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Establishment Size, Industry, and Wage Inequality: The Roles of Bonus and Rent Sharing

사업체 규모, 산업과 임금 불평등: 보너스와 수익 배분의 역할을 중심으로

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Abstract

Establishment Size, Industry, and Wage Inequality: The Roles of Bonus and Rent Sharing

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Despite the growing evidence on the relation between bonuses (or performance pay) and wage inequality, studies have focused on how bonuses influence wage inequality among jobs. This study provides new evidence on the large contribution of bonuses (i.e., performance pay and non-production pay) to wage inequality among employers via heterogeneous rent-sharing behaviors, focusing on industry affiliation and employer size. Using comprehensive Korean worker-level data, I first show that wage between-inequality at the industry-size level has substantially contributed to a growing wage inequality trend since 1994 even after controlling for observed and unobserved worker characteristics and factoring in sorting effects; this phenomenon is mainly due to the differences in bonuses between industry-size groups, while the effects of bonuses on within-inequality are limited. I then show the sources of the rising wage between-inequality in terms of firm-side factors using firm-level data merged with worker-level data at the industry-size-year level. I find that changes in the estimated prices of labor productivity (rent-sharing parameters) and the capital-to-labor ratio are the main factors in the increasing dispersal of between-inequality and that they became more positively correlated with wages between 2009 and 2015 than they were before 2009. This positive correlation is observed even more clearly when bonuses are included in wages. These findings show that employers exhibit rent-sharing behavior and compensate for capital dependency using bonuses, and bonus differentials among employers are translated into increased between-inequality of wages.

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Keywords: Wage Inequality, Bonus, Establishment Size, Industry, Labor Productivity, Capital-to-Labor Ratio, Rent-Sharing Behavior

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1 Introduction

It is well-known that employers' size and industry affiliation play important roles in explaining wage inequality among workers. Since the seminal papers of Brown and Medoff (1989) and Krueger and Summers (1988), several studies have explored the sources of the positive relation between employers' sizes and wages workers are paid, and wage differentials among industries.[1] In a standard competitive labor market model, one possible explanation for this phenomenon is the difference in labor quality across employer sizes and industries. Conflicting with this conventional explanation, however, empirical evidence has shown that wage gaps among employers come mainly from employers' heterogeneous characteristics or behaviors such as labor productivity, rent-sharing behavior, and technology dependence (e.g., Blanchflower et al., 1996; Arai, 2003; Faggio et al., 2010; Barth et al., 2016). Using the intuitions of those works, this study attempts to determine 1) how between-inequality at the industry and industry-size levels has contributed to the rising wage inequality over the last two decades in Korea and 2) their sources from the standpoint of firm-side factors using firm-level data merged with worker-level data at

[1] Previous works on the effects of employer size on wages include Moore (1911), Oi and Idson (1999), Bayard and Troske (1999), Lluis (2009), and Pedace (2010). Lallemand and Rycx (2007) review the literature on this topic. Groshen (1991), Gibbons and Katz (1992), Vainiomäki and Laaksonen (1995), Gannon et al. (2007), and Lazear and Shaw (2009) study inter-industry wage premiums in several countries.

the industry-size-year level. I also seek to shed light on the role of bonus, including performance pay and non-production pay, in these processes.

Amid the increasing accessibility of worker-level, firm-level, and linked employer-employee longitudinal data in many countries, new evidence has emerged on the significant contribution of employers to wage inequality, which has helped to explain changes in wage inequality (e.g., Abowd, Kramarz, and Margolis, 1999; Card, Heining, and Kline, 2013; Song et al., 2015). These studies identify both workers and their workplaces, allowing wage inequality to be perfectly decomposed into within- and between-firm inequalities. Despite their important contributions to finding the sources of wage inequality, however, they have not closely examined the effects of industry affiliation and employer size on wage inequality. I examine the contributions of employers' industry and size on wage inequality by combining the Korean Ministry of Employment and Labor's Wage Structure Survey (WSS), Korea's largest worker-level database, which provides data on employers' size and industry affiliation (using a two-digit code), with information on worker characteristics and representative firm-level balance sheet data taken from the Korea Enterprise Database (KED). Combining these two data sources produces a longitudinal dataset that contains comprehensive information on employees and employers at the industry-size-year level.

