A Search Model with a Quasi-Network

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Abstract

In a standard search model the expected duration of unemployment is independent of the duration of previous employment, as well as of the current length of the unemployment spell. This paper offers a network mechanism to generate these correlations. Here, employed workers invest in social contacts with other employed workers, which will help them find jobs in the event of unemployment. These social contacts "depreciate" because they can also become unemployed and unemployed contacts are assumed to be useless. In this model the longer you have been working, the more contacts you are likely to have, and the more contacts you have the shorter your expected unemployment duration will be. The model is a simple and tractable way of introducing network ideas in one of the workhorses of labour and macroeconomics. In the model the network is eroded during periods of high unemployment, and is therefore less productive in an absolute sense. Nevertheless, the number of job finders per contact in the unemployment pool increases during periods of high unemployment. Finally, the model provides guidance for indirect inference of network effects from the data.

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1 Introduction

In a textbook version of the Mortensen and Pissarides (1994) search model the expected duration of unemployment is independent of the duration of previous employment, as well as of the current length of the unemployment spell. These are clearly counterfactual implications, and, as an example, models of loss of skill during unemployment such as Pissarides (1992) and Larsen (2001) successfully generate duration dependence in unemployment.[1] This paper provides an alternative mechanism inspired by the growing literature on networks and their implications for labour markets.

Here, as a natural by-product of working activity, employed workers invest in social contacts with other employed workers. In turn these contacts will help them find jobs in the event of unemployment. These social contacts "depreciate" because they can also become unemployed and unemployed contacts are assumed to be useless. In this model the longer you have been working, the more contacts you are likely to have, and the more contacts you have the shorter your expected unemployment duration will be.

The assumption used here that unemployed workers do not constitute useful contacts stands in contrast with some of the literature on networks in labour markets, where the goal is to model the flow of information about available jobs.[2] In these models everyone is important because if an unemployed worker is offered two jobs he will pass one of the jobs onto another unemployed acquaintance. In the present paper there is an implicit assumption that these information propagation mechanisms are of second order in the dynamics of unemployment.[3] If what matters is who you know, or, as here, how many people you know, there is a presumption that it is best if these people are working.

A direct outcome of the model is that the network is less productive during periods of high unemployment, since unemployment duration increases and the network gets partially destroyed. The model also shows that this result is not inconsistent with the empirical finding that the fraction of people finding jobs through friends increases during times of high unemployment, suggesting that finding is only one part of the network picture.

The idea that the number of people one knows matters has some direct and indirect empirical support. Addison and Portugal (2002) show that personal contacts are a key way in which firms recruit. Using Danish data Weatherall (2008) finds that displaced workers that exit establishments with a small number of workers have a higher probability of becoming long term unemployed. Using U.S. data Addison and Portugal (1989) show that the length of tenure prior to unemployment has a positive impact on post displacement wages.

Simplifying assumptions aside, the mechanism presented here offers a mar-

[1] Also, models of endogenous search effort where a longer unemployment duration signals a lower quality imply the payoff of search and search intensity declines with duration.

[2] See for example Calvó-Armengol and Jackson (2007) and Galeotti and Merlino (2008).

[3] The fact that network use and density are correlated with unemployment does not *prove* that the network is *causing* unemployment behaviour. For example, it is difficult to disentangle the network implications developed here from those of human capital models.

riage between the search and the network literatures that we believe is interesting in its own right.

This paper explores first a deterministic model to highlight the properties of the resulting equilibrium which arise from the network structure. This version of the model allows for an examination of cross sectional properties of an artificial dataset, where we obtain the negative correlation between employment and unemployment durations. Following that, a model with aggregate shocks is developed and explored quantitatively. This version of the model allows us to evaluate time series properties of the model, including the cyclical properties of the network, and how they affect the labour market. Here, unemployment duration increases during recessions. This increase in duration is greater here as everyone has less active contacts and the network is partially destroyed. Given that zero contacts is a natural lower bound this makes all unemployed agents more alike, in particular those that find jobs have similar portfolios to those that remain unemployed. This suggests the network matters less in a downturn. On the other hand more jobs are created per contact because people have fewer contacts on average and there are more people looking for jobs. This suggests the network matters more. All this happens in the context of an exogenous network.

The model is also useful as it shows one must look into the detailed relationship between employment and unemployment durations if one wants to identify network effects in the data: the network has no *identifiable* effect on the properties of the aggregate unemployment rate.

Finally, the mechanics of this model have much in common with (and lend support to) the "Rest Unemployment" ideas of Alvarez and Shimer (2009). In our context, an unemployed agent would move to a different labour market only if two conditions occurred simultaneously: the unemployment rate in his market is high while in the other market it is low, and, his current market-specific portfolio of contacts has all but disappeared (which is a process that takes time).

2 Deterministic Model

2.1 Firms

There is a unit mass of workers. When a vacancy is created, the probability a vacancy meets an unemployed worker is denoted by α^f. In Montgomery (1991) the network helps in reducing the effects of adverse selection. In the present paper all workers are identical from the perspective of the firm so that this mechanism is absent. Danish survey data from Filges (2008) also contains information suggestive of the importance of personal contacts in the hiring process for firms: around one third of the latest hires across the firms surveyed were achieved through personal contacts. Here, this mechanism is summarized inside the matching function because in the standard search model each match is itself a firm, and so there are no current in-house workers to rely on.[4]

The value of posting a vacancy is

$$V = -k + \beta\alpha^f J + \beta(1 - \alpha^f)V$$

where k is the flow cost of keeping a vacancy open.

Free entry will drive V to zero so that $k = \beta\alpha^f J$, where J is the value of a filled vacancy. Here β is the discount factor (over one week). A filled job produces an output y, which is divided between the firm and the worker. The value of the wage, w, is above the unemployment output b the worker gets, which can be labelled home production. All matches have an exogenous break up rate of $1 - \lambda$.[5] The value of a filled vacancy is

$$J = y - w + \beta\lambda J + \beta(1 - \lambda)V = \frac{y - w}{1 - \beta\lambda}$$

which implies we must have

$$\alpha^f = \frac{k\,(1 - \beta\lambda)}{\beta(y - w)}$$

which is a constant. We can see that if the cost of vacancies rises relative to the wage then the equilibrium probability α^f must rise, which happens by decreasing vacancies relative to the number of unemployed.

2.2 Some probability algebra

The algebra that follows rests on the Pascal Triangle relationship. Employed workers create relationships or contacts in the course of their working activity. They can make at most one extra contact each period and the model is such that there will be a voluntary upper bound $\bar{n}$ on the number of contacts any worker is willing to have. This assumption that it takes time to reach the upper bound on contacts is essential for the model to be able to generate the correct correlation between employment and unemployment durations.

All workers face the same exogenous probability of losing their jobs, $(1 - \lambda)$, and we assume here that only employed workers count as contacts. Therefore workers lose contacts because their contacts can become unemployed. Given n employed contacts - and if there is no investment in an additional contact today - we have the following probability distribution over the set $[0, 1, 2, ..., n]$ contacts tomorrow:

$$f(n-k) = \left(\begin{array}{c} n \\ k \end{array} \right) (\lambda)^{n-k} (1 - \lambda)^k = \frac{n!}{k!(n-k)!} (\lambda)^{n-k} (1 - \lambda)^k$$

with $f(n) = \lambda^n$, and $f(0) = (1 - \lambda)^n$.

[4] Two exceptions to this modelling framework are Cooper, Haltiwanger, and Willis (2007), and Ortigueira and Faccini (2008), where firms have many workers.

[5] Well connected employees may have lower job destruction rates. Not here.

In case an additional contact is made today, the same type of distribution applies but over the set $[0, ..., n+1]$. The Pascal Triangle will give rise to two important matrices in this problem. The matrix M which governs transitions of **unemployed** agents, of which we show the examples with supports $[0,1]$ and $[0,1,2]$, corresponding to the upper bounds $\bar{n}=1$ and $\bar{n}=2$:

$$M = \left[\begin{array}{c|cc} & 0 & 1 \\ \hline 0 & 1 & 0 \\ 1 & (1-\lambda) & \lambda \end{array}\right], \quad M = \left[\begin{array}{c|ccc} & 0 & 1 & 2 \\ \hline 0 & 1 & 0 & 0 \\ 1 & (1-\lambda) & \lambda & 0 \\ 2 & (1-\lambda)^2 & 2\lambda(1-\lambda) & \lambda^2 \end{array}\right]$$

and the matrix $\hat{M}$ which governs the transitions of **employed** agents, of which we show the examples here also with supports $[0,1]$ and $[0,1,2]$:

$$\hat{M} = \left[\begin{array}{c|cc} & 0 & 1 \\ \hline 0 & (1-\lambda) & \lambda \\ 1 & (1-\lambda) & \lambda \end{array}\right], \quad \hat{M} = \left[\begin{array}{c|ccc} & 0 & 1 & 2 \\ \hline 0 & (1-\lambda) & \lambda & 0 \\ 1 & (1-\lambda)^2 & 2\lambda(1-\lambda) & \lambda^2 \\ 2 & (1-\lambda)^2 & 2\lambda(1-\lambda) & \lambda^2 \end{array}\right]$$

2.3 Workers

Managing contacts is costly and this cost increases in the number of contacts. This implies there will be a finite upper bound on the number of connections any worker accumulates. These connections or contacts are useful because they will help the worker find a job in the event of unemployment. The number of connections a worker has is his individual state variable or "network type". When the unemployed worker gets a job his "network type" vanishes. He then starts reconstructing his network from zero contacts. This is a simplifying assumption similar to the loss of specific human capital when a workers switches markets in Alvarez and Shimer (2009), and it has no effect on the economics of the model.[6]

There are two distributions that matter in this model. One is the distribution of the unemployed population over contacts, S_t^u, and the second one is the distribution of the employed population over contacts, S_t^e. The level of unemployment, $0 < \bar{u}_t < 1$, is also a state variable. All of these are summarized in the state vector S.

