Korea and the World Economy, Vol. 18, No. 2 (August 2017) 205-233

Matching Efficiency vs. Worker Flows: Accounting for Unemployment Dynamics in Korea*

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In this paper, we construct a modified version of Mortensen and Pissarides (1994) in order first, to estimate the matching efficiency in labor market and second, to investigate the impacts of matching efficiency and worker flows on the unemployment dynamics in Korea over the 2004-2011 periods. We find that the matching efficiency has fallen by 24.5% points for post-crisis period compared to pre-crisis period. Our decomposition finds that approximately 66% of the high frequency fluctuation of the unemployment rate is accounted for by the transition rates, while the matching efficiency accounts for only 2.1% of the unemployment fluctuations during the same periods in time.

JEL Classification: E24, J60, J63, J64
Keywords: matching efficiency, worker flows,
unemployment dynamics

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* Received January 31, 2017. Revised March 1, 2017. Accepted June 20, 2017. The authors acknowledge the anonymous referees and the editor for a constructive comments. All errors are ours.
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1. INTRODUCTION

Understanding the unemployment dynamics is important in evaluating the state of the labor market in an economy, the economic fluctuations and their implications on welfare. However, the unemployment dynamics are not easy to interpret. Its dynamics are in fact caused by a number of diverse factors; worker flows from employment to unemployment (separation), worker flows from unemployment to employment (job-finding), flows to labor market participation, and matching efficiency in a labor market.

Importance of worker flows across the labor market states has been investigated by a number of studies. Shimer (2012), Fujita and Ramey (2009) and Smith (2011) study the contribution of separation and job-finding rate in order to decompose unemployment fluctuations into the parts due to changes in inflow and outflow of worker flows. They find that the separation rate plays a significant role in unemployment dynamics. Kim and Lee (2014) decompose the unemployment dynamics in Korea and find that inflow to unemployment contributes substantially to unemployment fluctuations in Korea.

We study the impacts of matching efficiency and worker flows on the unemployment fluctuation in Korea during the 2004-2011 periods. Our analysis finds that approximately 66% of the high frequency fluctuation of the unemployment rate is accounted for by the transition rate λ_t's. The matching efficiency accounts for only 2.1% of the unemployment fluctuations during the periods.

We modify Mortensen and Pissarides model (1994) by introducing the third labor market state, non-participation, in Korean economy. Not only do we include the matching efficiency but we also appropriately include the worker transition rates across labor states. Particularly, for the Korean labor market the previous studies emphasize the importance of fluctuations in worker flows from non-participation in explaining the unemployment dynamics. Moon (2009) investigates the cyclical behavior of the Korean labor market by looking into cyclical transitions between labor market states of employment, unemployment and non-participation. He finds that employment fluctuation is well explained by the fluctuation of non-participation in Korea. In monthly data from 2004:m1 to 2011:m12, the gross worker flow from nonparticipation to employment (1.5% of working age population) is 3 times as large as the flow from unemployment to employment (0.5%) in Korea.[1)] Without incorporating the nonparticipation labor state, we miss these transitions of workers in our analysis for Korean labor market. Moreover, introducing the nonparticipation labor state makes our model more consistent with the worker flows data in the labor market.

Mortensen and Pissarides framework (1994) has three main components. First, it has an aggregate matching function, which is a production function with the number of unemployed and the number of open vacancies for recruiting taken as inputs and the flow of newly matched worker-employer pairs as the output. Matching efficiency is a multiplicative factor of the matching function. The second element is a free-entry condition for the creation of vacancies of the employers. The third component is a simple accounting relationship that states that the total flows in and out of each labor market state must be equal. A standard approach in the MP framework is to allow only for two labor market states (employment and unemployment) and to assume that the model is always at its steady state.

We use our model in order to measure the matching efficiency and evaluate its consequences during the 2004-2011 periods. Ours is not the first article to do this. Two closely related papers are Barlevy (2011) and Barnichon and Figura (2010). Barlevy (2011) follows the standard approach by postulating two labor market states, assuming a constant separation rate (that is, the rate at which workers transit from employment into unemployment), and by assuming that the model is at its steady state. On the contrary, Barnichon and Figura (2010) incorporate a third labor market state (nonparticipation) and allow the transition rates between the three labor market states to vary over time. Similar to Barlevy, Barnichon

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[1)] Growth worker flows are defined as a percentage of working age population as in Kim and Lee (2014).

and Figura assumes that the model is at its steady state and that only unemployed workers enter the matching function and there exists no worker flow from non-participation state to employment state in the model.

The remainder of this paper is organized as follows: section 2 provides the description of our data set and shows the labor market dynamics in Korea. Section 3 constructs our model economy. Section 4 estimates the matching efficiency from our model. In section 5, we decompose the unemployment fluctuation into worker flows and matching efficiency in order to study the contribution of worker flows including transition rates across labor market state and matching efficiency to unemployment dynamics.

2. DATA AND LABOR MARKET DYNAMICS IN KOREA

This section explains first, how we construct our data set for our analysis and second, shows the cyclicality of Korean labor market variables including work flows, vacancy rate, and unemployment rate.

We use the monthly Economically Active Population Survey (EAPS) from the Statistics Korea, the monthly data of the number of vacancies from Korea Employment Information Service (KEIS), and Composite Indexes of Business Indicators (CI) from the Statistics Korea. Data for the work flows across labor market states is obtained from Kim and Lee (2014).

Our data set covers the periods from 2004:m1 to 2011:m12 for our analysis. While the vacancy data from KEIS is available from 2004:m1 to recent, we have data for the worker flows and the transition rates across labor states only from 2000:m1 to 2011:m12. Hence, the coverage of our data set for analysis is limited to the overlapped periods from 2004:m1 to 2011:m12 since the recent data for worker flows and the transition rates is only available up to 2011:m12.

We make a data adjustment in measuring the total number of vacancies following Davis, Faberman and Haltiwanger (2010) for the US and Lee

(2015) for Korea.[2] They use a model of hiring dynamics to correct the underestimation problem in measuring the total number of vacancies. The stock of vacancies at the end of period t, v_t can be decomposed with three terms. First, a monthly flow θ_t of new vacancies increases the stock. Second, new matches decrease the stock of vacancies. Third, vacancies can be depreciated without being filled at the monthly rate δ_t, also lowering the stock. These three terms can explain the monthly law of motion for the vacancy stock at period t:

$$\begin{aligned} v_t &= (1-\eta_t)(1-\delta_t)(v_{t-1}+\theta_t) \\ &= v_{t-1}-\eta_t(v_{t-1}+\theta_t)+\theta_t-(1-\eta_t)\delta_t(v_{t-1}+\theta_t) \\ &= v_{t-1}-M_t+\xi_t, \end{aligned} \tag{1}$$

where $M_t = \eta_t\left(v_{t-1}+\theta_t\right)$, $\xi_t = \theta_t - \left(1-\eta_t\right)\delta_t\left(v_{t-1}+\theta_t\right)$. M_t is the total number of new matches including hires from new vacancies θ_t, ξ_t is the total number of net vacancies passed on to next month and η_t is the job-filling rate.

