Labor Market Segmentation, and Resource Allocation

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June 14, 2020

Abstract

This paper studies the effect of expected wage on the choice of individuals over the types of firms and contracts and the impact of the predicted wage gap across different job segments on time and resources. Using Korean Labor and Income Panel Study (1997-2017) data, we first show that wages are the most crucial determinant for the individuals' preference over types of employment. Then, we calculate inequality measures using counterfactual wages over different labor market segments estimated for each individual. We term this measure as the degree of labor market segment (DLMS), which quantifies the degree of market concentration each individual faces. We study the relationship between the DLMS and resource allocation. We find that the DLMS is positively related to money spent on private education, time spent non-employed. The DLMS is negatively associated with marital status and the number of children among married couples. We conclude that increased labor market segmentation leads workers to invest substantial amount of resources into career advancement.

1. Introduction

One of the critical features of the labor market in the global economy is the development of labor market segmentation, where the term is defined as the situation where workers with equal productivity earn different compensation depending on whom they work for (Magnac(1991)). Labor market segmentation may also imply differences in benefits such as insurance or on-the-job training, or limited job transition across different job categories. This global phenomenon attracted the attention of policymakers and the general public, and a number of existing studies and policy reports identified increasing globalization and technological advances as the possible mechanisms behind labor market segmentation. Nonetheless, there is still limited research that examines the effect of labor market segmentation on individuals' decisions on resource allocation, instead, the related literature mostly focuses on the impact of market concentration on wage determination, and its implication on macroeconomic variables such as unemployment, total factor productivity, and GDP. Even though the individual's decision on time and money allocation for labor market entry has been discussed as a possible underlying mechanism by which segmented labor market impacts macro aggregates, there is still little empirical study that supports this hypothesis.

In this article, we use detailed individual-level panel data from South Korea to address this research question. We investigate how wage differences across firms and contract types affect individuals' decisions on labor market entry, money spent on private education, and the number of household members. There has been an intense discussion among policymakers in South Korea that increased wage disparity across firms incentivized individuals to invest excessive resources on accumulating human capital, and thus delaying labor market participation. The subsequent ramifications of delayed labor market entrance are the delayed marriage and lowered fertility among married couple, which then affects macroeconomic variables such as unemployment, total factor productivity, and gross domestic product. While these debates are insightful and brought to the public interest, such statements are still not tested with rigorous empirical analysis. To validate the argument, a careful, two-fold empirical investigation is needed: first, whether the expected wage in different job segment affects individuals' decision making in job choice; second, how the wage gaps across different job segments affect their decision-making in time and money allocation to prepare for the labor market. This paper presents this empirical analysis based on the labor market features in South Korea, where job size and type of contract served as dividing lines for the segmentation of the labor market (see Ha and Lee (2013) and Schauer (2018)).

To motivate our discussion for the development of labor market segmentation in South Korea, we use data from the Wage Structure Survey (WSS, 1980-2017) to show the average real wage trend adjusted at a 2015 Korean won basis. Figure 1 shows the average real wage trend, indexed for large companies (hires more than 300 employees) and small and medium-sized enterprises (SMEs hence force, which we define as a business that recruits less than 300 employees). The average wage gap between workers in large-scale firms and ones in SMEs has steadily increased over the past few decades: employees at SMEs paid just 3 percent less on average than those who worked at a large-scale company in 1983. However, the gap started to expand after the 1997 Asian financial crisis, and as of 2017, it nearly doubled; the average wage for employees in a large firm is almost twice as much as the ones in SMEs.

If the wage gap across the company size reflected workers' abilities, such that workers sorted to the firms based on their characteristics, then we cannot say that there was a systematic market concentration that leads worker compensation to diverge. Thus, we further document firm size (a proxy for company productivity) as the source of the wage differentials by following the standard approach in the literature (Katz and Autor (1999)). After accounting for individual characteristics such as age, years of education, years of employment, working hours, and even dummies for industry and occupation, we estimate the following regression cross-sectionally for each year (1980-2017) to see the effect of firm size on wage.

$$\log wage_i = X_i'\beta + \alpha_m D_m + \gamma_j + \delta_k + \varepsilon_i \tag{1}$$

Where X_i denotes a vector of individual i-specific covariates, including age, years of schooling, years of work experience, and its squared terms, as well as hours of work. D_m is a dummy variable for working at the firms with more than 300 workers (defined as large firms in this study), γ_j represents industry fixed effect, and δ_k occupation fixed effect accordingly. Figure 2 plots the degree of wage variation that is explained by working at the large firm-size ($>$300) over time. The coefficient on the large firm dummy, α_m has been steadily increasing over time, which suggests that since the 1997 Asian financial crisis, the premium of working for large firms has been steadily growing, and laborers are facing an increasing gap in their potential earnings based on for whom they work.

Figure 3 illustrates the growing importance of SMEs in its share of employment: from 52 percent in 1980 to 90 percent in 2017. The figure infers that there has been a systemic shift in the labor force, and the workforce ratio of large-scale businesses has reduced over the years. Considering that about 90 percent of employees in SMEs are employed with contracts of a non-regular form as of 2017, the statistic also indicates that growing numbers of employees are hired with non-regular type contracts over the years. [1] This growing number of non-regular-type contract jobs and development of dualistic labor market is not just a Korean labor market issue; there is a vast amount of literature studies on this topic where the literature focuses on the role of institutions on the development of dualistic labor market (see, for example, Boeri, 2011; Boris, 2016; and Cahuc, 2016). Our paper diverts from the existing literature in that we concentrate on the impact of labor market segmentation on individual decision-making. The lessons from the case study for the Korean labor market offer a valuable perspective for other countries facing segments of the labor market.

To draw causal inference between the labor market segmentation and individuals' choice, we first show the wage relevance for the decision of individuals about which segment of the labor market they would be working. To validate our argument, we borrow an estimation strategy from migration literature (Dahl 2002) and apply it for individuals' choices in labor market segments. This method allows for unobserved individual-specific factors influencing earnings and decisions on the labor segment and controls the self-selection non-parametrically. Once we show the relevance of the expected wage for the individuals' decisions on the specific labor segment, we then use the counter-factual wages to construct widely used inequality measures-the Gini Coefficient, and the Theil Index. These inequality measures quantify how each worker's income spreads across labor market segments, and this index proxies for the intensity of labor market segmentation each worker faces. Using these indexes, we conduct a regression analysis to study the relationship between labor market segment and individuals' choice over labor market entrance, money spent on private education, and the number of children.

We provide the following empirical evidence that is consistent with our prediction on the role of wage on job choice, and time and money allocation: (1) The potential wage earned in each labor market segment is a determinant factor for individuals' choice on the labor market segment; (2) The degree of labor market segments (DLMS), proxied by the inequality index with the input of potential income in each labor market segment, increases across the years; (3) DLMS is positively

[1]We discuss the definition of regular and non-regular workers in section 2.

related to investment in private education (both the absolute amount and relative ratio from the total expenditure); (4) An increase in DLMS delays individuals' labor market entrance; and (5) DLMS is negatively associated with marital status. This suggest that increased segmentation leads to significant increases in resource investment trying to enter the high-paying segments.

Our paper is largely related to the traditional topic of how industrial structure affects the labor market. Voluminous works that study the relationship between goods and the labor market, but recently, several papers identifying product market concentration as a force behind lowered wage growth in the United States get attention. For instance, Autor at el. (2020), Kehrig and Vincent (2017), and De Locker et al. (2020) use micro-data to study how the rise in product market concentration affects labor share and wage. Some works expound on the deep reason for product market concentration. For instance, León-Ledesma et al. (2010) and Koh et al. (2016) argue that technological change and the role of institutions such as property right reinforced product market concentration, which then lowered the labor market share. Our paper builds on from those works as we study how rising wage gap, caused by polarising firm productivities and product market concentration, affect individuals' decision on resource allocation. Our work is also related to growing literature on the topic of Inequality of Opportunity. After Roemer's (1998) famous formulation of attributing variation in outcomes to variation in "circumstances" (factors outside an individual's control) and "effort" (factors within individual's control), the literature grew up both in theory and in empirics. Most of the works focus on developing indexes and conduct an empirical analysis to document inequality caused by circumstances (Peragine, 2004; Ferreira and Gignoux, 2011; Fleurbaey and Schokkaert, 2009; Aaberge et al. 2011; Almas 2011). Several works relate to inequality of opportunity with growth (Marrerro and Rodriguez, 2013). However, the current literature on the inequality of opportunity does not quantify wage inequality due to labor market segments as variation in outcome due to circumstances. Our current work is the first attempt to study the effect of income inequality caused by labor market segments.

The rest of the paper is structured as follows. Section 2 introduces the historical background of Korean labor market, data sources, and trend in labor market. Section 4 introduces an model and estimation approach for labor segmentation, and then our main regression analysis. Section 5 discuss the results from our individual-level estimation results for labor segment decision, and also for the relationship between the indicator for labor market segmentation and individuals' choices over education, labor market entrance, marriage, and a number of children.

2. Background: Korean Labor Market

2.1. Data and Definitions

We use the Korean Labor and Income Panel Study (KLIPS) survey for 1998-2017, a well-represented individual-level survey of the Korean labor market. This longitudinal data contains comprehensive information on both demographic and labor market activities, such as employment status, tenure, income, expenditure, education, job training, industry, region, size of the company they worked, and the type of employment contract. We use this survey to define the dualistic labor market where the scale of a business and the form of contract served as dividing lines for various parts of the labor market (Schauer (2018), Ha and Lee (2013)). We define four separate groups of wage earners based on the scale of the company and the form of contract. The classes listed are (1) SME with non-regular type contract (SME/NR), (2) SME with regular type contract (SME/R), (3) Large-sized firms with non-regular type contract (L/NR), and (4) Large sized firms with regular type contract (L/R).[2] For our main analysis, we use working-age population (18-66) as our sample. Our sample includes wage earners, unemployed, and non-employed. Our sample exempt from self-employed or unpaid family members, as (1) their income reporting has a significant measurement error, and thus cannot be directly compared with wage income, and (2) having self-employed individuals makes it impossible to differentiate labor income from capital income.

[2]Generally speaking, non-standard employment refers to types of employment which differ significantly from the standard employment which is defined as full-time, permanent salaried employment. Thus, non-standard employment typically includes part-time work, work of a fixed duration, self-employment and non-remunerated domestic work. In Korea, the term non-regular worker has been used mostly commonly.

Table I illustrates some basic demographic and employment-related characteristics of populations by the labor market segment. As shown in the statistics, we see a clear demographic difference between the SME/NR segment and the L/R segment in terms of education level and parent education. The comparison between the SME/R segment and the L/NR segment is nuanced, though SME/R group has slightly higher education and parent education compare to L/NR group. Also, we observe that the averages of initial age to enter the labor market is lowest for workers in the SME/NR group, and highest for workers in the L/R group. When it comes to the employment-related characteristics, we observe significant advantages of being in the L/R group: the average income difference of the L/R group compared to the other groups is about 0.66 Korean won, which is 7.3 percentage higher. As for the tenure, we find that the gap between regular and non-regular contract is significant for large-sized firms, though it is much nuanced in the case of L/Rs. Since the period of a fixed-term contract is longer for SMEs, SMEs also frequently close down their businesses.

Our descriptive statistics indicate that there is a double penalty of working in the SME/NR, whereas significant gains in working at the L/R group. Also, we infer that there is a sorting behavior: workers in the L/R group tend to have educated parents who can invest their children's education. In the next sub-section, we further elaborate on the development of the dualistic labor market in South Korea, which raises our research question on its impact on individuals' decisions on resource allocations.

2.2. Overview of Trends in labor market segmentation

We document development of labor market segmentation in South Korea as the background for our empirical analysis. Korean economy during 1980 and 1990 had been touted as the "Champion of Equitable Growth" that combines both high growth rate and inclusive labor market. The Asian financial crisis of 1997, however, marked an immediate end to the era of equitable growth. While the economy recovered rapidly from the recession, the quality of growth changed and the Korean economy began experiencing segmentation of the labor market.

During the crisis, the Korean government asked for a bailout from International Monetary Fund (IMF), but IMF bailout package required necessary economic restructuring program that included labor market flexibility. To meet the IMF requirement, the Korean government set up the Tripartite Commission to develop a social agreement and reform labor law for the first time in Korea's history. The revised regulation recognized collective dismissal in case there are urgent managerial needs, which include the transfer, merger and acquisition aiming at preventing the aggravation of fincancial dfficulties. The practice of hiring dispatching staff was also legally recognized: the 'Act relating to Security for Dispatched Jobs' (February 1998) established a legal basis for the already common commercial custom of employing dispatched workers, allowing firms to dispatch workers for tasks that require specialized knowledge, techniques or experiences on the temporary and non-regular basis.

Moreover, with the pressure for globalization and market power strengthened through restructuring process, large companies increased R & D expenditure to take higer-value-activities in the global value chain, and reduced their labor cost by increasing outsourcing and hiring non-regular employees. Also, large companies are often blamed for abusing their market power by requesting SMEs to cut manufacturing costs, which resulted in reducing labor costs for SMEs by hiring non-regular employees. Figure 4a shows the recruiting activity trend over years. We see a major increase in non-regular employment; both large firms and SMEs are steadily employing non-regular workers. We had just 13 per cent of the non-regular employees in the starting year of our survey, 1998, which rises to 31 percent in 2017. Figure 4b illustrates that this move towards recruiting ever-increasing numbers of non-regular workers is mainly driven by SME recruiting.