For simplicity of exposition we assume where convenient that $\bar{n}=1$, in which case the state vector S, effectively has three numbers, $S = (\bar{u}, u_0, e_0)$, where u_0 is the fraction of unemployed workers with zero contacts, and e_0 is the fraction of employed workers with zero contacts.[7]

Value of Unemployment

[6] We could allow them to keep their contacts when they find a new job. We could even allow for job to job transitions with no loss of contacts, or partial loss of contacts. The transition matrices described above would change but the qualitative nature of the problem would not.

[7] Even in this simplest of cases, the state space is a continuous cube in the unit interval.

The value of unemployment of a worker with zero contacts given state S satisfies

$$U_0(S) = b + \beta\alpha_0^w(S) W_0(S') + \beta(1 - \alpha_0^w(S)) U_0(S')$$

and similarly, the value of unemployment of a worker with one contact obeys:

$$U_1(S) = b + \beta\alpha_1^w(S) W_0(S') + \beta(1 - \alpha_1^w(S)) [(1 - \lambda) U_0(S') + \lambda U_1(S')]$$

Here, $\alpha_n^w(S)$ is the probability that an unemployed worker with n employed connections will find a vacancy this period, given the current state vector.

It is important to note here that, despite the fact that for each agent the transition of his own contacts is stochastic, the transition of the aggregate state vector is deterministic. That is why there are no expectational operators over S' in the equations above.

We can write this in matrix form as:

$$U(S) = b + \beta\alpha(S) W_0(S') + \beta T(S) U(S')$$

where $T(S) = Diag(1 - \alpha(S)) \times M$, and for the example with $\bar{n} = 1$ this yields:

$$\begin{aligned} \alpha(S) &= \begin{bmatrix} \alpha_0^w(S) \\ \alpha_1^w(S) \end{bmatrix}, U(S) = \begin{bmatrix} U_0(S) \\ U_1(S) \end{bmatrix}, \\ T(S) &= \begin{bmatrix} 1 - \alpha_0^w(S) & 0 \\ 0 & 1 - \alpha_1^w(S) \end{bmatrix} \times \begin{bmatrix} 1 & 0 \\ (1 - \lambda) & \lambda \end{bmatrix} \end{aligned}$$

Value of Employment

The value of being employed having already built n connections is then:

$$W_n(S) = \max \left\{ \begin{array}{c} w - g(n) + \beta(1 - \lambda) EU_j(S') + \beta\lambda EW_j(S') \\ w - c - g(n) + \beta(1 - \lambda)\tilde{E}U_j(S') + \beta\lambda\tilde{E}W_j(S') \end{array} \right.$$

There are two expectation signs in the above equation, because they are taken with respect to different probability distributions over different sets of contacts, with $\tilde{E}$ being taken over a support with one extra contact. Each period the worker has the choice of adding one connection to his private network at a cost $c > 0$. There is also a convex cost $g(n)$ of maintaining connections, which ensures the existence of a finite upper bound on the number of connections any individual creates, $\bar{n}$. This also ensures there are no "stars" in the network because no worker is willing to manage more than $\bar{n}$ contacts. If this cost $g(n)$ is not incurred the connections are lost. Note also the timing convention that $g(n)$ is associated with the beginning of period state variable.

An employed worker stops making contacts when

$$\begin{aligned} c &> \beta\lambda \left[\tilde{E}W_j(S') - EW_j(S')\right] \\ &\quad + \beta(1 - \lambda) \left[\tilde{E}U_j(S') - EU_j(S')\right] \end{aligned}$$

so that there is a decision rule whereby the worker stops investing at a given number of connections and then invests again when some of these connections are lost (because they have become unemployed).

In the example where $\bar{n}=1$, we have[8]

$$\begin{aligned} c &> \beta\lambda\left[(1-\lambda)^2 W_0 + 2\lambda(1-\lambda)W_1 + \lambda^2 W_2 - (1-\lambda)W_0 - \lambda W_1\right] \\ &\quad +\beta(1-\lambda)\left[(1-\lambda)^2 U_0 + 2\lambda(1-\lambda)U_1 + \lambda^2 U_2 - (1-\lambda)U_0 - \lambda U_1\right] \end{aligned}$$

Example

In our example with a maximum of one connection ($\bar{n}=1$) this is simpler and can be written with the pair of equations (where the maximization is already resolved in both of them):

$$\begin{aligned} W_0(S) &= w - c - g(0) + \beta(1-\lambda)EU_j(S') + \beta\lambda EW_j(S') \\ W_1(S) &= w - g(1) + \beta(1-\lambda)EU_j(S') + \beta\lambda EW_j(S') \end{aligned}$$

We can write this in matrix form as:

$$W(S) = wg + \beta(1-\lambda)\hat{M}U(S') + \beta\lambda\hat{M}W(S')$$

where

$$wg = \begin{bmatrix} w-c-g(0) \\ w-g(1) \end{bmatrix}, \quad \hat{M} = \begin{bmatrix} (1-\lambda) & \lambda \\ (1-\lambda) & \lambda \end{bmatrix}$$

In this example one contact is always desirable while $g(2)$ is such that two contacts are never desirable. In general we have $g(n+1) > g(n) \geq 0$.

A more substantive issue is that wages are exogenously set, as opposed to the standard practice of using Nash bargaining to do so. This is a tractability device.[9] However, Nash bargaining is not the only wage determination procedure, and following Cooper, Haltiwanger, and Willis (2007) we set output and wages to depend only on the aggregate state of the economy which, in this first version of the model without aggregate shocks, is constant.[10]

[8] Note that W_1 for $\bar{n}=1$ differs from W_1 for $\bar{n}=2$. The same is true for U_1. Multiple equilibria may arise in this model. We will assume a $g(n)$ function such that we get $\bar{n}$ constant, which greatly simplifies the solution of the model.

[9] Nash bargaining implies wages are affected by the outside option of unemployment which depends on the number of contacts a worker has. This then implies that for the firm it matters who they hire when they open a vacancy, and this expectation of who they will meet is affected by the cross sectional distribution of contacts, making the problem much more complicated.

[10] See also references in their paper. In their model the wage bill is firm specific and varies with idiosyncratic shocks because hours vary within the firm, but the outside option of the worker depends only on the aggregate state.

2.4 Mechanics of employment and unemployment

Two types of attrition are at work in this model: attrition on the number of contacts, and attrition on the transition to and out of unemployment. To characterize the mechanics for the unemployed population we need to detail two transitions: the transition from unemployment to unemployment, and the transition from employment to unemployment. Here we use the example where the maximum number of contacts is $\bar{n} = 1$.

Mechanics of Unemployment

Let $\begin{bmatrix} \bar{u}_0^t & \bar{u}_1^t \end{bmatrix}$ be a row vector containing the *number* of unemployed at time t by number of contacts,

$$\begin{bmatrix} \bar{u}_0^t & \bar{u}_1^t \end{bmatrix} \equiv \bar{u}_t \begin{bmatrix} u_0^t & u_1^t \end{bmatrix} \equiv \bar{u}_t \begin{bmatrix} u_0^t & 1 - u_0^t \end{bmatrix} \equiv \bar{u}_t \left(S_t^u\right)'$$

Here $\bar{u}_t$ is the unemployment rate (a scalar), $(\bar{u}_t S_t^u)$ is a *population* vector, and S_t^u is a *density* vector with elements summing to one. Now let $\begin{bmatrix} \tilde{u}_0^{t+1} & \tilde{u}_1^{t+1} \end{bmatrix}$ be the vector that contains *the subset* of these workers that remain unemployed the following period. The transition between unemployment and unemployment is then given by:

$$\begin{bmatrix} \tilde{u}_0^{t+1} & \tilde{u}_1^{t+1} \end{bmatrix} = \begin{bmatrix} \bar{u}_0^t & \bar{u}_1^t \end{bmatrix} \times \begin{bmatrix} 1 - \alpha_0^w\left(S_t\right) & 0 \\ 0 & 1 - \alpha_1^w\left(S_t\right) \end{bmatrix} \times \begin{bmatrix} 1 & 0 \\ (1 - \lambda) & \lambda \end{bmatrix}$$

The transition of total unemployment is an operator:

$$\left\{\bar{u}_t \left(S_t^u\right)' \equiv \begin{bmatrix} \bar{u}_0^t & \bar{u}_1^t \end{bmatrix}\right\} \Longrightarrow \begin{bmatrix} \bar{u}_0^{t+1} & \bar{u}_1^{t+1} \end{bmatrix}$$

To get this operator we must add the incoming cohort to our previous algebra.

