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Labor Market Dynamics and the Business Cycle

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Abstract

The characterizations of labor market dynamics and their implications for the study of business cycles are topics of debate. This paper re-examines a general equilibrium version of the search and matching model to see whether it fits the data. I use both Israeli and U.S. data. I seek to determine to what extent the model which explains stocks and worker flows can account for the business cycle facts. The paper shows that a DSGE model with search and matching in the labor market has limited success in matching the data for both the U.S. and Israel.

LABOR MARKET DYNAMICS AND THE BUSINESS CYCLE

1 Introduction

The characterizations of labor market dynamics and their implications for the study of business cycles are topics of debate. There are three, interrelated issues of concern: First, different empirical studies of gross worker flows and labor market dynamics over the past two decades have yielded contradictory findings. Second, debates have emerged regarding the implications of these worker flows for the understanding of the business cycle. The 'conventional wisdom,' based on the reading of Blanchard and Diamond (1989, 1990), Davis and Haltiwanger (1999), and Bleakley, Ferris, and Fuhrer (1999), was that worker separations from jobs are the more dominant cyclical phenomenon than hirings of workers, and that therefore it is important to analyze the causes for separations or job destruction. In particular, it was believed that in order to study the business cycle it is crucial to understand the spikes and volatility of employment destruction. This view was challenged by Hall (2005) and Shimer (2007), who claimed that separations are roughly constant over the cycle, and that the key to the understanding of the business cycle is in the cyclical behavior of the job finding rate. Third, there is also disagreement as to how much the search and matching model – a key model in this context – can explain the data. While the early studies of Merz (1995), Andolfatto (1996), and den Haan et al (2000) provided empirical support for the model, a number of subsequent papers claimed that the model does not fit the data (most notably, Shimer (2005)).

This paper re-examines a general equilibrium version of the search and matching model to see whether it fits the data. I use both Israeli and U.S. data. I seek to determine to what extent the model which explains stocks and worker flows can account for the business cycle facts.

The paper proceeds as follows: Section 2 discusses the background literature and the current debates. Then a general equilibrium version of this model is examined: Section 3 presents the model, Section 4 outlines the empirical methodology used and delineates calibration values, and Section 5 reports and discusses simulation results. Section 6 concludes.

2 The Literature

In this section I place the work below in context by discussing the findings of recent literature and the ensuing debates. I do so first in terms of the data and then in terms of the search and matching model, finally linking the two.

Data.

In terms of volatility, Blanchard and Diamond (1989, 1990) found that the amplitude of fluctuations in the flow out of employment is larger than that of the flow into employment, implying that changes in employment are dominated by movements in job destruction rather than in job creation. Similarly, Bleakley, Ferris, and Fuhrer (1999) found that once the trend is removed, the flows out of employment have more than twice the variance of the flows into employment. But recently, Hall (2005) and Shimer (2007) claimed that separation rates are not as volatile as job finding rates (not hiring rates) and that they can be taken roughly as constant (in detrended terms).

In terms of cyclical co-movement, Blanchard and Diamond (1989, 1990) found sharp differences between the cyclical behavior of the various flows. In particular, the EU flow increases in a recession while the EN flow decreases; the UE flow increases in a recession, while the NE flow decreases. Ritter (1993) reported that the net drop in employment during recessions is clearly dominated by job separations. Bleakley, Ferris, and Fuhrer (1999) found that the flow into voluntary quits declines fairly sharply during recessions, consistent with the notion that quits are largely motivated by prospects for finding another job. “Involuntary” separations – both layoffs and terminations – rise sharply during recessions and gradually taper off during the expansions that follow.

More recently, a new picture of worker flows cyclicality has been proposed. Hall (2005) developed estimates of separation rates and job-finding rates for the past 50 years, using historical data informed by the detailed recent data from JOLTS. He found that the separation rate is nearly constant while the job-finding rate shows high volatility at business-cycle and lower frequencies. He concluded that this necessitates a revised view of the labor market: during a recession unemployment rises entirely because jobs become harder to find. Recessions involve no increases in the flow of workers out of jobs. Another important finding from the new data is that a large fraction of workers departing jobs move to new jobs without intervening unemployment. Shimer (2007) reported that the job finding probability is strongly procyclical while the separation probability is nearly acyclical, particularly during the last two decades. He showed that these results are not due to compositional changes in the pool of searching workers, nor are they due to movements of workers in and out of the labor force. He too concluded that the results contradict the conventional wisdom of the last fifteen years. If one wants to understand fluctuations in unemployment, one must understand fluctuations in the transition rate from unemployment to employment, not fluctuations in the separation rate.