KEIS reports v_t which is the number of vacancies at the end of each period *t*. In our analysis, we need to measure the number of vacancies available at the beginning of each period *t*, which we denote as V_{t-1}. Using the law of motion for the vacancy stock as in equation (1), the latent variable V_{t-1} can be defined as the total number of posted vacancies plus the total number of new matches at t:

$$V_{t-1} \equiv v_{t-1}+\xi_t = v_t + M_t. \tag{2}$$

We use equation (2) to construct a data V_{t-1} for the number of vacancies available at the beginning of period *t*.

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[2] Davis, Faberman and Haltiwanger (2010) use Job Openings and Labor Turnover Survey (JOLTS) data. They find strong patterns in hiring and vacancy outcomes related to industry, employer size, the pace of worker turnover, and employer growth rates. Lee (2015) estimates the matching function in Korea by using 2SLS method.

The work flows and the transition rates across the labor market states are obtained from Kim and Lee (2014). They compute the data as follows: monthly transition rates, denoted as λ_t^{XY}, are calculated using the gross worker flows F_t^{XY} from X state to Y state. For example, the transition rate from employment state (E) to unemployment state (U) is computed as:

$$\lambda_t^{EU} = \frac{F_t^{EU}}{\sum_{Y \in \{E,U,N\}} F_t^{EY}}, \tag{3}$$

where three labor market states are denotes as employed, E, unemployed, U and nonparticipation N. Then, we seasonally adjust all the series using the US Census Bureau X-12 monthly seasonal adjustment method.

Given our dataset covering from 2004:m1 to 2011:m12, we closely follow the Reference Dates of Business Cycle announced by the Statistics Korea and we divide our whole sample periods into three sub-periods accordingly.

Figure 1 shows the separation rate and job-finding rate over the sample periods with the unemployment rate. Separation rate, s_t and job-finding

Figure 1 Separation Rate and Job-finding Rate with Unemployment Rate

Correlation with unemployment rate: 0.746 Correlation with unemployment rate: –0.008

Source: Statistics Korea.

Table 1 Cyclicality of Separation Rate and Job-finding Rate

	Whole Periods (2004:1-2011:12)		Pre-crisis Periods (2004:1-2007:12)		During-crisis Periods (2008:1-2009:2)		Post-crisis Periods (2009:3-2011:12)	
	ρ_i	$\frac{\sigma_i}{\sigma_y}$	ρ_i	$\frac{\sigma_i}{\sigma_y}$	ρ_i	$\frac{\sigma_i}{\sigma_y}$	ρ_i	$\frac{\sigma_i}{\sigma_y}$
Separation Rate	–0.375	0.0015	–0.430	0.0014	–0.374	0.0007	–0.191	0.0018
Job-finding Rate	0.077	0.0244	–0.120	0.0203	0.355	0.0160	0.437	0.0294

Notes: 1) ρ_i is the correlation between CI and i's variable. 2) σ_y and σ_i are the standard deviation of CI and i's variable, respectively.

rate, f_t are defined as in Shimer (2012):

$$s_t = \lambda_t^{EU} + \lambda_t^{EN}\left(\lambda_t^{NU} / \left(\lambda_t^{NU} + \lambda_t^{NE}\right)\right), \tag{4}$$

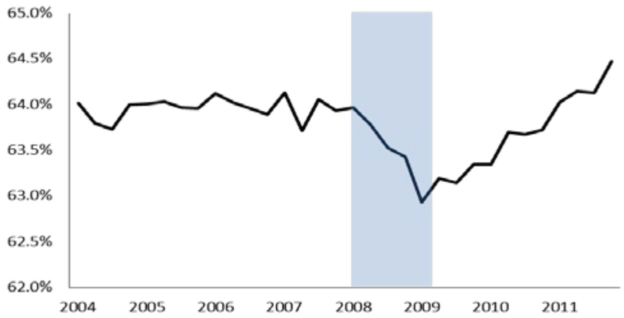
$$f_t = \lambda_t^{UE} + \lambda_t^{UN}\left(\lambda_t^{NE} / \left(\lambda_t^{NU} + \lambda_t^{NE}\right)\right). \tag{5}$$

The fluctuations of separation rate and job-finding rate are closely related with the unemployment rate over time. We confirm that the separation rate contributes more to the unemployment dynamics in Korea and shows the higher correlation (0.746) with the unemployment rate and this is consistent with Kim and Lee (2014).

Regarding to the cyclicality of separation and job-finding rate, we compute and compare the correlations with Composite Indexes of Business Indicators (CI) and the relative standard deviations in table 1. The separation rate is negatively correlated with business cycles with lower volatility over the whole sample periods, while the job-finding rate is less correlated with business cycle but has a higher volatility over business cycles. The cyclicality of two rates stays the same even during the post-crisis periods but the size of the correlation with CI has changed such that job finding rate has higher correlation during the post-crisis periods than during other two sub-periods. This results can be supported by the increase in employment rate and decreases in unemployment rate and non-participation rate during the post-crisis periods as you see in figure 2 below. Also, the increase in job-

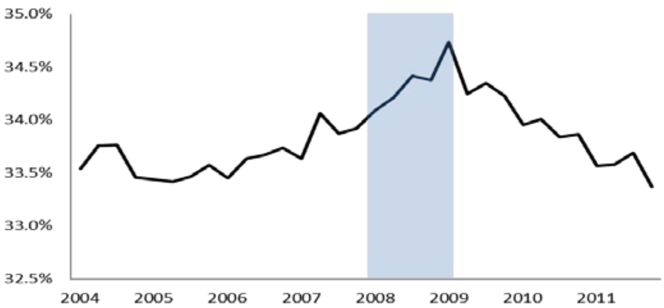
Figure 2 Employment, Unemployment and Non-participation Rate

Employment rate



Unemployment rate

Non-participation rate

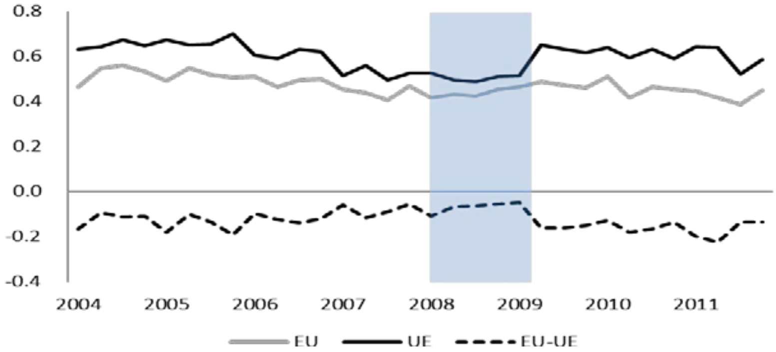


Source: Statistics Korea.