This study is novel in its focus on the role of bonuses in explaining wage inequality. The wage-setting system of the typical firm in Korea is a combination of fixed wages and bonuses; and the negotiations for wages are conducted at firm-level (decentralized industries).[2] Fixed wages are the contracted wages that must be paid regardless of the workers' and firms' performance. They are anchored by job position and increase along with promotion. By contrast, bonuses vary depending on the firm's situation and the worker's abilities. Some firms introduce bonuses mainly to obtain strategic flexibility of wage-setting and to hedge their performance risk. In this case, the entire performance of the firm and favorability to sharing rents with workers are closely linked to the amount of bonuses workers are paid. This leads to the increase of wage inequality between firms. Other firms use bonuses mainly to compensate different workers disproportionately. This can increase wage inequality within firms. In sum, bonus amounts are driven by three factors: the performance of the worker, the performance of his or her employer, and the attitude of the employer to sharing rents with workers. The performance of a worker may be evaluated as high; however, if the performance of the firm is poor, the worker will not be sufficiently compensated for his abil-

[2]Rusinek and Rycx (2013) investigate the impact of different collective bargaining arrangements on the relationship between firms' profitability and wages via rent-sharing. They show that in industries where agreements are usually renegotiated at firm-level (decentralized industries) wages and firm-level profits are more positively correlated than industries where firm-level wage renegotiation is less common (centralized industries).

ity. Moreover, if a highly profitable firm is not favorable to sharing rents with workers, its bonuses may be relatively low. Either of these situations may cause bonuses to affect wage inequality.

This study has two objectives. The first is to investigate how changes in between-inequality at the industry and industry-size levels influence changes in overall wage inequality between 1994 and 2015 in Korea. I show that the changes in inequality between industry-size groups have significantly contributed to the changes in overall wage inequality even when workers' observed and unobserved characteristics are controlled for and that this phenomenon has been amplified by the systematical differences in bonuses between industry-size groups. The second objective is to explore the sources of the contribution of between-inequality using firm factors such as labor productivity and the capital-to-labor ratio. I decompose their contributions into "quantity effects" and "price effects" following Machado and Mata (2005), and show that employers' heterogeneous rent-sharing behaviors along the wage distribution is a main element of the rising between-inequality.

This paper complements recent empirical works on wage determination and inequality. Blanchflower et al. (1996) provided a theoretical background on the relation between wages and employers' rent-sharing behavior. Using the wage bargaining model, they derived a simple wage equation and empirically demonstrated the positive association between wages and employers' rent-sharing behavior by blending microeconomic data on wages with industrial data. Using Swedish data on workers matched with firms' balance sheets, Arai (2003) showed that wages are positively correlated with the capital-to-labor ratio as well as employers' profits. Barth et al. (2016) showed that the change in wage variance among establishments contributes 65% of the increased variance in earnings from 1992 to 2007 in the U.S. They also showed that the wage gap between two-digit industries is an important factor in making wage inequality among establishments more dispersed. Lemieux et al. (2009) demonstrated the importance of performance pay in explaining wage inequality using data from PSID. They focused on the contribution of performance pay to within-inequality by comparing between performance-pay jobs and non-performance-pay jobs. They concluded that compensation for performance-pay jobs was more closely tied to worker characteristics and that changes in returns to skill due to technological change induced more firms to offer performance pay. I expand their analyses to examine the contributions of bonuses to wage inequality among employers in Korea.[3] Concerning methodology, Machado and Mata (2005) provide a method that allows me to observe the marginal effects of firm-side factors on wage inequality using quantile regression and integral transformation theorem.

