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Reassessing the Inflows and Outflows of Unemployment in Korea*

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Using data from the Economically Active Population Survey from 1986 to 2014, we comprehensively examine Korean unemployment dynamics using worker flows: inflow rates and outflow rates. We estimate both flow rates by carefully correcting for time aggregation bias, and quantify the contribution of changes in each flow rate to unemployment variability through steady-state and non-steady-state decompositions. Our baseline analysis reports the average of inflow rates as 1.6% and that of outflow rates as 48%. Moreover, despite the small size of the inflow rates, inflows account for 90% of unemployment variability. The significant contribution of inflows to unemployment fluctuation still appears even under a three-state model that includes inactive workers and heterogeneous flow rates by reasons for unemployment. The large contribution of inflows to unemployment changes despite high outflow rates is a unique feature of the Korean labor market not seen in previous studies of OECD countries.

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I. Introduction

Understanding the relationship between unemployment dynamics and the

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* We borrow the title from Shimer (2012) because we carefully apply his method to examine the characteristics of the Korean labor market. We thank Jang-Ok Cho, Kwanho Shin, Noh-Sun Kwark, Yongsung Chang and Joonyoung Hur for their comments to improve the paper. We also thank all seminar participants at the Macroeconomic Workshop at Kyungpook National University, 2017 Korean Econometric Society Summer Conference, and 2017 Korean International Economic Association Annual Meeting. Lastly, we wish to thank two anonymous referees for their helpful comments and suggestions. All errors are ours.
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business cycle is a classical question in macroeconomics. The variation in unemployment occurs as a result of changes in worker flows in and out of unemployment, and thus recent studies in the US and some European countries concentrate on the empirical properties of both flows and their impacts on unemployment dynamics. In this paper, we comprehensively investigate unemployment dynamics in Korea using worker flows: inflow rates (job separation rates) and outflow rates (job finding rates). In particular, we estimate the inflow and outflow rates with careful correction for time aggregation bias, and quantify the contribution of changes in each flow rate to unemployment variability through both steady-state and non-steady-state decompositions. Our analysis is extended to a three-state model that includes transitions out of the labor force and heterogeneous flow rates by reasons for unemployment. These extensions have not been thoroughly examined in previous Korean studies. In this sense, this paper represents a reassessment of the inflows and outflows of unemployment in Korea.

A common belief regarding the US labor market was that recessions began with a burst of layoffs. This belief had been settled as conventional wisdom after several empirical studies (Darby et al., 1985; Blanchard and Diamond, 1990; Davis and Haltiwanger, 1992). After two decades, the conventional wisdom was challenged by Shimer (2012). He points out that the flow rates in previous literature are mismeasured because they neglect some transitions between the two labor force statuses observed in data. The bias due to this ignorance is called time aggregation bias. He theoretically verifies the existence of time aggregation bias using a continuous time model, and empirically documents that the size is not small enough to ignore.

After Shimer (2012), the literature on unemployment dynamics has seriously considered the time aggregation issue and developed in two directions. The first strand focuses on the methodology used to estimate unbiased flow rates.[1] Shimer (2012) develops a new method to measure unbiased flow rates using short-term unemployment. Fujita and Ramey (2009) follow the standard approach but estimate flow rates without suffering from time aggregation bias. Their procedures are based on gross flow probabilities like previous literature (Darby et al., 1985; Blanchard and Diamond, 1990) but use the continuous time model to revise these probabilities. Shimer (2012) and Fujita and Ramey (2009) concentrate on inflows and outflows to unemployment, so the out-of-labor force margins are less discussed. Elsby et al. (2015) develop a procedure to estimate unbiased flow rates when the inactive margins are incorporated.

The second part of the literature discusses the extent to which inflows and

[1] Some papers pay more attention to the bias itself. Using more frequently collected data sets, Nekarda (2009) and Nordmeier (2014) estimate the size of the time aggregation bias. They find that the bias is substantial in terms of level but not affect the cyclical properties of flow rates.

outflows contribute to unemployment variability. Several studies strive to develop a device to quantify the contributions, referred to as a decomposition method. Shimer (2012) makes significant contributions to addressing time aggregation bias and estimating flow rates without suffering from the bias, but the decomposition methods are less discussed. He illustrates the importance of outflows for unemployment variability by computing the correlation between unemployment rates and one series of flow rates with other transitions fixed over time. Elsby et al. (2009) point out that this simple correlation may overstate the outflows' contribution because outflow rates are usually ten times larger than inflow rates. They suggest using the log difference in the decomposition. Nevertheless, the contributions are not measured numerically but only verified graphically. Fujita and Ramey (2009) develop a simple but well defined summary index to evaluate each flow hazard's contribution, the so-called beta method. They employ a variance decomposition to the log change of unemployment rates which are divided into the log difference of the two hazard rates. This index is important from a quantitative viewpoint because it can be used as a target moment to calibrate some parameters in structural models. However, their decomposition method only works well when actual unemployment is closely approximated by its steady-state value. Reacting to this, Elsby et al. (2013) devise a new decomposition method when unemployment deviates from steady-state unemployment. The decomposition with the steady-state unemployment rate is called a steady-state decomposition, while the decomposition with the actual unemployment rate is referred to as a non-steady-state decomposition.

Early Korean studies on unemployment dynamics concentrated on the stock dynamic analysis due to data limitations. Ryoo and Bai (1984) examine the Korean labor market with gross flow probabilities. Since the data was available only for April and May 1984, the transition probabilities are estimated only for one period. To the best of our knowledge, Nam and Rhee (1998) is the first paper to document some stylized facts on flow probabilities using a long time series. They use the same data set as Ryoo and Bai (1984) but construct the series from 1984 to 1992. They find that the downward trend in unemployment during the 1980s was driven by decreasing inflows, but the outflows from unemployment had no specific trend during the same period. Since Nam and Rhee (1998), several studies have applied the same method to estimate flow probabilities (Nam et al., 2005; Lee and Chung, 2005; Moon, 2008). None of these studies, however, correct for time aggregation bias. Nam and Rhee (1998) addresses the dominant impact of inflows on unemployment changes, but the size of the contribution has not been quantified.

The Korean labor market has been reexamined recently due to new methodologies developed in the literature. Three studies analyze unemployment dynamics with new methods: Nam and Lee (2012), Park (2014), and Kim and Lee (2014). Nam and Lee (2012) apply Shimer's short-term unemployment method to estimate flow rates and conclude that both inflows and outflows are important for unemployment changes. Although their flow rates are free from time aggregation bias, the contributions of each flow are not explicitly quantified. Park (2014) also estimates flow rates with short-term unemployment and reports the size of each flow hazard's contribution using a steady-state decomposition. He documents that inflows explain 85% of unemployment changes from 1986Q1 to 2011Q4. Unlike the previous two studies, Kim and Lee (2014) directly measure hazard rates from gross flow probabilities. They match the individual's labor force status with Korean micro data and construct a time series of transition probabilities across unemployment, employment and not in the labor force. Flow rates are directly converted from these probabilities based on the relationship between the probability and the rate under the Poisson process. They also find that inflows account for 80% of unemployment fluctuations from 2000Q1 to 2011Q4. Their three-state model, however, does not seem to properly correct for time aggregation bias.[2]

Our paper also reassesses unemployment dynamics with flow rates, but several distinctions are made from previous Korean studies. First, we correct for time aggregation bias carefully in estimating flow rates. Unbiased flow rates are estimated by both Fujita and Ramey (2009) and Shimer (2012). The second distinction is that the contribution of each flow rate to unemployment variability is quantified with steady-state and non-steady-state decompositions. Both decomposition methods are also extended to apply to the three-state environment. Lastly, two robustness checks are conducted to verify our empirical results. Two strong assumptions are made in Shimer's baseline analysis: no entry or exit from the labor force, and homogenous flow rates across all workers. We incorporate the inactive margins to drop the constant labor force assumption. Time aggregation bias is controlled and two types of decomposition methods are applied to compare the numbers from the baseline results. In the second robustness check, we allow heterogeneous flow rates across workers who are unemployed for different reasons. In this sense, we thoroughly reassess the inflows and outflows of unemployment in the Korean labor market, which is the main contribution of our paper.

The remainder of the paper is organized as follows. The new methodologies developed in the recent literature are reviewed in Section 2. We discuss the concept of time aggregation bias and the correcting procedures while estimating flow rates in two- and three-state economies. Two decomposition methods, namely, steady-state and non-steady-state decomposition, are explained to evaluate the contribution of each flow to unemployment variability. In Section 3, we document several empirical facts derived from an exploration of the Korean labor market from 1986 to 2014. Two robustness checks are performed in Section 4. First, we extend the model

[2] We find similar problems in studies of other countries, such as Smith (2011) for UK and Lin and Miyamoto (2012) for Japan.

to include inactive margins to relax the constant labor force assumption. We then disaggregate workers by reasons of unemployment, and introduce heterogeneous flow rates for each type of worker. Finally, we present our conclusions in Section 5.

II. Methodology

The first part of this section reviews the concept of time aggregation bias and two different procedures to estimate inflow and outflow rates without suffering from the bias. Next, we describe two recently developed decomposition methods to quantify the contributions of hazards to unemployment fluctuation. The time aggregation correction and decomposition methods are discussed for a two-state economy where entry and exit from the labor force are not allowed. We, then include the inactive margins and explain in detail proper ways to correct the bias and quantify the contributions of inflow and outflow rates.

2.1. Time Aggregation Bias

In most case, the labor force status for each individual is collected in monthly frequencies, so one has to connect two consecutive data points for each individual to measure the transition probabilities between E and U. These transition probabilities, however, do not take into account some inflows and outflows of unemployment between two discrete data points. The ignorance of these transits within very short intervals may create time aggregation bias when estimating flow probabilities. Shimer (2012) formally addresses this issue using a continuous time model.

