CHANGES IN MULTI-SEGMENTATION OF THE KOREAN LABOUR MARKET AND HETEROGENEOUS GAPS: THE LABYRINTH OF IN-WORK POVERTY (1116)

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Abstract. The purpose of this study is to identify the multi-segmented structure of the labour market based on regional dualism and to empirically examine the heterogeneous forms of gaps between classes and the existence of mobility constraints. Using data from the Korean Labor and Income Panel Study (KLIPS) 2018-2020, we conducted Latent Class Analysis (LCA) to identify the labour market structure between Capital Region (CR) and non-CR, and Latent Transition Analysis (LTA) to examine mobility between segments. We identified three-segments in CR and four in non-CR. Income gaps across segments were heterogeneous and an exclusive position of the top segments. Furthermore, there were significant underlying constraints on mobility across segments, with entry into the top-tier being very limited. These results suggest that the multi-segmentation and heterogeneous gaps can be observed in post-industrial societies, and deeper division may occur in labour market for non-CR with limited opportunities such as personal contact.

Keywords: Working Poor, Labour Market Segmentation, Multi-Segmentation, Mixture Model, Regional Disparities

1. Introduction

Labour market segmentation is a long-standing debate that has been going on for decades. Originating as a critique of Human Capital Theory that assume a single competitive labour market (Becker, 1964), the institutionalist debate has hypothesised segmented labour markets to explain socioeconomic phenomena more adequately (Doeringer and Piore, 1971; Gordon, 1972; Lindbeck and Snower, 1986, 1989). Continuing empirical evidence supports the assumption of divided labour markets (e.g., Rueda, 2005; Yoon and Chung, 2016). However, due to the nature of segmented labour markets, which cannot be directly observed, the number and properties of segments are predetermined.

Empirical studies focus on how to measure segmentation. Scholars have different criteria for this, with the classic ones being factors such as employment contracts, firm

size and wages (e.g., Doeringer and Piore, 1971; Osterman, 1975; Gordon et al., 1982; Schwander and Häusermann, 2013). However, there are growing consensus that a single indicator is inadequate to measure labour market segmentation and that multivariate data should be considered (Hudson, 2007; Chung, 2019). The assumption of a simple dualisation in a complex post-industrial societies also raises many issues. Recent studies have drawn attention to these limitations, building on decades of rich discussion and technological advances (e.g., Yoon and Chung, 2016; Lukac et al., 2019; Seo, 2021). While they address these issues, two challenges (inter-class mobility and regional disparities) need to be highlighted for further discussion.

Making this discussion even more important is the issue of in-work poverty. While there is no clear consensus on its causes, one of the structural factors is labour market segmentation (Peña-Casas and Latta, 2004). The challenge is that economic shocks are becoming more frequent as societies diversify and exposure to risk increases (Hassink, 2010; Fingleton, 2012; Martin, 2012). These shocks can be more damaging to the poor and create a vicious cycle of more poverty. It's therefore necessary to consider the link between in-work poverty and the segmented labour market.

This study aims to observe the patterns of labour market segmentation in Korea. Using the Korean Labor and Income Panel Study (KLIPS) from 2018 to 2020, we conduct a cross-sectional analysis using Latent Class Analysis (LCA). We assume a division based on various dimensions of precariousness, but do not predefine the number of segments to capture the possibility of multi-segmentation. Given the Korean context, i.e., regional dualism (Park, 1993; Lim, 2008; Kim, 2010; Ma et al., 2017), we present the results separately for Capital Region (CR) and non-CR. Finally, we conduct Latent Transition Analysis (LTA) based on the constructed panel data to identify the mobility between classes over time.

Therefore, the main concern of this study can be summarized as the possibility of multi-segments and the gaps between them and the regional disparities. First, in the second section, beginning with the theoretical background, a research gap will be identified through the literature review, and the hypotheses will be presented. The third section provides a brief description of the data, variables, and the research models. The fourth section will report the findings of the cross-sectional and panel analyses, which will be discussed in the fifth section. Finally, some implications will be drawn, along with limitations and directions for future research.

2. Theoretical Background and Literature Review

2.1. Segmented Labour Market Theories

Institutionalist economists refuse the assumption of a homogeneous labour market and view it as a result of the interaction between the institutions (e.g., individuals, firms). Labour market is segmented, with each governed by heterogeneous rules (Kerr, 1977). This institutionalization leads to structural problems such as low wages and poverty for certain groups. In Dual Labor Market Theory, the labour market is divided into primary market which is summarized as high-quality labour conditions, and secondary market which represents the unstable employment, low pay (Doeringer and Piore, 1971; Reich et al., 1973). The Insider-Outsider Theory provides the foundation for this dualisation theory (Lindbeck and Snower, 1986, 1989). Whereas Labor Market Segmentation Theory is based on the Radical Theory of Neo-Marxism, and the labour market is viewed as being segmented by a domination strategy for capital to control labour (Gordon, 1972). In short, the labour market is a place where class social relations are formed.

From an institutional perspective, labour market is inherently hierarchical with limited mobility, creating systemic forces such as involuntary low-wages, unemployment, and poverty (Doeringer and Piore, 1971; Reich et al., 1973; McDonald and Solow, 1985). In practice, it's unrealistic for employers to measure marginal productivity of workers directly, so it's measured indirectly based on job attributes (Thurow, 1975), and wages are determined based on this (Bulow and Summers, 1985). In addition, wages tend to be determined through collective bargaining between labour and management, and the wage gap between workers is the result of social values being reflected in wages through collective bargaining.

New Economic Sociology, which emphasising human behaviour, including economic behaviour, inherits this view by considering labour matching or assignment. The focus is on the existence of the realm of chance, and information derived from appropriate human contacts in job search is a factor in shaping better wages and labour conditions (Jencks et al., 1972). The role of social networks in the mechanism by which labour is allocated to each job goes beyond the supply-demand side and emphasises the the combination of two factors, i.e., the nature of matching (Granovetter and Tilly, 1988). The possibility of mismatching is another important factor in explaining the labour market.

2.2. How to Measure Labour Market Segmentation

2.2.1. Measuring Labour Market Segmentation

The insider-outsider dichotomy is dominant in measuring labour market segmentation, however, the criteria for distinguishing them varies slightly depending on the underlying theory. There is no clear consensus on the factors that best identify the presence of segmentation (Hudson, 2007), and challenges exist in identifying it and even when segmentation is measured, whether it is measured accurately (Boston, 1990). In addition to classical ones, concepts that have recently gained traction in segmentation

measurement include subjective insecurity, mobility constraints, and future insecurity (e.g., Davidsson and Naczyk, 2009; Kalleberg, 2014; Max and Picot, 2020). Nor should we overlook the role of unions, which have recently been reported to play a role in consolidating the exclusive position of insiders and widening the gap (Lee and Frankel, 2004; Rueda, 2005). The development of these concepts is an attempt to capture different aspects of an individual's socioeconomic status in a diversified labour market.

The assumption of upward entry constraints is a key feature of segmented labour market. In a dualised labour market, once a worker enters the external labour market, they are likely to trapped (Doeringer and Piore, 1971; Gordon, 1972). Furthermore, recent studies highlight the widening gap between the segments in many developed countries (Häusermann and Schwander, 2012). These point to the drawbacks of conducting only cross-sectional analysis in segmentation study. Employment contract status is variable (Schwander and Häusermann, 2013), and single-point studies fail to observe in and out (Biegert, 2014). While existing research captures changes in division over time (Yoon and Chung, 2016), iterations of cross-sectional analyses are limited in capturing mobility across classes.

Recent findings on segmented labour market suggest the possibility of multi-division. This is not an inherent problem with the dichotomous assumption itself, but restricting the segments to only two may not capture a wider range of possibilities. At first, the insider-outsider perspective can be further divided (Reich et al., 1973; Osterman, 1975; Edwards, 1979). Seo (2021) adheres to the insider-outsider view, but subdivides it into one insider group and three outsider groups. López-Roldán and Fachelli (2021) also propose subdivisions within a dualistic structure (i.e., upper and lower). Evidence for a triple-segmentation continues to emerge. Jessoula et al. (2010) argue for the existence of ‘mid-siders,’ a new tier between insiders and outsiders. Yoon and Chung (2016) propose ‘future insecure’ as the third segment, and Lukac et al. (2019) identify three groups (i.e., managerial, standard, and disadvantage), which comprised by seven subgroups.

It’s also essential to understand regional differences in labour market segmentation. At the macro level, patterns of segmentation across countries have been shown to be heterogeneous (e.g., Schwander and Häusermann, 2013; Lukac et al., 2019; López-Roldán and Fachelli, 2021; Seo, 2021). These cumulative findings suggest that division can be influenced by differences in socioeconomic and institutional contexts, from which we can infer heterogeneous patterns of division in regional labour markets.

2.2.2. Dimension of Precariousness

Concepts such as precarious work refer to a type of work which is low-wage, insecure, and often synonymous with poor quality employment (Kalleberg,2014; Olsthoorn, 2014). However, these are clearly broad concepts, and choosing indicators to measure segmentation is not an easy task. We can use a number of dimensions that have been discussed in empirical segmentation research over the past few decades; standard employment contracts, continuity of employment, income, and social protection have been discussed (Rogers and Rodgers, 1989). Based on cumulative discussions and recent interest, we have identified five dimensions of precariousness.

Employment Insecurity. Outsiders in the labour market can be seen as excluded from employment security (Davidsson and Naczyk, 2009). This dimension is the concept of contingent employment, which can be viewed as consisting of two sub-indicators: casual work and part-time/full-time. Several studies have measured division based on contractual arrangements (e.g., Rueda, 2005; Yoon and Chung, 2016; Lukac et al., 2019; Seo, 2021). The European Foundation and the International Labour Organization have also identified this as a major driver of segmentation (ILO, 2016; Eurofound, 2019). Furthermore, the precariousness of contractual terms may capture an important aspect of post-industrial societies where employment doesn't ensure security (Seo, 2021).

Objective Insecurity. Income level and occupational skills are two key indicators that have been used to measure labour market segmentation along with employment status. Olsthoorn (2014) and Yoon and Chung (2016) used the income insecurity as a key indicator of precariousness. This not only refers to one's current position in the labour market in terms of compensation and social benefits (Hudson, 2007; Olsthoorn, 2014; Kalleberg, 2014), but also extends to the dimension of future insecurity in that current wages determine social security coverage such as pensions (Kalleberg, 2014; Seo, 2021). Occupational skills are another useful indicator that has been used to capture segmentation (e.g., Boston, 1990; Yoon and Chung, 2016). Moreover, it’s worth considering that recent skill-biased technological change has accelerated economic inequality (Acemoglu 2002).

Subjective Insecurity. This recognises another dimension that may be ignored by objective indicators (Chung, 2019). Individual subjective experiences may capture precariousness better than indicators such as employment contracts (Green et al., 2001), and more attention needs to be paid to the psychological dimensions of labour conditions, even if they are closely related to employment contracts (Chung, 2019). Furthermore, in the event of an economic shock, the employment contract itself may not provide stability (Klandermans et al., 2010), and depending on the institutional context, contractual distinctions may become irrelevant (Håkansson and Isidorsson, 2012). Thus, subjective insecurity may help distinguish true outsiders (Marx and Picot, 2020).