Figure 5 illustrates the progression of average income inequalities across four separate groups. The wage increase of regular workers in the large firm (L/R) is most significant among the group of four. The most disadvantaged group is SME/NR, where, between 1998 and 2017, their wages increased by only 48 percent, which is much smaller than the average growth rate for the other three groups (78.7 percent). The most prominent wage divergence is observed between regular and non-regular workers. For example, the average hourly wage rate of non-regular employees in SMEs during 1998 is 94.4 percent of that for regular employees in SMEs, but decreases to 73.6 percent by 2017. Similarly, the average hourly wage rate of employees in SMEs as a non-regular worker was 56.4 percent of that for regular employees in large companies in 1998; however, the wage disparity between these two classes widened over the years, and in 2017 regular employees in small and medium-sized enterprises earned just 60.7 percent of the pay for employees in large permanent contract companies. Also noteworthy is the growing wage gap among regular employees. Regular employees in large firms earned just 177.4 percent more than regular employees in SMEs in 1998, but the wage disparity between these two classes widened, and in 2017 regular employees in large firms earned more than 241.7 percent more than regular employees in SMEs. Interestingly, we see no great difference among non-regular employees. Though the wage gap between different segments of the labor market also reflect differences among workers, the increasingly rising wage gap between these different segments indicates a deepening segmentation of the labor market over the years.

Table 2 shows the transition rate of workers in each group between 1998 and 1999, and between 2016 and 2017. The table suggests that there is limited chance for workers with lower segments of the labor market to migrate up to the upper one, and the rate of upward transition has been decreased dramatically over the years. In 1999, approximately 19.08 percent of workers from other inferior segments made to the R-L segments. However, in 2017, only 7.93 percent of workers from other segments converted their segments into the superior one. Another key observation to note is that once the workers are stuck in the SME/NR segment, then the chance to move into the different labor segments has become harder in 2017, relative to 1999. In 1999, 22.01 percent of workers in SME/NR segment were able to move up to the better segments, which deteriorated to 9.74 percent in 2017. Also, the chances of remaining in the best category , L/R, rose from 71.21 percent to 77.1 percent. These transition dynamics show the reduced upward mobility of workers from inferior segments.

Given the persistence and low expected income from the less-favored segment of labor, individuals in South Korea are increasingly encouraged to educate and defer their entry into the labor market, trying to get high-quality daily jobs at the initial placement. Expense on private education starts with private tutoring at a very early age, and continues to prepare for the entrance exam for higher education in high school. This test is of great importance as it is a major determinant for college entrance, which in turn plays a decisive role for the type of job that can be obtained. Studying for entrance exams and accumulation of certifications and diplomas often continues for those who are unable to secure a regular job in large firms out of college. While additional accumulation of human capital is generally seen as enhancing productivity and opportunities, the benefits of such investments have been questioned in this case, as it suggests that young people are investing heavily in education and postpone their entrance into the labor market, and it is therefore only normal to expect a reduced marriage rate and a reduced fertility rate as a side effect.

Firgure 6-7 show money spent for private education, marrital status of young people under the age of 37 and number of family members among married couples under the age of 37. We note that, over time, the amounts of money spent on private education, both the actual sum and its percentage from overall expenditures, have increased. We show this pattern with three different sample: non-employed, married individuals without children, and married individuals who have children. Across the samples, we see consistent increase of spending on private education, both in the absolute term and in the ratio. Time trend for marrital status and family size among married couple under the age of 37 years shows a decrease in the proportion of marital status and a decrease in the number of households among married couples. Overall, these figures indicate that individuals are encouraged to invest more time and money in education to secure jobs at the higher segment, which necessarily delay their decision on marriage. When it comes to the decision about the number of families among married couples, the graph indicates that married couples are encouraged to choose quality of children over quantity with deepening segment of the labor market. In the next session, we formally test the relationship between expected income, choice of job type, segments of the labor market, and individual resource allocation decisions.

3. Empirical Strategy

The descriptive statistics shown in the previous section predicts that the wage is the important factor to individual's occupational choice over job type. This also indicates that the rising wage gap across labor market segments delays individuals' entrance into the labor market and allows more investment in education. In this section, we provide an empirical evidence that supports the predictions of the hypothesis. The empirical study consists of two-fold: firstly, we confirm our hypothesis on the effect of wage on job type selection; secondly, we calculate counter-factual wages for different job types for each worker, and then construct a traditional inequality index using counter-factual wages. This index is a proxy for labor market segmentation each individual faces. Our regression analysis show labor market segments increases time spent for labor market entrance, and also finance for private education. In the following argument, we first introduce our identification strategy and then discuss the regression results.

3.1. Wage and Employment

In the first step of the analysis, we show the relevance of wage on the choice of job-type. We adopt the version of the Roy's migration model (Roy, 1951) to the study of individual choice of employment status and firm size. As discussed in the section 2, we distinguish between employment in the SME/NR, SME/R, L/NR, and L/R. Then, we define a mutually exclusive and exhaustive categorical variable, e_{it}, taking a value of 1 if individual i in year t is employed in the SME/NR, 2 if SME/R, 3 if L/NR, and 4 if L/R. Observing all relevant information, each individual compares the utility from working each job type and opts to maximize her/his utility. To write down formally, our empirical model has two interrelated equations: discrete job type choice equation (1) and a wage equation (2). That is, for $j = 1, ..., 4$,

$$U_{ijt} = \gamma w_{ijt} + \beta' X_{ijt} + \lambda_i \sigma_i + u_{ijt} \, (1)$$

$$ln \, w_{ijt} = Z_{ijt} \gamma_j + \pi_j \sigma_i + \epsilon_{ijt} \, (2)$$

In equation (1), the dependent variable is the latent utility that individual i earns in each job type j in year t. This depends on individual's earning (w_{ijt}) in each job type, their individual characteristics which are observed (X_{ijt}), and unobserved (σ_i), and idiosyncratic shock (u_{ijt}). We introduce unobserved individual characteristics in our model as the observed sample of individuals in a given job type may not be a random sample of the population. That is, the choice of the job type are usually a careful decision of individuals with the consideration of their preferences, aspiration, or likelihood of finding the position. Equation (2) specifies individual log wages in each job type as a function of observables, Z_{ijt}, and unobservable characteristics, σ_i and ϵ_{ijt}. Note that we assume for the unobserved individual heterogeneity that affects the individual i's decision for status-size pair and also, at the same time, earned income. Without assuming for unobserved heterogeneity in propensities to job type that are correlated with wage generating process, we will earn a biased estimators, which has been forthfully argued in the literature.

To control for unobserved heterogeneity, we introduce rich construction of the error term. Firstly, we include second-order polynomials of probability of working in a particular job segment based on the observable individual characteristics (Dahl (2002), Kennan and Walker (2011) or Bayer et al. (2011), among others). To construct the polynomial terms, we divide the population into 80 mutually exclusive cells defined by the observable characteristics of workers such as age, education, and gender. Then, for each cell, we compute the proportion of individuals for each of the four job types. These proportion of job type in each cell will be used to correct for unobserved individual characteristics. The calculation of these terms allows us to generate a polynomial function of the probability, $f(p_{ijt})$, that an individual i chooses to work in a job type j in year t, which non-parametrically corrects for unobserved individual characteristics. As those polynomial terms reflect the proportion of workers in each job-type categories, which then becomes an important information for individual with certain characteristics, these terms partially reflect for the demand side of the labor market. We additionally control for the individual fixed effect.

Our estimation of the systems of equations (1) and (2) is done in two stages. First, we estimate the proportion of workers for each of the four job types for each of the 80 mutually exclusive cells defined by age-education-gender. In each cell, the estimated proportion of individuals who work for a wage in the job type j in year t ($\hat{p}_{ijt},\ j = 1, 2, 3, 4$), their squared terms ($\hat{p}^2_{ijt},\ j = 1, 2, 3, 4$) and pairwise interaction terms ($\hat{p}_{ijt} \times \hat{p}_{ikt},\ j \neq k$) will be used in the next step as the predicted probability that an individual belonging to a particular cell chooses to work in the respective job type. We use the number of years worked in the current job and the indicator for the existence of labor union as an instrument such that it indirectly influences job-type choice only through current wage. So the identification of the earnings equation relies on the number of years worked in the current job, the existence of labor union and also non-parametric nature of the Dahl polynomial (defined below). We estimate equation (2) where Z_{ijt} includes a constant, a years of schooling, a female dummy, age and its square, a marital status dummy and nine occupational dummies. The inclusion of broad occupational categories in Z_{ijt} notably improves the prediction of counterfactual earnings and allows us to identify the earnings coefficient in the ensuing job-type choice model. Our equations (1) and (2) can be written as follows:

$$ln\, w_{ijt} = \alpha_j Z_{it} + \delta_{jt} + \phi_i + f(p_{ijt}) + \xi_{ijt} \, (3)$$

$$U_{ijt} = V_{ijt} + v^u_{ijt} = \gamma \hat{w}_{ijt} + \beta' X_{ijt} + v_{ijt} \, (4)$$

Once we correct for unobserved characteristics, we put individuals into a sub-sample with each job-type, and then conduct a regression analysis to estimate the coefficients. These coefficients then are used to calculate the counter-factual wages. Thus, the counterfactual wage for the whole population represents the estimated wage that each individual with certain observed and unobserved characteristics find job at the certain status-size category. Since there exists some error in the estimation of the cell probabilities ($\hat{p}_{ijt}$) in the first stage, the standard errors for Eq. (3) are bootstrapped with 1,000 replications. Once we conduct our first stage regression, then in our second stage, we use our estimated counterfactual wages to study its effect on the job-type choice. Next, we predict log earnings $\ln\hat{w}_{ijt}$ in all four job types for each individual in year t in the sample, using the estimated Eq. (4). The observable part of the utility associated to each job type is based on the earnings predictions computed in the first stage, as well as on a number of individual controls. We assume that the individual-job type-specific shock ξ_{ijt} follows an Extreme Value Type-I distribution, which generates distribution of v_{ijt} that is consistent with Generalized Extreme Value distribution. Specifically, we partition the four employment types into two nests: a singleton containing non-regular workers, and a duple with regular workers. The nested logit structure relaxes the independence of irrelevant alternatives (IIA) and rather assumes that there is a correlation in the error terms among non-regular workers and among regular workers, but do not have a correlation between non-regular and regular workers. The parameters to be estimated are the coefficient γ and the vectors of coefficients β. The main explanatory variable for the probability of choosing a particular job-type is our estimate of expected log earnings at that type ($\hat{w}_{ijt}$). We also include controls for all the variables that were used in the previous steps (Z_{it}), except the existence of union, the years of work experience ($tenure$), and its square term to allow them to work as instruments. As additional instruments in the second stage that do not directly affect wages, but indirectly affect wages through their impacts on an individual's job choice, exploiting the rich individual-level data, we include each individual's parents' years of schooling, and indicator variables for whether the current job provides severance payment and social insurance. Lastly, we use a correlated random-effects specification (Mundlak, 1978; Chamberlain,1982) to control for an individual-specific effect in the correlated random coefficient model:

$$v_{ijt} = \psi_{ij} + \overline{X}_i \xi_{jt} \; (5)$$

where $\overline{X}_i$ is the time averages of control variables for each individuals. We bootstrap standard errors to account for the two-stage estimation procedure.

3.2. The Effect of Dualistic Labor Market

In the previous sections, we calculated counterfactual wages of the four employment types for each individual worker. Using the four counterfactual wages, we calculate widely used inequality measures such as Gini Coefficient and Theil's index to quantify a degree of labor market segmentation faced by each individual workers in labor market. Our Appendix describes the exact formulae we used to construct the index. As this measure captures the degree of wage difference over the four possible job types, We use this index as a proxy for the degree of labor market segment faced by individuals. We study how the index is related with the decisions on labor market entrance and money spent for private education for themselves and for their children. Assuming $E(\epsilon_{ijt}|lnw_{ijt}, X_{ijt}, \alpha_i) = 0$, we use the following fixed-effect model:

$$y_{ijt} = \alpha_j S_{ijt} + \beta_i' X_{ijt} + \alpha_i + \epsilon_{ijt}(6)$$

Where S_{ijt} is the index for the degree of labor market segmentation, X_{ijt} control variables such as age polynomials, education polynomials, dummies for gender and marital status, occupation dummies, and industry dummies. We also control for the log of wage earning in the current job. We hypothesize that, for young working age population, DLMS is negatively related with marital status and the number of children as they tend to invest more for building up human capital. We also hypothesize that money spent for their own education increases as people wants to reduce the potential wage gap across the labor market segments. In the next section, we report our results.

4. Results

In this section, we estimate a two-equation Roy model for migration and earnings, which allows for unobserved heterogeneity in individual propensities to migrate that also affect earnings. Our estimation takes place in two steps, and we compute bootstrapped standard errors to account for the sequential nature of the estimation.