The stocks of each labor force status are provided in each discrete time, $t \in \{1,2,3,\cdots\}$. The elapsed time since t is $\tau \in [0,1)$, referred to "period t". During period t, unemployed workers find jobs (outflow) but employed workers lose their jobs and move into unemployment (inflow). All transitions occur by the flow rates according to a Poisson process. f_t is the instantaneous arrival rate from U to E, and s_t is the rate from E to U.[3] The unemployment change at $t+\tau$ is expressed with inflow and outflow rates, which are assumed to be constant within τ, in the following differential equation:

$$\frac{dU_{t+\tau}}{d\tau} = s_t E_{t+\tau} - f_t U_{t+\tau} = s_t L_{t+\tau} - (s_t + f_t) U_{t+\tau} . \tag{1}$$

[3] Each flow rate is converted to the flow probability in following manners:

$$F_t = 1 - \exp(-f_t) , \quad S_t = 1 - \exp(s_t) .$$

$s_t E_{t+\tau}$ is the inflow to unemployment, while the outflow from unemployment is captured by $(-f_t U_{t+\tau})$. The labor force, $L_{t+\tau}$, is defined as the sum of workers in U and E, so $E_{t+\tau}$ is replaced with $(L_{t+\tau} - U_{t+\tau})$ to write the equation with only $L_{t+\tau}$ and $U_{t+\tau}$. By dividing the equation with $L_{t+\tau}$, the stock version of unemployment dynamics is expressed in the change in the unemployment rate, which consists of the unemployment rate change $((du_{t+\tau}/d\tau)L_{t+\tau})$ and labor force stock change $(u_{t+\tau}(dL_{t+\tau}/d\tau))$. Shimer (2012) made a strong assumption that the labor force is constant within τ such that $dL_{t+\tau}/d\tau = 0$. Therefore, the flows to out of the labor force margins (N) are shut down, and all agents transit only between U and E. The dynamics of the unemployment rate are collapsed to the following differential equation:

$$\frac{du_{t+\tau}}{d\tau} = s_t - (s_t + f_t)u_{t+\tau}. \tag{2}$$

Solving the differential equation one period forward, we easily obtain the seminal equation (eq. (3)) of Shimer (2012).[4] Since all transitions within the periods are taken care of in the continuous time model, this equation does not suffer from time aggregation bias.

$$u_{t+1} = [1 - \exp(-(s_t + f_t))]\frac{s_t}{s_t + f_t} + \exp(-(s_t + f_t))u_t \tag{3}$$

The standard transition equation from the discrete time model is

$$u_{t+1} = \hat{S}_t(1 - u_t) - \hat{F}_t u_t = \hat{S}_t - (\hat{S}_t + \hat{F}_t)u_t. \tag{4}$$

$\hat{S}_t$ is the transition probability(or gross flow probability) from E to U, and $\hat{F}_t$ represents such probability from U to E. Each transition probability is measured by $\hat{S}_t = \frac{EU_t}{U_{t-1}}$ and $\hat{F}_t = \frac{UE_t}{E_{t-1}}$ from the data. However, this equation does not line up with eq. (3) because the discrete time model does not include the transitions within the interval. Therefore, the flow rates directly converted from $\hat{S}_t$ and $\hat{F}_t$ suffer from time aggregation bias. In order to obtain the true flow rates, we match eq. (4) and eq. (3) and rearrange the terms to express s_t and f_t with $\hat{S}_t$ and $\hat{F}_t$.

[4] The equation is the same as eq. (5) in Shimer (2012) except that the unemployment dynamics are expressed in the unemployment rate rather than the stock; there is otherwise no difference between these differential equations.

$$s_t = \frac{\hat{S}_t}{\hat{S}_t + \hat{F}_t}(-\ln(1-\hat{S}_t - \hat{F}_t)), \quad f_t = \frac{\hat{F}_t}{\hat{S}_t + \hat{F}_t}(-\ln(1-\hat{S}_t - \hat{F}_t)) \tag{5}$$

We refer to this procedure, which is provided by Fujita and Ramey (2009), as the gross flow probability approach. As long as one is able to compute $\hat{S}_t$ and $\hat{F}_t$ from the data, unbiased s_t and f_t are easily backed out. $\hat{S}_t$ and $\hat{F}_t$ require the panel data structure to estimate. However, the data set used to construct the official unemployment rate is not provided in this format in most cases. In order to overcome the data limitation, Shimer (2012) suggests a simple but robust method to estimate inflow and outflow hazard rates without suffering from the bias. He introduces the concept of short-term unemployment to unemployment dynamics and maps this idea to the data to estimate unbiased flow rates.

Short-term unemployed workers, $U_t^s(\tau)$, are defined as workers who are unemployed between t and $t+\tau$. Similar to eq. (1), changes in the number of these workers are written in the following differential equation:

$$\frac{dU_t^s(\tau)}{d\tau} = s_t E_{t+\tau} - f_t U_t^s(\tau) = \frac{dU_{t+\tau}(\tau)}{d\tau} - f_t(U_t^s(\tau) - U_{t+\tau}) \,. \tag{6}$$

Since outflow workers appears both in eq. (1) and eq. (6), $s_t E_{t+\tau}$ is replaced by eq. (1). Solving the differential equation one period ahead, we end up with the outflow probability as a function of unemployment and short-term unemployment stock.

$$F_t = 1 - \frac{U_{t+1} - U_{t+1}^s}{U_t} \quad \text{where} \quad U_{t+1}^s \equiv U_t^s(1) \tag{7}$$

This outflow measure is not subject to the time aggregation problem because F_t is just the complement of the probability that those unemployed at t remain unemployed at $t+1$. The difference between workers who are unemployed in the next period and the short-term unemployed workers pick up workers who exit unemployment after one period's survey but reenter prior to the next period's survey. In this sense, this outflow measure already takes care of all transitions between survey periods. The inflow rate is obtained from the unemployment rate dynamics by solving non-linear eq. (2) numerically. The crucial advantage of this measure is that it is easy to construct from the data. It requires only the stock of unemployed and short-term unemployed workers. Shimer's approach has been adopted by numerous non-US countries that face data problems in estimating the gross flow probabilities.

The two-state model, however, is based on a strong assumption: a constant labor force. We extend the model to explicitly consider the out-of-labor-force (N) margins in order to relax this assumption. Regardless of inactive margins, the time aggregation bias has to be corrected. The time aggregation correction in the three-state model is similar to the two-state model, but the actual procedure is more cumbersome due to the extra dimension.

The continuous version of the three-state transition matrix is provided in eq. (8). Since the agents are able to move in and out of the labor force, the transition matrix is enlarged to a 3 × 3 matrix.

$$\underbrace{\begin{bmatrix} \frac{dU_{t+\tau}}{d\tau} \\ \frac{dE_{t+\tau}}{d\tau} \\ \frac{dN_{t+1}}{d\tau} \end{bmatrix}}_{\frac{dS_{t+\tau}}{d\tau}} = \underbrace{\begin{bmatrix} -\lambda_t^{UE} - \lambda_t^{UN} & \lambda_t^{EU} & \lambda_t^{NU} \\ \lambda_t^{UE} & -\lambda_t^{EU} - \lambda_t^{EN} & \lambda_t^{NE} \\ \lambda_t^{UN} & \lambda_t^{EN} & -\lambda_t^{NU} - \lambda_t^{NE} \end{bmatrix}}_{\lambda_t} \underbrace{\begin{bmatrix} U_{t+\tau} \\ E_{t+\tau} \\ N_{t+\tau} \end{bmatrix}}_{S_{t+\tau}} \tag{8}$$

The labor force changes in $\tau \in [0,1)$ are determined by the transition matrix with the flow rates, λ_t s. For instance, the changes of unemployed workers in $\tau \in [0,1)$ consist of inflows from E and $N, (\lambda_t^{EU} E_t + \lambda_t^{NU} N_t)$, and outflows to E and $N, (-(\lambda_t^{UE} + \lambda_t^{UN}) U_t)$. Similar to the two-state case, we solve the system of differential equations one period forward to derive the next-period labor force stocks. Due to the complexity, it is difficult to provide an analytical solution like eq. (2) in the two-state model.[5]

The solution of the differential equation, eq. ((8)), is expressed in the following form:

$$S_{t+1} = \Lambda_t S_t = (V_t \exp(D_t) V_t^{-1}) S_t . \tag{9}$$

V_t is the matrix of eigenvectors of λ_t in the columns and D_t denotes the diagonal matrix of eigenvalues of λ_t. Eq. (9) is similar to eq. (3), but there is no comparable concept to short-term unemployment for N. Hence, we use the gross flow probabilities' approach to estimate all λ_t s from the data by using the following discrete version of transition matrix P_t:

[5] The analytical solutions also do not appear in Shimer (2012) or Elsby et al. (2015). In Elsby et al. (2015), three differential equations are reduced to two equations by using $U_t + E_t + N_t = 1$, but an analytical solution is not provided.

$$\underbrace{\begin{bmatrix} U_{t+1} \\ E_{t+1} \\ N_{t+1} \end{bmatrix}}_{S_{t+1}} = \underbrace{\begin{bmatrix} (1-p_t^{UE}-p_t^{UN}) & p_t^{EU} & p_t^{NU} \\ p_t^{UE} & (1-p_t^{EU}-p_t^{EN}) & p_t^{NE} \\ p_t^{UN} & p_t^{EN} & (1-p_t^{NU}-p_t^{NE}) \end{bmatrix}}_{P_t} \underbrace{\begin{bmatrix} U_t \\ E_t \\ N_t \end{bmatrix}}_{S_t}. \tag{10}$$

The transition probabilities matrix, P_t, is able to estimate directly from the data. By matching two different system equations – eq. (9) and eq. (10) – that describe the same labor force dynamics, we now have $\Lambda_t = P_t = V_t^P D_t^P (V_t^P)^{-1}$ where the second part is the eigendecomposition of P_t. Given the assumption that P_t has distinct and non-negative real eigenvalues, we have $V_t = V_t^P$ and $D_t = \log(D_t^P)$. Therefore, the unknown matrix λ_t can be backed out from the following equation:

$$\lambda_t = V_t^P \log(D_t^P)(V_t^P)^{-1}. \tag{11}$$

2.2. Decomposition Method

Once labor market flow rates are estimated properly, we are able to quantify the contribution of each flow rate to unemployment variability, the so-called decomposition method. In order to discuss the decomposition method, the concept of steady-state unemployment, $\overline{u}_t$, needs to be discussed first. Recall the unemployment rate dynamics in eq. (2). The steady-state unemployment rate is defined by inflow and outflow hazards when $\frac{du_{t+\tau}}{d\tau} = 0$:

$$\overline{u}_t = \frac{s_t}{s_t + f_t}. \tag{12}$$

The steady-state unemployment rate increases with s_t but declines with f_t. Thus, high unemployment rates are induced by either high s_t or low f_t. If the steady-state unemployment rate is a very good proxy for the actual unemployment rate from the data, one can replace u_t with $\overline{u}_t$ and analyze the relationship between $\overline{u}_t$ and flow rates. For instance, the correlation between $\overline{u}_t$ and u_t is 0.98 in the US. Hence, the steady-state unemployment rate is commonly used for the decomposition (Shimer, 2012; Fujita and Ramey, 2009; Elsby et al., 2009).