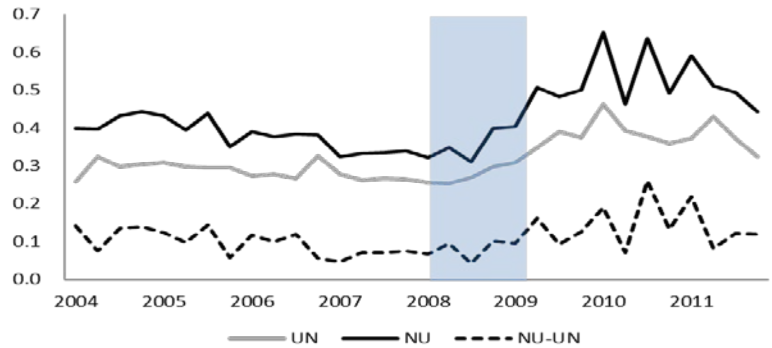
finding rate during the post-crisis periods can be explained by huge increase in worker flows from non-participation to unemployment (job-seekers) even with lower matching efficiency (figure 3).

Figure 3 Worker Flows and Net Flow

Gross flows and net flow between employment and unemployment (%)



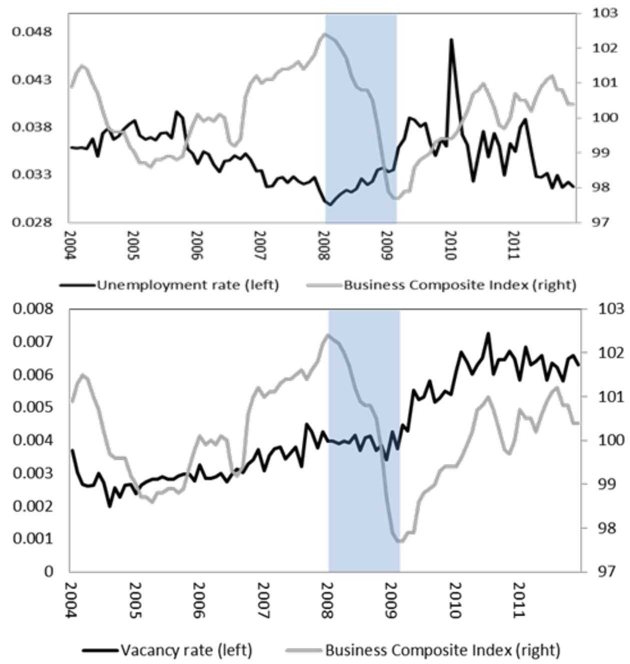
Gross flows and net flow between unemployment and non-participation (%)



Source: Statistics Korea.

Figure 4 and table 2 show the cyclicality of unemployment rate and vacancy rate over the sample periods in Korea. The unemployment rate is countercyclical (correlation coefficient equals to –0.606) over all sample periods. Particularly, the unemployment rate has been more responsive to the crisis periods than other periods in time. The vacancy rate becomes pro-cyclical (correlation coefficient equals to 0.747) in the post-crisis periods while it was less responsive to the cycles before. The correlation of vacancy rate over the whole sample periods is low because the vacancy did not drop significantly during the crisis periods. Other than the during-crisis periods, vacancy rate has higher correlation with business cycles.

Figure 4 Cyclicality of Unemployment Rate and Vacancy Rate



Source: Statistics Korea and Korea Employment Information Service.

Table 2 Cyclicality of Unemployment Rate and Vacancy Rate

	Whole Periods (2004:1-2011:12)		Pre-crisis Periods (2004:1-2007:12)		During-crisis Periods (2008:1-2009:2)		Post-crisis Periods (2009:3-2011:12)	
	ρ_i	$\frac{\sigma_i}{\sigma_y}$	ρ_i	$\frac{\sigma_i}{\sigma_y}$	ρ_i	$\frac{\sigma_i}{\sigma_y}$	ρ_i	$\frac{\sigma_i}{\sigma_y}$
Unemployment Rate	–0.606	0.0025	–0.760	0.0020	–0.911	0.0008	–0.470	0.0033
Vacancy Rate	0.089	0.0013	0.657	0.0005	0.215	0.0001	0.747	0.0007

Notes: ρ_i is the correlation between CI and i's variable. σ_y and σ_i are the standard deviation of CI and i's variable, respectively.

Table 3 and 4 show the serial correlations of the unemployment rate and vacancy rate with the business cycles. The unemployment rate is countercyclical (correlation coefficient equals to –0.659) with lags of 3

Table 3 Serial Correlation of Unemployment Rate and Business Composite Index

i	Unemployment Rate (+*i*)							
	Whole Periods (2004:1-2011:12)		Pre-crisis Periods (2004:1-2007:12)		During-crisis Periods (2008:1-2009:2)		Post-crisis Periods (2009:3-2011:12)	
	lead	lag	lead	lag	lead	lag	lead	lag
0	–0.606	–0.606	–0.760	–0.760	–0.912	–0.912	–0.469	–0.469
1	–0.549	–0.627	–0.730	–0.683	–0.820	–0.669	–0.388	–0.488
2	–0.478	–0.647	–0.706	–0.610	–0.690	–0.378	–0.300	–0.511
3	–0.379	–0.659	–0.674	–0.529	–0.456	–0.157	–0.137	–0.503
4	–0.294	–0.648	–0.658	–0.446	–0.215	–0.024	0.010	–0.483
5	–0.232	–0.595	–0.659	–0.334	–0.096	0.063	0.106	–0.415
6	–0.180	–0.519	–0.639	–0.219	–0.008	0.170	0.136	–0.317

Table 4 Serial Correlation of Vacancy Rate and Business Composite Index

i	Vacancy Rate (+*i*)							
	Whole Periods (2004:1-2011:12)		Pre-crisis Periods (2004:1-2007:12)		During-crisis Periods (2008:1-2009:2)		Post-crisis Periods (2009:3-2011:12)	
	lead	lag	lead	lag	lead	lag	lead	lag
0	0.089	0.089	0.657	0.657	0.214	0.214	0.747	0.747
1	0.130	0.050	0.660	0.538	0.204	0.123	0.649	0.698
2	0.162	0.017	0.691	0.460	0.463	0.089	0.519	0.616
3	0.190	–0.026	0.656	0.375	0.113	0.103	0.470	0.523
4	0.203	−0.056	0.588	0.335	0.014	0.086	0.406	0.449
5	0.211	−0.093	0.605	0.275	−0.169	0.046	0.305	0.382
6	0.209	−0.123	0.547	0.201	−0.076	−0.085	0.270	0.331

months over the entire sample periods. During the crisis periods, the coefficient is –0.912 without lags and for the post-crisis periods the unemployment rate is countercyclical with lags of 2 months. The vacancy rate is pro-cyclical with leads of 5 months during the whole periods while it is contemporaneously correlated with the business cycles for the post-crisis periods.

3. A MODIFIED VERSION OF MORTENSEN AND PISSARIDES MODEL

We modify Mortensen and Pissarides (1994) in which there are two labor market states (employment and unemployment) by introducing the third labor market state, nonparticipation. A main reason for this modification is that in data between 2004:m1 and 2011:m12, the gross worker flow from nonparticipation to employment (1.5) is 3 times as large as the flow from unemployment to employment (0.5) in Korea.[3] Without incorporating the nonparticipation labor state, we miss these transitions of workers in our analysis. Moreover, introducing the nonparticipation labor state makes our model more consistent with the worker flows data in the labor market.

