On-the-job search and finding a good job through social contacts\footnote{I would like to thank Marco van der Leij, Fernando Vega-Redondo, Paolo Pin, Carolina Silva, Miguel Sanchez Villalba, Dunia Lopez Pintado and Kiss Hubert János for their helpful comments and remarks. All remaining errors are mine.}

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Abstract

The interactions between on-the-job search and finding a job through social contacts are investigated in a Diamond-Mortensen-Pissarides search model with heterogeneous wages. Workers may find a job through their social contacts and on the formal market. The presence of social contacts increases the overall welfare in society as it rises the number of workers earning high wages and the number of high wage vacancies. However, unemployed workers finding a job through social ties earn lower wages on average than those who obtain a job on the formal market. This result follows from on-the-job search: employed workers pass only those offers on to their neighbors that pay (weakly) lower wages than their current wages earned. Despite the wage discount, unemployed workers still might find it beneficial to search via social ties because arrival rate of offers is higher for this channel than for the formal market when the number of neighbors is sufficiently large. There is a trade-off between unemployment duration and wages earned for workers obtaining a job via social ties.

**JEL Classification:** E24, D85, J64

**Keywords:** Social Networks, Labor Market Search, Wages
1 Introduction

It has been widely documented that workers search for employment using their social contacts, i.e. friends, relatives and acquaintances, in addition to searching using the formal market, in the form of answering advertisements or directly applying to employers. Different studies find that 30-60% of jobs are found using social connections (e.g. see Blau and Robins (1990), Holzer (1987)). Social networks may help to alleviate informational problems inherent to the labor markets: first, social contacts serve as information source in a market characterized by search frictions (Calvo-Armengol and Zenou (2005)), second, hiring through referrals provides additional information about unobservable worker characteristics to firms making asymmetric information problems less severe (Montgomery (1991)). This paper presents a Diamond-Mortensen-Pissarides search model where social contacts help to match workers to vacancies such that workers have two channels to find a job: the formal market and their social ties. Jobs are heterogeneous with respect to wages and workers can search on-the-job. The paper investigates the interactions between finding a job via social contacts and on-the-job search. First, the impact of social networks on the equilibrium and welfare is evaluated in a context where workers can switch to better-paying jobs. Second, it is studied how on-the-job search influences the expected wages of jobs obtainable through social contacts.

The results show that the presence of social networks increases welfare because the network channel serves as an additional information source what workers can use to find a job. There will be less workers unemployed and more workers employed in high wage jobs compared to the case when workers and firms can meet only on the formal market. Firms in the high wage sector post more vacancies as they can fill them by unemployed or low wage earning workers more easily. On the contrary, firms in the low wage sector post less vacancies because the workers they employ leave the job faster. Increasing network connectivity has exactly the same impact: as workers have more neighbors, they will have more chance to hear about useful job information.

Regarding the impact of on-the-job search on networking, it is shown that on-the-job search alters the wage distribution of jobs obtainable through neighbors in the social network. Low wage offers will be passed on by any employed worker while high wage offer only by high wage employed workers. This fact implies that an unemployed worker is more likely to hear about a low wage job than a high wage job via her social contacts. Consequently, the social network pays a wage discount compared to the formal market if the expected wages conditional on arrival are considered. The conditional wage expectation measures the
quality of arriving offers and is normalized by the arrival rate of offers. On the contrary, the unconditional wage expectation increases with the arrival rate of offers. It is shown in the paper that for low number of neighbors the arrival rate of offers via social contacts is low and the unconditional wage expectation of network search is lower than that of the formal market. This implies that an unemployed worker is better off choosing the formal market as job search method if she has only a few contacts. However, for larger number of neighbors the arrival rate of offers via contacts is high enough to make the unconditional wage expectation of network search to be larger than that of the formal market. A trade-off emerges between the arrival rate and the quality of offers obtained via social ties: a worker finding a job through social contacts will spend less time in unemployment but will be more likely to have a low wage job compared to a worker who obtains a job on the formal market. Numerical analysis of the model shows that the quality of offers obtainable via social network is higher if the network is more connected or the productivity level is higher. In both of these cases, the fraction of workers earning high wages will be larger which increases the likelihood of hearing about a high wage job through social contacts.

The presented model is within the literature on the impact of social networks on labor market processes started out of the book by Granovetter (1995). Many papers use the search and matching framework to study the labor market equilibrium with social networks (see e.g. Calvo-Armengol and Zenou (2005), Cahuc and Fontaine (2009)). Most of these papers analyze the impact of social networks in a model with homogeneous workers and jobs and, consequently, do not consider the case of on-the-job search. Calvo-Armengol and Jackson (2007) allows for on-the-job search in a model where vacancy posting is exogenous. Their main focus is on the correlation of wages earned between connected workers built up by the information transmission process on the social network. They do not analyze the welfare effects of networks or the comparison of expected wages between job search methods. To our knowledge, this paper is the first to study the impact of social networks in a search and matching model with on-the-job search.

The comparison of search methods regarding expected wages has a large theoretical and empirical literature with ambiguous conclusions on whether the network or the formal market pays a wage premium. There are different arguments why the jobs obtained via social contacts should pay higher wages. Montgomery (1991) argues that job referrals help to resolve the asymmetric information problem on the labor market and high ability workers tend to find jobs through informal methods. Dustmann et al. (2011), Simon and Warner (1992) and Galenianos (2012) also reason that the informal search methods are more informative about worker’s productivity which leads to a wage premium. Kugler (2003) points
out that job referrals monitor the referred workers in the workplace who, in consequence, put more effort and get paid more. On the contrary, some other articles argue that informal job search methods should pay lower wages than the formal market. Ponzo and Scoppa (2010) show that social contacts, particularly family members, often recommend each other for jobs where they lack the qualifications, which leads to lower wages. Bentolila et al. (2010) argues that young workers accept jobs in sectors where their productivity is lower because they find employment earlier using social contacts. They also obtain that, conditional on arrival, the network provides a wage discount compared to the formal market but the arrival rate of offers can be high enough to compensate the job seeker for the lower wages. The model presented here leads to the same conclusion, however, the underlying intuition comes from on-the-job search not from the workers’ occupational choice as in Bentolila et al. (2010). Our model can thus be seen as a new theoretical contribution which argues that social contacts pays a wage discount.

The empirical articles also show ambiguity regarding which search method leads to higher wages conditional on having obtained a job. Some estimates indicate that the job search via social ties results in a wage premium over the formal market (see e.g. Kugler (2003), Dustmann et al. (2011), Simon and Warner (1992)), while other studies find a wage discount (e.g. see Bentolila (2010)). In a cross country study, Pellizzari (2010) finds that social networks results in a wage premium in Austria, Belgium and the Netherlands while a wage discount is to be found in Greece, Italy, Portugal and the United Kingdom. Galenianos (2012) argues that the empirical literature can be divided into two groups according to being able to control for firm fixed-effects: papers controlling for firm fixed-effects find a wage premium for social networks while those who do not control, find a wage discount.