The incoming cohort is the transition from employment into unemployment and is given by

$$(1 - \lambda)\left(1 - \bar{u}_t\right)\left(S_t^e\right)' \hat{M} = (1 - \lambda)\left[\bar{e}_t \left(S_t^e\right)'\right] \hat{M}$$

where $\bar{e}_t$ is the employment rate (a scalar), $(\bar{e}_t S_t^e)$ is a *population* vector, and S_t^e is a *density* vector with elements summing to one. We have then:

$$\left(Z_{t+1}^u\right)' = \bar{u}_t \left(S_t^u\right)' \times T\left(S_t\right) + (1 - \lambda)\left(1 - \bar{u}_t\right)\left(S_t^e\right)' \hat{M}$$

which in our example:

$$\begin{aligned} \left(Z_{t+1}^u\right)' &\equiv \bar{u}_{t+1} \begin{bmatrix} u_0^{t+1} & 1 - u_0^{t+1} \end{bmatrix} \\ &= \bar{u}_t \begin{bmatrix} u_0^t & 1 - u_0^t \end{bmatrix} \times T\left(S_t\right) \\ &\quad + (1 - \lambda)\left(1 - \bar{u}_t\right) \begin{bmatrix} e_0^t & 1 - e_0^t \end{bmatrix} \times \hat{M} \end{aligned}$$

and then

$$\begin{aligned} \bar{u}_{t+1} &= \left(Z_{t+1}^u\right)' \times [1] \\ S_{t+1}^u &= Z_{t+1}^u / \bar{u}_{t+1} \end{aligned}$$

which gives both the unemployment level/rate and its distribution.

This is the last piece of the problem. We need it because we want to know the *distribution* of employment (the *level* we already know since we know unemployment from the previous equation). It involves the transition from unemployment into employment:

$$\bar{u}_t \left[\alpha \left(S_t^u\right)' S_t^u\right] \begin{bmatrix} 1 & 0 \end{bmatrix}$$

and the transition from employment to employment:

$$\lambda(1-\bar{u}_t)\left[\left(S_t^e\right)' \hat{M}\right]$$

to get:

$$\left(Z_{t+1}^e\right)' = \lambda(1-\bar{u}_t)\left[\left(S_t^e\right)' \hat{M}\right] + \bar{u}_t \left[\alpha \left(S_t^u\right)' S_t^u\right] \begin{bmatrix} 1 & 0 \end{bmatrix}$$

where

$$\left(Z_{t+1}^e\right)' \equiv \bar{e}_{t+1} \begin{bmatrix} e_0^{t+1} & 1-e_0^{t+1} \end{bmatrix} \equiv \left(1-\bar{u}_{t+1}\right) \begin{bmatrix} e_0^{t+1} & 1-e_0^{t+1} \end{bmatrix}$$

and in detail

$$\begin{aligned}
\left(Z_{t+1}^e\right)' &= \lambda(1-\bar{u}_t) \begin{bmatrix} e_0^t & 1-e_0^t \end{bmatrix} \hat{M} \\
&\quad + \bar{u}_t \begin{bmatrix} u_0^t & 1-u_0^t \end{bmatrix} \begin{bmatrix} \alpha_0^w\left(S_t\right) \\ \alpha_1^w\left(S_t\right) \end{bmatrix} \begin{bmatrix} 1 & 0 \end{bmatrix}
\end{aligned}$$

where $\alpha^w\left(S_t\right)'$ is a row vector. The distribution of employment by contacts next period is then:

$$S_{t+1}^e = Z_{t+1}^e / \left(\left(Z_{t+1}^e\right)' [1]\right)$$

2.5 Equilibrium

These last two sets of equations characterize the equilibrium given the current state variables. They are, however, overidentified in terms of computing the long run equilibrium. Each equation in steady state determines two of the three values we need to find, and which are $(\bar{u}, u_0, e_0)$. We have in steady state:

$$\begin{aligned}
\bar{u} \begin{bmatrix} u_0 & 1-u_0 \end{bmatrix} &= \bar{u} \begin{bmatrix} u_0 & 1-u_0 \end{bmatrix} \times \begin{bmatrix} 1-\alpha_0 & 0 \\ 0 & 1-\alpha_1 \end{bmatrix} \times M \\
&\quad + (1-\bar{u})(1-\lambda) \begin{bmatrix} e_0 & 1-e_0 \end{bmatrix} \times \hat{M}
\end{aligned}$$

$$\begin{aligned}
(1-\bar{u}) \begin{bmatrix} e_0 & 1-e_0 \end{bmatrix} &= \lambda(1-\bar{u}) \begin{bmatrix} e_0 & 1-e_0 \end{bmatrix} \times \hat{M} \\
&\quad + \bar{u} \begin{bmatrix} \alpha_0 & \alpha_1 \end{bmatrix} \begin{bmatrix} u_0 \\ 1-u_0 \end{bmatrix} \begin{bmatrix} 1 & 0 \end{bmatrix}
\end{aligned}$$

and to find the steady state we need only one of these equation plus the conditions that jobs created equal jobs destroyed:

$$\bar{u}\left[\begin{array}{cc}\alpha_0 & \alpha_1\end{array}\right]\left[\begin{array}{c}u_0\\ 1-u_0\end{array}\right]\left[\begin{array}{cc}1 & 0\end{array}\right]\left[\begin{array}{c}1\\ 1\end{array}\right]=(1-\bar{u})\,(1-\lambda)\left[\begin{array}{cc}e_0 & 1-e_0\end{array}\right]\times\hat{M}\left[\begin{array}{c}1\\ 1\end{array}\right]$$

This is a non linear system because α depends on vacancies, and vacancies depend on the distribution of unemployed workers over contacts, all in a nonlinear way. Numerically there was no problem finding the solution.

2.6 The matching function

The simple Cobb-Douglas matching function is not enough in this model. We want the matching function to have several standard properties. The total number of matches must be increasing in both the number of vacancies and the number of unemployed workers. And the probability that an unemployed worker finds a vacancy must be increasing in the number of vacancies and decreasing in the number of unemployed workers. Additionally, this probability must be increasing in the number of contacts a worker has. This extra feature of our problem provides us with the possibility of matching time patterns of job finding rates in the data which the standard model does not, and therefore may help us better understand the matching process.

Equilibrium consistency of the matching probabilities then implies for the total number of matches:

$$m=\sum_{i=0}^{\bar{n}}\alpha_i^w u_i\bar{u}$$

where

$$1=\sum_{i=0}^{\bar{n}}u_i$$

and for $\alpha_i^w=g\left(i,\bar{u},v\right)$ we must have *at least* that $g_i>0$, $g_{\bar{u}}<0$, and $g_v>0$. Note that we are not imposing that these probabilities depend explicitly on the distribution of workers over contacts. We now check whether a close relative of the standard Cobb-Douglas will satisfy our requirements. Consider the function

$$\alpha_i^w=\gamma\left(\frac{v}{\bar{u}}\right)^{\theta}\phi\left(i\right)$$

with $0<\theta<1$, and $\phi_i>0$.[11] This function satisfies all our derivatives above. Furthermore it also satisfies the condition that the total number of matches is increasing in both vacancies and unemployment:

$$m=\gamma\left(\frac{v}{\bar{u}}\right)^{\theta}\bar{u}\sum_{i=0}^{\bar{n}}\phi\left(i\right)u_i=\gamma\left(v\right)^{\theta}\left(\bar{u}\right)^{1-\theta}\sum_{i=0}^{\bar{n}}\phi\left(i\right)u_i$$

[11] The function ϕ could depend also on characteristics such as age, gender and education.

The final steps in the logic of this construction come from the side of the firm. We know that α^f is a constant:

$$\alpha^f = \frac{k\,(1-\beta\lambda)}{\beta(y-w)}$$

and because for the firm it does not matter which type of worker they meet, this probability can be written simply as $\alpha^f = m/v$. We then have

$$\frac{m}{v} = \gamma\left(\frac{\bar{u}}{v}\right)^{1-\theta}\sum_{i=0}^{\bar{n}}\phi\,(i)\,u_i = \frac{k\,(1-\beta\lambda)}{\beta(y-w)}$$

which then implies that vacancies depend on the *distribution* of types:

$$v = \bar{u}\left(\gamma\frac{\beta(y-w)}{k\,(1-\beta\lambda)}\sum_{i=0}^{\bar{n}}\phi\,(i)\,u_i\right)^{\frac{1}{1-\theta}}$$

This also provides an additional mechanism affecting the dynamics and volatility of vacancies. Given that vacancies depend on the distribution of contacts, worker probabilities also do:[12]

$$\alpha_i^w = g\,(i,\bar{u},v) = g\,(i,\bar{u},v\,(S^u))$$

This construction allows us to now specify the function $\phi\,(i)$ independently of any other considerations. Its main property is that it should be increasing in the number of contacts, but we should also define whether this function should be concave or convex. The following function:

$$\phi\,(i) = \frac{\log(\tau_0+\tau_1 i)}{N}$$

where N is an arbitrary number chosen for calibration purposes, is positive and strictly concave in (i). The choice of (N,τ_0,τ_1) ensures the match probability is positive even at zero contacts and grows with the number of contacts, and determines the shape of ϕ over the relevant range. We emphasize that we can choose any shape we want, either concave, linear or convex.

