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Abstract

This paper estimates a stylized search and matching model on data for Australia covering the period 1978-2008. Using Bayesian methods we find that the model does a fairly good job in replicating the data. Surprisingly, we find a large value for the worker's bargaining power and low vacancy posting costs. The model generates a strong Beveridge curve and matches the standard deviations of all variables but vacancies. We identify technology and separation shocks to be the main driver of fluctuations.

Keywords: Bayesian Methods, Business Cycle Fluctuations, Search and Matching, Unemployment.

JEL codes: C11, E24, E32, J6.

*I am grateful for the comments of one anonymous referee that helped to improve the paper. All remaining errors are my own.

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1 Introduction

The Australian labour market has performed exceptionally well over the past decades and, in particular, during the global financial crisis. Its unemployment rate is among the lowest in all OECD countries and structural unemployment remains unaffected, while it increases in the OECD. Moreover, Australia is a perfect example of a small open economy. Therefore, labour market dynamics in Australia are particularly interesting for economists and policy makers around the world. It is interesting to compare the results across countries and identify substantial differences that cause different evolution of key variables. Unfortunately, the search and matching literature has mainly focused on the United States and Europe.[1] In this paper we estimate a canonical search and matching model for the Australian economy.

This study aims at estimating deep parameters of the search model to shed light on the underlying properties and describing cyclical fluctuations using Bayesian techniques. For this purpose, we will estimate a set of key parameters that drive labour market dynamics. Hence, we provide evidence for parameters that are otherwise hard to calibrate (such as bargaining power or the elasticity of the matching function), which increases the usefulness of this model to study and predict labour market dynamics. Further, we analyze the source and size of fluctuations and evaluate the ability of the search and matching model to replicate cyclical patterns of the Australian labour market.

We find several interesting results. First, we find that all parameters are tightly estimated and shifted away from their respective priors. Therefore, the data set is informative and the parameters are identified. The worker's bargaining power is surprisingly large (roughly 0.8) compared with other empirical studies that find values between 0 and 0.3 for the United States. On average, we observe a low unemployment rate which is driven by low vacancy posting costs and low - but volatile - separations. Further, our results indicate that both margins - the creation and the destruction margin - are subject to large cyclical fluctuations.

Moreover, the estimated model is able to generate the empirically observed second moments fairly well. The only exception is the volatility of vacancies which is much too low. Nevertheless, the model replicates a quite strong Beveridge curve, viz. the negative relation between unemployment and vacancies.

Turning to the driving forces of fluctuations in the labour market, we find that out of the four shocks at hand, we find that the technology shock and the separation rate shock are the main driver of key variables. The technology shock is more important for output and vacancies, while the separation shock is more important for (un)employment and matches. Overall, we find that labour market variables show a large degree of interdependence. In addition, we find that over the short-run output is driven by technology and separation shocks, while over the long-run technology shocks clearly dominate. Unemployment is - over the short-run - almost entirely driven

[1]However, there a two exceptions. Lubik (2011) as well as Lin and Miyamoto (2012) estimate a search and matching model on unemployment and vacancy data for Hong Kong, Japan respectively.

by separation shocks, while in the long-run technology innovations explain roughly 20 percent of variation in unemployment.

The paper by Sheen and Wang (2012) estimates a small-open economy New Keynesian model with labour market frictions based on Blanchard and Galí (2010). This set-up is different to the search and matching model, since it does not rely on a matching function and vacancy posting. Here, in each period a constant share of the work force is separated, while hiring is costly for the firm. Hiring costs depend on the state of the labour market and creating frictions that generate equilibrium unemployment. They find significant evidence of hiring costs in the Australian labour market, being in the size of roughly one percent of GDP. Further, they show that the variance of unemployment is initially mainly driven by the technology shock, while over the long-run the labour supply preference shock dominates. For output, they find a key role for demand shocks over the short run, while the technology and the labour supply preference shock dominate over the long-run.

Further, our results add to the findings by Ponomareva and Sheen (2010) estimating transition probabilities in the labour market. They find that employment-to-unemployment transition rates are countercyclical but insignificantly large in a recession. On the contrary, unemployment-to-employment transitions are procyclical and quite important in a recession. This shows that during recessions job-finding rather than job-losing is the key problem.

Our results strongly contradict the findings by Chindamo and Uren (2010). They use a calibrated search and matching model to assess its ability to replicate empirically observed second moments. They find that the model is not able to generate enough volatility of key variables. In particular, the model is not able to match the standard deviation of unemployment and vacancies, as well as the negative correlation between them, while our model only does a bad job in replicating the volatility of vacancies. This crucial differences can be explained by the differences in methodological approaches. As we use an estimated instead of a calibrated model, we are able to generate dynamics that match the empirical observations. As a key difference, Chindamo and Uren (2010) calibrate vacancy posting cost to be 0.12, while the estimation gives a value of 0.01.[2] Hence, the search and matching model does, in fact, a fairly good job in replicating observed dynamics.

The paper is structured as follows. The next section derives the model and section 3 presents the data and calibrates the model and discusses the prior selection. Then, section 4 discusses the parameter estimates and analyzes the sources of fluctuations in the labour market. Moreover, we discuss the model's response to a technology and a separation shock. Finally, section 5 concludes.

2 Model Derivation

The description of our model economy proceeds in three steps and follows Prescott's narrative approach. First, we define the economy's preferences and technology and then present the underlying

[2] Other key parameters such as the opportunity costs in the bargaining process or the separation rate are similar across the two papers.

market structure. Finally, we derive the first-order necessary conditions and conclude with the definition of an equilibrium.

2.1 Preferences and Technology

We now present a general equilibrium model with flexible prices and labour market frictions in discrete time. Our economy inhibits two different agents; households and firms. The labour market is imperfect due to the assumption of search and matching frictions following Mortensen and Pissarides (1994).