The empirical results of this paper confirm that the rising trends

[3] See section 3.2 for the difference between bonus and performance pay.

in Korean wage inequality between 1994 and 2015 are associated with trends in between-inequality at the industry-size level rather than at the industry level. The industry-size level change in between-inequality contributes 44.03% of the change in wage inequality even after workers' observed characteristics and sorting effects are controlled for, while the industry-level contribution amounts to 11.33%. This means that the wage gap between employers of different sizes is the main factor in between-inequality. The contribution of industry size to between-inequality decreases to 29.35% when bonuses are not considered. This large drop shows that bonus differentials between industry-size groups play important roles in explaining between-inequality trends. Interestingly, the results of the longitudinal data show that the contributions of workers' unobserved characteristics to wage inequality trends are minor in spite of their large contribution to wage inequality levels, while the large contribution of between-inequality to wage inequality trends remains.

Investigating the sources of the changes in between-inequality from 2000 to 2015 shows that changes of rent-sharing parameter and the prices of capital–labor ratio are the main factors in the rising between-inequality. They become more positively correlated with wages between 2009 and 2015 than they are before 2009. The positive correlations are observed even more clearly when bonuses are included in wages. The changes in rent-sharing parameters between the two periods make between-inequality, measured as the variance in log real hourly wages, change from 0.131 to 0.1879, while between-inequality changes from 0.0901 to 0.0998 when bonuses are not considered. The change in the capital-to-labor ratio price shows similar effects on the change in between-inequality. These results imply that paying bonuses is one way firms share their rents with workers and compensate for heavy capital dependency.

The remainder of this paper is organized as follows. Section 2 describes the data and the sample selection process. Section 3 discusses the trends in wage inequality, focusing on a comparison between within- and between-inequality. Section 4 presents the results of a full variance decomposition, using the augmented Mincer-type earning equation, to control for worker characteristics and observe the contribution of between-inequality to wage inequality. Section 5 investigates the effects of firm-side factors on between-inequality trends. Finally, section 6 concludes the paper.

2 Data Description

2.1 WSS, KLIPS, and KED

WSS and KLIPS: Worker–level Data

The Wage Structure Survey (WSS) dataset is the largest worker-level dataset in Korea, with information on approximately 500,000 regular workers per year provided by the Korea Ministry of Employment and Labor. The survey has been conducted each June since 1980. The WSS data include monthly wage and hours worked in a month, as well as information on education, occupation, experience, union participation, gender, industry (two-digit code), and employer size (measured by the number of employees and comprising five categories: 10–29, 30–99, 100–299, 300–499, and 500+).[4,5] Since 2006, this dataset has also been providing establishment identifiers that can be used to observe the effects of firm heterogeneity on wage inequality.[6]

There are three advantages to using this dataset to study wage inequality. First, total monthly wages can be decomposed into regular wages, overtime wages, and bonuses. The provision of bonuses allows us to identify their effects on wage inequality. Second, the WSS is relatively free of measurement error because it has been gathered by establishment-level surveys.[7] Third, the survey is designed to control for sampling errors regarding industry and establishment size and provides a weight for each worker.[8] These weights allow the data to

[4]One employer size category, 5–9, has been added since the 1999 survey. To maintain data consistency, employees working in firms with fewer than 10 employees are excluded.

[5]The WSS data do not provide an industry classification more detailed than the two-digit codes. Barth et al. (2016) demonstrated that expanding industrial categories from one-digit to two-digits contributes significantly to wage inequality, while the effects of more detailed categories are modest.

[6]Unfortunately, since these establishment identifiers are randomly assigned by the Korea Ministry of Employment and Labor, I cannot combine this dataset with establishment-level micro data due to the absence of common identifiers.

[7]As the survey is implemented using firms' payrolls, measurement errors are much smaller than those of individual-level surveys.

[8]The Korea Ministry of Employment and Labor determines a worker's weight according to three factors: the design weight of the employee's workplace, the

represent the average worker rather than the average industry or size. All of the estimates reported in this paper are weighted using the sample weights.