4.1. Counter-factual Earnings

We first report our regression results for earning equations. We use the information on the hourly wage of workers in each job type. We estimate one equation for each of the four labor segments, on the sample of employed workers who report positive earnings. The dependent variable is the log of hourly earning (normalized to 2015 Korean won) for wage earners in each respective job type. The right-hand side includes a vector of occupational dummies, a polynomial in age, years of schooling and dummies for being female, and being married. Including occupational dummies allows for relatively high goodness of fit, which is essential in producing accurate predictions for counter-factual earnings. Even after controlling for individual observable characteristics, unobserved heterogeneity may bias our predictions for counter-factual wage. To address this concern, we produce selection-corrected earning, following the method of Dahl and additionally controlling for individual fixed effect. Our instrument variables only controlled for earning equation and thus identify the effect of expected wage on job-type choice are (1) average wage of individuals who are in the cell we constructed to control for Dahl's polynomials, (2) tenure and its square terms. For each job type, we estimate two models. The first model (labeled Mincer) does not control for Dahl's polynomials and amounts to a Mincer regression augmented with dummies of occupation and industry. The second model (labeled Dahl) corrects for self-selection into employment, by including a polynomial with the cell probabilities defined in the implementation section above.

The results are reported in Table 3. Two observations are worth noting. First, the coefficient on the log of average wage and tenure is significant across the different specifications. Second, The estimated results of the mincer equation and Dahl earning equations are very similar. That is, correcting for self-selection with Dahl's polynomials does not seem to make a sizeable quantitative difference in the predictions for after-tax earnings, suggesting that our rich set of observable characteristics and individual fixed effect captures most of the relevant heterogeneity. There are, however, reasons to prefer the earnings predictions that correct for self-selection. As the last row in Table 3 shows, we reject the null of joint zero values of the correction Dahl parameters. Second, our predicted earnings from Dahl earning equations differ from Mincer earning equation, which results in a significant difference in coefficient in our second stage regression.

4.2. Labor Market Segments

We now turn to the second stage of our estimation, the discrete occupational choice model based on the counterfactual wage. We consider of using conditional logit model and modified standard errors to address for the sequential nature of the estimation. Table 4 presents our estimates. Column 1 presents conditional logit model with the inclusion of correlated random effects. The main explanatory variable is the log of hourly wages, which we estimated with the inclusion of both observed and unobserved characteristics. Our estimated coefficient $\hat{\gamma}$ is positive and highly significant (2.230), indicating that higher expected earnings at a specific job segments increase the probability to locate there. The column 2 uses correlated random coefficient.

We now turn to the estimated coefficients of other controls. We observe that the coefficient of the schooling is not significant when we control for the unobserved individual characteristics with Dahl's polynomials. This means that Dahl's polynomials significantly reduces selection bias of Mincer equation, by absorbing individuals' unobserved characteristics and thus reducing coefficients on education variable. In our regression results with counter-factual earnings from Dahl's earning equation, which is our preferred one, we find that education plays at most a minimal role in influencing individuals' choice on labor segments conditioning on the projected earnings. Our estimated coefficients, $\hat{\gamma}$, shows that being females lowers propensity to work in the SME/R type and L/R type compare to SME/NR type, meaning that females tend to work as non-regular workers. The estimated coefficients are economically and statistically relevant, and our results show either the gender-based barrier to earn regular-type job or female's desire to stay as non-regular workers to spend more time for family work.

We further report the marginal effect of change in counter-factual wage on the choice on the labor market segment. The great advantage of the conditional logit model is that it delivers closed-form solutions for the choice probabilities (Eq. (6)). We can derive the probabilities as

$$Pr(U_{ijt} = j) = \frac{exp(\gamma \hat{w}_{ijt} + \beta' X_{ijt})}{\sum_j exp(\gamma \hat{w}_{ilt} + \beta' X_{ilt})} \quad (6)$$

for $j = 1, 2, ..., 4$.

We denote this elasticity by ϵ_{jk} as:

$$\epsilon_{jk} = \frac{\partial lnp_k}{\partial lnw_j} \; j, k = 1, 2, 3, 4$$

The matrix $\sum^{CL}$ collects the whole matrix of elasticities, where element (j, k) in the matrix corresponds to the percentage change in choice probability p_k associated to a 1 percent increase in log earnings at job type j, for $j, k = 1, 2, 3, 4$. The matrix collecting all elasticities ϵ_{jk} is

$$\sum^{CL} = \gamma \begin{pmatrix} 1-p_1 & -p_1 & -p_1 & -p_1 \\ -p_2 & 1-p_2 & -p_2 & -p_2 \\ -p_3 & -p_3 & 1-p_3 & -p_3 \\ -p_4 & -p_4 & -p_4 & 1-p_4 \end{pmatrix} \quad (7)$$

where γ represents the coefficient of log earnings in the latent utility model (Eq. 4).

We now comment on the magnitude of the impact of a marginal change in log earnings on job type choice suggested by our parameter estimates. We calculate the matrix of elasticities for each individual using our estimated coefficients and then average over the entire sample. Our results are reported in Table 5A and Table 5B. The magnitude of elasticities on our results with earning equation from Mincer is significantly larger than the ones with Dahl earning equation. Our results infer that Dahl's polynomial absorbs a significant portion of unobserved individual characteristics that affect wage payment; without including them, the estimated coefficient will be upwardly biased. So, our report will focus on the result of Dahl's earning equation.

Main diagonal elasticity is all positive, while all off-diagonal components are negative, as predicted because the former are own-elasticities, and the latter are cross-elasticities. The own elasticity for workers in L/R group is most significant among the four groups, followed by workers in SME/NR group, workers in SME/R group, and then workers in L/NR group. A 10 percent increase in earnings for workers in SME/NR group leads to an increase in the probability of choosing that job segment equal to 4.7 percent, whereas the same percentage increase in expected earnings in workers who are in SME/R group is associated with 1.8 percent. Interestingly, we do not find any significant effect of the expected wage for workers in the L/NR group. As pointed out in the policy reports (Ha and Lee (2013), the primary incentive for workers L/NR is to use their current position as a stepping stone to reach to L/R segment, and the remuneration is less of their concern. The estimated effects of a 10 percent increase in earning are related to a 5.3 percent increase in the probability of choosing the L/R job segment. Next, the elasticity associated with the probabilities of working in the L/R segment and SME/R segment in response to a 10 percent increase in the expected wage by working in the SME/NR segment is -4.1 percent and -0.6 percent respectively. As for the cross-elasticities concerning the wage increase in SME/R, we observe that a 10 percent increase in the wage at the SME/R segment decreases the probabilities of working at the SME/NR and L/R by 0.6 percent and 1.2 percent respectively. As for the cross-elasticity of wage increase for the L/NR, we observe that it only decreases the probability of working in the L/R segment by 0.00025, which is not economically significant. A 10 percent increase in wage at the L/R segments negatively affects the probability of finding jobs at SME/NR segment and SME/R segment by 4.1 percent and 1.2 percent, respectively. The main finding in our estimated results with the preferred specification is that the estimated effect of counter-factual wage is highly relevant for the choice of labor market segments. Our estimated results give credence that we can use counter-factual wages to construct an index that quantifies the individual-specific degree of labor market segment (DLMS). Our results in this section validate our index, leading to the discussion in the next session.

4.3. Labor Market Segment and Resource Allocation

Knowing the importance of expected wage in segment choice, we constructed an index for the degree of labor market segment (DLMS) that varies in the individual-level. Figure 8A shows the annual trend of the four DLMS we constructed with different inequality index, explained in our appendix. While Schauer (2018) provides empirical evidence that labor market duality in Korea has contributed to growing income inequality among workers, our estimated measure, DLMS, goes further to provide the degree of labor market duality each individual face, using the expected income for the same individuals across different labor market segments. While each measure is in a slightly different range, all of the four measures show sharply rising trends overall, indicating higher variation in wages across four possible employment paths for each individual i given the same individual's observable and unobservable characteristics. Figure 8B plots annual averages of the Gini and the Theil index by educational attainment. Similar to Figure 8A, all of the four indices show rising patterns for all education categories. As one can observe from Figure 8B, the averages of DLMS for people with the highest education is the lowest among the group. It means that workers with high human capital earn a similar income across job types, compared to ones with low human capital. Another key observation is that the gap in both measures between the group "less than college" and the group "advanced degree" has been steadily widened, suggesting additional evidence of labor market segmentation. The figure shows that individuals are increasingly incentivized to spend time and money to accumulate human capital so that they become less vulnerable to DLMS. This inference motivates us to conduct a regression analysis of the effect of rising wage differentials on individual worker's various labor market related decisions. In this section, we report our regression results on the effect of DLMS for choices on resource allocation. KLIPS contains rich information such as money spent on private education, total expenditure, marriage status, and household members. Also, as KLIPS is a panel data, we can study for the labor market entrance. We can interpret the estimated results as the effect of DLMS on individuals' resource allocation on human capital. We start to report on the expense of private education, and then labor market entrance, marriage decision, and the number of children that the married people have.

4.3.1. Private Education

Table 6 reports the regression results on the effect of DLMS on private education. We report our results with two different samples. The first sample consists of individuals who are not employed and who do not have children. The expenditure on education for this group is a proxy for investment for education to hit the better job segment. The second sample consists of individuals who are employed and without children. We may interpret the amount of expenditure made by this sample as an investment for enhancing their performance in the current job or moving up to the superior segment. Though we are not able to distinguish between the two motives with our regression results, our results still merit attention in that laborers often do not correctly know when they decide on education investment whether they would go different labor segments or move up within the same job segment. We can still interpret that wage differences due to market concentration incentivize individuals to invest more in private education.

The first four columns of Table 6 are the regression results with the sample of non-employed without children and the next four the results with the sample of employed without children. Across the sample and different indexes for DLMS, we find that DLMS is positively related to money spent on education. With a 10 percent increase in DLMS, we find that the non-employed, working-age population increased their education investment by 5.2~7.1 percent. With the sample of employed working-age populations without children, our results show that a 10 percent increase in DLMS is positively associated with an increase in education expenditure by 2.2~4.2 percent, depending on the index for DLMS.

Next, we report the regression results when we change our dependent variable as the ratio of monthly expenses on education is from the total monthly expenditure. Table 7 shows that the ratio of expenditure on education is still positively related to DLMS. With the sample of the non-employed, working-wage population without children, we find that 0.27-0.36 percentage increases in expenditure ratio in response to a 10 percent increase in DLMS. As for the employed people without children, we observe that 0.23-0.34 percentage increases. Our regression results on the education expense show a consistent, positive relationship with DLMS across indexes and samples, and even after controlling for current income. Our results show that the depth of labor market segmentation that each face does matter and affects the education investment. Our regression results, combined with figure 8, grant us the following inference: in response to the deepening labor market segment, people invest their money in private education to reduce the degree of labor market segments they face.

4.3.2. Labor Market Entrance, Marital Status, and Number of Children

As discussed in section 2, we hypothesize that the severity of the labor market segmentation deters the labor market entrance of the young people as they are incentivized to prepare themselves better to work in the superior labor market segment. Delayed labor market entrance necessarily delays marriage decisions, which then reduces the number of children for each couple. We report the results of the regression analysis that supports our hypothesis. Table 8 reports our regression results on the labor market entrance. Our sample for this regression is individuals who are less than 37 years old. We construct a binary variable that indicates 1 if the respondent is in the labor market, and 0 if the respondent is non-employed. Our results show that the working-age population who are less than 37 years old tend to delay labor market entrance in response to increase in DLMS: with 10 percent increase in DLMS, the labor market entrance among individuals who are less than 37 years reduces by 1.1-2.7, depending on the DLMS index.

Table 9 shows the relationship between DLMS and marital status under 37 years old working population. Our results show that the DLMS and marital status of young people are negatively related: with a 10 percent increase in DLMS, the marital status decreases by 0.7-1.0 percent, depending on the indexes. However, regression results with the DLMS index based on Gini do not show a statistically significant result. Table 10 reports our regression results on the number of children among married couples. We report our results with two different samples: (1) all married population and (2) employed and married population. Our results indicate that increased DLMS is negatively related to the number of children: with a 10 percent increase in DLMS, 1.0-3.6 percent of children reduces with our first sample; and 0.7-1.9 percent decrease is found with our second sample. Together with our reports on the relationship between DLMS, labor market entrance, and marital status reported in Tables 8 and 9, we draw an inference that increased structural wage gap due to market concentration further incentivize individuals to invest more in their human capital, both time and money-wise.

5. Conclusion

This paper studies the effect of labor market segmentation on individuals' decision on money and time use in South Korea. We use a conditional logit model in the first part of the study where the non-observed heterogeneity of the individuals that affects both pay and job-type decision is clearly modeled. Once we establish that the expected income is a determinant of job-type choice, we construct an index that quantifies individual-specific labor market segment.

Using individual panel data and exploiting individual-level labor market segmentation, we estimate their net impact on money spent on private schooling, labor market entry decisions. Our results show that segmentation of the labor market is positively related to money spent on private education for themselves and their children, time spent before entering into the labor market. We also shows that the labor market segmentation is positively related with marriage, and also number of children.