This challenging view has met with a number of replies. Davis (2005) showed that understating the cyclical variation in the separation rate would lead to an overstatement of the cyclical variation in the job finding rate. Relying on fluctuations mostly in the job finding rate to explain labor market outcomes leads to counter-factual implications. Simulating a drop in the job-finding rate as in a recession but with no change in the separation rate, he shows (see his Figure 2.17 and the discussion on pp. 142-144) the following: the E to U flow rises too little relative to the data and the U to E flow falls too much relative to the data. The way to obtain results in accordance with the data is to posit a sharp rise in the separation rate. Fujita and Ramey (2008) construct a decomposition of unemployment variability which contradicts Shimer's (2007) conclusions. They find that separation rates are highly countercyclical under alternative cyclical measures and filtering methods and that fluctuations in separation rates contribute substantially to overall unemployment variability. Elsby et al (2007) show that even with Shimer's (2007) methods and data there is an important role for countercyclical inflows into unemployment. Their conclusions are further strengthened when they refine Shimer's methods of correcting CPS labor force series for the 1994 redesign and for time aggregation and undertake a disaggregated analysis.

Model Performance. In terms of the fit of the search and matching model, Merz (1995), Andolfatto (1996), and den Haan et al (2000) have shown that the model is able to capture salient features of the data and improve on the performance of the standard RBC model. Using Israeli data, Yashiv (2000a) used structural estimation and found that the model generates a good fit of the data. Mortensen and Pissarides (1994) extended the basic Pissarides (1985) model to cater for endogenous separations in order to capture the stylized facts on the importance of job destruction.

However, subsequently, a number of papers claimed that the model does not fit the data well. In particular:

(i) Cole and Rogerson (1999) found that the model can account for business cycle facts only if the average duration of unemployment is relatively high (9 months or longer), substantially longer than in the actual data.

(ii) Fujita (2004) presented empirical tests showing that vacancies are much more persistent in the data than the low persistence implied by the model.

(iii) Veracierto (2008) has shown that the model fails to simultaneously account for the observed behavior of employment, unemployment, and out of the labor force worker pools. In particular, employment fluctuates as much as the labor force while in the data it is three times more variable, unemployment fluctuates as much as output while in the data it is six times more variable, and unemployment is acyclical while in the data it is strongly countercyclical. An underlying reason is that search decisions respond too little to aggregate productivity shocks.

(iv) Costain and Reiter (2008) argued that in a RBC model with matching, procyclical employment fluctuations occur when match productivity rises in booms. At the same time an increase in unemployment benefits negatively affects employment by reducing the match surplus. They then show that the standard model implies a close relationship between the two, but that this is strongly at odds with data. To reproduce business cycle fluctuations, matching must be quite elastic with respect to the surplus; but to reproduce the observed effects of unemployment benefits policies, matching must be, at the same time, more inelastic.

(v) In a highly influential paper, Shimer (2005) showed that the standard search and matching model can explain only a small fraction of cyclical fluctuations in the labor market, most notably those of unemployment and vacancies. The key reason for this result is that the standard model assumes that wages are determined by Nash bargaining, which in turn implies that wages are "too flexible." Thus, for example, following a positive productivity shock wages increase, absorbing the shock and thereby dampening the incentives of firms to create new jobs.

These critiques have received some responses. To cite some papers in this growing literature, Mortensen and Nagypal (2007) show that a modified version of the model can explain the magnitude of the empirical relationship between the vacancy–unemployment ratio and labor productivity when wages are the outcome of a strategic bargaining game and when the elasticity of the matching function and the opportunity cost of a match are set at reasonable values. The modified model also explains almost two thirds of the volatility in the ratio relative to that of productivity when separation shocks are taken into account, as well as the strong negative correlation between vacancies and unemployment. Pissarides (2007) summarizes microeconometric evidence on wages in new matches and shows that the key model elasticities are consistent with the evidence. He concludes that explanations of the 'Shimer puzzle' have to preserve the cyclical volatility of wages. Hagedorn and Manovskii (2008) propose a new way to calibrate the parameters of the model and find that the model is consistent with the key business cycle facts. In particular, it generates volatilities of unemployment, vacancies, and labor market tightness that are very close to those in the data. They do so using a relatively low value for the workers' bargaining parameter and a value of non-market activity that is fairly close to market productivity.

Data and Theory. There is a link between the afore-cited data issues and the theoretical issues. According to the Shimer-Hall view the main issue for the study of business cycles is explaining the pro-cyclicality and volatility of the job finding rate, as the separation rate is almost constant. The job finding rate depends on market tightness. The model, therefore, needs to account for the cyclical behavior of market tightness, but it is unable to do so in its standard form. This view needs to be contrasted with the earlier view, which posited that separations from employment are at least as important, if not more important, than hirings, both need to be explained, and the model is able to account for the major facts.