2.7 Unemployment Duration Algebra

Consider a worker who enters unemployment with zero contacts. His probability of reemployment is constant every period at α_0^w. Therefore he finds a job after one period with probability α_0^w. Finds a job after two periods with probability $\alpha_0^w(1-\alpha_0^w)$. After three periods with probability $\alpha_0^w(1-\alpha_0^w)^2$, etc. We have expected duration of unemployment given by

$$\begin{aligned} d_0 &= 1\alpha_0^w + 2\alpha_0^w(1-\alpha_0^w) + 3\alpha_0^w(1-\alpha_0^w)^2 + ... \\ &= \alpha_0^w\left[1 + 2(1-\alpha_0^w) + 3(1-\alpha_0^w)^2 + ...\right] \\ &= 1/\alpha_0^w \end{aligned}$$

[12] The level of unemployment at the start of the period summarizes all the useful information about the distribution of contacts in the *employed* population S_t^e.

This algebra, however, depends on the state vector:

$$\begin{aligned} d_0\left(S_t\right) &= 1\alpha_0^w\left(S_t\right)+2\alpha_0^w\left(S_{t+1}\right)\left(1-\alpha_0^w\left(S_t\right)\right) \\ &\quad +3\alpha_0^w\left(S_{t+2}\right)\left(1-\alpha_0^w\left(S_{t+1}\right)\right)\left(1-\alpha_0^w\left(S_t\right)\right)+... \end{aligned}$$

so that the value of this sum is not trivial to compute (even though the law of large numbers ensures the transition of the state vector is deterministic).

We can write the expected duration algebra for all contacts in matrix form as:

$$d\left(S_t\right)=\alpha^w\left(S_t\right)+2\alpha^w\left(S_{t+1}\right)T\left(S_t\right)+3\alpha^w\left(S_{t+2}\right)T\left(S_{t+1}\right)T\left(S_t\right)+...$$

and in steady state equilibrium we can write the expected duration algebra in matrix form as:

$$d=\left\{I+2T+3T^2+...\right\}\alpha^w=\left[I-T\right]^{-1}\left[I-T\right]^{-1}\alpha^w$$

where α^w is a column vector.

3 Numerical Simulations

The experiments conducted in this paper take the shortcut of setting $\bar{n}$ by postulating a $g(n)$ function such that the optimal $\bar{n}$ does not depend on the state variables in the problem. This circumvents the need to solve the optimization problem at each step and reduces the evolution of the economy to the mechanics presented above. There is a loss of the endogenous transmission mechanism which would come from changing $\bar{n}$ as the state of the world changes, but this is compensated by gain in numerical implementability.

Calibration

Here we follow Shimer (2005), Mortensen and Nagypal (2007), Cooper, Haltiwanger and Willis (2007), and Zhang (2008), adapting where appropriate for our weekly frequency. CHW use an annual interest rate of 4%, while Shimer uses a value around 5%. We use 5%. CHW report a value of θ, the weight of firms in the matching function, of 0.64. Shimer uses a value of 0.28 for this parameter. We use the mid point of these two values, 0.46, which is within the plausible range proposed by Petrongolo and Pissarides (2001).

CHW report a monthly job finding rate equal to 0.61, while Shimer reports a value of 0.45, and Zhang reports a value of 0.309 for Canadian data. Disregarding contacts this implies on a weekly frequency:

$$\alpha^w + (1-\alpha^w)\,\alpha^w + (1-\alpha^w)^2\,\alpha^w + (1-\alpha^w)^3\,\alpha^w = 0.61$$

which in turn implies $\alpha^w = 0.21$ or for Shimer's number $\alpha^w = 0.14$, while for Zhang's number it is $\alpha^w = 0.08825$.[13] We note here that over four weeks we expect few contacts to lose their jobs, so that we can use this number to benchmark $\alpha^w_{\bar{n}}$.

$$\alpha^w_{\bar{n}} = \gamma\left(\frac{v}{\bar{u}}\right)^{\theta}\phi(\bar{n})$$

and so we calibrate the ϕ function such that we obtain $\alpha^w_5 \approx 0.15$ in the experiment below.[14]

Shimer uses a quarterly separation rate of 10% which delivers an expected employment duration equal to 30 months or 130 weeks. This then implies a value of $(1-\lambda) = 1/130$, and we use this value. Zhang finds that Canadian jobs have an expected duration of 146 weeks. Given a value of the monthly separation rate in Canada of 0.03 we can compute a gross value of our weekly λ simply by doing $(1-\lambda) = 0.03/4.35 = 1/145$.[15] In the case of Shimer the separation rate used is 0.10 at the quarterly frequency, and a gross computation

[13] Lynch (1989) reports a value of 0.30 for the first week of unemployment. This number falls fast with duration though, suggesting the ϕ function is quite possibly convex rather than concave. Alternatively, this quick drop reflects mismeasurement by including in the unemployment pool job to job transitions (which require a week or two to clean up a desk).

[14] We achieve this by setting $(\tau_0 = 1.2, \tau_1 = 2, N = 18)$.

[15] This is not the only way to compute the weekly separation rate out of quarterly numbers. The reason is that we do not know how the following event is accounted for in the data: a firm and a worker separate 2 weeks into the quarter and 4 weeks later, well before the quarter is over, both the firm and the worker have found new matches.

yields $(1-\lambda) = 0.1/13 = 1/130$. The numbers match and the value of $1/130$ is our benchmark.

Given that the values of unemployment in Canada and the US reported by Zhang and by Shimer are respectively 0.0778 and 0.0567, the difference must come from the job finding rates we construct above.

CHW report that the average value of labor market tightness, the ratio v/u, is around 0.46. However, Shimer argues that this ratio is essentially meaningless and he calibrates it to equal 1, which in turn implies that in equilibrium $\alpha^w = \alpha^f$. We therefore use the vacancy cost k to target the vacancy filling rate directly to be $\alpha^f \approx 0.14$. This implies a value of $k = 16$. The tightness ratio is then implied by the rest.[16] CHW estimate $\gamma = 1.0072$, and we set this parameter to 1. We note here that in Shimer (2005), setting $\gamma \geq 1$, and at the same time normalizing the tightness ratio to be one, implies the ratio of matches over vacancies or over unemployment is greater than one. Irrespective of the frequency with which one looks at the data, this implies awkwardly that more matches are formed than vacancies or the number of unemployed workers. In the present paper, this is not the case because the matching function is different and the quantity

$$\sum_{i=0}^{\bar{n}} \phi(i)\, u_i$$

adds up to a small number, bringing down the number of matches formed.

The following table summarizes the calibration of the deterministic model:

Table 1: Deterministic Model Parameters

$\bar{n}$	$1-\lambda$	γ	θ	β	$y-w$	k	τ_0	τ_1	N	α^f
9	$\frac{1}{130}$	1	0.46	$(0.95)^{1/52}$	1	75*0.213	1.2	2	18	0.1387

Simulations

The following simulation outcomes average thirteen runs of a panel with four thousand individuals and four hundred periods. From each panel only about 200 individuals (5%) are unemployed in any period (week) of the panel. For these 200 individuals we measure the length of their current unemployment spell, the length of the employment spell that preceded it, and the number of contacts they have today. Then we compute three correlations. All this is done for the example with $\bar{n} = 9$.[17]

The top part of Table 2 shows first the correlation between the length of the current unemployment spell and the length of the employment spell that immediately preceded it, $(\rho_{u,e})$, then the correlation between the length of the

[16] Shimer sets the ratio $k/(y-w)$ to 0.213. Here since $y-w=1$ this would be the value of k. But these values do not work in our model. He also sets home production at $b = 0.4$.

[17] The model is run for a number of periods first until the unemployment rate and the contact distributions converge. It is from then on that the simulations begin, and all individuals begin the simulations with maximum contacts $\bar{n}$. After 400 periods the simulation stops and we pick the cross sectional status of the panel at this period.

Table 2: Correlations in artificial data

$\bar{n}=9$	$\rho_{u,e}$	$\rho_{u,E(u)}$	$\rho_{e,E(u)}$	$\bar{u}$	n
	-0.0925	0.6242	-0.1634	0.0431	2278
Expected Duration by Contacts (weeks)					
0	1	2	3	..	9
89.7	20.9	11.3	8.7	..	5.6

current unemployment spell and expected unemployment duration, $(\rho_{u,E(u)})$, and then the correlation between the length of the employment spell and current expected unemployment duration, $(\rho_{e,E(u)})$. It also shows the observed average unemployment rate and the total sum of unemployed agents over the thirteen panels. The bottom part shows expected unemployment duration by contacts in weeks and we see that given the shape of ϕ, there is a very large change going from zero to one active contact, followed by a smooth decline in expected duration.

Table 3 shows, for $\bar{n}=9$, the functions ϕ and α^w, and the histogram of the distribution of unemployed agents by contacts:

Table 3: Contacts in the matching function when max(n)=9

	0	1	2	3	4	5	6	7	8	9
ϕ	0.010	0.065	0.092	0.110	0.123	0.134	0.143	0.151	0.158	0.164
α^w	0.011	0.071	0.101	0.121	0.136	0.148	0.158	0.167	0.174	0.181
HU	32	40	28	28	25	28	48	130	459	1460

In this experiment only about 1.5% of the unemployed population (the 32 agents with zero contacts) is really long term unemployed. If we add the workers with one contact (which have 21 weeks of expected unemployment duration) this proportion comes up to 3.5% which is closer to the number found in Weatherall (2008) on Danish data.