Instead of formally measuring the contribution of each hazard to unemployment changes, Shimer (2012) constructs the hypothetical unemployment rates when one flow rate varies but the other is fixed, and he then simply computes the correlation between the actual and the hypothetical unemployment rates. He concludes that "the ins win" because the correlation between the actual and hypothetical unemployment rates is high when the inflow rate varies.[6] However, his method is likely to overestimate the outflow's effect because outflow rates are almost ten times larger than the inflow rates. Elsby et al. (2009) recognize this problem and suggest using the log difference of inflow and outflow rates instead of the rates themselves.

$$d\ln\overline{u}_t = (1-\overline{u}_t)d\ln s_t + (1-\overline{u}_t)(-d\ln f_t) = \overline{C}_{s,t} + \overline{C}_{f,t} \tag{13}$$

Based on Elsby et al.'s log difference decomposition, Fujita and Ramey (2009) take further step of summarizing the contributions with numbers. Applying the concept of beta in finance, they compute the covariance between $d\ln\overline{u}_t$ and $\overline{C}_{s,t}$ and $\overline{C}_{s,t}$, respectively. This decomposition is named the steady-state decomposition because the steady-state unemployment rates are used.

$$\overline{\beta}_s = \frac{\text{cov}(d\ln\overline{u}_t, \overline{C}_{s,t})}{\text{var}(d\ln\overline{u}_t)} = \frac{\text{cov}(d\ln\overline{u}_t, (1-\overline{u}_t)d\ln s_t)}{\text{var}(d\ln\overline{u}_t)}$$

$$\overline{\beta}_f = \frac{\text{cov}(d\ln\overline{u}_t, \overline{C}_{f,t})}{\text{var}(d\ln\overline{u}_t)} = \frac{\text{cov}(d\ln\overline{u}_t, (1-\overline{u}_t)(-d\ln f_t))}{\text{var}(d\ln\overline{u}_t)} \tag{14}$$

The steady-state decomposition works well only if the steady-state unemployment rate reasonably approximates the actual unemployment rate. However, if the steady-state unemployment rates do not trace the data well, the contributions using the actual unemployment rates perform badly. Elsby et al. (2013) devise a non-steady-state decomposition applied to some situations where the steady-state unemployment rates significantly deviate from the data.

Recall the unemployment dynamics in eq. (2). Using the definition of steady-state unemployment, we rewrite the next-period unemployment rate, u_{t+1}, as a weighted average of $\overline{u}_t$ and u_t where $\rho_t = 1-\exp(-s_t - f_t)$ is used as a weight.

$$u_{t+1} = \rho_{t+1}\overline{u}_t + (1-\rho_{t+1})u_t \tag{15}$$

When ρ_t gets larger, the actual unemployment rate converges to the steady-state one. The outflow rates, f_t, are usually much larger than inflow rates, s_t, so ρ_t heavily relies on the outflow rates. Since the outflow rates are high in US, ρ_t s are close to one and the steady-state unemployment rates approximate the actual ones well. In continental European countries, however, the outflow rates are relatively small compared to those of the US. Therefore, a large deviation between

[6] Nam and Rhee (1998) apply a similar method to examine how much inflows contribute to unemployment trends. They compute the hypothetical unemployment rate with fixed outflows and compare it with the actual unemployment rate graphically (figure 12 on page 60).

$\bar{u}_t$ and u_t occurs and the steady-state decomposition produces large residuals when u_t is used in the decomposition.

In order to deal with the deviation, the current variation in unemployment is decomposed recursively into current and past changes of each log hazard. The decomposition starts from eq. (15). Using a log-linear approximation of eq. (15) around $\bar{u}_t$, the logarithmic changes in the unemployment rate are separated into the steady-state unemployment rate and the previous unemployment variation with some coefficients in front. The steady-state unemployment component is the same as the steady-state decomposition. Since the unemployment change is defined as the sum of inflows ($C_{s,t}$), outflows ($C_{f,t}$), and initial deviation ($C_{0,t}$), we arrive at the last line in eq. (16) by solving the equation recursively. Finally, all components are consistent with current and past contributions. Just as with the steady-state decomposition, the beta variance decomposition is applied to summarize the contributions in some figures.

$$\begin{aligned} d\ln u_t &\equiv C_{s,t} + C_{f,t} + C_{0,t} \\ &= \rho_{t-1}\left\{(1-\bar{u}_{t-1})[d\ln s_t - d\ln f_t] + \frac{1-\rho_{t-2}}{\rho_{t-2}} d\ln u_{t-1}\right\} \\ &= \rho_{t-1}\left[\bar{C}_{s,t} + \frac{1-\rho_{t-2}}{\rho_{t-2}} C_{s,t-1}\right] + \rho_{t-1}\left[\bar{C}_{f,t} + \frac{1-\rho_{t-2}}{\rho_{t-2}} C_{f,t-1}\right] \\ &\quad + \rho_{t-1}\left[\frac{1-\rho_{t-2}}{\rho_{t-2}} C_{0,t-1}\right] \end{aligned} \tag{16}$$

Next, both the steady-state and non-steady-state decompositions are extended to the three-state model. As with the two-state case, the decomposition starts with characterizing the steady-state unemployment rate. In the steady state, all changes in stock variables are set to be zero in eq. (8), so U, E and N are expressed by λ_t^{ij}s in the transition matrix. Since the unemployment rate is U_t divided by $U_t + E_t$, the steady-state unemployment rate in the three-state model is as follows:

$$\bar{u}_t = \frac{\lambda_t^{EU} + \frac{\lambda_t^{EN}}{\lambda_t^{NU}+\lambda_t^{NE}} \lambda_t^{NU}}{\left[\lambda_t^{EU} + \frac{\lambda_t^{EN}}{\lambda_t^{NU}+\lambda_t^{NE}} \lambda_t^{NU}\right] + \left[\lambda_t^{UE} + \frac{\lambda_t^{UN}}{\lambda_t^{NE}+\lambda_t^{NU}} \lambda_t^{NE}\right]} = \frac{\tilde{s}_t}{\tilde{s}_t + \tilde{f}_t}. \tag{17}$$

The structure of $\bar{u}_t$ in the three-state case is analogous to that of $\bar{u}_t$ in the two-state one. The numerator consists of all inflows to unemployment, and the denominator is composed of inflows and outflows from unemployment. Some extra terms in eq. (17) capture the transitions between in and out of the labor force. In order to distinguish these flow rates from the two-state economy, the numerator denotes the total inflow rates, $\tilde{s}_t$, and the rest of denominator as total outflow rates, $\tilde{f}_t$.

The impact of labor force changes becomes clear when $\tilde{s}_t$ and $\tilde{f}_t$ are compared with s_t and f_t. If workers only transit between U and E, the inflow rate only corresponds to λ_t^{EU}. In this case, the inflow rate (λ_t^{EU}) is lower than the total inflow rate ($\tilde{s}_t$) because any inflows through N are excluded. λ_t^{UE} is lower than $\tilde{f}_t$ for the same reason. This situation does not apply to the flow rates estimated by short-term unemployment. Labor force participation is not explicitly considered in Shimer (2012), but it is not perfectly excluded in the unemployment or short-term unemployment stocks because these stock variables do not distinguish their origins. For example, short-term unemployed workers have an unemployment duration of less than a month, but originally they may have belonged to N and just moved to U. In this sense, flow rates estimated with short-term unemployment can be closer to the total flow rates than λ_t^{EU} or λ_t^{UE}. The difference in empirical results are due to differences in how the flow rates are conceptualized. Unlike Shimer (2012), Fujita and Ramey (2009) document the large contribution of inflow rates to unemployment variability. Since they favor a concentration on the flows only between E and U, λ_t^{EU} and λ_t^{UE} are examined. The contradictory results between Fujita and Ramey (2009) and Shimer (2012) are one of the reasons why we investigate the role of participation margins thoroughly.

First, we decompose the steady-state unemployment rate with the total flow rates, $\tilde{s}_t$ and $\tilde{f}_t$. The log difference of $\overline{u}_t$ is in eq. (18). The steady-state β values are easily calculated from eq. (18). We have β values for the total inflow and total outflow rates as in eq. (14). The only difference is that s_t and f_t are replaced by $\tilde{s}_t$ and $\tilde{f}_t$ which include transitions out of the labor force.

$$d\ln\overline{u}_t = (1-\overline{u}_t)d\ln\tilde{s}_t - (1-\overline{u}_t)d\ln\tilde{f}_t \tag{18}$$

The non-steady-state decomposition with total flow rates is also the same as the two-state decomposition. s_t and f_t are replaced by $\tilde{s}_t$ and $\tilde{f}_t$. C_0, the difference between u_t and $\overline{u}_t$ at the initial period, is the same in both cases because it is not affected by flow rates. However, $\tilde{s}_t$ and $\tilde{f}_t$ change $\tilde{\rho}_t$, the convergence speed from actual to steady-state unemployment.

$$\begin{aligned} d\ln u_t &\equiv C_{\tilde{s},t} + C_{\tilde{f},t} + C_{0,t} \\ &= \tilde{\rho}_{t-1}\left\{(1-\overline{u}_{t-1})[d\ln\tilde{s}_t - d\ln\tilde{f}_t] + \frac{1-\tilde{\rho}_{t-2}}{\tilde{\rho}_{t-2}}d\ln u_{t-1}\right\} \end{aligned}$$

$$= \tilde{\rho}_{t-1}\left[\overline{C}_{\tilde{s},t} + \frac{1-\tilde{\rho}_{t-2}}{\tilde{\rho}_{t-2}} C_{\tilde{s},t-1}\right] + \tilde{\rho}_{t-1}\left[\overline{C}_{\tilde{f},t} + \frac{1-\tilde{\rho}_{t-2}}{\tilde{\rho}_{t-2}} C_{\tilde{f},t-1}\right] + \tilde{\rho}_{t-1}\left[\frac{1-\tilde{\rho}_{t-2}}{\tilde{\rho}_{t-2}} C_{0,t-1}\right] \quad (19)$$

The total flow rates consist of flows between U and E and flows through N, so we are able to distinguish the contribution of each flow rate in more detail. The detailed steady-state decomposition is in eq. (20), where the first line is the same as eq. (18) and the rest of the lines separate the contribution from total flows by direct and indirect effects within each flow.

