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The Evolution of Job Reallocation in the Korean Manufacturing Sector*

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We investigate the evolution of job reallocation from an industrial perspective using job flows in the Korean manufacturing sector from 1986 to 2015. After measuring job reallocation for each of 22 manufacturing industries, we decompose industrial job reallocation rates into three parts driven by common, industry-specific, and idiosyncratic allocation components, employing a Bayesian dynamic latent factor model. The common factor plays the largest role in driving industrial job reallocation rates and its influence on the evolution of job flows intensifies after the 1997 financial crisis. The relative importance of the common and the industry-specific factors differs depending on firm size.

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1. INTRODUCTION

This paper investigates the driving forces behind the fluctuations in job reallocation across Korean manufacturing firms. Job reallocation, the consequence of employment adjustments, plays a crucial role in improving firms' performance and economic growth. The extensive literature on job reallocation reveals that job flows exhibit dynamic behaviors, actively responding to the business cycle and to various economic shocks. Braun *et al*. (2006) find that technology shocks have long-lasting effects on job creation and destruction in the U.S. Herrera and Karaki (2015) show that positive oil price shocks lead to an increase in job reallocation across the U.S. manufacturing. After exploring job flows in the manufacturing sectors in Latin America, Haltiwanger *et al*. (2004) find that cut-off of tariffs and currency depreciation enhance job reallocation within sectors.

Studying job flows in Korea, Hyun (2016) uncovers evidence that the 1997 financial crisis and the subsequent labor market reforms intensify job reallocation and make job reallocation more procyclical than before, and that the magnitude of job reallocation differs across groups of firms that are similar in size, industry, and financial conditions. Likewise, the literature on labor markets demonstrates that industrial heterogeneity, such as employment practices and capital adjustment patterns, affects labor market dynamics (Brainard and Cutler, 1993; Den Reijer, 2011) and that employment actively responds to aggregate and sectoral shocks (Davis and Haltiwanger, 2004; Pilossoph, 2012).

The aforementioned prior studies raise several intriguing questions about the causes of different variations in sectoral job reallocation rates. Which plays the main driving role in variation in job reallocation, common or sectoral shocks? Do the shocks have the same relative influence on all industrial job reallocation rates? Is the relative influence of the shocks attributable to industries' characteristics, such as employment practices and industrial growth? The answers to these questions can shed light on the distinct features of industrial job reallocation dynamics and their driving forces. These questions also have relevance to a growing strand of the macroeconomics literature on the effects of sectoral shocks on the macroeconomy (see, e.g., Foerster *et al*., 2011; Horvath, 2000). Furthermore, it is interesting to examine whether the relative importance of common and sectoral shocks changes before and after important economic events, such as a financial crisis.

To find answers to these questions, this paper explores the driving forces behind the evolution of job reallocation in the Korean manufacturing sector between 1986 and 2015, from an industrial perspective. The data on the manufacturing sector in Korea are suitable for our research purpose. The Korean manufacturing industries exhibit substantial heterogeneity in industrial growth, employment, and job reallocation, and have different responses to the 1997 financial (Bank of Korea, 1994, 2009; Hyun, 2016; Kang and Orazam, 2003). Industrial job reallocation varies across industries, though all industries exhibit high job reallocation rates. Such a rich heterogeneity across industries, which reflects both the differing labor market conditions and different responses to shocks, provides an ideal testing ground to examine whether common or industry-specific factors are more relevant to the evolution of job reallocation rates.

After calculating 22 industrial job reallocation rates based on two-digit manufacturing industries, we exploit the Bayesian dynamic latent factor model to decompose each job reallocation rate into three components: those driven by the common, industry-specific, and idiosyncratic factors. Then, we examine the properties of the common and industry-specific factors and the extent to which these factors drive industrial job reallocation rates.

We find that the common factor, which accounts for comovements across the 22 industrial job reallocation rates, rose sharply in response to the 1997 financial crisis, then decreased gradually until 2015. While industry-specific factors exhibit similar patterns of fluctuation the common factor behaves, such as an increase around the 1997 crisis, they show substantial heterogeneity across industries. Importantly, the common factor accounts for the largest fraction (on average 41.2%) of job reallocation fluctuations.

Focusing on the 1999-2015 period, the influence of the common factor on the evolution of job flows strengthens. The enhanced role of the common factor in driving job reallocation after the 1997 financial crisis is associated with the reduction in heterogeneity in job reallocation across industries.

Next, we uncover evidence that the common factor plays a modest role in driving the job reallocation of large firms, while for small firms, the factor accounts for the largest fraction of job reallocation variability. These results suggest that small firms' employment behaviors are more affected by aggregate shocks, while large firms' employment behaviors are more affected by sectoral shocks.

The rest of this paper unfolds as follows. Section 2 explains the data source and job reallocation in the Korean manufacturing sector. Section 3 outlines the Bayesian dynamic latent factor model. Section 4 investigates the driving forces of job reallocation from the industrial perspective. Section 5 examines the relative importance of driving forces with respect to firm size. Section 6 concludes.