Future Insecurity. This concept can be summarized as opportunities for job advancement. Fewer possibilities for advancement may limit ongoing job security, movement to better jobs, or promotion (Kalleberg, 2014), and thus can be used as a predictor of whether a given individual is a temporary outsider or will remain in the external labour market for an indefinite time (Seo, 2021). In turn, it's worth noting that it's an indicator that can be used to determine a particular individual's potential for upward mobility, which can overcome the limitations of cross-sectional studies (Seo, 2021).

Union Protection. Workers can expect to be empowered by participating in the improvement of their working conditions through unions, such as wage bargaining (Anker et al., 2003; Ghai, 2003). However, contrary to their initial purpose of preventing labour rights abuses, unions have recently been reported to exercise monopoly power in wage bargaining at the firm level (Lee, 2011). By consolidating the status of union members, it widens the gap between labour market segments (Lee and Frankel, 2004; Rueda, 2005).

In segmented labour market, precarious workers can be classified as outsiders (Standing, 2011), victims have been identified as women, youth, low-educated, and Small and Medium-sized Enterprises (SMEs) workers (e.g., Hudson, 2007; Schwander and Hauserman, 2013; Ha and Lee, 2013; Yoon and Jung, 2016).

2.3. Context in Korea

The Korean labour market has undergone two major structural transitions: the Great Labour Movement and the Asian financial crisis. Earlier studies of Korean labour markets paid much attention to union revitalisation and the impact of the Great Labour Movement in 1987 (Song, 1999). This accelerated and expanded the dual system of internal and external labour markets. In addition, the 1997 Asian financial crisis marked the end of rapid and equitable economic growth in Korea since the start of industrialisation in the 1960s (OECD, 2011; Ha and Lee, 2013; Kwon, 2015). Although Korea recovered quickly from the shock, the post-crisis economic growth trend was not the previous one (Kwon, 2015). The flexibilisation of the labour market in the process of neoliberal globalisation required by the World Bank and International Monetary Fund as part of the rescue package led to fundamental structural changes in employment (Ha and Lee, 2013). Income inequality has increased significantly, with a sharp rise in the number of low-wage or/and contingent workers.

About 25 years after two major structural shifts, the interplay of low-skill substitution due to skill-biased technological change and advances in automation, the declining middle class, post-crisis labour market concerns (i.e., widening income gap, growth without employment), and economic shocks that are becoming more frequent in a complex post-industrial society are exacerbating the problem of labour market

segmentation. In light of this, it may be premature to conclude that the Korean labour market is dichotomous structure, as Ha and Lee (2013) and Schauer (2018) do, rather than divided (Chung and Jung, 2016; Kwon, 2015). Moreover, in Korea, there's a regional dualism (i.e., CR and non-CR) (Kim, 2010). CR, consists of Seoul capital city, Incheon metropolitan city, and Gyeonggi province, closely linked socioeconomically based on geographical proximity, covers about 10% of the entire nation's territory, is home to more than half of the population (Ma et al., 2017). Aside from political, and cultural concentrations, the persistent trend of human capital concentration has been noted for decades (Park, 1993; Lim, 2008).

Based on these findings, we suggest as follows:

H. 1a. Multi-segmentation will be captured in the Korean labour market.

H. 1b. Regional differences in the labour market will be identified, with more segments observed for non-CR due to limited opportunities.

H. 1c. The characteristics of outsiders, i.e., female, young, low-educated, SMEs, will not be significantly different from those previously reported.

We will also examine mobility and gaps between classes; given the assumption of multi-segmentation, gaps and mobility between classes may not be homogeneous. Given the increasingly entrenched position of the top tier, we hypothesise as follows:

H. 2a. The income gap between classes is widening. Specifically, the gap between the top and the rest of the class is widening.

H. 2b. There will be constraints on upward mobility. Specifically, there will be significant difficulties in entering the top-tier, while more fluid movement will be observed between the lower-tiers.

3. Data and Methods

3.1. Data and Variables

3.1.1. Data

This study uses data from the 21st to 23rd waves (2018-2020) of the KLIPS. It's an annual survey that provides detailed information about workers and is a nationally representative sample built through two-stage cluster systematic sampling using the Population and Housing Census (by Statistics Korea) as the sampling framework. Given the research objectives, the analysis was limited to wage earners aged 18 to 65. We aggregate data by region to identify differences between CR and non-CR.

3.1.2. Indicators

Seven observables that comprise the five concepts of precariousness are used to capture labour market segmentation. Employment Insecurity consists of two variables: employment contract type and part-time work. Each is coded as permanent (1) or non-permanent (0), and full-time (1) or part-time (0). Objective Insecurity is also measured by two variables (i.e., income and skill). Income level were categorized as high-income (2), middle-income (1), or low-income (0), with each cut-off at 3/2 and 2/3 of the median hourly wage for wage earners. Occupational skills were categorized as high-skilled (2), middle-skilled (1), or low-skilled (0) according to the Korean Standard Classification of Occupations compiled by Statistics Korea. Subjective Insecurity was measured through yes (1) or no (0) responses to the question, 'Unless you have done something particularly wrong, could you keep your current job for as long as you want' (Anderson and Pontusson, 2007). Future Insecurity is measured by a yes (1) or no (0) response to whether the company provides education or job training to improve job performance (Kalleberg, 2014). Union Protection is measured by responding yes (1) or no (0) to whether you are a member of a union.

3.1.3. Independent Variables

A conditional model of the independent variable is considered to determine its effect on the latent class distinction to identify the characteristics of the outsider. Age was categorised into young (0), middle-aged (1), and old (2), based on the ages of 35 and 50. Gender was dummy coded as male (0) and female (1). Education refers to final educational attainment and consists of elementary school, middle school, high school, junior college, university, and graduate school graduation. They were coded from (0) to (5) in sequence. To focus on the impact of industry on classification across lower tiers, we used whether they were employed in manufacturing; yes (1) or no (0). Finally, we classified firms as large (1), or SMEs (0) based on their size. In Korea, companies with less than 300 employees are generally classified as SMEs (Ha and Lee, 2013). Tab. 1 presents descriptive statistics of observables; see Appendix 1A for CR and Appendix 1B for non-CR.

Table 1. Descriptive Statistics, Korea

	Concepts	Variables		2018 (N=6,756)	2019 (N=6,647)	2020 (N=6,411)
Indicator	Employment Insecurity	employment contract	non-regular	2,063 4,693	2,009 4,638	1,854 4,557
		part-time	part-	589	604	561

		work	full-	6,167	6,043	5,850
	Objective	income	low	1,089	1,055	957
	Insecurity		middle	4,150	4,274	4,081
			high	1,517	1,318	1,373
		skill	low	1,880	1,839	1,710
			middle	3,105	3,078	2,976
			high	1,771	1,730	1,725
	Subjective		non-secure	1,039	962	855
	Insecurity		secure	5,717	5,685	5,556
	Future		non-secure	6,418	6,299	6,157
	Insecurity		secure	338	348	254
	Union		non-protection	5,770	5,652	5,391
	Protection		protection	986	995	1,020
Covariates	Age		young	1,600	1,523	1,394
			medium	3,089	3,038	2,957
			old	2,067	2,086	2,060
	Gender		male	3,960	3,864	3,729
			female	2,796	2,783	2,682
	Education		elementary school	204	177	139
			middle school	424	390	334
			high school	2,591	2,517	2,461
			junior college	1,311	1,304	1,282
			university	1,961	1,985	1,921
			graduate school	265	274	274
	Industry		non-manufacture	5,017	4,980	4,797
			manufacture	1,739	1,667	1,614
	Firm		SMEs	6,088	5,981	5,782
	Size		large	668	666	629

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3.2. Methods: Mixture Model

A mixture model is a statistical model that uses categorical latent variables to identify subgroups within a population of unknown composition. LCA is a type of mixture model used for person-centred classification (Collins and Lanza, 2009; Hickendorff et al., 2018), which groups individuals with similar characteristics into the same class. LTA is a longitudinal extension of LCA that can examine transitions between classes over time. The research model is shown in Fig. 1. Mplus version 8.8 was used for the mixture model, with supplementary use of STATA version 16.0 and SPSS version 23.0.

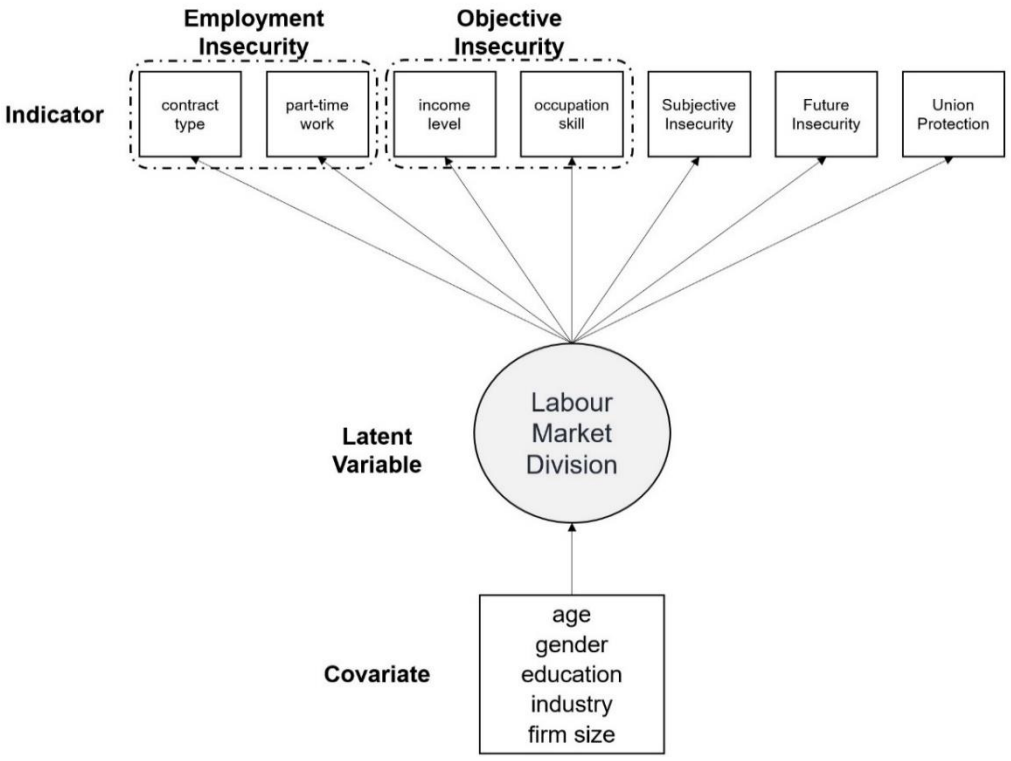
3.2.1. Latent Class Analysis

LCA is a statistical procedure used to categorise individuals into unobserved latent classes based on differences in responses to observables (Collins and Lanza, 2009). It has the advantage that the number of clusters doesn't need to be predetermined and provides goodness-of-fit statistics for rational decisions. Furthermore, LCA provides posterior probabilities that quantify the uncertainty of class membership, and can handle differently scaled indicators, which provides a significant advantage for handling multivariate data (Schreiber, 2017). For LCA reviews, see Collins and Lanza (2009), Muthén and Muthén (2017, CH.7), Schreiber (2017), Hickendorff et al. (2018), Weller et al. (2020), and Sinha et al. (2021).