We assume that there are two types of agents: firms and workers. Each firm has one job available, which can either be filled or vacant. The expected discounted value of profits generated by a filled job is equal to J_t units of the numeraire. Posting a vacant job requires k units of the numeraire. There are an infinite number of potential firms. Workers can be in one of three states: employed, unemployed or nonparticipated. Unlike Mortensen and Pissarides (1994), not only unemployed workers but also some fraction of non-participants can newly be matched with posted vacancies. The new matches can be formulated according to the following matching function:

$$M_t = A_t \left(U_t + \psi_t N_t \right)^{\alpha} V_t^{1-\alpha}, \tag{6}$$

where M_t is the total number of new matches, U_t is the total number of unemployed workers, N_t is nonparticipation, V_t is the total number of posted vacancies, A_t is the productivity of the matching function, $0 < \psi_t < 1$ and $0 < \alpha < 1$. Observe that ψ_t can be interpreted as the fraction of the total number of workers who reports they are nonparticipants but search for

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[3] See Kim and Lee (2014) for more details.

jobs anyway. Alternatively, ψ_t can be interpreted as the search intensity of nonparticipant workers.

The transition rate from employment to unemployment λ_t^{EU}, the transition rate from employment to nonparticipation λ_t^{EN}, the transition rate from unemployment to employment λ_t^{UE}, the transition rate from unemployment to nonparticipation λ_t^{UN}, the transition rate from nonparticipation to unemployment λ_t^{NU}, and the transition rate from nonparticipation to employment λ_t^{NE} are assumed to be exogenous to the model.

Normalizing to one the total number of workers in the economy for all periods t:

$$E_t + U_t + N_t = 1. \tag{7}$$

The evolution of workers across labor market states then can be described by the following equations:

$$\dot{E}_t = M_t - \left(\lambda_t^{EU} + \lambda_t^{EN}\right)E_t, \tag{8}$$

$$\dot{U}_t = \lambda_t^{EU}E_t + \lambda_t^{NU}N_t - \left(\lambda_t^{UE} + \lambda_t^{UN}\right)U_t, \tag{9}$$

$$\dot{N}_t = \lambda_t^{EN}E_t + \lambda_t^{UN}U_t - \left(\lambda_t^{NE} + \lambda_t^{NU}\right)N_t. \tag{10}$$

Equation (8) states that change in employment is equal to all inflow transitions into employment (either from unemployment or nonparticipation), minus the outflow of total separations (either to unemployment or nonparticipation). Equation (9) states that change in unemployment is equal to all transitions into unemployment (either from employment or nonparticipation), minus all transitions out of unemployment (either to employment or nonparticipation). Equation (10) states that change in nonparticipation is equal to all transitions into nonparticipation (either from employment or unemployment), minus all transitions out of nonparticipation (either to employment or unemployment).

Firms in the economy maximize their profits by satisfying the following zero profit condition:

$$k = \left(\frac{M_t}{V_t}\right) J_t, \tag{11}$$

that is, the cost of posting a vacancy k must be equal to the probability of filling a vacancy M_t / V_t times the expected discounted value of profits generated by a filled job, J_t. If this condition was not satisfied, the total number of vacancies created would be either zero or infinity, depending on the direction of the resulting inequality.

The transition rate from unemployment into employment λ_t^{UE} is given by:

$$\lambda_t^{UE} = \left(\frac{M_t}{U_t}\right)\left(\frac{U_t}{U_t + \psi_t N_t}\right) = \frac{A_t \left(U_t + \psi_t N_t\right)^{\alpha} V_t^{1-\alpha}}{U_t + \psi_t N_t}, \tag{12}$$

since a fraction $\left(\frac{U_t}{U_t + \psi_t N_t}\right)$ of the total matches M_t is formed with unemployed workers. Similarly, the transition rate from nonparticipation into employment λ_t^{NE} is given by:

$$\lambda_t^{NE} = \left(\frac{M_t}{N_t}\right)\left(\frac{\psi_t N_t}{U_t + \psi_t N_t}\right) = \psi_t \frac{A_t \left(U_t + \psi_t N_t\right)^{\alpha} V_t^{1-\alpha}}{U_t + \psi_t N_t}, \tag{13}$$

since a fraction $\left(\frac{\psi_t N_t}{U_t + \psi_t N_t}\right)$ of the total matches M_t is formed with nonparticipant workers. Notice that the search intensity of nonparticipant workers, ψ_t can be obtained from data as:

$$\psi_t = \frac{\lambda_t^{UE}}{\lambda_t^{NE}}. \tag{14}$$

Given equation (6), we can rewrite equations (8), (9), (10) and (11) for the evolution of three labor states as follows:

$$\dot{E}_t = A_t\left(U_t + \psi_t N_t\right)^{\alpha} V_t^{1-\alpha} - \left(\lambda_t^{EU} + \lambda_t^{EN}\right)E_t, \tag{15}$$

$$\dot{U}_t = \lambda_t^{EU}E_t + \lambda_t^{NU}N_t - \left(\lambda_t^{UE} + \lambda_t^{UN}\right)U_t, \tag{16}$$

$$\dot{N}_t = \lambda_t^{EN}E_t + \lambda_t^{UN}U_t - \left(\lambda_t^{NE} + \lambda_t^{NU}\right)N_t, \tag{17}$$

$$V_t = \frac{J_t}{k}A_t\left(U_t + \psi_t N_t\right)^{\alpha} V_t^{1-\alpha}. \tag{18}$$

Note that the matching efficiency A_t, the transition rates λ_t, and the expected discounted value of profits generated by a filled job J_t are exogenous to the model. Given the total number of workers unemployed U_0 and the total number of nonparticipation N_0 at period zero, the model generates an endogenous sequence for $\left\{E_t,\ V_t,\ U_{t+1},\ N_{t+1}\right\}_{t=0}^{\infty}$.