2. DATA AND INDUSTRIAL JOB REALLOCATION

2.1. Data Set

This study relies on a business data source, KISLINE, that is operated by National Information and Credit Evaluation (NICE), the leading credit rating agency in Korea. Among 24 manufacturing industries, we exclude the tobacco industry from the dataset because the industry is monopolistic, dominated by few firms. Also, we remove firms that are categorized as miscellaneous industry because this category does not represent a true specific industry.

The dataset includes 302,168 observations of 32,352 firms, among which privately held firms account for 91.1%.[1)] The dataset spans from 1985 to

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[1)] The extensive coverage of our dataset enables us to construct job flows that represent the

2015; therefore, job flows start in 1986 and end in 2015. The long sample period allows us to examine if and how job reallocation patterns and the driving forces behind them change in response to the 1997 Asian financial crisis and the 2008-2009 global financial crisis.

2.2. Job Reallocation in the Manufacturing Sector, 1986-2015

Using the methodology proposed by Davis *et al*. (1996), we construct industrial gross job reallocation and excess job reallocation based on 22 two-digit manufacturing industries.[2)] Gross job reallocation (SUM_{it}) in an industry i of year t, as shown in equation (1), is defined as the sum of job creation and destruction. Job creation (POS_{it}) in industry i of year t is defined as the weighted sum of employment growth rates over firms of the industry i, which grow between year t–1 and year t (Hyun, 2016). Likewise, job destruction (NEG_{it}) is defined as the weighted sum of the absolute values of negative employment growth rates over firms that belong to industry i in year t whose employment shrinks between year t–1 and year t (Hyun, 2016). Then, the net employment growth rate (NET_{it}), as shown in equation (2), is calculated by subtracting job destruction from job creation. Finally, excess job reallocation (EXC_{it}) is calculated as the difference between gross job reallocation and the absolute value of the net job growth rate, as shown in equation (3).

$$SUM_{it} = POS_{it} + NEG_{it}, \tag{1}$$
$$NET_{it} = POS_{it} - NEG_{it}, \tag{2}$$
$$EXC_{it} = SUM_{it} - |NET_{it,}|. \tag{3}$$

In order to explore the driving forces behind dynamic patterns of job

complete Korean manufacturing sector. Indeed, the total assets and the employment size of this dataset account for 43.9% (48.2%) and 52.8% (59.4%) of regular employment in the manufacturing sector in 1995 (2008).

[2)] For more details on the methodology that measures job flows, refer to Davis and Haltiwanger (1992) and Davis *et al*. (1996).

reallocation, we use both SUM and EXC because each flow contains different information on employment adjustments. SUM is the main indicator that measures the extent of job reshuffling and implies the heterogeneity in firm-level employment adjustments, as Davis *et al*. (1996) point out. EXC provides important information that SUM does not capture as it is a measure of simultaneous job creation and destruction (Davis *et al*., 1996). Also, EXC measures the extent to which sectoral job creation and destruction, occurred in a sector, exceed the minimum amount of job reallocation within the sector that is necessary to meet sectoral employment growth. Therefore, each flow has its own economic relevance and using both flows gives us a more comprehensive understanding of the job reallocation process and labor market dynamics.

Table 1 reports industry-level job flows (SUM and EXC) for the whole

Table 1 Industrial Job Reallocation

	Total Period		Pre-crisis Period		Post-crisis Period	
	SUM	EXC	SUM	EXC	SUM	EXC
Manufacturing	12.87	10.13	11.80	9.06	15.63	13.66
Food	11.53	8.72	10.13	6.90	12.36	10.67
Beverage	11.63	6.64	10.38	4.58	11.95	7.87
Textiles	13.99	8.32	12.08	6.62	18.47	11.09
Apparel	16.07	12.22	13.86	10.58	17.50	13.73
Leather	17.47	10.26	18.24	8.70	19.52	12.46
Lumber	13.85	8.36	11.03	4.02	15.97	11.87
Paper	10.91	8.60	11.03	8.82	10.54	9.08
Printing	11.32	8.67	8.74	5.63	13.99	11.25
Petroleum	10.28	5.67	12.395	7.44	7.54	5.05
Chemicals	11.47	8.16	10.76	7.52	13.78	11.55
Medicine	8.67	5.50	7.14	5.58	10.74	7.05
Rubber and Plastic	15.70	9.62	11.99	8.86	24.51	11.76
Stone · Clay · Glass	12.04	9.39	10.71	8.15	13.79	12.43
Primary Metal	9.26	6.82	9.05	6.99	8.84	7.30
Fabricated Metal	13.00	9.62	11.88	7.47	14.30	11.99
Electronic Component	15.61	10.68	14.07	8.23	20.63	15.71
Optical Instrument	15.92	10.26	15.51	9.46	18.05	12.28
Electronic Machinery	14.70	10.74	12.71	8.36	16.45	14.04
Other Machinery	13.86	9.85	11.87	7.24	17.24	13.67
Auto	10.99	5.87	11.42	3.78	12.97	9.84
Other Transportation	10.27	5.88	13.87	8.54	9.55	4.34
Furniture	13.61	9.25	10.89	6.17	17.26	14.28