3 General Equilibrium Model

I present a formulation of a DSGE model with search and matching and examine its performance. I follow the implementation to a DSGE setting by Den Haan, Ramey, and Watson (2000) and Krause and Lubik (2007) of the Mortensen and Pissarides (1994) model.

3.1 Environment

There is a continuum of infinitely-lived households, which maximize an intertemporal utility function via choice of consumption (C). There is a continuum of identical firms, which maximize the discounted value of expected profits via the choice of job vacancies and threshold productivity. Hence the discussion will be in terms of a representative household and a representative firm. Within the firm there is a continuum of jobs. Productivity has an aggregate component, evolving according to an AR1 process, and a job-specific component. The latter is drawn each period from a time-invariant distribution (with density $g(a)$ and cdf $G(a)$). Workers and firms are faced with different frictions such as different locations leading to regional mismatch or lags and asymmetries in the transmission of information.

These frictions are embedded in the concept of a matching function which produces hires (M) out of vacancies (V) and unemployment (U), leaving certain jobs unfilled and certain workers unemployed. Workers are assumed to be separated from jobs at a stochastic rate δ_t; the latter has an exogenous part, to be denoted by δ^x, and an endogenous part δ^n. δ^n is the result of the existence of an optimal threshold $\underline{a_t}$ for job specific productivity, below which the job and the worker separate.

3.2 Households

Households maximize utility:

$$\max_C \epsilon_0 \sum_{t=0}^{\infty} \beta^t U(C_t) \tag{1}$$

subject to the budget constraint:

$$C_t + B_t = W_t E_t + b_t U_t + R_{t-1} B_{t-1} - T_t + \Pi_t \tag{2}$$

where ϵ is the expectations operator, C is consumption, β is a discount factor, B is the stock of debt in real terms, bearing gross interest R, WE is labor income (elaborated below), bU is the income of unemployed household members, which can be thought of as total output of a home production sector with $b > 0$, T are taxes, and Π are firm profits (owned by households).

The F.O.C. is:

$$U_{C_t} = \beta R_t \epsilon_t U_{C_{t+1}} \tag{3}$$

In what follows I shall use the notation:

$$\lambda_t \equiv U_{C_t}$$

3.3 Firms

Firms maximize profits:

$$\max_{\{V,\underline{a}\}} \Pi_0 = \epsilon_0 \sum_{t=0}^{\infty} \beta^t \frac{\lambda_t}{\lambda_0} \left[F_t - W_t E_t - \Gamma_t\right] \tag{4}$$

subject to

$$E_{t+1} = (1-\delta_t)E_t + Q_t V_t \tag{5}$$

where Γ are vacancy and hiring costs, explained below, and Q is the rate at which vacancies are filled. The F.O.C are:

$$\frac{\partial \Gamma_t}{\partial V_t} = Q_t \beta \epsilon_t \frac{\lambda_{t+1}}{\lambda_t} \left[\begin{array}{c} \frac{\partial F_{t+1}}{\partial E_{t+1}} - \frac{\partial \Gamma_{t+1}}{\partial E_{t+1}} - \frac{\partial (W_{t+1}E_{t+1})}{\partial E_{t+1}} \\ +(1-\delta_{t+2}) \frac{\frac{\partial \Gamma_{t+1}}{\partial V_{t+1}}}{Q_{t+1}} \end{array} \right] \tag{6}$$

$$\frac{\partial F_t}{\partial \underline{a}_t} - \frac{\partial \Gamma_t}{\partial \underline{a}_t} - \frac{\partial (W_t E_t)}{\partial \underline{a}_t} = \epsilon_t \Lambda_{t+1} \left[E_t \frac{\partial \delta_t}{\partial \underline{a}_t} \right] \tag{7}$$

Equation (6) is the job creation equation determining optimal vacancies V_t by equating the marginal benefit and the marginal cost of a vacancy. Equation (7) is the job destruction condition,determining $\underline{a}_t$.

3.4 Matching

A matching function captures the frictions in the matching process; it satisfies the following properties:

$$\begin{aligned} M_t &= \widetilde{M}(U_t, V_t) \\ \frac{\partial \widetilde{M}}{\partial U} &> 0, \ \frac{\partial \widetilde{M}}{\partial V} > 0 \end{aligned} \tag{8}$$

3.5 Wage Determination

The Nash wage solution is given by:

$$W(a_t) = \arg\max(J_t^E - J_t^U)^{\xi}(J_t^F - J_t^V)^{1-\xi} \tag{9}$$

where ξ is the bargaining power of workers, J_t^E is the present value of employment, J_t^U is the present value of unemployment, J_t^F is the present value of a filled job, and J_t^V is the present value of an unfilled vacancy. Free entry of firms generates

$$J_t^V = 0 \tag{10}$$

This solution works out to be:

$$\begin{aligned} W(a_t) \quad = \quad & \chi_t \left[\frac{\partial F_t}{\partial E_t} - \frac{\partial \Gamma_t}{\partial E_t} - E_t \frac{\partial W_t}{\partial E_t}\right] + \chi_t P_t \Lambda_t \\ & + (1 - \chi_t)\, b_t \\ & \chi_t = \frac{\xi}{(\xi + (1-\xi)\,\tau)} \end{aligned} \tag{11}$$

postulating that $b_t = \tau W_t$.