2.1.1 Households

We assume that our economy is populated by a continuum of infinitively-lived, homogeneous households. Each household consists of a continuum of family members of measure one. They equally share total income and risk among all family members as in Merz (1995). Households preferences are represented by the following utility function

$$\mathbb{E}_t \sum_{t=0}^{\infty} \beta_t \gamma_t \ln(C_t), \tag{1}$$

where $\beta \in (0, 1)$ is the discount factor and $\mathbb{E}_t$ denotes the mathematical expectation operator. Consumption is denoted by C_t and γ_t denotes a preference shock that follows a first-order autoregressive process

$$\ln \gamma_t = \varrho_\gamma \ln \gamma_{t-1} + e_{\gamma,t}, \tag{2}$$

where $0 < \varrho_\gamma < 1$ is the autocorrelation term and its innovation is i.i.d. over time and normally distributed

$$e_{\gamma,t} \sim N(0, \sigma_\gamma). \tag{3}$$

2.1.2 Firms

Our economy is populated by a continuum of identical firms. They use the following production technology

$$Y_t = Z_t N_t^\alpha, \tag{4}$$

to produce goods. Here, $0 < \alpha < 1$ determines the curvature of technology in labour. Further, Z_t is a Hicks-neutral aggregate technology shock following a first-order autoregressive process

$$\ln Z_t = \varrho_Z \ln Z_{t-1} + e_{Z,t}, \tag{5}$$

where $0 < \varrho_Z < 1$ is the autocorrelation term and its innovation is i.i.d. over time and normally distributed

$$e_{Z,t} \sim N(0, \sigma_Z). \tag{6}$$

2.2 Market Structure

While the good market is perfectly competitive, the labour market is imperfect due to the assumption of search and matching frictions. Trade in the labour market is uncoordinated, costly, and time-consuming. Search takes place on a discrete and closed market. Workers can be employed or unemployed. Firms have one job that is either filled or vacant. If the job is filled, it is subject to the probability of being destroyed at the rate ρ_t. We assume that the separation rate follows an AR(1) process

$$\ln \rho_t = \varrho_\rho \ln \rho_{t-1} + e_{\rho,t}. \tag{7}$$

Again, the autocorrelation term is denoted by $0 < \varrho_\rho < 1$ and the innovation term, $e_{\rho,t}$, is i.i.d. over time and normally distributed,

$$e_{\rho,t} \sim N\left(0, \sigma_\rho\right). \tag{8}$$

Along the hiring margin, firms create jobs at the rate $M\left(U_t, V_t\right)$ at the non-state-contingent cost of $c > 0$ units of output per vacancy, where M is the homogeneous-of-degree-one-matching-function,

$$M\left(U_t, V_t\right) = m_t U_t^\mu V_t^{1-\mu}. \tag{9}$$

We assume that m_t gives the time-varying match efficiency which is assumed to be driven by an AR(1) process

$$\ln m_t = \varrho_m \ln m_{t-1} + e_{m,t}, \tag{10}$$

where $0 < \varrho_m < 1$ and $e_{m,t}$ is i.i.d. over time and normally distributed,

$$e_{m,t} \sim N\left(0, \sigma_m\right). \tag{11}$$

Further, $\mu > 0$ is the elasticity of the matching function with respect to unemployment and V_t is the vacancy rate. The vacancy-to-unemployment ratio, $\theta_t = V_t/U_t$, reflects labour market tightness. Then, the job matching rate is

$$q\left(\theta_t\right) = \frac{M\left(U_t, V_t\right)}{V_t} = m_t \theta_t^{-\mu}, \tag{12}$$

and the job finding rate is

$$p\left(\theta_t\right) = m_t \theta_t^{1-\mu}. \tag{13}$$

Combining entry and exit definitions yields the evolution of employment

$$N_t = \left(1 - \rho_t\right)\left(N_{t-1} + M_{t-1}\right). \tag{14}$$

Similarly, the evolution of aggregate unemployment can be written as

$$U_t = 1 - N_t. \tag{15}$$

2.3 Optimization and Equilibrium

Optimization of all agents defines the equilibrium. We start with the households utility maximization problem and continue with the firms profit maximization problem. Then, we solve the bargaining problem between firm and worker and determine the optimal wage. We conclude with a definition of the equilibrium.

2.3.1 Households

We assume that the economy begins with all households having identical financial wealth and consumption histories. This assumption assures that this homogeneity will continue and it allows us to only consider the optimal decisions of a representative household. The representative household faces the following budget constraint

$$C_t + T_t = W_t N_t + bU_t, \tag{16}$$

where unemployment benefits b are financed by lump-sum taxes, T_t, while W_t denotes the real wage. Then, the household maximizes (1) subject to (16), which gives the standard first-order condition for consumption

$$\frac{\gamma_t}{C_t} = \lambda_t, \tag{17}$$

where λ_t is the marginal utility of consumption.

2.3.2 Firms

The representative firm in our economy solves its profit maximization problem by choosing the optimal path for $\{N_t, V_t\}_{t=0}^{\infty}$ by maximizing

$$\mathbb{E}_t \sum_{t=0}^{\infty} \beta^t \lambda_t \left[Z_t N_t^{\alpha} - W_t N_t - cV_t \right], \tag{18}$$

subject to the evolution of employment eq. (14). The term in parenthesis gives real revenue depleted by total wage costs and vacancy posting costs.