While the impact of labor market segmentation has been intensively discussed with growing globalization and technological advance, this is the first paper that attempt to construct individual-level labor market segment, and study its impact on the use of individual resources. Given the evidence in our paper, particular attention should be paid to the effects of labor market segment.When salaries are increasingly determined by the type of employment that individuals work in, rather than their own merit, individuals living in advanced countries such as South Korea that are able to afford their time and energy can increase their resources to accumulate their human capital. Our current paper does not analyze whether the increased expenditures to build a human capital are good for a society. Whether this investment can be an significant driver of long-term economic development or a waste of resources can be explored in the future work.

Also, our results suggests that it is worthwhile to further investigate whether parents choose the quality of children over quantity as deepening job market segment necessitates excessive investment to children's education to be included in the superior segment of the labor market.

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Appendix

A. Proxy for the Degree of Labor Market Segmentation (DLMS)

A1. The Gini Coefficient

First of all, we apply the Gini Coefficient, widely used inequality measures (Gini, 1912) to quantify the DLMS faced by each individual. The Gini Coefficient measures the overall dispersion of a certain variable, designed such that the closer to zero the Coefficient is, the closer to perfect equality. In the context of the four counterfactual wages, the Gini Index in this study measures the overall dispersion of each individual's possible wages. Thus, if the Coefficient is closer to one for a certain individual, it means she faces more unequal possible employment opportunities. Specifically, we denote g_{it} for the Gini index calculated by using the respondent i's counterfactual wages in year t, had the respondent worked at each of the four labor segments (m); (1) non-regular SME jobs (NR-SME), (2) non-regular job in the large-sized firms (NR-L), (3) regular job in the SMEs (R-SME), and (4) regular job in the large-sized firms (R-L).Then,

$$g_{it} = \frac{1}{2n^2 \bar{w}_{it}} \sum_{j=1}^{4} \sum_{k=1}^{4} |cwage_{ijt} - cwage_{ikt}| \quad (A.1)$$

where n indicates the number of possible employment types (and thus $n = 4$), $\bar{w}_{it} = \frac{1}{4} \sum_{j=1}^{4} cwage_{ijt}$ is the mean value of the four counterfactual wages for individual i in year t, $cwage_{imt}$ indicates the counterfactual wages had the respondent i worked as employment type m in year t.

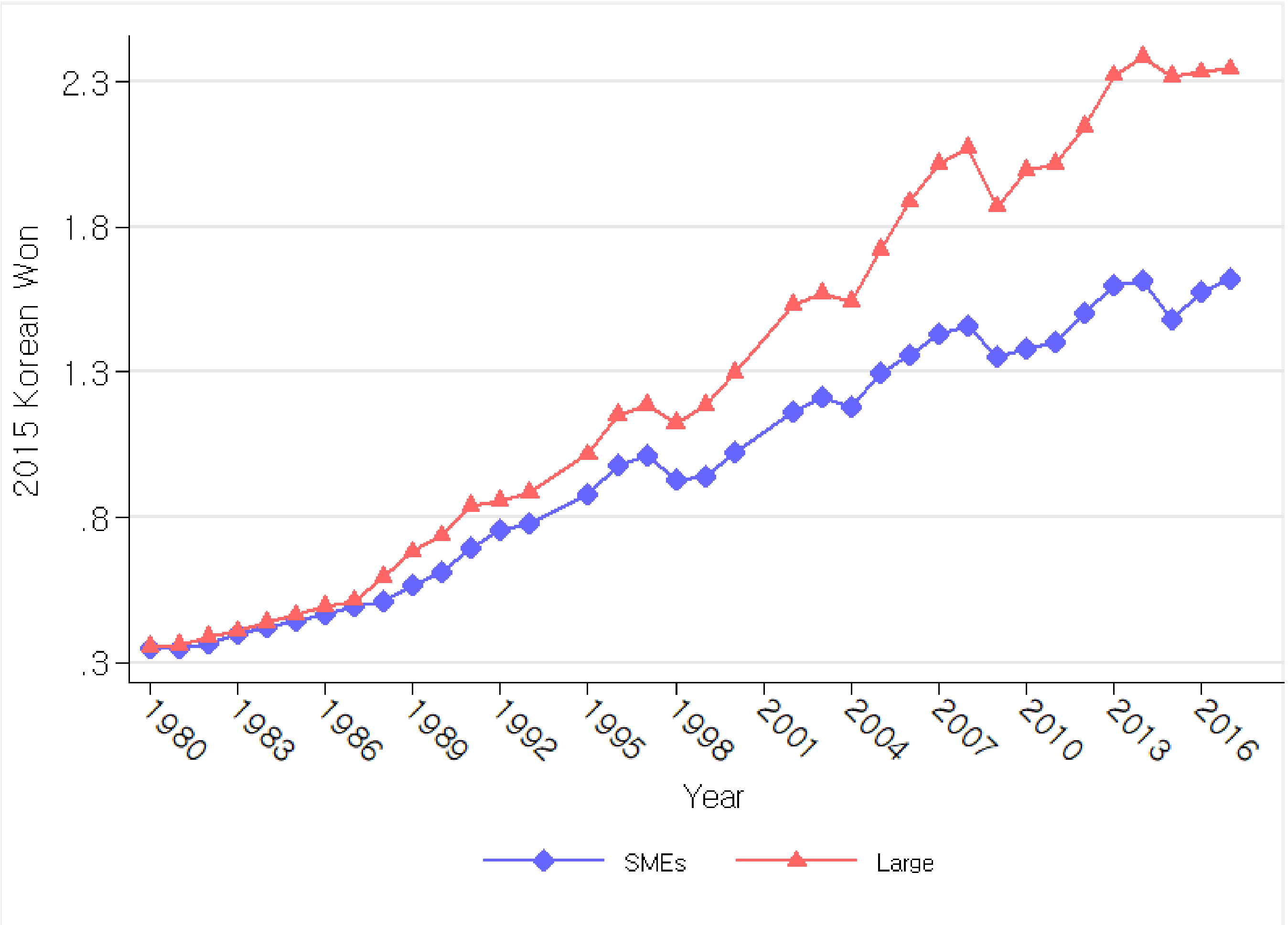
A2. Theil Index

The second inequality measure adopted here is based on Theil (1979). Similar to the Gini coefficient, the Theil index is designed to capture the degree of dispersion of a variable, and thus it has been widely used to quantify the income inequality. Additional advantage of using the Theil index is that it enables us to flexibly assign different weights (α) for the different parts of the income distribution. The most commonly used values for α are 0, 1, and 2, all of which are used in this paper to quantify the DLMS. Specifically, we define q_{it}^{α} as the Theil index with α for an individual i in year t such that:

$$
q_{it}^{\alpha} = \begin{cases} \frac{1}{N\alpha(\alpha-1)} \sum_{j=1}^{4} \left[\left(\frac{cwage_{ijt}}{\bar{w}_{it}} \right)^{\alpha} - 1 \right], & \alpha = 2 \\ \\ \frac{1}{n} \sum_{j=1}^{4} \frac{cwage_{ijt}}{\bar{w}_{it}} \ln \left(\frac{cwage_{ijt}}{\bar{w}_{it}} \right), & \alpha = 1 \\ \\ -\frac{1}{N} \sum_{j=1}^{4} \ln \left(\frac{cwage_{ijt}}{\bar{w}_{it}} \right), & \alpha = 0 \end{cases} \qquad (A.2)
$$

where n indicates the number of possible employment types (and thus $n = 4$), $\bar{w}_{it}$ is the mean value of the four counterfactual wages for individual i in year t, $cwage_{mt}$ indicates the counterfactual wages had the respondent i worked as employment type m in year t.

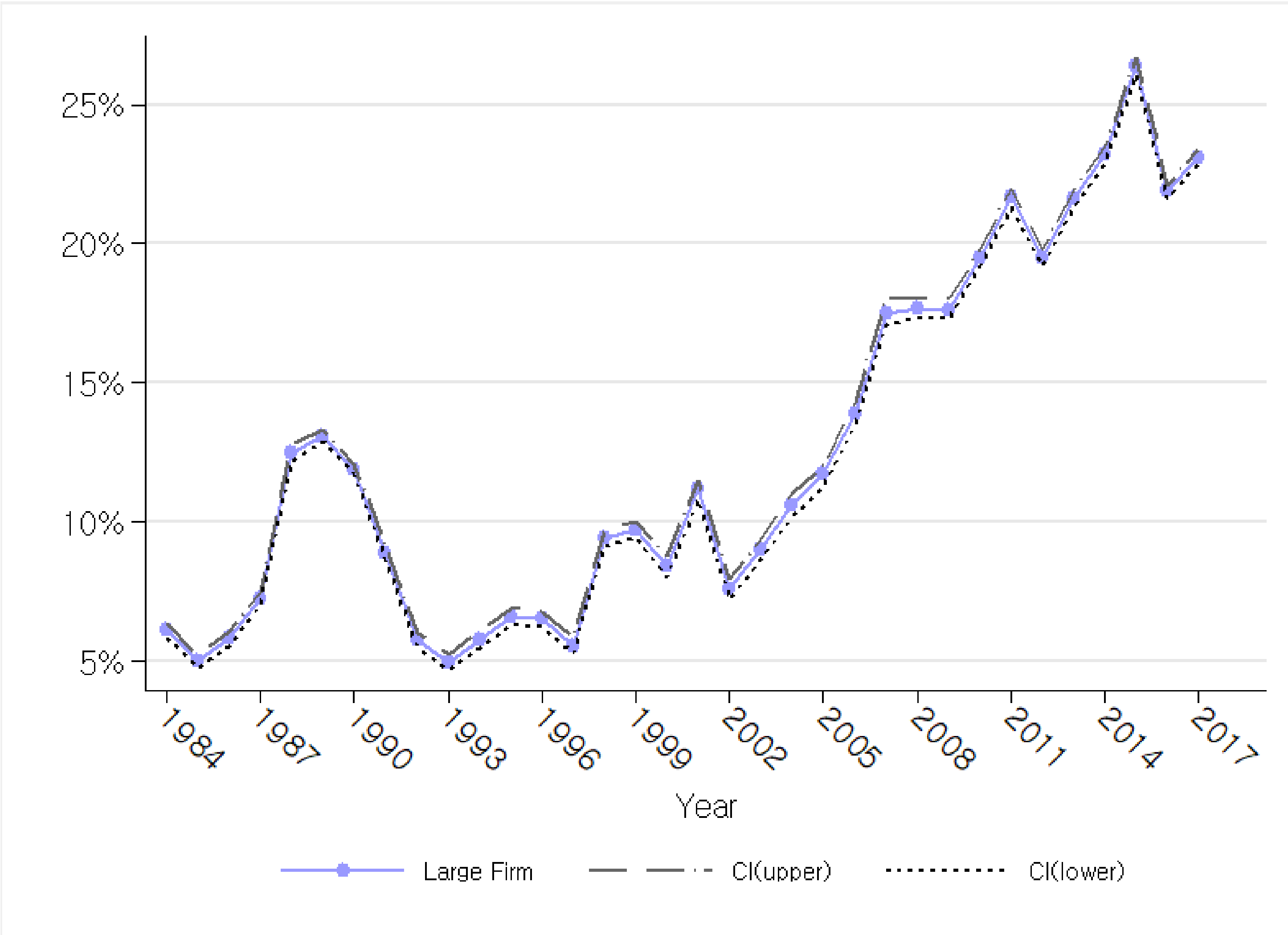
Figure 1. Average Hourly Wage by Firm Size



Source: *Wage Structure Survey*, 1980 - 2017

Notes: The graph plots the average hourly wage rate of all working individuals by firm size. Firms with less than 300 employees are defined as "SMEs (Small and Medium Enterprises)", whereas we define "Large" firm if the firm hires more than 300 employees. *Wage Structure Survey* data includes each respondent's monthly nominal wages (excluding overtime wages, since hours of overtime work data is not available), along with monthly estimated hours of work. We directly calculate hourly wage rate by diving monthly nominal wages by hours of worker per month. Average wages are then deflated by 2015 Consumer Price Index (CPI) at local province level. The regional CPI data is available at Statistics Korea (KOSTAT).