3.1. Steady State Analysis

Assuming a constant matching efficiency A, normalized to a unity, a constant separation rate λ, and constant expected discounted value of profits generated by a filled job J, a steady state of the model economy is such that the endogenous path for $\left\{E_t, V_t, U_{t+1}, N_{t+1}\right\}_{t=0}^{\infty}$ that the model generates is constant over time. That is, that $\dot{E}_t = \dot{U}_t = \dot{N}_t = 0$ for all $t \geq 0$. A steady state $\left(E, V, U, N\right)$ can be interpreted as the total matches, vacancies, and unemployment that the economy will converge to in the long run. From equations (7), (15), (17) and (18), we have the conditions for a steady state as follows:

$$\left(\lambda^{EU} + \lambda^{EN}\right)\left(1 - U - N\right) = A\left(U + \psi N\right)^{\alpha} V^{1-\alpha}, \tag{19}$$

$$\left(\lambda^{NE} + \lambda^{NU} + \lambda^{EN}\right)N = \lambda^{EN}\left(1 - U\right) + \lambda^{UN}U, \tag{20}$$

$$k = \frac{A\left(U + \psi N\right)^{\alpha} V^{1-\alpha}}{V}J. \tag{21}$$

We can then calibrate this model by choosing the value α of elasticity of job searcher and set the value $\alpha = 0.573$ such that equation (22) holds with the average values of the variables between 2004:m1 and 2007:m12. We find that the calibrated value of α is in line with the estimates surveyed in Petrongolo and Pissarides (2001) and Hall and Schulhofer-Wohl (2015):

$$\alpha = \frac{\ln\left(\left(\lambda^{EU} + \lambda^{EN}\right)\left(1 - U - N\right)\right) - \ln V}{\ln \dfrac{U + \psi N}{V}}. \tag{22}$$

We make an explicit the assumption that the economy at any month *t* can be safely described by the steady-state equations (19), (20) and (21) as in Shimer (2012) and other labor literature. It is convenient to rewrite the steady state system of equations as:

$$\left(\lambda_t^{EU} + \lambda_t^{EN}\right)\left(1 - U_t - N_t\right) = A_t\left(U_t + \psi_t N_t\right)^{\alpha} V_t^{1-\alpha}, \tag{23}$$

$$\left(\lambda_t^{NE} + \lambda_t^{NU} + \lambda_t^{EN}\right) N_t = \lambda_t^{EN}\left(1 - U_t\right) + \lambda_t^{UN} U_t, \tag{24}$$

$$k = \frac{A_t\left(U_t + \psi_t N_t\right)^{\alpha} V_t^{1-\alpha}}{V_t} J_t. \tag{25}$$

We now estimate the exogenous variables of the matching efficiency and expected discounted value of profits generated by a filled job, $\left\{A_t,\, J_t\right\}_{t=0}^{\infty}$ with equation (23) and (25), given data for $\left\{E_t,\, V_t,\, U_{t+1},\, N_{t+1}\right\}_{t=0}^{\infty}$ as follows:

$$A_t = \frac{\left(\lambda_t^{EU} + \lambda_t^{EN}\right)\left(1 - U_t - N_t\right)}{\left(U_t + \psi_t N_t\right)^{\alpha} V_t^{1-\alpha}}, \tag{26}$$

$$J_t = \frac{V_t^{\alpha}}{A_t\left(U_t + \psi_t N_t\right)^{\alpha}}, \tag{27}$$

where the job-posting cost k is normalized to 1.

4. ESTIMATE OF MATCHING EFFICIENCY $\{A_t\}_{t=2004:1}^{2011:12}$

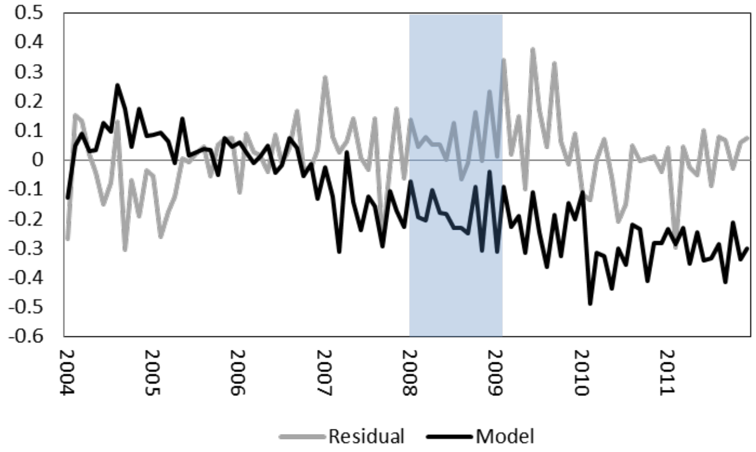
This section estimates the sequence of the matching efficiency A_t, which is regarded as an exogenous variable in our model. We estimate the matching efficiency by use of the model structure as in equation (26). Alternatively, we can estimate the matching efficiency $\tilde{A}_t$ as a residual of matching function by OLS (ordinary least square) like a Solow residual. We can run OLS[4)] of the matching function as follows:

$$\ln \tilde{A}_t = \ln \frac{M_t}{V_t} - \hat{\alpha}_{OLS} \ln \frac{U_t + \psi_t N_t}{V_t}. \tag{28}$$

We now then can compare the two estimates of matching efficiency A_t and $\tilde{A}_t$; the former is the estimate from our model structure while the latter is the estimate from OLS.

Figure 5 shows the log deviation of matching efficiencies, $d\ln A_t$ and $d\ln \tilde{A}_t$ from its average values between 2004:m1 and 2007:m12. This

Figure 5 Estimated Matching Efficiency A_t and $\tilde{A}_t$ in Log



4) The OLS estimate coefficient $\hat{\alpha}$ is 0.089.

Table 5 Average Values of Estimates for Matching Efficiency

Matching Efficiency	Whole Periods (2004:1-2011:12)	Pre-crisis Periods (2004:1-2007:12)	During-crisis Periods (2008:1-2009:2)	Post-crisis Periods (2009:3-2011:12)
$\tilde{A}_t$ from OLS	1.008 (0.128)	0.986 (0.119)	1.078 (0.118)	1.010 (0.134)
A_t from Model	0.897 (0.149)	1.008 (0.116)	0.846 (0.071)	0.761 (0.066)

Note: standard deviation in parenthesis.

shows that the estimate from OLS exhibits very different from the one obtained from our model structure. Table 5 compares the summary statistics of the estimates.

Two estimated sequences of matching efficiency A_t and $\tilde{A}_t$ are very different over time. The estimate $\tilde{A}_t$ from OLS implies that the matching efficiency increases by 9.3% during the financial crisis compared with the level before the crisis and then after the crisis, it drops by 6.3% than the during-crisis periods level. On the other hand, the estimate A_t from our model structure implies that the matching efficiency drops by 19% during the crisis and it does not recover but further drops and reaches at the level of efficiency lower by 24.4% than the pre-crisis periods level.

5. ACCOUNTING FOR THE UNEMPLOYMENT DYNAMICS: MATCHING EFFICIENCY VS. WORKER FLOWS

This section utilizes the model structure in previous sections in order to investigate the impacts of matching efficiency and worker flows on the unemployment dynamics in Korea over the 2004-2011 periods. Unlike Shimer (2012) for the U.S. economy and Kim and Lee (2014) for the Korean economy, our model structure incorporates not only worker flows but also matching efficiency in the labor market dynamics. Once we estimate the exogenous variables of the model, we can simulate the economy and measure the relative contribution of the exogenous variables on unemployment fluctuations.

5.1. Decomposition of Unemployment Fluctuations: Contribution Indices

Using equation (23), (24) and (25), we derive unemployment rate, U_t in the model:

$$U_t = \frac{C_t D_t - C_t \lambda_t^{EN} - \left(A_t^{\frac{1}{\alpha}} J_t^{\frac{1-\alpha}{\alpha}} \right) \psi_t \lambda_t^{EN}}{\left(A_t^{\frac{1}{\alpha}} J_t^{\frac{1-\alpha}{\alpha}} \right) \left(D_t + \psi_t \lambda_t^{UN} - \psi_t \lambda_t^{EN} \right) + C_t D_t - C_t \lambda_t^{EN} + C_t \lambda_t^{UN}}, \quad (29)$$

where $C_t = \lambda_t^{EU} + \lambda_t^{EN}$, $D_t = \lambda_t^{NE} + \lambda_t^{NU} + \lambda_t^{EN}$.