The first-order necessary conditions are

$$\begin{aligned} \partial N_t : \tau_t &= \alpha \ \frac{Y_t}{N_t} - W_t + \mathbb{E}_t \left\{ (1-\rho_t) \beta_{t+1} \tau_{t+1} \right\}, & (19) \\ \partial V_t : c &= \ \mathbb{E}_t \left\{ \beta_{t+1} (1-\rho_t) q(\theta_t) \tau_{t+1} \right\}, & (20) \end{aligned}$$

where $\beta_{t+1} = \beta \frac{\lambda_{t+1}}{\lambda_t}$ is the stochastic discount factor and τ_t is the multiplier on the evolution of employment. Using these two equations yields the job creation condition

$$\frac{c}{q(\theta_t)} = \mathbb{E}_t \left\{ (1-\rho_t) \beta_{t+1} \left[\alpha \frac{Y_{t+1}}{N_{t+1}} - W_{t+1} + \frac{c}{q(\theta_{t+1})} \right] \right\}. \tag{21}$$

The left-hand side of this equation gives the hiring costs which equal the benefits of creating a new job. The latter depends on the marginal product of labour depleted by the wage and increased by saved hiring costs in the next period in case of non-separation.

2.3.3 Wage Bargaining

We will follow the mainstream of the search and matching literature (e.g. Trigari (2006) and Krause and Lubik (2007)) and assume that wages are determined by individual Nash bargaining. The surplus created by the match is split by maximizing the Nash product

$$W_t = \underset{\{W_t\}}{\arg\max} \left[(\mathcal{W}_t - \mathcal{U}_t)^{\eta} (\mathcal{J}_t - \mathcal{V}_t)^{1-\eta} \right]. \tag{22}$$

The first term is the worker's surplus, the latter term is the firm's surplus, and $0 \leq \eta \leq 1$ is the exogenously determined, constant relative bargaining power.

Let us determine the value functions describing the worker's options, $\mathcal{W}_t$ and $\mathcal{U}_t$. In terms of a Bellman equation the value of being employed for the worker, $\mathcal{W}_t$, is

$$\mathcal{W}_t = W_t + \mathbb{E}_t \beta_{t+1} \left[\left(1 - \rho_{t+1}\right) \mathcal{W}_{t+1} + \rho_{t+1} \mathcal{U}_{t+1} \right]. \tag{23}$$

The value consists of the wage, the discounted continuation value of being employed in the next period, and - conditional on being laid-off - the value of being unemployed, $\mathcal{U}_t$.

This value function can be written as

$$\mathcal{U}_t = b + \mathbb{E}_t \beta_{t+1} \left[\theta_t q\left(\theta_t\right) \left(1 - \rho_{t+1}\right) \mathcal{W}_{t+1} + \left(1 - \theta_t q\left(\theta_t\right) \left(1 - \rho_{t+1}\right)\right) \mathcal{U}_{t+1} \right], \tag{24}$$

which is driven by the value of unemployment payments, b, the discounted continuation value of being unemployed, and, if she is matched, she receives the value of future employment.

Moreover, let us determine the firm's options. Due to a free entry condition the equilibrium value of $\mathcal{V}_t$ will be driven to zero. For the firm the asset value of the job, $\mathcal{J}_t$, is equal to the multiplier on the evolution of employment eq. (19). It depends on the real revenue, the wage, and if the job is not destroyed, the discounted future value. Otherwise, the job is destroyed and hence has zero value. The asset value is given by

$$\mathcal{J}_t = \alpha \frac{Y_t}{N_t} - W_t + \mathbb{E}_t \left[(1 - \rho_t) \beta_{t+1} \mathcal{J}_{t+1} \right]. \tag{25}$$

Then, the individual real wage satisfies the optimality condition

$$\mathcal{W}_t - \mathcal{U}_t = \frac{\eta}{1 - \eta} \mathcal{J}_t. \tag{26}$$

Substituting in the value functions gives an explicit expression for the wage

$$W_t = \eta \left(\alpha \frac{Y_t}{N_t} + c\theta_t \right) + (1 - \eta)\, b. \tag{27}$$

The wedge between the real wage and the reservation wage is increasing in every time-dependent component and the worker's bargaining power.

2.3.4 Equilibrium

We define an equilibrium in our economy as follows.

Definition

An equilibrium for given initial conditions, the stochastic processes $\{Z_t, \rho_t, \gamma_t, m_t\}$ and a set of prices $\{W_t\}$, is a tuple of processes for $\{C_t, Y_t, V_t, M_t, N_t, U_t, \theta_t, \lambda_t\}$ such that

1. Household optimality

Given $\{W_t\}$ the process for $\{C_t\}$ solve the optimization problem, maximizing (1) subject to (16).

2. Profit maximization

The processes for $\{Y_t, V_t, M_t, N_t, U_t, \theta_t, \lambda_t\}$ solve the firm maximization problem, maximizing (18) subject to (12), and (14). Further they obey labour market restrictions (9) and (15).

3. Wage determination

Firm and worker engage in Nash bargaining and wages are set according to (27).

4. Market clearing

In the symmetric equilibrium, factor and goods market clear and any feasible allocation must satisfy the aggregate resource constraint

$$Y_t = C_t + cV_t. \tag{28}$$

As common in the literature, we assume that the consumption good is used to pay vacancy posting costs. Furthermore, the government pays unemployment benefits and finances them by collecting lump-sum transfers, i.e. runs a balanced budget at all times. Then, the set of equations forming the equilibrium is linearized around the non-stochastic steady-state.

3 Estimation

3.1 Data

For our estimation the set of available time series consists of output, consumption, employment, unemployment, wages, vacancies, and investment. All time series are taken from the Reserve Bank of Australia. Our sample covers the period from 1978:Q3 to 2008:Q2, which gives us 120 observations. We use quarterly, seasonally adjusted series and chain volume measures in 2009/10 Australian Dollar. Then, all time series are written in logarithmic scale and are detrended using a Hodrick-Prescott filter with $\lambda = 1600$.