sample (1986-2015) period, the pre-crisis (1986-1996) period, and the post-crisis (1999-2015) period. The table shows that industrial gross and excess job reallocation rates show substantial intensity. Such uniformly high industrial job reallocation rates indicate that every industry experiences considerable heterogeneity in the direction of employment growth (Davis *et al*., 1996; Liu, 2013). In other words, some firms in an industry increase their number of employees, while other firms in the same industry decrease their number of employees, which implies that firm-level employment patterns are significantly different in any given year.

3. BAYESIAN DYNAMIC LATENT FACTOR MODEL

This section briefly describes the Bayesian dynamic latent factor model, proposed by Otrok and Whiteman (1998) and Kose *et al*. (2003). Factor analytic approaches are a popular methodology in the empirical macroeconomics literature, used to examine the sources of dynamic movements in time-series variables (Crucini *et al*., 2011; Foerster *et al*., 2011; Forni and Reichlin, 1998; Horvath, 2000). The Bayesian dynamic latent factor model, developed by Otrok and Whiteman (1998), starts to be widely adopted in the empirical macroeconomics literature to examine the comovements in regional business cycles (e.g., Crucini *et al*., 2011; Kose *et al*., 2003) and the common and sector-level sources of fluctuations in sectoral economic variables (e.g., Liu, 2013).

We assume that two factors drive industrial job reallocation rates. The first is a common factor that affects all job reallocation rates in all manufacturing industries, and the other is an industry-specific factor that affects the corresponding industry's job reallocation rate. Under this assumption, we allow for a common factor and an industry-specific factor to identify the distinction between sources of variation common to all job reallocation rates and those specific to an industry. The dynamic latent factor model with the two factors is specified as:

$$y_{ijt} = \beta_{ij}^{c} F_t + \beta_{ij}^{m} f_{it}^{m} + \varepsilon_{ijt}, \tag{4}$$

where y_{ijt} denotes job reallocation. i and j respectively indicate two-digit industry ($i = 1, \ldots, 22$) and job reallocation (j=1: SUM and j=2: EXC). t denotes year ($t = 1986, \ldots, 2015$). F_t is the common factor to which all job reallocation rates respond. The change in the common factor causes all job flows to move. f_{it}^{m} is an industry-specific factor for each industry i. β_{ij}^{c} and β_{ij}^{m} are factor loads for the common and industry-specific factors, respectively. These factor loads measure the direction and sensitivity of job flows' responses to the factors. When the sign of a factor load is positive (negative), the corresponding job flow increases (decreases) in response to an increase in the corresponding factor. As the magnitude of a factor load increases, the factor has more influence on changes in the corresponding job flow. ε_{ijt} is an idiosyncratic component that consists of a flow-specific factor and measurement error. Idiosyncratic components are assumed to be normally distributed, but are allowed to be serially correlated. The two factors and the component behave in a p-order autoregressive process, AR(p), as presented in (5) to (7).

$$F_t = \theta_1^{c} F_{t-1} + \theta_2^{c} F_{t-2} + L + u_t^{c}, \tag{5}$$

$$f_{it}^{m} = \theta_1^{m} f_{it-1}^{m} + \theta_2^{m} f_{it-2}^{m} + L + u_{it}^{m}, \tag{6}$$

$$\varepsilon_{ijt} = \theta_1^{I} \varepsilon_{ijt-1} + \theta_2^{I} \varepsilon_{ijt-2} + L + u_{ijt}^{I}. \tag{7}$$

An innovation, u_{ijt}, is assumed to be a zero mean, contemporaneously uncorrelated normal random variable. All comovements are mediated by the factors, which all have autoregressive representations (Kose *et al*., 2003). We follow the Bayesian procedures proposed by Crucini *et al*. (2011) and Kose *et al*. (2003) to estimate the two factors and the idiosyncratic components. Posterior distribution properties for the model parameters and factors are based on 50,000 Markov chain Monte Carlo (MCMC) replications after 5,000 burn-in replications. For robustness checks on the convergence of posterior distribution of factors, we redo the estimation; changing the number of replications (30,000, 50,000, and 70,000). Since all the results yield a very similar distribution of factors and idiosyncratic components, we provide the results of the 50,000 replications in the next section. To save space, we avoid providing detailed technical explanations of the Bayesian estimation procedure. For more technical details on the estimation procedure, refer to Otrok and Whiteman (1998, pp. 998-1006), and Kose *et al*. (2003, pp. 1218-1221).