2 Model

This section describes the model assumptions and derives the equilibrium conditions.

In the model there are two types of firms: one with low productivity \( y_L \), the other with high productivity \( y_H \). The vacancy rate of these two types of jobs are endogenously determined and are denoted by \( v_L \) and \( v_H \), respectively. Workers are homogeneous and can be employed by any of the firms. Workers employed at low productivity firms earn lower wages than workers employed at high productivity firms. There is on-the-job search: employees earning low wages can move to other firms paying higher wages if they become aware of a vacancy. The labor market is characterized by search frictions. Workers may hear
about job offers through two channels: on the formal market (direct arrival) or from their social contacts (indirect arrival).

**Direct arrival of offers.** The arrival rate of offers on the formal market depends on the vacancy rate of the two types of jobs. The direct arrival rate of low productivity offers to any worker is given by:

\[ q^M_L(v_L) = A v_L^{(1-\alpha)} \]  

(1)

where \( v_L \) is the vacancy rate of low productivity jobs, \( A \) and \( \alpha \) are technology parameters with \( \alpha \in (0, 1) \). Note that this arrival rate does not depend on the fraction of unemployed workers because in this model both unemployed and employed workers can hear about employment opportunities.\(^1\) Denote the unemployment rate by \( u \), the fraction of workers employed in low (high) wage jobs by \( e_L \) (\( e_H \)). The receiver of the arriving offer is randomly chosen from the set of all workers. The direct arrival rate of low productivity jobs to unemployed workers therefore is given by \( u q_L(v_L) \), to workers employed in low wage jobs is \( e_L q_L(v_L) \) and to workers employed in high wage jobs is \( e_H q_L(v_L) \).

Similarly, the direct arrival rate of high wage offers is given by:

\[ q^M_H(v_H) = A v_H^{(1-\alpha)} \]  

(2)

Direct arrival rate of high wage jobs to unemployed workers is \( u q_H(v_L) \), to low wage employees \( e_L q_H(v_H) \) and to high wage employees \( e_H q_H(v_H) \).

**On-the-job search and transmission of job information.** It is assumed that unemployed agents accept offers of any type. This behavior is rational if the wage difference between the two job types is low enough as that means that waiting for a high wage offer is too costly when an individual can accept a low wage job.

Low wage employed workers may switch to a high wage job if they hear about a vacancy. Thus, they forward only low wage offers to their social contacts. It is supposed that they pass any low wage job offer on to a randomly chosen unemployed neighbor in the social network. If they do not have any unemployed neighbor, the offer is lost, nobody takes up the job. Hence, the job information can travel only one step in the network. Similar assumptions have been used in Calvó-Armengol and Zenou (2005) and Calvó-Armengol and Jackson (2004).

High wage workers cannot upgrade their situations, so they forward any offer of which they become aware. If they hear about a low wage offer, they pass it on to one unemployed

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\(^1\)In this case the matching function is \( q^M_L(v_L) = A(u + e)^\alpha v_L^{(1-\alpha)} \) where \( u \) is the unemployment rate, \( e \) is the employment rate and \( e + u = 1 \).
contact at random. When they learn of a high wage offer, they also consider their low wage friends. They choose one contact at random from the pool of unemployed and low wage employed neighbors.

Hence, the wage distribution of vacancies one unemployed worker can learn of by using her contacts is determined by the composition of her neighborhood: having more employed contacts earning high wages increases the probability of getting a high wage offer. This phenomenon has been described in sociology both theoretically and empirically. Social resource theory states that an individual’s social capital consists of the attained status of their social contacts (see e.g. Lin (1999)). Empirical studies document that the social status, prestige and wages of the social contact used to obtain a job positively influences the status and wages attained by an individual (see e.g. Marsden and Hurlbert (1988) and Marsden and Gorman (2001)). On-the-job search can thus serve as an explanation for this phenomenon.

Network structure. The network structure is assumed to be a regular random graph: every worker has $k$ social contacts randomly chosen from the entire population of workers.

Homogeneous mixing assumption. Any time any worker can be found in one of the three states: unemployed, employed in low wage job, employed in high wage job. To derive the equilibrium conditions, the so-called homogeneous mixing assumption is supposed which means that the network connections of a given individual are randomly redrawn at each instant of time. This assumption implies that the state of a neighbor is independent of the state of an individual connected to her. Moreover, the probability that a neighbor can be found in a particular state is equal to the population frequency of that state. For example, the probability that a neighbor is unemployed is given by the unemployment rate in the economy. Hence, this assumption does not take into account that the states of connected agents are correlated in the limit (see Calvo-Armengol and Jackson (2004, 2007)). By applying the homogeneous mixing assumption, the model is based on a representative individual who is connected to other $k$ representative individuals.

Arrival of offers through social contacts. Workers may find a job not only on the formal market but also via their social contacts. First, we look at the case when an unemployed worker finds a low wage job through her contacts. She has $ke_L$ low wage employed contacts and $ke_H$ high wage employed contacts on average. Each contact knows about a low wage job with probability $q_L^M(v_L)$. Each of these contacts chooses a random unemployed worker among their neighbors as the receiver of job information. The number of unemployed contacts is randomly drawn from the binomial distribution $B(k, u)$ since each of the $k$ contacts is unemployed with probability $u$. Thus, the probability that a given
unemployed among the $k$ contacts receives the information is given by the following formula:\footnote{For a similar derivation see Calvó-Armengol and Zenou (2005).}

$$\sum_{i=0}^{k-1} \binom{k-1}{i} u^i (1-u)^{k-i-1} \frac{1}{i+1} = \frac{1-(1-u)^k}{uk}$$

(3)

where in the summation $i$ is the number of other social contacts who compete for the same information about job offers.

The probability that a given unemployed worker finds a low wage job through any of her contacts thus is the following:

$$q_N^L(u,v_L) = k(e_L + e_H)q_M^L(v_L) \frac{1-(1-u)^k}{uk} = (1-u)q_M^L(v_L) \frac{1-(1-u)^k}{u}$$

(4)

Second, consider the case when an unemployed worker or a low wage employee finds a high wage job through their high wage contacts as other contacts do not pass high wage offers on to their neighbors. Any of these individuals has $ke_H$ high wage contacts on average. Any of these contacts has $q_H^M(v_H)$ probability of being aware of a high wage offer. When she has an offer, she chooses a random agent out of the pool of unemployed and low wage employed neighbors of hers. Similarly to the previous case, the number of such neighbors is randomly drawn from the binomial distribution $B(k, u + e_L)$. Hence, a given unemployed or low wage employed worker has the following probability to be chosen as receiver of the information:

$$\sum_{i=0}^{k-1} \binom{k-1}{i} (u + e_L)^i (1-(u + e_L))^{k-i-1} \frac{1}{i+1} = \frac{1-e_H^k}{k(1-e_H)}$$