Output (GGDPECCVGDP) is measured by the by the gross domestic product and consumption (GGDPECCVPSH) is private household consumption. The time series for employment (GLFSEPTSA) and unemployment (GLFSUPSA) are on a monthly basis, aggregated to a quarterly basis. Wages (GLCAWE) are measured by the time series for average weekly earnings for all employees.

Moreover, the time series provided for vacancies (GLFOSVT) is based on survey evidence covering all Australian employers, except the farm sector and private households.

3.2 Calibration and Prior Selection

The calibration is on a quarterly basis, summarized in table 1.

Table 1: Calibration and prior selection.

Parameter	Value	Parameter	Value	Std	Family
β	0.99	α	2/3	0.1	Beta
N	0.9	ρ	0.05	0.01	Beta
U	0.1	η	0.5	0.05	Normal
m	0.4	μ	0.4	0.01	Beta
q	0.7	c	0.05	0.01	Gamma
b	0.61				

The discount factor β, is set to its standard value of 0.99, implying an interest rate of 4 percent per annum. The unemployment rate is set to 10 percent, which is larger as the current unemployment rate in Australia of 5.4 percent. This relatively high value of steady state unemployment reflects the shortcoming of the unemployment rate namely the nonconformity of effective searchers and unemployed workers as in Cole and Rogerson (1999). Employment is then given by $N = 1-U$. Then, steady state matches are given by $M = \frac{\rho}{1-\rho}N$.

The job finding rate, q, is set to 0.7 which is in line with Chindamo and Uren (2010). Using the calibrated values, we can use the equation for the law of employment, the matching function, and the definition of labour market tightness to find the steady state value of labour market tightness, $\theta = \left[\frac{1-U}{U}\frac{\rho}{1-\rho}\frac{1}{m}\right]^{\frac{1}{1-\mu}}$. Then, vacancies can be found by using $V = \theta U$. Further, the value for unemployment benefits, b, is found by using the job creation condition,

$$b = \alpha\frac{Y}{N} - \frac{\frac{c}{m}\left[1-(1-\rho)\beta\right]}{(1-\rho)(1-\eta)\beta}\theta^{\mu} - \frac{\eta}{1-\eta}\kappa\theta. \tag{29}$$

Given the values of the other parameters, we find a value of 0.61 for b, which gives a replacement ratio, b/W, of 0.89, where steady state wages are taken from eq. (27).

We aim at estimating several deep parameters describing the labour market as well as the underlying shock processes. In what follows, we describe our prior specifications.

For the labour share, we choose a beta distribution with mean 2/3 and standard deviation 0.1. This value is close to the average labour share in Australia (see Bentolila and Saint-Paul (2003)). Vacancy posting costs are assumed to be gamma distributed with mean 0.05 and standard deviation 0.01, which is an average value between low (0.01) and high (0.1) vacancy posting costs.

Further, for the bargaining power we impose that it is normally distributed with mean 0.5 and standard deviation 0.05. Therefore, we assume symmetric bargaining in the first place. The prior density of ρ, the parameter that governs separations in steady state, belongs to the beta family and has a mean of 0.05 and a standard deviation of 0.01. This prior is in line with the calibration of Chindamo and Uren (2010). Then, the elasticity of the matching function μ, is assumed to be beta distributed with mean 0.4 and standard deviation 0.01.

Let us now turn to the priors related to our four exogenous processes. First, we set the priors for the autocorrelation parameters. We assume that the autocorrelation parameters in the AR processes follow beta distributions with mean 0.9 and standard deviation 0.05. Finally, all standard deviations of the underlying shocks are assumed to follow an inverse Gamma distribution with mean 0.1 and standard deviation 1.

4 Results

The empirical (macro) literature focused on developing and applying full information Bayesian techniques to estimate even large-scale DSGE models. However, there exists a trade-off between the estimation of small structural models and the estimation of large structural models. The estimation of small and therefore stylized models may lead to misspecifications, while estimating large models could lead to identification problems. Bayesian methods are capable of dealing with both problems. We apply those standard Bayesian techniques to estimate the search and matching model presented on Australian labour market data. To obtain our results, we use four MCMC chains with 250.000 draws each.

4.1 Posteriors

In this section we discuss the posterior estimates and the implications for labour market dynamics. Table 2 presents the posterior estimates as well as the 95 % confidence bands for the five deep parameters and the eight parameters describing the exogenous processes. In addition, figure 1 presents the prior and posterior density functions for selected parameters. We observe that the posterior estimates are significantly shifted away from the prior assumptions which, given that all parameters are tightly estimated, implies that the data is informative and the parameters are identified.

The posterior mean of the separation rate is 0.07. The 5th and 95th percentiles are 0.05, 0.09 respectively. Furthermore, the elasticity of the matching function with respect to unemployment, μ, is estimated to be 0.4, with the 5th and 95th percentiles are 0.38, 0.42 respectively. Those two parameters allow us to draw conclusions about the ins and outs of unemployment. We find that the separation rate is almost half of the estimated rate for the United States by Lubik (2009) of 0.12. Further, the estimated standard deviation of the separation rate in Australia is 0.21, while it is roughly 0.1 in the U.S. economy. Hence, while separations are low on average, they increase significantly when the economy enters a recession. Moreover, in the following upswing separations