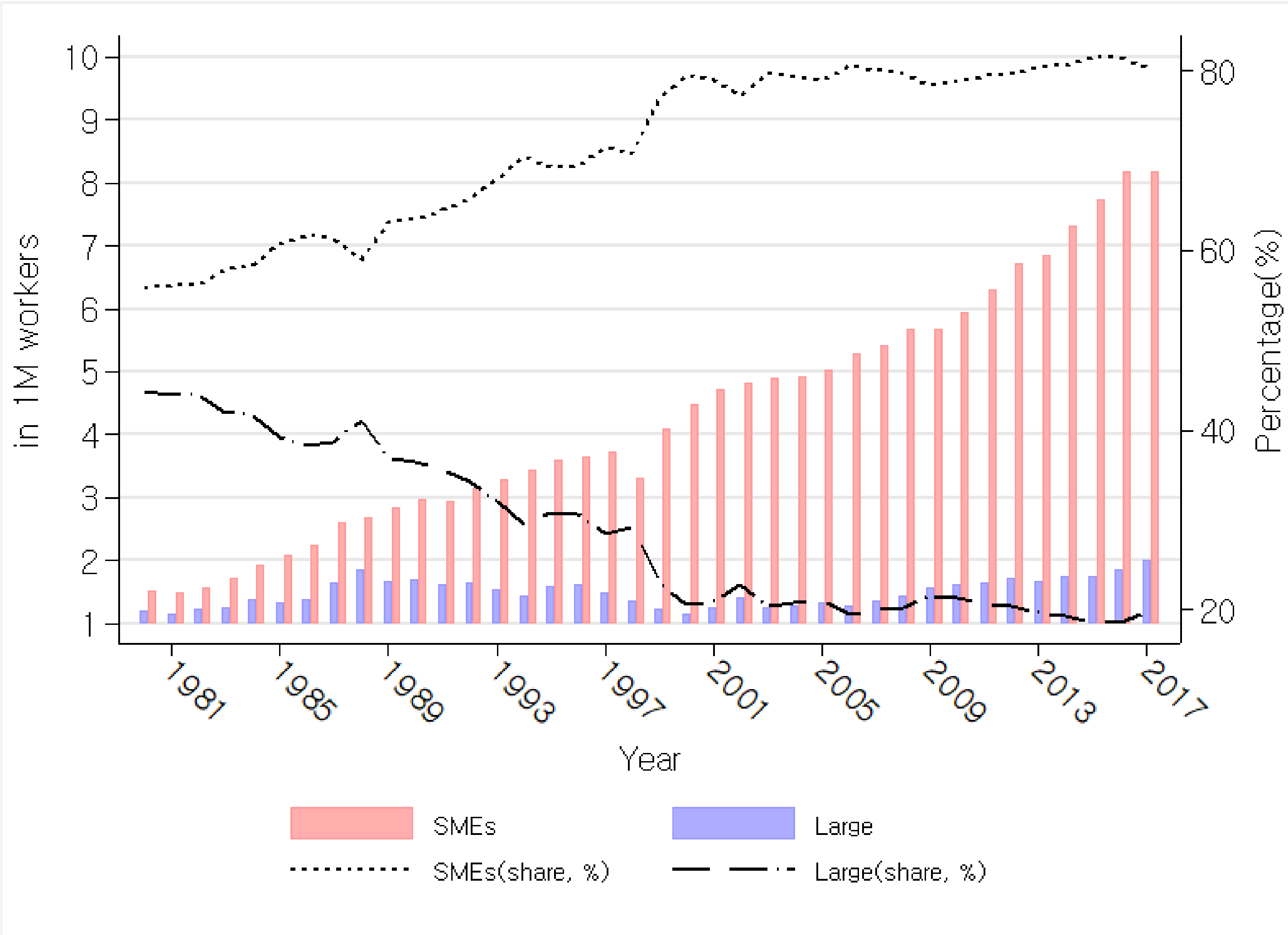
Figure 2. Coefficient on Firm Size on wage regression



Source: *Wage Structure Survey*, 1980 - 2017

Notes: The graph plots the estimated coefficients on D_M (a dummy for large firms) from the equation (1) from 1984 to 2017. The two types of dotted lines correspond to 95% confidence intervals for the estimated α_M.

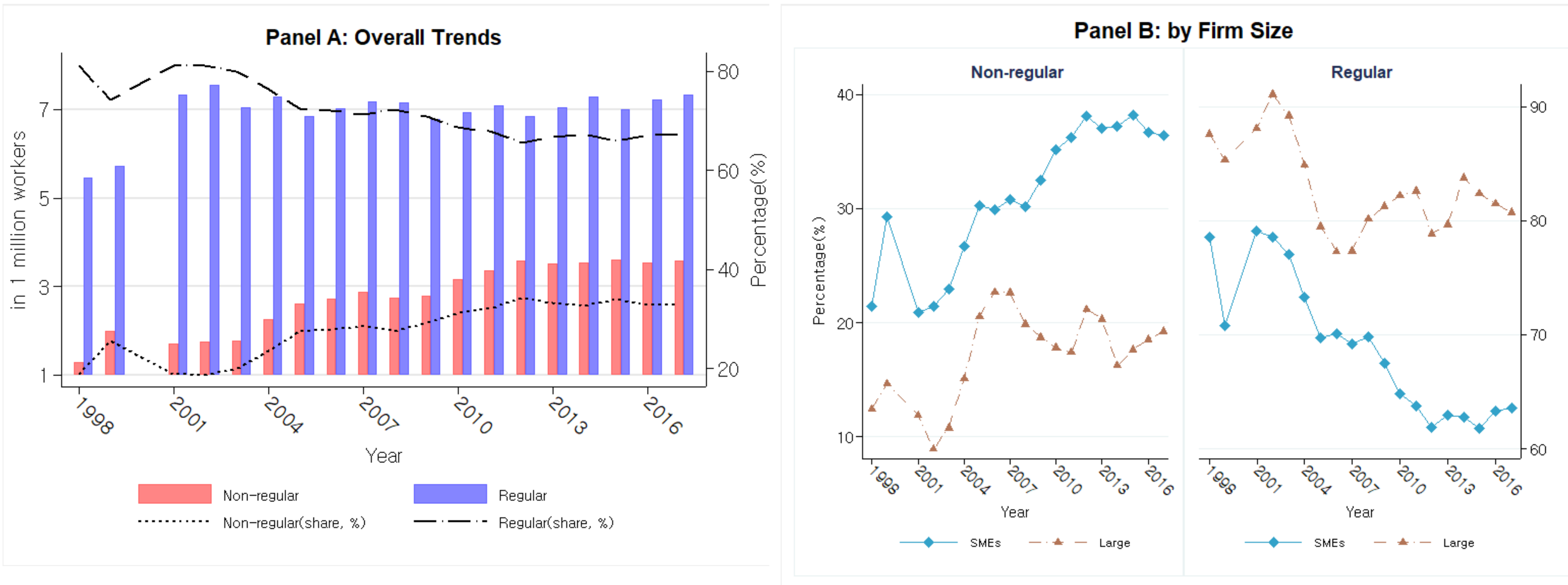
Figure 3. Employment Trends over Time by Firm Size



Source: *Wage Structure Survey*, 1980 - 2017

Notes: The bar graph plots the trend of the number of employed in SMEs and large firms from 1980 to 2017. The two dotted lines indicate the employment share of workers in SMEs and large firms, respectively, out of the total number of workers.

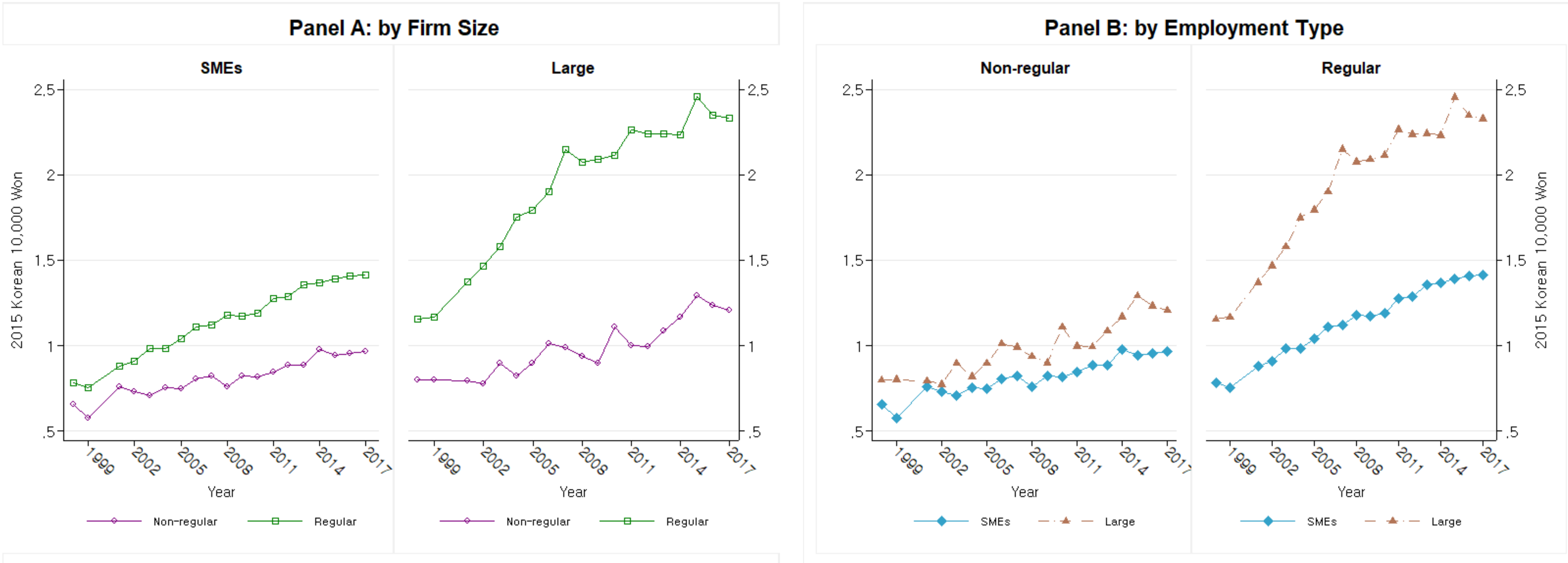
Figure 4. Share of Regular/Non-regular Workers by Firm Size



Source: *Korean Labor & Income Panel Study (KLIPS)*, 1998 – 2017

Notes: In addition to the formal classification of irregular workers defined by the tripartite committee of National Assembly in July 2002, KLIPS also includes a questionnaire that asks whether the respondents consider themselves as regular or non-regular workers. Although it is subjectively self-determining mainly based on the employment duration, the record shows that more than 80 percent of self-declared non-regular workers were actually turned out to be consistent with the formal classifications. Given its simplicity, we directly rely on the self-declaring classification of non-regular status. There was no question asking the respondent's employment type in 2000 survey, and thus not reported in the graph.

Figure 5. Average Real Hourly Wage Rate



Source: *Korean Labor & Income Panel Study (KLIPS)*, 1998 – 2017

Notes: Average wages are deflated by 2015 Consumer Price Index (CPI) at local province level. The regional CPI data is available at Statistics Korea (KOSTAT). *KLIPS* data includes each respondent's monthly nominal wages (excluding overtime wages), along with weekly estimated hours of work. Following KLIPS's instruction on calculating weekly wages, we compute weekly wages by diving monthly nominal wages by 4.3 (weeks). Hourly wage rates are then calculated by dividing weekly wages by actual hours of worked per week. Then, hourly wages are deflated by 2015 Consumer Price Index (CPI) at local province level. The regional CPI data is available at Statistics Korea (KOSTAT).

Figure 6A. Money Spent for Private Education

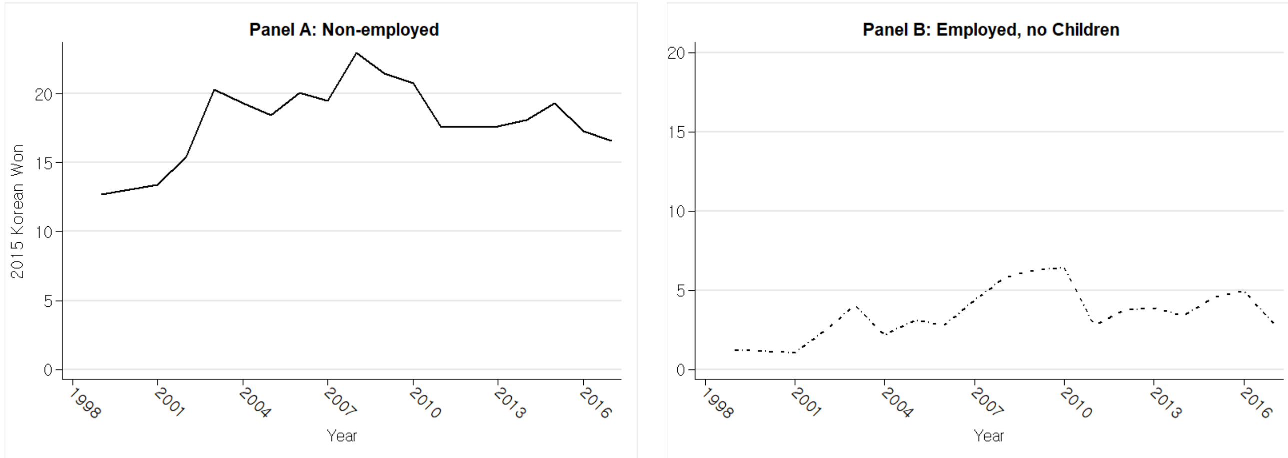
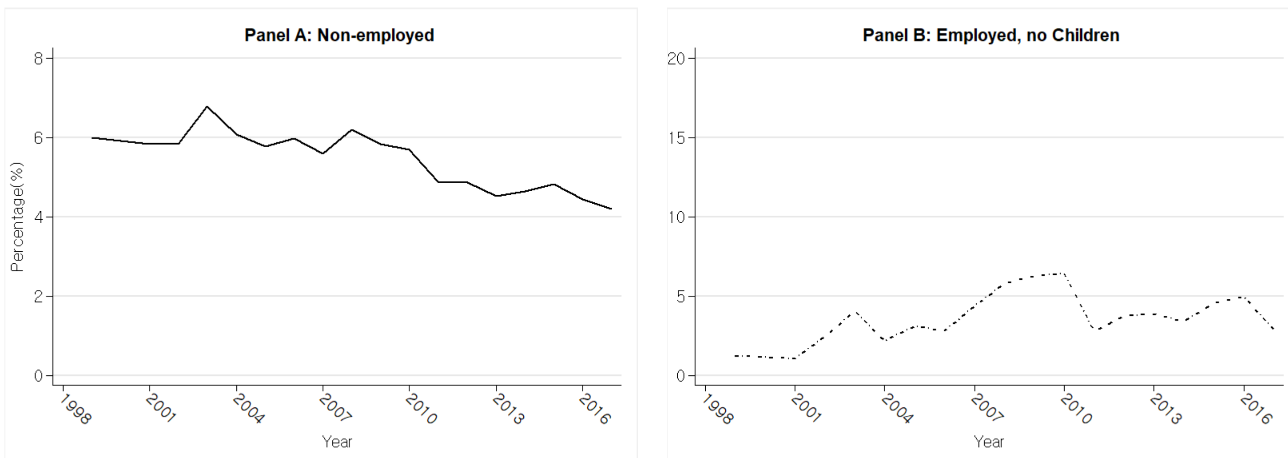