(5)

The probability that a given unemployed or low wage employed worker finds a high wage job through any of her contacts is the following:

$$q_H^N(e_H,v_H) = ke_Hq_H^M(v_H) \frac{1-e_H^k}{k(1-e_H)} = e_Hq_H^M(v_H) \frac{1-e_H^k}{1-e_H}$$

(6)

**Matching function.** Based on the previous derivations, it is possible to write down the aggregate number of matches between firms and workers. Matches occur on the formal market and via social contacts. It is assumed that the worker uses these two channels simultaneously and accepts the first arriving offer, independently of which channel provides that offer. The model is written in continuous time which implies that at some instant of time the worker can hear about an offer only from one channel. Hence, the total arrival rate
of offers is the sum of the arrival rate on the formal market and via social contacts. Low productivity firms will hire unemployed workers, the total number of matches is given by:

\[ uq_L(u, v_L) = uq_L^M(v_L) + uq_L^N(u, v_L) = uq_L^M(v_L) \left(1 + (1 - u) \frac{1 - (1 - u)^k}{u}\right) \]

The number of matches between unemployed workers and high productivity firms is the following:

\[ uq_H(e_H, v_H) = uq_H^M(v_H) + uq_H^N(e_H, v_H) = uq_H^M(v_H) \left(1 + e_H \frac{1 - e_H^k}{1 - e_H}\right) \]

The number of matches between employees earning low wages and high productivity firms is as follows:

\[ e_L q_H(e_H, v_H) = e_L q_H^M(v_H) + e_L q_H^N(e_H, v_H) = e_L q_H^N(e_H, v_H) \left(1 + e_H \frac{1 - e_H^k}{1 - e_H}\right) \]

**Job separations.** For both type of jobs, separations happen according to a Poisson arrival process with parameter \( \lambda \).

**Steady state conditions.** The model predictions are investigated in the steady state where the inflows and outflows are equal for both low and high wage jobs. The steady state equation for low wage jobs is as follows:

\[ uq_L(u, v_L) = \lambda e_L + e_L q_H(e_H, v_H) \] (7)

Note that the outflows include both job separations and the fraction of low wage employed workers who find better paying jobs.

The steady state equation for high wage jobs is given by:

\[ uq_H(e_H, v_H) + e_L q_H(e_H, v_H) = \lambda e_H \] (8)

The inflow to high wage jobs consists of the unemployed and low wage employed workers who find a high wage job through any of the search methods.

**Job creation equations.** The vacancy rates of low and high wage jobs are endogenously determined within the model. A firm may decide whether to enter in any of the sectors. Free-entry condition implies that as long as the value of a vacancy in any of the sectors is positive, there will be new firms entering the market pushing down the value to
zero. Let us consider first the sector of low productivity firms. Define the vacancy filling rate of the low productivity sector as:

$$q^F_L(u, v_L) = \frac{q_L(u, v_L)}{v_L}$$

Note that this function is decreasing in $v_L$: as there are more low wage vacancies, it is more difficult for a given firm to fill its vacancy. Firms may meet unemployed workers through any of the information channels.

Firms having a vacant job have to pay vacancy maintaining cost $c$. The value of a vacancy in this sector in the steady state is given by:

$$\delta V_L = -c + uq^F_L(u, v_L)(J_L - V_L)$$

where $\delta$ is the discount rate and $J_L$ is the value of a filled job in this sector. The value of a vacancy consists of the costs paid by the firm and the future value realized when the firm hires a worker.

The firm’s discounted value when it employs a worker is as follows:

$$\delta J_L = (1 - \beta)y_L + \lambda(V_L - J_L) + q_H(e_H, v_H)(V_L - J_L)$$

The firm produces $y_L$ when it employs a worker and keeps $(1 - \beta)$ share of the output. Consequently, the worker earns the exogenous amount of $w_L = \beta y_L$. The match may be terminated by the exogenous separation or in case the worker finds a better paying job.

Given the free-entry condition, the value of vacancies is driven down to zero: $V_L = 0$. It is possible to express $J_L$ from the previous two equations and making the two values equal gives the job creation condition for low productivity jobs:

$$J_L = \frac{c}{uq^F_L(u, v_L)} = \frac{(1 - \beta)y_L}{\delta + \lambda + q_H(e_H, v_H)}$$

(9)

Turning to the high productivity sector, define the vacancy filling rate of this sector as:

$$q^F_H(e_H, v_H) = \frac{q_H(e_H, v_H)}{v_H}$$

Note that this function is decreasing in $v_H$.

The discounted value of a vacancy is given by:

$$\delta V_H = -c + uq^F_H(e_H, v_H)(J_H - V_H) + e_Lq^F_H(e_H, v_H)(J_H - V_H)$$
A firm maintaining a vacancy need to pay a cost $c$. A high wage vacancy might be filled by an unemployed worker or a job-to-job mover.

The discounted value of a filled job in this sector is as follows:

$$\delta J_H = (1 - \beta)y_H + \lambda(V_H - J_H)$$

where $y_H$ is the productivity in this sector and the firm keeps $(1 - \beta)$ share of the output. The worker earns $w_H = \beta y_H$.

Free-entry condition again implies that the value of a vacancy is equal to zero: $V_H = 0$. Applying this condition and expressing $J_H$ from the previous two equations gives the job creation condition for high wage jobs:

$$J_H = \frac{c}{(1 - \epsilon_H)q_H^F(e_H, v_H)} = \frac{(1 - \beta)y_h}{\delta + \lambda} \quad (10)$$

**Equilibrium.** The equilibrium of the model is defined by the two steady state and the two job creation conditions.

**Definition** The equilibrium of the model is given by the quadruple \{u, e_H, v_L, v_H\} satisfying the steady state equations (7), (8) and the job creation conditions (9) and (10).

The following proposition states the conditions under which a unique equilibrium exists.

**Proposition 1** A unique equilibrium exists if

$$A^{\frac{1}{\gamma}} \left[ \frac{(1 - \gamma)y_H}{(\delta + \lambda)c} \right]^{\frac{1 - \gamma}{\gamma}} > \lambda$$

### 3 Results

#### 3.1 Impact of the presence of network channel

This section compares the model in the presence and absence of network channel. To our best knowledge, the impact of finding a job through social contacts has not been studied in a dynamic search model with on-the-job search. The model of Calvo-Armengol and Jackson (2007) also allows for on-the-job search but their main focus is on the correlation of wages and employment rates between connected workers. Here we focus on the impact of network search on the aggregate outcome of the labor market and the welfare of the economy.
**Proposition 2** In the model with social network, the unemployment rate \((u)\) is lower and the high wage employment rate \((e_H)\) is higher than in the model without social network.