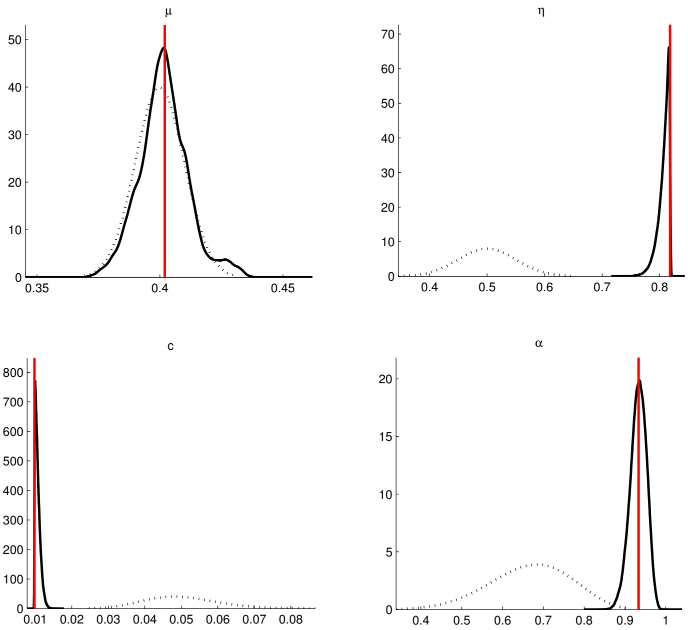

Figure 1: Prior and posterior density for selected parameters.

decrease as rapidly as before, hence, creating a low mean.

While we have discussed the inflow into unemployment, let us turn to the outflow of unemployment. In the search and matching model at hand, it is driven by the creation of new matches. As we have discussed before, the job matching rate is eq. (12), while the job finding rate is given by eq. (13). Both equations are mainly driven by the elasticity parameter, μ, which is much lower compared with the estimate for the United States of 0.74 by Lubik (2009). A low value of the elasticity parameter μ implies that on the one hand, the finding rate reacts more elastically to changes in labour market tightness. Put differently, the finding rate reacts stronger to changes in the labour market. As a consequence, it is easier for job seekers to exit unemployment compared to the United States. On the other hand, the matching rate is less sensitive to changes in labour market conditions and hence, firms vacancy posting decisions (see the job creation condition eq. (21)) are less affected by changes in labour market tightness.

Our estimate for vacancy posting costs c, has a median value of 0.01, with the 5th and 95th percentiles of 0.0098 and 0.0117. In contrast to the existing literature (see e.g. Lubik (2009, 2011)) we are able to identify this parameter. While this parameter is usually calibrated to a value close to 0.05 for the U.S. we obtain a much lower value of 0.01 for Australia. It implies significantly lower costs of posting vacancies and, hence, firms have more incentives to post vacancies compared with the U.S. economy. Further, if the economy enters a recession, firms will have less incentives to reduce vacancy posting activities compared with the U.S. economy. Along this line, in the following upswing low vacancy posting costs will lead to more vacancies posted as in the United States and more jobs created.

Next, we want to discuss the estimate for the worker's bargaining power, η. The posterior mean is 0.81 and the 95 % confidence interval is $[0.79, 0.82]$. This result is particularly surprising, as the estimates for the United States is 0.03. The implications are severe: while in the U.S. almost the entire surplus goes to the firm, in Australia 80 percent of the surplus generated by the match goes to the worker and only 20 percent are left for the firm. This might explain the low value obtained for vacancy posting costs, as firms have less incentives to post vacancies if their share of the surplus is small. Hence, a low value of vacancy posting costs will compensate for the small surplus share.

The estimate of the elasticity of the production function, α, is 0.92 which implies less curvature of the production function.

Finally, we want to discuss the posterior estimates of the underlying disturbances. For the autocorrelation parameters, we find that the values are close to 0.9 for most shocks. The only exception is the shock to the separation rate which shows a persistence coefficient of 0.63. Nevertheless, the results imply that the search and matching model generates a strong internal propagation mechanism that is able to replicate the persistence in the data, which is in line with the results for the U.S. by Lubik (2009). However, the relatively low value of persistence in the separation rate is in contrast with the results by Lubik (2011). He finds that the separation rate is an autocorrelated process with AR(1) parameter of 0.86 for Hong Kong. In contrast, Lin and Miyamoto (2012) find a much lower value of persistence (0.31) of the separation shock for Japan. In Australia we find an intermediate value for the exogenous persistence of the separation shock.

For the standard deviation of shocks we find that the separation rate shock is the most volatile one, which is a consistent finding with the low persistence and our description of the ins and outs of unemployment. Along this line, we find that the shock to the match efficiency is also much more volatile than the preference shock and the technology shock.

In Japan, we find that technology and separation shocks have nearly the same standard deviation of 0.03. Therefore, the technology shock in Australia is three times as volatile in Japan, while the separation shock is five times less volatile. In summation, we can draw the conclusion that the

Table 2: Posterior estimates.

Parameter	Mean	5 %	95 %	Parameter	Mean	5 %	95 %
ρ	0.07	0.05	0.09	ϱ_m	0.86	0.78	0.93
μ	0.40	0.38	0.42	ϱ_γ	0.90	0.86	0.95
c	0.01	0.01	0.01	σ_Z	0.01	0.01	0.01
η	0.81	0.79	0.82	σ_ρ	0.16	0.11	0.21
α	0.93	0.90	0.97	σ_m	0.10	0.05	0.14
ϱ_Z	0.92	0.87	0.97	σ_γ	0.08	0.04	0.12
ϱ_ρ	0.63	0.55	0.72				

Australian labour market has a low average unemployment rate driven by low vacancy posting

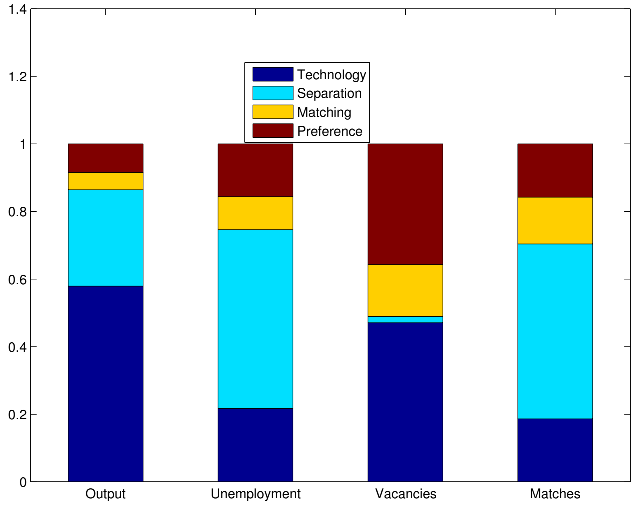

Figure 2: Unconditional variance decomposition.

costs and low but volatile separations. Both margins - the creation and the destruction margin - are subject to large cyclical fluctuations.

