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Ejarque, Joao Miguel

Publication date:
2010

Document version
Publisher's PDF, also known as Version of record

Citation for published version (APA):
Ejarque, J. M. (2010). *A Search Model with a Quasi-Network*. Department of Economics, University of Copenhagen.

Discussion Papers
Department of Economics
University of Copenhagen

No. 10-23

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João Miguel Ejarque

Øster Farimagsgade 5, Building 26, DK-1353 Copenhagen K., Denmark
Tel.: +45 35 32 30 01 – Fax: +45 35 32 30 00
http://www.econ.ku.dk

ISSN: 1601-2461 (E)

A Search Model with a Quasi-Network

João Miguel Ejarque*,†

First Version, February 2009
This Version, September 2010

Abstract

This paper adds a quasi-network to a search model of the labor market. Fitting the model to an average unemployment rate and to other moments in the data implies the presence of the network is not noticeable in the basic properties of the unemployment and job finding rates. However, the network creates downward sloping reemployment hazards which the basic model does not, and under increasing network returns these hazards are significantly convex as we see in the data. Going into more detail we find that the network gets partially destroyed in periods of high unemployment and generates less job creation per link, while at the same time the jobs it does create, it does so with fewer links.

JEL Classification: D83, D85, E24, J21, J64.

Keywords: Duration, Networks, Search, Unemployment.

*I thank generous support from FCT grant PTDC/ECO/74894/2006. Contact: João Miguel Ejarque, Centre for Applied Microeconometrics, Department of Economics, University of Copenhagen, Øster Farimagsgade 5 DK-1353, Copenhagen K, Denmark. Joao.Ejarque@econ.ku.dk.

†I thank John Kennes, Melvyn Coles, and seminar participants at the University of Essex, the University of Copenhagen, the Bank of Portugal, CESifo Venice 2009, Nordic Econometric Meeting 2009, EALE 2009 and SED 2010.

1 Introduction

This paper adds a quasi-network to the Mortensen-Pissarides (1994) search model of the labor market. If personal and professional relationships are important for labor market outcomes it is useful to have an equilibrium framework to examine their contribution.

In this paper employed agents accumulate professional contacts during working activity. These contacts then help agents find jobs in the event of unemployment. The longer agents work, the more contacts they are likely to have, and the more contacts they have the higher their job finding probability is when unemployed, and the shorter their expected unemployment duration is. Only the *number* of contacts matters in the model and unemployed agents cannot add to their portfolios.[1] The number of contacts an agent has falls because one's contacts can themselves become unemployed, and unemployed contacts are assumed to be useless (for the purpose of finding a job). Assuming that unemployed workers are not useful contacts contrasts with some of the literature on networks in labour markets. However, if what matters is how many people you know there is a presumption that it is best if these people are working.

The approach of this paper is to emphasize the dynamics and the general equilibrium nature of the problem, and in this way complements other papers in the literature that either use a partial equilibrium model (Galeotti and Merlino (2008) have exogenous vacancies) or limit the analysis to steady state properties (Chuhai (2010)).

It is the nature of these models that if we keep all else constant and increase a measure of network density, the unemployment rate will fall, and along with it other statistics in the equilibrium will be different. In this paper we take a different approach. We impose that all variations of the model deliver the same average unemployment rate of 6%. Fitting the unemployment rate and other moments in the data implies the presence of the network is not noticeable in the basic properties of the unemployment and job finding rates. However, the network generates downward sloping reemployment hazards which the standard model does not. This occurs because not all newly unemployed agents enter unemployment with the same number of contacts, and also because the longer unemployment lasts the more the number of contacts of an unemployed agent is eroded, reducing his job finding probability. The exact shape of this hazard is linked to the existence of increasing or diminishing returns to the number of contacts for an individual agent. This characteristic is inserted in a matching function which, as standard in the literature, is adapted to account for the network. The model suggests the evidence of convex hazards points to increasing returns.

A key implication of the model is that the network depreciates during periods of high unemployment. This embodies the idea that high unemployment destroys productive links. On the other hand, the calibrated model also generates an increase in the importance of contacts when unemployment is high, for

[1] Weatherall (2008) finds that displaced workers that exit establishments with a small number of workers have a higher probability of becoming long term unemployed.

those that do find jobs. On average fewer jobs are created per network contact in the entire market, but more jobs are created per network contact of those that find jobs.

Networks have been a part of labor economics for a while. In Montgomery (1991) the network alleviates adverse selection, and Addison and Portugal (2002) show that personal contacts are a key way in which firms recruit.[2] One implication of a model where networks take time to build and also take time to dissipate is that duration patterns emerge, in particular relating employment and unemployment. The mechanism is similar to that of models of learning by doing and of loss of skill during unemployment.[3] The present paper suggests a different view of skills which carries a potential identification problem.

Finally, the mechanics of this model have much in common with (and lend support to) the "Rest Unemployment" ideas of Jovanovich (1987) and Alvarez and Shimer (2008). 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] Filges (2008) also finds that around 1/3 of hires occurr via personal contacts. See Calvó-Armengol and Jackson (2007), Galeotti and Merlino (2008), for a network-centered approach, and Chuhai (2010) for a paper related to this one.

[3] See Pissarides (1992) and Larsen (2001) for loss of skill. Addison and Portugal (1989) show that longer tenure prior to unemployment increases post-displacement wages.

2 Model

2.1 Workers

There is a unit mass of workers. Workers build professional relationships (contacts) while on the job. 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.[4] Workers lose contacts because their contacts can become unemployed and the exogenous job destruction probability, $1-\lambda$, is identical for every firm-worker match.

These assumptions induce a Pascal Triangle relationship. Given n employed contacts - and if there is no investment in an additional contact today - a worker has the following probability distribution over the set $[0, 1, 2, ..., n]$ contacts tomorrow:[5]

$$f(n-k) = \binom{n}{k} (\lambda)^{n-k} (1-\lambda)^k = \frac{n!}{k!(n-k)!} (\lambda)^{n-k} (1-\lambda)^k \tag{1}$$

with $f(n) = \lambda^n$, and $f(0) = (1-\lambda)^n$. In case an additional contact is made today, the same type of distribution applies but over the set $[0, ..., n+1]$. The Pascal Triangle delivers two matrices in this problem. The matrix M which governs contact transitions of unemployed agents, and the matrix $\hat{M}$ which governs the transitions of employed agents. For the support $[0, 1]$ corresponding to the upper bound $\bar{n} = 1$ these matrices are:

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

where element (i, j) is the probability of having $j-1$ contacts tomorrow given $i-1$ contacts today.

On the worker's side of the model we make several strong assuptions. First, in a general version of this model workers make a decision every period on whether to accumulate an additional contact. We eliminate this decision by assuming a cost function of managing contacts which is flat at zero up to an exogenous positive integer $\bar{n}$, and infinite above that. Imposing an upper bound for everyone eliminates network stars and makes it easier to focus on the number of contacts rather than on who these contacts are. Second, we assume that unemployed contacts are useless for the purpose of finding a job. If worker A has a link to worker B and worker B loses his job, worker B will disappear from A's portfolio, but not vice versa. Third, we assume that when the unemployed

[4] Thus it takes time to reach the upper bound on contacts. This is essential for the model to be able to generate the correct correlation between employment and unemployment durations.

[5] In Chuhai (2010) the entire network is resampled every period and has no time dependence. Workers at any given point in time have only the unconditional expectation of where they will be in the network for next period. Each link is formed with probability q, and for n workers the number of contacts (k) of workers is distributed with binomial probability $p(k) = \binom{n}{k} q^k (1-q)^{(n-k)}$.

worker gets a job he loses all contacts. He then starts reconstructing his network from zero contacts. This assumption is similar to the loss of specific human capital when a workers switches markets in Alvarez and Shimer (2009). By itself, this assumption is innocuous in this paper. But it links well with the previous assumption since if a worker in a new job loses all contacts, then there is no point in keeping an unemployed worker in a contact portfolio as "dormant" to exploit the fact that he may find a job again (and be useful again). Fourth, we abstract from wage determination and model the firm's net profit directly instead of deriving it via exogenous output and endogenous wages. We follow the spirit of Cooper, Haltiwanger, and Willis (2007) where wages depend only on the aggregate state of the economy.[6,7] Because we work with an exogenous $\bar{n}$, this wage setting assumption is consistent with modelling the stochastic process for net profits directly. Deviating from these four assumptions considerably complicates the analysis.

2.2 Firms

Firms post vacancies and there is no distinction between a filled vacancy and a firm. The probability a vacancy meets an unemployed worker is denoted by α^f.

Workers are identical from the perspective of the firm. In Montgomery (1991) firms rely on in-house workers for references. Here, because one firm equals one worker, this mechanism is summarized inside the matching function.[8] In a reduced form way the model contains the ideas of information flow from the network literature. But firms do not explicitly use the network to hire because they do not care who they hire. The network just provides a faster match between a vacancy and any worker available.