The critical limitation of the WSS dataset for studying wage inequality is that self-employed workers, non-regular workers, and workers working in establishments with fewer than five employees cannot be considered due to the survey design. Since this limitation may lead to a biased evaluation of the overall inequality of wages in Korea, the results have to be interpreted for regular workers in establishments with more than five employees. Another limitation is that, as the WSS comprises cross-sectional data, unobserved heterogeneity among workers cannot be controlled for.[9]

To observe the effects of unobserved worker heterogeneity on wage inequality and check the robustness of the results derived from the WSS data, I use Korean Labor and Income Panel Study (KLIPS) data, which have longitudinal features and provide information on workers similar to that provided by the WSS for the 1998–2015 period. Unfortunately, the KLIPS data provide information on only 5,000 regular employees each year and is thus less representative. However, as wage inequality (measured by the variance in log real hourly wages)

probability of sampling the worker, and a post-stratification adjustment coefficient. The Ministry also outlines its method of using the weight.

[9]Several recent studies on wage inequality using large longitudinal worker datasets have reported that unobserved heterogeneity among workers contributes significantly to changes in wage inequality in the U.S. and Germany (e.g., Card, Heining, and Kline, 2013; Song et al., 2015).

in the two datasets shows similar rising trends between 1998 and 2008, there appears to be no serious problem with using the KLIPS to check the robustness of the results from the WSS.

KED: Firm–level Balance Sheet Data

The Korea Enterprise Database (KED) offers data on financial statements and the number of regular workers at Korean firms in order to assign credit ratings. It covers 2000 to 2015 and 50% of Korean firms.[10] This database is useful for studying wage inequality because it includes many small firms with fewer than 50 regular employees, unlike other available firm-level balance sheet data. In 2015, small firms with fewer than 50 employees accounted for 89.32% of all firms, and their share of sales was 22.7%. The high share of small firms and their low share of sales clearly reflect the skewed distributional structure among Korean firms.

Merged Data

To observe the effects of worker characteristics and firm-side factors on wage inequality, worker- and firm-level data must be merged into one dataset. Because the worker-level datasets (WSS, KLIPS) do not provide public firm identifiers, I cannot construct a linked employer–employee dataset like the U.S. Longitudinal Employer House-

[10] According to Korea's National Tax Service, firms with more than 10 regular employees totaled about 145,000 in 2014, and the KED covers about 70,700 firms.

hold Dynamics (LEHD). However, data on industry (two-digit), establishment size (five categories), and year can be used to link between worker- and firm-level data. Thus, I aggregate the WSS and KED using industry-size identifiers per year and combine them to construct longitudinal data at the industry-size level.[11] Although inequality between firms cannot be observed using the combined dataset, inequality between industry-size groups and its sources can be captured using worker- and firm-side variables aggregated in industry-size cells.

2.2 Sample Selection

For the main analysis, samples are restricted to regular workers between the ages of 20 and 60. I exclude those who work fewer than 10 days per month and who earn less than the minimum hourly wage.[12] I also exclude the agriculture industry and several industries in service sector, such as education, health, and social work (e.g., hospital), as well as arts-, sports-, and recreation-related services (e.g., creativity and arts-related services), membership organizations, repair and other personal services (e.g., labor organizations and religious orga-

[11] One possible criticism of this process is that the WSS provide establishment-level data, while the KED provides firm-level data. As Korea is a small country, its numbers of establishments and firms do not differ significantly. According to Korea Statistics, the number of establishments and firms with more than five regular employees total 68,989 and 65,059 in the manufacturing sector, respectively. Firms with more than two establishments constitute conglomerates such as Samsung and Hyundai. As establishments in such conglomerates have more than 500 employees, the biases induced by combining establishment-level and firm-level data are not large enough to contaminate the main results of this study.