4.2 Variance Decomposition

In the following we want to discuss the main driving forces of business cycle fluctuations in the Australian labour market. Figure 2 presents the unconditional variance decomposition.

We only present the unconditional variance decomposition for four variables, as the decomposition for output and consumption is virtually identical as well as the decomposition for unemployment and employment is identical. Further, and by construction, separations are entirely driven by the underlying exogenous process.

We find that output is mainly driven by the technology shock (almost 60 percent of total variation), while the separation shock explains roughly 25 percent. The remaining 15 percent are jointly explained by the preference and matching shock. Compared with the U.S. we find that the technology shock is slightly less important, as it explains 71 percent of variation in output according to Lubik (2009).

For unemployment, we find that the technology shock explains almost 20 percent of total variation, while the separation shock seems to be the main driver, explaining more than 50 percent. Further, the remaining percentages are explained by the preference shock and the matching shock. As for output, the preference shock is slightly more important than the matching shock. This contradicts the finding of Lubik (2009) that the matching shock explains 92 percent of the variation in unemployment in the United States.

Turning to vacancies, we find that the technology shock drives roughly 50 percent of the variation, while the preference shock explains a share of more than 30 percent. The matching shock is much more important than the separation shock, while they jointly only account for roughly 20

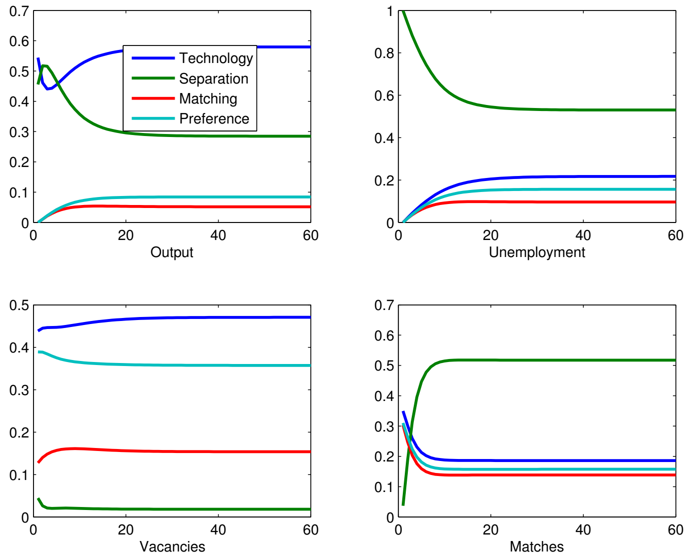

Figure 3: Conditional variance decomposition for 60 quarters.

percent. This finding is consistent with the findings for the U.S. by Lubik (2009), which can be explained by the channel through which the preference shock (as being a demand side shock) operates. It mainly affects the stochastic discount factor in the job creation condition and, therefore, the discounted value of a job.

Matches are mainly driven by the separation shock, while the technology and preference shock jointly explain roughly 30 percent of variation. Surprisingly, the matching shock only explains as little as 15 percent of total variation in matches.

Let us now turn to the conditional variance decomposition of key variables over 60 simulated quarters presented in figure 3.

For output, we observe that the technology shock and the separation shock are almost equally important on impact, while in the long-run the technology shock clearly is the main driver of total variation. Moreover, we observe that for roughly five quarters the separation shock even explains more variation than the technology shock before the technology shock takes over. Matching and preference shock explain almost no variation in output on impact, but gain over time.

For (un)employment we find that the separation shock explains almost all of the variation on impact. However, its share of total variation decreases rather quickly and converges to roughly 60 percent as explained above. On the contrary, the other three shocks generate no variation on impact, but quickly become more and more important. As discussed, the technology shock is more important than the preference shock and the matching shock. The composition of variation in vacancies does not vary too strongly over time. We already know that the technology shock and the preference shock jointly explain roughly 80 percent of total variation. The matching shock adds another 15 percent and the remaining 5 percent are generated by variation in the separation rate. Over time, the technology and the matching shock become slightly more important, while the two

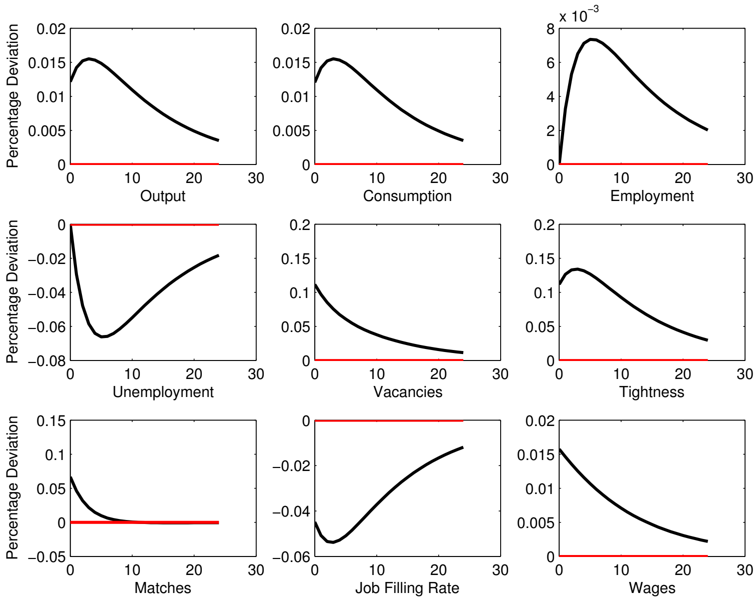

Figure 4: Technology shock. Horizontal axes measure quarters, vertical axes deviations from steady state.

other shock lose some explanatory power.