The value of posting a vacancy is

$$V = -k + \beta\alpha^f J + \beta(1-\alpha^f)V \tag{2}$$

where k is the flow cost of keeping a vacancy open and β is the (weekly) discount factor. Free entry will drive V to zero so that $k = \beta\alpha^f J$, where J is the value of a filled vacancy. A filled job produces an output y from which wages are paid. All matches have an exogenous break up rate of $1-\lambda$. The value of a filled vacancy is

$$J = y - w + \beta\lambda J + \beta(1-\lambda)V = \frac{y-w}{1-\beta\lambda} \tag{3}$$

so that $\alpha^f = (k/\beta)(1-\beta\lambda)/(y-w)$, which is a constant. The reason this is constant is that the expected duration of a job depends only on λ and all workers start a new job with zero contacts. In addition, vacancies adjust freely every period. In this model if k rises then, all else equal, equilibrium α^f will rise, and this happens by decreasing vacancies relative to the number of unemployed.

[6] Nash bargaining implies wages are affected by the outside option of unemployment which depends on the number of contacts a worker has.

[7] See also references in their paper.

[8] Exceptions to this modelling framework include Cooper, Haltiwanger, and Willis (2007), and Ortigueira and Faccini (2010).

2.3 Mechanics of employment and unemployment

We detail the transitions into and out of unemployment using the example where the maximum number of contacts is $\bar{n} = 1$.

The transitions into unemployment have two components. Those between unemployment and unemployment:

$$\bar{u}_t \begin{bmatrix} u_0^t & u_1^t \end{bmatrix} \times \begin{bmatrix} 1 - \alpha_0^w(S_t) & 0 \\ 0 & 1 - \alpha_1^w(S_t) \end{bmatrix} \times M \tag{4.1}$$

where $\bar{u}_t$ is the unemployment rate at the start of period t, and $\alpha_j^w(S_t)$ is the probability an unemployed worker with j contacts finds a job this period given the current state of the world (S_t). The vector $\begin{bmatrix} u_0^t & u_1^t \end{bmatrix}$ contains the beginning of period densities of unemployed workers over contacts and its elements are all non negative and sum to 1 so that here $u_1^t = 1 - u_0^t$. The transition from employment to unemployment is given by:

$$(1-\lambda)(1-\bar{u}_t) \begin{bmatrix} e_0^t & 1 - e_0^t \end{bmatrix} \times \hat{M} \tag{4.2}$$

where the vector $\begin{bmatrix} e_0^t & 1 - e_0^t \end{bmatrix}$ contains the beginning of period densities of employed workers over contacts. Summing these two objects yields a vector of $\bar{n} + 1$ elements (in this case 2) detailing the number of unemployed workers - which in this case is also the unemployment rate - and their distribution over contacts, $\begin{bmatrix} \bar{u}_{t+1} u_0^{t+1} & \bar{u}_{t+1}(1 - u_0^{t+1}) \end{bmatrix}$. Next period's unemployment rate, $\bar{u}_{t+1}$, is given by summing the elements of this vector.

The transitions into employment include first those from unemployment into employment:

$$\bar{u}_t \begin{bmatrix} u_0^t & 1 - u_0^t \end{bmatrix} \begin{bmatrix} \alpha_0^w(S_t) \\ \alpha_1^w(S_t) \end{bmatrix} \begin{bmatrix} 1 & 0 \end{bmatrix} \tag{5.1}$$

where the vector $\begin{bmatrix} 1 & 0 \end{bmatrix}$ allocates all job finders into the zero contact bin next period, and also those from employment to employment:

$$\lambda(1-\bar{u}_t) \begin{bmatrix} e_0^t & 1 - e_0^t \end{bmatrix} \hat{M} \tag{5.2}$$

and summing these two objects we obtain next period's employment levels and distribution of employed workers by contacts, $(1 - \bar{u}_{t+1}) \begin{bmatrix} e_0^{t+1} & 1 - e_0^{t+1} \end{bmatrix}$.

2.4 Equilibrium

These previous equations characterize the equilibrium given the current state of the world. They are, however, overidentified in terms of computing the long run equilibrium. Each transition determines two of the three steady state values we need to find, and which in the example are $S = (\bar{u}, u_0, e_0)$. For example, the dynamics into unemployment imply:

$$\begin{aligned} \bar{u} \begin{bmatrix} u_0 & 1 - u_0 \end{bmatrix} &= \bar{u} \begin{bmatrix} u_0 & 1 - u_0 \end{bmatrix} \times \begin{bmatrix} 1 - \alpha_0^w & 0 \\ 0 & 1 - \alpha_1^w \end{bmatrix} \times M \\ &\quad + (1-\bar{u})(1-\lambda) \begin{bmatrix} e_0 & 1 - e_0 \end{bmatrix} \times \hat{M} \end{aligned} \tag{6}$$

and to find the steady state we add the condition that jobs created equal jobs destroyed:

$$\bar{u} \begin{bmatrix} u_0 & 1-u_0 \end{bmatrix} \begin{bmatrix} \alpha_0^w \\ \alpha_1^w \end{bmatrix} \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} \tag{7}$$
$$= \quad (1-\bar{u})(1-\lambda) \begin{bmatrix} e_0 & 1-e_0 \end{bmatrix} \times \hat{M} \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

Equations 6 and 7 form a non linear system as α^w depends on vacancies, and vacancies depend on the distribution of unemployed workers over contacts in a nonlinear way. Numerically, however, there is no problem solving the model.

2.5 The matching function

We need to determine α^w and so we need to define the matching function. We want this 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.

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

$$m = \sum_{i=0}^{\bar{n}} \alpha_i^w u_i \bar{u} \tag{8}$$

and for some function g such that $\alpha_i^w = g(i, \bar{u}, v)$ 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 Cobb-Douglas will satisfy our requirements. Consider the function

$$\alpha_i^w = g(i, \bar{u}, v) = \gamma \left(\frac{v}{\bar{u}}\right)^\theta \phi(i) \tag{9}$$

with $0 < \theta < 1$, and $\partial\phi/\partial i > 0$. 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:

$$m = \gamma \left(\frac{v}{\bar{u}}\right)^\theta \bar{u} \sum_{i=0}^{\bar{n}} \phi(i) u_i = \gamma (v)^\theta (\bar{u})^{1-\theta} \sum_{i=0}^{\bar{n}} \phi(i) u_i \tag{10}$$

Note that the number of matches is affected by the network. In particular, the more destroyed the network is (the less average contacts unemployed workers have keeping all else constant) the lower the number of matches, so that the idea that networks reduces frictions is embodied in the model. What is not affected by the network is the ratio m/v, which is exogenous due to - among other things - the complete flexibility of vacancies. More importantly, we see that output and wages enter the model only here and do so only together. This is why using Nash Bargaining to determine wages can be replaced by a characterization of the stochastic properties of net profits.

The final steps of this construction come from the side of the firm. Given that α^f is a constant 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

$$\frac{m}{v} = \gamma \left(\frac{\bar{u}}{v}\right)^{1-\theta} \sum_{i=0}^{\bar{n}} \phi(i) u_i = \frac{k(1-\beta\lambda)}{\beta(y-w)} \tag{11}$$

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

$$v = \bar{u} \left(\gamma \frac{\beta(y-w)}{k(1-\beta\lambda)} \sum_{i=0}^{\bar{n}} \phi(i) u_i \right)^{\frac{1}{1-\theta}} \tag{12}$$

but of course vacancies adjust completely such that J, the value of a filled vacancy, does not depend on any distribution.

Now, given that vacancies depend on the distribution of contacts, job finding probabilities also do, $\alpha_i^w = g(i, \bar{u}, v(*))$, and so do average job finding probabilities,

$$\frac{m_t}{\bar{u}_t} = \left(\frac{y-w}{1-\beta\lambda}\right)^{\frac{\theta}{1-\theta}} \left(\gamma \sum_{i=0}^{\bar{n}} \phi(i) u_i\right)^{\frac{1}{1-\theta}} \left(\frac{\beta}{k}\right)^{\frac{\theta}{1-\theta}} \tag{13}$$

This construction allows us to now specify the function $\phi(i)$ independently of other considerations.[9] Its main property is that it should be increasing in the number of contacts. But its shape is also important. A convex function embodies an idea of increasing returns to network density. However, convexity may be problematic because ϕ is a reduced form for (part of) a probability function. With convexity we are forced to rely on the ad-hoc cost function of managing contacts in order to ensure boundedness in the problem. Nevertheless, one empirical fact suggests convexity: Lynch (1989) reports a value of 0.30 for the finding rate in the first week of unemployment, and then this number falls fast in the following weeks.[10] On the other hand, if we think of an environment where not everyone is equally valuable as a contact, diminishing returns may result.

With this in mind we use the following function: $\phi(i) = \phi_0 + \phi_1 (i)^{\phi_2}$. This function has one free parameter ϕ_2 which is used to get concavity or convexity. We set $\phi_2 = 2$ in the convex case and $\phi_2 = 0.5$ in the concave case. We then choose two numbers for $\phi(\bar{n})$ and $\phi(0)$ to pin down the other two parameters.

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

[10] This quick drop could reflect hidden job to job transitions which would show up as very short unemployment durations. However, the reemployment hazards in Addison and Portugal (2003) are also consistent with a convex ϕ function at short durations.

Our function $\phi(i)$ is a reduced form of introducing the mechanics of how job offers arrive, something which other papers in the literature develop in more detail (see Galeotti and Merlino (2008), Chuhai (2010) and references therein). For our purposes a reduced form is enough, but more importantly, our notion of network is that of an effective network. Being linked to an unemployed worker here is assumed to be useless, and unemployed workers cannot develop more links to employed people (which here are the links that matter). This is an extreme view, and sidesteps the idea that information about a vacancy flows through the network until it finds an adequate recipient, and so more links, employed or unemployed, have value.