[12] The share of workers who earn less than the minimum hourly wage accounts for less than 1% of the observations. Considering such wages could lead to measurement errors.

nizations), and extraterritorial organizations; the association between wages and firm characteristics are not likely to be meaningful in those industries. The Korean government has revised its industry classification twice, in 2000 and 2007 (i.e., the 8^{th} and 9^{th} Korea Standard Industry Classification [KSIC], respectively) since 1994. Because the recent revision provides more detailed classifications, I aggregate some industries for time-series consistency over the analysis periods.[13] The manipulation of industry classification applies equally to all datasets (i.e., WSS, KLIPS, KED). The number of workers in the WSS data and firms in the KED (two-digit industries) are presented in Table A1 and A2 in the appendix. Figure A1 in the appendix presents the wage variance trends in the original WSS data and the sample data restricted by the criteria mentioned above. The gap between the two lines is minor, indicating that the effect of the sample restrictions on wage inequality trends is small.

2.3 Two Types of Wages

Two types of real (adjusted by CPI, 2015=100) hourly wages, fixed and total wages, are used in this study. Their definitions are as follows:

$$\text{Hourly Fixed Wage} = \frac{\text{regular wage} + \text{overtime wage}}{\text{working hours}} \quad (1)$$

[13] For instance, the food and beverage industries belonged to the same industry under the two-digit classification in the 7^{th} and 8^{th} KSIC but were separated in the 9^{th} KSIC. Thus, I integrated them after 2007 to maintain classification consistency.

$$\text{Hourly Total Wage} \quad = \quad \text{hourly fixed wage} + \frac{\text{bonus}/12}{\text{working hours}} \tag{2}$$

As mentioned in section 2.1, while regular wage, overtime wage, and working hours provided in the WSS data are monthly (based on the June of each year), bonuses are yearly data. They are thus divided by 12 to convert yearly data into monthly data. The difference between the two types of wages concerns whether bonuses are included; the difference in their variance can therefore be interpreted as the effects of bonuses on wage inequality.

I must address the difference between performance pay and bonuses. Unlike previous works such as Lemieux et al. (2009) and Bryan and Bryson (2016), this study uses the term "bonus" instead of "performance pay" because the bonuses considered in this paper include non-production pay, defined as cash payments that are not explicitly related to formula for productivity, such as holiday bonuses.[14,15] One can argue that non-production pay must be included in fixed wages because it is determined by wage contracts. Non-production pay is closer to bonuses, however, for two reasons: 1) the differences in non-

[14]This definition of "non-proudction pay" is taken from Gittleman and Pierce (2015).

[15]Considering several types of wages, Gittleman and Pierce (2015) consider a job to be a performance-pay job if either of two conditions holds: the job has non-production bonuses such as holiday bonuses and cash profit-sharing bonuses; or it has wages tied to commissions, piece-rate wages, production bonuses, or other incentives. They use "incentive-pay jobs" to denote jobs that meet only the second condition. By contrast, Lemieux et al. (2009) and Bryan and Bryson (2016) define performance-pay jobs as jobs for which wages are, at least partly, determined by variable pay components such as bonus, commission, and piece-rate.

production pay among firms are great, as large firms typically provide non-production pay as a fringe benefit, while most small firms provide none at all; 2) non-production pay can be more easily adjusted than fixed wages can. Gittleman and Pierce (2015) also pointed out that non-production payments stem from annual bonus plans but may also reflect a variety of incentive plans.

Table 1 shows the average log real hourly wages by industry (one-digit) and establishment size using data from the WSS. The weighted standard deviations (labeled "Weighted S.D.") are calculated using the weights provided in the WSS data. Two things are to be noted. First, the weighted S.D. of industry average wages and the wage differences between size 1 (10–29) and size 5 (500+), labeled "Size 5–Size 1"), are larger for total wages than for fixed wages in all years. This indicates that bonuses are a factor in making the wage distribution more dispersed. Second, while the differences in the weighted S.D. of industry average wages between the total wage and fixed wage are relatively stable over time, the differences in wages between size 1 and size 5 become much larger as time goes on.