To compare the model without and with social network, it suffices to set the number of neighbors \(k\) to zero and to some positive number, respectively. The presence of social network facilitates the encounters between firms and workers. The network as additional information source makes it easier for unemployed workers to find a job and for low wage employees to find a better paying job. In general, higher network connectivity leads to lower unemployment rate and higher fraction of workers earning high wages. Note that Calvó-Armengol and Zenou (2005) obtain different result on regular graphs: a critical value of \(k\) exists which minimizes the unemployment rate. The reason is that offers simultaneously reach different individuals in their model which leads to offer congestion in the case of high connectivity: many offers are passed to the same unemployed agent who makes use of only one of them and does not pass the other ones further along in the network. On the contrary, offers sequentially arrive in the model presented here and this possibility is thus excluded. Higher connectivity facilitates the placement of unneeded offers.\(^3\)

The impact of the presence of network and network connectivity on other endogenous variables is numerically evaluated. Table 1 summarizes the parameter values used.\(^4\) The number of neighbors \(k\) is changed between 0 and 15 by step 1 where \(k = 0\) is the version without social network. The model is solved for different values of productivity in the highly productive sector: \(y_H\) is moved between 0.8 and 1.2 by 0.1. In the low productivity sector, the productivity is 85\% of that in the other sector \((y_L = 0.85y_H)\). Firms keep half of the value produced, \(\beta = 0.5\). The elasticity of the market arrival rate of offers with respect to vacancy rate \((\alpha)\) is set to 0.4. This parameter ranges from 0.3 to 0.5 in the estimations (see Petrongolo and Pissarides (2001)). The value of the other technology parameter of the matching \(A\) and the vacancy posting costs \(c\) are calculated to match the long-term unemployment rate \(u = 0.0567\) and vacancy rate \(v = 0.0359\) in Shimer (2005).\(^5\) This gives the values \(A = 2.098\) and \(c = 1.266\). The value of the job separation rate \((\lambda)\) and discount rate \((\delta)\) come from the estimations of Shimer (2005). The results are shown on Figure 1 and

\(^3\)Note also that the congestion effect pointed out by Calvó-Armengol and Zenou (2005) would be diminished if the job information travelled more than one step in the network. Ioannides and Soetevelt (2006) also challenge their non-monotonicity result: assuming Poisson degree distribution, they obtain that higher average connectivity implies higher employment.

\(^4\)For these parameter values, the condition for the existence of equilibrium, outlined in Proposition 1, is satisfied.

\(^5\)In this calibration exercise we used the values \(k = 5, y_H = 1, y_L = 0.85\).
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Table 1: Parameter values used for numerical solution

The first panel of Figure 1 and 2 confirm that higher connectivity leads to lower unemployment rate and higher fraction of workers employed in high wage jobs. The same happens when the productivity level becomes higher. The productivity increase makes more beneficial for firms to post vacancies (see the 2nd panel on the left on Figure 2). This makes it easier to find jobs, the unemployment rate hence decreases. For any parameter value, there are more high productivity jobs than low because in the high productivity sector gains of vacancy postings are higher and it is easier to find a worker due to on-the-job search. The presence of network and network connectivity influence vacancy posting in two ways. First, for given unemployment rate, more information flow between workers makes it easier for firms to find a worker willing to take up their job. Second, the unemployment rate decreases as there are more connections between workers which makes it more difficult to find a worker for the vacancies. The first effect enhances vacancy posting while the second hinders it. As shown on Figure 2 (1st panel on the left), there are more vacancies in the high productivity sector as the connectivity rises. The first effect dominates the second as increasing degree not only makes it easier to find unemployed workers but also low wage employed. Therefore, the fraction of high wage employed rises with connectivity (see the 1st panel on the left). For low wage jobs, the opposite holds. Since low productivity firms can only employ unemployed workers, their chances to find one decrease as the network gets more connected. Moreover, as low wage employed workers can easily move to other job, the exit rate from low wage employment becomes higher. Firms thus post less vacancies (2nd panel on the right, Figure 2) and, consequently, there are less workers employed in this sector.
Interestingly, the vacancy rate of the low productivity sector decreases as the productivity of both sectors increase. This is because at the same time there are more vacancies posted in the high wage sector which makes it easier for low wage earners to move to the other sector.

Figure 1: Value of endogenous variables as the function of number of neighbors for different values of productivity in the high wage sector. Left unemployment rate \( u \), right: welfare: \( e_L q_L + e_H y_H - (v_L + v_H) c \)
Figure 2: Value of endogenous variables as the function of number of neighbors for different values of productivity in the high wage sector. Left, up: fraction of workers earning high wages ($e_H$), right, up: fraction of workers earning low wages ($e_L$), left, down: vacancy rate in the high wage sector ($v_H$), right, down: vacancy rate in the low wage sector ($v_L$).

The aggregate welfare of the society can be defined as the total product produced minus the total vacancy costs paid (assuming that unemployed workers earn 0): $e_L y_L + e_H y_H - (v_L + v_H) c$. As network connectivity becomes higher, $e_L$ and $v_L$ decrease while $e_H$ and $v_H$ increase. The overall impact on welfare is ambiguous but the numerical solution suggests that the total welfare increases as the number of neighbors rises (see the right panel on Figure 1).

In sum, the presence of network channel and higher network connectivity lead to lower unemployment rate and more workers working for high wages. In addition, there will be more vacancies posted in the high productivity sector and less in the low productivity sector. The total welfare in the economy also becomes higher.
3.2 Comparison of two search channels

In this section different properties of the two search methods, formal market and social network, are compared. On-the-job search naturally changes the characteristics of looking for a job via social contacts. Since workers earning low wages do not transmit offers which improve their wage, there will be less offers passed on to contacts and high wage offers will have lower chances to be transmitted. Both of these consequences make the search through social contacts less attractive.

The decision of an individual regarding which search method to use to look for a job depends on the arrival rate of offers and the quality of arriving offers through the search methods. The quality of offers provided by the two search methods is analyzed conditioned on the event that an offer reached the individual. Technically, this is captured by the conditional wage expectation on arrival. This expectation is compared between the two search methods, social networks and formal market. This comparison disregards that the arrival rate of offers differs between the two channels of information since the expectations are normalized by the arrival rate. The conditional wage expectation is a relevant statistics as it is estimated by the empirical literature. Estimation of the expected wage of a search method is based on information obtained from employed individuals who answer the question "By what means were you first informed about your current job?". Individuals are provided with possible answers regarding social contacts (family, friends etc.) and different formal methods, e.g. by answering adverts in newspapers, employment agencies, directly applying to firms etc. Based on this answer, two groups of individuals are established and the average wages between these two groups are compared, controlling for the characteristics of the employee and the job. Hence, these wages are conditioned on the employment status of the individual.

Two kinds of expectation for each search method are defined. The first is the wage expectation of an offer which reaches an unemployed individual by a given search method. In the case of formal market, this expectation is defined as follows.