3 Numerical Simulations

3.1 Parameters

We follow Shimer (2005), Mortensen and Nagypal (2007), Cooper, Haltiwanger and Willis (2007), and Zhang (2008), adapting where appropriate for a 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).

Shimer uses a quarterly separation rate of 10% which delivers an expected employment duration equal to 30 months or 130 weeks, and so we set $\lambda = 1 - 1/130$.[11,12]

We normalize net profits, $(y - w)$, to 1, and use the vacancy cost k to target the vacancy filling rate directly to Shimer's value, $\alpha^f = 0.14$. Given β and λ this implies $k \approx 16$. The tightness ratio is then implied by the rest.[13]

CHW estimate $\gamma = 1.0072$. Shimer (2005), sets $\gamma \geq 1$, and also normalizes the tightness ratio to be one. This implies the ratio of matches over vacancies or over unemployment is greater than one. In the present paper, this is not the case since the quantity

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

adds up to a small number, bringing down the number of matches formed. Rather than set a value we use γ to ensure we obtain an unemployment rate of 6%. We note that if our model is the truth the empirical exercise of CHW is not well specified and therefore we cannot say that having $\gamma \neq 1$ is incompatible with the data.

[11] Zhang finds that Canadian jobs have an expected duration of 146 weeks. Given a monthly separation rate of 0.03 the weekly λ is given by $(1 - \lambda) = 0.03/4.35 = 1/145$.

[12] This underestimates destruction. In the data a firm and a worker may separate 2 weeks into the quarter and 4 weeks later both the firm and the worker may have found new matches.

[13] CHW report that the average value of labor market tightness, the ratio v/u, is around 0.46. Shimer calibrates it to equal 1 (which implies in equilibrium $\alpha^w = \alpha^f$).

CHW report a monthly job finding rate equal to 0.61, while Shimer reports a value of 0.45. Disregarding contacts this implies in a weekly frequency:

$$\alpha^w + (1-\alpha^w)\,\alpha^w + (1-\alpha^w)^2\,\alpha^w + (1-\alpha^w)^3\,\alpha^w = 0.45 \tag{14}$$

which in turn yields $\alpha^w = 0.14$.[14] In this section we use an example with $\bar{n} = 9$. Throughout $\alpha^f = 0.14$, $\lambda = 1 - 1/130$, $\beta = (0.95)^{1/52}$, $\theta = 0.46$, and $y - w = 1$. Table 1 shows some other parameters and resulting averages for u, v/u and α^w:

Table 1: Deterministic Model Parameters

ϕ Function	γ	$\phi(0)$	$\phi(\bar{n})$	ϕ_2	u	v/u	α^w
Convex	0.5925	0.04	0.28	2.0	0.06	0.86	0.12
Concave	0.5925	0.01	0.22	0.5	0.06	0.86	0.12

Figure 1 shows both the $\phi(i)$ function (upper lines) and the resulting equilibrium $\alpha^w(i)$ function (lower lines) for the case where $\bar{n} = 9$. They are closely related, which suggests the empirical job finding hazard - which derives from α^w - may help identify the ϕ function.

Figure 1: ϕ and α^w functions

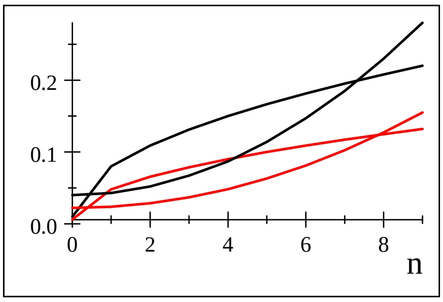


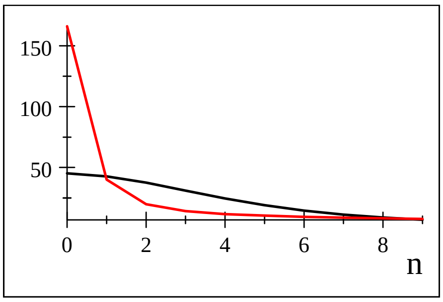
Figure 2 shows the expected duration of unemployment (in weeks) generated by our parameter values. The concave model with our low value of $\phi(0) = 0.01$ generates a very large expected duration (166 weeks) for those unfortunate enough to lose all their friends. The convex model is not as agressive since $\phi(0) = 0.04$ generates "only" an expected duration of 45 weeks.

3.2 Simulation Results

In this section we look at some key correlations. Our simulations average ten panels of 4350 individuals which, at a 6% steady state unemployment rate, yields on average 261 unemployed workers. We pick these unemployed workers in the

[14] Zhang reports a monthly value of 0.309 for Canadian data, implying $\alpha^w = 0.08825$.

Figure 2: Expected Duration of Unemployment



last artificial cross section generated.[15] For each unemployed individual we measure the length *to date* of their current unemployment spell, (u), the length of the employment spell that preceded it, (e), and the number of contacts they have today. From the number of contacts they have we can compute *analytically* their expected duration of unemployment from this period onwards, $(E(u))$. We can do this because we pick the cohort at a time series point where contact distributions have converged to their ergodic state. Average correlations among these three objects are shown in the first three columns of Table 2.

Table 2: Correlations

	1	2	3	4
ϕ Function	ρ(u,e)	ρ(u,E(u))	ρ(e,E(u))	ρ(u,e) RD
Convex	-0.18	0.64	-0.37	-0.124
Concave	-0.14	0.72	-0.21	-0.055

The correlation between employment and unemployment durations for the unemployed in the last cross section is negative. The correlation between current unemployment (employment) duration and expected onward duration is positive (negative). In addition to these three numbers, column four shows the correlation between complete realized unemployment durations and complete realized employment durations. This measure follows a large number of workers from the moment they first become unemployed until they find a new job, and has less composition bias. All the correlations in Table 2 are zero in the absence of the network.

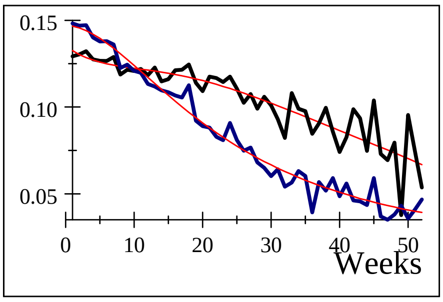
3.2.1 Hazards

With our artificial data we can also compute reemployment hazards. We pick workers as they become unemployed and for each worker we measure his du-

[15] The model is first run until the unemployment rate and the contact distributions converge. After that all individuals begin life with maximum contacts $\bar{n}$. After a few hundred periods the simulation stops and we pick the cross section of the panel at this point.

ration of the unemployment spell, without using any information on individual contact portfolios. This hazard is computed up to 104 weeks, and uses about 42 thousand unemployment spells. Figure 3 shows only the first 52 weeks of this hazard. The smooth line is a projection of the realized hazard onto a 7th order polinomial in time.

Figure 3: Reemployment Hazards



The strongest distinguishing feature between the two cases is the slope, where the concave ϕ case is the more flat of the two. A downward sloping hazard arises naturally here both because of composition effects (the 42 thousand workers have different numbers of contacts when they enter unemployment) and because of the decay in contact portfolios as workers remain unemployed for long periods. If the ϕ function was a constant the network would disappear and the hazard would be horizontal. We also do not have endogenous incentive effects which can make the hazard eventually upward sloping (as when previously accumulated savings run out and workers lower their demand levels for a job).

Apart from the difference in slopes, given these parameter values neither function is able to induce the steep drop in the hazard at the start of the unemployment spell noted by Lynch (1989). At this point we cannot say much about the properties of the network without adding aggregate shocks. We do this in the next section and will return to the hazards then.

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. A realization of the aggregate state yields a value for the pair (λ, y). The transition between x_1 and x_2 is governed by the Markov matrix:

$$\Pi = \begin{bmatrix} q & 1-q \\ 1-p & p \end{bmatrix} \tag{15}$$

4.1 Firms

The value of posting a vacancy is indexed by the aggregate state:

$$V(x_i) = -k + \beta\alpha^f(x_i) E_i(J) + \beta(1-\alpha^f(x_i))E_i(V) \tag{16}$$

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

$$J(x_i) = y_i - w_i + \beta\lambda_i E_i(J) + \beta(1-\lambda_i)E_i(V) \tag{17}$$

and in matrix form

$$J = \begin{bmatrix} J(x_1) \\ J(x_2) \end{bmatrix} = \begin{bmatrix} y_1 - w_1 \\ y_2 - w_2 \end{bmatrix} + \beta \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \Pi \begin{bmatrix} J(x_1) \\ J(x_2) \end{bmatrix} \tag{18.1}$$

$$J = [I - \beta\Lambda\Pi]^{-1} \begin{bmatrix} y_1 - w_1 \\ y_2 - w_2 \end{bmatrix} \tag{18.2}$$

which implies α^f is a vector of constants implied by:

$$1/\alpha^f = \begin{bmatrix} 1/\alpha^f(x_1) \\ 1/\alpha^f(x_2) \end{bmatrix} = \frac{\beta}{k}\Pi J \tag{19}$$

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 the general problem it is possible for the maximum number of contacts to vary with the aggregate state. The transition matrix M for unemployed workers is the same as before but uses the maximum $\bar{n}(x_i)$. The transition matrix $\hat{M}$ has dimension given by the maximum $\bar{n}(x_i)$, but its composition changes with the aggregate state. However, since we kill this choice, we keep $\bar{n}$ constant across the aggregate states rather than go for an ad-hoc guess of what this choice would imply.[16] Finally, the appendix extends the mechanics of employment and unemployment and the matching function to this environment.

