Economics Letters 144 (2016) 37–40

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

The implications of labor market network for business cycles

Marcelo Arbex[a,*], Sidney Caetano[b], Dennis O'Dea[c]

[a] Department of Economics, University of Windsor, 401 Sunset Avenue, Windsor, Ontario, Canada
[b] Department of Economics, Federal University of Juiz de Fora, Juiz de Fora, Brazil
[c] Department of Economics, University of Washington, Seattle, USA

HIGHLIGHTS

- We embed a frictional labor market with formal and informal search in an RBC model.
- Labor market networks is an important job information transmission channel.
- Network and direct search amplify the economy's response to a technological shock.
- Network search has important quantitative consequences for the business cycle.

ARTICLE INFO

Article history:
Received 14 January 2016
Received in revised form
20 April 2016
Accepted 22 April 2016
Available online 4 May 2016

JEL classification:
D85
E24
E32
J64

Keywords:
Business cycles
Labor markets
Social networks
Job search

ABSTRACT

We embed a frictional labor market with formal and informal search in an RBC model. Even in a model with exogenous search effort the interaction between formal and informal (network) search methods can help in generating more volatility in unemployment.

1. Introduction

We reconsider a conventional framework of a real business cycle model with job search (e.g., Merz (1995) and Andolfatto (1996)) in which we embed a social network model along the lines of models of the transmission of job offers in large, complex networks (Calvo-Armengol and Jackson, 2004). In our model, workers are endowed with peers exogenously and engage in network search to affect their labor market outcomes, a channel absent from most previous quantitative studies of business cycles. We derive a matching function using the mean-field approach (Vega-Redondo, 2007) to take into account both network and direct search efforts by workers.[1] Network in the labor market, in addition to direct search, reduce informational and search frictions and amplify the response of output and employment to a technological shock.

Our approach is consistent not only with labor-market stylized facts and business cycles features, but also with empirical evidence pointing towards the importance of networks in the labor market as an information transmission mechanism. At least one third of employees find job through their social contacts, workers with more social contacts are on average more likely to be employed and more likely to receive and pass a job opportunity (Ioannides and Loury, 2004; Topa, 2011). On the other hand, the relationship

* Corresponding author. Tel.: +1 519 2533000.
E-mail address: arbex@uwindsor.ca (M. Arbex).

[1] Arbex and O'Dea (2014) use a similar approach to study optimal taxation when jobs are found through a social network. For alternative matching models with social networks, see for instance, Calvo-Armengol and Zenou (2005), Ioannides and Soetevent (2006), and Fontaine (2007).

http://dx.doi.org/10.1016/j.econlet.2016.04.028
0165-1765/

between jobs found via a worker's network and his wage is quite debated (see Loury (2006) and Dustmann et al. (forthcoming)).

We focus on the network structure of social interactions, i.e., the strategic interaction between peers is fixed not by agents search efforts but by the network structure. Our analysis is restricted to the interaction between formal and informal search within a worker's decision, and search efforts are not strategically chosen. When both search efforts are endogenous, individual search effort and network investment can be either strategic substitutes (Merlino, 2014) or strategic complements (Cabrales et al., 2011). Tumen (2012) studies social interactions and unemployment fluctuations, and the strategic relationship between both search efforts leads to multiple equilibria, a feature not present in our approach.

We assume power-law distributions, as these networks have a number of attractive features that match well many properties of empirical social networks (Jackson, 2008). In our model, even though job search efforts are exogenously given, social contacts provide individuals with the opportunity to learn about vacancies faster. The additional channel through which workers can find jobs (i.e., network search) does not trigger a virtuous circle but has important quantitative consequences for the business cycle, as it amplifies the economy's short-run response to a productivity shock, that cannot be ignored.

2. The model

2.1. Demography, network search and employment

In a typical household there are a measure n_t of employed family members and a measure $1 - n_t$ of unemployed family members. Employed members supply labor hours l_t. Unemployed workers search for jobs actively making an exogenous (time) effort e and spend time x in social activities, which develop their social connections, increasing the strength of their ties to their peers.