3.1 Convex versus concave matching technologies

This is an important characteristic. As we will see, the model predicts that in a recession the duration of unemployment increases. Unemployed agents will then be pushed in the direction of the zero contact boundary. The shape of the ϕ function close to the origin then matters for the characterization of cyclical behaviour of conditional unemployment duration. The shape of ϕ has theoretical background. A convex function embodies an idea of increasing returns to network density. However, convexity is problematic because ϕ is a reduced form for (part of) a probability function.[18] It is unclear how to match the ideas of Granovetter (1973) and the evidence about them - see Granovetter (1983) - with

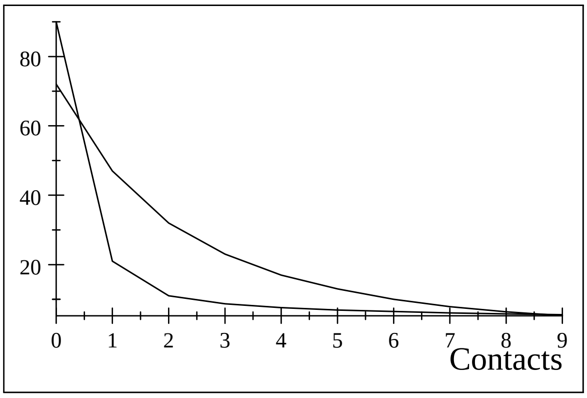
[18] If maintaining links in a network is costly and if not everyone is equally valuable diminishing returns may result (even if an additional link may induce external increasing returns).

the shape of the ϕ function, because even if we consider the marginal link (here the nth link) as the weakest, and if weak ties get you the most jobs, there still is an issue of diminishing returns to how many weak ties one chooses to have. As discussed below we find support for diminishing returns.

Here we pick the experiment with $\bar{n} = 9$ and compare the distributional implications of a convex function ϕ, keeping the unemployment rate at roughly the same level. The convex ϕ function has three parameters $(\tau_0, \tau_1, \tau_2) = (1.15, 0.6, 0.015)$, and is constructed as follows. First define $\phi_j = (\tau_0)^j - \tau_1$. Then redefine $\phi_j = -\tau_2 + \phi_j / \left(\sum_{j=0}^{nbar} \phi_j \right)$.

Figure 2 shows (on the vertical axis) expected unemployment duration in weeks given the number of contacts, and we can see that the convex ϕ function induces a much flatter relationship without the large drop going from zero to one contact:

Figure 1: Expected Unemployment Duration in Weeks



The correlations and unemployment rates are given in Table 4:

Table 4: Correlations

$\bar{n} = 9$	Concave	Convex
ρ_1	-0.0925	-0.2194
ρ_2	0.6242	0.7495
ρ_3	-0.1634	-0.3471
$\bar{u}$	0.0431	0.0465
n	2278	2420

The job finding rates and realized contact distribution of unemployed workers are given in Table 5:

Table 5: Contacts with a convex matching function

$\bar{n} = 9$	0	1	2	3	4	5	6	7	8	9
ϕ	0.013	0.023	0.035	0.049	0.065	0.084	0.105	0.129	0.157	0.189
α^w	0.014	0.025	0.038	0.053	0.070	0.089	0.112	0.138	0.167	0.202
HU	74	138	74	56	46	50	56	135	446	1345

We can see that while the signs of the different correlations are the same, both the magnitude of the correlations and the shape of the distributions change with the shape of the ϕ function, which is good news for identification.

In actual data we do not observe how many contacts people have. What we do observe are conditional unemployment durations, and those are the patterns a model of networks must try to match.[19] Taking a cohort of artificial agents that lose their jobs at a given point in time, and following their reabsorption into employment, we find that the hazard of leaving unemployment is flatter when we use a convex ϕ function. If we track also the contacts of the group that remains behind in unemployment we see that their loss of contacts is also slower in the case of a convex function.

More iportantly, when ϕ is concave we obtain long durations of unemployment when we have a large number of observations, because there will always be some workers unfortunate enough to lose all their contacts and be trapped in unemployment for long periods. Accordingly, concave functions induce very low hazards at the tail. This does not happen with a convex ϕ function and suggests we want to use a concave function.[20]

At this stage there is a variety of moments that characterize the dynamic behavior of the model which we cannot measure without adding aggregate shocks. We do this in the next section.

[19] Exact identification is always hard, particularly if the conditional duration function is not simply shifted by the initial condition (initial number of contacts) but changes non-linearly.

[20] Neither the concave nor the convex functions used here are able to induce a steep drop in the beggining of the unemployment spell note by Lynch.

4 Aggregate Shocks

The aggregate state affects productivity, y, and the destruction rate, λ. For simplicity of exposition we work here with two aggregate states, indexed x_1 and x_2. The transition between them is governed by the Markov matrix:

$$\Pi = \begin{bmatrix} q & 1-q \\ 1-p & p \end{bmatrix}$$

A reaization of the aggregate state is a realization of a value for the pair (λ, y).

4.1 Firms

The value of posting a vacancy is now

$$V(x_i) = -k + \beta\alpha^f(x_i) E_i(J) + \beta(1-\alpha^f(x_i))E_i(V)$$

where the probability a vacancy meets an unemployed worker is denoted by $\alpha^f(x_i)$. Free entry implies $V = 0$ whatever the state so that

$$k_i = \beta\alpha^f(x_i) E_i(J)$$

A filled job produces an output $y_i \equiv y(x_i)$, which is divided between the firm and the worker, with $w_i \equiv w(x_i) > b$. Matches have an exogenous break up rate of $1 - \lambda_i \equiv 1 - \lambda(x_i)$. The value of a filled vacancy is

$$J(x_i) = y_i - w_i + \beta\lambda_i E_i(J) + \beta(1-\lambda_i)E_i(V)$$

and in matrix form

$$\begin{aligned} J &= \begin{bmatrix} J(x_1) \\ J(x_2) \end{bmatrix} = \begin{bmatrix} y_1 - w_1 \\ y_2 - w_2 \end{bmatrix} + \beta \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \Pi \begin{bmatrix} J(x_1) \\ J(x_2) \end{bmatrix} \\ J &= [I - \beta Diag(\lambda)\Pi]^{-1} \begin{bmatrix} y_1 - w_1 \\ y_2 - w_2 \end{bmatrix} \end{aligned}$$

which implies we must have a vector of constants with dimension given by the number of aggregate states:

$$\begin{aligned} \frac{1}{\alpha^f(x_i)} &= \frac{\beta}{k_i} E_i(J) \\ 1/\alpha^f &= \begin{bmatrix} 1/\alpha^f(x_1) \\ 1/\alpha^f(x_2) \end{bmatrix} = \frac{\beta}{k}\Pi J \end{aligned}$$

4.2 Probability matrices.

We still have the transition matrices M and $\hat{M}$ as before, and one difference is that they are indexed by the aggregate state since the destruction rate varies with the aggregate shock, $\lambda(x_i)$. This is, however not the only difference. In our example of two states we will assume that it is possible for the maximum number of contacts to differ in state zero and state one. In this case the two transition matrices change in a subtle way. We give here an example where $\bar{n}(x_2) = 2$, and $\bar{n}(x_1) = 1$. We have then for unemployed agents in state i:

$$M(x_i) = \begin{bmatrix} 1 & 0 & 0 \\ (1-\lambda_i) & \lambda_i & 0 \\ (1-\lambda_i)^2 & 2\lambda_i(1-\lambda) & \lambda_i^2 \end{bmatrix}$$

with $i = 1, 2$, while for **employed** agents we have:

$$\begin{aligned} \hat{M}(x_2) &= \begin{bmatrix} (1-\lambda_2) & \lambda_2 & 0 \\ (1-\lambda_2)^2 & 2\lambda_2(1-\lambda_2) & \lambda_2^2 \\ (1-\lambda_2)^2 & 2\lambda_2(1-\lambda_2) & \lambda_2^2 \end{bmatrix} \\ \hat{M}(x_1) &= \begin{bmatrix} (1-\lambda_1) & \lambda_1 & 0 \\ (1-\lambda_1) & \lambda_1 & 0 \\ (1-\lambda_1)^2 & 2\lambda_1(1-\lambda_1) & \lambda_1^2 \end{bmatrix} \end{aligned}$$

which marks a qualitative difference from the deterministic model.

We emphasize here that the exercise with aggregate shocks will keep $\bar{n}$ constant across the aggregate states. This will allow us to see the impact of the mere inclusion of this mechanism in the standard model, without the contributions of *changes* in its intensity.[21]

4.3 Mechanics

The transition from unemployment to unemployment when the current aggregate state is x_t is now:

$$\begin{aligned} [\tilde{u}_{t+1}] &= \bar{u}_t [u_t] \times T(x_t, S_t) \\ T(x_t, S_t) &= Diag(1 - \alpha^w (x_t, S_t)) \times M(\lambda_t) \end{aligned}$$

The incoming cohort (employment into unemployment) is:

$$(1-\lambda_t)(1-\bar{u}_t)[e_t]\hat{M}(\lambda_t)$$

The transition of employment into employment is:

$$\left(Z_{t+1}^e\right)' = \lambda_t(1-\bar{u}_t)[e_t]\hat{M}(\lambda_t)$$

and the transition of unemployment into employment yields the scalar:

$$\alpha(x_t, S_t)\bar{u}_t[u_t]$$

We will proceed with the simplifying assumption that the maximum number of contacts never changes, $\bar{n}(x_t) = \bar{n}$.

