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Abstract

I specify a simple search and matching model of the labor market and estimate it on unemployment and vacancy data for Hong Kong over the period 2000-2010 using Bayesian methods. The model fits the data remarkably well. The estimation shows that the main driver of fluctuations in the labor market are productivity shocks, with cyclical movements in the separation rate playing only a subordinate role. The parameter estimates are broadly consistent with those found in the literature. In order to replicate the volatility of unemployment and vacancies the model estimates require a high replacement ratio and a low bargaining power for workers in addition to two extraneous sources of uncertainty. The estimates are robust to a relaxation of the prior information and small changes in the underlying model specification, which suggests that the data are informative and that the model is well specified. Overall, the Hong Kong labor market can be characterised by having a low degree of churning in normal times, but rapid firings and hirings in recessions and expansions.

JEL Classification: C11, C51, E24, J64
Keywords: Search and Matching, Unemployment, Vacancies, Beveridge Curve, Bayesian Estimation

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1 Introduction

The search and matching model has become the workhorse framework for addressing a wide host of labor market issues in macroeconomics. However, the literature focuses almost exclusively on the economies of the U.S. and the Euro area. Much less research is conducted on labor market dynamics in other countries. In this paper, I add to the literature by analyzing aggregate labor market dynamics in Hong Kong from the perspective of a standard search and matching model. I focus on two broad empirical aspects. First, I study how well the theoretical search and matching model describes the behavior of labor market variables. Second, I provide estimates of the structural labor market parameters as benchmarks for future research.

In order to address these issues I develop a simple search and matching model of the labor market that serves as a data-generating process. That is, I describe the observed outcomes of unemployment and vacancy postings as arising from the interplay of job-seeking workers and of firms searching for employees. Both types of agents solve dynamic optimization problems that trade off the benefits of being in an employment relationship against the costs of being idle. Since search is costly in this framework this creates rents that both parties share. The outside option of a worker is being unemployed and drawing benefits, which forms the lower bound of a bargaining set. A firm's cost of not being active on the labor market is foregone revenue. This sets an upper bound. Within this bargaining set the parties distribute surplus between payments to workers (i.e., wages) and profits.

Workers and firms form employment relationships after being matched on the labor market. The matching process is captured by a matching function that combines unemployed job seekers and open positions into new hires. The matching function is a "black box" (as described by Petrongolo and Pissarides, 2001) with scant microfoundations, but it helps generate salient labor market movements. What is attractive about this framework is that it not only provides a rationale for the existence of equilibrium unemployment, but it also describes the dynamics of unemployment, vacancies, and job-finding rates, all of which are important metrics for evaluating a country's economic performance.

I estimate the model using Bayesian methods for quarterly data on unemployment and vacancies over the sample period from 2000 to 2010. The data choice is limited by the public availability and quality of labor market data. Nevertheless, these two variables are at the core of the search and matching model and are the objects of interest of commentators and policymakers.

I want to emphasize two aspects of my empirical approach that have so far been rarely used in the search and matching literature. First, I assume that the model is driven by a persistent shock to the separation rate of workers into unemployment, and by a more standard productivity shock. Since I estimate the model on two data series, the theoretical specification requires two exogenous sources of variation in order to avoid stochastic singularity in the likelihood function. Shocks that affect the dynamic behavior of employment directly are thus natural candidates.[1]

The second novelty is that I conduct an extensive preliminary analysis to help set the priors for the Bayesian estimation. Priors are typically chosen based on previous empirical findings, or from extraneous sources such as a variable's long-run behavior. I depart from this convention by gathering prior information from a limited-information approach to the empirical model. I estimate simple reduced-form relationships derived from the model, where I do not explicitly impose all cross-equation restrictions that the full general equilibrium model provides. Specifically, I estimate a dynamic equation for the evolution of unemployment and fit a regression line to the Beveridge curve, which is a reduced-form relationship between unemployment and vacancies. Prior means and standard deviations are then backed out from the estimates of the reduced-form regressions. This approach allows me to derive sharp restrictions on the prior, which then can be used to assess the degree of potential misspecification or lack of identification in the model. For parameters on which no information at all is available within the context of my modelling exercise, I impose uninformative priors.

The Bayesian estimation delivers the following results. First, the search and matching model is capable of describing labor market dynamics in Hong Kong exceedingly well. This is measured by the fit of the model when compared to less restrictive time series models and by the ability of the model to closely match the observable data series. Moreover, the model captures key moments of labor market dynamics. What drives this finding is that the parameter estimates are close to the suggested calibration of Hagedorn and Manovskii (2008), specifically a high outside option of the worker in terms of a high replacement rate in combination with a low degree of bargaining parameter. This renders the implied wage process relatively sluggish and keeps the incentives for firms to post vacancies, and thus their volatility, quite high. At the same time, the use of two persistent shocks and two

[1] Shimer's (2005) critique of the search and matching model is based on a one-shock model. In contrast, Lubik (2009) shows that a search and matching model with two shocks is quite consistent with U.S. data. Moreover, if data on both unemployment and vacancies are used in the estimation then a shock that affects the separation rate or the matching process is required for identification purposes (see Lubik, 2011).

observables brings the reduced-form representation of the restricted structural model close to that of an unrestricted vector autoregression (VAR). Consequently, the goodness of fit is not that surprising.

Moreover, the parameter estimates are broadly in line with other empirical studies that look at U.S. data. Specifically, the separation rate is somewhat lower than in the U.S., as are the match elasticity and the match efficiency. The main driver of unemployment and vacancy fluctuations is productivity, with shocks to separations only playing a subordinate role. This suggests that the Hong Kong labor market exhibits not much churning in normal times. Firms tend to stick to their workers, possibly because the low degree of match efficiency makes it difficult and costly to replace normal turnover. However, in times of economic distress unemployment rises sharply due to a willingness to fire quickly and to substantially reduce hirings. When the economy improves, the large size of the pool of potential hires, i.e., the unemployed, in combination with the relative inelasticity of the matching probability to labor market tightness, stimulates firms' hiring decisions. Overall, the estimation results paint the picture of a dynamic labor market, the workings of which, however, could be improved by reducing any residual matching frictions.

To the best of my knowledge, this is the first structural empirical study of the labor market search and matching model for Hong Kong. The paper that comes closest to mine is Tse et al. (2002), who focus on the Beveridge curve and the (reduced-form) relationship between unemployment and vacancies in Hong Kong. Although their paper is informed by the logic of the search and matching model as encapsulated in the Beveridge curve, the authors do not perform a structural estimation. Any inferences about structural parameters can therefore be only informal. Moreover, the paper uses annual data and covers a period from 1976 to 1997, which does not overlap with my sample. However, the paper establishes the existence of a Beveridge curve for Hong Kong, both in aggregate and in sectoral data, which I do not address.

The paper is structured as follows. In the next section, I discuss the available labor market data for Hong Kong and present a few summary statistics. Section 3 introduces a simple search and matching model of the labor market that serves as data-generating process for my empirical analysis. The following section contains the estimation results and robustness checks. I first describe how to obtain priors from a preliminary data analysis using reduced-form relationships. Given this benchmark prior, I then estimate the model using Bayesian methods, discuss the results, model fit, the source of fluctuations in the labor market, and the transmission mechanism. I then conduct robustness checks with respect to the informativeness of the prior and small changes in the model specification. Section 5 concludes.