To estimate the optimal model, a maximum likelihood with robust standard errors (MLR) estimator was used, and several initial value sets are iteratively introduced to avoid local maxima, as pointed out by Muthén and Muthén (2017) and Uebersax (2000). The analysis is performed by increasing the number of latent classes by one, and the final model is selected based on statistical criteria such as information criterion, chi-square test, and entropy. Covariates that may affect classification are controlled using the 'three-step approach' (Vermut, 2010; Asparouhov and Muthén, 2014), specifically the R3STEP (Auxiliary) syntax, which estimates the relationship between independent variables and latent classes using multinomial logit coefficients.

3.2.2. Latent Transition Analysis

LTA estimates transition probabilities, which represent the likelihood that an individual switches from one latent class at time *t* to each latent class at time *t+1*. Thus, it can be useful when trying to capture inter-tier mobility in the labour market over time. When conducting an LTA including indicators and covariates at all time points, a 'three-step approach' is applied, as variables at earlier time-points can influence the formation of latent classes at later time-points (Asparouhov and Muthén, 2014; Nylund-Gibson et al., 2014). The first step involves performing LCA at each time point to determine the optimal number of latent class. Then, each individual is assigned to a class based on the highest probability, introducing some classification error. The final model combines the LCA from each time-point with fixed classification error. For reviews of LTA, see Asparouhov and Muthén (2014), Nylund-Gibson et al. (2014), Muthén and Muthén (2017, CH.8), and Hickendorff et al. (2018).


Employment Insecurity
Objective Insecurity
Indicator
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Labour Market Division
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industry
firm size

(A) LCA

(B) LTA

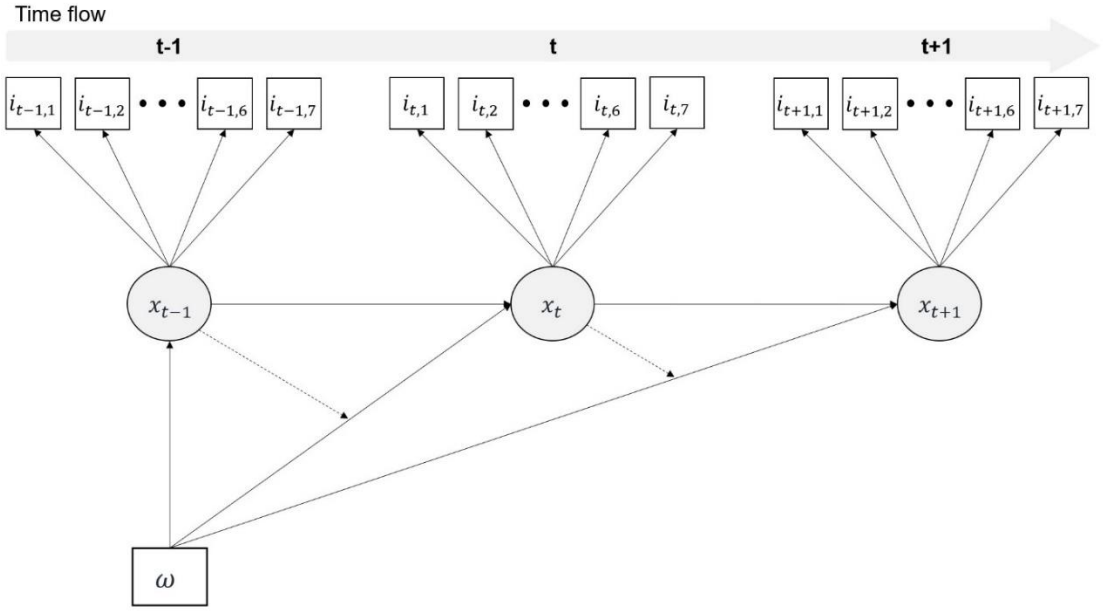
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Figure 1. Research Model

4. Empirical Results

4.1. LCA

LCA was performed by year, increasing the number of latent classes from two to six, and compared statistical criteria to determine the optimal number of latent classes (Tab. 2); Appendix 2A for CR and Appendix 2B for non-CR. The information criterion, which used in here, were Akaike Information Criterion (Akaike, 1974), Bayesian Information Criterion (BIC) and Sample-size Adjusted BIC (SABIC) (Schwarz, 1978; Sclove, 1987). For chi-square tests, we utilized the Lo-Mendell-Rubin adjusted Likelihood Ratio Test (LMR LRT), the Vuong-Lo-Mendell-Rubin Test (VLMRT) (Lo et al., 2001), and the parametric Bootstrapped Likelihood Ratio Test (BLRT) (McLachlan and Peel, 2000). Entropy, which measures the quality of classification, has also been reported.

Table 2. Model Fit Statistics, Korea

Year	Class	LL	AIC	BIC	SABIC	VLMRT	LMR LRT	BLRT	Entropy
2018	2	-23602.7	47241.1	47370.6	47310.3	0.000	0.000	0.000	0.876
	3	-23242.5	46542.9	46740.6	46648.5	0.000	0.000	0.000	0.737
	4	-23064.1	46205.0	46470.9	46347.0	0.000	0.000	0.000	0.764
	5	-22985.4	46067.5	46401.6	46245.9	0.000	0.000	0.000	0.729
	6	-22938.2	45994.8	46397.1	46209.6	0.046	0.047	0.000	0.705
2019	2	-23108.8	46254.8	46384.0	46323.6	0.000	0.000	0.000	0.877
	3	-22736.5	45530.8	45728.1	45635.9	0.000	0.000	0.000	0.718
	4	-22555.2	45187.2	45452.4	45328.5	0.000	0.000	0.000	0.756
	5	-22482.3	45062.3	45395.6	45239.9	0.000	0.000	0.000	0.741
	6	-22448.4	45013.9	45415.2	45227.7	0.000	0.000	0.000	0.759
2020	2	-21968.1	43974.3	44102.8	44042.5	0.000	0.000	0.000	0.883
	3	-21617.1	43292.2	43488.4	43396.2	0.000	0.000	0.000	0.708
	4	-21457.6	42993.2	43257.0	43133.1	0.000	0.000	0.000	0.749
	5	-21390.3	42878.6	43210.2	43054.5	0.000	0.000	0.000	0.768
	6	-21360.6	42839.2	43238.4	43050.9	0.507	0.510	0.000	0.751

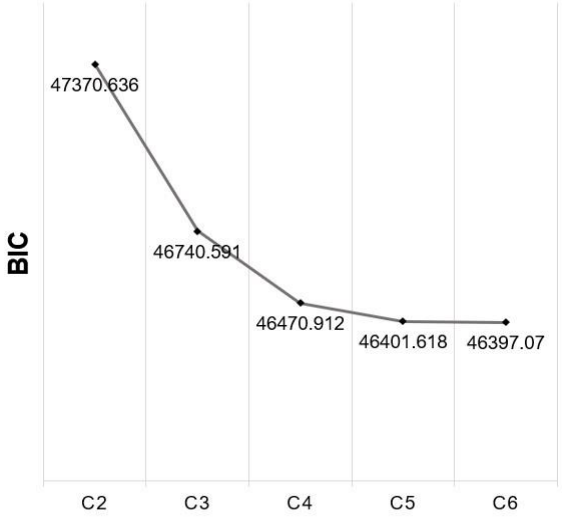
While there is some consensus that BLRT provides the most accurate assessment of model fit, followed by BIC (Vermut, 2002; Nylund et al., 2007), several studies have emphasised the need to consider multiple criteria, including theoretical interpretability (Nylunde et al., 2007; Hickendorff et al., 2018; Weller et al., 2020). Since it was not possible to assess goodness-of-fit with BLRT, we used BIC as our key criterion. The optimal solution is found at the point where an 'elbow plot' forms by plotting the BIC (Sinha et al., 2021). Fig. 2A-2C shows that an 'elbow plot' is forming in four-class solution. Three segments were observed in CR (Appendix 3A-3C) and four in non-CR (Appendix 3D-3F). The entropy value is generally considered ideal if it's above 0.8, but no clear threshold (Muthén, 2008), a value around 0.75 can be considered good. The average posterior probability represents the average probability that individuals assigned to a particular class actually belong to that class. Thus, a value closer to 1 is more desirable, and 0.8 is considered good (Weden and Zabin, 2005). It is shown as diagonal matrix as in Tab. 3; see Appendix 4A for CR and Appendix 4B for non-CR. Finally, considering the interpretability dimension, we conclude that final model with four-segments for nation and non-CR and three-segments for CR (*H. 1a, H. 1b*).

Table 3. Average Latent Class Posterior Probabilities, Korea

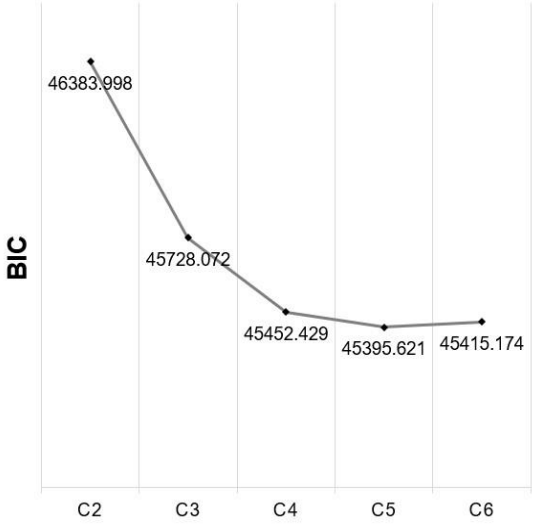
		C1	C2	C3	C4
2018	C1	**0.842**	0.156	0.000	0.003
	C2	0.097	**0.899**	0.002	0.002
	C3	0.000	0.004	**0.879**	0.117

	C4	0.008	0.000	0.146	**0.846**
2019	C1	**0.906**	0.000	0.093	0.001
	C2	0.000	**0.903**	0.000	0.097
	C3	0.140	0.001	**0.858**	0.001
	C4	0.009	0.185	0.000	**0.806**
2020	C1	**0.874**	0.126	0.000	0.000
	C2	0.148	**0.839**	0.000	0.013
	C3	0.002	0.000	**0.869**	0.130
	C4	0.000	0.002	0.124	**0.875**