$$\begin{aligned} d\ln u_t &= (1-\overline{u}_t)d\ln\tilde{s}_t - (1-\overline{u}_t)d\ln\tilde{f}_t \\ &= (1-\overline{u}_t)\omega_t^{EU} d\ln\lambda_t^{EU} + (1-\overline{u}_t)(1-\omega_t^{EU})d\ln(\alpha_t\lambda_t^{NU}) \\ &\quad -(1-\overline{u}_t)\omega_t^{UE} d\ln\lambda_t^{UE} - (1-\overline{u}_t)(1-\omega_t^{UE})d\ln(\beta_t\lambda_t^{UN}) \end{aligned} \quad (20)$$

where

$$\alpha_t = \frac{\lambda_t^{EN}}{\lambda_t^{NU}+\lambda_t^{NE}},\quad \beta_t = \frac{\lambda_t^{NE}}{\lambda_t^{NU}+\lambda_t^{NE}},$$
$$\omega_t^{EU} = \frac{\lambda_t^{EU}}{\lambda_t^{EU}+\alpha_t\lambda_t^{EN}},\quad \omega_t^{UE} = \frac{\lambda_t^{UE}}{\lambda_t^{UE}+\beta_t\lambda_t^{UN}}.$$

The non-steady-state decomposition in the three-state model is also separated into detailed components, direct flows from E and indirect flows through N. The structure is similar to the two-state one. Each element consists of the contributions from the steady-state and the previous periods. Eq. (21) presents the four components in the non-steady-state version, where the β values are estimated.

$$\begin{aligned} d\ln u_t &= C_{\lambda^{EU},t} + C_{\lambda^{ENU},t} + C_{\lambda^{UE},t} + C_{\lambda^{UNE},t} + C_{0,t} \\ &= \tilde{\rho}_{t-1}\left[\overline{C}_{\lambda_t^{EU}} + \frac{1-\tilde{\rho}_{t-2}}{\tilde{\rho}_{t-2}} C_{\lambda^{EU},t-1}\right] + \tilde{\rho}_{t-1}\left[\overline{C}_{\lambda_t^{NU}} + \frac{1-\tilde{\rho}_{t-2}}{\tilde{\rho}_{t-2}} C_{\lambda^{EN},t-1}\right] \\ &\quad + \tilde{\rho}_{t-1}\left[\overline{C}_{\lambda_t^{UE}} + \frac{1-\tilde{\rho}_{t-2}}{\tilde{\rho}_{t-2}} C_{\lambda^{UE},t-1}\right] + \tilde{\rho}_{t-1}\left[\overline{C}_{\lambda_t^{NE}} + \frac{1-\tilde{\rho}_{t-2}}{\tilde{\rho}_{t-2}} C_{\lambda^{UN},t-1}\right] \\ &\quad + \tilde{\rho}_{t-1}\left[\frac{1-\tilde{\rho}_{t-2}}{\tilde{\rho}_{t-2}} C_{0,t-1}\right] \end{aligned} \quad (21)$$

where

$$\tilde{\rho}_{t-1} = 1 - \exp(-(\lambda_t^{EU} + \alpha_t \lambda_t^{EN} + \lambda_t^{UE} + \beta_t \lambda_t^{UN}))$$
$$C_{\lambda^{EU},0} = 0\,,\ \ C_{\lambda^{ENU},0} = 0\,,\ \ C_{\lambda^{UE},0} = 0\,,\ \ C_{\lambda^{UNE},0} = 0\,,\ \ C_{0,0} = d\ln u_0$$

Smith (2011) has developed a similar decomposition method in the three-state environment. Our main difference is that we give the non-steady-state decomposition with transitions via N while she provides only the steady-state decomposition via N. Another difference is in how $\bar{u}_t$ is decomposed. Smith (2011) writes the discrete version of the decomposition, but we express it in the log difference which is consistent with Elsby et al. (2009), Fujita and Ramey (2009), and Elsby et al. (2013). Hence, our results are more comparable to the cross-country results of Elsby et al. (2013). Although we consider inactive margins in our investigation of unemployment dynamics, we do not focus on the contributions of $N \rightarrow E$ or $N \rightarrow U$ themselves. The full decomposition is studied by Elsby et al. (2015). They develop a new decomposition method to evaluate the contributions of all flow rates to the unemployment rate to concentrate on the participation margins. However, our extension focuses on relaxing the strict assumption of a constant labor force imposed in Shimer (2012), so an extended study of the Korean labor market in line with Elsby et al. (2015) is left for further research.[7]

III. Reassessment

Using data from *the Economically Active Population Survey* (hereafter EAPS) collected by the National Statistics Office (NSO), we measure inflow and outflow rates of unemployment from 1986 to 2014. Quarterly flow rates are estimated using the following procedures. First, we construct stock variables from the EAPS data. The unemployment, employment and short-term unemployment stocks are easily computed by summing up the number of workers with individual weights in the EAPS. All monthly stock variables are seasonally adjusted with X-12. Secondly, we compute monthly outflow rates, f_t, with eq. (7) and numerically solve eq. (2) to obtain inflow rates, s_t. Finally, the quarterly averages of monthly flow rates are taken to remove substantial high-frequency fluctuations that likely reflect

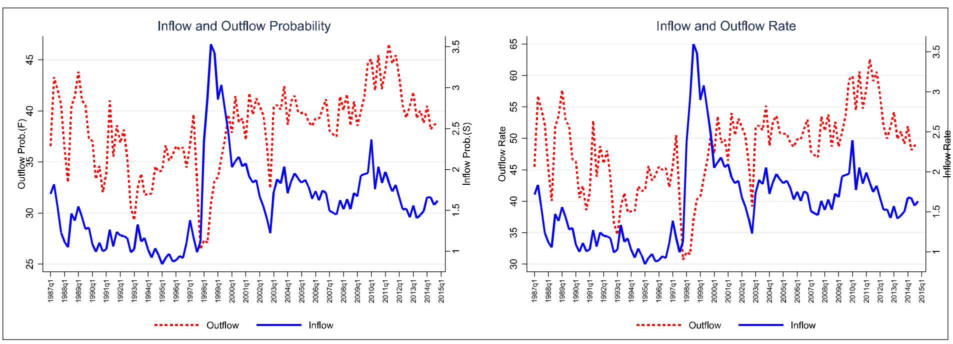
[7] Data limitation also presents an obstacle to extending the decomposition like Elsby et al. (2015). The panel structure is essential to analyze the impact of N on unemployment. We are only able to construct the panel up to 2004 with data from the *Economically Active Population Survey*. Therefore, our benchmark analysis is based on Shimer (2012) and Elsby et al. (2013), and the role of N is only used as a robustness check for whether changes in the labor force affect the results like in the US case.

measurement error in the EAPS.[8] The quarterly series of inflow, outflow, and unemployment rates are used in the following analysis.

3.1. The Inflows and Outflows of Unemployment in Korea

Figure 1 presents inflows, in solid lines, and outflows, in dashed lines, from 1987Q1 to 2014Q4.[9] The probabilities are placed in the left panel, and flow rates in right.[10] Several facts stand out. The outflow rate average of 48.0% is much higher than the inflow rate average of 1.6%. During the 1996-1999 Korean Financial Crisis, inflow hazards spike but outflow rates fall dramatically. Both hazard rates display different patterns before and after the crisis. Low inflow rates are observed in the pre-crisis period, which drove the low unemployment rate.

[Figure 1] Inflows and Outflows: 1987Q1 - 2014Q4



Before the decomposition results are reported, we examine whether the steady-state unemployment rate is a good proxy for the actual one. The steady-state unemployment rate is computed from estimated flow rates using eq. (12).

Figure 2 shows the actual unemployment rate (solid line) and steady-state unemployment rate (dashed line) from 1987 to 2014. The shaded areas indicate the offcial recession dates from the NSO. The steady-state unemployment rate traces the actual rate quite well except during several recession periods. As discussed in Elsby et al. (2013), the steady-state unemployment rate converges rapidly to the actual rate when the outflow rates are large. We document that the average outflow rate in Korea is the second highest among OECD countries, so it is natural that the

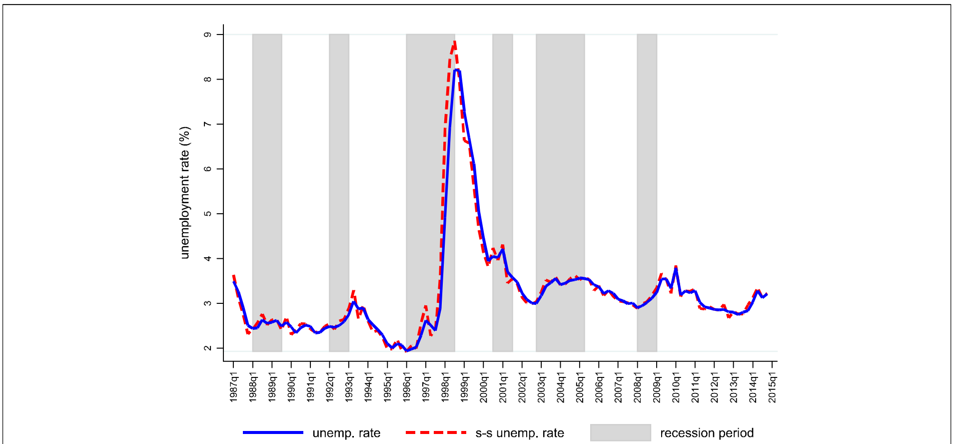
[8] Note that the quarterly averaging of the monthly flow rates or seasonal adjustment of stock variables have nothing to do with the time aggregation bias correction. The bias is already corrected while estimating each flow rate from eq. (2) and (7).

[9] The data starts from 1986Q1, but due to lags, we have the steady-state decomposition from 1986Q2 and non-steady-state decomposition from 1986Q3. For consistency, all figures plot from 1987Q1.

[10] A summary statistics table is provided in the appendix.

steady-state unemployment rate provides a good approximation. A non-steady-state decomposition, nevertheless, is still necessary because of some deviations observed in recession periods.[11]

[Figure 2] Unemployment Rate in Korea: 1987Q1 -2014Q4



The contributions of each flow's changes to unemployment variability are summarized in table 1. We report the results from the steady-state and non-steady-state decompositions. In the steady-state decomposition, we use the log change of the steady-state and actual unemployment rates. The steady-state decomposition shows that 81.0% of unemployment changes are driven by inflow changes. Despite their small size, inflow rates explain most unemployment variability in Korea. When we use the actual unemployment rate in the decomposition, the contribution of inflows is inflated to 110.3% but that of outflows drops to 6.6%. Moreover, -16.9% of unemployment variability is unexplained. The residual component in Korea is quite large compared to the other OECD countries analyzed by Elsby et al. (2013). Hence, it is reasonable to investigate the non-steady-state decomposition results. When the contributions from previous periods are included, the inflow's contribution increases by 9 percentage points, but the outflow's contribution decreases by 10 percentage points. The initial deviation accounts for 1.0%, but the residual is almost negligible. In the end, we find that unemployment variability in Korea is mostly explained by inflow changes, and outflows have very small impacts on it.