**Definition** The conditional wage expectation of market search for an unemployed worker is defined as follows:

$$w_{cond}^{MU} = \frac{uq_L^M(v_L)w_L + uq_H^M(v_H)w_H}{uq_L^M(v_L) + uq_H^M(v_H)}$$

Here $uq_L^M(v_L)$ is the market arrival rate of low wage offers to unemployed workers and $uq_H^M(v_H)$ is the market arrival rate of high wage offers.

The same type of expectation can be defined for the network search.
**Definition** The conditional wage expectation of network search for an unemployed individual is defined as follows:

\[
 w_{\text{cond}}^{N,U} = \frac{u q_L^N(u, v_L) w_L + u q_H^N(e_H, v_H) w_H}{u q_L^N(u, v_L) + u q_H^N(e_H, v_H)}
\]

Here \( u q_L^N(u, v_L) \) (\( u q_H^N(e_H, v_H) \)) is the network arrival rate of low (high) wage offers to unemployed workers. See equation (4) and (6) for the definition of these arrival rates.

The second type of expectation is the conditional wage expectation of a useful offer reaching any job seeker, either unemployed or low wage employed individuals. This expectation represents the average quality of offers reaching any job seeker who used that method and thus obtained a job. Precisely the same expectation is estimated by the empirical papers using pooled sample of unemployed workers and job-to-job movers.

We have the following definition for the market search.

**Definition** The conditional wage expectation of market search for any job seeker is defined as follows:

\[
 w_{\text{cond}}^{M} = \frac{u q_L^M(v_L) w_L + (u + e_L) q_H^M(v_H) w_H}{u q_L^M(v_L) + (u + e_L) q_H^M(v_H)}
\]

Since low wage employed workers accept only high paying jobs, in this expectation, only the arrival rate of good offers changes compared to the previously defined expectation \( w_{\text{cond}}^{M,U} \).

As for network search, the wage expectation is given by the following definition.

**Definition** The conditional wage expectation of network search for any job seeker is defined as follows:

\[
 w_{\text{cond}}^{N} = \frac{u q_L^N(u, v_L) w_L + (u + e_L) q_H^N(e_H, v_H) w_H}{u q_L^N(u, v_L) + (u + e_L) q_H^N(e_H, v_H)}
\]

The following result relates the conditional wage expectations of the two job search channels\(^6\):

\[\text{Note that } w_{\text{cond}}^{N} > w_{\text{cond}}^{N,U} \text{ and } w_{\text{cond}}^{M} > w_{\text{cond}}^{M,U} \text{ since } w_H > w_L.\]
Proposition 3 The conditional wage expectation for an unemployed worker searching on the formal market is always higher than the wage expectation through the social network: $w_{U,M}^{cond} > w_{U,N}^{cond}$. The conditional wage expectation for any job seeker on the formal market is always higher than the wage expectation through the social network: $w_{M}^{cond} > w_{N}^{cond}$.

The network channel results in lower paying jobs for the job seekers on average as low paying jobs have a higher chance to be transmitted by social contacts than high paying jobs. The reason for this is that low wage employed agents themselves use the high wage offers and they do not pass them to their unemployed social contacts. If there was no on-the-job search in the model and low wage employed workers transmitted any kind of jobs to their social contacts, there would be no difference in the conditional wage expectation between the two search methods.\(^7\)

These results are based on the assumption that the arriving vacancies are randomly distributed among workers. However in reality, employed workers might have easier access to information on new openings that are similar to their current job, because, for instance, they become aware of the vacancies of their actual employer. The model can be modified to incorporate this possibility. Assume that only unemployed and high wage employed workers can hear about high wage offers by the direct market arrival. Unemployed workers have probability $u$ to hear about an arriving offer and with probability $1-u$ the offer goes to a high wage employed worker. Low wage employed workers thus cannot hear about this kind of offers through the direct arrival, only via their social contacts who are earning high wages. Similarly, low wage offers go to an unemployed worker with probability $u$ and to a low wage employed worker with probability $1-u$.

In this case, the arrival rate of high wage offers through social contacts changes to:

$$q_{H}^{S}(e_{H}, u, v_{H})' = kq_{H}^{M}(v_{H})(1-u)\frac{1-e_{H}^{k}}{(1-e_{H})^{k}}$$ (11)

A given worker has $k$ social ties. Each of them is aware of a high wage offer with probability $q_{H}^{M}(v_{H})(1-u)$ and passes that offer to the given worker with probability $\frac{1-e_{H}^{k}}{(1-e_{H})^{k}}$. Note that the arrival rate of low wage offers via social contacts does not change since,

\(^7\)If there was no on-the-job search and high wage employed workers transmitted high wage offers to a randomly chosen unemployed worker (not to a randomly chosen unemployed or low wage employed worker), the arrival rate of high-wage offers through social contacts would be:

$$q_{H}^{S}(u, v_{H}) = (1-u)q_{H}^{M}(v_{H})\frac{1-(1-u)^{k}}{u}$$

This implies that the conditional wage expectation are equal between search methods.
as before, every low wage offer arriving to employed workers is passed on to unemployed neighbors.

The following proposition compares the conditional expected wages of different search methods under this modification of the model.

**Proposition 4** Consider the case when employed workers can hear about jobs similar to their employment.

(i) The conditional wage expectation for an unemployed worker searching on the formal market is always higher than the wage expectation through the social network: \( w_{cond}^{U,M} > w_{cond}^{U,N} \).

(ii) The conditional wage expectation for any job seeker on the formal market is always lower than the wage expectation through the social network: \( w_{cond}^{M} < w_{cond}^{N} \).

When only high wage employed workers can hear about high wage jobs, it is guaranteed that all high wage offers going to employed workers will be transmitted in the social network. The average wage of via social contacts arriving offers thus will be higher than under random arrival where some of the high wage offers were directly taken by low wage employed workers. Despite this effect, the average wage obtainable by an unemployed worker is still higher for the formal market than for the social network. However, when the average wages of offers arriving to any job seeker, unemployed or low wage employed, are compared, the social network does better. Recall that the wage expectation for any job seeker is higher than the wage expectation for unemployed workers because the former includes low wage employed workers as well who accept only high wage offers. When employed workers can hear only about jobs similar to their employment, low wage employed workers can hear about high wage offers only through social contacts but not on the formal market. This implies that \( w_{cond}^{N} > w_{cond}^{N,U} \) and \( w_{cond}^{M} = w_{cond}^{M,U} \). The search through social network therefore pays a wage premium compared to the formal market when all job searchers are considered: \( w_{cond}^{M} < w_{cond}^{N} \).