Note: Bolds are those > 0.8



(A) 2018



(B) 2019

(C) 2020

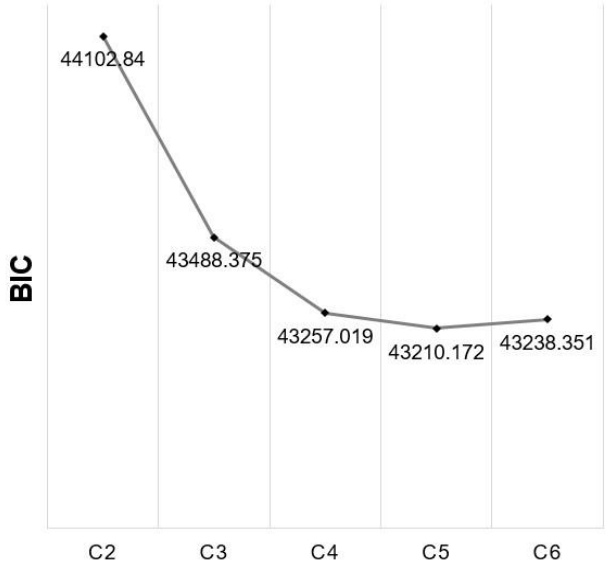


Figure 2. Changes of BIC in Korea

Table 4A. Item Response Probabilities, Korea, 2018

N=6,756	insider (C1)	core-mid (C2)	outsider (C3)	marginal-mid (C4)
Class Size (%)	24.7	44.7	13.1	17.5
Contract Type				
Non-Permanent	0.009	0.000	**0.985**	**0.995**
Permanent	**0.991**	**1.000**	0.015	0.005
Part-time Work				
Part-time	0.000	0.003	0.478	0.133
Full-time	**1.000**	**0.997**	0.522	**0.867**
Income Level				
Low	0.001	0.109	**0.715**	0.107
Middle	0.262	**0.837**	0.285	**0.790**
High	**0.737**	0.054	0.000	0.102
Occupational Skill				
Low	0.045	0.216	**0.861**	0.331
Middle	0.557	0.514	0.085	0.464
High	0.398	0.270	0.055	0.205

Subjective Insecurity				
Non-Secure	0.004	0.023	0.510	0.433
Secure	**0.996**	**0.977**	0.490	0.567
Future Insecurity				
Non-Secure	**0.880**	**0.977**	**0.990**	**0.951**
Secure	0.120	0.023	0.010	0.049
Union Protection				
Non-Protection	0.584	**0.935**	**1.000**	**0.920**
Protection	0.416	0.065	0.000	0.080

Note: Bolds are those > 0.7, which determine the attributes of each tier (Collins and Lanza, 2009).

Based on the set of item (i.e., indicator) response probabilities, each class can be characterised, and in Korea (Tab. 4A), the following hierarchical distinction is possible. First, those aggregated in the leftmost column of Tab. 4A can be identified as regular, full-time, high-income workers, indicating high subjective security. Although the Future Insecurity and Union Protection items do not have a high response rate, they are clearly distinguished from the others and are labelled as insiders based on literature (e.g., Schwander and Häusermann, 2013). Second, workers in the second column of Tab. 4A show a marked difference in income levels from insiders. There are also notable differences in terms of Union Protection and Future Insecurity. Despite low externality, they may struggle in maintaining their status in any economic shock. On this basis, we call them the core-middle class. They are similar to 'future insecure' in Yoon and Chung (2016) and 'dead-end insiders' in Seo (2021). Third, workers grouped in the rightmost column of Tab. 4A are the most distinct from the core-middle in responses to 'non-permanent' and Subjective Insecurity. They are mostly plagued by psychological insecurity stemming from contractual arrangements, and may have a more externalised status even at moderate wages. Thus, we classify them as marginal-middle class. Finally, the rest are the outsiders, who are highly precarious in all indicators. Even a mild shock can get them fired at any time.

Table 4B. Item Response Probabilities, CR and non-CR, 2018

	CR (N=3,542)			non-CR (N=3,214)			
	insider	middle class	outsider	insider	core-mid	marginal-mid	outsider
	C1	C2	C3	C1	C2	C3	C4
Class Size (%)	27.8	46.3	25.9	22.7	45.1	17.5	14.7
Contract Type							
Non-Permanent	0.028	0.065	**0.989**	0.006	0.000	**0.970**	**0.994**
Permanent	**0.972**	**0.932**	0.011	**0.994**	**1.000**	0.030	0.006
Part-time Work							
Part-time	0.002	0.003	0.314	0.000	0.001	0.115	0.481
Full-time	**0.998**	**0.997**	0.686	**1.000**	**0.999**	**0.885**	0.519
Income Level							
Low	0.000	0.107	0.378	0.005	0.110	0.085	**0.752**
Middle	0.214	**0.893**	0.561	0.286	**0.808**	**0.826**	0.246
High	**0.789**	0.000	0.061	**0.709**	0.081	0.090	0.003
Occupational Skill							
Low	0.058	0.215	0.600	0.044	**0.213**	0.310	**0.855**
Middle	0.477	0.498	0.263	0.635	0.547	0.483	0.107
High	0.465	0.288	0.136	0.321	0.239	0.207	0.039
Subjective Insecurity							
Non-Secure	0.008	0.019	0.508	0.000	0.025	0.421	0.553
Secure	**0.992**	**0.981**	0.492	**1.000**	**0.975**	0.579	0.447
Future Insecurity							
Non-Secure	**0.918**	**0.983**	**0.987**	**0.834**	**0.969**	**0.920**	**0.986**
Secure	0.082	0.017	0.013	0.166	0.031	0.080	0.014
Union Protection							
Non-Protection	0.686	**0.920**	**0.962**	0.469	**0.950**	**0.913**	**1.000**
Protection	0.314	0.080	0.038	0.531	0.050	0.087	0.000

Note: Bolds are those > 0.7

Tab. 4B shows the item response probabilities across regions, and for non-CR, four-class solution were derived, which can be classified as above. However, in CR, three-class solution was derived. They were categorised as insider, middle class, and outsider based on Tab. 4B. It should be pointed out that direct comparisons are not meaningful as different numbers of classes have been derived for each region: the middle class in CR is not a simple sum of the core and marginal-middle in non-CR. Same interpretation was possible for each year, see Appendices 5A-5D.

Conditional models with additional covariates can provide more detailed information about the class. Extract and validate the multinominal logit coefficient for the reference class, which is the first-listed group in the cell. We can confirm that the context in Korea is consistent with existing findings that female, the young, and low-educated workers are characterised as outsiders (Tab. 5). It also suggests that the outsiders are not so much represented by blue-collar workers who once made up the middle class. Finally, the response to firm size highlights the difference between insiders and others (*H. 1c*). Similar results were observed by region and year (Appendix 6A-6H).

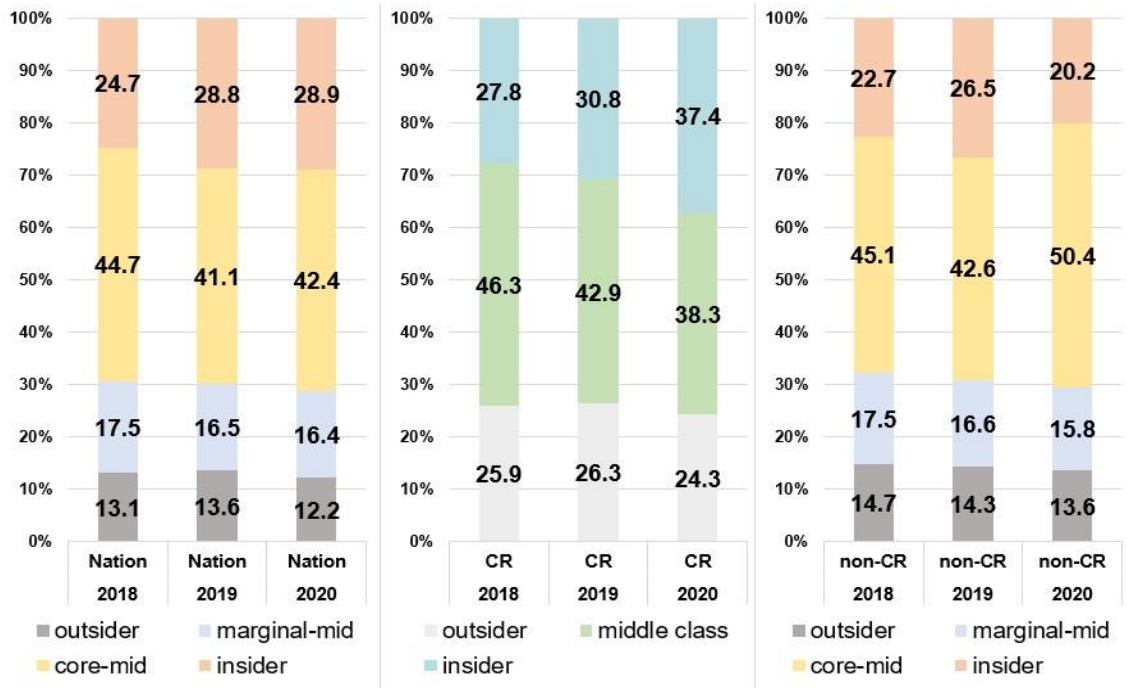
We aim to gain some insights by listing the cross-sectional analyses before the panelised analysis, recognising the need for cautious interpretation due to the short timeline. Changes in the proportions of each class are more pronounced in CR, and we can infer that there is more fluid movement between classes than in non-CR (Fig. 3A-3C). However, this has limitations in clearly capturing the individual interclass movements over time. The average income line for each decile can be used to identify the wage gap (Fig. 4A-4C). Wages in the top tier are overwhelmingly high, which is a clear reflection of the capital concentration. Furthermore, the trend of the income gap is more variable in CR than in non-CR, suggesting that the gap has not widened significantly, but at least it is not shrinking (*H. 2a*).

Table 5. Relationship with Covariate, Korea, 2018

		Age	Gender	Education	Industry	Firm Size
outsider vs. insider	Est. C.	0.626***	-3.796***	1.939***	2.802***	5.100***
	S.E.	0.122	0.217	0.093	0.270	0.721
outsider vs. core-mid	Est. C.	-0.179	-1.542***	1.018***	2.549***	0.974
	S.E.	0.094	0.145	0.075	0.243	0.709
outsider vs. marginal-mid	Est. C.	0.315**	-1.963***	0.809***	1.574***	2.180**
	S.E.	0.121	0.166	0.089	0.275	0.743
marginal-mid vs. core-mid	Est. C.	0.311***	-1.834***	1.130***	1.228***	2.920***
	S.E.	0.085	0.176	0.061	0.127	0.222
marginal-mid vs. insider	Est. C.	-0.494***	0.421***	0.209***	0.975***	-1.205***
	S.E.	0.063	0.084	0.044	0.103	0.292
core-mid vs. insider	Est. C.	0.805***	-2.254***	0.920***	0.253*	4.126***