3.6 Functional Forms

For functional forms the following will be used:

CRRA utility defined over consumption.

$$U(C_t) = \frac{C_t^{1-\omega}}{1-\omega}$$

Hiring costs refer to the costs incurred in all stages of recruiting: the cost of posting, advertising and screening – pertaining to all vacancies (V), and the cost of training and disrupting production – pertaining to actual hires (QV). For the functional form I use a power function formulation. This modelling relates to the same rationale being used in the capital adjustment costs/Tobin's Q literature. It emerged as the preferred one – for example as performing better than polynomials of various degrees – in structural estimation of this model reported in Yashiv (2000a,b) and in Merz and Yashiv (2007). The former studies used an Israeli data-set that is uniquely suited for such estimation with a directly measured vacancy series that fits well the model's definitions. The latter study used U.S. data. Formally this function is given by:

$$\Gamma_t = \frac{\Theta}{1+\gamma}(\frac{\phi V_t + (1-\phi)Q_t V_t}{E_t})^{\gamma+1} F_t \tag{12}$$

Hiring costs are a function of the weighted average of the number of vacancies and the number of hires. They are internal to production and hence are proportional to output. Note that Θ is a scale parameter, ϕ is the weight given to vacancies as distinct from actual hires, and γ expresses the degree of convexity.

The function is linearly homogenous in V, E and F. It encompasses the cases of a fixed cost per vacancy (i.e. linear costs, $\gamma = 0$) and increasing costs ($\gamma > 0$). Note, in particular, two special cases: when $\gamma = 0$ and $\phi = 1$, I get $\Gamma_t = \Theta V_t \frac{F_t}{E_t}$, which is the standard specification in much of the literature. When $\gamma = 1$, I get the quadratic formulation $\Gamma_t = \frac{\Theta}{2}(\frac{\phi V_t+(1-\phi)Q_t V_t}{E_t})^2 F_t$, which is analogous to the standard formulation in "Tobin's q" models of investment where costs are quadratic in $\frac{I}{K}$.

The separation rate is now given by:

$$\begin{aligned} \delta_t &= \delta_t^x + (1-\delta_t^x)\delta_t^n \qquad (13) \\ \delta_t^n &= G(\underline{a_t}) \end{aligned}$$

Production embeds both aggregate productivity and idiosyncratic productivity as follows.

Each worker-job pair in firm i job j produces:

$$\widetilde{f}_{ijt} = A_t a_{ijt} \tag{14}$$

Total output of firm i (across jobs) is given by:

$$f_{it} = A_t e_{it} \int_{\underline{a_t}}^{\infty} a_t \frac{g(a_t)}{1 - G(\underline{a_t}))} da_t$$

Total output in the economy is given by:

$$F_t = A_t E_t \int_{\underline{a_t}}^{\infty} a_t \frac{g(a_t)}{1 - G(\underline{a_t}))} da_t \tag{15}$$

where e_{it} and E_t are the mass of employment relationships at time t, at the firm and aggregate levels, respectively.

The wage bill is now also affected by idiosyncratic productivity.

$$W_t E_t = E_t \int_{\underline{a_t}}^{\infty} W(a_t) \frac{g(a_t)}{1 - G(\underline{a_t}))} da_t \tag{16}$$

Empirical work [see the survey by Petrongolo and Pissarides (2001)] has shown that a Cobb-Douglas function is useful for parameterizing it:

$$M_t = \mu U_t^{\sigma} V_t^{1-\sigma} \tag{17}$$

where μ stands for matching technology. The parameter σ reflects the relative contribution of unemployment to the matching process and determines the elasticity of the hazard rates with respect to market tightness $\frac{V_t}{U_t}$.[1]

[1] The hazard rates – P, the worker probability of finding a job, and Q, the firm's probability of filling the vacancy – are derived as follows:

$$P_t = \frac{M_t}{U_t} = \mu(\frac{V_t}{U_t})^{1-\sigma}$$

$$Q_t = \frac{M_t}{V_t} = \mu \left(\frac{V_t}{U_t}\right)^{-\sigma}$$

3.7 Shocks

Aggregate productivity is modeled as follows:

$$\ln A_{t+1} = \rho_A \ln A_t + \sigma_A \tag{18}$$

Idiosyncratic productivity shocks are drawn from an i.i.d log normal distribution g with CDF G:

$$a \sim LN(g) \tag{19}$$

3.8 Equilibrium

The endogenous variables to be solved are $C, V, \underline{a}, U$, and W. Knowing these the variables M, E, Q, P, and δ^n can be determined. The exogenous variables are τ and δ^x,the parameters of the aggregate productivity process A (ρ_A and σ_A), and the functional form and moments of the idiosyncratic productivity shocks distribution $g(a)$.