2 Data and Stylized Facts

I collect quarterly labor market data from the Census and Statistics Department (CSD) of the Government of Hong Kong (available at: `www.censtatd.gov.hk`). The sample period is 2000:1 to 2010:2 due to limited data availability for vacancies. The data are seasonally adjusted using the X-12 method. My focus is on the relationship between unemployment and vacancies. The unemployment rate is obtained from the General Household Survey. It is computed as the fraction of the labor force that self-reports as not having a job, but actively searching for one. However, the CSD also includes "discouraged workers" in the unemployment number. These are unemployed workers who have not been actively searching because they believed that work was not available. The headline U.S. unemployment rate, labeled U-3, excludes these workers. They are reported in a broader measure, U-6, which also counts people working part time who want to work full time. The ratio between the broader and the headline measure is remarkably stable in the U.S. I therefore proceed under this assumption for Hong Kong as well.[2] Arguably, a measure for labor market pressures should include these wider categories of non-workers as they are likely to search more actively when conditions improve.[3]

The aggregate vacancy series is a composite of reported private sector vacancies and open positions in the civil service. The data are obtained from the Quarterly Survey of Employment and Vacancies (SEV), which does not fully cover some industries due to "operational difficulties" according to the "Concepts and Methods" document of the CSD. Examples of the missing sections within industries are hawkers, taxis and light busses, work activities within domestic households, and, surprisingly, monetary authorities. These subcomponents are possibly important quantity-wise. They capture, however, activities that might be classified as belonging to an informal labor market, which are not easily modeled in a simple search and matching framework. More critically, the vacancy data miss the entire construction sector, which plays a central role in the Great Recession in the U.S. Nevertheless, I use this series as the best available data on aggregate hiring decisions in

[2] A second difference in measurement compared to the U.S. is that the Hong Kong labor force includes those aged 15 years and older, while the U.S. labor force data start counting a year later.

[3] This issue bears on the calibration of the search and matching model, especially with regard to the corresponding steady-state unemployment rate in the model. Cole and Rogerson (1999), Krause and Lubik (2007), and Trigari (2007) all choose high values, ranging from 12% to 27% on this account.

Hong Kong. Future research would investigate these data limitations further.

The series for vacancies and unemployment are shown in Figure 1. Both series are scaled by the total labor force. The top panel depicts the data over the sample period, while the middle panel shows labor market tightness, i.e., the ratio between vacancies and unemployment. The unemployment rate exhibits a fair degree of movement, reaching a peak of 8.3% in the third quarter of 2003 and a trough of 3.1% in early 2008. Hong Kong did not escape the world-wide recession of 2008-2009, when unemployment increased again to 5.4%, but it has come down recently. The average unemployment rate over the last decade is 5.5%. In contrast, the vacancy rate appears excessively stable. It varies between 0.5% in the first quarter of 2003 and 1.7% in early 2008, with a mean of 1.03%. Labor market tightness reaches a peak in 2008 with the peak of the business cycle on the back of low unemployment and peak vacancy creation. The panel also shows the recent pick-up in tightness as the economy is coming out of the slump.

Table 1 reports some business cycle statistics. These are computed from the raw data. As indicated by the graphs, the unemployment rate is four times more volatile than the vacancy rate, with standard deviations of 1.38 and 0.32, respectively. Adjusting for differences in the level of the series, the coefficients of variation are 0.25 and 0.31, respectively, which suggests enough variation in the vacancy series to be informative in the estimation. Similarly, the coefficient of variation of tightness is 0.53.

The bottom panel in Figure 1 depicts the Beveridge curve as a scatter plot of vacancies against unemployment. The relationship is downward-sloping and the contemporaneous correlation is -0.78.[4] This is a bit lower than the corresponding value for the U.S. (-0.89). Intuitively, large movements in unemployment are thus needed to generate sizeable changes in vacancy postings, which likely stems from the inelasticity of the vacancy rate to unemployment. This seems a priori surprising as the Hong Kong labor market is presumably very liberalized with few barriers and costs of hiring and firing people. My empirical analysis will study this aspect closely later on.

3 The Model

I now develop a simple search and matching model of the labor market that I use as a data-generating process for the empirical analysis. The model is closely related to the one described in Lubik (2009). Although seemingly simple, the model captures salient labor market flows.

[4] The existence of a Beveridge curve for Hong Kong has already been established by Tse et al. (2002).

Time is discrete and the time period is a quarter. The model economy is populated by a continuum of identical firms that employ workers, each of whom inelastically supplies one unit of labor.[5] Output Y of a typical firm is linear in employment N:

$$Y_t = A_t N_t. \tag{1}$$

A is an aggregate productivity process that obeys the law of motion:

$$\log A_t = (1 - \rho_A) \log A + \rho_A \log A_{t-1} + \varepsilon_{A,t}, \tag{2}$$

where $0 < \rho_A < 1$, $A > 0$, and $\varepsilon_{A,t} \sim \mathcal{N}(0, \sigma_A^2)$.

The labor market matching process combines unemployed job seekers U with job openings (vacancies) V. This can be represented by a constant returns matching function, $M_t = mU_t^{\xi} V_t^{1-\xi}$, where $m > 0$ is match efficiency, and $0 < \xi < 1$ is the match elasticity. Unemployment is defined as:

$$U_t = 1 - N_t, \tag{3}$$

where the labor force is normalized to one.

Inflows to unemployment arise from job destruction at rate $0 < \rho < 1$. Although I do not model a firm's separation decision from workers explicitly, I allow for time variation in the destruction rate. Specifically, I assume that separation ρ is a stochastic process with the law of motion:

$$\log \rho_t = (1 - \rho_\rho) \log \rho + \rho_\rho \log \rho_{t-1} + \varepsilon_{\rho,t}, \tag{4}$$

where $0 < \rho_\rho < 1$, $1 > \rho > 0$, and $\varepsilon_{\rho,t} \sim \mathcal{N}(0, \sigma_\rho^2)$.

The dynamics of employment are governed by the following relationship:

$$N_t = (1 - \rho_t) \left[N_{t-1} + mU_{t-1}^{\xi} V_{t-1}^{1-\xi} \right]. \tag{5}$$

This is a stock-flow identity that relates the stock of employed workers N to the flow of new hires $M = mU^{\xi} V^{1-\xi}$ into employment. The timing assumption is such that once a worker is matched with a firm, the labor market closes. This implies that if a newly hired worker and a firm separate, the worker cannot reenter the pool of searchers immediately and has to wait one period before searching again.

[5] For expositional convenience, I present the problem of a representative firm and abstract from firm-specific indices.

The matching function can be used to define the job finding rate, i.e., the probability that a worker will be matched with a firm:

$$p(\theta_t) = \frac{M_t}{U_t} = m\theta_t^{1-\xi}, \tag{6}$$

and the job matching rate, i.e., the probability that a firm is matched with a worker:

$$q(\theta_t) = \frac{M_t}{V_t} = m\theta_t^{-\xi}, \tag{7}$$

where $\theta_t = V_t/U_t$ is labor market tightness. From the perspective of an individual firm, the aggregate match probability $q(\theta_t)$ is exogenous and unaffected by individual decisions. Hence, for individual firms new hires are linear in the number of vacancies posted: $M_{it} = q(\theta_t)V_{it}$.

A firm chooses the optimal number of vacancies V_t to be posted and its employment level N_t by maximizing the intertemporal profit function:

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[A_t N_t - W_t N_t - \kappa V_t\right], \tag{8}$$

subject to the employment accumulation equation (5). Profits are discounted at rate $0 < \beta < 1$. Wages paid to the workers are W, while $\kappa > 0$ is a firm's fixed cost of opening a vacancy. The first-order conditions are:

$$N_t \quad : \qquad \mu_t = A_t - W_t + \beta E_t\left[(1-\rho_{t+1})\mu_{t+1}\right], \tag{9}$$

$$V_t \quad : \qquad \kappa = \beta q(\theta_t) E_t\left[(1-\rho_{t+1})\mu_{t+1}\right], \tag{10}$$

where μ_t is the multiplier on the employment equation.