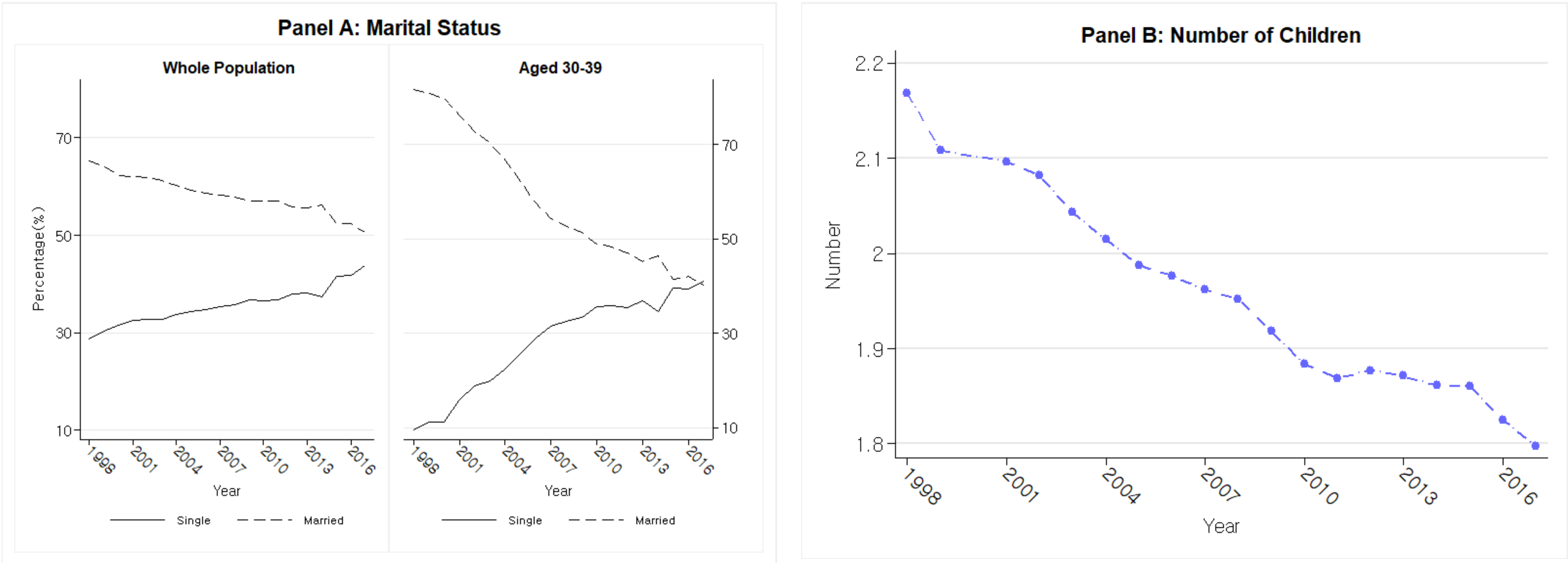
Figure 6B. Money Spent for Education/Total Expenditure



Source: *Korean Labor & Income Panel Study (KLIPS)*,, 1998 – 2017

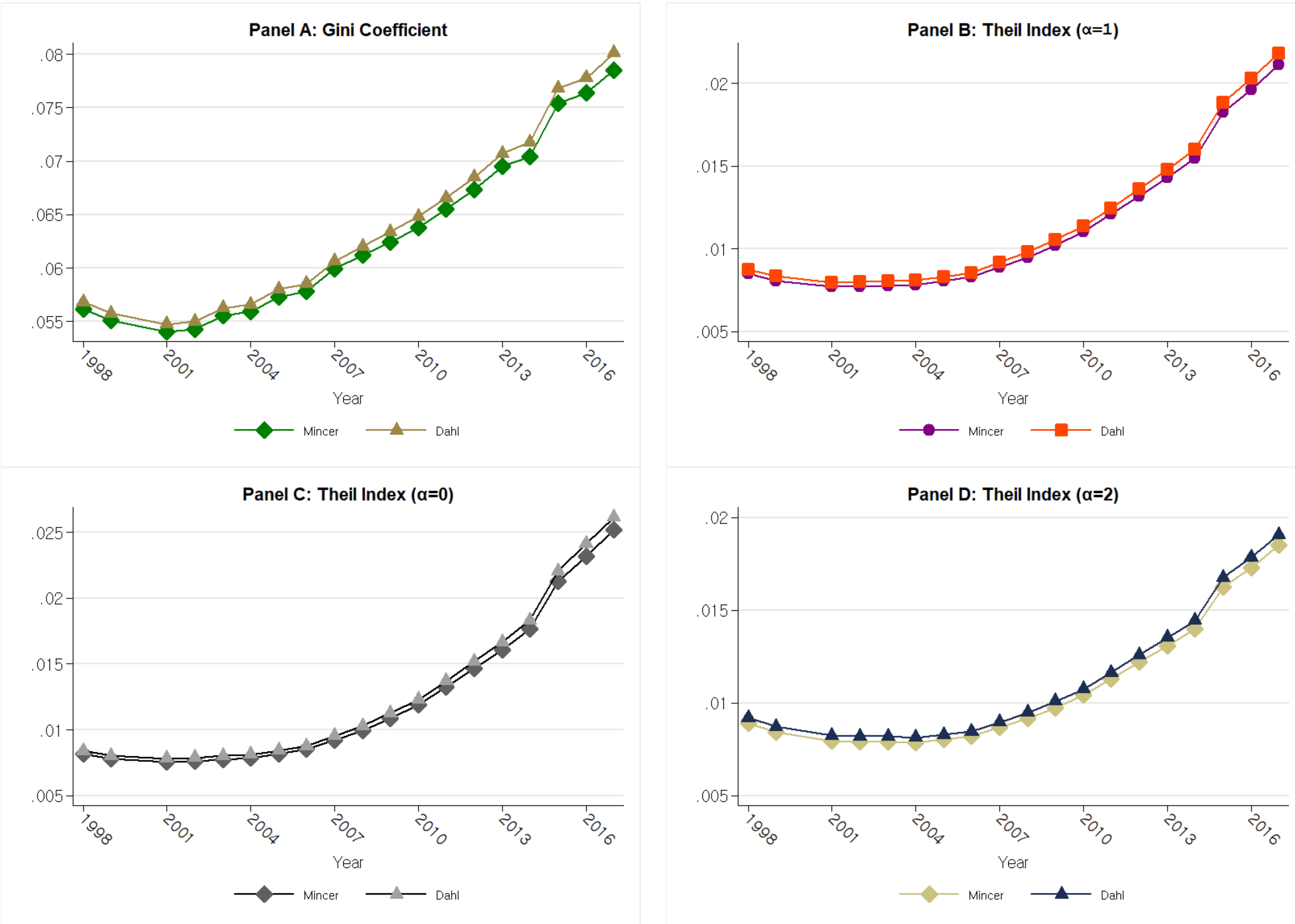
Notes: The two graphs plot monthly average spending on private education for the three groups; "non-employed (unemployed or not in the labor force)" in Panel A, "married couple without a child" in Panel B, "married couple with positive number of children" in Panel C. Spending on private education includes tuition for private academies (including childcare facilities), pay for tutors, etc. Monthly spending on private education is deflated by 2015 Consumer Price Index (CPI) at local province level. Figure 6B plots the share of monthly spending on private education out of total monthly spending (deflated by 2015 CPI) for the three groups.

Figure 7. Marital Status and the Number of Children among Married Couple



Source: *Korean Labor & Income Panel Study (KLIPS)*,, 1998 – 2017

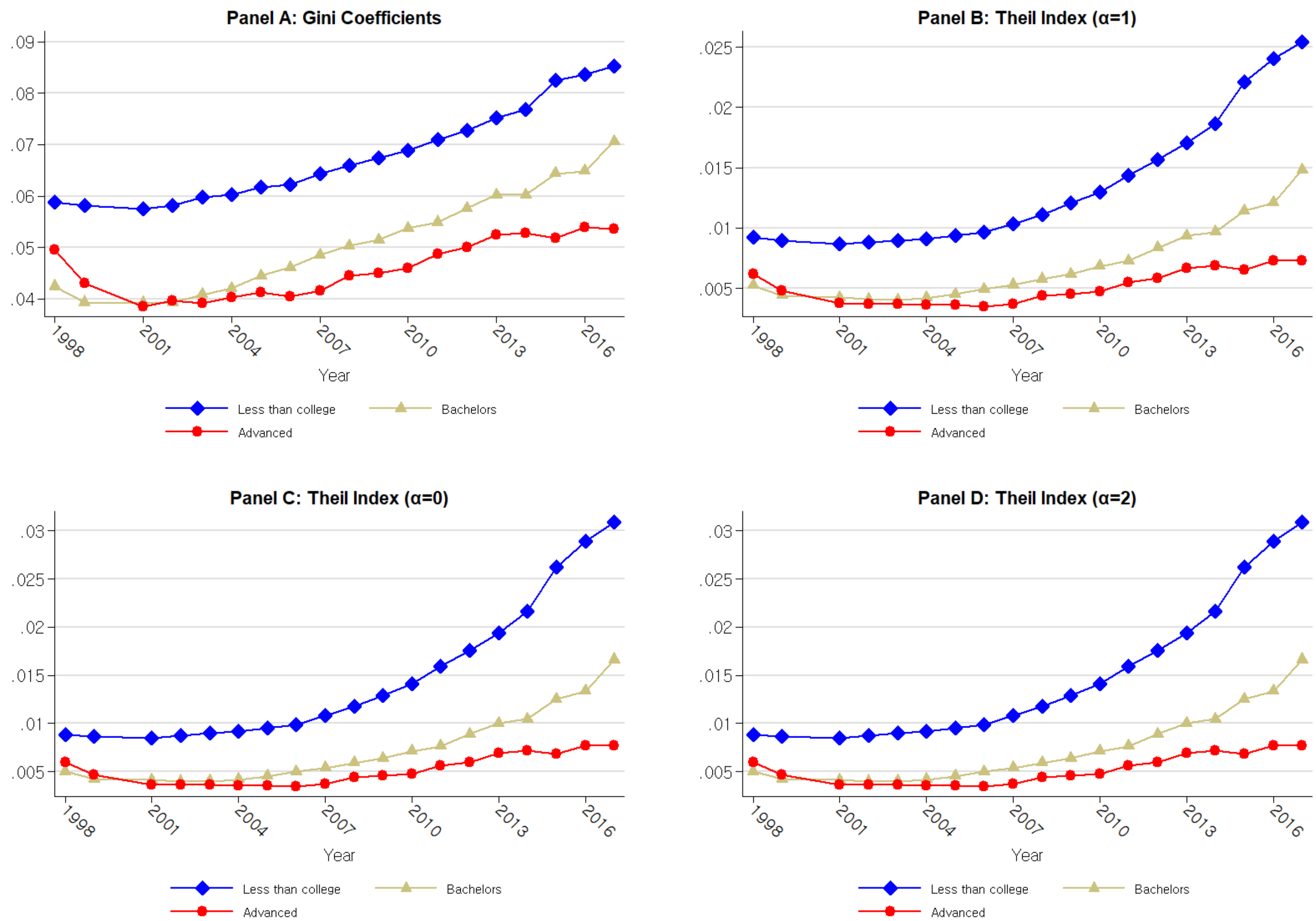
Figure 8A. The Proxy for Labor Market Segmentation



Source: *Korean Labor & Income Panel Study (KLIPS)*, 1998 – 2017

Notes: The graph plots annual averages of the two inequality indices, Gini, and Theil, to illustrate the extent to which workers' counter-factual wages are dispersed over the four possible occupation paths. Applying the Gini Coefficient (Gini, 1912), we estimate the individual-level dispersion of the four counterfactual wages, such that the closer to one, it indicates more unequal employment opportunities an individual might face. Similarly, based on Theil (1979), we compute three variants of the Theil index with $\alpha = 0, 1, 2$.