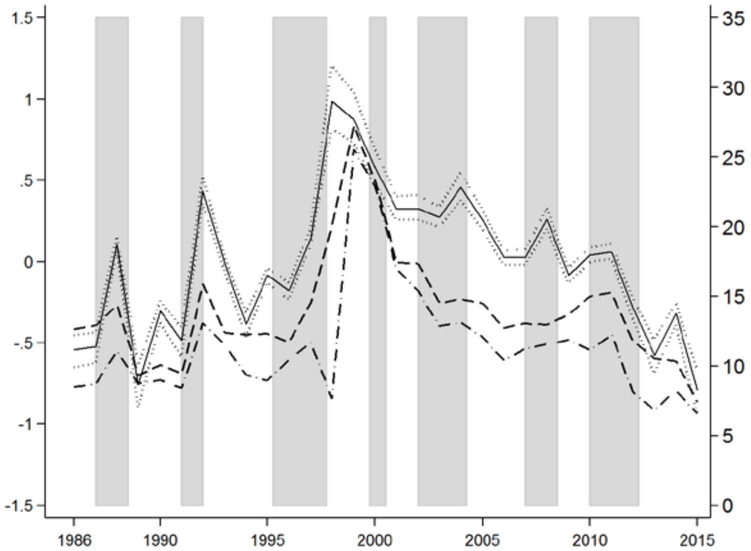
4. EMPIRICAL RESULTS

4.1. The Common Factor

Figure 1 plots the common factor (solid line), defined as the median (50% quantile), and 33% and 66% quantile bands (dotted lines) of the posterior distributions for the common factor, along with the manufacturing sector-level SUM (dashed line) and EXC (dot-dashed line). The vertical shaded areas denote recession periods. The narrowness of the bands indicates that the factors are estimated precisely (Kose *et al*., 2003). Before the 1997 financial crisis, the factor showed an upward trend with temporary, but significant increases during the first two recessions. Particularly, the factor experienced a sharp and pronounced increase, reached a peak in 1998. Then it decreased continuously during the post-crisis period, which spans from 1999 to 2015. Exceptionally, the decline in the factor seemed to stop around the time of the global financial crisis.

In addition, the figure shows that the common factor moved in accordance with the two manufacturing sector job reallocation rates. In order to better understand the properties of the common factor, we examine the coefficients of correlation between the factor and several macroeconomic variables (GDP growth, unemployment rate, and production index), as shown in table 2. The factor was negatively correlated with GDP growth (–0.22) during the

Figure 1 Common Factor and the Job Reallocation



Notes: This figure depicts the common factor (solid line) that explains the common movements of gross and excess job reallocation rates across 22 2-digit manufacturing industries. The dotted lines around the common factor indicate 0.33 and 0.66 quantiles for the posterior distributions of the factor. Dashed and dot-dashed lines respectively denote gross job reallocation (SUM) and excess job reallocation (EXC) for the manufacturing sector. The factors and confidence bands are scaled on the left *Y*-axis and the two job reallocation rates are scaled on the right *Y*-axis. The vertical shaded areas correspond to recessions.

whole sample period. Combined with the fact that the factor comoved with manufacturing sector job reallocation, the countercyclicality of the factor suggests that, during recessions, the driving force that affected job reallocation in all industries intensifies in a direction that facilitates the reshuffling of jobs across firms. Importantly, after the crisis, the factor displayed strong procyclicality (+0.55), suggesting that the factor strengthened as the economy improved. Also, the factor showed similar cyclical patterns with the production index and was positively correlated with the unemployment rate.[3)]

[3)] To save space, the results of the factor loads are not presented in the paper. They are available from the authors upon request.