Combining these two first-order conditions results in the *job creation condition* (JCC):

$$\frac{\kappa}{q(\theta_t)} = \beta E_t\left[(1-\rho_{t+1})\left(A_{t+1} - W_{t+1} + \frac{\kappa}{q(\theta_{t+1})}\right)\right]. \tag{11}$$

This captures the tradeoff faced by the firm: The marginal effective cost of posting a vacancy, $\frac{\kappa}{q(\theta_t)}$, that is, the per-vacancy cost κ adjusted for the probability that the position is filled, is weighed against the discounted benefit from the match. The latter consists of the surplus generated by the production process net of wage payments to the workers, plus the benefit of not having to post a vacancy again in the next period.

In order to close the model, I need to specify how wages are determined. In contrast with neoclassical models of the labor market, the search model is silent about this. Any wage process within the bargaining set, which is defined by the outside options of the two parties involved, is consistent with an equilibrium. I assume in line with the existing literature that wages are determined based on the Nash bargaining solution: Surpluses accruing to the matched parties are split according to a rule that maximizes their weighted average. Denoting the workers' weight in the bargaining process as $\eta \in [0,1]$, this implies the sharing rule:

$$\mathcal{W}_t - \mathcal{U}_t = \frac{\eta}{1-\eta}\mathcal{J}_t, \tag{12}$$

where $\mathcal{W}_t$ is the asset value of employment, $\mathcal{U}_t$ is the value of being unemployed, and $\mathcal{J}_t$ is the value of the marginal worker to the firm.[6]

The value of employment to a worker is described by the following Bellman equation:

$$\mathcal{W}_t = W_t + E_t\beta[(1-\rho_{t+1})\mathcal{W}_{t+1} + \rho_{t+1}\mathcal{U}_{t+1}]. \tag{13}$$

Workers receive the wage W_t, and transition into unemployment next period with probability ρ_{t+1}. The value of searching for a job, when the worker is currently unemployed, is:

$$\mathcal{U}_t = b + E_t\beta[p_t(1-\rho_{t+1})\mathcal{W}_{t+1} + (1 - p_t(1-\rho_{t+1}))\mathcal{U}_{t+1}]. \tag{14}$$

An unemployed searcher receives benefits b and transitions into employment with probability $p_t(1-\rho_{t+1})$. Recall that the job finding rate p_t is defined as $p(\theta_t) = M(V_t, U_t)/U_t$, which is decreasing in tightness θ_t. It is adjusted for the probability that a completed match gets dissolved before production begins next period. The marginal value of a worker $\mathcal{J}_t$ is equivalent to the multiplier on the employment equation, $\mathcal{J}_t = \mu_t$, so that the respective first-order condition defines the Bellman equation for the value of a job (see Krause and Lubik, 2007).

I substitute the asset equations into the sharing rule (12) and, after some algebra, find the wage equation:

$$W_t = \eta\left(A_t + \kappa\theta_t\right) + (1-\eta)b. \tag{15}$$

Wage payments are a weighted average of the worker's marginal product A_t, which the worker can appropriate at a fraction η, and the outside option b, of which the firm obtains the portion $(1-\eta)$. Moreover, the presence of fixed vacancy posting costs leads to a hold-up problem where the worker extracts an additional $\eta\kappa\theta_t$ from the firm.

Finally, I can substitute the wage equation (15) into (11) to derive an alternative representation of the job creation condition:

$$\frac{\kappa}{m}\theta_t^{\xi} = \beta E_t(1-\rho_{t+1})\left[(1-\eta)\left(A_{t+1} - b\right) - \eta\kappa\theta_{t+1} + \frac{\kappa}{m}\theta_{t+1}^{\xi}\right]. \tag{16}$$

[6] In models with one-worker firms, the net surplus of a firm is given by $\mathcal{J}_t - \mathcal{V}_t$, with $\mathcal{V}_t$ the value of a vacant job. By free entry, $\mathcal{V}_t$ is then assumed to be driven to zero.

Note that this expression is a first-order expectational difference equation in labor market tightness, with productivity and separation rate shocks as driving processes. The Appendix contains a summary of the relevant equations, their steady-state equivalents, and the linearized version of the model, which is used in the estimation.

4 Estimation and Empirical Results

The purpose of this paper is threefold. First, I am interested in how well the search and matching model can describe basic labor market dynamics in Hong Kong. This can be regarded as an assessment of the applicability of this framework to the special case of the Hong Kong labor market. Second, I provide estimates of key parameters of the search and matching model, which may prove to be useful for future research. Finally, the paper attempts to determine the salient sources of labor market fluctuations in Hong Kong.

The estimation proceeds in two steps. First, I perform a preliminary empirical analysis of the model by estimating key relationships in a semi-reduced form. I will then use the estimation results to form priors for the structural parameters. The second step is to estimate the full structural model using likelihood-based methods. Specifically, I estimate the model using Bayesian methods, which combine the information contained in the priors with the information contained in the observable data as seen through the prism of the likelihood function of the structural model. A detailed description of Bayesian estimation of search and matching models can be found in Lubik (2009).

4.1 Preliminary Data Analysis and Bayesian Priors

In Bayesian analysis, there are two sources of information, namely the data and information gained prior to the actual empirical analysis. The latter is captured and summarized in the prior distribution over the parameters, while the data is summarized by the likelihood function as interpreted through the prism of the structural model. The likelihood function is then used to update the prior using Bayes' Law, which results in the posterior distribution. Bayesians regard both sources of information as equally valid. A critical issue is, of course, how priors are obtained. A possible source is previous empirical work or actual personal beliefs. But priors can also be chosen for computational expediency, such as conjugate priors that simplify the computation of the posterior distribution. Alternatively, researchers may choose to impose uninformative priors so that the information in the likelihood function is used exclusively.

Since this paper presents, to the best of my knowledge, the first full-fledged empirical application of the search and matching model to the Hong Kong labor market, I cannot rely on other studies for setting the priors. Instead, I obtain prior information from the following implicit thought experiment: Suppose that I do not have any previous knowledge about the labor market data. However, I do have a vague notion about how employment evolves and I am willing to capture this with a law of motion as in equations (5) or (17). I then use simple statistical techniques to extract information on the likely properties of the random parameters. This ranges from first moments (which are used to back out other structural parameters) to the reduced-form regressions described in the text.

The Bayesian likelihood-based approach imposes the full set of cross-equation restrictions implied by the theoretical model. If the latter is misspecified, then the estimates are potentially biased. On the other hand, using limited-information methods tends to alleviate misspecification problems. Hence, derivation of priors in this way allows the researcher to judge the validity of the model along this dimension. The priors resulting from this exercise are reported in Table 2.

The employment equation (5) describes a relationship between unemployment and vacancies. I compute a first-order approximation in natural logarithms around the steady state and use the definition of employment (3). After some algebra, I can express this relationship as follows:

$$\widetilde{U}_t = \left(1 - \rho - \rho\xi\frac{1-\overline{U}}{\overline{U}}\right)\widetilde{U}_{t-1} - \rho\left(1-\xi\right)\frac{1-\overline{U}}{\overline{U}}\widetilde{V}_{t-1} + \frac{\rho}{1-\rho}\frac{1-\overline{U}}{\overline{U}}\widetilde{\rho}_t. \tag{17}$$

This explains the evolution of unemployment as a first-order autoregressive process with "driving terms" $\widetilde{V}_{t-1}$ and the unobserved process $\widetilde{\rho}_t$. Absent data on the separation rate, I regress unemployment on its own lag and lagged vacancies only.[7] Time variation in the unobserved separation rate manifests itself as serial correlation in the regression error term, which I have to control for by using instrumental variables in the estimation. I also compute Newey-West standard errors that correct for residual serial correlation and heteroskedasticity.