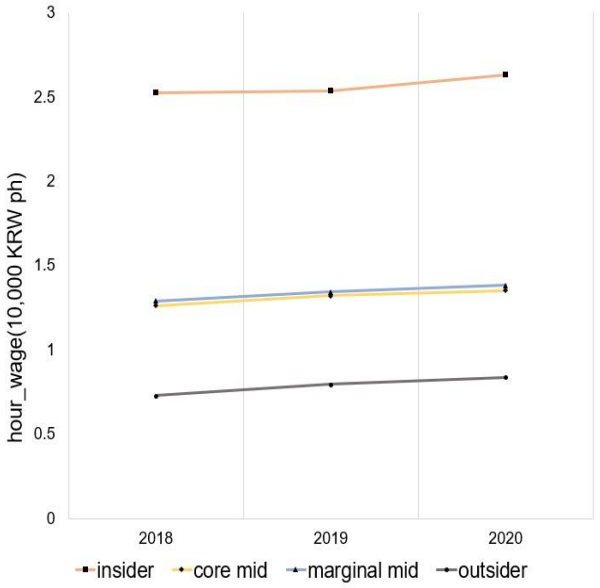
S.E.	0.080	0.177	0.058	0.122	0.295

* $p < .05$, ** $p < .01$, *** $p < .001$



(A) Nation (B) CR (C) non-CR

Figure 3. Changes in estimated labour market share



(A) Korea

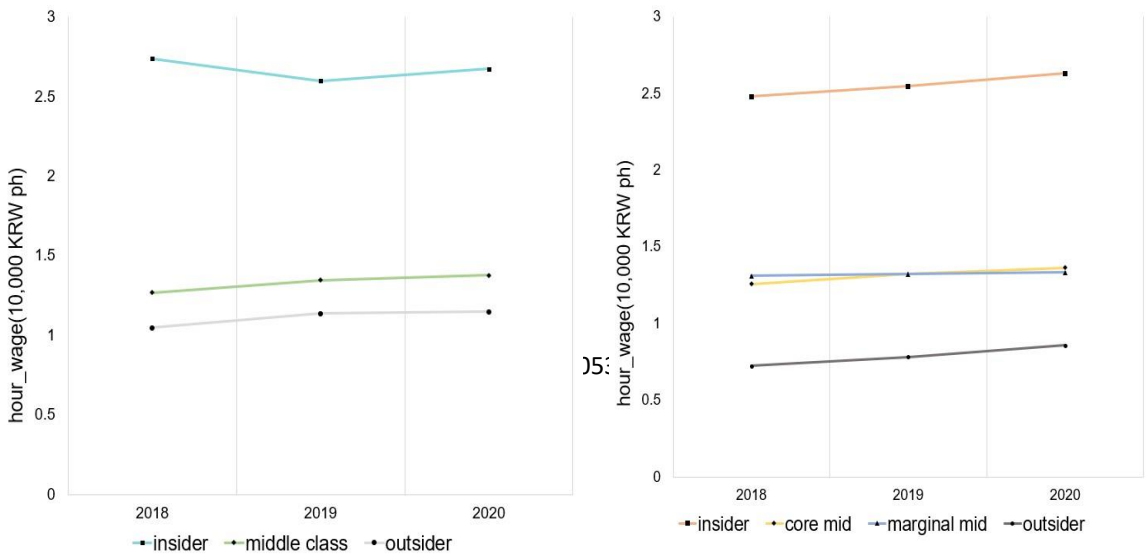
(B) CR (C) non-CR

Figure 4. Changes in average hourly wage by class, 2018-2020

4.2. LTA

To investigate mobility between classes, we conducted LTA with panel data. We studied the transition probabilities up to 2020 for wage earners aged 18-65 in 2018. As each region was analysed separately, difficulties existed in accounting for inter-regional migration; therefore, they were excluded from the analysis along with panel dropouts. First, we performed an LCA for each year to derive the best-fit model and then checked the mobility of each class. Four-class were derived for the nation and non-CR, and three for CR.

Table 7A-7C. show the transition matrices by region, where the value in each cell is the



probability of moving from one class to another over time from 't' to 't+1'. That is, the diagonal matrix in bold is the probability of no movement across classes. However, it's difficult to determine the direction of movement, as the majority of workers remain in their positions and only small amounts of movement are captured. Thus, we can only see rough trends in the coloured areas. Red cells represent less movement, green represents movement between lower-classes, and yellow represents movement in the upper-classes (Table. 7A-7C). This means that it can be characterised by two large clumps: the movement in the yellow area and the movement in the green area. The effect of the independent variables on cross-tier movement can also be validated, but due to the extremely limited cross-tier movement, no significant results were obtained.

Table 7A. Transition Matrix by time-point, Korea (N=4,235)

2018 → 2019	2019 insider	2019 core-mid	2019 marginal-mid	2019 outsider
2018 insider	**0.975 (1,105)**	0.021 (24)	0.000 (0)	0.004 (5)
2018 core-mid	0.006 (9)	**0.977 (1,533)**	0.004 (6)	0.013 (20)
2018 marginal-mid	0.009 (4)	0.027 (13)	**0.948 (446)**	0.016 (8)
2018 outsider	0.001 (1)	0.046 (49)	0.013 (14)	**0.94 (999)**

2019 → 2020	2020 insider	2020 core-mid	2020 marginal-mid	2020 outsider
2019 insider	**0.997 (1,101)**	0.003 (3)	0.000 (0)	0.000 (0)
2019 core-mid	0.009 (15)	**0.973 (1573)**	0.005 (8)	0.013 (21)
2019 marginal-mid	0.008 (4)	0.017 (8)	**0.958 (452)**	0.017 (8)
2019 outsider	0.004 (4)	0.015 (16)	0.009 (9)	**0.972 (1,013)**

Note: The value in brackets is the number of people corresponding to the probability

Table 7B. Transition Matrix by time-point, CR (N=2,186)

Table 7C. Transition Matrix by time-point, non-CR (N=2,049)

2018 → 2019	2019 insider	2019 core-mid	2019 marginal-mid	2019 outsider
2018 mid insider cla	**0.831 (325)**	0.079 (31)	0.086 (34)	0.004 (2)
outsider	(11)	(25)	**(495)**	

2019 → 2020	2020 insider	2020 core-mid	2020 marginal-mid	2020 outsider
2019 mid insider cla	**0.930 (359)**	0.064 (25)	0.004 (2)	0.001 (0)
wor poor	(8)	(6)	**(497)**	

core -mid	0.001 (1)	**0.988 (639)**	0.006 (4)	0.005 (3)	core -mid	0.012 (8)	**0.967 (634)**	0.008 (5)	0.014 (9)
marginal -mid	0.001 (1)	0.004 (2)	**0.976 (458)**	0.019 (9)	marginal -mid	0.012 (6)	0.023 (11)	**0.958 (455)**	0.007 (3)
outsider	0.017 (9)	0.021 (11)	0.021 (11)	**0.941 (510)**	working poor	0.006 (3)	0.002 (1)	0.024 (13)	**0.967 (515)**

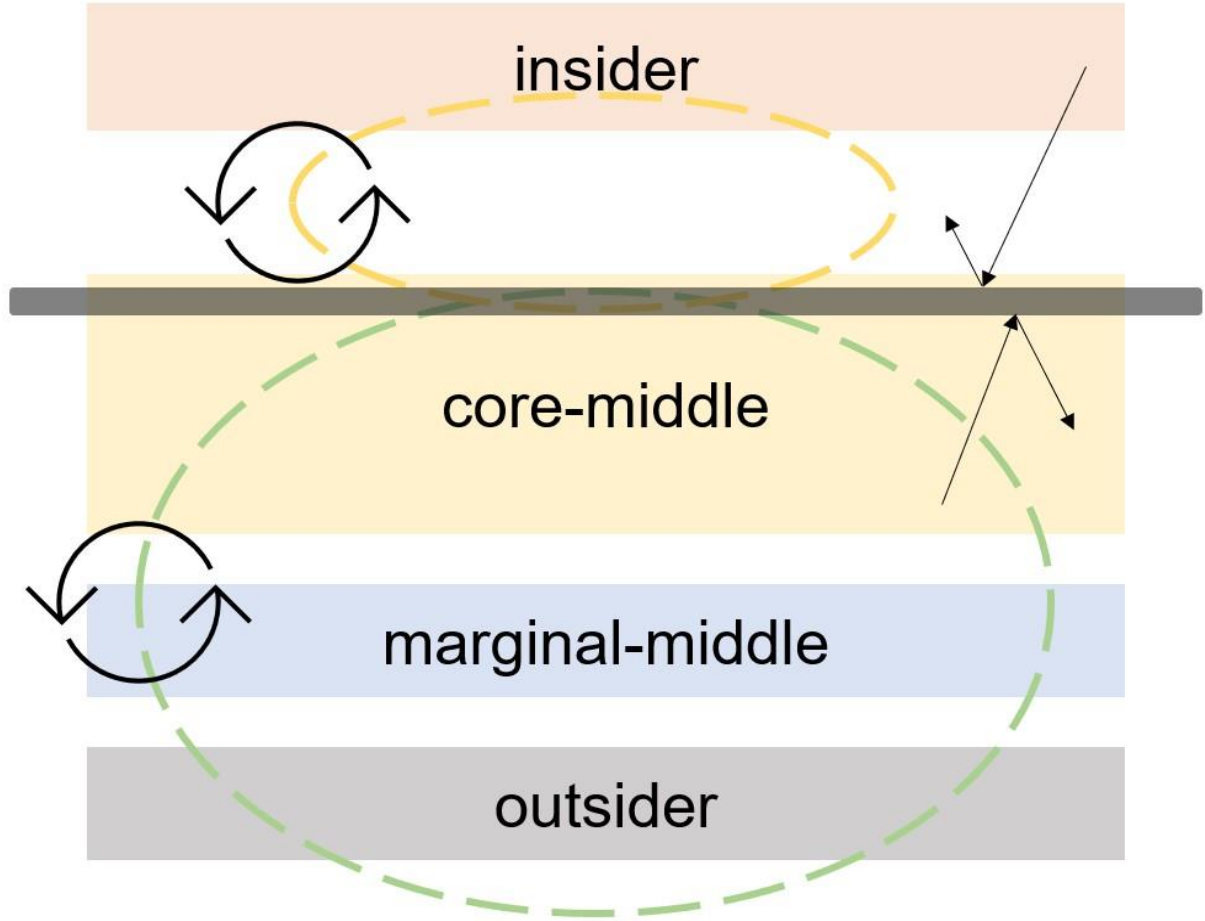


Figure 5. Schematizing Multi-Segmentation and Heterogeneous Gaps

5. Discussions

5.1. Multi-Segmentation and Heterogeneous Gaps

Recent findings suggest the possibility of multi-segmentation (Jessoula et al., 2010; López-Roldán and Fachelli, 2021; Seo, 2021), and this study contributes to the debate. Several findings have proposed subgroups within the framework of dualism (López-

Roldán and Fachelli, 2021; Seo, 2021), but this may be a matter of interpretation. In this study, four- or three-segments were identified (Fig. 3A-3C). The interpretation may depend on whether those labelled as 'middle' are seen as a separate group between insiders and outsiders, as in Jessoula et al. (2010), or as a subset of outsiders. Furthermore, a generalised flow of two chunks can be inferred (Tab. 7A-7C), and the dimension of mobility constraints must also be taken into account. If one wants to adhere to the assumption of a dual structure, the line between insiders and outsiders needs to be clarified. The two generalised mobility clusters identified in this study can be represented as in Fig. 5. This is based on the fact that only the bottom end of the internal labour market is open (Doeringer and Piore, 1971). It's important to note that this may not mean that outsiders can enter the internal labour market through gradual ascent. Those who reach the second tier through a sequence of difficult gateways will face the thickest wall (i.e., translucent grey line in Fig. 5). This actual barrier may be the threshold of the ideal dual structure proposed by Doeringer and Piore (1971). Whether dualisation, multi-segmentation, or sub-segmentation within dual structure is true, the implication of the findings identifying multi-segmentation is the inadequacy of adhering to strict dual structure assumption when studying segmented labour markets in post-industrial societies.