Table 2 Correlation between Factors and Macroeconomic Variables

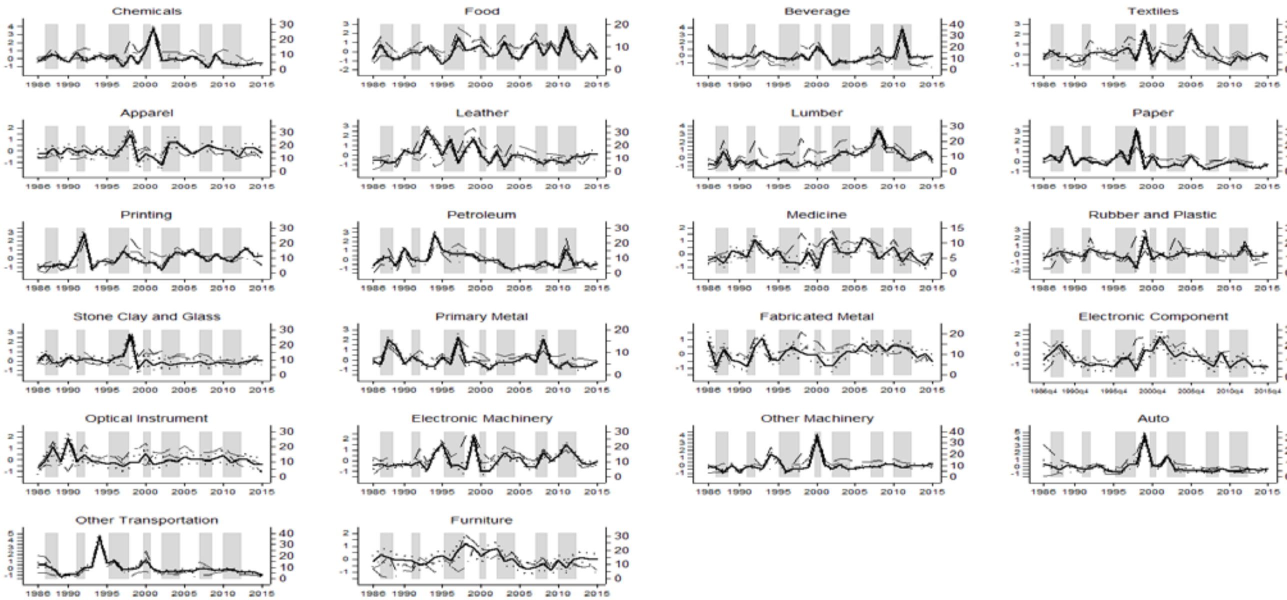
	GDP Growth	Jobless Rate	Production
Common Factor	–0.22 (0.55*)	0.52* (0.59*)	–0.09 (0.26)
Industry-specific Factor			
Food	0.05 (0.05)	–0.04 (0.00)	0.01 (0.01)
Beverage	–0.04 (0.00)	0.04 (–0.20)	–0.07 (–0.03)
Textiles	0.25 (0.17)	0.11 (0.66*)	–0.04 (–0.24)
Apparel	–0.47* (–0.28)	0.34 (–0.13)	–0.40* (–0.30)
Leather	0.23 (0.55*)	0.40* (0.61*)	–0.13 (–0.29)
Lumber	0.08 (0.04)	–0.05 (0.14)	0.14 (0.22)
Paper	–0.56* (–0.28)	0.41* (–0.37)	–0.49* (–0.05)
Printing	–0.16 (–0.13)	0.06 (0.24)	–0.03 (–0.54*)
Petroleum	0.17 (–0.07)	–0.05 (–0.08)	–0.27 (0.13)
Chemicals	–0.27 (–0.47*)	–0.04 (–0.27)	–0.33 (–0.33)
Medicine	0.04 (0.04)	0.02 (0.07)	0.03 (0.20)
Rubber and Plastic	0.48* (0.40)	0.00 (0.75*)	0.25 (–0.12)
Stone, Clay and Glass	–0.55* (–0.34)	0.43* (–0.67*)	–0.43* (0.35)
Primary Metal	–0.13 (–0.12)	–0.28 (–0.03)	0.19 (0.09)
Fabricated Metal	–0.12 (0.38)	0.15 (0.32)	0.01 (0.39)
Electronic Component	0.06 (–0.30)	–0.40* (0.07)	–0.12 (–0.23)
Optical Instrument	0.16 (0.35)	–0.02 (–0.08)	0.15 (0.21)
Electronic Machinery	0.45* (0.37)	0.12 (0.66*)	0.14 (–0.13)
Other Machinery	0.27 (0.19)	–0.17 (–0.28)	0.16 (0.16)
Auto	0.38* (0.53*)	0.38 (0.72*)	–0.05 (–0.09)
Other Transportation	0.30 (0.32)	–0.06 (–0.15)	–0.11 (–0.31)
Furniture	–0.03 (0.17)	0.24 (–0.04)	–0.25 (0.07)

Notes: All series are HP-filtered cyclical components. The GDP growth rate and unemployment rate represent time-series for the Korean economy. Production index represents time-series for each 2-digit manufacturing industry. * denotes statistical significance at the 5% level.

4.2. Industry-specific Factors

Figure 2 depicts industry-specific factors (solid line) and the 33% and 66% quantile bands (dotted lines) of their posterior distributions, as well as the corresponding SUM (dashed line) in 22 two-digit manufacturing industries. Industry-specific factors exhibited movements similar to those of the relevant industrial job reallocation rate. While most industry-specific factors experienced a significant increase around the 1997 financial crisis, they showed substantial heterogeneity across the industries. For instance, the industry-specific factor of the optical instrument industry is quite flat from

Figure 2 Industry-specific Factors and Industrial Job Reallocation



Notes: The figure depicts the industry-specific factors (solid lines) in 22 2-digit manufacturing industries and 0.33 and 0.66 quantiles (dotted lines) for the posterior distributions of the respective factors, along with gross (dashed lines) job reallocation rates. The factors and confidence bands are scaled on the left *Y*-axis and the reallocation rates are scaled on the right *Y*-axis. The vertical shaded lines correspond to recessions.

1990 on, while the factor of the other transportation industry experiences a significant rise from 1990 to 1993, followed by a sharp drop in the subsequent two years. The lumber industry's factor shows a long-lasting increase around the 1997 financial crisis and until 2008. All these results suggest that considerable industrial level heterogeneity exists; this is associated with the source of the reshuffling of employees across industries, as Davis *et al*. (1996) suggests. Due to the different patterns of the industry-specific factors, their cyclicality also differs across industries, as reported in table 2. Interestingly, whether procyclical or countercyclical, the cyclicality of the factors of main manufacturing industries, such as chemical, auto, and electronic component, was stronger than that of other industries.