Figure 8B. The Proxy for Labor Market Segmentation by Educational Attainment



Source: *Korean Labor & Income Panel Study (KLIPS)*, 1998 – 2017

Notes: The graph plots annual averages of the Gini, and Theil, by education level. We decompose educational attainments into the three categories; 1. "less than college" includes high-school drop-outs, high school graduates and some years in college; 2. "bachelors" includes individuals with a degree from 4-year university/college; 3. "advanced" includes those with professional degrees, masters, and doctorates.

Table 1: Descriptive statistics by Employment type and Firm sizes

Variables	SMEs (5 - 299 employees)				Large (more than 300 employees)				Non-Employed	
	Non-regular		Regular		Non-regular		Regular			
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
Demographic Variables										
Age	42.54	12.71	38.44	10.74	37.81	12.06	37.73	9.44	37.31	15.44
Male	0.52	0.5	0.619	0.486	0.39	0.49	0.70	0.46	0.39	0.49
Female	0.48	0.50	0.38	0.49	0.61	0.49	0.30	0.46	0.62	0.49
Years of Schooling	11.99	3.23	13.47	2.77	13.26	2.81	14.60	2.67	12.47	3.39
Education Categories										
High school or less	0.70	0.46	0.45	0.50	0.53	0.50	0.29	0.46	0.59	0.49
Some years in college	0.16	0.37	0.23	0.42	0.23	0.42	0.22	0.41	0.26	0.44
Bachelors	0.13	0.33	0.29	0.45	0.21	0.40	0.41	0.49	0.15	0.35
Advanced degree	0.02	0.13	0.03	0.18	0.03	0.18	0.08	0.27	0.01	0.10
Marital Status										
Single	0.30	0.46	0.36	0.48	0.42	0.49	0.30	0.46	0.46	0.50
Married	0.59	0.49	0.59	0.49	0.53	0.50	0.67	0.47	0.49	0.50
Divorced/Widowed/Separated	0.11	0.31	0.05	0.21	0.06	0.23	0.02	0.16	0.06	0.23
Number of Children	2.06	0.80	1.93	0.93	1.99	0.67	1.84	0.73	2.27	1.05
Number of Household Members	3.40	1.33	3.50	1.26	3.46	1.28	3.55	1.19	3.68	1.14
Monthly spending on education	12.06	26.23	18.43	35.91	18.50	35.01	31.92	47.60	18.24	38.43
Share of spending on education	4.37%	8.61%	5.80%	9.74%	5.55%	9.46%	8.19%	10.87%	4.84%	9.14%
Employment Variables										
Labor Market Entrance Age	23.13	6.98	23.05	5.64	22.97	6.70	23.10	4.64		
Log(Hourly wage rate)	8.87	0.55	9.18	0.57	9.04	0.56	9.69	0.61		
Hours worked	43.83	16.21	48.03	11.58	42.76	13.10	43.63	8.26		
Tenure	4.14	5.64	5.48	6.20	3.48	4.53	9.81	8.29		
Observations	18,489		37,779		2,990		14,332		76,963	

Sources: *Korean Labor & Income Panel Study* , 1998 - 2017

Notes: Wages are deflated by 2015 Consumer Price Index at a province level. 'Non-employed' includes individuals who are either unemployed (looking for jobs) or not in the labor force. We combine unemployed individuals and those who are not in the labor force, since it is subjective to differentiate between the unemployed from those who are not in the labor force. For example, individuals who are willing to take job offers voluntarily remain out of the labor force to acquire additional years of schooling, who are not classified as unemployed. Due to these statistical ambiguities that arise when calculating unemployment rate, we decide to not to distinguish the unemployed from those not in the labor force, but rather to combine them.

Table 2: Transition Dynamics across Employment Types

A. Years (1998 - 1999)

		To				
		SMEs/NR	**SMEs/R**	**Large/NR**	**Large/R**	**Non-employed**
	SMEs/NR	52.03%	17.63%	2.35%	2.03%	25.97%
	SMEs/R	3.59%	75.43%	0.28%	6.94%	13.75%
From	**Large/NR**	14.69%	5.33%	50.06%	10.11%	19.81%
	Large/R	0.35%	19.09%	1.45%	71.21%	7.90%
	Non-employed	7.64%	7.80%	0.83%	1.35%	82.38%

B. Years (2016 - 2017)

		To				
		SMEs/NR	**SMEs/R**	**Large/NR**	**Large/R**	**Non-employed**
	SMEs/NR	78.05%	5.82%	3.50%	0.42%	12.20%
	SMEs/R	1.80%	86.25%	0.14%	4.64%	7.16%
From	**Large/NR**	22.85%	2.08%	54.43%	2.87%	17.78%
	Large/R	0.00%	18.60%	0.22%	77.10%	4.07%
	Non-employed	6.18%	5.29%	0.94%	1.64%	85.95%

Sources: *Korean Labor & Income Panel Study* , 1998 - 2017

Notes: We calculate the transition dynamics that workers in each labor segment change their employment types between the two consecutive years, for the first (1998 - 1999) and the last sample period (2016 - 2017).

Table 3: First Stage Earnings Equation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	(1) SMEs/NR				**(2) SMEs/R**				**(3) Large/NR**				**(4) Large/R**			
	Mincer		Dahl		Mincer		Dahl		Mincer		Dahl		Mincer		Dahl	
Log(Avg.Group Wage)	0.283***	0.271***	0.318***	0.306***	0.234***	0.216***	0.241***	0.225***	0.291**	0.276**	0.263**	0.258**	0.353***	0.351***	0.384***	0.386***
	(0.044)	(0.044)	(0.050)	(0.051)	(0.022)	(0.020)	(0.025)	(0.022)	(0.119)	(0.120)	(0.122)	(0.114)	(0.036)	(0.037)	(0.041)	(0.042)
Tenure	0.008***	0.006**	0.008***	0.006**	0.012***	0.011***	0.012***	0.010***	0.021**	0.017*	0.021**	0.017	0.010***	0.010***	0.011***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)	(0.009)	(0.010)	(0.009)	(0.011)	(0.003)	(0.003)	(0.003)	(0.003)
Tenure squared	-0.000	-0.000	-0.000	-0.000	-0.000*	-0.000*	-0.000*	-0.000*	-0.001**	-0.001**	-0.001**	-0.001	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.064***	0.062***	0.071***	0.068***	0.273***	0.271***	0.279***	0.277***	0.050**	0.054***	0.060**	0.064**	0.065***	0.065***	0.065***	0.064***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)	(0.020)	(0.021)	(0.023)	(0.026)	(0.008)	(0.008)	(0.008)	(0.008)
Age squared	-0.000***	-0.000***	-0.000***	-0.000***	-0.001***	-0.001***	-0.001***	-0.001***	-0.000	-0.000	-0.000	-0.000	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.032	-0.039	-0.029	-0.036	-0.036	-0.034	-0.039	-0.037	-0.262	-0.254	-0.258	-0.249	0.045	0.046	0.051	0.053
	(0.027)	(0.029)	(0.027)	(0.037)	(0.025)	(0.025)	(0.025)	(0.028)	(0.168)	(0.167)	(0.158)	(0.247)	(0.046)	(0.046)	(0.046)	(0.047)
Schooling	0.001	0.000	0.000	0.000	0.001	0.001	0.001	0.001	0.009*	0.009*	0.009**	0.009	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.004)	(0.007)	(0.001)	(0.001)	(0.001)	(0.002)
Schooling squared	-0.004	-0.005	-0.006	-0.008	0.014	0.010	0.013	0.009	-0.037	-0.058	-0.035	-0.057	0.023	0.021	0.025	0.024
	(0.023)	(0.022)	(0.023)	(0.021)	(0.011)	(0.011)	(0.011)	(0.011)	(0.065)	(0.056)	(0.065)	(0.056)	(0.016)	(0.017)	(0.016)	(0.018)
Unemp_rate	-0.008	-0.008	-0.008	-0.008	0.001	-0.000	0.002	0.000	0.006	0.001	0.012	0.005	0.014*	0.011	0.014*	0.012
	(0.011)	(0.010)	(0.011)	(0.010)	(0.006)	(0.006)	(0.006)	(0.005)	(0.028)	(0.027)	(0.028)	(0.028)	(0.008)	(0.008)	(0.008)	(0.008)
Constant	4.708***	5.048***	5.568***	6.101***	-0.369	-0.035	-0.445	-0.065	6.573***	6.515***	7.754***	7.497***	4.010***	4.104***	3.271***	3.305***
	(0.364)	(0.393)	(0.849)	(0.880)	(0.330)	(0.328)	(0.469)	(0.471)	(1.423)	(1.512)	(2.218)	(2.614)	(0.446)	(0.447)	(0.677)	(0.690)
Observations	18,335	18,204	18,335	18,204	37,575	37,171	37,575	37,171	2,972	2,958	2,972	2,958	14,280	14,153	14,280	14,153
R-squared	0.14	0.16	0.14	0.16	0.31	0.32	0.31	0.33	0.15	0.18	0.16	0.18	0.471	0.475	0.472	0.476
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Occupation FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
F-statistics on Dahl poly.			29.42	40.72			15.50	191.6			4.692	7.611			8.391	122.7
p-value on Dahl poly.			0.001	7.49e-09			0.078	0			0.860	0.055			0.495	0
Relevance (Instruments)	16.51	14.62	51.93	27.47	5.89	70.52	182.4	17.26	71.22	4.701	11.05	3.673	44.99	44.40	131.7	9.632
Relevance *p*-value	0	0	0	0.001	0	0	0	0.045	0	0.003	0.012	0.932	0	0	0	0.381

Source: *Korean Labor & Income Panel Survey,* 1998 - 2017

Notes: Following Dahl's self-selection correcting methodology (Dahl, 2002), we divide the population into 80 mutually exclusive cells defined by 10 age categories, 4 education categories, and 2 gender categories, in order to control for unobserved individual heterogeneity. Then, we estimate the proportion of workers for each of the four labor segments, denoted as "Dahl polynomials" throughout this paper, and then include these terms in the wage equation (equation (3)) as the predicted probability that an individual belonging to a particular group cell chooses to work in the respective labor segment. Log(Avg.Group Wage) is a log of annual average wages of all working individuals in each group cell we constructed for calculating Dahl polynomials in which an individual is included. We code industries and occupations based on the 8th Korean Standard Industrial Classification and the 5th Korean Standard Classification of Occupations, respectively, both at the 2-digit level. Since the identification of the earnings equation relies on the number of years worked in the current job (tenure), and the average wage of all working individuals in the group, along with the Dahl polynomials, we report the F-statistics and the *p*-value for the joint significance/relevance of these instruments. The standard errors are bootstrapped with 1,000 replications when the second-order Dahl polynomials in cell probabilities (not reported) are included. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Individual Choice on Labor Market Segments

Variables	(1) Conditional Logit Mincer	(2) Conditional Logit Dahl
Counter-factual wages	8.465***	2.230***
	(0.281)	(0.177)
SMEs/R		
Age	-1.624***	-0.340***
	(0.059)	(0.0384)
Age squared	-0.001***	-0.001***
	(0.000)	(0.000)
Female	-0.853***	-0.806***
	(0.030)	(0.030)
Schooling	0.086	0.128
	(0.141)	(0.147)
Schooling squared	-0.003	-0.004
	(0.005)	(0.005)
Large/NR		
Age	0.038	0.014
	(0.027)	(0.027)
Age squared	-0.000	0.000
	(0.000)	(0.000)
Female	0.154***	0.083
	(0.056)	(0.057)
Schooling	1.444***	0.142
	(0.239)	(0.241)
Schooling squared	-0.056***	-0.004
	(0.009)	(0.008)
Large/R		
Age	-0.016	0.002
	(0.018)	(0.018)
Age squared	-0.002***	-0.002***
	(0.000)	(0.000)
Female	-0.487***	-0.663***
	(0.038)	(0.037)
Schooling	-0.788***	-0.158
	(0.171)	(0.180)
Schooling squared	0.027***	0.008
	(0.006)	(0.006)
Number of Cases	72,486	72,500
Dahl's polynomials	No	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Occupation FE	Yes	Yes
Correlated Random Effects	Yes	Yes
Log Likelihood	-65,814.00	-66,576.37

Sources: *Korean Labor & Income Panel Study* , 1998 - 2017

Notes: The dependent variable is four alternatives of employment paths, where 'SMEs/NR' is the base alternative. The number of cases is the total number of individuals included in the sample. Individual choices are estimated using alternative specific conditional logit model based on McFadden (1978). The first specification (column 1) estimates alternative specific conditional logit model after computing the four counter-factual wages with the exclusion of the Dahl polynomials (Mincer-type earnings function) in the first stage. The specification (2) estimates the same conditional logit model with the four counter-factual wages that are estimated with the inclusion of the Dahl polynomials. In addition to the regressors reported on the table, we additionally include controls for marital status, local unemployment rate, and alternative-specific constants, as well as the correlated random-effects (Mundlak, 1978; Chamberlain, 1982) that are calculated by including the time averages of continuous control variables for each individual. The standard errors (in parentheses) are bootstrapped with 1,000 replications. *** p<0.01, ** p<0.05, * p<0.1.