[21] Note also that the aggregate states are ordered by their total match productivity values. It is a priori unclear what the variation of $\bar{n}$ should be for different values of y. Furthermore if the aggregate state is multidimensional this is even harder to predict.

4.4 The matching function

With a constant $\bar{n}$ the algebra here is trivial again. From the firm side we know that α^f is a constant which depends on the aggregate state and where $\alpha^f(x_t) = m(x_t)/v_t$. All we now need is

$$\frac{m_t}{v_t} = \gamma \left(\frac{\bar{u}_t}{v_t}\right)^{1-\theta} \sum_{i=0}^{\bar{n}} \phi(i)\, u_{i,t} = \alpha^f(x_t)$$

which then implies

$$v_t(x_t) = \bar{u}_t \left(\frac{\gamma}{\alpha^f(x_t)} \sum_{i=0}^{\bar{n}} \phi(i)\, u_{i,t}\right)^{\frac{1}{1-\theta}}$$

We see that it is only through the expectation of J inside $\alpha^f(x_t)$ that the parameters of the matrix Π enter vacancies and affect dynamics, in the world where $\bar{n}$ is fixed. Other than that the matrix Π manifests itself through the realized path of the aggregate shock.

Discussion

We can also explore having (N, τ_0, τ_1) change with the aggregate state. This requires discussion. Is it the case that in good times the contribution of a contact for finding a job is smaller than in bad times (perhaps because its is easier to find a job without contacts in good times)? Or is the contribution of a contact for finding a job higher in good times? One reason this matters is because the distribution of contacts can either smooth or magnify the effect of the aggregate shock. We have no a-priory reason to think one way or another, and perhaps the data could tell us something about this. At this stage we do not pursue these ideas, and the ϕ function is not affected by aggregate shocks.

4.5 Unemployment Duration Algebra

Consider a worker who enters unemployment with zero contacts. His probability of reemployment α_0^w now can change every period depending on the aggregate state. We can show that for zero contacts, given initial aggregate state x_t, expected duration is given by

$$\begin{aligned} d_0(x_t) &= \alpha_0^w(x_t) + 2(1-\alpha_0^w(x_t))\Pi_t\left[\alpha_0^w\right] \\ &\quad +3(1-\alpha_0^w(x_t))\Pi_t\left[Diag\left(1-\alpha_0^w\right)\Pi\right]\left[\alpha_0^w\right] \\ &\quad +4(1-\alpha_0^w(x_t))\Pi_t\left[Diag\left(1-\alpha_0^w\right)\Pi\right]^2\left[\alpha_0^w\right] + ... \\ &= \alpha_0^w(x_t) + (1-\alpha_0^w(x_t))\Pi_t\left[(I-Z)^{-1}\left(1+(I-Z)^{-1}\right)\right]\left[\alpha_0^w\right] \end{aligned}$$

However, this is not enough. In practice the computation of expected unemployment duration is much harder because as aggregate shocks hit, the distribution of workers over contacts changes. The $\alpha_n^w(x)$ functions are themselves changing over time because the distributions are changing.

To overcome this difficulty, in the stochastic model we measure actual durations. Once we pick a cross section of workers at a given period, we measure its characteristics both backward and forward looking. For all workers at this moment we measure their unemployment spell to date, the length of the previous employment spell, and the length of the subsequent duration of unemployment from this period onwards. Rather than measuring expected duration of unemployment we measure observed subsequent duration.

5 Numerical Simulations

While the dynamics arising from the proper solution to the model are more interesting, we only study the time series behavior of this economy under a constant $\bar{n}$. We extend the calibration used previously using new moments. The following table summarizes means (μ), standard deviations (σ), and serial correlations (ρ), for the US and Canadian economies taken from Zhang (2008).[22]

Table 6: Data: USA and Canada

		u	v	v/u	α^w	δ	y
CA	σ	0.162	0.237	0.367	0.105	0.096	0.021
US	σ	0.190	0.202	0.382	0.118	0.075	0.020
CA	ρ_1	0.956	0.956	0.959	0.791	0.795	0.876
US	ρ_1	0.936	0.940	0.941	0.908	0.733	0.878
CA	μ	0.078			0.309	0.030	
US	μ	0.057			0.452	0.023	

And also the following correlations[23]

Table 7: Quarterly data. USA and Canada

	$\rho(v,u)$	$\rho(v/u,\alpha^w)$	$\rho(\delta,y)$
CA	-0.689	0.753	-0.396
US	-0.894	0.948	-0.524

The correlation between the destruction rate, $1-\lambda \equiv \delta$, and productivity (y), dictates the construction of the shocks. We form the two shocks as different linear combinations of two identical and independent Markov processes x_1 and x_2:

$$\begin{aligned} y - w &= x_1 + x_2 \\ \delta &= x_1 - \psi x_2 \end{aligned}$$

where the support of δ is constructed around the value 1/130 and the support of $y-w$ is constructed around 1. With the parameter ψ set at 3.1, the correlation between the two variables is around -0.3. Both x_1 and x_2 are generated from

[22] The top four rows have moments for quarterly frequency data, while the bottom two rows have moments for monthly frequency data. The data are measured always as $log(x_t) - log(\bar{x})$, where $\bar{x}$ is the Hodrick-Prescot trend. CHW estimate the serial correlation of market tightness to be 0.93 using monthly data. The average monthly separation rate for the US is computed simply as 0.1 (the quarterly rate in Shimer (2005)) divided by 4.3482, which is the average number of weeks in a month - a year has 365.25 days on average.

[23] Despite these numbers we note that Torres (2009) finds for both the U.S. and Portugal that the job finding probability is procyclical and the job separation probability has no clear pattern. Both probabilities are in Portugal half of those in the U.S. economy. The contribution of the job finding rate is larger than the contribution of the job separation rate to the changes in the unemployment rate. See also Shimer (2005b).

a discretization of an AR1 process on a five point support using Tauchen's method.[24] The serial correlation parameter is 0.968. The standard deviation is set to match the standard deviation of productivity, although we fall short in the present calibration.

One aside on the impact of shocks is important here. The expression determining vacancies induces a strong positive relationship between vacancies and unemployment. This is counteracted by the productivity shock. In the benchmark where both (λ, y) are shocks, their movements nearly cancel each other's impact inside the matching function, resulting in a positive correlation between vacancies and unemployment of 0.92, while at the same time the correlation between the job destruction rate and productivity is around -0.3. If we kill the job destruction shock, the job destruction rate then has a zero correlation with productivity, but on the other hand the correlation between vacancies and unemployment is negative and closer to the data at around -0.74. We can see how endogenous wage determination - which is absent here - helps in the macthing of these two quantities by bringing in an additional source of variation to the ratio $k\left(1-\beta\lambda\right)/(y-w)$.[25] We stress that matching these moments is not the aim of the current paper.

Table 8 shows moments of the baseline stochastic model with the concave ϕ function used so far, and for $\bar{n} = 104$. Everything is identical to the previous numerical experiments except where adjustments must be made for the stochastic nature of the problem. The initial run of the model is made using a constant realization of the aggregate state at its highest value. After convergence the stochastic path of aggregate shocks (to productivity and job destruction) is used for the following 624 periods, and we make use of the last 520 weeks which are ten years of (artificial) data.

Table 8: Baseline model moments

	u	v	v/u	α^w	δ	y	$\hat{\alpha}^m$	$\hat{\delta}^m$
σ_w	0.128	0.058	0.078	0.050	0.102	0.0171		
σ_m	0.128	0.057	0.078	0.051	0.103	0.0172	0.108	0.156
ρ_{1w}	0.999	0.967	0.986	0.992	0.975	0.972		
ρ_{1m}	0.989	0.891	0.954	0.978	0.908	0.863	0.293	0.607
μ_w	0.065	0.061	0.95	0.121	0.0083	1.005		
μ_m	0.065	0.061	0.95	0.121	0.0083	1.005	0.400	0.033

We have data here for weekly and monthly frequencies. The monthly frequency data is sampled every fourth week, - in the first 6 columns - except in the last two columns where the relevant measure must be constructed.

The job finding rate at lower frequencies - $\hat{\alpha}^m$ for monthly - is defined as a moving average and thus has weekly realizations. For the monthly frequency,

[24] We suspect the Ornstein-Uhlenbeck process used by Shimmer may be useful to tackle some correlations arising from time aggregation.

[25] In fact, the best way to do this is the point of Hall (2005), Hagedorn and Manovski (2007) and Mortensen and Nagypal (2007).

we take the unemployed population at the start of each week and construct a finding rate over (the *subsequent)* four weeks as follows:

$$\begin{aligned}\hat{\alpha}_t^m &= \alpha_t^w + \alpha_{t+1}^w\left(1-\alpha_t^w\right) + \alpha_{t+2}^w\left(1-\alpha_{t+1}^w\right)\left(1-\alpha_t^w\right) \\ &\quad + \alpha_{t+3}^w\left(1-\alpha_{t+2}^w\right)\left(1-\alpha_{t+1}^w\right)\left(1-\alpha_t^w\right)\end{aligned}$$

where each weekly α_t^w is the weighed average over contacts

$$\alpha_t^w = \sum_{j=0}^{n} \alpha_t^w\left(j\right) u_j$$

The serial correlation of α^w is measured by first sampling it every fourth week and then running an AR1 regression on this sampled time series. The other measures are also taken on the sampled time series.