[16] It is unclear how $\bar{n}$ should vary with y, let alone with a multidimensional state.

5 Numerical Simulations

5.1 Parameters and Stochastic Processes

We must extend our calibration. Table 3 summarizes means (μ), standard deviations (σ), and serial correlations (ρ), of the unemployment rate, vacancies, market tightness ratio, job finding rate, separation rate ($\delta \equiv 1 - \lambda$), and of productivity, for the US economy, taken from Zhang (2008).[17] CHW estimate the

Table 3: USA Quarterly and Monthly Data Moments

	u	v	v/u	α^w	δ	y
σ	**0.190**	**0.202**	**0.382**	**0.118**	**0.075**	0.020
ρ_1	0.936	0.940	0.941	0.908	0.733	0.878
μ	0.057			**0.452**		

first order serial correlation of market tightness to be 0.93 using monthly data, which is nearly the same as we see here. All these moments have substantial first order serial correlation, which implies we need highly serially correlated shocks at the weekly frequency. The quarterly data has also the following correlations: $\rho(v,u) = -0.894$, $\rho(v/u, \alpha^w) = 0.948$, and $\rho(\delta, y) = -0.524$.

We note that it is not possible to have $\rho(\delta, y) < 0$ if λ is an exogenous constant. Therefore we have job destruction shocks. We also want a job finding rate that is more volatile than the job destruction rate ($0.118/0.075 = 1.57$).[18] To generate these properties what matters in the model is the net surplus $y - w$, and not output or productivity itself. Procyclical but rigid wages imply $y - w$ moves proportionally more than y alone (they amplify the shocks to y). Our wage setting assumption is consistent with these properties of $y - w$.

At the weekly frequency we form the two shocks as different linear combinations of two identical and independent Markov processes x_1 and x_2:

$$y - w = \xi(x_1 + x_2) \tag{20.1}$$

$$\delta = x_1 - \psi x_2 \tag{20.2}$$

where the support of δ is constructed around the value 1/130 and the support of $y - w$ is detailed below. The parameter ψ is set at 3 inducing a weekly negative correlation between the two variables of around -0.40, and ξ is chosen to generate enough relative volatility.

The two variables x_1 and x_2 are generated from a discretization of a normal AR1 process x on a 13-point support using Tauchen (1986). The serial correla-

[17] The σ and ρ_1 are computed with quarterly data, while the mean uses monthly data. The data are measured as $log(x_t) - log(\bar{x})$, where $\bar{x}$ is the Hodrick-Prescot trend.

[18] 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. See also Shimer (2007). However, Yashiv (2007) Fujita and Ramey (2009), and Petrongolo and Pissarides (2008) find that the job destruction rate is also quite volatile.

tion parameter is 0.983.[19] Indepently of the standard deviation value this yields the Markov transition matrix for x. The overall matrix is a Kronecker product of two identical matrices, and it is the same for both $y-w$ and δ. However, the support vectors of δ and $y-w$ are different and thus are generated differently. To ensure a positive value of $y-w$ we generate the support vector z of an AR1 Normal random variable using Tauchen as above for a given standard deviation, and then compute the vector $z = z + 1 + abs(\min(z))$. The support of $y-w$ is then the Kronecker of this z by itself.

The support of δ is not generated the same way. It cannot be normal or log normal because of the unit interval bound. It is a linear spaced vector centered around 1/130, and then the overall support for δ is the appropriate Kronecker product of this vector.

One aside on the impact of shocks is important here. We need high persistence in order to get a large negative correlation between vacancies and unemployment. Equation 12 suggests a positive relationship between vacancies and unemployment. However, vacancies adjust to productivity shocks which enter with a power of $1/(1-\theta) \approx 2$, while the unemployment rate enters with a power of 1. If productivity shocks are persistent, high productivity will increase vacancies and lower unemployment, overriding the positive direct effect that the unemployment rate has on vacancy creation. If productivity shocks are iid, the correlation between vacancies and unemployment is positive.[20]

Finally, the stochastic environment keeps the parameter values used before, only this time we set $\bar{n} = 104$, for two years of network formation horizon. The value $\alpha^f = 0.14$ still defines k using the median of the shocks, but then, once the constant k is set, we generate a vector for α^f as in section 4.1. The job destruction mean and median is 1/130, β and θ are the same. The parameter γ again adjusts with the environment to get a 6% unemployment rate.

5.2 Time Aggregation

5.2.1 Job finding rate

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. Unless we are at the exact weekly frequency we need to match an interval measure with a point measure. The job finding rate at lower frequencies - $\hat{\alpha}^m$ for monthly - is defined as a moving average and thus has weekly realizations. For a monthly measure we can use either a four week interval before or after the time point with equal legitimacy, but they yield different results.

A different issue is the population used. A consistent way to measure the job finding rate over an interval is to pick the workers who become unemployed

[19] 0.99^13 = 0.878, the quarterly serial correlation of productivity, and 0.9765^13=0.734, the value for the destruction rate. As our two shocks are not independent we set the weekly serial correlation at 0.983 to get the intermediate value of 0.800.

[20] Endogenous wage determination effectively plays the role of picking the right relationship between (λ, y) by changing how the ratio $k(1-\beta\lambda)/(y-w)$ moves. On this see Hall (2005), Hagedorn and Manovski (2007), Mortensen and Nagypal (2007).

at a given point in time and follow only them, as they are reabsorbed into employment.[21] These workers will all share an identical aggregate state history, and the population will be well defined from the start. A monthly finding rate is then computed each week for a 4-week-*ahead* interval as:

$$\begin{aligned}\hat{\alpha}_t^m &= \alpha_t^w + \alpha_{t+1}^w\left(1-\alpha_t^w\right) + \alpha_{t+2}^w\left(1-\alpha_{t+1}^w\right)\left(1-\alpha_t^w\right) \\ &\quad + \alpha_{t+3}^w\left(1-\alpha_{t+2}^w\right)\left(1-\alpha_{t+1}^w\right)\left(1-\alpha_t^w\right)\end{aligned} \tag{21}$$

and we use this forward looking measure because we want a greater "causality" going from unemployment at t to the job finding rate $\hat{\alpha}_t^m$. For α_{t+j}^w we use the empirical measure:

$$\alpha_{t+j}^w = \frac{\text{number of job finders in week t+j}}{\text{number of unemployed at the start of week t+j}}$$

and where the number of job finders in week t+j is measured as the number of workers that are unemployed at the start of week t+j, but are employed at the start of week t+j+1, and the number of unemployed at the start of week t+j is the remaining subset of the set of job losers from week t.

The monthly rate is then relative to the number of workers who lose their job in week t (so that at t+3 the population of unemployed is the remainder after some of the initial workers find jobs in the previous 3 weeks).

Note also that our empirical measure obeys the limit condition

$$\lim_{\#\text{workers}\to\infty} \alpha_t^w = \sum_{j=0}^{n} \alpha_t^w(j)\, u_j \tag{22}$$

as the number of workers gets large.

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 mean and standard deviation are also taken on the sampled time series.

5.2.2 Job separation rate

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 an exact measure. For the monthly frequency we have the forward looking measure:

$$\begin{aligned}\hat{\delta}_t^m &= \delta_t + \delta_{t+1}(1-\delta_t) + \delta_{t+2}\left(1-\delta_{t+1}\right)\left(1-\delta_t\right) \\ &\quad + \delta_{t+3}\left(1-\delta_{t+2}\right)\left(1-\delta_{t+1}\right)\left(1-\delta_t\right)\end{aligned} \tag{23}$$

where δ_t is simply the realized destruction rate in week t. In the model this is just $\delta_t = 1 - \lambda_t$, but again an empirical measure uses

$$\delta_{t+j} = \frac{\text{number of job losses in week t+j}}{\text{number of employed workers at the start of week t+j}}$$

[21] If we pick all unemployed workers at a given point in time, rather than just those that lose their jobs that period, this biases the job finding rate since long durations and lower individual job finding rates are over represented in the stock of unemployed.

and where the number of job losses in week t+j is measured as the number of workers that are employed at the start of week t+j but unemployed at the start of week t+j+1.

Finally, this measure does not suffer from composition biases, so we can use the current number of employed workers at every point, and do not need to keep track of the time t cohort of employed workers.

5.3 Simulated Moments

We first run the model until convergence with a constant realization of the aggregate state (at its median value). After convergence we use the stochastic path of aggregate shocks (to productivity and job destruction) for the following 728 periods, but we eliminate the first 208 periods (4 years) and use the last 520. The same realization of random variables is used in every experiment.[22]

Table A1 in the appendix shows moments for the weekly frequency, for both the concave and convex specifications for the function ϕ. For each specification four scenarios are used, a baseline case with both shocks, a variation with a constant ϕ function (no network), a variation with only productivity shocks (lambda constant), and a variation with iid shocks. The top section of Table A1 shows moments for aggregate variables. These are constructed exactly according to the model. The bottom section of Table A1 shows results for a panel with 6900 workers which results in an average of 414 unemployed, and 51 workers losing their job (and finding one) each week. The top section can be viewed as the exact limit of a large panel.