The coefficients of the regression are functions of the structural parameters ρ and ξ and the steady-state unemployment rate $\overline{U}$. I set the latter to mean unemployment over the sample of 5.5%, which then allows me to back out the other parameters. Given a sample average of 5.5% unemployment, the point estimate of the separation rate is $\widehat{\rho} = 0.045$ with a standard error of 0.004, and the estimate of the match elasticity is $\widehat{\xi} = 0.469$ with a standard error of 0.011. Both estimates are highly significant below the 1% level. The

[7] Data on job separations, measured as transitions from employment to unemployment, were not easily obtainable for this project. It would be very worthwhile to investigate this in future research.

estimates are obtained with a non-linear instrumental variables procedure, with lags of the two endogenous variables and real per-capita GDP as instruments. The estimates are very robust with respect to the instrument set and the chosen least-squares procedure.

Consequently, I set tight priors for these two parameters based on the point estimates and the small standard errors. Since the parameters are restricted to lie on the unit interval, I choose Beta-distributions for the priors. While the estimates are consistent with the typical values used in the calibration literature, they fall toward the lower end of the range. For instance, Petrongolo and Pissarides (2001), in a survey of the empirical literature of the matching function, suggest the match elasticity ξ to be in the interval $(0.50, 0.70)$. Similarly, the separation rate ρ is typically calibrated in the range $(0.05, 0.10)$. My results suggest that the Hong Kong labor market exhibits somewhat different characteristics than its U.S. counterpart.

The prior for the level parameter in the matching function, the match efficiency m, is chosen based on information from the Beveridge curve, depicted in Figure 1. The contemporaneous realizations of unemployment and vacancies are equilibrium outcomes of the interaction of job creation decisions and the employment dynamics embodied in Eqs. (5) and (11). They should therefore be analyzed as the point-in-time realization of a dynamic stochastic equilibrium model. However, much of the search and matching literature (e.g., Shimer, 2005) argues that labor market adjustment is fairly rapid and that realized data are always close to their steady state. I therefore derive a theoretical representation of the Beveridge curve from the steady-state version of the employment equation (5). In log terms, this implies:

$$\log \overline{V} = \frac{1}{1-\xi} \log \left(\frac{\rho}{1-\rho} \frac{1}{m} \right) + \frac{1}{1-\xi} \log(1-\overline{U}) - \frac{\xi}{1-\xi} \log \overline{U}. \tag{18}$$

I fit a regression line to this relationship using non-linear least squares. The point estimate of m is 0.34 with a standard error of 0.18. I set my prior accordingly, using a Gamma-distribution due to the non-negativity of the parameter's support.

I choose priors for the remaining parameters as follows. I set the discount factor $\beta = 0.99$. I choose an uninformative prior for the bargaining parameter η. Specifically, I assume that the prior is uniform on the support $\eta \in (0, 1)$. The share parameter is typically calibrated at 0.5 on agnostic grounds, or it is chosen to coincide with the match elasticity ξ in order to implement the socially efficient allocation on account of imposing the so-called Hosios condition. On the other hand, small values of η can bring the search and matching model closer to the data (e.g., Cole and Rogerson, 1999; Lubik, 2009). I therefore remain agnostic on this parameter and impose an uninformative prior.

Since I treat the steady-state unemployment rate as a target variable for the empirical analysis, I need to back out another parameter endogenously. The steady-state job creation condition implies that the benefit parameter $b = A - \frac{\eta}{1-\eta}\kappa\overline{\theta} - \frac{1-\beta(1-\rho)}{\beta(1-\rho)}\frac{1}{1-\eta}\frac{\kappa}{m}\overline{\theta}^{\xi}$. I normalize mean productivity $A = 1$. Steady-state tightness $\overline{\theta} = \overline{V}/\overline{U}$, where $\overline{U}$ is the mean of unemployment over the sample; $\overline{V}$ can then be computed from the Beveridge-curve relationship above (18). Setting a prior for the vacancy cost parameter κ then induces a prior distribution on b and vice versa. That is, these two parameters are not separately identified. I choose a prior for κ that is tightly concentrated around a mean of 0.05. This is based on the results reported in Lubik (2009).

At the prior mean, the model implies a value for the benefit parameter $b = 0.70$, and a replacement ratio $b/\overline{W}$ of 72%. This value is halfway between the "extreme" calibrations of Shimer (2005) and Hagedorn and Manovskii (2008). The latter authors show that a very high value of the outside option of the worker is required for the standard search and matching model to match the data. I will therefore consider the implied posterior value for b as a rough plausibility check on the model. Finally, I have to set priors for the exogenous driving processes. There is not much further guidance I can draw from the data. Since the model has weak internal propagation (see Lubik, 2009), I set a fairly high degree of mean autocorrelation, with $\rho_\rho = \rho_A = 0.90$, but with reasonably wide standard errors.

4.2 Bayesian Parameter Estimates

I estimate the model by constructing the likelihood function from its state-space representation using the Kalman filter. The likelihood function is then used to update the prior by applying Bayes' law. This results in a posterior distribution over the model parameters, which can then be used for inference. Detailed descriptions of the empirical philosophy and the estimation procedure can be found in An and Schorfheide (2007). The model is estimated over the sample period 2000:1 to 2010:2 for data on the unemployment rate and the vacancy rate. The parameter estimates are listed in Table 3.[8] I report two sets of estimates: the mode of the posterior distribution and its mean. The latter is most commonly reported in the literature, but the former gives additional guidance as to the shape of the posterior and the information contained in the data relative to the prior.

There are two broad observations. First, the posterior means are almost identical to the prior means, with the important exception of the bargaining parameter η; second, the

[8] The estimation results are obtained from 250,000 draws from the posterior distribution using a Markov-Chain Monte-Carlo algorithm. The chains converge rather quickly. Experiments with a larger number of draws leave the posterior means unaffected.

parameter estimates are broadly similar to what can be found in U.S. data (e.g., Lubik, 2009). The latter observation suggests that key labor market dynamics are, in fact, very similar in industrialized countries despite potentially large differences in their labor market institutions. On the other hand, it could be argued that the tightness of the chosen priors, that is, small variations around the mean, dominates the posterior distribution. This concern can, of course, not be dismissed out of hand. I will therefore study the implications of my benchmark prior choice by performing a robustness analysis that relaxes the priors. Moreover, tight priors are not problematic *per se* if they are informative. The posterior distribution would then be more concentrated, but in the same location as the prior.

The average separation rate ρ and the match elasticity ξ have identical prior and posterior means and mode. This is to some extent driven by the tightness of the prior, but the posterior distribution is also more concentrated with a standard deviation that is 30% smaller.[9] The posterior mean of the match elasticity $\xi = 0.47$ is outside the range reported in the empirical study by Petrongolo and Pissarides (2001); there is also no overlap with the 90% coverage region. As a reference point, Lubik (2009) reports an estimated value of 0.74 for U.S. data. Similarly, the separation rate in Hong Kong is $\rho = 0.044$, while it is slightly higher in the U.S. at 0.055.