4.3. Variance Decomposition

Having identified and determined the properties of the factors, we now address an important question: which factor plays a greater role in driving the dynamic movement of job reallocation rates? To find the answer, we decompose the variance of each job reallocation rate into the portion that is driven by the three allocative components (the common factor, the industry-specific factor, and the idiosyncratic component). The variance of job flows for orthogonal factors can be specified as equation (8). The fraction of the variation in the job reallocation of industry i that is driven by the common factor, ϕ_{ij}^{c}, is shown in equation (9). The variance shares of the industry-specific factor and the idiosyncratic component are defined similarly.

$$\mathrm{Var}\left(y_{ijt}\right)=\left(\beta_{ij}^{c}\right)^{2}\mathrm{Var}(F_{t})+\left(\beta_{ij}^{m}\right)^{2}\mathrm{Var}\left(f_{it}^{m}\right)+\mathrm{Var}(\varepsilon_{ijt}), \tag{8}$$

$$\phi_{ij}^{c}=\left(\beta_{ij}^{c}\right)^{2}\mathrm{Var}(F_{t})\,/\,\mathrm{Var}\left(y_{ijt}\right). \tag{9}$$

Table 3 summarizes the results of variance decomposition for job flows in the 22 industries over the whole sample (1986-2015) period. We uncover

Table 3 Variance Decomposition (1986-2015)

	Gross Reallocation			Excess Reallocation		
	C	I	Idio	C	I	Idio
Food	0.401	0.320	0.274	0.007	0.510	0.479
Beverage	0.037	0.468	0.490	0.002	0.436	0.559
Textiles	0.053	0.480	0.462	0.002	0.415	0.581
Apparel	0.546	0.171	0.277	0.069	0.648	0.278
Leather	0.372	0.419	0.208	0.162	0.624	0.214
Lumber	0.143	0.521	0.332	0.101	0.573	0.320
Paper	0.702	0.074	0.216	0.106	0.331	0.563
Printing	0.028	0.854	0.114	0.005	0.905	0.086
Petroleum	0.125	0.448	0.426	0.370	0.197	0.428
Chemicals	0.548	0.199	0.246	0.188	0.295	0.519
Medicine	0.415	0.242	0.336	0.051	0.266	0.677
Rubber and Plastic	0.049	0.756	0.192	0.008	0.788	0.201
Stone, Clay and Glass	0.704	0.169	0.120	0.179	0.486	0.325
Primary Metal	0.199	0.413	0.382	0.130	0.491	0.375
Fabricated Metal	0.289	0.538	0.166	0.002	0.737	0.258
Electronic Component	0.233	0.164	0.595	0.002	0.119	0.877
Optical Instrument	0.002	0.811	0.185	0.097	0.543	0.356
Electronic Machinery	0.137	0.587	0.269	0.034	0.578	0.382
Other Machinery	0.003	0.569	0.425	0.068	0.784	0.140
Auto	0.126	0.250	0.620	0.007	0.506	0.483
Other Transportation	0.039	0.235	0.723	0.012	0.390	0.595
Furniture	0.558	0.154	0.281	0.009	0.494	0.492
Average	0.260	0.402	0.334	0.073	0.505	0.418

Notes: This table reports the variance decomposition for gross and excess job reallocation in 22 manufacturing industries. C, I, and Idio are short for common factor, industry-specific factor, and idiosyncratic components, respectively. The variance share attributable to the relevant factor is reported in each cell. Each number indicates the median of posterior share.

evidence that the common factor is the major driving force behind the variation in job reallocation rates. On average, the common factor accounts for more than 40% of the SUM and EXC in 12 and 10 industries, respectively. In addition, industry-specific factors also explain, on average, 32.4% of the fluctuation in SUM and 32.8% of the change in EXC. Interestingly, when we focus on SUM, the common factor is dominant in light industries, such as textile (53.9%), apparel (57.6%), lumber (46.7%), printing (56.2%), and furniture (77.0%). On the other hand, industry-specific factors are more influential in heavy industries, such as chemical (43.4%), electronic machinery (56.7%), other machinery (53.2%), optical

(56.2%), petroleum (55.7%), auto (41.1%), and other transportation (77.0%). These results suggest that the industry to which firms belong has substantial influence on whether their employment behaviors are more responsive to aggregate or industry-specific shocks. Idiosyncratic components, which comprise variable-specific factors and measurement error, contribute the smallest fraction of the variability in job flows: 25.6% of SUM and 29.3% of EXC, on average.