The first-order Taylor approximation around its value at the previous period yields:

$$\begin{aligned} \Delta U_t = {} & c_A \Delta A_t + c_J \Delta J_t + c_{EU} \Delta \lambda_t^{EU} + c_{EN} \Delta \lambda_t^{EN} + c_{UE} \Delta \lambda_t^{UE} + c_{UN} \Delta \lambda_t^{UN} \\ & + c_{NE} \Delta \lambda_t^{NE} + c_{NU} \Delta \lambda_t^{NU}, \end{aligned} \quad (30)$$

where Δ is the differential from the previous period and c_i is the constant coefficient on changes in a factor i.

We can then decompose the unemployment fluctuation into each contributors by noting as Fujita and Ramsey (2009) that

$$\begin{aligned} \mathrm{Var}\left(\Delta U_t\right) = {} & \mathrm{Cov}\left(\Delta U_t, c_A \Delta A_t\right) + \mathrm{Cov}\left(\Delta U_t, c_J \Delta J_t\right) + \mathrm{Cov}\left(\Delta U_t, c_{EU} \Delta \lambda_t^{EU}\right) \\ & + \mathrm{Cov}(\Delta U_t, c_{EN} \Delta \lambda_t^{EN}) + \mathrm{Cov}(\Delta U_t, c_{UE} \Delta \lambda_t^{UE}) \\ & + \mathrm{Cov}(\Delta U_t, c_{UN} \Delta \lambda_t^{UN}) + \mathrm{Cov}(\Delta U_t, c_{NE} \Delta \lambda_t^{NE}) \\ & + \mathrm{Cov}(\Delta U_t, c_{NU} \Delta \lambda_t^{NU}). \end{aligned} \quad (31)$$

Table 6 Decomposition of Unemployment Fluctuations from Previous Period

Exogenous Variables	Contribution Index
Matching efficiency (β_A)	0.021
Value of filled jobs (β_J)	0.319
Transition rates (β_λ)	0.661
Sum	1.000

We quantify the relative contribution of the exogenous variables, A_t, J_t, λ_t^{EU}, λ_t^{EN}, λ_t^{UE}, λ_t^{UN}, λ_t^{NE}, λ_t^{NU} by computing the contribution index as follow:

$$\beta_i = \frac{\operatorname{cov}\left(\Delta U_t, c_i \times \Delta i_t\right)}{\operatorname{var}\left(\Delta U_t\right)}, \tag{32}$$

where $i \in \{A, J, EU, EN, UE, UN, NE, NU\}$. So that, for example, $\frac{\operatorname{cov}\left(\Delta u, c_A \times \Delta A\right)}{\operatorname{var}\left(\Delta u\right)}$ measures the fraction of unemployment's variance due to the movements of matching efficiency.

In order to measure the contribution of transition rates as a whole, we sum the contribution indices of all transition rates to aggregate the contribution of transition rates on the unemployment and obtain

$$\beta_\lambda = \sum_j \beta_{\lambda_t^j}, \tag{33}$$

where $j \in \{EU, EN, UE, UN, NE, NU\}$.

Table 6 reports the contribution of the exogenous variables A_t, λ_t's and J_t to the fluctuation of unemployment rate. For the periods from January 2004 to the end of 2011, while all exogenous variables contribute to the fluctuation of the unemployment rate to some extent, approximately 66% of the high frequency fluctuation of the unemployment rate is accounted for by the transition rate λ_t's. The matching efficiency accounts for only 2.1% of the unemployment fluctuations during the periods. Notice that the expected discounted value of profits generated by a filled job accounts for approximately 32% of the unemployment fluctuation as well.

5.2. Decomposition of Unemployment Fluctuations: Counterfactual Simulations

Once all of the parameter values in the model are specified, we compute the sequence of exogenous variables and we can use them for simulation. The simulation method follows the business cycle accounting procedure of Chari *et al*. (2007) and this method is closely related to the method known as Shimer decomposition in Shimer (2012).

With the sequence of exogenous variables we computed from the earlier section, we plug the exogenous variables A_t, λ_t's and J_t one by one into the model to generate the simulated unemployment rates in order to decompose the quantitative impact of each shock on the unemployment rate over the entire periods.

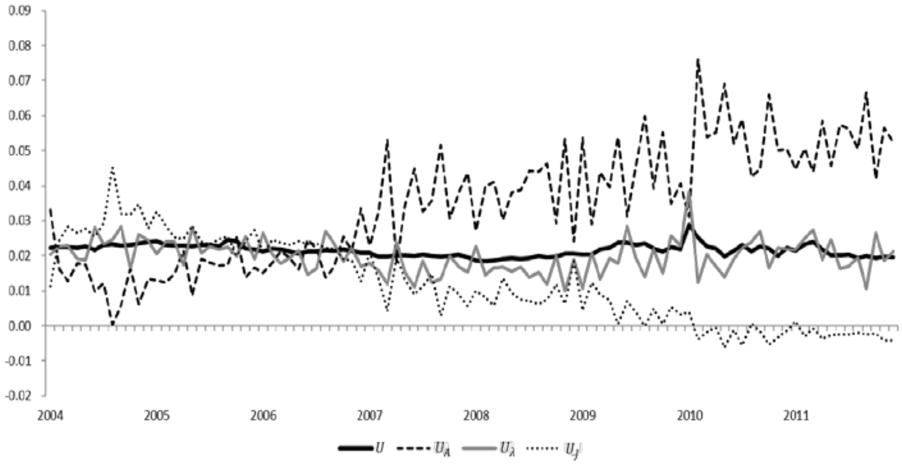
Suppose that we can define the unemployment rate as a function of exogenous variables in the model economy as follows:

$$u_t = U(A_t,\ \lambda_t\text{'s},\ J_t). \tag{34}$$

We denote the simulated unemployment rates with matching efficiency, those with the transition rate and those with the value of filled job as $u_{A,\,t}$, $u_{\lambda,\,t}$ and $u_{J,\,t}$, respectively. For example, $u_{A,\,t}$ is the simulated unemployment rate obtained from the model economy in the case where transition rates and the value of filled job stay fixed and constant at the pre-crisis level, but matching efficiency varies over time.

$$u_{A,\,t} = U(A_t,\ \bar{\lambda}\text{'s},\ \bar{J}), \tag{35}$$

Figure 6 Counterfactual Simulation Results



$$u_{\lambda,t} = U(\bar{A},\ \lambda_t\text{'s},\ \bar{J}), \tag{36}$$

$$u_{J,t} = U(\bar{A},\ \bar{\lambda}\text{'s},\ J_t), \tag{37}$$

where $\bar{A}$, $\bar{\lambda}$'s and $\bar{J}$ denote the average values of the exogenous variables A_t, λ_t's and J_t during the pre-crisis periods.