This suggests some differences in how the labor markets in both countries function. The composition of the unemployment pool is determined by inflows and outflows from and to employment. Inflows into unemployment are generated by separations. Despite a general perception of the freewheeling capitalism of Hong Kong's economy, mean job separations, i.e., the average rate of layoffs, are actually lower than in the U.S. Exits out of unemployment are the result of successful matching and are determined by the job-finding rate $p(\theta_t) = m\theta_t^{1-\xi}$. The lower value of ξ in Hong Kong implies that matches react more elastically to the tightness of the labor market over the business cycle, so that workers exit unemployment faster than in the U.S. Similarly, the job-matching rate $q(\theta_t) = m\theta_t^{-\xi}$ reacts less elastically to movements in tightness, and firms are consequentially less discouraged to post vacancies when, say, aggregate tightness increases.

However, this line of reasoning abstracts from the presence of separation shocks in the model. Specifically, there may be substantial movement in separations when the economy enters a recession despite a low degree of churning in normal times. This is somewhat borne

[9] I experimented with different starting values in the algorithm that finds the mode, but ended up at the same value. This strongly suggests that the parameters are well identified. That this need not be the case is shown in Lubik (2011), where in U.S. data the prior and posterior mean differ by 0.2 in the case of the match elasticity.

out by the estimation. The estimated standard deviation of the exogenous (log) separation rate is 0.13, which is 30% higher than the corresponding value in U.S. data (see Lubik, 2009), albeit at a lower mean. Consequently, separations are relatively more volatile in Hong Kong over the business cycle. When the economy enters a recession, workers are laid off at a high rate, which drops dramatically in the recovery phase to produce a low mean. The unemployment pool therefore fills up quickly due to rising inflows, but ebbs rapidly following a business cycle trough when outflows are created by strong hiring. Therefore, Hong Kong's labor market does appear to be characterized by high cyclical turnover, that is, quick hiring and firing, which overall delivers low unemployment.

I estimate the posterior mean of the match efficiency $m = 0.27$, which is between the mode and the prior mean. The latter, however, is contained in the 90% posterior coverage interval. Recall that the prior was based on information related to the intercept in a steady-state Beveridge-curve relation, whereas in the estimated full model m affects the dynamics of tightness and its response to both shocks. This suggests a tension between the steady state and the dynamics of the aggregate labor market variables, which the estimation algorithm resolves by pulling the posterior mean downward from its prior. In economic terms, generating a given amount of new matches requires a high number of posted vacancies and a large unemployment pool.

The estimates for the job creation cost κ suggest that this parameter is not identified, as the mean and mode coincide and the posterior distribution overlaps with the prior. This finding is similar to the existing literature and is a main reason why κ is often calibrated to a fixed number. Finally, the posterior mean of the bargaining parameter $\eta = 0.06$, where the mode is at the lower bound of the permissible range, that is, at $\eta = 0$. Since the prior on this parameter is uniform, the shape of the posterior is exclusively determined by the information in the data. The estimate moves the model in the direction of the Cole and Rogerson (1999) and Hagedorn and Manovskii (2008) calibration, which implies a replacement rate of 97%. The posterior means and modes of the autoregressive coefficients of the exogenous processes do not differ much from their prior means. The data pull up ρ_A somewhat as an important source of persistence. On the other hand, the estimated standard deviation of the separation rate innovation is almost an order of magnitude larger than that of the productivity innovation. I will study their relative importance in driving business cycles in the next section.

To summarize, the Bayesian estimates of the structural labor market parameters are broadly consistent with those found in the literature. There are small differences for specific parameters, such as the separation rate and the match elasticity, but these just serve to illuminate the nature of the Hong Kong labor market. The estimates also show that the model parameters are by and large well identified and that the information gained from limited information methods is broadly consistent with that from a full-information likelihood-based analysis.

4.3 Sources of Labor Market Fluctuations

I now dig deeper into the determinants of labor market movements in Hong Kong. First, I am interested in the sources of business cycles, specifically how much productivity and separation rate shocks contribute to movements in unemployment and vacancies. This can be assessed by computing variance decompositions for these variables, which isolate the contributions of individual shocks to the overall volatility in the respective variables. The variance decomposition for the benchmark specification is reported in Table 4. Both shocks play an important role, but productivity shocks more so. They explain 60% of the volatility in unemployment and 80% in vacancies. Separation shocks are relatively more important in driving unemployment than vacancies since they effectively act as a residual in the employment equation (5). However, the 90% coverage intervals are very wide, which implies a high degree of uncertainty regarding the relative importance of the shocks.

Figure 2 depicts impulse response functions of unemployment and vacancies to positive one-standard deviation shocks to productivity and the separation rate. They are computed at the posterior means of the structural parameters. A persistent increase in productivity raises the expected return to having an employed worker. This prompts firms to post more vacancies since they can more easily cover job creation costs out of the surplus from hiring a worker. Moreover, the low estimated bargaining power of workers implies that firms can appropriate more of this higher surplus so that it is not eaten up by excessive wage increases. This leads to a persistent response of vacancy creation. Since employment is a state variable on account of the timing convention of the matching process, unemployment does not respond contemporaneously to the shock. In the following periods, however, it falls persistently as the new hires enter employment.

The lower half of the graph depicts the response to an increase in the separation rate. By assumption, separations act contemporaneously on employment. Consequently unemployment jumps up on impact. This increase in the pool of job seekers *ceteris paribus* lowers labor market tightness $\theta_t = V_t/U_t$, reduces the congestion effect for a firm having to compete with other firms for a given number of searchers, and increases the job-matching rate. Consequently, firms post more vacancies. There is an opposing effect in that a persistent rise in separations lowers the expected value of a filled position. The graph shows that the first effect dominates not least on account of the high elasticity of the job finding rate to movements in tightness. In the following period, unemployment rises again, as the separation shock now also affects new hires on top of existing employees.[10]

I now assess the ability of the model to capture the observed behavior of unemployment and vacancies. I first look at the fit of the two time series by comparing the actual data with the implied series. These are depicted in Figure 3. The graph clearly shows that the model fits the data remarkably well. This is consistent with the view espoused in Lubik (2009) that the search and matching model is a good data-generating process for unemployment and vacancies, contrary to the argument in Shimer (2005). This requires, however, the use of two exogenous disturbances (productivity and separation rate shocks in my case). Moreover, the estimation pushes the parameters toward values that might be considered a priori implausible (e.g., Hagedorn and Manovskii, 2008), specifically a low bargaining weight for the worker and a high value on being unemployed. In a sense, the model is designed to fit the data well as its reduced-form representation can be written in terms of two endogenous variables only, namely unemployment and vacancies, which happen to be the observables used in the estimation in the first place.[11] A more proper evaluation of the validity of the model would assess its predictions for unobserved variables, such as the wage rate. I leave this to future research.

The lower panel of Figure 3 shows the behavior of the two filtered shock series. The series are indexed to their respective means so that deviations can be interpreted in terms of percentages.[12] The process for productivity is fairly smooth and is almost a mirror image of the unemployment rate. The long decline of unemployment from its peak in mid-2003 to its trough in early 2008 is commensurate with a persistent rise in productivity. The worldwide recession hits Hong Kong in 2008 as productivity falls sharply below trend and recovers only slowly. The recession in the early part of the decade is consistent with a persistent decline in productivity. However, it is interesting to note that unemployment continues declining for more than a year in the early 2000s even though productivity started falling

[10] Recall that in the impact period separations only affect current employees and not new matches. The hump-shaped pattern depends on the persistence of the separation shock and carries over to vacancy postings as the unemployment pool gets more than replenished from old and new laid-off workers.