Finally, the shock to the separation rate explains 50 percent of total variation in matches over the long-run, but is almost of no importance on impact. It strongly gains over time, as the other three shocks jointly, and at the same pace, lose importance. Each one of the remaining three shocks explains around 20 percent of variation, where the technology shock explains a bit more and the matching shock explains a bit less than the preference shock.

Out of the four shocks, we find that the technology shock and the separation rate shock are the main driver of key variables. The technology shock is more important for output and vacancies, while the separation shock is more important for (un)employment and matches. We also find differences in the importance of shocks over the short- and long-run. While technology and separation shock are equally important for the variation in output over the short-run, the technology shock clearly dominates over the long-run. Similarly, unemployment is mainly driven by innovations to the separation rate in the short-run, while the other shocks gain in the long-run. Overall, we find that labour market variables show a large degree of interdependence.

4.3 Impulse Responses

In this section we want to discuss the reaction of our model to innovations in aggregate technology and the separation rate. We choose those two shocks as they appear to be the main drivers of the Australian labour market. Figure 4 presents the estimated impulse response functions for a positive technology shock.

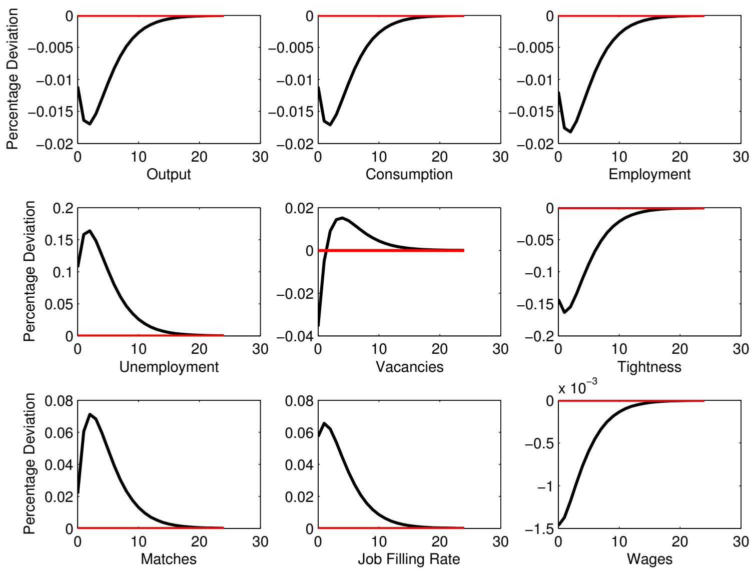

Figure 5: Separation shock. Horizontal axes measure quarters, vertical axes deviations from steady state.

An increase in productivity shifts the production frontier outside and the firm is able to produce more output. Higher output and consumption will create an incentive for the firm to raise the employment level. As the job destruction margin is exogenous, the entire adjustment process has to take place via the job creation margin. Hence, we find that firms start posting vacancies such that the number of matches increases. The job filling (or matching) rate decreases, as vacancies increase more strongly than matches do. Intuitively, if a firm posts a vacancy it decreases the probability for other firms to fill a vacancy (congestion externality). This can also be seen in the increase in labour market tightness. Overall, we find that increased vacancy posting activities lead to higher employment and lower unemployment. Finally, optimal wage setting implies that the firm and worker share surpluses and, hence, wages increase in response to the shock.

Further, we observe a large hump-shaped behaviour in all variables but wages and matches. This is another indication that the - stylized - model generates enough internal propagation to generate persistent adjustment paths.

Let us turn to figure 5 presenting the response of our model economy to an innovation in the separation rate.

Intuitively, an increase in the separation rate will increase the outflow of jobs. Hence, we observe that unemployment increases, as the firm is not able to counter the adverse effects of separations by increased hiring (as hiring will only be effective in the next period). As a consequence, employment decreases which directly spills-over to the production function, shifting the production frontier inside. Hence, output and consumption decrease. Vacancies decrease as the marginal product of labour decreases and, mainly, because the separation rate increases which reduces the expected, discounted value of a worker. Further, lower vacancy posting and higher unemployment decrease labour market tightness. Higher unemployment implies a larger pool of job searchers which causes negative search externalities for other searchers, i.e. reduces the job finding probability of all other searchers. Nevertheless, the increase in unemployment is larger than the drop in vacancies such that, via the matching function, more matches are created, since more searchers are on the market. Therefore, matches increase and the job filling rate increases. Finally, a lower marginal product of labour and lower labour market tightness decrease the cyclical component in the wage equation driving dower optimal wages. Again, we find a large internal propagation mechanism, generating large hump-shaped behaviours.

4.4 Second Moments

In this section we want to assess the ability of our estimated search and matching model to replicate observed second moments. Table 3 presents the relative standard deviations of key variables w.r.t. output and the corresponding values taken from the estimated model. The moments obtained for the data are constructed from the time series discussed in section 3.1. We write the time series in logarithmic terms, HP-filter them, and compute the standard deviation of each time series relative to output.