Table A1 shows us that iid shocks result in a strongly positive correlation betweeen unemployment and vacancies, and that a constant λ naturally results in a zero correlation between productivity and the job destruction rate, both of which rule out specifications close to these.

Comparing the top section with the bottom section of Table A1, the moments of the unemployment rate are quite close (indicating the panel is not too small) but there is some difference in standard deviations and serial correlations in the job finding and job destruction rates. The reason the panel unemployment rate is very accurate is that it is measured on average from the ratio 414/6900, and both numbers are large enough to ensure statistical accuracy. The job finding rate is measured on average from the ratio 51/414, which is reasonable but nevertheless an order of magnitude smaller than the numbers used for the unemployment rate. From the third and seventh columns (constant lambda), bottom section, we see that the small panel induces a significant variability in the job destruction rate which should be zero.

One other interesting fact coming out of this table is that there is little difference among columns 1, 2, 5, and 6: both baselines and both constant ϕ cases. Once we fix the unemployment rate concavity is similar to convexity, and the absence of the network has no significant impact on the aggregate properties

[22] The initial realization of the aggregate shock is the median, and the cross sections of contacts are initialized at the ergodic distributions generated by the median shock.

of the model. Finally, the last two rows of Table A1 show that unemployment duration is negatively correlated with previous employment duration, and that unemployment duration rises in periods of high unemployment.

5.3.1 Lower Frequencies

Table A2 contains moments for monthly and quarterly frequencies and gives us a few facts by comparison with the weekly frequency and with the data. First, all means are accurate. Second, as we lower the frequency (from weekly, to monthly, to quarterly) the standard deviation of the job finding and job destruction rates falls, and in particular the panel job finding rate is very flat with a standard deviation of 0.050 instead of the data value of 0.118. Third, the three correlations we care about, $\rho(v, u)$, $\rho(v/u, \alpha^w)$, and $\rho(\delta, y)$, are not significantly affected by the frequency, and have acceptable values for the quarterly frequency if we compare to the data. Finally, the model is a little less volatile than the data with the current parameterization as the standard deviation of the unemployment rate is 0.152 which in the data is 0.190.

5.3.2 Duration

The correlation between the unemployment rate and the realized duration of unemployment is positive. This correlation is measured by taking each period only the cohort of workers that lose their job. Losing a job in period j is defined by having a job in period j but not having it in period j+1. We compute the cohort's average realized duration of that single unemployment spell. Then we compute the unemployment rate verified at the time they start unemployment (j+1).[23] This is done for 428 weeks and we correlate the time series of average cohort duration with the time series of the unemployment rate. Table 4 shows this correlation along with the time series average of average cohort durations (8 weeks), the time series standard deviation of average durations (1.8 weeks), average cohort size (51 workers), and the time series standard deviation of average cohort size (8 workers).[24]

The correlation is positive for all cases except for iid shocks where it is approximately zero. Having a stochastic λ has a significant impact on this correlation. Also, unemployment duration increases when unemployment rises even in the absence of the network (columns 2 and 6). Shutting down the network has negligible effects except for the standard deviation of unemployment duration which falls significantly. This antecipates a point we will make below, namely that one of the interesting issues of the cyclical behaviour of the network is what happens to the distribution of durations when unemployment rates increase. There will be winners and losers.

[23] The serial correlation of shocks at the weekly level is so high that this is almost identical to what we get using the unemployment rate at j.

[24] Smaller average cohort sizes bias the correlation downwards, but from an average cohort size of 40 up to 50 the value of this correlation does not change much.

Table 4: Duration in the Stochastic Model

	Concave ϕ				Convex ϕ			
	1	2	3	4	5	6	7	8
	BL	CF	CL	IID	BL	CF	CL	IID
$\rho\,(udur, urate)$	0.51	0.49	0.37	0.03	0.55	0.49	0.38	0.05
U-rate	6.02	6.02	6.00	6.01	6.02	6.00	5.99	6.00
Duration in Weeks								
Mean	8.01	8.11	8.10	8.10	8.28	8.06	8.29	8.32
St. Dev.	1.70	1.32	1.60	1.40	1.95	1.31	1.87	1.65
Cohort Size								
Mean	51.1	51.1	50.2	50.2	51.1	51.1	50.3	50.3
St. Dev.	7.97	7.94	7.44	8.26	7.94	7.94	7.43	8.25
γ	1.020	0.665	1.010	0.994	1.444	0.674	1.429	1.405

Given the average unemployment duration of 8 weeks, the expected loss of contacts over this period is of 6%. Someone entering unemployment with 100 contacts on his portfolio will expect to have 94 contacts after 8 weeks, $100 \times E(\lambda)^8 = 94$. The issue then is how this average loss of contacts affects the hiring probability, and here is where concavity or convexity of the ϕ function matters. With the current parameterization these functions are perhaps not concave or convex enough for this to matter much over a short horizon such as 8 weeks.

To check the impact of extra curvature we ran the model with $\phi_2 = 0.25$, and $\phi_2 = 4$, for the concave and convex cases. The results are contained in Table A4. The differences are small. But some patterns emerge in the cyclical behaviour of the network and we discuss them below.

5.4 Network productivity

5.4.1 Measures

In this paper, by construction close to 100% of jobs are found with use of contacts (inside the ϕ function) - the only exception being the finding rate for workers with zero contacts. This is not the case in the data. 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.[25] Given our model we cannot reproduce the statistic they use so we must look at other measures to understand the contribution of our network.

Here, although exogenous, the network changes cyclically. In particular two things happen in periods of high unemployment.

[25] The authors believe this positive correlation is only possible with an endogenous increase in the activity of networking during periods of unemployment. They also state that "between 30% and 50% of jobs are filled through social exchange of information.", which is consistent with Filges (2008) and with Addison and Portugal (2002).

On one hand, lower output occurs at the same time as higher job destruction rates.[26] In the baseline cases more workers lose their jobs (the number of job losses is positively correlated with the unemployment) just when vacancies drop (vacancies are negatively correlated with unemployment).

But more inflow into unemployment acts to raise the average number of contacts of the unemployment pool. This is a composition effect. On the other hand, lower vacancies and more unemployed workers reduce the job finding rate, and a duration effect is triggered. Longer durations imply more of the portfolio of each unemployed worker vanishes before finding a job. So, the fall in vacancies and the increase in unemployment duration induces a "depreciation" of the network. The task now is to see the contribution of these different effects.

Table A3 contains the correlation with the unemployment rate for a number of variables in the model. We first focus our attention on the behaviour of three objects: the average contacts of all unemployed (row C), the average number of contacts of the cohort of job finders (the subset of the unemployed that finds a job in the period) (row R2), and the average number of contacts of the cohort of non finders (the subset of the unemployed that does not find a job in the period) (row T). All numbers are negative except if shocks are iid. But the difference between job finders and non finders falls:

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

This gap (row N) falls when unemployment rises. Workers become more alike (this does not mean that having more contacts is no longer an advantage). This fall in the gap is also more pronounced if ϕ is convex (-0.455 in column 5 versus -0.204 in column 1) since the recently unemployed (which are now more) experience a faster drop in the job finding rate from their loss of contacts than they do with a concave function.

We can try to view this mechanism as "network productivity". Consider the following two ratios:

$$\begin{aligned} NP_2 &= \frac{\text{Number of Job Finders}}{\text{Total Contacts of Job Finders}} \\ NP_3 &= \frac{\text{Number of Job Finders}}{\text{Total Contacts of the Unemployed}} \end{aligned}$$

The first is the inverse of average contacts of job finders. This is positively correlated with the unemployment rate (row R1). One may say that Job Finders "get more" out of their contacts in bad times. The second ratio (row S1) may be viewed as a measure of the average productivity of the network. This is negatively correlated with the unemployment rate. We have then two apparently conflicting ideas: during periods of high unemployment the network is less productive on average, but more important if you want to find a job.

[26] Note that lower job survival rates (λ), magnify the effect of lower productivity inside the matching function. Both effects make the ratio $(y-w)/(1-\beta\lambda)$ move in the same direction.

All of this happens with an exogenous network. We conjecture that with an endogenous network where agents create more links during unemployment, our measures of network productivity should be lower since such a model would have to fit the same facts with a higher number of contacts during high unemployment periods. However, whether the network is more or less productive during periods of high unemployment is perhaps not the most interesting feature to focus on. More interestingly, an endogenous network might reduce the cyclical volatility of job finding rates by creating more contacts during periods of recession (and therefore increasing the job finding rate and reducing the unemployment rate) and fewer contacts during periods of low unemployment.[27] Here concavity or convexity matter again since with a convex ϕ an unemployed worker with few contacts will have little incentive to spend effort networking, while if ϕ is concave it is the well connected worker that has no incentive to spend effort developing his network. Again, this shape has implications for heterogeneity and conditional duration of unemployment.[28]

We can see a little of this despite the exogenous nature of our network. From equation 9, the marginal value of a contact in terms of the job finding rate for an individual agent is given by $\gamma\left(v/\bar{u}\right)^{\theta}\left[\phi\left(i\right)-\phi\left(i-1\right)\right]$ and does not depend on the distribution of contacts other than via the $v/\bar{u}$ ratio. In turn, the $v/\bar{u}$ ratio is low when unemployment is high because the correlation between vacancies and unemployment is negative. Since $\theta>0$, the marginal increase in the job finding rate from an additional contact is lower in periods of high unemployment. Note that the job finding rate is lower in periods of high unemployment even though, with a higher job destruction rate, more (and well connected) agents now enter the unemployment pool. But fundamentally, for any difference in contacts $i_1 - i_0 > 0$, the difference $\phi\left(i_1\right)-\phi\left(i_0\right)>0$ is independent of the business cycle. However, the difference *in job finding rates*, $\gamma\left(v/\bar{u}\right)^{\theta}\left[\phi\left(i_1\right)-\phi\left(i_0\right)\right]$, is smaller during periods of high unemployment.