[11] Lubik (2011) shows the exact reduced-form representation of the two-equation search and matching model and demonstrates how the exogenous shocks in effect act as regression errors.

[12] The mean productivity level is normalized to one in the model, whereas the mean separation rate is estimated at 0.044.

from mid-2000 on.[13]

The separation rate ρ is relatively more volatile than productivity and there are less obvious trend movements. Two observations do stand out, however. The onset of the recession in Hong Kong in 2001 is marked by a sharp rise in separations, which increases the size of the unemployment pool initially. Separations then remain elevated for about a year. In combination with the decline in productivity, this slowly drives up unemployment. The second recession of the decade was heralded by a rise in separations over the course of two quarters. However, separations fell back within a year to their pre-recession level, which dampened the depth of the downturn. This observation also helps to explain the behavior of unemployment and productivity at the beginning of the decade. Despite the fall in the latter, the unemployment picture kept improving on account of a persistent decline in separations. Firms were willing to hold on to their employees despite declining productivity. This was not the case in the last recession as firms resorted to firings early in the productivity downturn.

This narrative supports the notion of an asymmetric nature of the cyclical determinants of unemployment in Hong Kong. At the start of a recession, unemployment rises sharply due to a spike in separations. Over the course of the downturn separations return gradually to their mean, but often overshoot. The recovery only begins, however, when productivity starts rising persistently and firms start posting vacancies again. More succinctly, the pool of the unemployed fills sharply through separations, but drains only gradually through sustained vacancy postings.

I can now summarize the insights developed in this section. First, I find that the simple search and matching model captures aggregate labor market dynamics in Hong Kong remarkably well along several dimensions. Second, the estimated model is consistent with the typical dynamic behavior of unemployment and vacancies over the business cycle. Adverse productivity shocks raise unemployment and lower vacancy postings, while increased exogenous separations generate higher unemployment but stimulate vacancy postings. The main driver of business cycles in the labor market are productivity movements, but separation shocks play a crucial role in the onset of recessions.

[13] It is worth emphasizing that the "productivity shock" is clearly not a productivity shock. I use this terminology because in the model $A_t = Y_t/N_t$ corresponds to measured labor productivity by virtue of the linear production function. At the same time, A_t acts as a residual in the job creation condition (16) after controlling for movements in the separation rate. Obviously, A_t would pick up variations due to movements in any other shock that would not affect the employment equation; for instance, movements in the outside option b or the bargaining parameter η. This is a problem for any kind of structural model, where the theoretical model has more variables than are used in the estimation. Consequently, issues about identification arise.

4.4 Robustness

The first robustness check I conduct is to relax the priors. Instead of using the information from the preliminary data analysis, I impose generally uninformative priors and also change some means. Specifically, I increase the standard deviation of the prior on the separation rate ρ and the match elasticity ξ by an order of magnitude and I also shift the prior mean toward 0.08 and 0.70, respectively. Both values are chosen because they lie at the opposite end of the typical range in the literature. I double both the standard deviation of the match efficiency m as well as its mean, while leaving the uniform prior on the bargaining parameter unaffected. I fix the vacancy cost parameter κ at a value of 0.05 as in the benchmark prior. Experimentation with different priors has shown that there is virtually no information in the data about this parameter, which is therefore identified by the prior. Finally, I center the prior mean of the lag coefficients of the shocks on 0.5 with a very wide standard deviation. The results of the estimation under this alternative prior are reported in Table 5.

The posterior means are very close to those estimated under the benchmark prior. In all cases, the 95% coverage region under the less informative prior contain the posterior means and coverage intervals under the benchmark. The main exception is the autocorrelation coefficient of the separation rate shock, which is estimated at $\rho_\rho = 0.52$. The posterior mean of the bargaining parameter η at 0.18 is also somewhat higher than in the benchmark. The estimation algorithm still pushes in the direction of the Hagedorn and Manovskii (2008) calibration in order to match the volatility of unemployment and vacancies. These differences in parameter estimates do not change the dynamic responses of the model variables to the exogenous shocks in a noticeable manner.

I also experiment with imposing various kinds of priors on the bargaining parameter η.[14] In the first experiment, I keep the benchmark prior for all parameters, but tighten the prior on η. Specifically, I impose a Beta distribution with mean 0.5 and standard deviation of 0.05. The posterior mean of η is now 0.16 with a 90% coverage interval [0.03, 0.38]. The other posterior means are not substantially affected. The tightness of the prior does prevent the posterior from attaining a mode at zero, but the estimate is still strongly pulled downwards. In the second experiment, I combine the wide prior from the first robustness check above with the same tight prior on η. The posteriors of all parameters are largely unaffected, except for the bargaining parameter. Its posterior mean is now 0.24 [0.09,0.47]. Noticeably, the fit of the model under these two experiments as measured by the marginal data density declines, which suggests that the estimation strongly prefers a very low bargaining weight.

[14] I am grateful to an anonymous referee for suggesting this robustness check.

The second robustness check introduces exogenous movements in match efficiency m as the second disturbance in place of the separation rate, which is now treated as a fixed parameter. I specify the process for the level parameter as a first-order autoregressive process. Either disturbance acts as residual in the employment equation. The main difference is timing since separation shocks in the baseline specification affect current employment whereas shocks to the match efficiency operate with a one-period lag. I impose the same tight prior as in the benchmark specification. The results are also reported in Table 5. The posterior means are remarkably close to those under the benchmark specification. The main difference is that the matching shock now plays a much larger role in explaining unemployment and vacancy dynamics.

Overall, I conclude that the data are very informative with respect to the model parameters and that the choice of the prior does not affect the posterior means in an economically significant way. This conclusion is supported by the invariance of the impulse response functions and the variance decompositions across various prior choices. As it turns out, the preliminary data analysis was reasonably successful in identifying key structural parameters, specifically, the match elasticity and the separation rate. What this limited-information approach cannot adjudicate, however, is how well the search and matching approach fits the data overall. As the Bayesian estimation reveals, the conclusion is unambiguously affirmative in the case of the Hong Kong labor market.

5 Conclusion

To the best of my knowledge, this is the first paper to study the Hong Kong labor market from the perspective of a search and matching model that is estimated by Bayesian methods. The structural estimation allows me to draw a few quite sharp conclusions. First, the search and matching approach to the labor market describes Hong Kong very well. It would therefore be a useful starting point to study a host of labor market issues, such as the introduction of a minimum wage or labor market reform in the context of a business cycle model. Second, this paper provides estimates for key structural labor market parameters, which can be used by other researchers in calibration exercises. The estimates are broadly in line with existing ones for other countries. Third, the paper provides a narrative for the unemployment experience in Hong Kong over the last decade.

However, the exercise in this paper is somewhat limited by the small-scale nature of the model. Future research might therefore consider the following extensions. First, it seems imperative to bring more data to bear on the empirical analysis. This involves extending the sample period to pre-2000. While unemployment data are publicly available at monthly frequency from 1981 on, the vacancy data are not. However, the lack of the latter could be compensated for by including other series in the estimation, such as wages or the job-finding rate. Additionally, data on the separation rate would help pin down the behavior of a variable that in this paper has been treated as an exogenous shock. Adding more data would also allow the researcher to expand the model framework. Second, it would be interesting to extend the theoretical model by adding, for instance, a monetary sector as in Krause and Lubik (2007), in order to study the transmission of monetary policy shocks to the labor market.