Figure 6 shows the counterfactually simulated unemployment rates as a result of plugging each series of shocks one by one into the model economy. This shows that transition rates are the most important in accounting for the fluctuation in the unemployment rate through the entire periods. Matching efficiency alone would have increased the unemployment rate as high as 5.06% for the post-crisis periods if the matching efficiency remains at the pre-crisis level (table 7).

Table 7 shows the average values of simulated unemployment rates for the entire periods. The unemployment rate in data is 2.15% for the whole sample periods. The simulated unemployment rate with transition rate is most close to the data, particularly for pre-crisis periods and post-crisis periods. Significant drops in matching efficiency for the during-crisis and post-crisis periods imply that the unemployment rate would have been as

Table 7 Average Values of Simulated Unemployment Rates

Simulated Unemployment Rates	Whole Periods (2004:1-2011:12)	Pre-crisis Periods (2004:1-2007:12)	During-crisis Periods (2008:1-2009:2)	Post-crisis Periods (2009:3-2011:12)
Data (u_t)	0.0215 (0.0017)	0.0218 (0.0014)	0.0196 (0.0007)	0.0219 (0.0019)
Transition Rates $(u_{\lambda,t})$	0.0198 (0.0049)	0.0204 (0.0044)	0.0161 (0.0037)	0.0206 (0.0054)
Matching Efficiency $(u_{A,t})$	0.0344 (0.0170)	0.0218 (0.0115)	0.0385 (0.0091)	0.0506 (0.0103)
Value of Unfilled Jobs $(u_{J,t})$	0.0121 (0.0121)	0.0218 (0.0084)	0.0092 (0.0037)	-0.0004 (0.0038)

Note: Standard deviation in parenthesis.

Table 8 Correlation between Actual and Simulated Unemployment Rates

	Relative Stdev. $\left(\frac{\sigma_{u_{i,t}}}{\sigma_{u_t}}\right)$	Correlation			
		Whole Periods (2004:1-2011:12)	Pre-crisis Periods (2004:1-2007:12)	During-crisis Periods (2008:1-2009:2)	Post-crisis Periods (2009:3-2011:12)
$u_{\lambda,t}$	2.873	0.521	0.556	–0.193	0.428
$u_{A,t}$	9.913	–0.267	–0.715	0.138	–0.246
$u_{J,t}$	7.024	0.282	0.770	0.201	0.362

Note: $\sigma_{u_{i,t}}$ and σ_{u_t} are the standard deviation of simulated and actual unemployment rate, respectively.

high as 3.85% for the during-crisis periods and 5.06% for the post-crisis periods.

Table 8 shows that the simulated unemployment rates are more volatile than the data. The simulated data with transition rates has a lowest relative volatility out of them and also is most closely correlated with the data unemployment rate. Our decomposition exercise suggests that transition rates, work flows across labor market states contribute to account for the monthly fluctuations of unemployment rate during the sample periods in Korea.

6. DISCUSSION: ROBUSTNESS CHECK

In Korea, there exists another survey data available for vacancies and new matches in labor market by Korea Ministry of Employment and Labor and it is called as Establishment's Labor Force Survey (ELFS), which is a Korean-version of BLS's JOLTS in the US. This survey continues from 2009:m6 to recent.

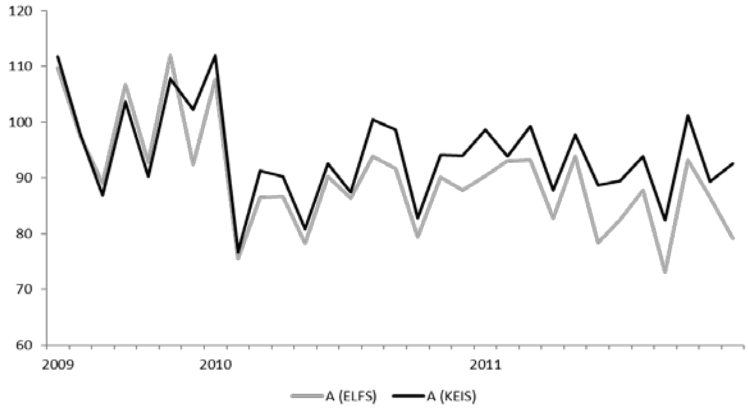
This section explains why we use the data for vacancies from Korean Employment Information Service (KEIS). First, we have data for worker flows and transition rates only available from 2000:m1 to 2011:m12. If we use the data from ELFS, the overlapped time periods of two data sets cover only from 2009:m6 to 2011:m12. With KEIS data, we expand the analysis periods from 2004:m1 to 2011:m12.

Second, we choose the longer time windows (2004:m1 to 2011:m12) available with KEIS data since we can divide the whole sample period into three sub-periods (pre-crisis, during-crisis and post-crisis) according to "Reference Dates of Business Cycle" announced by the Statistics Korea. However, the time periods (2009:m6 to 2011:m12) for which we could have used data with ELFS were turbulent periods over the Korean business cycles, which also make our calibration difficult since it is hard to find relatively stable periods in an economy.

Third, we can still compute and estimate the matching efficiency with ELFS and compare the results with one calcualted as KEIS data.

Figure 7 shows that matching efficiencies with KEIS data and the estimates with ELFS. We find that these two estimates are highly correlated with each other (correlation: 0.9028). Figure 7 and table 9 both show that the matching efficiency has decreased over the sample periods. The estimate for matching efficiency from ELFS in table 9 suggests that the

Figure 7 Estimated Matching Efficiencies: KEIS vs. ELFS



Note: we normalized the average level of matching efficiency from 2009:m6 to 2009:m12 at 100.