4 Methodology

I log-linearize the equation system describing the model dynamics around its steady state. The resulting linear rational expectations model is solved using the method described in Sims (2002).The model is calibrated and then simulated.[2] The calibration of the parameters is summarized in Table 1.

Table 1

U.S. For the matching function elasticity σ I use Blanchard and Diamond's (1989) estimate of 0.4. Structural estimation of the model using U.S. corporate sector data in

[2] I thank Michal Krause and Thomas Lubik for generously sharing with me their calibration-simulation MATLAB code.

Merz and Yashiv (2007) indicates a value of γ, the convexity parameter of the hiring cost function, around 2, i.e. a cubic function ($\gamma + 1 = 3$) for hiring costs. These costs fall on vacancies and on actual hires, with ϕ being the weight on the former. I follow the estimates in Yashiv (2000a) and set it at 0.3. I also experiment below with the values of $\gamma = 0, \phi = 1$, which are prevalent in the literature. The wage bargaining parameter ξ is set to be the symmetric case 0.5. .For the CRRA utility parameter, I use the fairly standard coefficient $\omega = 2$. The discount factor β is set at 0.99. For the aggregate productivity shock I choose the parameters $\rho_A = 0.95$ and $\sigma_A = 0.0049$ so as to match the moments of U.S. GDP time series; in order to calibrate the two moments of the lognormal distribution assumed for idiosyncratic productivity, I normalize the mean to zero and choose the second moment so as to replicate the observed volatility of the job destruction rate. The standard deviation is therefore 0.12. Finally, for steady state values of the exogenous separation rate, total separation rate, and labor market outcomes (u, v, P, Q) I do the following: for the job finding rate, P, I use the data average value. For the steady state unemployment rate u, I take into account the fact that the official rate may not be the relevant one. There are people out of the labor force that transit directly into employment and in terms of the model should be considered as unemployed. So while official unemployed averaged 6%, the wider measure can be high as 12%. Therefore I use the latter measure for the benchmark and as one variation I use 6%. There is also uncertainty with respect to the value of δ; I use 10% for the benchmark which is a relatively high estimate and 5% as a variation. Following the argument in den Haan et al. (2000), I choose an exogenous job destruction rate δ^x of 0068. The values of v and Q are then determined using the Beveridge curve relation and the definition of the matching function.

Israel. For the matching function elasticity σ I use Yashiv's (2000a) estimate of 0.3. Structural estimation of the model using Israeli data in Yashiv (2000a) indicates a value of γ, the convexity parameter of the hiring cost function, around 2 or 3. These costs fall on vacancies and on actual hires, with ϕ being the weight on the former. I use the estimates in

Yashiv (2000a) and set it at 0.3. Following Yashiv (2004) the wage bargaining parameter ξ is set to be 0.2. I follow Balsam and Eckstein (2000) and use $\omega = 1.4$ for the CRRA utility parameter, β =0.99 for the discount factor, and $\rho_A = 0.95$ and $\sigma_A = 0.0049$ for teh aggregate productivity process. In order to calibrate the two moments of the lognormal distribution assumed for idiosyncratic productivity, I normalize the mean to zero and choose the second moment so as to replicate the observed volatility of the job destruction rate. The standard deviation is therefore 0.12. Finally, for steady state values of the exogenous separation rate, total separation rate, and labor market outcomes (u, v, P, Q) I use the values from Yashiv (2004).

5 Results

5.1 Overview

Table 2 reports the results of the simulation of the benchmark model using the two alternatives of linear $(\gamma = 0, \phi = 1)$ and convex $(\gamma = 2, , \phi = 0.3)$ hiring costs functions.

Table 2

The table indicates the following key findings:

U.S.

(i) The baseline model with linear vacancy costs (fixed marginal costs) performs badly: unemployment, vacancies, market tightness and real wages are not as volatile as in the data. The standard deviation of vacancies is 16% of the data figure, unemployment volatility is 63% of the data figure, and tightness volatility is 28% of actual volatility. Job creation and job destruction are excessively volatile relative to the data. Vacancies are not as persistent as the data indicate. Wages are too pro-cyclical relative to the data. The co-movement of unemployment and vacancies is positively signed while in the data it is highly negative and endogenous job creation and destruction are also positively correlated, counter-factually.

The model is able to capture the properties of output, mostly because of the formulation of the driving technology shock.