Due to the possibility of multi-segmentation, attention should also be paid to heterogeneous gaps: more than two segments will inevitably create more than one gap. The short period of analysis and the constraints on the interpretation of mobility did not allow us to identify all the gaps between segments in detail, but we were able to confirm the dominant position of the upper segments, even in the context of broader trends. Future research should focus on the gaps between the lower segments. Especially those enjoying median wages. If they show downward movement, even without widening gap with the top segment, it could contribute to the consolidation of the top-tier and lead to broader discussions about the decline of the middle class. It would also shed light on whether they should be viewed as a separate class, such as the midsider, or a sub-sector of the outsider. There’s a need to go beyond assuming the number of class in segmentation studies and consider mobility constraints together to draw more reasonable borderlines.

5.2. Regional Disparities and Labour Market

It’s necessary to understand the differences between regional labor markets. In Korea, regional dualism stands out in the general context (Park, 1993; Lim, 2008; Kim, 2010), and we find significant differences in this study. More segments are observed in non-CR, which may be due to more concentrated opportunities and active inflows and outflows in CR (Park, 1993; Lim, 2008), implying the possibility of a more fixed pattern developing

in non-CR. The active movement of the top tier in non-CR is a downward movement (Tab. 7C), which may be part of a self-reinforcing sorting process. These socio-structural differences between regions may stem from the existence of what New Economic Sociology calls the area of chance, whereby individuals may experience involuntary socioeconomic stigma effect based on where they choose to work and live. Moreover, in countries like Korea, where the landmass is relatively small and socio-economic concentration is high in a single region, these differences can be stark.

Regional differences in labour market structure are not unrelated to regional disparities, which have been the subject of much recent debate. Studies on segmented labour market mainly focus on defining precarious work and measuring segmentation. Thus, they fail to explicitly consider dimensions of productivity or spillover effects based on spatial proximity. However, the phenomena do not occur independently. Regions with higher shares of internal labour markets may generate better surpluses. The homogeneity or heterogeneity of labour market structures between geographically adjacent regions will provide a link between the two topics by considering migration dynamics.

5.3. The Labyrinth of Working Poor

The problem with being outsider in a segmented labour market is escape constraints. They work hard, but their status does not move upwards. Here we can indirectly consider another social problem: in-work poverty. Since in-work poverty can be identified at both the individual- and household-level, there is an error in equating the working poor with outsiders. However, the link between working poverty and low-wage work can compensate for this (Brülle et al., 2019). Basically, there are significant constraints on class mobility (Fig. 7A-7C), and while detailed mobility cannot be discussed, two flows of mobility can be used to discuss the stagnation of working poor. Only the top-tier benefits from full-security across all categories (Tab. 4A-4B and Appendix 5A-5B). Whether they remain at the bottom or move along a cycle that spans several lower tiers (Fig. 5), the fact remains that if they cannot enter the internal labour market, they are trapped.

The implication of this segmentation is that the occurrence of an economic shock can completely push the lowest class down, especially given the recent increase in exposure to risk in the general context (Hassink, 2010; Fingleton, 2012; Martin, 2012). Whatever the cause of the shock, outsiders are consumed as a buffer for insiders (Rueda, 2005), which creates further entrenched divisions, and the next external shock leads to a vicious cycle of poverty. Reproducing each other could mean a potential virtuous circle. The blueprint should be drawn by removing the thickest barriers to entering the internal labour market. However, this is not a simple task, and there is a need to find the

political clues for at least incremental improvements. For example, very simple but obvious policies such as expanding employment opportunities in manufacturing can be used as steppingstones for upward mobility of outsiders (Tab. 5 and Appendix 6A-6H), and can be a starting point for escaping in-work poverty. If one can show that the downward mobility from the second lowest to the lowest tier is not significant. This again emphasises the importance of focusing on heterogeneous gaps.

6. Conclusions

This study contributes to the limited but valuable discussion on the multi-segmentation and regional heterogeneity of labour markets and the trapping of the working poor. The following should be considered in urban planning. First, opportunities are highly concentrated in the CR, which means that regional differences in labour markets need to be taken into account. Moreover, this division makes it difficult for outsiders to find a way out of the vicious circle. Policymakers who want to address inequality will need to consider the above points collectively, recognising that inequality is not a separate phenomenon - whether at the individual, socio-structural, or regional level - it just has a different focus.

This study has the following limitations. First, the self-employed are not included in the analysis. In Korea, a quarter of the total labour force is self-employed; thus, the labour market estimated in this study is a wage labour market. Furthermore, half of them are vulnerable groups with no employment (Shin, 2013). This obviously poses problems when discussing the proportions, characteristics, and mobility of the lower classes. Second, the study sought to derive the most reasonable hierarchical solution by region, and a different number of segments were observed in CR and non-CR. While the differences between the two regions can be identified, direct comparisons are unavailable. Fortunately, multi-group LCA for intergroup comparisons are being reported (Lukac et al., 2019), and direct comparisons across regions may be possible by fixing the response probabilities and deriving a constant number of solutions. Finally, the time series is not long enough for panel analysis. The dimension of mobility is not limited to one-way movement; patterns such as entry, exit, and re-entry may better explain gaps.

Future research on segmented labour markets will need to revisit these limitations. Furthermore, when considering multi-segmentation, it will be necessary to focus on heterogeneous gaps, especially mobility and gaps in the mid-income group. The link between interregional migration and class mobility may also be an interesting topic, and

a comprehensive consideration of these issues will provide better insight for segmentation research.

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Appendix

Appendix 1A. Descriptive Statistics, CR

	Concepts	Variables		2018 (N=3,542)	2019 (N=3,549)	2020 (N=3,363)
Indicator	Employment Insecurity	employment	non-regular	1,042	1,005	952
			regular	2,500	2,494	2,411
		part-time work	part-time	295	318	295
			full-time	3,247	3,231	3,068
	Objective Insecurity	income	low	522	499	451
			middle	2,190	2,308	2,135
			high	830	742	777
		skill	low	960	960	891
			middle	1,527	1,535	1,461
			high	1,055	1,054	1,011
	Subjective Insecurity		non-secure	505	469	394
			secure	3,037	3,080	2,969
	Future Insecurity		non-secure	3,421	3,448	3,309
			secure	121	101	54
	Union Protection		non-protection	3,066	3,062	2,874
			protection	479	487	489
Covariates	Age		young	869	847	733
			medium	1,659	1,649	1,584
			old	1,014	1,053	1,046
	Gender		male	2,019	2,013	1,891
			female	1,523	1,536	1,472

	Education	elementary school	92	94	70
		middle school	183	174	158
		high school	1,359	1,322	1,285
		junior college	637	655	622
		university	1,111	1,136	1,065
		graduate school	160	168	163
	Industry	non-manufacture	2,730	2,779	2,611
		manufacture	812	770	752
	Firm Size	SMEs	3,173	3,194	2,874
		large	369	355	489

Appendix 1B. Descriptive Statistics, non-CR

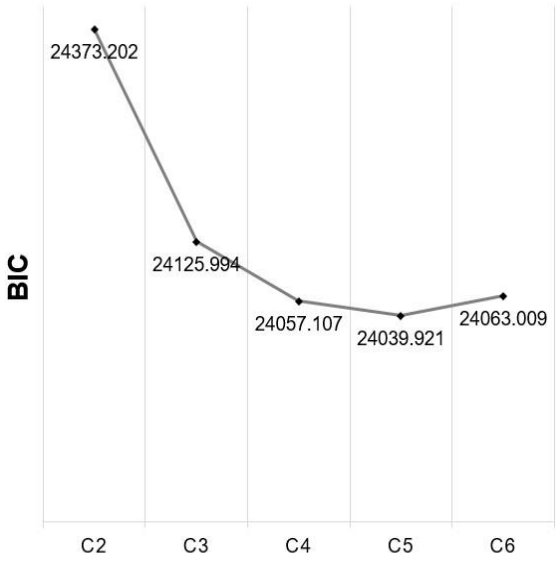
	Concepts	Variables		2018 (N=3,214)	2019 (N=3,098)	2020 (N=3,048)
Indicator	Employment Insecurity	employment	non-regular	1,021	954	902
			part-time	2,193	2,144	2,146
		part-time work	full-time	294	286	266
				2,920	2,812	2,782
	Objective Insecurity	income	low	567	556	506
			middle	1,960	1,966	1,946
			high	687	576	596
		skill	low	920	879	819
			middle	1,578	1,543	1,515
			high	716	676	714
	Subjective Insecurity	non-secure		534	493	461
		secure		2,680	2,605	2,587
	Future Insecurity	non-secure		2,997	2,851	2,848
		secure		217	247	200
	Union Protection	non-protection		2,704	2,590	2,517
		protection		510	508	531
Covariates	Age	young		731	676	1,394
		medium		1,430	1,389	2,957
		old		1,053	1,033	2,060
	Gender	male		1,941	1,851	3,729
		female		1,273	1,247	2,682
	Education	elementary school		112	83	139
		middle school		241	216	334

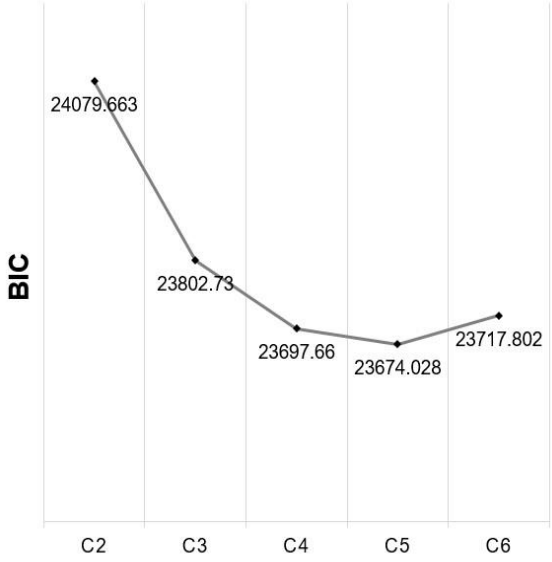
Appendix 2A. Model Fit Statistics, CR

Year	Classes	LL	AIC	BIC	SABIC	VLMR	LMR	BLRT	Entropy
2018	2	-12109.0	24255.9	24373.2	24312.8	0.000	0.000	0.000	0.888
	3	-11944.5	23947.0	24126.0	24033.8	0.000	0.000	0.000	0.787
	4	-11869.2	23816.4	24057.1	23933.2	0.006	0.006	0.000	0.79
	5	-11819.7	23737.5	24039.9	23884.2	0.011	0.012	0.000	0.772
	6	-11790.4	23698.8	24063.0	23875.8	0.217	0.220	0.000	0.798
2019	2	-11962.2	23962.3	24079.7	24019.3	0.000	0.000	0.000	0.888
	3	-11782.8	23623.7	23802.7	23710.6	0.000	0.000	0.000	0.744
	4	-11689.4	23456.9	23697.7	23573.7	0.000	0.000	0.000	0.768
	5	-11636.7	23371.5	23674.0	23518.3	0.001	0.001	0.000	0.757
	6	-11617.8	23353.5	23717.8	23530.3	0.000	0.000	0.000	0.765
2020	2	-11090.0	22218.1	22334.4	22274.0	0.000	0.000	0.000	0.896
	3	-10927.4	21912.7	22090.2	21998.1	0.000	0.000	0.000	0.71
	4	-10850.4	21778.8	22017.5	21893.6	0.000	0.000	0.000	0.75
	5	-10802.4	21702.8	22002.7	21847.0	0.000	0.000	0.000	0.801
	6	-10782.1	21682.2	22043.3	21855.8	0.123	0.123	0.000	0.816

high school	1,232	1,195	2,461
junior college	674	649	1,282
Industry	non-manufacture	2,287	2,201	4,797
	manufacture	927	897	1,614
Firm Size	SMEs	2,915	2,787	5,782
	large	299	311	629