[11] Park (2014) reports only the steady-state decomposition due to high correlation between the steady-state and the actual unemployment rates. Similar patterns show up in figure 2. However, we find a substantial amount of residuals from the steady-state decomposition when the actual unemployment rate is used (table 1). Non-steady-state decomposition, therefore, is relevant to the Korean labor market.

[Table 1] Contributions of Inflows and Outflows to Unemployment Changes

Period	Dcmp.	$d\ln y_t$	β_s	β_f	β_0	Residual
All	ss	$d\ln \overline{u}_t$	81.0%	19.0%	-	-
(1987-2014)	ss	$d\ln u_t$	110.3%	6.6%	-	-16.9%
	nss	$d\ln u_t$	90.0%	9.0%	1.0%	0.1%
Pre Crisis	ss	$d\ln \overline{u}_t$	81.6%	18.3%	-	-
(1987-1995)	ss	$d\ln u_t$	132.9%	3.9%	-	-36.7%
	nss	$d\ln u_t$	85.3%	7.7%	14.7%	-7.8%
Post Crisis	ss	$d\ln \overline{u}_t$	93.9%	6.0%	-	-
(2000-2014)	ss	$d\ln u_t$	130.8%	-11.1%	-	-19.7%
	nss	$d\ln u_t$	115.8%	-16.1%	0.6%	-0.2%

Notes: ss stands for steady-state and nss for non-steady-state decomposition.

Figures 1 and 2 show that the structure of labor market has changed since the Korean Financial Crisis. We split the sample period into two subperiods, the pre-crisis period (1987-1995) and the post-crisis period (2000-2014), and apply the decomposition for each subperiod. In the steady-state decomposition, the contribution of inflows increases by 12.3 percentage points after the crisis, but that of outflows decreases by 12.3 percentage points. The unemployment rate has slightly risen in the post-crisis period due to the increase in inflow rates. We find similar features in unemployment fluctuation: the impact of inflow changes has been enhanced after the crisis. More striking results appear in the non-steady-state decomposition. While β_s increases from 85.3% to 115.8% (a 30.5 percentage point increase), β_f shrinks from 7.7% to -16.1%. The sign of β_f turns to negative, which implies that outflows impede unemployment increases during recession periods. To understand the decomposition results better, we investigate the change of flow rates by each recession episode, as in Elsby et al. (2009).

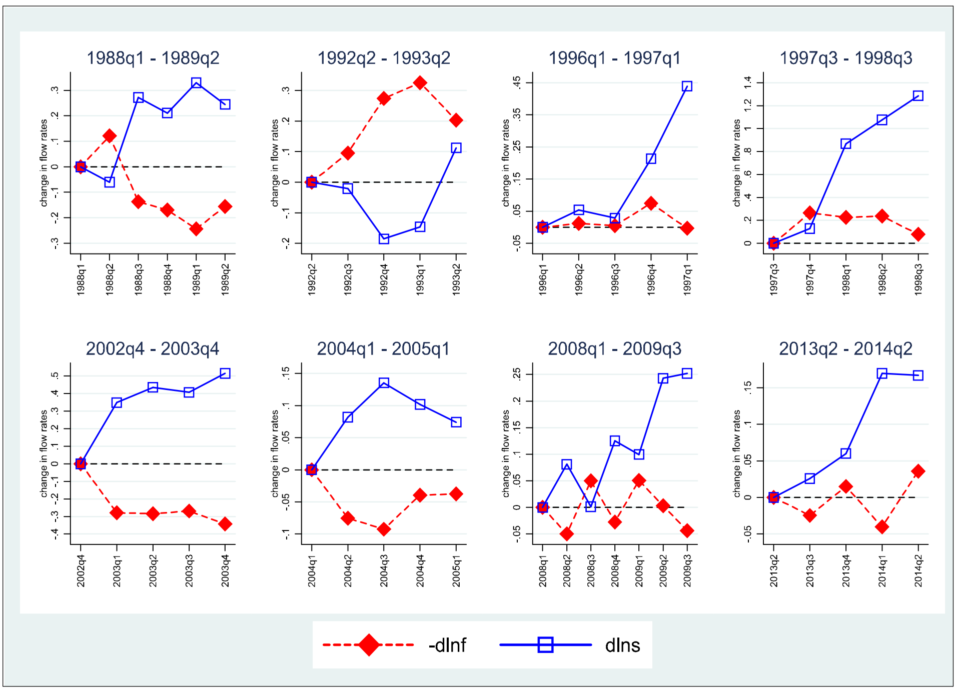
Korea experienced six recession episodes from 1987 to 2014. Since the recession periods did not coincide with unemployment increases, we adjust the periods using minimum and maximum unemployment rates following Elsby et al. (2009). Eight cases from five recession episodes are analyzed.[12] For each recession episode, we examine the accumulated flow changes from the trough to peak of unemployment and report the results in figure 3. The log differences of each flow are normalized to zero at the first date, and then accumulated until the last date of each case.[13] The

[12] We exclude the 2000-2001 recession because the unemployment rate decreased. The 1996-1999 and 2003-2005 recessions are divided into two subperiods in order to remove certain periods when the unemployment rate decreased. Even thought the period of 2013-2014 has not been declared as a recession, we include this period because unemployment steadily rose during the period.

[13] Note that we accumulate the negative value of the log differences for outflows because outflows are inversely related to unemployment changes.

upper panel presents the results from pre-crisis periods and the lower panel from post-crisis periods. Inflows exhibit a clear and dominant impact on unemployment fluctuations, other than during the 1992-93 recession. Outflows display only a mild contribution to unemployment changes prior to and during crisis, but a stronger negative impact on unemployment is observed in post-crisis periods. From these results, we may expect that the unemployment rate might have gone up more if the outflows had decreased during the recession, as it did in the US.

[Figure 3] Changes in Log Inflow and Outflow Rates by Recession



During the Korean economic crisis from 1996 to 1999, the unemployment rate sharply increased to 8.5% but then rapidly returned the pre-crisis level. The nature of unemployment dynamics, however, has dramatically changed since the crisis. In particular, both the level and contribution of inflows to unemployment have increased greatly. These changes may be explained by two distinct labor reforms that were implemented in Korea after the Korean Financial Crisis: the introduction of so-called “administrative terminations” due to urgent business necessity, and a system by which workers could be dispatched to firms by temporary staffing agencies. Making it easier to release employees from their jobs is likely to increases inflows, and at the same time, a dispatched workers system may affect both inflows and outflows positively because it gives firms more flexibility in hiring or extending the contracts of current workers. Thus, these reforms may provide some explanation for the large changes in the Korean labor market after the crisis However, caution is required in further interpreting these findings because any causality is not analyzed. In section 4, we introduce heterogeneity in flow rates and examine unemployment dynamics by reasons for unemployment; job losers, job leavers, and labor force entrants. These results provide some indirect evidence of the impact of institutional changes on the labor market.

3.2. Comparison with Other Countries

The Korean labor market is characterized by two features: the high outflow and low inflow rates and the significant contribution of inflow changes to unemployment variation. For a better understanding, we compare Korean labor market features with other countries' outcomes from Elsby et al. (2013). Despite the difference in the data used, our results are comparable with theirs because we use the same estimation procedures and decomposition methods.[14]

[Figure 4] Average Inflow and Outflow Rates across Countries

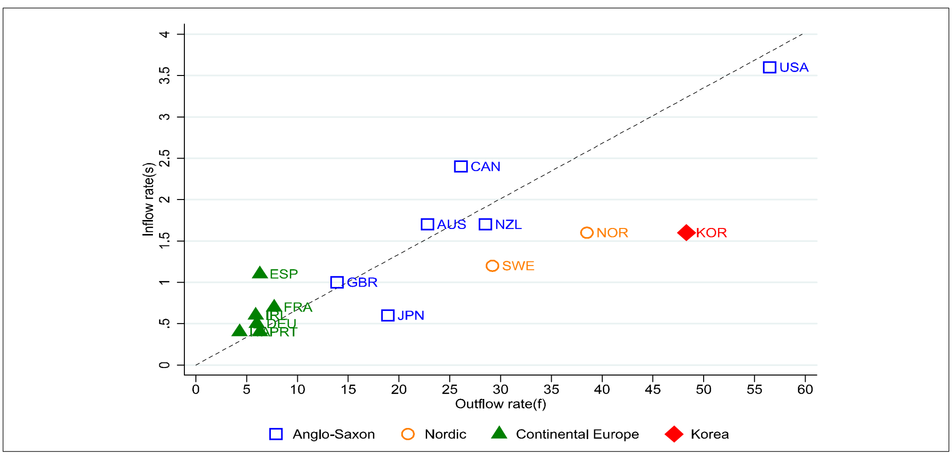
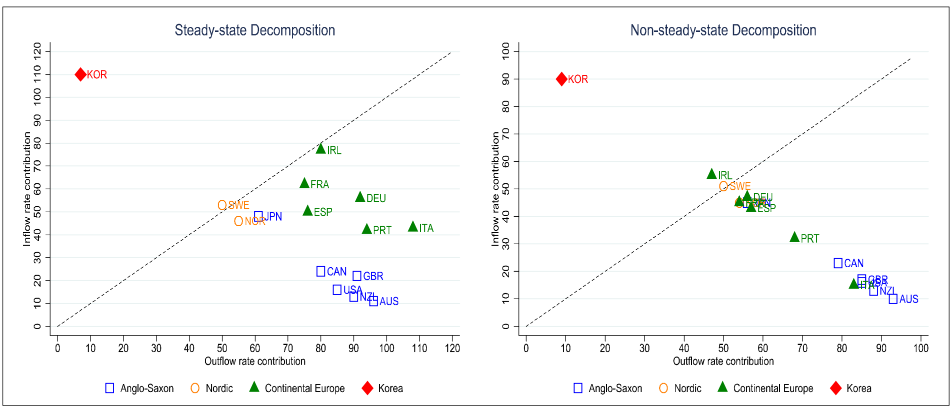


Figure 4 illustrates the average inflow and outflow rates in fourteen OECD countries and Korea. The dashed line presents all sets of both rates, which generate an average unemployment rate of 6.3%. Since the unemployment rate decreases with high outflow rates, countries below the dashed line have lower-than-average unemployment rates. Despite the distinct features of each country, they can be organized into three groups: Anglo-Saxon, Nordic, and the continental European countries. The continental European countries are well known for their high unemployment rates and long unemployment durations, features that are explained

[14] Elsby et al. (2013) do not provide any Korean estimates because Korean unemployment duration data is not available in the OECD data set.

by their smaller outflow rates. The Nordic countries of Sweden and Norway, have low unemployment rates because of their high exit rates from unemployment. Unlike with the continental European or Nordic countries, both flow rates are dispersed in the Anglo-Saxon countries. The UK has smaller flow rates than other Anglo-Saxon countries, while the US has much higher inflow and outflow rates than any other countries. Elsby et al. (2013) stress that for this reason it is not proper to consider the US labor market as a benchmark. We place our estimates from Korea in figure 4. Korea's low unemployment rate, which is well known and is confirmed in figure 4, is generated by the second highest outflow rate among these countries.