How do we reconcile this with our finding above? Everyone has fewer contacts so the comparison is not between i_1 and i_0 at time t, $\gamma\left(v/\bar{u}\right)^{\theta}\left[\phi\left(i_{1,t}\right)-\phi\left(i_{0,t}\right)\right]$, but between them at time t, $\gamma\left(v/\bar{u}\right)^{\theta}\left[\phi\left(i_{1,t}\right)-\phi\left(i_{0,t}\right)\right]$, and also at time t+j with $\gamma\left(v/\bar{u}\right)^{\theta}\left[\phi\left(i_{1,t+j}\right)-\phi\left(i_{0,t+j}\right)\right]$. Since everyone is losing contacts this difference is affected by a different $v/\bar{u}$ ratio, and by being in a different region of the function ϕ. Our experiments show that during periods of high unemployment the standard deviation of the distribution of contacts of unemployed workers is lower when ϕ is concave and higher when it is convex.

5.4.2 Other properties

The correlation of the unemployment rate with the fraction of job finders with less than $\tau\bar{n}$ contacts, where $0<\tau<1$, (we use $\tau=0.75$, and $\tau=0.5$) hammers home the fact that everyone sees its portfolio depreciate during periods of high

[27] This suggests an identification issue arising from the volatility of shocks, the wage determination process, and the network component.

[28] In this respect a complete network is as neutral as a non existent network since in both cases all agents are identical.

unemployment. This correlation is positive (rows J and K) so that this tail grows fat, but it barely moves if shocks are iid and, at the lower end (row K) it requires job destruction shocks to do so.

The comparison of rows A and D and columns 1 and 3 reveals one interesting part of the mechanism. The number of job finders rises during periods of high unemployment because the number of job losers also rises. Column 3 shows that if the job destruction rate is a constant then the *number* of job *finders* is essentially uncorrelated with the unemployment rate. On the other hand, Row D shows that the fraction of job finders (job finding rate) falls in periods of high unemployment and that shutting down the network or having a constant λ do not significantly affect this correlation. The behaviour of the aggregate job finding rate is driven by ouput shocks and the vacancy behaviour they induce. Unemployment rates are driven by productivity. The network has mainly cyclical distributional effects (some find jobs while others do not).

5.4.3 More curvature

We ran the model with $\phi_2 = 0.25$, and $\phi_2 = 4$, for the concave and convex cases. Changing the curvature implies adjusting the parameter γ to keep unemployment at 6%. Table 4 shows that in the concave case the average contact gap between job finders and non finders falls less in the concave case and more in the convex case (row N). High levels of convexity imply very connected people lose their contacts faster and become quickly like everyone else. High levels of concavity do the opposite. Also, the tail of contacts of job finders increases less in the concave case and more in the convex case (rows J and K).

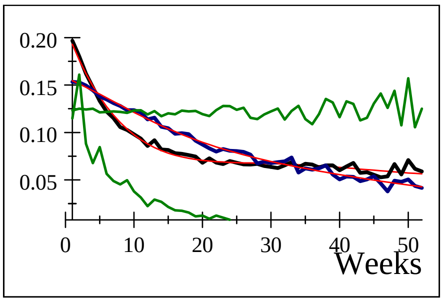
5.4.4 Hazards

Figure 4 shows the convexity of the hazard generated by the convex baseline case. By comparison the concave case generates a much less convex downward sloping hazard. If we shut down the network function and replace it with a constant ϕ we have the horizontal hazard shown which has a mean value of 0.1231. These three hazards are computed using approximately 115 thousand individual duration spells (all the spells in the 5 panels), and do not control for the cycle in the artificial data.

The fourth (and lowest) line in figure 4 is an empirical hazard and is also convex towards the origin. This line uses data on a cohort of 18473 Danish workers that start their unemployment spell in the first quarter of 2002. The unconditional density of unemployment duration is shown here only for the first 24 weeks and 4975 observations.[29]

[29] This is mereley an illustration of convexity. In the data there are many observations of short-short durations: short employment spells followed by short unemployment spells which this model does not replicate. At this stage we do not have access to information on individual characteristics in this data so we cannot control for heterogeneity or get a bigger panel.

Figure 4: Reemployment Hazards



6 Conclusion

In this paper we add a quasi network to the Mortensen-Pissarides search model. 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. The duration of unemployment is not independent of the duration of employment.

In the model average network productivity is lower during periods of high unemployment. As workers lose their jobs and spend more time unemployed, their useful contacts are also eroded by unemployment. However, the aggregate job finding rate falls driven by the fall in vacancies which itself is driven by the profitability shock. Importantly, it falls faster than the portfolios of contacts depreciate, which means fewer jobs are created per contact. One could interpret this as a fall in network productivity during periods of high unemployment. On the other hand, those workers finding jobs also see an average deterioration of their contact portfolios. But for them the portfolio falls faster than their numbers. The reason the number of job finders does not fall as fast as their contacts is that there are more unemployed workers looking for jobs which acts to increase the number of job finders. So, the number of job finders per contact of job finder actually rises during periods of high unemployment. One could interpret this as an increase in the productivity of the network.

Our approach is to impose that all variations of the model deliver the same average unemployment rate of 6%. Fitting the unemployment rate and other moments in the data implies the presence of the network is not noticeable either in the basic properties of the unemployment and job finding rates, or in a host of other moments.

A visible exception to his is of course the downward sloping reemployment hazard we obtain when we have a network, and which we do not in its absence. Other theories such as learning and loss of skill can also generate downward sloping hazards. Nevertheless, the convexity of the hazard towards the origin contains information about the characteristics of the network in our context.

The model suggests implications of network mechanisms in the labour market. 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, 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.

Finally, the current model has much in common with the "Rest Unemployment" ideas of Jovanovic (1987), and Alvarez and Shimer (2008). 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 "successful" in that they have had long previous employment spells.[30] 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.

[30] 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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7 A1. Unemployment duration algebra

7.1 Duration in the Deterministic Model

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

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

This algebra, however, depends on the state vector:

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

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:

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

where the matrix T is given by $T = Diag(1-\alpha^w)M$, and in steady state equilibrium we can write the expected duration algebra in matrix form as:

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

where α^w is a column vector.

7.2 Duration in the stochastic model

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. The analytic computation of expected unemployment duration is intractable because as aggregate shocks hit, the distribution of workers over contacts changes. The $\alpha_n^w(x)$ functions are changing over time because x changing. Therefore here 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. Rather than measuring expected duration of unemployment we measure observed subsequent duration from any point we start following a worker.

8 A2: Stochastic Process

We have two independent random variables, (x_1, x_2) so that

$$\begin{aligned} y - w &= \xi\left(x_1 + x_2\right) \\ \delta &= x_1 - \psi x_2 \end{aligned}$$

Then the weekly variances are

$$\frac{\sigma_{y-w}^2}{\sigma_\delta^2} = \frac{\xi^2(\sigma_1^2 + \sigma_2^2)}{\sigma_1^2 + \psi^2 \sigma_2^2}$$

and the weekly correlation coefficient is given by

$$\rho(y - w, \delta) = \frac{\xi\left(\sigma_1^2 - \psi \sigma_2^2\right)}{\sqrt{\xi^2\left(\sigma_1^2 + \sigma_2^2\right)}\sqrt{\sigma_1^2 + \psi^2 \sigma_2^2}}$$

and assuming they both have the same variance, $\sigma_1^2 = \sigma_2^2 = \sigma^2$, and setting $\psi = 3$, this reduces to

$$\begin{aligned} \rho(y - w, \delta) &= \frac{(1 - \psi)}{\sqrt{2}\sqrt{1 + \psi^2}} = \frac{-1}{\sqrt{5}} = -0.4472 \\ \frac{\sigma_{y-w}^2}{\sigma_\delta^2} &= \frac{2\xi^2}{1 + \psi^2} = \frac{\xi^2}{5} \\ \sqrt{\frac{\sigma_{y-w}^2}{\sigma_\delta^2}} &= \sqrt{\frac{\xi^2}{5}} = \frac{\xi}{\sqrt{5}} = M \Rightarrow \xi = 2.2361M \end{aligned}$$

and the parameter ξ is set such that the ratio of weekly standard deviations is around M.

8.1 Probability matrices.

With aggregate shocks the transition matrices M and $\hat{M}$ are indexed by the aggregate state since the destruction rate varies with the aggregate shock, $\lambda\left(x_i\right)$. This is, however not the only difference. In an example with two states we could have that the maximum number of contacts differs in state zero and state one. In this case the $\hat{M}$ matrix changes in a subtle way. We give here an example where $\bar{n}\left(x_2\right) = 2$, and $\bar{n}\left(x_1\right) = 1$. We have then for unemployed agents in state i:

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

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.[31]

8.2 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:

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

and the transition of unemployment into employment yields the scalar:

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

8.3 The matching function

With a constant $\bar{n}$ the algebra here is trivial. 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

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

which then implies

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

[31] 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.