Appendix 3. Changes of BIC in CR and non-CR

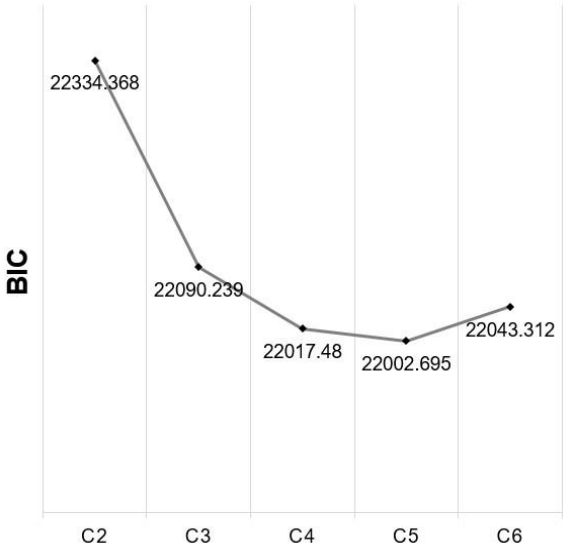




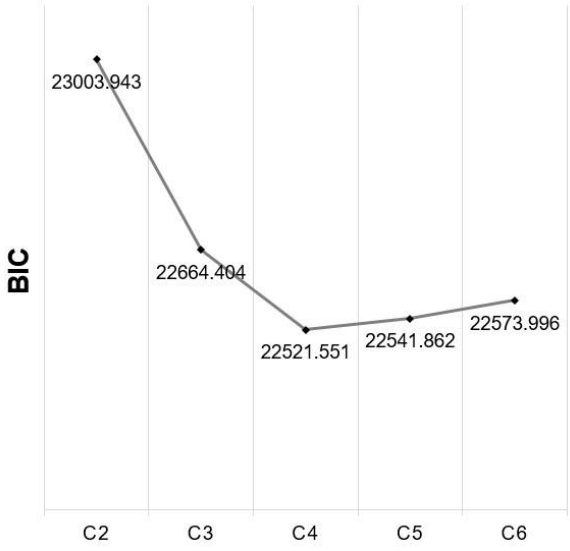
Appendix 2B. Model Fit Statistics, non-CR

Year	Class	LL	AIC	BIC	SABIC	VLMRT	LMR LRT	BLRT	Entropy
2018	2	-11425.3	22888.5	23003.9	22943.6	0.000	0.000	0.000	0.870
	3	-11215.1	22488.2	22664.4	22572.3	0.000	0.000	0.000	0.749
	4	-11103.3	22284.6	22521.6	22397.6	0.000	0.000	0.000	0.766
	5	-11073.1	22244.2	22541.9	22386.2	0.000	0.000	0.000	0.733
	6	-11048.8	22215.6	22574.0	22386.5	0.012	0.013	0.000	0.763
2019	2	-11045.3	22128.5	22243.2	22182.9	0.000	0.000	0.000	0.871
	3	-10836.9	21731.7	21906.9	21814.7	0.000	0.000	0.000	0.728
	4	-10745.1	21568.1	21803.6	21679.7	0.000	0.000	0.000	0.760
	5	-10716.7	21531.4	21827.3	21671.6	0.465	0.469	0.000	0.770
	6	-10692.4	21502.8	21859.1	21671.6	0.900	0.903	0.000	0.799
2020	2	-10772.7	21583.5	21697.9	21637.5	0.000	0.000	0.000	0.875
	3	-10552.0	21162.0	21336.6	21244.5	0.000	0.000	0.000	0.755
	4	-10462.9	21003.8	21238.7	21114.8	0.000	0.000	0.000	0.788
	5	-10444.5	20987.0	21282.1	21126.4	0.139	0.142	0.000	0.766
	6	-10429.8	20977.6	21332.9	21145.4	0.268	0.272	0.004	0.764

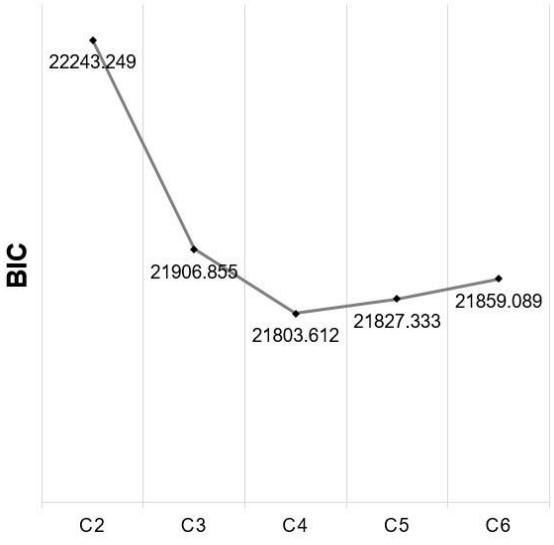
(A) CR, 2018 (B) CR, 2019



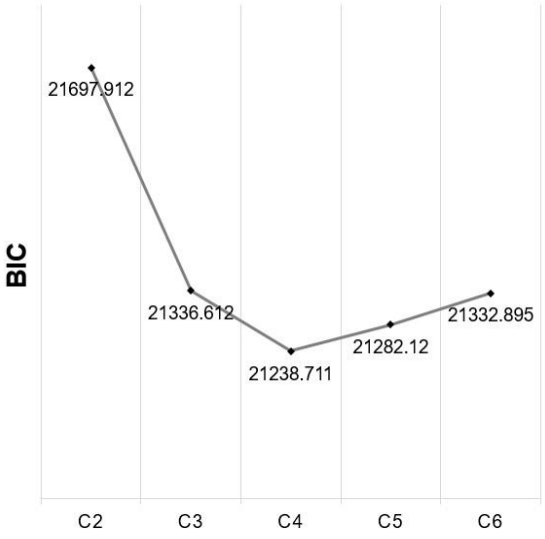
(C) CR, 2020



(D) non-CR, 2018



(E) non-CR, 2019



(D) non-CR, 2020

Appendix 4A. Average Latent Class Posterior Probabilities, CR

		C1	C2	C3
2018	C1	**0.870**	0.113	0.017
	C2	0.003	**0.987**	0.010
	C3	0.083	0.004	**0.913**
2019	C1	**0.904**	0.011	0.085
	C2	0.012	**0.932**	0.056
	C3	0.000	0.155	**0.845**
2020	C1	**0.955**	0.010	0.035
	C2	0.008	**0.934**	0.058
	C3	0.222	0.031	0.747

Note: Bolds are those > 0.8

Appendix 4B. Average Latent Class Posterior Probabilities, non-CR

		C1	C2	C3	C4
2018	C1	**0.814**	0.184	0.002	0.000
	C2	0.081	**0.908**	0.010	0.002
	C3	0.007	0.001	**0.855**	0.138
	C4	0.000	0.000	0.093	**0.907**
2019	C1	**0.822**	0.172	0.006	0.000
	C2	0.102	**0.898**	0.000	0.000
	C3	0.003	0.000	**0.906**	0.091
	C4	0.004	0.000	0.129	**0.867**
2020	C1	0.766	0.232	0.002	0.000
	C2	0.054	**0.944**	0.000	0.002
	C3	0.002	0.000	**0.916**	0.081
	C4	0.000	0.008	0.208	0.784

Note: Bolds are those > 0.8

Appendix 5A. Item Response Probabilities, Korea, 2019

N=6,647	outsider (C1)	marginal-mid (C2)	core-mid (C3)	Insider (C4)
Class Size (%)	12.2	16.4	42.4	28.9
Contract Type				
Non-Permanent	**0.993**	**1.000**	0.000	0.012
Permanent	0.007	0.000	**1.000**	**0.988**
Part-time Work				
Part-time	0.524	0.131	0.005	0.000
Full-time	0.476	**0.869**	**0.995**	**1.000**
Income Level				
Low	0.686	0.109	0.114	0.000
Middle	0.311	**0.837**	**0.847**	0.365
High	0.003	0.054	0.039	0.635
Occupational Skill				
Low	**0.825**	0.331	0.228	0.051
Middle	0.098	0.472	0.501	0.562
High	0.077	0.197	0.271	0.387
Subjective Insecurity				
Non-Secure	0.476	0.401	0.019	0.004
Secure	0.524	0.599	**0.981**	**0.996**
Future Insecurity				
Non-Secure	**0.997**	**0.950**	**0.985**	**0.916**
Secure	0.003	0.050	0.015	0.084
Union Protection				
Non-Protection	**0.997**	**0.924**	**0.953**	0.563
Protection	0.003	0.076	0.047	0.437

Note: Bolds are those > 0.7

Appendix 5B. Item Response Probabilities, Korea, 2020

N=6,411	insider (C1)	outsider (C2)	core-mid (C3)	marginal-mid (C4)
Class Size (%)	28.8	13.6	41.1	16.5
Contract Type				
Non-Permanent	0.007	**0.997**	0.000	**0.998**
Permanent	**0.993**	0.003	**1.000**	0.002
Part-time Work				
Part-time	0.000	0.469	0.005	0.151
Full-time	**1.000**	0.531	**0.995**	**0.849**
Income Level				
Low	0.000	0.667	0.128	0.093
Middle	0.394	0.333	**0.854**	**0.807**
High	0.606	0.000	0.018	0.100
Occupational Skill				
Low	0.057	**0.859**	0.229	0.297
Middle	0.541	0.095	0.500	0.485
High	0.372	0.045	0.270	0.218
Subjective Insecurity				
Non-Secure	0.002	0.491	0.023	0.437
Secure	**0.998**	0.539	**0.977**	0.563
Future Insecurity				
Non-Secure	**0.889**	**0.988**	**0.961**	**0.942**
Secure	0.111	0.012	0.039	0.058
Union Protection				
Non-Protection	0.582	**0.993**	**1.000**	**0.924**
Protection	0.418	0.007	0.000	0.076