[Figure 5] Inflow and Outflow Contributions across Countries



The decomposition results also vary greatly across countries. Figure 5 compares the contributions of each flow in OECD countries. The steady-state decomposition results are in the left panel and the non-steady-state results in the right. The 45-degree line is included as a dashed line, representing the equal contribution of inflow and outflow rates. Since the Anglo-Saxon countries are located far below the dashed line, the unemployment variability is mostly driven by outflows from unemployment. The inflow changes, however, account for more than the outflow changes in the continental European countries, which are located higher than the Anglo-Saxon countries relative to the dashed line. Nordic countries are present near the 45-degree line, which represents a 50:50 split of inflow-outflow contributions, and similar patterns are observed in the non-steady-state decomposition.[15] Based on these results, Elsby et al. (2013) emphasize that inflow rates are important for

[15] Unlike with the steady-state figures, all countries line up well on the diagonal without large variations in the non-steady-state decomposition. Theoretically, βs sum up to 100 percent, so all countries should be located on the diagonal, but they are dispersed in the steady-state case. This difference happens because of the deviation between the steady-state and actual unemployment rates, and necessitates the non-steady-state decomposition.

unemployment fluctuation and caution against the US case. Korea, meanwhile, exhibits decomposition results that are completely different from most of the other countries. It is located above the 45-degree line and has a 90:10 inflow-outflow split. Ireland has the highest inflow contribution other than Korea, but inflows account for only 55% of unemployment variability. Some continental European countries have noticeably high inflow contributions, but none exceeds 50%. Therefore, the Korean case, in which inflow changes account for 90% of unemployment fluctuation, is unique.

In sum, the Korean labor market displays several interesting and distinctive features. First, the average outflow rate, 48%, is substantially higher than those of non-US OECD countries. Another unique feature appears in the decomposition results: inflow variability explains 90% of unemployment fluctuation in Korea. Despite the high level of outflow changes, they have almost no impact on unemployment variation. Continental European countries report almost equal contributions from both rates, where Ireland has the largest contribution of inflows at 55%. Anglo-Saxon countries, however, have 15:85 inflow-outflow splits. None of these countries share Korea's 90% inflow contribution.

IV. Robustness

So far, we have made two strong assumptions for the sake of simplicity: no entry and exit from the labor force, and homogeneous flow rates for all types of workers. As a robustness check, following Shimer (2012), we examine whether the contribution of each flow is changed when these assumptions are relaxed. First, we drop the constant labor force assumption and allow all agents to transit across E, U, and N. The movements of workers in and out of the labor force, especially flows from U to N, are not negligible,[16] and they may affect unemployment fluctuation. In addition, several existing studies[17] reveal that labor force participation margins are an important factor affecting labor market fluctuations.[18] This section, therefore, relaxes the restriction that workers are only either employed or unemployed.[19] Secondly, we introduce heterogeneous flow rates, disaggregating workers by reasons for unemployment: job losers, job leavers, and new entrants

[16] See table 7 and figure 9 in the Appendix.

[17] Garibaldi and Wasmer (2005), Pries and Rogerson (2009), Krusell et al. (2011), Elsby et al. (2015), Krusell et al. (2017), etc.

[18] For example, the difference in the contribution of inflow rates to unemployment changes between Fujita and Ramey (2009) and Shimer (2012) stems partly from the treatment of participation margins in estimating flow rates.

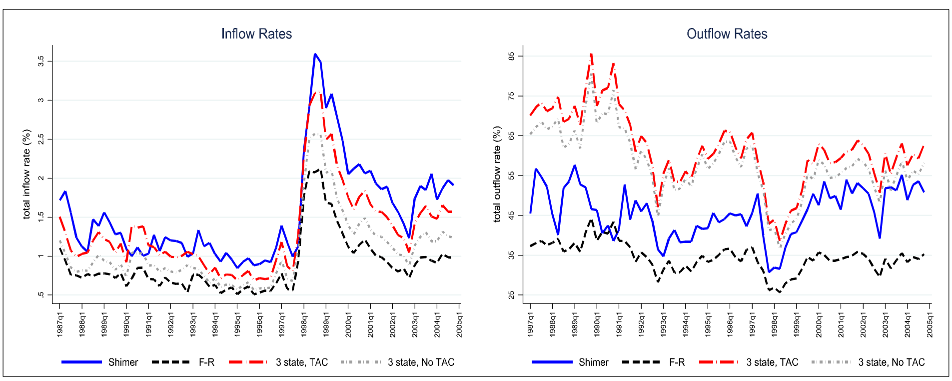
[19] The time aggregation correction and the decomposition methods in the three-state economy are explained in section 2.

from out of the labor force. The cyclical behaviors of flow rates may be different between job losers and leavers due to the reasons for separation and the incentives to find a new job. To this end, inflow and outflow rates are separately measured for each type of unemployed worker. The contribution of each flow rate from the three types of unemployed workers are quantified to verify whether inflows are still the main driving force.

4.1. Labor Force Entry and Exit

Unemployment dynamics in the three-state economy are examined in two steps. First, we analyze the dynamics with total inflows and outflows, which aggregate the direct flows between E and U and the flows through N. Since a full transition matrix is required in the analysis, we are able to obtain transitions only between E and U and estimate s_t and f_t like Fujita and Ramey (2009). All flow rates from different measures are compared. Secondly, we separate the contributions in detail and investigate the role of the participation margins. The results are provided up to 2004 because the EAPS does not provide some variables used in the matching process after 2004. The matching processes and six flow rates measured from the transition matrix are provided in the Appendix.

[Figure 6] Total Inflow and Outflow Rates by Different Methods



The total flow rates consist of the direct flow rates between U and E (λ_t^{UE}, λ_t^{EU}) and flow rates via N. In addition, we are able to estimate λ_t^{EU} and λ_t^{UE} using eq. (5). We compare these flow rates with those estimated in section 3. Figure 6 displays both hazard rates measured by different methods.[20] The solid line presents flow rates from the previous section (hereafter SH), and all flow rates measured with the transition matrix are presented with dashed lines.[21] Three

[20] Summary statistics for the total flow rates are provided in the Appendix.

[21] All figures are provided up to 2004 due to the availability of transition matrixes.

methods are used to measure the flow rates with the transition matrix. The rates measured by the Fujita and Ramey method (hereafter FR) are presented in black dashed lines. The red dashed line illustrates the flow rates with time aggregation correction (hereafter 3 state, TAC) and the gray lines present the flow rates without time aggregation correction (hereafter 3 state, No TAC).[22] These types of flow rates are used in Smith (2011), Lin and Miyamoto (2012), and Kim and Lee (2014).

Two distinct features are observed in figure 6. The first feature is that both (FR) flow rates are much smaller than all other rates. The lower flow rates in comparison to the three-state cases are no surprise because the indirect transits through N are ignored. We also observe that both flow rates between E and U are consistently lower than flow rates measured by the (SH) method, which are also observed in the US labor market by Fujita and Ramey (2009), because transitions through participation margins are not controlled. Despite the differences in level, all rates display comparable cyclical behaviors. Inflow rates mostly move in the same direction over the business cycle. Outflows also move in the same direction, but some differences appear between the (SH) rates and the others. Secondly, we identify the importance of time aggregation bias. Our results indicate that time aggregation affects the levels of rates but not their cyclical properties or contributions to unemployment variability.

[Table 2] Decomposition by Total Flows: 1987-2004

Method	Dcmp.	$d\ln y_t$	β_s	β_f	β_0	Residual
Shimer	ss	$d\ln\overline{u}_t$	78.7%	21.7%	-	-
	ss	$d\ln u_t$	106.7%	9.7%	-	-16.4%
	nss	$d\ln u_t$	87.4%	11.9%	1.1%	-0.5%
Fujita & Ramey	ss	$d\ln\overline{u}_t$	89.3%	11.1%	-	-
	ss	$d\ln u_t$	95.7%	0.1%	-	4.2%
	nss	$d\ln u_t$	84.0%	7.2%	1.2%	7.6%
3 state, TAC	ss	$d\ln\overline{u}_t$	80.5%	19.8%	-	-
	ss	$d\ln u_t$	95.2%	4.3%	-	0.5%
	nss	$d\ln u_t$	90.2%	8.8%	1.1%	-0.1%
3 state, No TAC	ss	$d\ln\overline{u}_t$	76.1%	24.1%	-	-
	ss	$d\ln u_t$	93.6%	6.4%	-	0.0%
	nss	$d\ln u_t$	88.8%	10.7%	1.1%	-0.7%

Note: ss stands for the steady-state and nss for the non-steady-state decomposition.

[22] These flow rates are computed by directly converting the transition probabilities to hazard rates. The transition probabilities, P^{ij} , are extracted from the data, and the flow rates are transformed with $\lambda^{ij} = -\log(1-P^{ij})$.

The decomposition results are reported in table 2.[23] Regardless of the measure, we consistently find a dominant impact of inflows on unemployment variation in both the steady-state and non-steady-state decompositions. Two important findings occur in these decomposition results. First, the 90:10 inflow-outflow spilt in the (FR) method remains, even though any contribution through N is excluded since the (FR) method restricts transitions to those directly between E and U. This result implies changes in the unemployment rate depend mostly on flows within the labor force. In the US labor market, dominant contributions from outflows are documented by Shimer (2012), but the opposite results are reported by Fujita and Ramey (2009). As pointed out by Fujita and Ramey (2009), the difference in the inflow-outflow splits stems from the treatment of participation margins when estimating inflow and outflow rates. This controversy, however, does not arise in Korean unemployment dynamics. Secondly, we find that time aggregation bias has almost no impact on the inflow-outflow splits. Despite the substantial differences between 3 state, TAC and 3 state, NO TAC in terms of level, the decomposition results are the same in both cases. Time aggregation bias matters only for the level of flow rates and does not change the cyclical properties.