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.

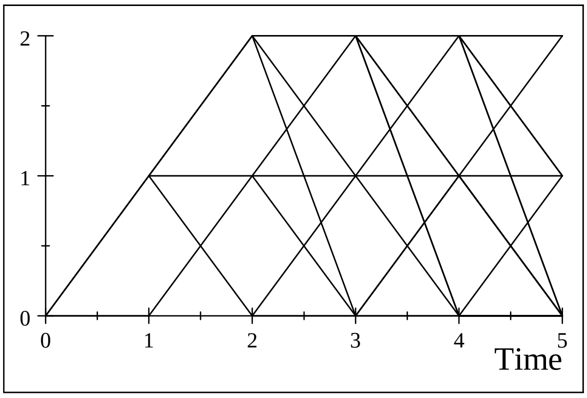
9 A3: The Contact distribution in the deterministic model.

Given an upper bound $\bar{n}$ on the number of connections we can derive the expected distribution of connections at the point of job destruction for a given agent, when he starts working. Starting from zero in a new job the worker makes a connection in the first period and continues making a new connection each period until he reaches $\bar{n}$ connections. But the worker can also lose its job along the way, as can his connections.

If the worker is unemployed after one period of work, an event which occurs with probability $(1-\lambda)$, the worker can have either zero or one contacts with respective probabilities $((1-\lambda), \lambda)$. If he becomes unemployed after two periods, which happens with probability $\lambda(1-\lambda)$, he can have entered the second period with one contact (probability λ), and then he can have $[0,1,2]$ contacts at the end of period two with probability vector $\left((1-\lambda)^2, 2\lambda(1-\lambda), \lambda^2\right)$. But he can also have entered the second period with only zero contacts - an event with probability $(1-\lambda)$ - and then he can have at most one contact as above.

If we assume that the upper bound on the number of contacts is 2, we have the graphic representation of the probability paths shown in figure 1, where the probability associated with each final node is, among all paths, the fraction that ends in that node.

Figure 5: The distribution of contacts at job destruction



We can write this algorithm in matrix form. Here we use an example where $\bar{n} = 2$. All the algebra is from the perspective of time zero, when the worker starts his new job. The first period transition is between zero contacts and the set of $(0,1)$ possible contacts, which defines a (1×3) transition vector over the set $[0,1,2]$, given by $\hat{M}_0 = \begin{bmatrix} (1-\lambda) & \lambda & 0 \end{bmatrix}$.

The second period transition is between the set of $(0,1)$ possible contacts and the set of $(0,1,2)$ possible contacts, which defines a transition matrix (with one extra rows of zeros):

$$\hat{M}_1 = \begin{bmatrix} (1-\lambda) & \lambda & 0 \\ (1-\lambda)^2 & 2\lambda(1-\lambda) & \lambda^2 \\ 0 & 0 & 0 \end{bmatrix}$$

Since we are assuming that $\bar{n} = 2$, the third period transition is between the set of $(0,1,2)$ possible contacts and the set of $(0,1,2)$ possible contacts, which defines a (3×3) transition matrix:

$$\hat{M}_2 = \begin{bmatrix} (1-\lambda) & \lambda & 0 \\ (1-\lambda)^2 & 2\lambda(1-\lambda) & \lambda^2 \\ (1-\lambda)^2 & 2\lambda(1-\lambda) & \lambda^2 \end{bmatrix}$$

This generates the following sequence:

$$\begin{gathered}(1-\lambda)\hat{M}_0, \quad \lambda(1-\lambda)\hat{M}_0\hat{M}_1, \quad \lambda^2(1-\lambda)\hat{M}_0\hat{M}_1\hat{M}_2, \\ \lambda^3(1-\lambda)\hat{M}_0\hat{M}_1(\hat{M}_2)^2, \quad \lambda^4(1-\lambda)\hat{M}_0\hat{M}_1(\hat{M}_2)^3, \ldots\end{gathered}$$

and we can show that the distribution of connections contains a matrix geometric series which converges to $\left(I - \lambda\hat{M}_2\right)^{-1}$, if all the eigenvalues of $\hat{T} = \lambda\hat{M}_2$ are less than 1 in absolute value. The probability of losing the job after k periods of employment is $\lambda^{k-1}(1-\lambda)$. Taking this into account, after some algebra the density over contacts becomes

$$S^e = (1-\lambda)\hat{M}_0\left[I + \lambda\hat{M}_1\left(I - \lambda\hat{M}_2\right)^{-1}\right]$$

and this is a vector with three elements which sum to one.

$$S^e = \begin{bmatrix} e_0 & e_1 & 1 - e_0 - e_1 \end{bmatrix}$$

where e_0 is the fraction of the employed population with zero contacts.

We repeat the algebra quickly for the example where $\bar{n} = 1$. All the algebra is from the perspective of time zero, when the worker starts his new job.

The first period transition is between zero contacts and the set of $(0,1)$ possible contacts, which defines the transition vector over the set $[0,1]$, $\hat{M}_0 = \begin{bmatrix} (1-\lambda) & \lambda \end{bmatrix}$. The second period transition (and the last step) is between the set of (0,1) possible contacts and the set of (0,1) possible contacts, which defines a a (2×2) transition matrix:

$$\hat{M}_1 = \begin{bmatrix} (1-\lambda) & \lambda \\ (1-\lambda) & \lambda \end{bmatrix}$$

After some algebra the density over contacts becomes

$$\begin{aligned} D^0 &= (1-\lambda)\,\hat{M}_0\left(I-\lambda\hat{M}_1\right)^{-1} \\ &= \begin{bmatrix} e_0 & 1-e_0 \end{bmatrix} = \begin{bmatrix} 1-\lambda & \lambda \end{bmatrix} \end{aligned}$$

and in steady state equilibrium this is the density over contacts of the employed population, S^e, as well as the equilibrium distribution over contacts of the cohort entering unemployment (since the probability of losing a job does not depend on the number of contacts). The last equality is specific to the $\bar{n}=1$ example and is easy to prove. The correspondence of D^0 to the Pascal Triangle expression is not generalizable.

10 Tables

Table 5: Table A1. Stochastic Model Statistics, Weekly Frequency

	Concave ϕ				Convex ϕ			
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
	BL	**CF**	**CL**	**IID**	**BL**	**CF**	**CL**	**IID**
Aggregate Variables								
U Rate, Mean	6.020	6.020	6.000	6.010	6.020	6.000	5.990	6.000
Std-log	0.151	0.135	0.076	0.019	0.172	0.136	0.085	0.021
Ar1	0.999	0.999	0.999	0.891	0.999	0.999	0.999	0.904
JF Rate, Mean	0.123	0.122	0.121	0.121	0.123	0.123	0.122	0.121
Std-log	0.115	0.097	0.086	0.009	0.138	0.097	0.095	0.016
Ar1	0.989	0.984	0.984	0.909	0.992	0.984	0.986	0.806
JDRate, Mean	.0077	.0077	.0077	.0077	.0077	.0077	.0077	.0077
Std-log	0.065	0.065	0	0.072	0.065	0.065	0	0.072
Ar1	0.970	0.970	0	0.010	0.970	0.970	0	0.010
V/U, Mean	0.857	0.852	0.845	0.858	0.864	0.856	0.848	0.859
Corr(v,u)	-0.542	-0.541	-0.792	0.900	-0.537	-0.541	-0.775	0.743
Corr(v/u,JFR)	0.979	0.999	0.993	1.000	0.973	0.999	0.989	1.000
Corr(JDR,y-w)	-0.727	-0.727	0	-0.430	-0.727	-0.727	0	-0.430
Panel Variables								
U Rate, Mean	6.020	6.010	6.010	6.010	6.030	5.980	6.000	6.000
Std-log	0.150	0.138	0.076	0.025	0.171	0.138	0.084	0.025
Ar1	0.996	0.996	0.988	0.837	0.997	0.996	0.991	0.835
JF Rate, Mean	0.122	0.123	0.121	0.120	0.123	0.123	0.122	0.121
Std-log	0.118	0.109	0.098	0.062	0.134	0.109	0.103	0.061
Ar1	0.738	0.698	0.611	0.065	0.817	0.701	0.673	0.112
JD Rate, Mean	.0078	.0078	.0077	.0077	.0078	.0078	.0077	.0077
Std-log	0.092	0.092	0.063	0.099	0.092	0.092	0.063	0.099
Ar1	0.502	0.503	-0.058	-0.005	0.502	0.503	-0.062	-0.013
Corr(Udur,Edur)	-0.315	0	-0.316	-0.318	-0.441	0	-0.444	-0.446
Corr(URate,Udur)	0.511	0.494	0.372	0.032	0.546	0.494	0.375	0.047
γ	1.020	0.665	1.010	0.994	1.444	0.674	1.429	1.405

BL = Baseline, CF = Constant ϕ, CL = Constant λ, IID = iid Shocks
5 Panels, each 6900 Workers. Time Series: 208+468 weeks. First 208 weeks cut.
Corr(Udur,Edur) uses 5 panels with 23000 job loser durations each