(ii) Moving to the richer formulation of hiring costs, which are (i) convex; (ii) a function of vacancy and hiring rates; and (iii) a function of average productivity, the results are mixed: in general the series become much more volatile. The model comes closer to the data in terms of real wages and market tightness. For example, the standard deviation of market tightness is 77% of actual volatility, compared to 28% in the linear case. But now the model moves much further away from the data on output and on job creation and destruction. Persistence statistics are slightly worse, with the counter-factual decline in the persistence of wages and vacancies. There is one notable improvement – the co-movement between unemployment and vacancies turns negative; note that many studies indicated that the positive co-movement typically obtained is a key problem with model predictions.

(iii) How sensitive are these results to the calibration of parameter values and to the steady state? Does the model fit improve under alternative values? Table 3 reports variations of parameter and steady state values for the richer hiring costs formulation. I try different values for the variance of the productivity distribution (different values of σ_{LN} from 0.05 to 0.14), a higher persistence parameter for aggregate productivity ($\rho_A = 0.99$), very low and very high values for the worker bargaining parameter ($\eta = 0.05, 0.95$), and two alternative steady state configurations (reported in the table and discussed above).

Table 3

First, results are very sensitive to the calibration of the shocks (persistence and volatility of the aggregate shock and variance of the idiosyncratic shock), of the bargaining parameter, and of the steady state rates of unemployment, separation, and vacancy matching. For example, output volatility varies wildly across calibration values. As the calibration of key parameters is not grounded in strong micro-based studies, uncertainty about true parameter values is meaningful here.

Second, in some of the alternative cases the model moments approach the data moments relative to the benchmark calibration. Does the model fit improve?

– The model gets closer to the data with low values of σ_{LN} w.r.t. the volatility of output and market tightness and w.r.t. the negative correlation between job creation and job destruction; with high values of σ_{LN} it gets closer to the data w.r.t. the persistence of wages and vacancies and w.r.t. the negative correlation between unemployment and vacancies; with intermediate values of σ_{LN} it is closer to the data w.r.t. the volatility of vacancies. But there is no single value that would bring the model consistently closer to fit the data.

– Real wages and vacancies become more persistent with higher persistence of the aggregate productivity shock or with very high or very low values of worker bargaining power.

– The negative co-movement between unemployment and vacancies is better captured with higher persistence of the aggregate productivity shock and with very low values of worker bargaining power.

Israel.

(i) The baseline model with linear vacancy costs (fixed marginal costs) performs badly: output is far too volatile, while wages and unemployment are not as volatile as in the data. The standard deviation of unemployment is 32% of the data figure. Output, wages, and unemployment persistence are much higher than the data indicate. Wages are too pro-cyclical relative to the data.

(ii) Moving to the richer formulation of hiring costs, output volatility comes much closer to the data; wages and unemployment volatilities are also closer but the fit is not as good. Persistence of all series drop but no sufficiently so. Wages remain highly pro-cyclical, counterfactually. Again, a notable improvement is that the co-movement between unemployment and vacancies turns negative.

5.2 Discussion

The emerging picture for the U.S. is the following: the model with fixed marginal vacancy costs is for the most part not sufficiently volatile, gets the co-movement of the key variables wrong, and misses to some extent the persistence statistics. The model with the richer formulation of hiring costs (convex and depending on vacancy and hiring rates and on average output) typically generates more volatile outcomes, in some cases excessively so; fits the u-v correlation much better; and fits the persistence statistics slightly less well. Moments, and hence model performance, are sensitive to calibrated parameter values, often highly so.

Israeli data indicate a few similarities and some big differences in the dynamics. The similarities include output volatility (slightly more volatile than in the U.S) and the procyclicality of wages (which is about the same across the two economies). The differences are that real wages are more volatile than output (while in the U.S. they are less so), unemployment is far more volatile than output (30 times as much in Israel, 7 times as much in the U.S.), and the variables are much less persistent in Israel. The model does not seem to fit these data for the most part.

The implication, then, is that the model needs to be modified in an attempt to generate a better fit with the data. There are many ways in which this can be attempted. One relates to the formulation of the driving shocks. In particular, the calibration of the log normal idiosyncratic productivity distribution is essential and needs to be based on more solid empirical knowledge (one issue is persistence of these shocks) . Likewise, different calibration of other parameters may yield a better fit; here, too, econometric micro studies may be needed. Another way is to modify the set up of the model. Possibilities include adding capital and capital adjustment costs, interacting with hiring costs (Merz and Yashiv (2007) point to the importance of this aspect of modelling); adding leisure-work choice to the households problem; and allowing for worker search on the job. A third avenue of exploration is to modify the model more substantially, in particular by changing its wage setting mechanism.

