due to individual characteristics, such as ethnicity. Effects of social networks on labor market outcomes through any of these channels are not reflected in the results presented here.

## Appendix

In this Appendix, I derive an expression for the wage of workers with identical job finding probabilities. Then I illustrate how the wage for heterogeneous workers can be approximated.

If all workers have identical employment probabilities the value of all filled jobs to the firm are identical, as well: $p_i = \overline{p}$ and $\overline{V}_F = V_F(i)$ for all $i$. The gains for workers and firms are given by:

$$G_A = V_E - V_U = \frac{\bar{w} - z}{1 - \beta\left(\pi_{11} - \bar{p}\right)},$$

$$G_B = V_F - V_V = \frac{y - \bar{w}}{1 - \beta\pi_{11}\left(1 - \theta\right)}.$$

The wage, $\bar{w}$, can be derived by using $\left(1-\alpha\right)G_A = \alpha G_B$:

$$\left(1-\alpha\right)\frac{\bar{w} - z}{1 - \beta\left(\pi_{11} - \bar{p}\right)} = \alpha\frac{y - \bar{w}}{1 - \beta\pi_{11}\left(1 - \theta\right)}, \tag{A1}$$

$$\bar{w} = \frac{\alpha\left(1 - \beta\pi_{11} + \beta\bar{p}\right)y + \left(1-\alpha\right)\left(1 - \beta\pi_{11} + \beta\pi_{11}\theta\right)z}{\left(1 - \beta\pi_{11} + \left(1-\alpha\right)\beta\pi_{11}\theta + \alpha\beta\bar{p}\right)}. \tag{A2}$$

If both parties have equal bargaining power ($\alpha = .5$) the wage is given by:

$$\bar{w} = \frac{\left(1 - \beta\pi_{11} + \beta\bar{p}\right)y + \left(1 - \beta\pi_{11} + \beta\pi_{11}\theta\right)z}{\left(2 - 2\beta\pi_{11} + \beta\pi_{11}\theta + \beta\bar{p}\right)}.$$

If workers have different job finding probabilities the value of a filled job to a firm depends on the wage negotiated with the respective worker, $i$. Equation (A1) becomes now:

$$\left(1-\alpha\right)G_A\left(i\right) = \left(1-\alpha\right)\frac{w_i - z}{1 - \beta\pi_{11} - p_i} = \alpha\frac{y - w_i}{\left(1 - \beta\pi_{11}\right)} + \alpha Q = \alpha G_B\left(i\right),$$

with $Q = \dfrac{\left(\beta - \beta\pi_{11}\right)V_I}{\left(1 - \beta\pi_{11}\right)} - V_V$.

The term $Q$ captures the value of the outside option of the firm and does not vary across workers. I approximate $Q$ using equation (A2) and using the average job finding probability for heterogeneous workers to obtain $\bar{p}$.

$$w_i = \frac{\left(1 - \beta\pi_{11} + \beta p_i\right)\alpha y + \left(1 - \beta\pi_{11}\right)\left(1-\alpha\right)z}{\left(1 - \beta\pi_{11} + \alpha\beta p_i\right)} + \frac{\left(1 - \beta\pi_{11} + \beta p_i\right)\left(1 - \beta\pi_{11}\right)\alpha}{\left(1 - \beta\pi_{11} + \alpha\beta p_i\right)}Q.$$

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