The impact of different parameters on the conditional expected wage difference between the two search methods is numerically evaluated using the parameter values outlined above. Figure 3 shows the different characteristics of the two job search methods. As for the conditional wage expectation obtainable for an unemployed worker (left upper panel), the results show that as the number of neighbors \( k \) increases, the formal market pays a smaller wage premium compared to the social network. Network connectivity has two effects on the
wages obtainable through social contacts. First, as $k$ increases, the fraction of high wage employed workers rises (see Figure 3, right upper panel). This implies that there will be more new high wage offers transmitted to social contacts which makes the expected wages higher. Second, there is a direct effect of connectivity on the expected wage of network search. As an additional link is added for an individual, the probability that this link will transmit a low wage offer is higher than that it will transmit a high wage offer. This occurs because a low wage offer can be transmitted by any employed worker while a high wage offer only by a high wage employed worker. A neighbor is employed with probability $e$ and high wage employed with probability $e_H$ where $e > e_H$. The numerical results suggest that the first effect is larger and the wages obtainable through the network increase with connectivity (see 2nd panel on the right). Network connectivity also influences the conditional expected wages of market search through the vacancy postings. As there are more links in the network, there will be more high wage jobs posted relatively to low wage jobs. This makes the conditional expected wages of market search higher as well (see 2nd panel on the left). The market pays a wage premium, but it is decreasing with the number of neighbors. The wage premium also decreases as the productivity level rises. The productivity increase implies that there will be more workers employed in the high wage sector and, therefore, more high wage offers will be transmitted by the network.

Now we turn to the discussion of unconditional wage expectations of the two search methods. This wage expectation differs between the search methods for two reasons. First, as we have seen before, the quality of offers arriving through the two methods (measured by the conditional wage expectation) is different. Second, the arrival rate of offers differs between the two methods. Both of these characteristics of a search channel are important for an unemployed job seeker: assuming she is risk neutral, she decides which search method to use based on the wage expectation.

For the definition of wage expectation of the search methods, it is assumed that when no offer arrives using a search method, the worker gets 0. The wage expectation defined here is equal to the conditional wage expectation, defined above, multiplied by the arrival rate of offers via the given search channel. We have the following two definitions.

Definition The wage expectation of the market search for an unemployed worker is defined as follows:

$$w^{M,U} = q^{M}_L(v_L)w_L + q^{M}_H(v_H)w_H$$
Figure 3: Different characteristics of the two search methods, depicted as the function of number of neighbors for different values of productivity in the high wage sector. 1st line: left: difference of conditional wage expectation between market and network; Right: difference of unconditional wage expectation between market and network. 2nd line: left: market conditional wage exp.; right: network conditional wage exp. 3rd line: left: market unconditional wage exp., right: network unconditional wage exp. 4th line: left: market arrival rate of offers; right: network arrival rate of offers.

**Definition** The wage expectation of the network search for an unemployed worker is defined as follows:

\[ w^{N,U} = q^N_L(v_L)w_L + q^N_H(v_H)w_H \]

The following result states that when the social network consists of pairs, unemployed job seekers should always choose the formal market to look for a job since the wage expectation is higher than in the case of using social contacts.

**Proposition 5** If the network consists of pairs \((k = 1)\), the wage expectation of the formal market \((w^{M,U})\) is always higher than the wage expectation of the network search \((w^{N,U})\).
When workers have only one contact, the likelihood of hearing about a new job through social contacts is too low and it's always better to look for a job on the formal market. This is because a given neighbor always has the same probability to hear about an offer as the individual herself but she transmits the offer only if she is (high wage) employed which happens with a probability less than one. Figure 3 shows how things change when the number of neighbors is higher than one. As network connectivity rises, the arrival rate of offers via social contacts increases (see 4th panel on the right). The wage expectation of this search method becomes higher than that of the formal market although the network pays lower wages conditional on finding a job than the market (see 1st and 3rd panel on the right). The numerical results suggest that this happens for \( k \geq 2 \), however, if the unemployment rate is higher than the calibrated 5.67%, we expect that the threshold in network connectivity will be higher. The arrival rate of offers on the market slightly decreases with network connectivity because there will be less vacancies posted in the low productivity sector. The network transmits more offers as the productivity level rises because there will be more (high wage) employed neighbors who pass information to their contacts.

The findings described in this section suggest that for low network connectivity the formal market as search channel is better than the network both in terms of arrival rate and quality of offers. When the network is more connected, the network arrival rate of offers is higher and a trade-off between unemployment duration and obtainable wages emerges for the unemployed job seeker using social contacts. The wage discount provided by the search via social ties is smaller when the network connectivity or the productivity level is higher.

4 Empirical analysis

The theoretical model presented above showed that on-the-job search implies that a job obtained via social contacts pays a wage discount compared to jobs found on the formal market. In this section an empirical analysis is carried out to verify this prediction using the European Community Household Panel dataset. This dataset was collected between 1994 and 2001 in 15 countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, the Netherlands, Luxembourg, Ireland, Italy, Portugal, Spain, Sweden and the United Kingdom. For 14 countries, with the exception of Sweden, the dataset contains a question about job search methods: "By what means were you first informed about your present job?", with the following possible answers: 1. by applying to the employer directly, 2. by inserting or answering adverts in newspapers, TV, radio, 3. through employment or vocational guidance
agency, 4. through family, friends or other contacts, 5. started own business or joined family business, 6. other. Based on this question a dummy variable representing network search is constructed, it takes the value 1 if the individuals answered 4 to the previous question and 0 otherwise.

The dataset contains information on individual characteristics such as education, gender, employment status, wages, occupation etc. Table 2 shows summary statistics of the sample used which contains 131870 observations in total. Individuals who find job through social contacts on average have lower wages, with a difference of 1.47 dollars per hour. They are less educated, more likely to work in the industry and in smaller firms, and less likely to have a public sector job.

The following model is used to estimate the impact of search method used on wages:

$$\log w_{it} = \alpha + \beta \times \text{Network}_{it} + \gamma \times X_{it} + \epsilon_{it}$$

where \text{Network} represents whether the individual obtained her job through social contacts. Based on the theoretical model’s predictions, \( \beta < 0 \) is expected. In one set of regressions, the vector of other control variables \( X_{it} \) contains individual characteristics, such as sex, experience, experience squared, dummies for having primary, secondary or tertiary education, being in the first job, being a job-to-job mover and time and country dummies. In another set of regressions, job characteristics are also added, such as firm size, industry and occupation dummies, dummies indicating whether the job is full time, is a job with permanent or fixed contract, whether the job is in the public sector. Firstly, the model is estimated by OLS. OLS estimates might be biased since individuals using social contacts might differ in unobserved abilities from those who find job on the formal market where competition for jobs is more intense. To control for unobserved constant abilities the models is also estimated by fixed-effects estimator. Estimation results are shown in Table 3.

Individuals finding a job through social contacts indeed earn lower wages. This relationship is significant at 1% level in the OLS estimations and at 10% level in the FE estimations. OLS estimates indicate a 2.5-6% wage discount for networkers while according to the FE estimations the difference is less than 1%. Workers who directly move from one job to another have higher wages than those who find employment after being unemployed. This finding confirms the model’s assumption that workers switch to jobs where wages are higher. Other control variables also have the expected sign: female workers earn less, experience positively influences wages but has a decreasing return, higher education increases wages, larger or public firms pay higher wages. Hourly wages are higher in a permanent job and lower in a full-time job.