[Table 3] Decomposition in Three-state models: 1986-2004

Method	Dcmp.	$d\ln y_t$	Total inflow		Total outflow		β_0	Residual
			β_{EU}	β_{ENU}	β_{UE}	β_{UNE}		
3 state, TAC	ss	$d\ln\overline{u}_t$	45.9%	34.3%	9.2%	0.2%	-	-
	ss	$d\ln u_t$	68.9%	33.9%	-2.7%	-6.3%	-	6.2%
	nss	$d\ln u_t$	65.8%	31.8%	1.1%	-5.4%	1.1%	5.6%
3 state, no TAC	ss	$d\ln\overline{u}_t$	42.9%	31.2%	13.9%	0.3%	-	-
	ss	$d\ln u_t$	66.5%	33.8%	-0.2%	-6.4%	-	6.4%
	nss	$d\ln u_t$	63.6%	31.6%	3.5%	-5.4%	1.1%	5.6%

Note: ss stands for the steady-state and nss for the non-steady-state decomposition.

The final decomposition results are presented in table 3. The contributions of total inflows and outflows are separated into direct and indirect flows. About 60% of unemployment variability is accounted for by direct flows from E to U and around 30% by indirect flows, amounting to a 90% contribution of total flows. In contrast, combined outflows have negligible impacts on unemployment changes. $U \rightarrow E$ outflows still have a positive contribution, but $N \rightarrow E$ rates display negative impacts on unemployment changes, which may explain the negative contribution of outflows observed during some recessions (section 4).

[23] For comparison, we recompute the contribution of each flow from 1987 to 2004 using the (SH) method.

4.2. Disaggregation by Reasons for Unemployment

Next, we relax the homogeneous flow rates for all workers. Workers may have different hazard rates depending on the circumstances under which they are separated from their current jobs. Job losers are involuntarily separated from their positions, while job leavers choose to exit their workplaces. Accordingly, the outflow hazard rates may also vary because of different incentives to find new jobs. We therefore allow heterogeneous flow rates based on the reason for unemployment. Unemployed workers are categorized into three groups: job losers (layoffs), job leavers (quits), and new entrants from out of the labor force. The detailed types are provided in the Appendix.

[Figure 7] Shares of Unemployment by Reason: 1987Q1 -2014Q4

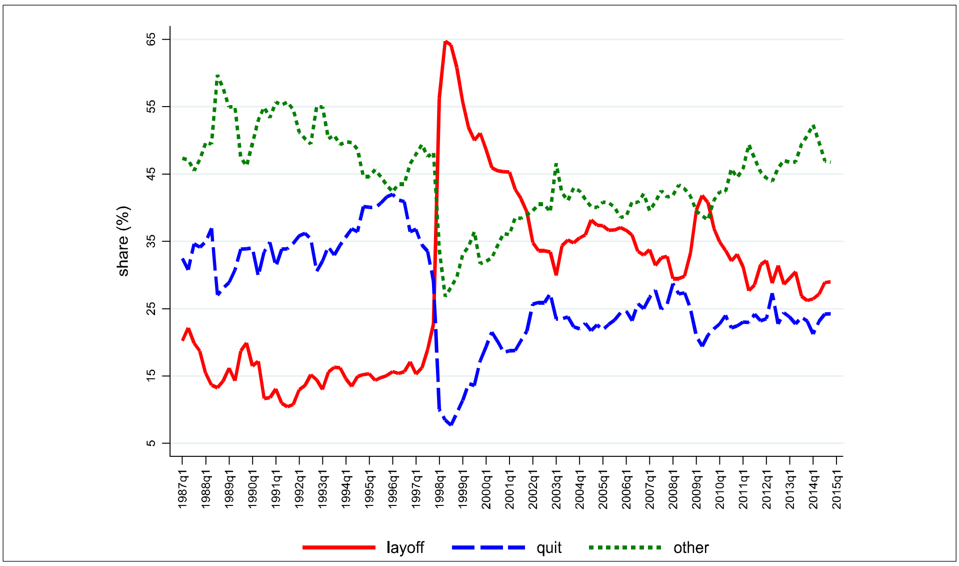
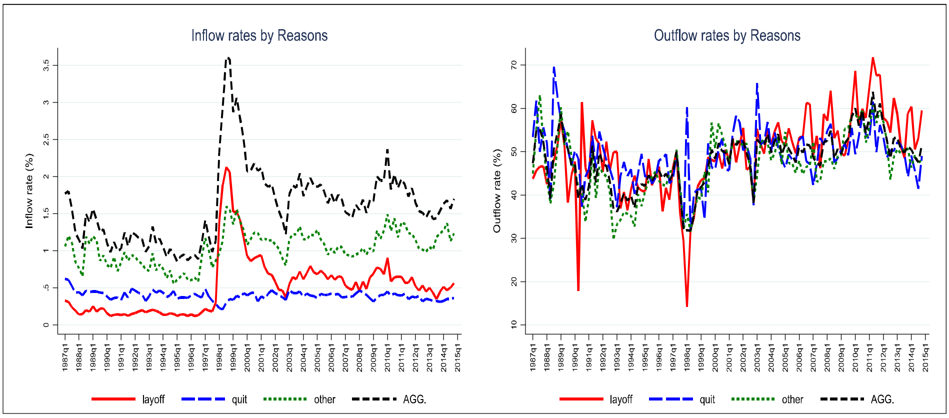


Figure 7 displays the shares of each type of unemployed worker. The share of new entrants has dropped considerably since the crisis but it accounts for the highest share of unemployed workers except during the crisis period. Both quits and layoffs, however, have dramatically changed since the crisis. Before the crisis about 35% of unemployed workers had left their jobs voluntarily, but only about 15% had been laid off. In the middle of the crisis, the share of layoffs spiked up to 65%, while new entrants and quits showed severe drops. The layoffs and quits have started to recover, but neither has yet returned to its pre-crisis share. Moreover, the shares of layoffs and quits have reversed their positions: quitters now account for 25% of the unemployed, while losers make up 35%.

[Figure 8] Inflow and Outflow Rates by Reason: 1987Q1-2014Q4



Both rates by reasons for unemployment are provided in figure 8.[24] The inflow rates in the left panel show large heterogeneities in both level and cyclicality across the reasons. Despite the level difference, the inflow rates of job losers trace the aggregate inflow rates quite well, especially after the crisis. These flow rates were lower than others until 1997, but they rose to twice their pre-crisis levels after the sudden jump during the crisis. The inflow rates of job leavers are very different from those of job losers in that the former are much less volatile and even pro-cyclical. The different cyclical properties between job leavers and job losers show up in the 1996-1999 crisis and the 2008-2009 recession. In contrast, the outflow rates in the right panel are similar across all types of workers. Elsby et al. (2009) document considerably lower outflow rates for job losers than job leavers or entrants in the US, but we do not find such patterns in Korea. Despite the similar flow rates, we do observe different cyclical patterns by reasons for unemployment. The outflow rates of job losers co-move with the unemployment rate, but those of job leavers display countercyclical patterns. These cyclical properties also differ from those seen in the US labor market, where all outflow rates move counter to unemployment fluctuations.

The steady-state and non-steady-state decomposition results are provided in table 4. These results consistently present the dominant contribution of inflow rates versus that of outflow rates regardless of reasons for unemployment: the total contribution of inflows is 89.0% and 95.6% in the steady-state and non-steady-state decompositions, respectively. Of this contribution, 63.0% is explained by layoffs and 29.6% by new entrants, but job leavers account for only 7.3%. When we compute

[24] We apply a similar method in Elsby et al. (2009) to estimate flow rates. The outflow rates are easily estimated from eq. (7) because the unemployment and short-term unemployment rates can be separated by reasons for unemployment. We follow the methodology presented in the appendix of Elsby et al. (2009) to measure the inflow rates.

the sum of inflow and outflow contributions by reasons for unemployment, we find that 65.2% of aggregate unemployment variability is explained by layoffs and 30.8% by new entrants. The contribution from job leavers, however, is very small. These results are consistent with figure 8, which illustrates that the dynamics of aggregate inflows and inflows of laid-off workers are very similar.

[Table 4] Contributions of Inflows and Outflows on Unemployment Changes by Reasons

Period	Dcmp.	$d\ln y_t$	β_s			β_f			β_0	Residual
			layoff	quit	other	layoff	quit	other		
All	ss	$d\ln\overline{u}_t$	56.1%	6.5%	26.4%	12.8%	2.8%	8.3%	-	-12.8%
(1987-2014)	ss	$d\ln u_t$	81.3%	7.2%	32.1%	0.8%	-0.5%	5.9%	-	-10.5%
	nss	$d\ln u_t$	68.0%	3.3%	24.3%	5.3%	1.2%	5.3%	1.1%	-8.5%
Pre Crisis	ss	$d\ln\overline{u}_t$	12.2%	21.0%	53.1%	6.0%	1.5%	8.9%	-	-2.8%
(1987-1995)	ss	$d\ln u_t$	23.8%	33.1%	86.9%	-5.8%	-8.4%	13.6%	-	-7.9%
	nss	$d\ln u_t$	14.1%	19.0%	56.9%	-4.8%	5.0%	6.4%	16.3%	-12.6%
Post Crisis	ss	$d\ln\overline{u}_t$	51.2%	6.8%	27.6%	-0.7%	4.7%	7.9%	-	2.5%
(2000-2014)	ss	$d\ln u_t$	70.1%	11.5%	45.3%	-12.0%	4.7%	-1.2%	-	1.8%
	nss	$d\ln u_t$	58.9%	9.1%	40.2%	-10.6%	2.6%	-3.0%	0.2%	2.7%

Note: ss stands for the steady-state and nss for the non-steady-state decomposition.

We also perform decompositions for each subperiod as in table 1. The total contributions of inflows confirm the earlier results regardless of the time period. In the steady-state decomposition, inflows account for 86.3% and 85.6% in the pre-and post-crisis periods, respectively. The non-steady-state decomposition also presents similar results: 90% in the pre-crisis period and 108.2% after the crisis. However, when the inflows' contributions are disaggregated by reasons for unemployment, we observe considerable dissimilarities between the pre-and post-crisis periods. Until 1995, the inflow hazards of new entrants are the main driving force of unemployment variability, with contributions of 53.1-56.9%. The inflow contributions of quits and layoffs are much smaller: 19.0% and 14.1%, respectively. These patterns change dramatically after the crisis. The inflow hazards of layoffs have become the dominant source of unemployment variability. Their contributions rise to 51.2-70.1% after the crisis, while the contributions from new entrants and quits are cut by more than half. The contributions of outflows also feature interesting patterns. Positive outflow contributions are reported for all unemployment reasons during the pre-crisis period, but the signs turn to negative for job losers and new entrants after the crisis. As discussed in section 3, the impact of inflows on unemployment variability has increased since the 1996-1999 crisis. The introduction of official layoffs and workers dispatched by temporary staffing agencies are offered as possible explanations for these structural changes in the Korean labor market. These explanations are indirectly supported by our findings that the contributions of layoffs have substantially increased since the crisis.