We find that the standard deviation of unemployment in the data (7.20) is fairly well replicated by the model (7.07). Similarly, we find that the model replicates the volatility of employment fairly well (0.96 vs. 0.79). However, while the model fits unemployment, it fails to match the volatility of vacancies. In the data, the standard deviation is 13.26 but is 5.23 in the model. This is a consequence of our estimate for the bargaining power η. It seems to be a broad consensus (see e.g. Hagedorn and Manovskii (2008)) that a low bargaining power and a high outside option are needed to replicate the second moment of vacancies. As we estimate a very large value of the bargaining power, the model fails to match the volatility of vacancies. This also implies that the model can not match the volatility of labour market tightness (18.91 vs. 10.02).

Moreover, we find that the model does a good job in replicating the standard deviation of wages (0.84 vs. 0.60). Finally, the model is able to generate the negative correlation between unemployment and vacancies, the well-known Beveridge curve. However, the Beveridge curve generated by the model is significantly less strong as in the data (-0.68 vs. -0.31).

4.5 Robustness

Our results show that the technology shock and the separation rate shock are the main driver of labour market dynamics in Australia. In this section, we want to check whether our results are robust to using other shocks then the separation rate shock. Further, we can ensure that the model with separation shocks is the best specification to explain the data. For this purpose, table 4 presents the point estimates for key parameters for five models and the log-likelihood. The benchmark results are the one discussed above, the next two models use a shock to the bargaining power, η, and a shock to the vacancy posting costs, c, instead of the separation shock. The last two models additionally use a shock to the bargaining power, vacancy posting costs respectively.

Table 3: Second moments: standard deviation relative to output.

Variable	Data	Model
U	7.20	7.07
V	13.26	5.23
N	0.96	0.79
θ	18.91	10.02
W	0.84	0.60
$corr\,(U,V)$	-0.68	-0.31

Table 4: Robustness - posterior estimates.

Parameter	Benchmark	η	c	Add η	Add c
ρ	0.07	0.05	0.05	0.06	0.05
μ	0.40	0.42	0.41	0.41	0.40
c	0.01	0.09	0.11	0.11	0.13
η	0.81	0.51	0.56	0.54	0.57
LLN	735.96	1261.87	1244.77	1275.23	1250.80

We find that the separation rate and the match efficiency are stable across the different approaches. However, we find that the vacancy posting costs are much higher (roughly ten times) as in the benchmark model. The values of roughly 0.1 are in line with the calibration used in Chindamo and Uren (2010). This value is twice as large as the value obtained by Lubik (2009) for the U.S.. Further, the bargaining power, η, varies between 0.51 (symmetric bargaining) and 0.81. However, still significantly larger than the estimate for the U.S. of 0.03.

One of the shortcomings of the benchmark model is that it fails to generate enough volatility of vacancies. Our robustness checks reveal that a combination of higher vacancy posting costs (around 0.1) and symmetric bargaining in fact doubles the standard deviation compared to the benchmark model. Along this line, also the volatility of unemployed increases by roughly 50 percent compared with the benchmark model. This finding should be intuitive. A smaller bargaining power for workers will leave a larger share of the surplus to the firm, hence, creating more incentives to react to exogenous disturbances. As it turns out, this effect dominates the adverse effects on vacancy posting created by larger vacancy posting costs.

Finally, although we find significant variation across different model specifications, our benchmark model, with low vacancy posting costs and a large bargaining power, generates the lowest log-likelihood of all models. Therefore, our benchmark model explains the observed dynamics better than the other specifications. Put differently, it seems that the data prefers the model with the separation shock and then requires low vacancy posting costs and a high bargaining power.

5 Conclusion

This paper estimates a canonical search and matching model on data for Australia over the period 1978-2008 using Bayesian methods. We estimate deep parameters to discuss underlying properties and cyclical fluctuations. Several findings stand out. The worker's bargaining power is surprisingly large compared to other studies. On average, we observe a low unemployment rate which is driven by low vacancy posting costs and low - but volatile - separations. Further, our results indicate that both margins - the creation and the destruction margin - are subject to large cyclical fluctuations.

Moreover, the estimated model is able to generate the empirically observed second moments fairly well. The only exception is the volatility of vacancies which is much too low. This is mainly due to the large value of the bargaining power. Nevertheless, the model replicates a quite strong Beveridge curve. The model is able to replicate the dynamics of key labour market variables, such as (un)employment and wages.

We find that the technology shock and the separation rate shock are the main driver of business cycle fluctuations. The technology shock is more important for output and vacancies, while the separation shock is more important for (un)employment and matches. In addition, we find that over the short-run output is driven by technology and separation shocks, while over the long-run technology shocks clearly dominate. Unemployment is - over the short-run - almost entirely driven by separation shocks, while in the long-run technology innovations become quite important as well. A robustness check to different specifications of exogenous disturbances shows that the data prefers the model with the separation shock.

We want to stress two limiting factors that are not included in our estimation. First, the model does not account for changes in the institutional background. For example, in 1996 and 2004 the employment protection legislation index (constructed by the OECD) increased significantly, which is not accounted for. In general, those structural changes may have large effects on the dynamics and transmission channels in the labour market. Second, the Australian labour market is characterized by over-qualification. The OECD reports that roughly 40 percent of Australian workers possess higher qualifications as required. This mismatch creates significant costs for firms. On the one hand, firms face additional hiring costs as they have to screen the worker more intensively and might have to change job requirements and wages. On the other hand, workers overqualified for their jobs are more likely to provide less effort due to less satisfaction and are more likely for on-the-job-search; both factors reducing labour productivity.

Finally, Karanassou and Sala (2010) show that capital accumulation and the international role played by the Australian economy are crucial factors in explaining the behaviour of the labour market between 1990 and the early 2000s. However, a sneak peak on future research shows that the introduction of capital into the search and matching model does not significantly alter the point estimates. Furthermore, future research should consider real wage rigidity and New Keynesian elements, as Sheen and Wang (2012) show that demand side shocks seem to be of significant importance for fluctuations.

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