6 Conclusions

A DSGE model with search and matching in the labor market has limited success in matching the data for both the U.S. and Israel, despite very different data patterns. Key points of success are the matching of the Beveridge curve relationship; in the U.S., output and unemployment behavior is captured to a great extent; in Israel, output behavior and the persistence of wages is well captured. Beyond these points, the model does not match the volatility, persistence, and co-movement of the variables in question.

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Table 1

Calibration Values

Quarterly

a. Parameters, Exogenous Shocks and Steady State Values

Parameter/Variable	**symbol**	**U.S.**	**Israel**
Utility, CRRA	ω	2	1.4
Discounting	β	0.99	0.99
Worker bargaining	ξ	0.5	0.2
Matching	σ	0.4	0.3
Hiring (convexity)	γ	2	2
Hiring (vacancy weight)	ϕ	0.3	0.3
Unemployment rate	u	0.12	0.07
Job finding rate	P	0.80	0.55
Exogenous separation rate	δ^x	0.068	0.028
Separation rate	δ	0.10	0.04
Persistence of aggregate shock	ρ_A	0.90	0.95
Std of aggregate shock	σ_A	0.0049	0.035
Mean of idiosyncratic shock	μ_{LN}	0	0
Std. of idiosyncratic shock	σ_{LN}	0.12	0.12

b. Implied Values

Parameter/Variable	**symbol**	**U.S.**	**Israel**
Matching scale parameter	μ	0.74	0.72
Hiring scale parameter	Θ	4.72	78.3
Vacancy rate	v	0.14	0.048
Market tightness	$\frac{v}{u}$	1.16	0.69
Matching rate	Q	0.7	0.8

Table 2

Model and Data Moments:

Benchmark

a. U.S.

Relative standard deviations (reative to output)

	data	linear vacancy costs	convex vacancy costs
Output (own s.d)	1.62	1.65	7.78
Real Wages	0.69	0.30	0.42
Unemployment	6.90	4.33	10.63
Vacancies	8.27	1.32	1.23
Market Tightness	14.96	4.19	11.58
JCR	2.55	7.75	14.62
JDR	3.73	7.88	14.77

Autocorrelation

	data	linear vacancy costs	convex vacancy costs
Output	0.87	0.98	0.99
Real Wage	0.91	0.85	0.69
Unemployment	0.91	0.91	0.98
Vacancies	0.92	0.60	0.43
Market Tightness	0.92	0.98	0.99

Correlations

	data	linear vacancy costs	convex vacancy costs
$\rho(w, Y)$	0.57	0.86	0.88
$\rho(u, v)$	-0.95	0.27	-0.72
$\rho(JDR, JCR)$	-0.36	0.51	0.91

b. Israel

Relative standard deviations (reative to output)

	data	**linear vacancy costs**	**convex vacancy costs**
Output (own s.d)	2.20	27.79	1.56
Real Wages	1. 21	0.17	0.31
Unemployment	30. 10	9.74	17.28
Vacancies	–	2.49	4.35
Market Tightness	–	8.23	21.38

Autocorrelation

	data	**linear vacancy costs**	**convex vacancy costs**
Output	0.57	0.98	0.90
Real Wage	0.68	0.98	0.60
Unemployment	0.27	0.98	0.94
Vacancies	–	0.80	0.67
Market Tightness	–	0.98	0.92

Correlations

	data	**linear vacancy costs**	**convex vacancy costs**
$\rho(w, Y)$	0.63	0.99	0.99
$\rho(u, v)$	–	0.68	-0.92

Notes:

1. Linear costs use $\gamma = 0, \phi = 1$.Convex costs use $\gamma = 2, \phi = 0.3$.

Table 3

Model and Data Moments:

Variations

a. Absolute standard deviations

	U.S. data	**benchmark**
Output	1.62	7.89
Real Wage	1.12	3.27
Unemployment	11. 18	83.87
Vacancies	13. 40	9.6
Tightness	24. 24	91.29
JCR	4. 13	115.3
JDR	6. 04	116.6

	U.S. data	$\boldsymbol{\sigma}_{LN} = 0.05$	$\boldsymbol{\sigma}_{LN} = 0.07$	$\boldsymbol{\sigma}_{LN} = 0.09$	$\boldsymbol{\sigma}_{LN} = 0.14$
Output	1.62	3.73	4.55	5.52	13.20
Real Wage	1.12	3.55	2.71	2.61	5.26
Unemployment	11. 18	42.0	46.22	56.29	145.6
Vacancies	13. 40	26.44	14.54	10.32	14.13
Tightness	24. 24	37.61	47.85	60.44	158.9
JCR	4. 13	106.7	79.99	82.93	197.8
JDR	6. 04	100.3	78.46	83.18	198.6