There are several details here. When we pick the unemployment rate at a given point in time that is a well defined measure at any frequency. But the job finding rate is not as well defined because if we are not at the exact weekly frequency we need to match an interval measure with a point measure. We can use either an interval before the time point or an interval after the time point with equal legitimacy, but they yield different results.[26] In addition, the measure $\hat{\alpha}_t^m$ defined above may overestimate the job finding rate, and if the ϕ function is concave this can be potentially serious. A consistent way to measure the job finding rate over an interval is to pick the workers who become unemployed at a given point in time and follow them as they are reabsorbed into employment.

The job destruction rate at lower frequencies, $\hat{\delta}^m$, is constructed in a similar way, but because λ is exogenous and does not depend on type this is a correct measure. For the monthly frequency we have the forward looking measure:

$$\begin{aligned}\hat{\delta}_t^m &= \delta_t + \delta_{t+1}(1-\delta_t) + \delta_{t+2}\left(1-\delta_{t+1}\right)\left(1-\delta_t\right) \\ &\quad + \delta_{t+3}\left(1-\delta_{t+2}\right)\left(1-\delta_{t+1}\right)\left(1-\delta_t\right)\end{aligned}$$

where δ_t is simply the realized destruction rate in week t. It is worth noting how both $\hat{\alpha}_t^m$ and $\hat{\delta}_t^m$ perform: $\hat{\alpha}_t^m$ is more volatile than α_t, but not serially correlated enough and $\hat{\delta}_t^m$, given that it is calibrated, fares better when loosely compared to the data. Finally, vacancies and unemployment are strongly positively correlated:

Table 9: Baseline model moments

	$\rho\left(v,u\right)$	$\rho\left(v/u,\alpha^w\right)$	$\rho\left(v/u,\hat{\alpha}^m\right)$	$\rho\left(\delta,y\right)$	$\rho\left(\hat{\delta},y\right)$
w	0.925	0.971		-0.306	
m	0.922	0.970	0.962	-0.314	-0.289

[26] One can also use two weeks before the point and two weeks after the point for example.

5.0.1 Network productivity

In this paper, by construction close to 100% of jobs are found with some unspecified use of contacts (inside the ϕ function) - the only exception being the finding rate for workers with zero contacts. We therefore construct different statistics in order to understand what happens during unemployment. And in order to understand the contribution of the network structure we compare the results of running a model with the active network (a function $\phi(i)$) and an alternative model without the network (a function $\phi(i) = \phi$). We also show the results of other experiments to isolate the contribution of different parts of the model.

In an interesting paper, Galeotti and Merlino (2008) use the measure: "the proportion of newly employed workers that found a job through a friend or acquaintance that worked in the same place as the new employee". This measure is positively correlated (0.44) with the unemployment rate, a fact the authors claim is only possible with an endogenous increase in the activity of networking during periods of unemployment.[27]

In this paper the network is exogenous but changes cyclically. In particular the network is partially destroyed in periods of high unemployment because unemployment duration increases and longer durations imply more of the portfolio of each unemployed worker vanishes before finding a job. However, longer durations alone do not imply the network is "less productive" during periods of high unemployment. It all depends on what measure we choose to look at.

The first statistic we look at is the difference between, on one hand, the average number of contacts of the cohort of unemployed workers, and, on the other hand, the average number of contacts of the subset of the unemployed that finds a job in the period (job finders):

$$NP_1 = \frac{\text{Total Contacts of Job Finders}}{\text{Number of Job Finders}} - \frac{\text{Total Contacts of all Unemployed}}{\text{Number of Unemployed}}$$

If NP1 is positively correlated with the unemployment rate, job finders become even better connected than the average unemployed worker during hard times, suggesting only the connected people find jobs.

It is not clear whether the average number of contacts of the unemployed population should rise or fall as the unemployment rate increases. This is because as unemployment increases more workers with lots of contacts enter the unemployment pool, but at the same time unemployment duration increases.

We know a priory less about what happens to the average number of contacts of job finders. This depends on the shape of the job finding rate function which depends on the shape of the distribution of contacts and of the ϕ function.

The second statistic we look at is the fraction of job finders with less than

[27] These authors also state that "between 30% and 50% of jobs are filled through social exchange of information.", and this number matches well with the numbers obtained from the Danish survey, and with the findings of Addison and Portugal (2002).

$\frac{\bar{n}}{4}$ contacts.

$$NP_2 = \frac{\text{Number of Job Finders with less than } \frac{\bar{n}}{4} \text{ contacts}}{\text{Number of Job Finders}}$$

Given that realized unemployment duration is positively correlated with the unemployment rate at the time of job destruction, we expect this tail to grow fat during periods of high unemployment.

Our third and fourth statistics are:

$$NP_3 = \frac{\text{Number of Job Finders}}{\text{Average Contacts of the Unemployed}}$$
$$NP_4 = \frac{\text{Number of Job Finders}}{\text{Total Contacts of the Unemployed}}$$

which are more direct measures of the productivity of contacts. If these objects are positively correlated with the unemployment rate we can say that the network is more productive during periods of high unemployment.

Duration

Before looking at the behaviour of the above measures, it is useful to look at the correlation between the unemployment rate and the duration of unemployment. Here we use two measures of this correlation in different experiments. In the first measure (ρ^1) we take in each period only the cohort of workers that enters unemployment that period, and measure the cohort average realized duration of that single unemployment spell. Then we correlate this average with the unemployment rate verified at the time they lost their job. The second measure (ρ^2) does exactly the same for the entire group of unemployed workers at each point in time, measuring their onward unemployment duration and correlating the average with the unemployment rate at that initial time period. The following table summarizes the results of our experiments, where the last four columns each represent a single deviation from the baseline:[28]

Table 10: Correlation between u-rate and u-duration

	13 Panels	Baseline	No Network	Constant λ	iid shocks	Convex ϕ
ρ^1	mean	0.263	0.083	0.080	0.020	0.688
	std	(0.027)	(0.043)	(0.040)	(0.029)	(0.022)
ρ^2	mean	0.727	0.197	0.470	0.245	0.817
	std	(0.051)	(0.157)	(0.107)	(0.151)	(0.032)
	n1	70	71	65	65	72
	n2	560	616	490	500	380
ρ^1: those that start unemployment at t ρ^2: all unemployed at t						

These correlations are generally positive, which is no surprise. Also, we see that the stochastic λ has a significant impact on duration as does the presence

[28] These are averages of 13 numbers, each computed from a panel of 9 thousand workers of which between 400 and 600 workers are unemployed each period (n2), and of which around 60 to 70 lose their job each period (n1).

of the network. We can see the difference between the baseline case and the no-network (flat ϕ) case if we consider what happens to the subgroup that enters unemployment in a given period, versus the larger set of all unemployed that period. In the baseline case these groups are different because if you were already unemployed chances are your contacts are few and a period of high unemployment with a concave fi function is bad news for duration. If on the other hand you just lost your job, even though the unemployment rate is high, you may still ride out this recession with sufficient contacts such that your unemployment duration will not be too affected. So: In a model without a network, we expect the difference in this correlation between the two groups to be smaller than if a network is present. It remains to identify what small means.

Network productivity

We are now ready to examine our "network productivity" measures. The following table shows the weekly frequency correlation between these network productivity measures (and their components) and the unemployment rate in an artificial panel with 117000 workers and 520 weeks.[29]

Table 11: NP and Unemployment, Baseline with (y,lambda) shocks

	ACJF	ACU	NP1	NP2	NP3	NP4	U
ACJF	1	0.96	0.55	-0.87	-0.85	-0.49	-0.78
ACU		1	0.29	-0.78	-0.84	-0.54	-0.75
NP1			1	-0.64	-0.40	-0.07	-0.42
NP2				1	0.74	0.36	0.71
NP3					1	0.45	0.95
NP4						1	0.16

In the baseline case we see that the average number of contacts falls as unemployment rises. Even though workers typically have lots of contacts when they lose their jobs and the arrival of more new people into the unemployment pool acts to increase the average number of contacts when unemployment increases, the fact that duration rises with the unemployment rate pushes the average number of contacts of an unemployed agent down. More importantly, the network gap between job finders and the average unemployed (NP1) falls as unemployment rises.

We see also that the lower tail of contacts (NP2) grows as unemployment rises. The network is being destroyed by high unemployment and longer durations. Since this (fewer contacts) is an absorbing state, it explains why in another sense the network matters less: every one is more similar.

Finally, NP3 and also NP4 are positively correlated with unemployment giving the opposite suggestion that the productivity of the network rises in periods of high unemployment - note that this happens here with an exogenous network structure. The immediate reason why this is so is that when the unemployment rate rises, there are also more workers finding jobs simply because there are

[29] We use the concave ϕ function described above with $N = 32$.

more workers unemployed.[30] However, if we use a convex function ϕ, we will obtain a negative correlation between NP4 and the unemployment rate.

So: on one hand every one is more similar, suggesting the network matters less, and on the other hand more jobs are created per contact, suggesting the network matters more. But the network is exogenous so the notion of a cyclical behaviour of network productivity is misleading.