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Appendix: Model Equations

The full general equilibrium model consists of the following equations:

$$
\begin{aligned}
N_t &= (1-\rho_t)\left[N_{t-1} + mU_{t-1}^{\xi}V_{t-1}^{1-\xi}\right], \\
\frac{\kappa}{m}\theta_t^{\xi} &= \beta E_t\left[(1-\rho_{t+1})\left(A_{t+1} - W_{t+1} + \frac{\kappa}{m}\theta_{t+1}^{\xi}\right)\right], \\
W_t &= \eta\left(A_t + \kappa\theta_t\right) + (1-\eta)b, \\
\theta_t &= \frac{V_t}{U_t}, \\
N_t &= 1 - U_t, \\
\log A_t &= (1-\rho_A)\log A + \rho_A \log A_{t-1} + \varepsilon_{A,t}, \\
\log \rho_t &= (1-\rho_\rho)\log \rho + \rho_\rho \log \rho_{t-1} + \varepsilon_{\rho,t}.
\end{aligned}
$$

The first equation is the employment accumulation equation, followed by the job creation condition. The third equation describes the Nash-bargained wage, while the following two equations define labor market tightness and relate employment to unemployment. The description of the model is completed by the law of motions of the two exogenous stochastic processes.

I first solve for the deterministic steady state of the model. After substituting the wage equation I find the following steady-state relationships:

$$
\begin{aligned}
\overline{N} &= \frac{1-\rho}{\rho} m\overline{V}^{1-\xi}\overline{U}^{\xi}, \\
(1-\eta)(1-b) &= \frac{1-\beta(1-\rho)}{\beta(1-\rho)}\frac{\kappa}{m}\overline{\theta}^{\xi} + \kappa\eta\overline{\theta}.
\end{aligned}
$$

Note that the second equation is non-linear in θ, and that there is, in general, no analytical solution available. For given $\overline{U}$, however, I can solve for $\overline{\theta}$ from the first steady-state condition:

$$\frac{\overline{N}}{1-\overline{N}} = \frac{1-\overline{U}}{\overline{U}} = \frac{1-\rho}{\rho} m\overline{\theta}^{1-\xi}.$$

$\overline{\theta}$ then pins down the value of b required for the job creation condition to hold in steady state:

$$b = A - \frac{1-\beta(1-\rho)}{\beta(1-\rho)(1-\eta)}\frac{\kappa}{m}\overline{\theta}^{\xi} - \frac{\kappa\eta}{(1-\eta)}\overline{\theta}.$$

The rest of the steady-state values then follow immediately. As explained in the text, I treat the steady-state unemployment rate as a parameter, since it simplifies estimation.

The model is log-linearized around the steady state. I normalize aggregate productivity $A = 1$, while I estimate the steady-state level of separations ρ. Denote the log-deviations of a variable from its steady state as $\widetilde{x}_t = \log x_t - \log x$. I reduce the system to one in two endogenous variables only, viz. $\widetilde{N}_t$ and $\widetilde{\theta}_t$, by substituting the wage equation into the job creation condition, and the two definitional equations into the employment equations. The resulting linearized equation system is:

$$\begin{aligned}
\widetilde{N}_t &= \left(1 - \frac{\rho}{\overline{U}}\right)\widetilde{N}_{t-1} + \rho(1-\xi)\widetilde{\theta}_{t-1} - \frac{\rho}{1-\rho}\widetilde{\rho}_t, \\
\xi\widetilde{\theta}_t &= \beta(1-\rho)\left(\xi - \eta m\overline{\theta}^{1-\xi}\right)E_t\widetilde{\theta}_{t+1} + \beta\,(1-\rho)\,\frac{m}{\kappa\overline{\theta}^{\xi}}E_t\widetilde{A}_{t+1} - \frac{\rho}{1-\rho}E_t\widetilde{\rho}_{t+1}, \\
\widetilde{A}_t &= \rho_A\widetilde{A}_{t-1} + \varepsilon_{A,t}, \\
\widetilde{\rho}_t &= \rho_\rho\widetilde{\rho}_t + \varepsilon_{\rho,t}.
\end{aligned}$$

The four equations form a linear rational expectations model in two endogenous variables and two exogenous shocks. The model has the special feature that it is block-diagonal: The job creation condition is an expectational difference equation in $\widetilde{\theta}_t$ only and could thus be solved independently from the rest of system. The solution for tightness then feeds into employment dynamics as a driving process. It can easily be demonstrated that the system possesses a unique solution over the admissible parameter space.

Table 1: Stylized Facts and Model Fit

	Data: HK	Model
Second Moments		
$\sigma(U)$	1.38	1.29
$\sigma(V)$	0.32	0.28
$\sigma(\theta)$	0.11	0.10
$\rho(U,V)$	-0.78	-0.71
Overall Fit		
MDD	74.31	72.98

Note: The statistics are computed from the raw data. $\sigma(\cdot)$ denotes the standard deviation, $\rho(\cdot)$ the correlation coefficient of the respective variables. MDD is the marginal data density of the estimated model.

Table 2: Benchmark Prior Distributions

Parameter	Mean	St.Dev.	Distr.	Source
Separation Rate ρ	0.045	0.004	Beta	Unempl. Dynamics Eq. (17)
Match Elasticity ξ	0.47	0.011	Beta	Unempl. Dynamics Eq. (17)
Match Efficiency m	0.34	0.18	Gamma	Beveridge Curve Eq. (18)
Bargaining η	0.50	0.25	Uniform	Uninformative Prior
Job Creation Cost κ	0.05	0.001	Gamma	Lubik (2009)
Discount Factor β	0.99	- -	Fixed	Annual Real Interest Rate
Benefit b	0.70	- -	Imputed	SS Job Creation; $\overline{U} = 0.055$

Note: The table lists the prior distributions of parameters to be estimated (their means and standard deviations) and how this information was obtained.

Table 3: Benchmark Posterior Estimates

		Prior	Posterior		
		Mean	Mode	Mean	90% Interval
Separation Rate	ρ	0.045	0.044	0.044	[0.038, 0.050]
Match Elasticity	ξ	0.47	0.47	0.47	[0.46, 0.49]
Match Efficiency	m	0.34	0.22	0.27	[0.13, 0.39]
Bargaining	η	0.50	0.00	0.06	[0.00, 0.12]
Job Creation Cost	κ	0.05	0.050	0.050	[0.048, 0.052]
AR-coefficient Technology	ρ_A	0.90	0.93	0.91	[0.86, 0.97]
AR-coefficient Separation	ρ_ρ	0.90	0.90	0.86	[0.76, 0.96]
StD. Technology	σ_A	0.01	0.007	0.012	[0.003, 0.020]
StD. Separation	σ_ρ	0.01	0.064	0.066	[0.051, 0.080]

Table 4: Variance Decomposition

	Productivity	Separation
U	0.61	0.39
	[0.33, 0.89]	[0.11, 0.67]
V	0.81	0.19
	[0.68, 0.95]	[0.05, 0.32]

Table 5: Robustness

		Benchmark	Wide Prior		Match. Shock	
		Mean	Mean	90% Interval	Mean	90% Interval
Separation Rate	ρ	0.044	0.039	[0.028, 0.050]	0.041	[0.034, 0.050]
Match Elasticity	ξ	0.47	0.52	[0.43, 0.61]	0.50	[0.48, 0.54]
Match Efficiency	m	0.27	0.36	[0.16, 0.56]	0.31	[0.17, 0.42]
Bargaining	η	0.06	0.18	[0.00, 0.37]	0.07	[0.00, 0.14]
Job Creation Cost	κ	0.050	0.050	[0.048, 0.052]	0.050	[0.048, 0.052]
AR-coeff. Technology	ρ_A	0.91	0.88	[0.80, 0.95]	0.86	[0.80, 0.2]
AR-coeff. Separation/Matching	$\rho_{\rho/m}$	0.86	0.52	[0.29, 0.75]	0.90	[0.83, 0.94]
StD. Technology	σ_A	0.012	0.016	[0.003, 0.034]	0.010	[0.005, 0.021]
StD. Separation/Matching	$\sigma_{\rho/m}$	0.066	0.070	[0.045, 0.094]	0.071	[0.059, 0.092]