V. Conclusion

This paper analyzes unemployment dynamics in Korea using inflows and outflows to unemployment. Unlike previous Korean studies, we carefully correct for time aggregation bias when estimating flow rates. In addition to performing a steady-state decomposition, we evaluate the flow rates' contributions to unemployment variability using a non-steady-state decomposition because some deviations are detected between the steady-state and actual unemployment rates. As robustness checks, we relax some strict assumptions in the baseline analysis. In order to examine the role of participation margins, we extend the two-state economy to a three-state economy, which allows workers to move in and out of the labor force. As a second robustness check, we introduce heterogeneous flow rates by reasons for unemployment to verify whether our empirical results are different between job losers and job leavers.

We document some outstanding features in the Korea labor market compared to other OECD countries. Korea's average inflow rate is estimated at 1.6%, comparable to other OECD members, but its average outflow rate of 48% is relatively high, except in comparison to the US. The high outflow rate explains why Korea's unemployment rate is low by OECD standards. We divide the sample periods into two subperiods: those before and after the Korean Financial Crisis in the late 1990s. Both flow rates have increased slightly since the crisis, but the inflow rates have increased more than outflow rates, which has raised the unemployment rate in the post-crisis period. We find the most striking results for Korea in the decompositions: the inflow rate accounts for 90% of unemployment variability. Both the steady-state and non-steady-state decompositions confirm the superior contributions of inflows to unemployment changes. Moreover, the dominant contributions from inflows appear in the both pre-crisis and post-crisis periods, but the contributions are greater after the crisis. Large impacts of inflows are not reported in any other OECD countries (Elsby et al., 2013). We confirm the same results even under relaxed assumptions. First, we allow workers to transit in and out of the labor force. Of the 90% contribution of inflows to unemployment variability, 60% is explained by the direct transitions from employment and 30% by indirect transitions through participation margins. The strong influences from inflows are also robust to heterogeneous flow rates by reasons for unemployment. But while the dominant impacts of inflows appear in all unemployed workers, the magnitudes differ. Inflows of job losers and new entrants explain most unemployment variability, while the contributions of job leavers' inflows are small.

Our findings from Korea add an empirical contribution to the recent literature on unemployment dynamics. After Shimer (2012) and Hall (2005), labor market research has paid less attention to the inflows into unemployment. Consequently, some recent macroeconomic modelings on the labor market treat the inflow rates as constant like Shimer (2005). In response, studies such as Fujita and Ramey (2009), Elsby et al. (2009), and Elsby et al. (2013) have urged caution regarding this trend and have emphasized the importance of inflows on unemployment fluctuations. Our findings, in which Korean unemployment dynamics are almost entirely explained by inflow changes, add more strong empirical evidence to these studies.

At the same time, our results provide some Korea-specific implications for modeling choice. The Korean labor market is characterized by two distinctive features: high outflow rates from unemployment and a dominant contribution (90%) of inflow changes to unemployment fluctuation. Because of the high average outflow rates, models for the Korean labor market should match the short unemployment duration, as the Korean labor market is not explained by models developed for continental European countries that produce long unemployment durations. The most important ingredient for unemployment fluctuation in Korea is time-varying inflow rates to generate unemployment fluctuation. Any labor market models with constant inflow rates cannot match the unemployment dynamics in Korea. Therefore, the model should incorporate endogenous separation from employment as in Bils et al. (2012) and Fujita and Ramey (2012), or time-varying inflow rates, even if exogenous, over the business cycle.

A. Data

A.1. The Short-term Unemployed Workers from EAPS Data

EAPS data, which is used to construct the official unemployment rate in Korea, is the underlying micro data from the collection of labor force status information from approximately 32,000 households in every year. NSO publishes monthly data on employment, unemployment and unemployment duration, but the shortest unemployment duration is provided in less than three months. To construct the unemployed workers with duration of less than a month, we access the micro data and construct the short-term unemployed worker series.

One natural questions arises: why is short-term unemployment defined as that lasting less than a month rather than a longer duration (perhaps of three or more months)?[25] Elsby et al. (2013) point out that outflow rates measured by a one-month unemployment duration work well for countries where outflow rates from unemployment are relatively high. Nevertheless, in countries with low exit rates, the estimates may be noisy if they are estimated with a duration of only one month, so they suggest using other unemployment durations to reduce the noise. In this sense, it is possible to use other duration information while estimating the exit rates in Korea. These estimates, however, are not necessarily the same as the hazard rates estimated using a duration of only one month, because the outflow rates decrease as the unemployment duration increases if there exists a negative duration dependence. If there is a duration dependence, Elsby et al. (2013) suggest that it is better to use a one-month duration for estimating the exit rate from unemployment because this measure provides the least biased estimates. Since the hypothesis of no-duration dependency is not rejected in Korea, we estimate the outflow rates with a one-month unemployment duration.

A.2. Constructing Transition Probabilities from EAPS

It is possible to match EAPS data to individuals over two consecutive months up to 2004. First, we match individuals between two consecutive months using household and individual identification numbers. We then remove some

[25] We thank Jang-Ok Cho for raising this question. The duration is critical to measure the outflow rates, but it has received less attention in the literature. He also pointed out that unemployed workers with a jobless duration less than one month may not be important from a policy standpoint, as labor market policy may focus on long-term unemployment. His points are well taken but left for future research. There are not many Korean studies that investigate labor market flows or unemployment durations. Our study tries to provide a better and more complete picture of the Korean labor market as a first step for further research. Therefore, in this paper, we apply the well developed methods from the previous studies.

inconsistent matches by inspecting demographics. For instance, individuals with the same IDs but different genders or birth dates are eliminated. Since the household IDs are reset every year, individuals in December and the following January cannot be matched using ID numbers. However, household members can still be verified by using data on the number of household members to match households between December and the following January. Once the households are linked using the numbers of members, we use each member's demographics such as gender and birth dates to match households between the December and January data. The matching rates and accuracy are improved as the number of members increases. When the data is arranged in a panel structure, we compute the stock variables for all transitions and seasonally adjust these stocks with X-12, and then calculate the transition matrix with these monthly stocks. We apply the eigendecomposition method in section 2 to the transition matrix and estimate flow rates with time aggregation bias corrected. Finally, monthly flow rates are converted into quarterly rates by simple average within each quarter.

A.3. Reasons for Unemployment

The EAPS collects data on reasons for unemployment. The detailed questionnaire changes after 1998, but the unemployed can still be categorized into three groups: job losers, job leavers and new entrants. Job losers (or layoffs) are workers who are unemployed because of firm closures, layoffs, terminations of temporary jobs or business slumps. We classify job leavers (or quits) as unemployed workers who left their jobs in search of better pay or working conditions. Unemployed workers who left their jobs because they would like to open their own businesses, or who closed down their own businesses, are also categorized as job leavers. The remainder of unemployed workers are identified as others (or new entrants). These workers are unemployed for reasons such as personal or family reasons, childcare, housework, disability, and retirement.

B. Summary Statistics

[Table 5] Summary Statistics of Labor Market Variables

Period	u_t	$\overline{u}_t$	f_t	s_t	F_t	S_t
All	3.24%	3.26%	48.03%	1.61%	38.01%	1.59%
	(1.12%)	(1.19%)	(6.50%)	(0.52%)	(4.08%)	(0.51%)
Pre Crisis	2.55%	2.55%	45.21%	1.18%	36.26%	1.17%
(1987-1995)	(0.31%)	(0.34%)	(6.00%)	(0.23%)	(3.78%)	(0.23%)
Crisis	4.50%	4.71%	41.71%	2.01%	33.99%	1.99%
(1996-1999)	(2.42%)	(2.54%)	(6.23%)	(1.02%)	(4.17%)	(1.00%)
Post Crisis	3.28%	3.28%	51.82%	1.76%	40.39%	1.74%
(2000-2014)	(0.37%)	(0.36%)	(4.08%)	(0.23%)	(2.42%)	(0.22%)

Note: Standard deviation in parenthesis.

[Table 6] Summary Statistics of Total Flows: 1986 -2004

Method	$\overline{u}_t$	f_t	s_t	F_t	S_t
Shimer	3.32%	45.66%	1.55%	36.53%	1.54%
	(1.46%)	(6.27%)	(0.62%)	(4.01%)	(0.61%)
Fujita & Ramey	2.59%	34.47%	0.89%	29.11%	0.89%
	(1.27%)	(3.59%)	(0.36%)	(2.54%)	(0.36%)
3 state, TAC	2.20%	61.72%	1.32%	45.83%	1.31%
	(1.23%)	(9.05%)	(0.54%)	(4.92%)	(0.53%)
3 state, no TAC	1.91%	57.99%	1.07%	43.82%	1.06%
	(1.11%)	(8.15%)	(0.45%)	(4.60%)	(0.44%)

Note: Standard deviation in parenthesis.

[Table 7] Summary Statistics in Three-state Models: 1986 -2004

Variable	Method	Total inflow		Total outflow		$E \Leftrightarrow N$	
		EU	NU	UE	UN	NE	EN
Flow rate	TAC	0.86%	0.88%	33.53%	11.56%	4.52%	2.92%
		(0.34%)	(0.46%)	(4.33%)	(3.81%)	(1.00%)	(0.70%)
	no T.A.C.	0.69%	0.71%	31.03%	9.91%	4.54%	2.87%
		(0.28%)	(0.37%)	(3.80%)	(3.07%)	(0.96%)	(0.67%)
Flow prob.	TAC	0.86%	0.88%	28.42%	10.85%	4.41%	2.87%
		(0.34%)	(0.45%)	(3.08%)	(3.39%)	(0.95%)	(0.68%)
	no T.A.C.	0.69%	0.70%	26.62%	9.39%	4.43%	2.83%
		(0.28%)	(0.36%)	(2.78%)	(2.78%)	(0.92%)	(0.65%)

Note: Standard deviation in parenthesis.

C. Flow Rates in the Three-state Model

[Figure 9] Flow Rates in the Three-state Model

Figure 9 illustrates the series of six flow rates across labor force statuses. The first two panels present outflows from U, and the second two panels are the inflows to U. For comparison, the outflow and inflow rates estimated in section 3 are demonstrated in the UE and EU rates. The outflow rates from unemployment are much larger than any other flow rates, and the outflows to E are about three times larger than the outflows to N. Inflow rates to unemployment are lower than $E \Leftrightarrow N$ flow rates. There are significant deviations in inflow and outflow rates whether time aggregation bias is corrected or not. $E \Leftrightarrow N$ rates, however, are free from the bias.

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