We further examine whether the fraction of job flows explained by the three components changes after the 1997 financial crisis, because that crisis led to structural changes in various firms' decisions, such as employment and

Table 4 Variance Decomposition (1999-2015)

	Gross Reallocation			Excess Reallocation		
	C	I	Idio	C	I	Idio
Food	0.245	0.529	0.226	0.416	0.301	0.282
Beverage	0.101	0.624	0.274	0.128	0.519	0.353
Textiles	0.517	0.230	0.253	0.338	0.246	0.417
Apparel	0.341	0.466	0.192	0.288	0.485	0.227
Leather	0.122	0.092	0.782	0.391	0.075	0.528
Lumber	0.620	0.237	0.143	0.537	0.292	0.171
Paper	0.008	0.550	0.441	0.320	0.511	0.165
Printing	0.511	0.128	0.359	0.388	0.212	0.400
Petroleum	0.162	0.409	0.428	0.082	0.602	0.316
Chemicals	0.776	0.164	0.059	0.593	0.313	0.094
Medicine	0.463	0.343	0.194	0.418	0.432	0.149
Rubber and Plastic	0.698	0.197	0.104	0.573	0.289	0.138
Stone, Clay and Glass	0.652	0.190	0.158	0.670	0.198	0.133
Primary Metal	0.689	0.247	0.062	0.457	0.407	0.138
Fabricated Metal	0.803	0.158	0.039	0.727	0.216	0.058
Electronic Component	0.833	0.129	0.037	0.637	0.281	0.084
Optical Instrument	0.597	0.083	0.312	0.660	0.058	0.274
Electronic Machinery	0.634	0.208	0.159	0.629	0.179	0.193
Other Machinery	0.872	0.048	0.078	0.713	0.119	0.172
Auto	0.839	0.131	0.029	0.636	0.310	0.052
Other Transportation	0.441	0.239	0.320	0.380	0.408	0.211
Furniture	0.422	0.386	0.192	0.563	0.309	0.127
Average	0.516	0.263	0.220	0.479	0.307	0.213

Notes: This table reports the variance decomposition for gross and excess job reallocation in 22 manufacturing industries. C, I, and Idio are short for common factor, industry-specific factor, and idiosyncratic components, respectively. The variance share attributable to the relevant factor is reported in each cell. Each number indicates the median of posterior share.

external financing, as the literature documents (Hyun and Minetti, 2014; Hyun, 2016). As we observe in section 2.2, given the changes in the pattern of industrial job flows, we can state that the influence of the common factor increases after the 1997 financial crisis. Table 4 confirms this hypothesis. Namely, the common factor accounts for, on average, 45.4% and 48.9% of the fluctuation in SUM and EXC, respectively.

5. FIRM SIZE AND DRIVING FORCES

This section further investigates whether the driving forces behind job reallocation differ depending on firm size. It is well known that firm size is a key determinant in firms' employment and financing decisions, which causes small firms and large firms respond to economic shocks differently (Covas and Den Haan, 2011; Gertler and Gilchrist, 1994; Mehrotra and Sergeyev, 2014). In particular, prior studies on job reallocation document that job reallocation patterns differ between large and small firms (e.g., Davis *et al*., 1996; Haltiwanger *et al*, 2006). Also, several studies on Korean businesses show that firm size has economic relevance to account for corporate behaviors, such as financing and employment (e.g., Hahm and Kang, 2007; Hyun, 2016; Hyun and Minetti, 2014).

Therefore, it is interesting and important to examine whether the dynamic pattern and the relative importance of the common and industry-specific factors differ by firm size. To do so, we sort firms into quartiles based on total assets and calculate industrial job reallocation rates for each quartile. We use the first and the fourth quartile as the group of small firms and large firms, respectively, for the comparisons. To save space, we focus on the results of variance decomposition for each group of firms.[4)]

[4)] The results of common and industry-specific factors are available from the authors. Briefly mentioning, the common factor for large firms is very flat and its magnitude is modest in most periods, while the common factor for small firms is more intense and shows dynamic patterns.

5.1. Variance Decomposition

As table 5 shows, the common factor plays the least important role in the job reallocation variations of large firms, while industry-specific factors are the major driving forces behind the job reallocation rates of large firms (40.2% of SUM and 50.5% of EXC). This result implies that large firms'

Table 5 Variance Decomposition (Large Firms, 1999-2015)