Table 6: Table A2. Stochastic Model, Monthly and Quarterly Frequencies

	Concave ϕ				Convex ϕ			
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
	BL	**CF**	**CL**	**IID**	**BL**	**CF**	**CL**	**IID**
Monthly Frequency								
Aggregate Variables								
U Rate, mean	6.020	6.020	6.000	6.000	6.020	5.990	5.990	6.000
Std-log	0.152	0.136	0.076	0.019	0.173	0.136	0.085	0.021
Ar1	0.989	0.984	0.986	0.653	0.992	0.984	0.990	0.740
Corr(v,u)	-0.542	-0.533	-0.795	0.900	-0.539	-0.533	-0.778	0.747
Panel Variables								
U Rate, mean	6.020	6.010	6.010	6.000	6.020	5.980	6.000	5.990
Std-log	0.151	0.137	0.076	0.025	0.171	0.137	0.085	0.024
Ar1	0.980	0.973	0.955	0.507	0.986	0.973	0.966	0.593
JF Rate, Mean	0.483	0.418	0.480	0.478	0.533	0.419	0.532	0.530
Std-log	0.096	0.106	0.085	0.061	0.098	0.106	0.081	0.060
Ar1	0.686	0.602	0.561	0.156	0.694	0.603	0.521	0.078
JD Rate, Mean	0.031	0.031	0.030	0.031	0.031	0.031	0.030	0.030
Std-log	0.069	0.069	0.033	0.051	0.069	0.069	0.033	0.051
Ar1	0.666	0.680	-0.113	-0.037	0.670	0.680	-0.102	-0.037
Corr(v/u,JFR)	0.769	0.750	0.660	0.270	0.820	0.745	0.695	0.289
Corr(JDR,y-w)	-0.611	-0.620	0.631	-0.244	-0.613	-0.620	0.070	-0.255
Quarterly Frequency								
Aggregate Variables								
U Rate, mean	6.020	6.010	5.990	6.010	6.020	5.980	5.980	6.010
Std-log	0.152	0.135	0.076	0.021	0.174	0.135	0.085	0.022
Ar1	0.936	0.891	0.917	0.490	0.951	0.890	0.936	0.617
Corr(v,u)	-0.601	-0.578	-0.834	0.910	-0.602	-0.578	-0.818	0.758
Panel Variables								
U Rate, mean	6.000	5.980	5.990	6.000	6.010	5.960	5.980	6.000
Std-log	0.148	0.137	0.073	0.027	0.172	0.136	0.084	0.025
Ar1	0.925	0.879	0.888	0.368	0.940	0.879	0.898	0.353
JF Rate, mean	0.841	0.813	0.841	0.843	0.827	0.814	0.827	0.830
Std-log	0.050	0.059	0.041	0.026	0.053	0.059	0.043	0.032
Ar1	0.638	0.584	0.575	0.198	0.575	0.595	0.410	0.044
JDRate, mean	0.096	0.096	0.096	0.096	0.096	0.096	0.096	0.096
Std	0.058	0.058	0.016	0.027	0.058	0.058	0.016	0.027
Ar1	0.700	0.697	0.021	0.106	0.697	0.698	0.007	0.097
Corr(v/u,JFR)	0.835	0.838	0.780	-0.162	0.777	0.840	0.694	-0.170
Corr(JDR,y-w)	-0.683	-0.688	0.135	-0.068	-0.681	-0.688	0.157	-0.052
γ	1.020	0.665	1.010	0.994	1.444	0.674	1.429	1.405

BL = Baseline, CF = Constant ϕ, CL = Constant λ, IID = iid Shocks
Panel Size: 6900 Workers. Time Series: 624 weeks
Corr(Udur,Edur) uses two panels with 23000 job loser durations each

Table 7: Table A3. Correlations with the Unemployment Rate

	Panel Data Correlations							
	Concave ϕ				Convex ϕ			
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Variables	**BL**	**CF**	**CL**	**IID**	**BL**	**CF**	**CL**	**IID**
A: Number of Job Finders (JF)	0.479	0.533	-0.020	0.415	0.474	0.534	-0.050	0.412
B: Number of Non Finders	0.998	0.998	0.993	0.945	0.999	0.997	0.995	0.944
C: G/(Number of Unemployed)	-0.577	-0.631	-0.297	0.176	-0.630	-0.629	-0.238	0.022
D: Fraction of Job Finders	-0.825	-0.776	-0.734	0.054	-0.885	-0.777	-0.792	0.055
E: Total Contacts of Job Finders	0.170	0.263	-0.128	0.341	0.115	0.264	-0.171	0.352
F: Total Contacts of Non Finders	0.944	0.966	0.937	0.807	0.976	0.966	0.962	0.781
G: Total Contacts of All Unemployed	0.937	0.966	0.938	0.845	0.970	0.966	0.962	0.807
H: Number of JF with n<0.75 $\bar{n}$	0.624	0.616	0.153	0.387	0.616	0.617	0.116	0.379
I: Number of JF with n<0.50 $\bar{n}$	0.597	0.597	0.035	0.301	0.603	0.597	0.046	0.279
J: Fraction of JF with n<0.75 $\bar{n}$	0.491	0.445	0.285	0.062	0.491	0.444	0.261	0.050
K: Fraction of JF with n<0.50 $\bar{n}$	0.424	0.406	0.060	0.010	0.463	0.407	0.103	-0.025
L: Number of Job Losers	0.420	0.494	-0.132	-0.055	0.381	0.494	-0.147	-0.055
M: Fraction of Job Losers	0.501	0.563	-0.060	-0.039	0.477	0.563	-0.067	-0.039
N: NP1 = E/A - F/B	-0.204	0.015	-0.192	-0.095	-0.455	0.012	-0.321	0.002
O: NP1 = (E/A) / (F/B)	-0.013	0.013	-0.163	-0.118	-0.298	0.010	-0.338	0
P: NP2 = H/A	0.491	0.445	0.285	0.062	0.491	0.444	0.261	0.050
Q: NP2 = I/A	0.424	0.406	0.060	0.010	0.463	0.407	0.103	-0.025
R1: NP3 = A/E	0.513	0.496	0.241	0.026	0.540	0.496	0.257	-0.003
R2: NP3 = E/A	-0.521	-0.501	-0.245	-0.027	-0.547	-0.501	-0.257	0.005
S1: NP4 = A/G	-0.699	-0.625	-0.681	0.003	-0.828	-0.628	-0.723	0.052
S2: NP4 = G/A	0.687	0.615	0.667	-0.003	0.818	0.617	0.749	-0.054
T: F/B	-0.466	-0.622	-0.089	0.193	-0.378	-0.620	0.180	0.008
γ	1.020	0.665	1.010	0.994	1.444	0.674	1.429	1.405

BL = Baseline, CF = Constant ϕ, CL = Constant λ, IID = iid Shocks

Panel: 6900 workers. Average number of unemployed: 414. Average number of job losses per week: 51.

Table 8: Table A4. Changing Curvature

	Panel Data Correlations			
	Concave ϕ		**Convex ϕ**	
	1	**2**	**3**	**4**
Curvature of ϕ function (ϕ_2)	**0.5**	**0.25**	**2**	**4**
A: Number of Job Finders (JF)	0.479	0.510	0.474	0.473
B: Number of Non Finders	0.998	0.998	0.999	0.999
C: G/(Number of Unemployed)	-0.577	-0.624	-0.630	-0.649
D: Fraction of Job Finders	-0.825	-0.812	-0.885	-0.890
E: Total Contacts of Job Finders	0.170	0.223	0.115	0.103
F: Total Contacts of Non Finders	0.944	0.958	0.976	0.987
G: Total Contacts of All Unemployed	0.937	0.955	0.970	0.983
H: Number of JF with n<0.75 $\bar{n}$	0.624	0.611	0.616	0.609
I: Number of JF with n<0.50 $\bar{n}$	0.597	0.588	0.603	0.626
J: Fraction of JF with n<0.75 $\bar{n}$	0.491	0.449	0.491	0.496
K: Fraction of JF with n<0.50 $\bar{n}$	0.424	0.404	0.463	0.501
L: Number of Job Losers	0.420	0.457	0.381	0.383
M: Fraction of Job Losers	0.501	0.533	0.477	0.480
N: NP1 = E/A - F/B	-0.204	-0.036	-0.455	-0.516
O: NP1 = (E/A) / (F/B)	-0.013	0.064	-0.298	-0.444
P: NP2 = H/A	0.491	0.449	0.491	0.496
Q: NP2 = I/A	0.424	0.404	0.463	0.501
R1: NP3 = A/E	0.513	0.500	0.540	0.563
R2: NP3 = E/A	-0.521	-0.500	-0.547	-0.563
S1: NP4 = A/G	-0.699	-0.658	-0.828	-0.848
S2: NP4 = G/A	0.687	0.658	0.818	0.848
T: F/B	-0.466	-0.578	-0.378	-0.336
$\rho(udur, urate)$	0.51	0.537	0.55	0.572
Urate	6.02	6.04	6.02	6.00
Duration in Weeks				
Mean	8.01	8.05	8.28	8.23
Stdev	1.70	1.43	1.95	1.89
Cohort Size				
Mean	51.1	51.1	51.1	51.1
Stdev	7.97	7.90	7.94	7.90
γ	1.020	0.769	1.444	1.9375

Panel: 6900 workers, average 414 unemployed and 51 job losses per week