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5 Conclusions

The interactions between on-the-job search and finding a job through social contacts have been investigated in a Diamond-Mortensen-Pissarides search model. Workers may find a job through their social ties or on the formal market. The presence of social networks as search channel increases the overall welfare of society: number of unemployed workers decrease, number of workers earning high wages becomes larger and there are more high wage vacancies posted.

On-the-job search alters the wage distribution of offers obtained by unemployed workers through social ties since employed workers do not pass those offers on to their neighbors that pay higher wages than their current wages earned. This makes the conditional expected wages of search through contacts lower than that of searching on the formal market. The quality of offers is lower using social ties than on the formal market. This conclusion is robust to modifications of assumptions on the arrival process.

When the number of neighbors is low, the arrival rate of offers is lower for the network channel than for the formal market. It hence is more beneficial for the unemployed workers to search on the formal market. However, when the number of neighbors is high enough, offers more frequently arrive through the network than on the formal market. Trade-off between unemployment duration and wages emerges for unemployed workers getting a job via social ties. The wages of offers obtained via social ties increase as individuals have more neighbors or the productivity level is larger.

6 References


7 Appendix A: Proofs

Proposition 1

Proof Note that the equilibrium conditions (8) and (10) depend only on $e_H$ and $v_H$ and not on the other endogenous variables. The first step of the proof hence is to show that these two equilibrium conditions determine a single value of $e_H$ and $v_H$.

We may simplify condition (8) in the following way:

$$u_q^M(v_H) \left(1 + e_H \frac{1 - e_H^k}{1 - e_H} + e_L q_H^M(v_H) \left(1 + e_H \frac{1 - e_H^k}{1 - e_H} \right) = \lambda e_H \right.$$  

$$(1 - e_H) q_H^M(v_H) \left(1 + e_H \frac{1 - e_H^k}{1 - e_H} \right) = \lambda e_H$$

We arrive to the following equation:

$$q_H^M(v_H) \left(1 - e_H + e_H(1 - e_H^k) \right) = \lambda e_H \quad (12)$$

First, we express $v_H$ from equation (10):

$$B \equiv \frac{(1 - \gamma)y_H}{\delta + \lambda}$$

Define $B \equiv \frac{(1 - \gamma)y_H}{\delta + \lambda}$ and $f(e_H) \equiv (1 - e_H + e_H(1 - e_H^k))$. Note that $f'(e_H) < 0$ since

$$\frac{\partial f(e_H)}{\partial e_H} = -e_H^k(1 + k) < 0.$$

Expressing $v_H$ from this equation gives:

$$v_H(e_H) = \left[ \frac{BAf(e_H)}{c} \right]^\frac{1}{\alpha}$$
Note that $\frac{\partial v}{\partial e_H} > 0$.

We can substitute this expression into (8) which gives a function of $e_H$ only:

$$h(e_H) \equiv q_M^H(v_H(e_H))f(e_H) - \lambda e_H$$

Derivating this equation with respect to $e_H$ gives:

$$\frac{\partial q_M^H(v_H)}{\partial v_H} \frac{\partial v_H}{\partial e_H} f(e_H) + q_M^H(e_H) \frac{\partial f(e_H)}{\partial e_H} - \lambda < 0$$

The first term is negative since $\frac{\partial v}{\partial e_H} < 0$ and the second term is negative too: $\frac{\partial f(e_H)}{\partial e_H} < 0$.

Hence $h'(e_H) < 0$.

We need to show that there exists an $e_H \in (0, 1)$ such that $h(e_H) = 0$. Consider the point $e_H = 1$. Here $f(1) = 0$, $v_H = 0$, $h(1) = -\lambda$. Consider the point $e_H = 0$. Here $f(0) = 1$, thus $v_H = \left[\frac{BA}{c}\right]^\frac{1}{\alpha}$. To have an interior solution in $e_H$, we need to have $h(0) > 0$ since $h'(e_H) < 0$. The condition that guarantees this is:

$$A \left[\frac{BA}{c}\right]^\frac{1-\alpha}{\alpha} - \lambda > 0$$

As we increase $e_H$, $h(e_H)$ changes sign and it is monotone decreasing in $e_H$, so there should be an $e^*_H \in (0, 1)$. This also defines $v^*_H$.

In the second step, we will see that given the equilibrium $e^*_H$ and $v^*_H$, conditions (7) and (9) define unique equilibrium $u$ and $v_L$.

First, we can express $v_L$ as a function of $u$ from condition (9):

$$\frac{c}{A\nu_L^{-\alpha}(u + (1 - u)(1 - (1 - u)^k))} - \frac{(1 - \beta)\nu_L}{\delta + \lambda + q_H(e_H, v_H)} = 0$$

Define $D \equiv \frac{(1-\beta)\nu_L}{\delta + \lambda + q_H(e_H, v_H)}$ and $g(u) \equiv (u + (1 - u)(1 - (1 - u)^k))$. Note that $g'(u) = (1 + k)(1 - u)^k > 0$.

We can express $v_L$:

$$v_L(u) = \left[\frac{DAg(u)}{c}\right]^\frac{1}{2}$$

Note that $v'_L(u) > 0$.

Now we turn to condition (7) and simplify it:

$$uq_L(u, v_L) = \lambda e_L + e_Lq_H(e_H, v_H)$$
That is,
\[ uq_L^M(v_L) \left( 1 + (1 - u)(1 - (1 - u)k)\frac{1}{u} \right) = (1 - u - e_H)^\lambda + q_H^M(v_H) \left( 1 + e_H \frac{1 - e_H}{1 - e_H} \right) \]

Thus,
\[ uq_L^M(v_L) \left( 1 + (1 - u)(1 - (1 - u)k)\frac{1}{u} \right) = (1 - u)\lambda - uq_H^M(v_H) \left( 1 + e_H \frac{1 - e_H}{1 - e_H} \right) + (1 - e_H)q_H^M(v_H) \left( 1 + e_H \frac{1 - e_H}{1 - e_H} \right) - \lambda e_H \]  

Here the last two terms of the right-hand side are equal to zero because of condition (8).

So, the equation simplifies to:
\[ l(u) \equiv q_L^M(v_L(u))g(u) - (1 - u)\lambda + uq_H^M(v_H) \left( 1 + e_H \frac{1 - e_H}{1 - e_H} \right) = 0 \]  

Derivating with respect to \( u \) gives:
\[ \frac{\partial q_L^M(v_L)}{\partial v_L} \frac{\partial v_L}{\partial u} g(u) + g'(u)q_L^M(v_L) + \lambda + q_H^M(v_H) \left( 1 + e_H \frac{1 - e_H}{1 - e_H} \right) > 0 \]

This derivative is positive since \( \frac{\partial q_L}{\partial u} > 0 \) and \( g'(u) > 0 \).