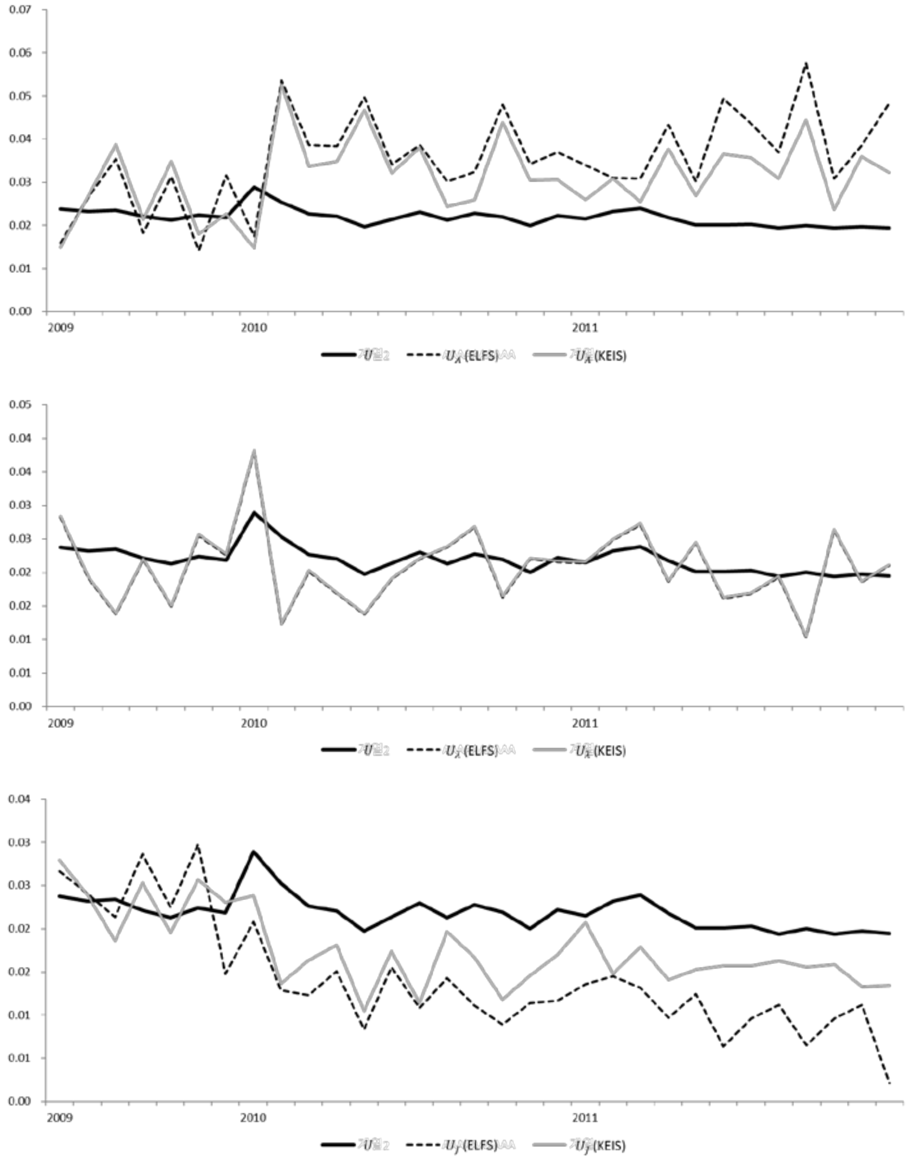
Table 9 Average Values of Estimates for Matching Efficiency

Matching Efficiency	ELFS	KEIS
2009:06-2009:12	100	100
2010:01-2011:12	86.96	92.30

matching efficiency dropped more than the one with KEIS data.

We again conduct the counterfactual simulations with our new estimates from ELFS and compare the results with the ones with KEIS data. Figure 8 shows the simulated unemployment rates calculated by plugging one exogenous variable by one. Figure 8 again confirms that the transition rates account for the unemployment dynamics again.

Figure 8 Counterfactual Simulation Results Using ELFS and KEIS Data



7. CONCLUSION

Previous studies suggest that the matching efficiency and worker flows are significant contributing factors that account for the unemployment dynamics. This paper uses a modified Mortensen and Pissarides model to investigate the impact of the matching efficiency and worker flows on the unemployment fluctuation in Korea over the 2004-2011 periods. In order to correct the underestimation problem in measuring the total number of vacancies, we make a data adjustment following Davis, Faberman and Haltiwanger (2010).

A number of papers study the contribution of separation and job-finding rate in order to decompose unemployment fluctuations. While Shimer (2012) for the U.S. economy and Kim and Lee (2014) for the Korean economy consider worker flows in accounting for the unemployment dynamics, our model structure incorporates not only worker flows but also matching efficiency in the labor market dynamics. Furthermore, we extend Mortensen and Pissarides (1994) in which there are two labor market states (employment and unemployment) by introducing the third labor market state, nonparticipation. Without incorporating the nonparticipation labor state, we miss the worker flow from nonparticipation to employment.

Our analysis finds that approximately 66% of the high frequency fluctuation of the unemployment rate is accounted for by the transition rates λ_t. The matching efficiency accounts for only 2.1% of the unemployment fluctuations during the periods.

This paper finds that worker flows are the most important contributors of the unemployment dynamics in Korea. Kim and Lee (2014) find that inflow to unemployment contributes substantially to unemployment fluctuations and particularly inflow through inactivity plays a larger role in unemployment dynamics in Korea.

We also find that the matching efficiency was kept constantly decreased over the entire sample periods and even after the global financial crisis, it stays lower and did not return to the pre-crisis level. We believe that this downward trend of the matching efficiency has to be re-investigated with recent data after the financial crisis. We leave this project for future research.

REFERENCES

Barlevy, G., "Evaluating the Role of Labor Market Mismatch in Rising Unemployment, " *Economic Perspectives*, 35(3), 2011, pp. 81-95.

Barnichon, R. and A. Figura, "What Drives Movements in the Unemployment Rate? A Decomposition of the Beveridge Curve," FEDS Working Paper, No. 2010-48, 2010.

Chari, V. V., P. J. Kehoe, and E. R. McGrattan, "Business Cycle Accounting," *Econometrica*, 75(3), 2007, pp. 781-836.

Davis, S. J., R. J. Faberman, J. Haltiwanger, R. Jarmin, and J. Miranda, "Business Volatility, Job Destruction, and Unemployment," *American Economic Journal: Macroeconomics*, 2(2), 2010, pp. 259-287.

Fujita, S. and G. Ramey, "The Cyclicality of Separation and Job Finding Rates," *International Economic Review*, 50(2), 2009, pp. 415-430.

Gadi, B., "Evaluating the Role of Labor Market Mismatch in Rising Unemployment," *Economic Perspectives*, 35(3), 2011, pp. 82-96.

Hall, R. and S. Schulhofer-Wohl, "Measuring Job-Finding Rates and Matching Efficiency with Heterogeneous Jobseekers," NBER Working Paper No. 20939, 2015.

Kim, S. and J. Lee, "Accounting for Ins and Outs of Unemployment of Korea," *Korea and the World Economy*, 15(1), 2014, pp. 17-44.

Lee, D., "Estimation of Aggregate Matching Function in Korea," *Korean Journal of Labour Economics*, 13(1), 2015, pp. 1-30.

Moon, W., "Explaining the Cyclical Behavior of the Korean Labor Market," Bank of Korea Working Paper Series, Economic Papers, 12(1), 2009, pp. 113-114.

Mortensen, D. T. and C. A. Pissarides, "Job Creation and Job Destruction in the Theory of Unemployment," *The Review of Economic Studies*, 61(3), 1994, pp. 397-415.

Petrongolo, B. and C. A. Pissarides, "Looking into the Black Box: A Survey of the Matching Function," *Journal of Economic Literature*, 39(2), 2001, pp. 390-431.

Shimer, R., "Reassesing the Ins and Outs of Unemployment," *Review of Economic Dynamics*, 15(2), 2012, pp. 127-148.

Smith, J. C., "The Ins and Outs of UK Unemployment," *Economic Journal*, 121(552), 2011, pp. 402-444.

Veracierto, M., "Workers Flows and Matching Efficiency," *Economic Perspectives*, 35(4), 2011, pp. 147-169.