Table 5A. Conditional Logit Elasticities (Mincer)

		To			
		∂p_1	∂p_2	∂p_3	∂p_4
From	$\partial(clwage_1)$	1.776	-0.035	-7.5e-21	-1.741
		(0.174)	(0.011)	(1.2e-20)	(0.170)
	$\partial(clwage_2)$	-0.035	0.124	-3.9e-22	-0.089
		(0.011)	(0.035)	(6.4e-22)	(0.026)
	$\partial(clwage_3)$	-7.5e-21	-3.9e-22	2.7e-20	-1.9e-20
		(2.4e-21)	(1.9e-22)	(4.3e-20)	(6.3e-21)
	$\partial(clwage_4)$	-1.741	-0.0894	-1.9e-20	1.831
		(0.170)	(0.026)	(3.0e-20)	(0.164)

Table 5B. Conditional Logit Elasticities (Dahl)

		To			
		∂p_1	∂p_2	∂p_3	∂p_4
From	$\partial(clwage_1)$	0.479	-0.066	-0.000	-0.414
		(0.049)	(0.017)	(0.000)	(0.047)
	$\partial(clwage_2)$	-0.066	0.190	-4.0e-06	-0.124
		(0.017)	(0.046)	-3.9e-06	(0.032)
	$\partial(clwage_3)$	-0.000	-4.0e-06	0.000	-0.000
		(0.000)	-3.9e-06	(0.000)	(0.000)
	$\partial(clwage_4)$	-0.414	-0.124	-0.000	0.538
		(0.047)	(0.032)	(0.000)	(0.044)

Sources: *Korean Labor & Income Panel Study* , 1998 - 2017

Notes: We calculate the marginal effect of an increase in the counter-factual wages in each of the four labor segments on the probabilities that an average worker will choose each labor segment, based on the estimates of the conditional logit model (Table 4). The probablities on the diagonals indicate elasticities, and the elements on the off-diagonals indicate cross-elasticities. The estimates of Table 5A are derived from the first specification of the conditional logit model after estimating the four counter-factual wages with the exclusion of the Dahl polynomials (Mincer-type wage equation), whereas the estimates of Table 5B are calculated from the estimates of the conditional logit model after estimating the counter-factual wages with the inclusion of the Dahl polynomials in the earnings function. The standard errors (in parentheses) are bootstrapped with 1,000 replications.

Table 6: Expenditures on Private Education

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Expenditure on Private Education)				Log(Expenditure on Private Education)			
	Sample: Non-employed, No Child				**Sample: Employed, No Child**			
Log(Gini)	0.714*				0.416**			
	(0.422)				(0.178)			
Log(Theil0)		0.666***				0.235***		
		(0.194)				(0.081)		
Log(Theil)			0.578***				0.229***	
			(0.192)				(0.078)	
Log(Theil2)				0.518***				0.225***
				(0.192)				(0.079)
Log(Wage)					0.023	0.023	0.023	0.023
					(0.025)	(0.025)	(0.026)	(0.025)
Age	0.194	0.263	0.240	0.224	-0.064***	-0.062***	-0.062***	-0.063***
	(1.025)	(1.022)	(1.006)	(1.022)	(0.013)	(0.013)	(0.013)	(0.014)
Age squared	0.004***	0.003***	0.004***	0.004***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.153**	0.150**	0.151**	0.152**	-0.003	-0.001	-0.001	-0.002
	(0.069)	(0.070)	(0.070)	(0.068)	(0.035)	(0.035)	(0.034)	(0.035)
Schooling	-0.083	-0.067	-0.071	-0.074	-0.003	-0.003	-0.003	-0.003
	(0.171)	(0.182)	(0.173)	(0.175)	(0.100)	(0.101)	(0.101)	(0.099)
Schooling squared	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	-0.002	-0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
Unemp Rate	0.052*	0.051*	0.052*	0.052*	-0.026	-0.025	-0.025	-0.025
	(0.030)	(0.030)	(0.028)	(0.028)	(0.019)	(0.019)	(0.019)	(0.020)
Constant	0.416	0.224	0.302	0.336	3.665***	3.616***	3.602***	3.595***
	(17.37)	(17.45)	(17.15)	(17.44)	(0.976)	(0.925)	(0.922)	(0.927)
Observations	25,906	25,906	25,906	25,906	24,501	24,501	24,501	24,501
R-squared	0.11	0.11	0.11	0.11	0.02	0.02	0.02	0.02
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	No	Yes	Yes	Yes	Yes

Sources: Korean Labor & Income Panel Study, 1998 - 2017

Notes: The dependent variable is the log of monthly spending on private education, listed in the column heading. Expenditures on private education are deflated by 2015 Consumer Price Index at a province level. Using the four counter-factual wages calculated from the estimation of the earnings function (equation (3)) with year-, industry-, and occupation fixed effects included, along with the Dahl polynomials, we calculate Gini coefficient and the three Theil indices as a proxy for the degree of labor market segmentation faced by each individual. The specifications (1) - (4) estimate the effect of labor market segmentation on private education expenses, using all non-employed individuals (either 'unemployed' or 'not in the labor force') without a child, whereas the specifications (5) - (8) includes working individuals without a child. Industry and occupation fixed effects are included for the specifications (5) - (8), whereas they are not included for the specifications (1) - (4), since non-employed individuals do not have corresponding data. Standard errors are bootstrapped with 1,000 replications, reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: The Share of Monthly Spending on Private Education

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log(Private Education/Total Expense)				Log(Private Education/Total Expense)			
	Sample: Non-employed, No Children				**Sample: Employed, No Children**			
Log(Gini)	0.035*				0.034***			
	(0.020)				(0.013)			
Log(Theil0)		0.036***				0.023***		
		(0.009)				(0.007)		
Log(Theil)			0.031***				0.024***	
			(0.009)				(0.007)	
Log(Theil2)				0.027***				0.025***
				(0.009)				(0.007)
Log(Wage)					0.003**	0.003**	0.003**	0.003**
					(0.001)	(0.001)	(0.001)	(0.001)
Age	0.007	0.011	0.010	0.009	0.008***	0.008***	0.008***	0.008***
	(0.048)	(0.048)	(0.048)	(0.049)	(0.001)	(0.001)	(0.001)	(0.001)
Age squared	0.000***	0.000***	0.000***	0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.013***	0.013***	0.013***	0.013***	0.009***	0.008***	0.008***	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Schooling	-0.008	-0.007	-0.007	-0.007	-0.001	-0.001	-0.001	-0.001
	(0.010)	(0.010)	(0.011)	(0.010)	(0.004)	(0.004)	(0.005)	(0.004)
Schooling squared	0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemp Rate	0.004***	0.004***	0.004***	0.004***	0.002*	0.002*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.030	0.029	0.031	0.031	-0.107*	-0.076	-0.071	-0.067
	(0.793)	(0.803)	(0.791)	(0.807)	(0.059)	(0.056)	(0.058)	(0.057)
Observations	27,827	27,827	27,827	27,827	33,682	33,682	33,682	33,682
R-squared	0.10	0.10	0.10	0.10	0.12	0.12	0.12	0.12
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	No	Yes	Yes	Yes	Yes

Sources: Korean Labor & Income Panel Study, 1998 - 2017

Notes: The dependent variable is the log of the share of monthly spending on private education. Similar to Table 6, the specifications (1) - (4) estimate the effect of labor market segmentation on the share of private education expenses, using all non-employed individuals (either 'unemployed' or 'not in the labor force') without a child, whereas the specifications (5) - (8) includes working individuals without a child. Standard errors are bootstrapped with 1,000 replications, reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Individual Choice on Labor Market Entrance

Variables	(1)	(2)	(3)	(4)
	Labor Market Entrance (1 = Enter, 0 = Not Enter)			
Log(Gini)	-0.279***			
	(0.069)			
Log(Theil0)		-0.111***		
		(0.028)		
Log(Theil)			-0.114***	
			(0.029)	
Log(Theil2)				-0.118***
				(0.030)
Age	0.193	0.192	0.193	0.194
	(0.714)	(0.726)	(0.721)	(0.742)
Age squared	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.195***	-0.197***	-0.196***	-0.196***
	(0.012)	(0.013)	(0.012)	(0.012)
Schooling	-0.111***	-0.108***	-0.108***	-0.109***
	(0.025)	(0.027)	(0.026)	(0.025)
Schooling squared	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Unemp Rate	0.008	0.007	0.007	0.007
	(0.005)	(0.006)	(0.005)	(0.005)
Constant	-3.196	-2.946	-2.989	-3.027
	(13.28)	(13.50)	(13.40)	(13.80)
Observations	69,717	69,717	69,717	69,717
R-squared	0.16	0.16	0.16	0.16
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Sources: Korean Labor & Income Panel Study, 1998 - 2017

Notes: The sample in the specifications (1) - (4) include all individuals less than 37 years old, who enter the labor market in the current period. The dependent variable is an indicator that equals one if an individual enters labor market and chooses among the four job type categories in the current year, and that equals zero, otherwise. We calculate Gini coefficient and the three Theil indices, using the four counter-factual wages calculated from the estimation of the earnings function (equation (3)) with year-, industry-, and occupation fixed effects included, along with the Dahl polynomials. The standard errors (in parentheses) are bootstrapped with 1,000 replications. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: The Effect of Labor Market Segmentation on Marital Status

Variables	(1)	(2)	(3)	(4)
	Marital Status (1 = Married, 0 = Not Married)			
	Sample: (All individuals whose $age \leq 37$)			
Log(Gini)	0.075			
	(0.051)			
Log(Theil0)		-0.103***		
		(0.025)		
Log(Theil)			-0.091***	
			(0.025)	
Log(Theil2)				-0.077***
				(0.025)
Age	-0.124	-0.150	-0.146	-0.143
	(0.121)	(0.116)	(0.113)	(0.118)
Age squared	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Schooling	-0.036**	-0.046**	-0.046**	-0.045**
	(0.018)	(0.018)	(0.018)	(0.019)
Schooling squared	0.001**	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Unemp Rate	-0.005	-0.003	-0.003	-0.003
	(0.005)	(0.005)	(0.005)	(0.005)
Constant	2.687	2.390	2.387	2.399
	(2.256)	(2.164)	(2.106)	(2.197)
Observations	69,739	69,739	69,739	69,739
R-squared	0.27	0.27	0.27	0.27
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No
Occupation FE	No	No	No	No

Sources: Korean Labor & Income Panel Study, 1998 - 2017

Notes: The table reports the estimates from the estimation of the effect of labor market segmentation on the number of household members using all individuals who are less than 37 years old, where the degree of labor market segmentation at the individual level is proxied by the Gini and the Theil index we calculate from the estimation of the earnings equation (3), including individual-, and year- fixed effects, along with the Dahl polynomials. We use "37 years old" as a threshold by which an average individual decides to get married or not. The standard errors (in parentheses) are bootstrapped with 1,000 replications. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: The Effect of Labor Market Segmentation on the Number of Children

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Number of Children				Number of Children			
	Sample: All married				**Sample: Employed and married**			
Log(Gini)	-0.360***				-0.189***			
	(0.070)				(0.060)			
Log(Theil0)		-0.138***				-0.088***		
		(0.033)				(0.030)		
Log(Theil)			-0.120***				-0.081***	
			(0.033)				(0.029)	
Log(Theil2)				-0.104***				-0.074**
				(0.033)				(0.029)
Log(Wage)					0.002	0.002	0.002	0.002
					(0.007)	(0.007)	(0.007)	(0.007)
Age	0.210***	0.207***	0.207***	0.206***	0.377***	0.380***	0.382***	0.385***
	(0.078)	(0.078)	(0.077)	(0.076)	(0.014)	(0.013)	(0.013)	(0.013)
Age squared	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Schooling	-0.069**	-0.067**	-0.066**	-0.065**	-0.037	-0.036	-0.036	-0.035
	(0.027)	(0.027)	(0.027)	(0.027)	(0.030)	(0.030)	(0.030)	(0.030)
Schooling squared	0.003***	0.003***	0.003***	0.003***	0.002*	0.002*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemp Rate	-0.004	-0.005	-0.005	-0.006	-0.012*	-0.012*	-0.012*	-0.013*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)
Constant	-4.036	-3.611	-3.499	-3.390	-8.828***	-8.839***	-8.873***	-8.902***
	(2.708)	(2.684)	(2.658)	(2.634)	(0.406)	(0.408)	(0.407)	(0.407)
Observations	92,476	92,476	92,476	92,476	48,804	48,804	48,804	48,804
R-squared	0.30	0.30	0.30	0.30	0.33	0.33	0.33	0.33
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
Occupation FE	No	No	No	No	Yes	Yes	Yes	Yes

Sources: Korean Labor & Income Panel Study, 1998 - 2017

Notes: The specifications in (1) - (4) columns estimate the effect of labor market segmentation on the number of children using all married individuals who are married, where the Gini and the Theil index are calculated from the estimation of the earnings equation (3), including individual-, and year- fixed effects, along with the Dahl polynomials. The specifications in (5) - (8) columns estimate the same model using currently employed and married workers, where the Gini and the Theil index are derived from the estimation of the earnings equation (3), including individual-, year-, industry-, and occupation fixed effects, along with the Dahl polynomials. The standard errors (in parentheses) are bootstrapped with 1,000 replications. *** p<0.01, ** p<0.05, * p<0.1.