We need to see that there exists a \( u \) such that \( l(u) = 0, l'(u) > 0 \). By \( u = 0, g(0) = 0, v_L(0) = 0, l(0) = -\lambda \). By \( u = 1, g(1) = 1, v_L = \left[ \frac{DAg}{c} \right]^{\frac{1}{n}} \) and
\[ l(1) = A \left[ \frac{DAg}{c} \right]^{\frac{1}{n}} + q_H^M(v_H) \left( 1 + e_H \frac{1 - e_H}{1 - e_H} \right) > 0 \]

Since as we increase \( u \), \( l(u) \) changes sign and \( l(u) \) is monotone increasing in \( u \), there exists a \( u^* \in (0, 1) \). This also determines \( v_L^* \).

**Proposition 2**

We need to compare the case of \( k = 0 \) to the case of \( k > 0 \). We use the notation of the previous proof. First, we can see that \( e_H \) goes up as \( k \) increases. If \( k \) becomes higher, \( v_H(e_H) \), as defined in the previous proof, increases since \( e_H < 1 \). This shifts \( h(e_H) \) upward. \( h(e_H) \) is decreasing in \( e_H \) and as we shift it upward, it will be equal to zero at a higher \( e_H \).

As \( k \) increases, \( g(u) \), as defined above, becomes higher (because \( 1 - u < 1 \) ), this makes \( v_L(u) \) to be higher. If \( v_L(u) \) increases, \( l(u) \) shifts upward. Simultaneously, \( e_H \) increases which also makes \( l(u) \) to be higher. \( l(u) \) is an increasing function of \( u \). As \( l(u) \) shifts upward, the solution of \( l(u) = 0 \) becomes lower. The unemployment rate thus decreases.
Proposition 3

Proof To compare $w_{\text{cond}}^{U,N}$ and $w_{\text{cond}}^{U,N}$, it is sufficient to compare the ratio of low and high paying job arrival rates between the two search methods. The arrival rate of low wage jobs on the formal market is $q^M_L(v_L)$ and the arrival rate of high wage jobs is $q^M_H(v_H)$. The social network provides low wage jobs at a rate $q^M_L(v_L)((1-u)/(1-u)^k)$ and high wage jobs at a rate $q^M_H(v_H)e^{1-e^k_{H}}$. Then,

$$w_{\text{cond}}^{U,M} > w_{\text{cond}}^{U,N} \iff \frac{q^M_H(v_H)}{q^M_L(v_L)} > \frac{q^M_H(v_H)e^{1-e^k_{H}}}{q^M_L(v_L)((1-u)/(1-(1-u)^k))}$$

Equivalently,

$$\frac{e(1-e^k)}{1-e} > \frac{1-e^k_{H}}{1-e^k}$$

where $e = 1 - u$ is the employment rate.

Taking into account that $e \geq e_H$, this inequality holds if $f(x) \equiv \frac{x(1-x^k)}{1-x}$ is increasing in $x$ when $x \in (0,1)$. Taking the derivative with respect to $x$:

$$\frac{\partial f(x)}{\partial x} = \frac{1 + (k(-1+x) - 1)x^k}{(-1+x)^2}$$

The sign depends on the sign of the nominator. The nominator is decreasing in $x$, it’s derivative is $(1+k)(-1+x)x^{-1+k} \leq 0$ because $x \leq 1$. Hence, the nominator is positive if it is positive for $x = 1$ where it takes the value 0. Hence, $\frac{\partial f(x)}{\partial x} > 0$ when $x \in [0,1]$.

To compare the conditional expected wages for any job searcher $w_{\text{cond}}^N$ and $w_{\text{cond}}^N$, we need to compare the same quantities:

$$w_{\text{cond}}^{U,M} > w_{\text{cond}}^{U,N} \iff \frac{(u + e_L)q^M_H(v_H)}{uq^M_L(v_L)} > \frac{(u + e_L)q^M_H(v_H)e^{1-e^k_{H}}}{uq^M_L(v_L)((1-u)/(1-(1-u)^k))}$$

Proposition 4

Proof (i) We need to show that $w_{\text{cond}}^{U,M} > w_{\text{cond}}^{U,N}$. We again need to compare the ratio of arrival rate of good and bad offers between search methods, now using expression (11).

$$\frac{uq^M_H(v_H)}{uq^M_L(v_L)} > \frac{q^M_H(v_H)e^{1-e^k_{H}}}{q^M_L(v_L)(1-e)}$$
This holds if:

\[ \frac{1 - e_H^k}{1 - e_H} < \frac{1 - e^k}{1 - e} \]

where \( e_H \leq e \). The function \( \frac{1-x^k}{1-x} \) is increasing in \( x \). It’s derivative is

\[ 1 + \frac{1 + (k(-1 + x) - x)x^{k-1}}{(-1 + x)^2} \]

The sign of the derivative depends on the nominator which is strictly decreasing in \( x \) and takes the value 0 at \( x = 1 \). It thus is positive for \( x < 1 \).

(ii) We need to show that \( w_{cond}^M < w_{cond}^N \). Note that now \( w_{cond}^M = w_{cond}^{U,M} \) since low wage employed workers cannot find a high wage job on the market.

\[ \frac{uq_H^M(v_H)}{uq_L^M(v_L)} < \frac{(u + e_L)q_H^M(v_H)e^{1-e_H}}{uq_L^M(v_L)e^{1-e} (1 - e_k)} \]

After simplification this gives:

\[ 1 < \frac{1 - e_H^k}{1 - e^k} \]

which holds since \( e_H < e \). \( \square \)

**Proposition 5**

When \( k = 1 \), \( q_L^N(u,v_L) = q_L^M(v_L)(1-u) \) and \( q_H^N(e_H,v_H) = q_H^M(v_H)e_H \). Since \( 1-u < 1 \) and \( e_H < 1 \), both arrival rates via social ties are smaller than that on the formal market. Hence, \( w_{N,U}^N < w_{M,U}^M \). \( \square \)

8 Appendix B: Tables
<table>
<thead>
<tr>
<th>Variable</th>
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<th>Other search method Mean</th>
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Table 2: Descriptive statistics. Standard deviation in parenthesis
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<th>FE without job characteristics</th>
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<td>(30.86)</td>
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</table>

Table 3: Estimation results, robust t-statistics are in parenthesis. * significant at 10%, ** significant at 5%, *** significant at 1% level. Industry dummies: industry, service; Occupation dummies: professionals, technicians and associate professionals, clerks, service workers and shop and market sales workers, skilled agricultural and fishery workers, craft and related trade workers, plant and machine operators and assemblers, elementary occupations. Reference group for regression with job characteristics: use other search method than contacts, male, have tertiary education, agriculture, legislators senior officials and managers, part-time job, private job, not first job, small firm, other contract type, 1994, Germany.