	Gross Reallocation			Excess Reallocation		
	C	I	Idio	C	I	Idio
Food	0.401	0.320	0.274	0.007	0.510	0.479
Beverage	0.037	0.468	0.490	0.002	0.436	0.559
Textiles	0.053	0.480	0.462	0.002	0.415	0.581
Apparel	0.546	0.171	0.277	0.069	0.648	0.278
Leather	0.372	0.419	0.208	0.162	0.624	0.214
Lumber	0.143	0.521	0.332	0.101	0.573	0.320
Paper	0.702	0.074	0.216	0.106	0.331	0.563
Printing	0.028	0.854	0.114	0.005	0.905	0.086
Petroleum	0.125	0.448	0.426	0.370	0.197	0.428
Chemicals	0.548	0.199	0.246	0.188	0.295	0.519
Medicine	0.415	0.242	0.336	0.051	0.266	0.677
Rubber and Plastic	0.049	0.756	0.192	0.008	0.788	0.201
Stone, Clay and Glass	0.704	0.169	0.120	0.179	0.486	0.325
Primary Metal	0.199	0.413	0.382	0.130	0.491	0.375
Fabricated Metal	0.289	0.538	0.166	0.002	0.737	0.258
Electronic Component	0.233	0.164	0.595	0.002	0.119	0.877
Optical Instrument	0.002	0.811	0.185	0.097	0.543	0.356
Electronic Machinery	0.137	0.587	0.269	0.034	0.578	0.382
Other Machinery	0.003	0.569	0.425	0.068	0.784	0.140
Auto	0.126	0.250	0.620	0.007	0.506	0.483
Other Transportation	0.039	0.235	0.723	0.012	0.390	0.595
Furniture	0.558	0.154	0.281	0.009	0.494	0.492
Average	0.260	0.402	0.334	0.073	0.505	0.418

Notes: This table reports the variance decomposition for gross and excess job reallocation by large firms in 22 manufacturing industries. C, I, and Idio are short for common factor, industry-specific factor, and idiosyncratic components, respectively. The variance share attributable to the relevant factor is reported in each cell. Each number indicates the median.

Table 6 Variance Decomposition (Small Firms, 1999-2015)

	Gross Reallocation			Excess Reallocation		
	C	I	Idio	C	I	Idio
Food	0.245	0.529	0.226	0.416	0.301	0.282
Beverage	0.101	0.624	0.274	0.128	0.519	0.353
Textiles	0.517	0.230	0.253	0.338	0.246	0.417
Apparel	0.341	0.466	0.192	0.288	0.485	0.227
Leather	0.122	0.092	0.782	0.391	0.075	0.528
Lumber	0.620	0.237	0.143	0.537	0.292	0.171
Paper	0.008	0.550	0.441	0.320	0.511	0.165
Printing	0.511	0.128	0.359	0.388	0.212	0.400
Petroleum	0.162	0.409	0.428	0.082	0.602	0.316
Chemicals	0.776	0.164	0.059	0.593	0.313	0.094
Medicine	0.463	0.343	0.194	0.418	0.432	0.149
Rubber and Plastic	0.698	0.197	0.104	0.573	0.289	0.138
Stone, Clay and Glass	0.652	0.190	0.158	0.670	0.198	0.133
Primary Metal	0.689	0.247	0.062	0.457	0.407	0.138
Fabricated Metal	0.803	0.158	0.039	0.727	0.216	0.058
Electronic Component	0.833	0.129	0.037	0.637	0.281	0.084
Optical Instrument	0.597	0.083	0.312	0.660	0.058	0.274
Electronic Machinery	0.634	0.208	0.159	0.629	0.179	0.193
Other Machinery	0.872	0.048	0.078	0.713	0.119	0.172
Auto	0.839	0.131	0.029	0.636	0.310	0.052
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Furniture	0.422	0.386	0.192	0.563	0.309	0.127
Average	0.516	0.263	0.220	0.479	0.307	0.213

Notes: This table reports the variance decomposition for gross and excess job reallocation by small firms in 22 manufacturing industries. C, I, and Idio are short for common factor, industry-specific factor, and idiosyncratic components, respectively. The variance share attributable to the relevant factor is reported in each cell of post.

employment is largely attributable to industrial labor market conditions, consistent with earlier work that finds that large firms' external financing behaviors and employment adjustments are more responsive to sectoral shocks than to aggregate shocks (Gertler and Gilchrist, 1994; Kashyap *et al.*, 1994).

For small firms, the common factor accounts for the largest part of job reallocation fluctuations (51.6% of SUM and 47.9% of EXC). Industry-specific factors play a less important role for small firms, on average explaining 26.3% (SUM) and 30.7% (EXC) of the variability in their job reallocation rates. This result provides a useful insight: small firms' employment dynamics are largely attributable to national labor market conditions. Overall, the results of the variance decomposition by large and small firms suggest that the type of economic shock to which firms' employment adjustments are most sensitive depends on firm size, although it differs across industries.

6. CONCLUSION

This study examines the driving forces behind the dynamic evolution of job reallocation in emerging markets, which is an under-explored topic, using job flows in the Korean manufacturing sector from 1986 to 2015. After calculating job reallocation rates for each of 22 manufacturing industries, we use a Bayesian dynamic factor model to decompose each industrial job reallocation rate into common, industry-specific, and idiosyncratic allocation components.

We find evidence that the common factor's impact on job reallocation rises following the 1997 financial crisis and that the factor also behaves cyclically. The common factor is the main driver of reallocation dynamics. After the 1997 financial crisis, the common factor accounts for a larger fraction of job reallocation fluctuations than, which explains the decrease in industry-level heterogeneity in job reallocation after the crisis. The common factor and the industry-specific factors are the major contributors to job flow variation for small and large firms, respectively. Namely, large firms' employment size is most sensitive to shocks unique to their industries.

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