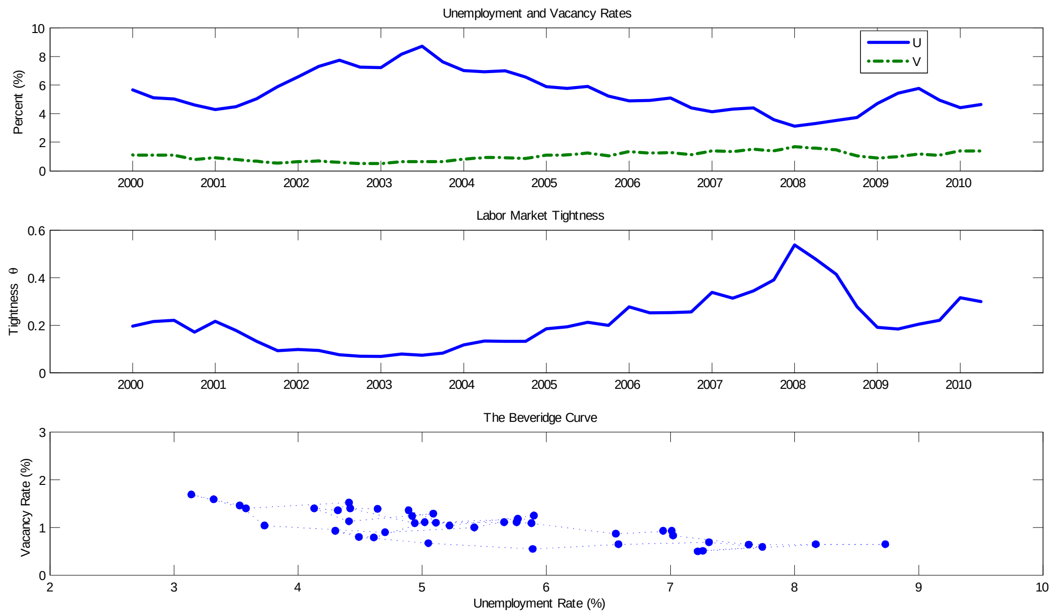

Figure 1: Unemployment, Vacancies, and the Beveridge Curve

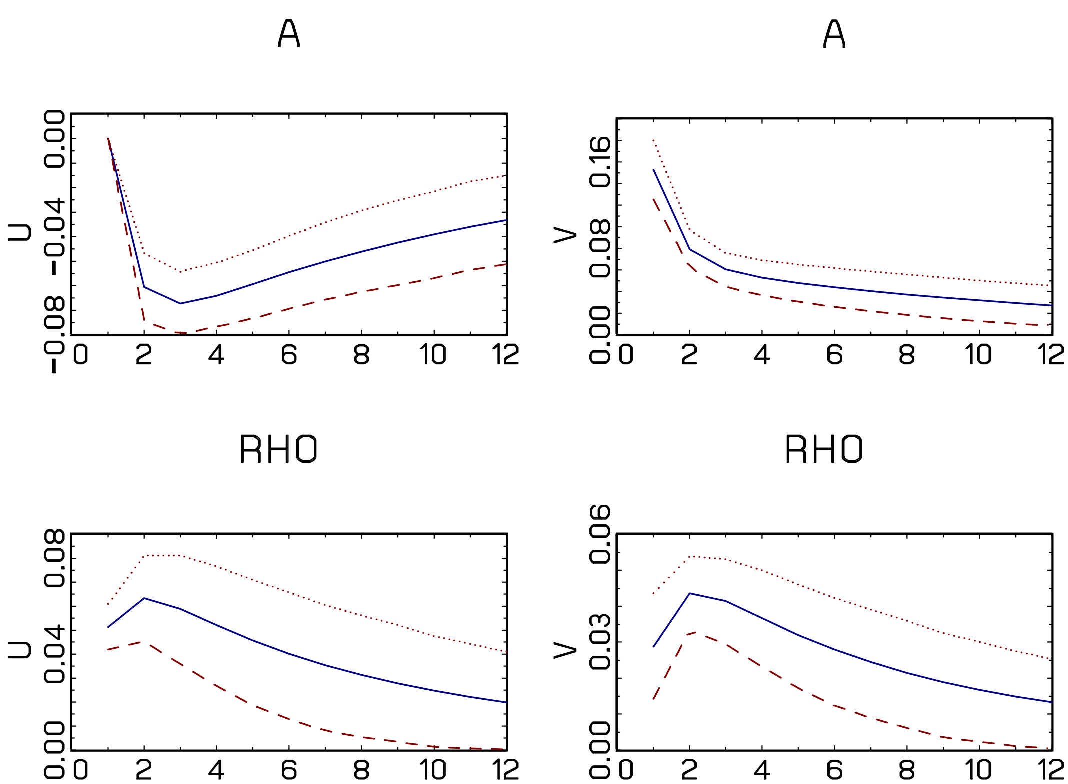

Figure 2: Impulse Response Functions: Benchmark Model

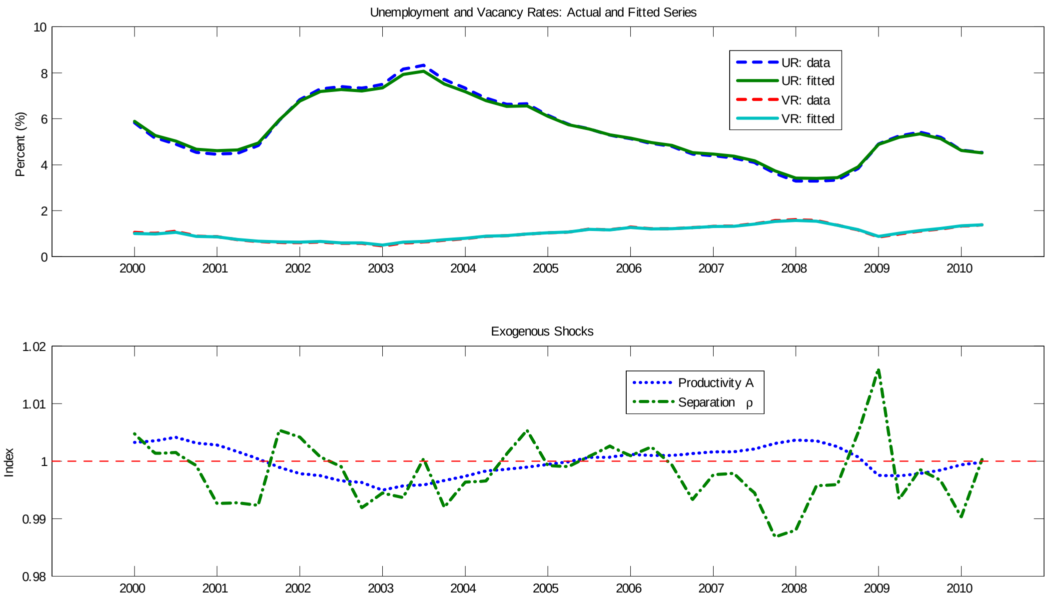

Figure 3: Filtered Series from the Estimated Benchmark Model