How does this change when the network is shut down (a flat ϕ function)? Here we summarize for our experiments the last column from the previous table:

Table 12: Network Productivity Correlation with Unemployment Rate

	ACJF	ACU	NP1	NP2	NP3	NP4
Baseline	-0.78	-0.75	-0.42	0.71	0.95	0.16
Flat ϕ	-0.68	-0.71	0.03	0.69	0.92	0.30
Constant λ	-0.29	-0.54	0.09	0.00	0.54	0.19
iid shocks	-0.17	-0.25	0.02	0.04	0.69	0.15
Convex ϕ	-0.83	-0.85	-0.57	0.77	0.96	-0.63

Essentially, when we shut down the network the group of job finders becomes statistically identical to all other unemployed (NP1 is now orthogonal to the unemployment rate). Also, NP4 is still positively related to the unemployment rate (and more than before!) suggesting a positive correlation in these indicators does not provide enough identification. We also see in the bottom row that with our convex function NP4 becomes negatively correlated with the unemployment rate. In the context of this model this points to using a concave function.[31]

At this point we emphasize that there is no normative value from looking at these measures, since it is not obviously good or bad how a measure of "network productivity" is correlated with unemployment.

There is one final important remark to make regarding the shutting down of the network, namely what happens to the aggregate properties of the unemployment rate:

Shutting down the network has virtually no effect on observable properties of the aggregate unemployment rate, but does affect duration. We need conditional duration moments to infer anything about possible effects of connectivity.

[30] Because wages are exogenously fixed, and because the job destruction shock counteracts the effect of low productivity in the matching function, we cannot destroy the strong positive link between vacancies and unemployment. The effect above is intuitive: low productivity implies less vacancies are created, but a high job destruction rate, implies that more vacancies are required every period (even though jobs are less valuable because they last a shorter period they are still worth filling with a worker and so a high job destruction rate increases vacancy creation).

[31] This does not *disprove* Galleoti and Merlino's point because the function ϕ could really be convex, and the network activity could be (being higher in recessions) fundamental to the workings of the labor market.

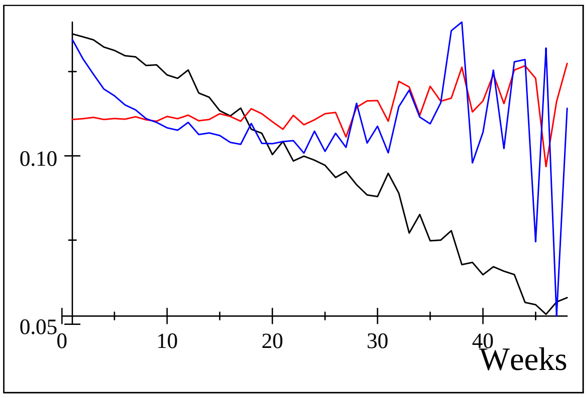
Table 13: Basic Properties of Unemployment Rate

	$m(u)$	$\sigma(u)$	$\rho_1(u)$	$\rho(u, udur)$
Baseline	0.063	0.129	0.997	0.26
Flat ϕ	0.069	0.115	0.997	0.08

5.0.2 Duration hazards

The last exercise in this paper plots the evolution of the job finding rate over 48 weeks for a representative worker from the moment he first loses his job.[32] We show three cases: the baseline where the job finding rate drops with time almost in a straight line, the No-network case which is horizontal and seems to increase slightly as time passes, and the convex ϕ case which is concave but falls right at the end although with a very high volatility here due to the numbers being smaller in this case.

Figure 2: Evolution of Job Finding Rate



In the baseline, the typical number of contacts of the unemployed worker is 62 at the start and drops to 4 after 52 weeks. Without the network contacts are 62 at the start and drop to 39 after 52 weeks, but they have of course no bearing on the picture. With a convex function contacts are 62 at the start and drop to 24 after 52 weeks.

5.0.3 Duration

This model delivers clear implications for the pattern of employment and unemployment durations. Specifically, it predicts that workers separating from jobs with longer durations, will have on average shorter unemployment durations. It

[32] We measure the evolution of the job finding rate for every group of workers that loses its job in a given period (we follow this group for 4 years until they almost all find a job), and average over the time series (over the many cohorts of freshly unemployed). The aggregate variation in productivity and in job destruction is this way averaged out.

also generates exponential decay in unemployment duration. These are patterns we can look for in the data.

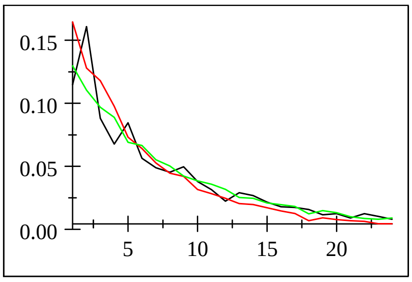
We now construct a duration matrix in the same manner as what we also obtain from the data.[33] From our artificial data we select a given period, and for that period we select first all employed workers. Then we follow these employed workers for the next 13 weeks and extract all those that start an unemployment spell in this period. Then we measure the length of their subsequent unemployment spell, as well as the length of their previous employment spell.

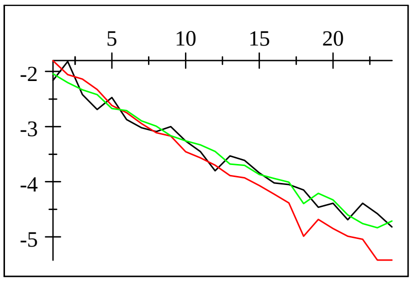
The element (i,j) of this matrix has the number of unemployed workers that find a job after (j) weeks of unemployment, following a previous employment spell of (i) weeks. Dividing by the total number of elements in the matrix this is a joint density value $f(i,j)$. There are several aspects of this density matrix which are of interest. The first obvious one is the correlation coefficient between durations. In our baseline model the artificial data yields

$$\rho_d^{week} = \frac{\sum\sum (x_i - \bar{x})(y_j - \bar{y}) f(x_i, y_j)}{\left[\sum (x_i - \bar{x})^2 g(x_i)\right]^{1/2} \left[\sum (y_j - \bar{y})^2 g(y_j)\right]^{1/2}} = -0.1918$$

and here, the empirical counterpart of this measure is positive at 0.121.[34]

But other less obvious characteristics have to do with where the matrix is populated, and how the shape of this density matches what we obtain from the data. A first indicator is the pattern of exponential decay in unemployment duration. We have data on a cohort of 18473 Danish workers that start their unemployment spell in first quarter of 2002. The unconditional density of unemployment duration - here shown only for the first 24 weeks and 4975 observations - is concave (left picture) and log-linear as we can see in the right hand side picture:





In red (thinner line) we have the corresponding values for the artificial data. But these pictures are misleading. In the data there are many observations of short-short durations: short employment spells followed by short unemployment spells which this model cannot replicate. This points to likely heterogeneity in both jobs and workers and needs to be looked into more.

[33] In the data we select all Danish workers that start an unemployment spell in the first quarter of 2002.

[34] In a simulation with $\bar{n} = 52$, this value is -0.147.

6 Conclusion

In this paper we construct a version of the Mortensen-Pissarides search model where the duration of unemployment is not independent of the duration of employment. Here, in the course of their working activity, employed workers invest in social contacts with other employed workers. These professional contacts will help them find jobs in the event of unemployment. These social contacts are a type of capital, similar to experience or skill. In the same spirit they also"depreciate" during unemployment spells. Here this happens because the contacts a worker has acquired can also become unemployed and unemployed contacts are assumed to be useless - an extreme version of less useful. In this model the longer you have been working, the more contacts you are likely to have, and the more contacts you have the shorter your expected unemployment duration will be.

We simulate a stochastic version of the model to generate duration moments as well as "network productivity" moments. This is a model where the network is important, but the network productivity is lower during periods of high unemployment. This makes sense: as workers lose their jobs and spend more time unemployed, their contacts vanish faster and matter less. This result is not inconsistent with the empirical finding that the fraction of people finding jobs through friends increases during times of high unemployment because in the model the average number of contacts of job finders is positively correlated with the unemployment rate.

Much identification work remains to be done. The model generates exponential decay in unemployment duration, and this is exactly what we see in the data. This is no more than very superficial evidence of network mechanisms and can be replicated with other theories. However, the exact shape - slope and intercept - of the duration density may provide further identifying variation. Also, the entire shape of the joint density of unemployment versus employment duration may provide identification.

Finally, the model can be extended to tackle other possible implications of network mechanisms in the labour market.[35] For example, we see in the data that workers displaced (due to firm closure) from smaller firms have a higher chance of becoming long term unemployed. This is over and above individual and sector characteristics. This suggests market structures where average firm size is bigger may be more efficient in terms of unemployment dynamics.

The current model has much in common with the "Rest Unemployment" ideas of Alvarez and Shimer (2009). It is easy to think of a version of the current model with two markets where unemployed agents “trapped in one market” wait around unemployed even if there is work available in the other market because their market-specific portfolio of contacts induces them to not pay the switching costs too early. These may be well connected people who have been

[35] An interesting extension of this model is to consider the vacancy supply model of Cooper, Haltiwanger and Willis (2007) to see how the richer dynamics of vacancies induced by this mechanism interact with the network structure.

"successful" in that they have had long previous employment spells.[36] Moving will only happen in such a model when two conditions occur simultaneously: the unemployment rate in my market is very high while in the other market it is very low, and, my portfolio of contacts has all but disappeared into unemployment. Importantly, given the similarity of predictions, it seems difficult to disentangle effects of connectivity from those of human capital specificity.

[36] In both models the decision to move may depend on the cross sectional distribution of contacts (here) or skills (there), so that the state space is big.

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