	U.S. data	$\rho_A = 0.99$	$\sigma_A = 0.01$
Output	1.62	43.17	16.45
Real Wage	1.12	16.09	6.77
Unemployment	11.18	466.6	174.8
Vacancies	13.40	43.49	19.91
Tightness	24.24	510	190.4
JCR	4.13	630.8	239.7
JDR	6.04	632.5	242.6

	U.S. data	$\eta = \mathbf{0.05}$	$\eta = \mathbf{0.95}$
Output	1.62	3.16	6.47
Real Wage	1.12	0.23	6.24
Unemployment	11.18	23.88	90.5
Vacancies	13.40	9.92	28.94
Tightness	24.24	33.80	62.13
JCR	4.13	19.30	184.8
JDR	6.04	21.23	185.6

	U.S. data	$\rho_x = 0.077$ $q = 0.7$ $p = 0.8$ $u = 0.12$	$\rho_x = 0.035$ $q = 0.98$ $p = 0.8$ $u = 0.06$
Output	1.62	5.57	9.56
Real Wage	1.12	2.90	3.89
Unemployment	11.18	61.71	228.3
Vacancies	13.40	7.66	6.80
Tightness	24.24	64.45	229.9
JCR	4.13	96.44	332.3
JDR	6.04	96.74	335.3

b. Autocorrelation

	U.S. data	**benchmark**
Output	0.87	0.99
Real Wage	0.91	0.69
Unemployment	0.91	0.98
Vacancies	0.92	0.43
Market Tightness	0.92	0.99

	U.S. data	$\sigma_{LN} = 0.05$	$\sigma_{LN} = 0.07$	$\sigma_{LN} = 0.09$	$\sigma_{LN} = 0.14$
Output	0.87	0.98	0.986	0.99	0.99
Real Wage	0.91	-0.53	-0.12	0.32	0.89
Unemployment	0.91	0.50	0.87	0.96	0.97
Vacancies	0.92	-0.74	-0.53	-0.16	0.81
Tightness	0.92	0.95	0.985	0.99	0.99

	U.S. data	$\rho_A = 0.99$	$\sigma_A = 0.01$
Output	0.87	0.99	0.99
Real Wage	0.91	0.99	0.71
Unemployment	0.91	0.99	0.98
Vacancies	0.92	0.98	0.47
Tightness	0.92	0.99	0.99

	U.S. data	$\eta = \mathbf{0.05}$	$\eta = \mathbf{0.95}$
Output	0.87	0.99	0.99
Real Wage	0.91	0.99	0.90
Unemployment	0.91	0.99	0.99
Vacancies	0.92	0.99	0.95
Tightness	0.92	0.99	0.99

	U.S. data	$\rho_x = 0.077$ $q = 0.7$ $p = 0.8$ $u = 0.12$	$\rho_x = 0.035$ $q = 0.98$ $p = 0.8$ $u = 0.06$
Output	0.87	0.99	0.99
Real Wage	0.91	0.42	0.76
Unemployment	0.91	0.97	0.99
Vacancies	0.92	-0.23	-0.20
Tightness	0.92	0.99	0.99

c. Correlations

	U.S. data	**benchmark**
$\rho(w, Y)$	0.57	0.88
$\rho(u, v)$	-0.95	-0.72
$\rho(JDR, JCR)$	-0.36	0.91

	U.S. data	$\boldsymbol{\sigma}_{LN} = 0.05$	$\boldsymbol{\sigma}_{LN} = 0.07$	$\boldsymbol{\sigma}_{LN} = 0.09$	$\boldsymbol{\sigma}_{LN} = 0.14$
$\rho(w, Y)$	0.57	0.30	0.56	0.74	0.96
$\rho(u, v)$	-0.95	0.48	0.01	-0.35	-0.91
$\rho(JDR, JCR)$	-0.36	-0.36	0.35	0.72	0.97

	U.S. data	$\boldsymbol{\rho}_A = 0.99$	$\boldsymbol{\sigma}_A = 0.01$
$\rho(w, Y)$	0.57	0.995	0.89
$\rho(u, v)$	-0.95	-0.996	-0.74
$\rho(JDR, JCR)$	-0.36	0.991	0.92

	U.S. data	$\boldsymbol{\eta} = \mathbf{0.05}$	$\boldsymbol{\eta} = \mathbf{0.95}$
$\rho(w, Y)$	0.57	0.998	0.95
$\rho(u, v)$	-0.95	-0.999	0.98
$\rho(JDR, JCR)$	-0.36	0.84	0.97

	U.S. data	$\rho_x = 0.077$ $q = 0.7$ $p = 0.8$ $u = 0.12$	$\rho_x = 0.035$ $q = 0.98$ $p = 0.8$ $u = 0.06$
$\rho(w, Y)$	0.57	0.776	0.91
$\rho(u, v)$	-0.95	-0.29	-0.22
$\rho(JDR, JCR)$	-0.36	0.81	0.97