Workers are connected to one another in a social network, whose structure is exogenous. Each agent may have peers to whom she passes information when employed, and from whom she may receive information when unemployed. A network is described by a *degree distribution* $\{D_z\}_{z=1}^{\infty}$, where D_z is the proportion of agents who have $z \in [1, \infty)$ peers.[2] We assume power-law distributions (workers with many links are more likely to have access to job information) and apply the mean field approach (Vega-Redondo, 2007).[3]

The probability a given agent has s peers is $\psi_s = (sD_s)/\langle z\rangle$, where $\langle z\rangle = \int_{z=1}^{\infty}(zD_z)\,dz$ is the *average degree* in the network. Note that $\psi_s \neq D_s$, i.e., the probability one of your peers has s links is not equal to the proportion of the population that has s links. This is because agents with many peers, and a large s, are disproportionately likely to be your peers, so we must scale D_s by $s/\langle z\rangle$. This gives the probability that a peer with s links passes a worker a job. The employment rate among those workers with s peers is n_s. Each employee contacts unemployed friends with a probability ρ_t (Fontaine, 2007).

The rate at which job information is passed from employed workers to their unemployed peers depends on how much effort, x, agents spent on social activities, i.e., $\varphi(x_t) = x^{1-\lambda}$, where λ measures the efficacy of this technology.[4] Employed workers pass job information to peers with probability $\varphi(x)/s$.

Integrating over all possible s, the probability a worker is passed job information from a peer is therefore

$$\Omega_t = \int_{s=1}^{\infty}\rho_t\frac{\varphi(x)}{s}n_{s,t}\psi_s ds = \rho_t\frac{\varphi(x)}{\langle z\rangle}n_t. \tag{1}$$

Hence, the probability a worker of type z receives at least one offer via a peer in his social network is $p_t = 1-(1-\Omega_t)^z$. And the aggregate probability workers of different types z receive job offers via their network peers is

$$P_t = \int_{z=1}^{\infty}p_tD_zdz. \tag{2}$$

Meetings between jobs and workers are stochastic, and are modeled by means of a standard matching function embedded with network search as follows

$$M_t = v_t^{\alpha}\left[(1-n_t)\left(e^{\gamma}P_t^{(1-\gamma)}\right)\right]^{1-\alpha}, \quad 0\le\alpha\le1, 0\le\gamma\le1 \tag{3}$$

where M_t represents the number of job matches that are created in time period t and γ is the relative weight of direct search on the aggregate job arrival rate, $(1-n_t)e^{\gamma}P_t^{(1-\gamma)}$.

Following Pissarides (1990), the aggregate employment evolves according to the dynamic equation:

$$n_{t+1} = (1-\sigma)n_t + M_t, \tag{4}$$

where $\sigma \in (0,1)$ is the exogenous job separation rate (independent across agents).

2.2. Households, firms and the economy's resource constraint

Preferences of the household are represented by the following utility function

$$E_0\sum_{t=0}^{\infty}\beta^t\left[log(c_t) + n_t\phi_1\frac{(1-l_t)^{1-\eta}}{(1-\eta)}\right.$$
$$\left. + (1-n)\phi_2\left(\gamma\frac{(1-e)^{1-\eta}}{(1-\eta)} + (1-\gamma)\frac{(1-x)^{1-\eta}}{(1-\eta)}\right)\right], \tag{5}$$

where E denotes the expectation operator, β is the discount rate which lies in $(0,1)$, c_t is consumption, ϕ_1, ϕ_2 are the weight on leisure depending on the household's employment status and $\eta \neq 1$.

Job–worker pairs are formed as a firm undertakes recruiting activities, and, on the other hand, unemployed workers search directly for a job or learn about it through their networks. Let v_t be the total number of new jobs made available by firms during the period t, each vacancy incurring a flow cost equal to $\kappa > 0$, measured in units of physical output.

Output y_t is produced according to a standard neoclassical production technology $F(k_t, n_tl_t; \varepsilon_t) = exp(\varepsilon_t)\Psi k_t^{\theta}(n_tl_t)^{1-\theta}$, where k_t is the capital stock, $0 \le \theta \le 1$, $\Psi > 0$. The productivity shock ε_t evolves as an AR(1) process: $\varepsilon_t = \rho_\epsilon\varepsilon_{t-1} + \tilde{\epsilon}_t$, where $0 < \rho_\epsilon < 1$ and $\tilde{\epsilon}_t$ is an *i.i.d.* random variable. The aggregate resource constraint of the economy must be satisfied

$$c_t + k_{t+1} + \kappa v_t = y_t + (1-\delta)k_t. \tag{6}$$

[2] This is common to approximate the discrete number of network connections with a continuous variable, so rather than $z \in 1, \dots, \infty$ we use this half-closed interval.

[3] This approach relies on the assumption that there are no systemic differences between each worker's local neighborhoods (*homogeneous mixing*). Because the network is large, an agent could not infer anything about their employment status beyond the average in the network.

[4] Galeotti and Merlino (2014) investigate the implications of the feedback between labor market conditions and investment (time and effort) in social networks in matching vacancies with job seekers.