Note: Bolds are those > 0.7

Appendix 5C. Item Response Probabilities, CR and non-CR, 2019

CR (N=3,549)	non-CR (N=3,098)

	outsider	insider	middle class	marginal - mid	outsider	insider	core -mid
	C1	C2	C3	C1	C2	C3	C4
Class Size (%)	26.3	30.8	42.9	16.63	14.24	26.5	42.63
Contract Type							
Non-Permanent	**1.000**	0.029	0.058	**0.986**	**1.000**	0.006	0.000
Permanent	0.000	**0.971**	**0.942**	0.014	0.000	**0.994**	**1.000**
Part-time Work							
Part-time	0.329	0.000	0.007	0.144	0.474	0.000	0.002
Full-time	0.671	**1.000**	**0.993**	**0.856**	0.526	**1.000**	**0.998**
Income Level							
Low	0.345	0.000	0.116	0.119	**0.713**	0.001	0.136
Middle	0.597	0.370	**0.884**	**0.802**	0.287	0.402	**0.830**
High	0.058	0.630	0.000	0.078	0.000	0.597	0.034
Occupational Skill							
Low	0.588	0.065	0.223	0.302	**0.857**	0.042	0.235
Middle	0.273	0.485	0.493	0.504	0.100	0.669	0.522
High	0.140	0.449	0.284	0.194	0.043	0.290	0.242
Subjective Insecurity							
Non-Secure	0.472	0.003	0.016	0.435	0.517	0.002	0.030
Secure	0.528	**0.997**	**0.984**	0.565	0.483	**0.998**	**0.970**
Future Insecurity							
Non-Secure	**0.986**	**0.926**	**0.995**	**0.893**	**0.986**	**0.845**	**0.956**
Secure	0.014	0.074	0.005	0.107	0.014	0.155	0.044
Union Protection							
Non-Protection	**0.962**	0.650	**0.954**	**0.912**	**0.996**	0.496	**0.964**
Protection	0.038	0.350	0.046	0.088	0.004	0.504	0.036

Note: Bolds are those > 0.7

Appendix 5D. Item Response Probabilities, CR and non-CR, 2020

	CR (N=3,363)			non-CR (N=3,048)			
	insider	outsider	middle class	insider	core-mid	marginal-mid	outsider
	C1	C2	C3	C1	C2	C3	C4
Class Size (%)	37.4	24.3	38.3	20.2	50.4	15.8	13.6
Contract Type							
Non-Permanent	0.028	**0.999**	**0.077**	0.019	**0.000**	**1.000**	**0.990**
Permanent	**0.972**	0.001	0.923	**0.981**	1.000	0.000	0.010
Part-time Work							
Part-time	0.000	0.349	0.007	0.000	0.002	0.096	0.521
Full-time	**1.000**	0.651	**0.993**	**1.000**	**0.998**	**0.904**	0.479
Income Level							
Low	0.000	0.361	0.121	0.000	0.106	0.114	0.696
Middle	0.417	0.585	**0.879**	0.303	**0.808**	**0.827**	0.290
High	0.583	0.054	0.000	0.697	0.086	0.059	0.014
Occupational Skill							
Low	0.058	0.612	0.247	0.028	0.217	0.301	**0.781**
Middle	0.496	0.246	0.494	0.655	0.526	0.524	0.123
High	0.446	0.142	0.259	0.317	0.257	0.175	0.095
Subjective Insecurity							
Non-Secure	0.007	0.455	0.010	0.000	0.026	0.426	0.524
Secure	**0.993**	0.545	**0.990**	**1.000**	**0.974**	0.574	0.476
Future Insecurity							
Non-Secure	**0.963**	**0.990**	**1.000**	**0.842**	**0.963**	**0.908**	**0.996**
Secure	0.037	0.010	0.000	0.158	0.037	0.092	0.004
Union Protection							
Non-Protection	0.672	**0.968**	**0.960**	0.372	**0.936**	**0.905**	**1.000**
Protection	0.328	0.032	0.040	0.628	0.064	0.095	0.000

Note: Bolds are those > 0.7

Appendix 6A. Relationship with Covariate, Korea, 2019

	Age	Gender	Education	Industry	Firm Size

outsider vs. insider	Est. C.	0.410***	-3.288***	1.666***	2.772***	5.328***
	S.E.	0.116	0.187	0.085	0.296	1.087
outsider vs. core-mid	Est. C.	-0.343***	-1.445***	0.897***	2.521***	0.83
	S.E.	0.093	0.143	0.071	0.272	1.152
outsider vs. marginal-mid	Est. C.	0.163	-1.927***	0.705***	1.595***	2.985**
	S.E.	0.125	0.171	0.088	0.316	1.113
marginal-mid vs. core-mid	Est. C.	0.247**	-1.361***	0.961***	1.176***	2.343***
	S.E.	0.081	0.144	0.056	0.121	0.192
marginal-mid vs. insider	Est. C.	-0.506***	0.482***	0.192***	0.926***	-2.155***
	S.E.	0.068	0.09	0.047	0.112	0.456
core-mid vs. insider	Est. C.	0.753***	-1.843***	0.769***	0.250*	4.498***
	S.E.	0.072	0.14	0.051	0.116	0.45

* $p < .05$, ** $p < .01$, *** $p < .001$

Appendix 6B. Relationship with Covariate, Korea, 2020

		Age	Gender	Education	Industry	Firm Size
outsider vs. insider	Est. C.	0.530***	-3.349***	1.851***	2.286***	5.123***
	S.E.	0.126	0.197	0.095	0.271	0.767
outsider vs. core-mid	Est. C.	-0.241*	-1.622***	0.879***	1.904***	1.088
	S.E.	0.098	0.158	0.077	0.24	0.818
outsider vs. marginal-mid	Est. C.	0.249	-1.991***	0.691***	1.124***	2.554**
	S.E.	0.132	0.186	0.097	0.291	0.804
marginal-mid vs. core-mid	Est. C.	0.281**	-1.358***	1.160***	1.162***	2.569***
	S.E.	0.089	0.145	0.066	0.131	0.231
marginal-mid vs. insider	Est. C.	-0.490***	0.369***	0.188***	0.780***	-1.466***
	S.E.	0.07	0.092	0.05	0.116	0.344
core-mid vs. insider	Est. C.	0.771***	-1.726***	0.972***	0.382**	4.034***
	S.E.	0.082	0.138	0.06	0.126	0.314

* $p < .05$, ** $p < .01$, *** $p < .001$

Appendix 6C. Relationship with Covariate, CR, 2018

		Age	Gender	Education	Industry	Firm Size
outsider vs. insider	Est. C.	0.412***	-2.103***	1.537***	1.673***	2.753***
	S.E.	0.106	0.161	0.084	0.178	0.335
outsider vs.	Est. C.	-0.509***	-0.06	0.594***	1.522***	0.347

middle class	S.E.	0.08	0.104	0.062	0.155	0.353
middle class vs.	Est. C.	0.922***	-2.042***	0.943***	0.151	2.406***
insider	S.E.	0.096	0.15	0.07	0.14	0.217

* $p < .05$, ** $p < .01$, *** $p < .001$

Appendix 6D. Relationship with Covariate, CR, 2019

		Age	Gender	Education	Industry	Firm Size
outsider vs.	Est. C.	0.249*	-1.585***	1.338***	1.865***	2.443***
insider	S.E.	0.103	0.153	0.08	0.185	0.305
outsider vs.	Est. C.	-0.554***	-0.125	0.473***	1.533***	-1.257*
middle class	S.E.	0.079	0.102	0.058	0.163	0.492
middle class vs.	Est. C.	0.803***	-1.460***	0.865***	0.332*	3.701***
insider	S.E.	0.095	0.153	0.069	0.153	0.434

* $p < .05$, ** $p < .01$, *** $p < .001$

Appendix 6E. Relationship with Covariate, CR, 2020

		Age	Gender	Education	Industry	Firm Size
outsider vs.	Est. C.	0.129	-1.830***	1.476***	1.759***	2.390***
insider	S.E.	0.115	0.155	0.093	0.192	0.338
outsider vs.	Est. C.	-0.591***	-0.591***	0.379***	1.409***	-1.887*
middle class	S.E.	0.091	0.114	0.067	0.168	0.884
middle class vs.	Est. C.	0.719***	-1.238***	1.096***	0.349*	4.277***
insider	S.E.	0.106	0.15	0.079	0.17	0.825

* $p < .05$, ** $p < .01$, *** $p < .001$

Appendix 6F. Relationship with Covariate, non-CR, 2018

		Age	Gender	Education	Industry	Firm Size
outsider vs.	Est. C.	0.562**	-4.053***	1.598***	2.676***	6.65
insider	S.E.	0.173	0.327	0.129	0.371	3.766
outsider vs.	Est. C.	-0.206	-1.577***	0.979***	2.624***	1.42
core-mid	S.E.	0.134	0.206	0.107	0.335	3.803

outsider vs.	Est. C.	0.303	-1.929***	0.742***	1.711***	3.851
marginal-mid	S.E.	0.178	0.244	0.134	0.381	3.813
marginal-mid vs.	Est. C.	0.258*	-2.124***	0.856***	0.965***	2.799***
core-mid	S.E.	0.122	0.278	0.083	0.173	0.326
marginal-mid vs.	Est. C.	-0.51***	0.352**	0.237**	0.913***	-2.43**
insider	S.E.	0.099	0.132	0.069	0.149	0.786
core-mid vs.	Est. C.	0.768***	-2.476***	0.619***	0.052	5.23***
insider	S.E.	0.111	0.279	0.076	0.169	0.777

* $p < .05$, ** $p < .01$, *** $p < .001$

Appendix 6G. Relationship with Covariate, non-CR, 2019

		Age	Gender	Education	Industry	Firm Size
outsider vs.	Est. C.	0.562**	-4.053***	1.598***	2.676***	6.65
insider	S.E.	0.173	0.327	0.129	0.371	3.766
outsider vs.	Est. C.	-0.206	-1.577***	0.979***	2.624***	1.42
core-mid	S.E.	0.134	0.206	0.107	0.335	3.803
outsider vs.	Est. C.	0.303	-1.929***	0.742***	1.711***	3.851
marginal-mid	S.E.	0.178	0.244	0.134	0.381	3.813
marginal-mid vs.	Est. C.	0.258*	-2.124***	0.856***	0.965***	2.799***
core-mid	S.E.	0.122	0.278	0.083	0.173	0.326
marginal-mid vs.	Est. C.	-0.51***	0.352**	0.237**	0.913***	-2.43**
insider	S.E.	0.099	0.132	0.069	0.149	0.786
core-mid vs.	Est. C.	0.768***	-2.476***	0.619***	0.052	5.23***
insider	S.E.	0.111	0.279	0.076	0.169	0.777

* $p < .05$, ** $p < .01$, *** $p < .001$

Appendix 6H. Relationship with Covariate, non-CR, 2020

		Age	Gender	Education	Industry	Firm Size
outsider vs.	Est. C.	0.812***	-4.021***	1.605***	2.396***	25.228***
insider	S.E.	0.181	0.379	0.142	0.359	0.411
outsider vs.	Est. C.	-0.038	-1.509***	0.801***	1.933***	20.999***
core-mid	S.E.	0.133	0.185	0.104	0.306	0.422
outsider vs.	Est. C.	0.308	-1.766***	0.478**	1.166**	21.908***
marginal-mid	S.E.	0.185	0.238	0.138	0.371	0

marginal-mid vs.	Est. C.	0.504***	-2.255***	1.127***	1.23***	3.32***
core-mid	S.E.	0.141	0.349	0.11	0.208	0.411
marginal-mid vs.	Est. C.	-0.346**	0.256	0.323***	0.767***	-0.908*
insider	S.E.	0.1	0.139	0.073	0.157	0.422
core-mid vs.	Est. C.	0.85***	-2.512***	0.804***	0.463*	4.228***
insider	S.E.	0.124	0.346	0.099	0.193	0.411

* $p < .05$, ** $p < .01$, *** $p < .001$