Table 1: The Comparison of Two Types of Wages by Industry and Establishment Size

Industry and Size	Average of (log real hourly) Wages					
	1994		2008		2015	
	Total	Fixed	Total	Fixed	Total	Fixed
Industry (one-digit)						
Mining and Quarrying	0.0423	-0.1373	0.5906	0.4346	0.5831	0.4452
Manufacturing	-0.2561	-0.4705	0.3845	0.1781	0.5230	0.3469
Electricity, Gas, Steam and Water Supply	0.1848	-0.1005	1.0061	0.7098	1.0684	0.8429
Construction	0.0559	-0.1170	0.4300	0.3312	0.6670	0.5849
Wholesale and Retail Trade	-0.1761	-0.3701	0.4473	0.2915	0.4102	0.2916
Accommodation and Food Service Activities	-0.2971	-0.4703	0.0401	-0.0447	-0.0128	-0.0462
Transportation	-0.1796	-0.3489	0.4345	0.2608	0.4504	0.3193
Financial and Insurance Activities	0.2542	-0.0964	0.9156	0.6283	0.9403	0.6971
Real Estate Activities and Renting and Leasing	-0.3942	-0.5837	0.2184	0.1203	0.2781	0.2112
Weighted S.D.	0.1678	0.1414	0.1777	0.1482	0.1728	0.1415
Establishment Size (Five Categories)						
Size 1: 10–29	-0.2441	-0.3955	0.2633	0.1521	0.3456	0.2523
Size 2: 30–99	-0.2700	-0.4449	0.3104	0.1743	0.3798	0.2767
Size 3: 100–299	-0.1818	-0.4026	0.4204	0.2284	0.4455	0.2931
Size 4: 300–499	-0.0874	-0.3476	0.6388	0.4022	0.6580	0.4474
Size 5: 500+	0.0324	-0.2829	0.8799	0.5117	1.0991	0.7563
Log Differences: Size 5-Size 1	0.2765	0.1125	0.6166	0.3596	0.7535	0.5040

Notes. This table shows the average log real hourly wages by industry (one-digit) and establishment size using data from the WSS. The difference between total wages and fixed wages concerns whether bonuses are included. The weighted standard deviations (labeled "Weighted S.D.") are calculated using the workers' weights provided in the WSS data.

3 Trends in Between–Inequality of Wages

In this section, I first conduct a simple variance decomposition to observe the trends in wage inequality within and between groups using the WSS data without considering worker characteristics. I then observe the distributional features in the changes in wage inequality by wage percentiles to determine which wage percentiles are more affected by between-inequality. Industry (two-digit), industry-size (two-digit and five categories), and establishments are treated as groups to observe their contributions to wage inequality.

3.1 Simple Variance Decomposition

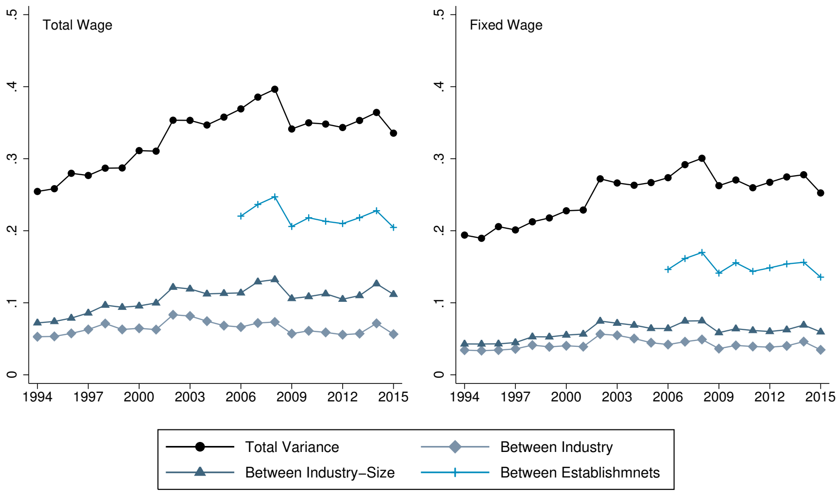
The variance of log real hourly wages can be decomposed into two components, within- and between-variance. Let $w_{i,g}$ be the log real hourly wage of worker i in group g, and $\bar{w}_g$ be the average log real wages of workers employed by group g. The two variances can be expressed by the following equations where $Var(\bar{w}_g)$ and $Var(w_{i,g} - \bar{w}_g)$ present the between- and within-variance, respectively:

$$w_{i,g} \equiv \bar{w}_g + (w_{i,g} - \bar{w}_g) \tag{3}$$

$$Var(w_{i,g}) = Var(\bar{w}_g) + Var(w_{i,g} - \bar{w}_g) \tag{4}$$

I calculate each variance of equation (4) using the workers' weights, $\theta_{i,g}$, provided by the WSS data, where the sum of the weights is equal

Figure 1: Trends in Between–Group Variances: 1994–2015



Notes. This Figure plots the trends in total variance and between-group variances calculated using equation (6) for total wages and fixed wages. The difference between total wages and fixed wages concerns whether bonuses are included. Industry (two-digit), industry-size (two-digit and five categories), and establishments are treated as groups. The list of included industries is in Table A1 in appendix. The numbers of establishments and workers used in this figure are 55,504 (2006-2015) and 6,601,829 (1994-2015), respectively.

to 1 ($\sum_g \sum_i \theta_{i,g} = 1$) within each year. The group weight is equal to the sum of the workers' weights in that group ($\theta_g = \sum_i \theta_{i,g}$) within a year. With the weight, equations (3) and (4) can be rewritten as follows where $\bar{w}$ presents the weighted grand mean of the log real hourly wages:

$$\sum_{i,g} \theta_{i,g}(w_{i,g} - \bar{w})^2 = \sum_{i,g} \theta_{i,g}\{(w_{i,g} - \bar{w}_g) + (\bar{w}_g - \bar{w})\}^2 \tag{5}$$

$$= \underbrace{\sum_{i,g} \theta_{i,g}(w_{i,g} - \bar{w}_g)^2}_{\text{Within-group variance}} + \underbrace{\sum_{g} \theta_g(\bar{w}_g - \bar{w})^2}_{\text{Between-group variance}} \tag{6}$$

Figure 1 plots the trends in total variance and between-group variances calculated using equation (6) for total wages and fixed wages. There are two notable features in Figure 1. First, although the levels and trends of between-industry variance (shown by the line marked with diamonds) are relatively stable over time, the variance between industry-size groups (shown by the line marked with triangles) shows an increasing trend between 1994 and 2008. This suggests that the rising wage inequality is more attributable to the increase in the variation in wages across establishment sizes than to that across industries. This pattern is clearer in the left plot for total wages, indicating that differences in bonuses between establishment sizes play an important role in the widening between-inequality at the industry-size level. Second, the variance between industry-size groups contributes significantly to the between-establishment variance (shown by line marked with +). In the left plot for total wages, the contributions of the variances between industry-size groups to the variances between establishments account for 51.6% (=0.1137/0.2204) and 54.6% (=0.1117/0.2046) of the total in 2006 and 2015, respectively, suggesting that industry and establishment size play an important role in explaining the effects of establishment heterogeneity on wage inequality.

Table 2 summarizes the results of the simple variance decomposition for the two types of wages. The variance between industries contributes 4.4% of the increased variance of total wages between 1994

Table 2: Within– and Between–Variances by Groups and Their Contributions

Group	Variance	1994	2001	2008	2015	2015-1994	
						Change	Share
Total Wage							
Total		0.2546	0.3105	0.3965	0.3355	0.081	
Industry	Within	0.2017	0.2477	0.3231	0.2791	0.077	0.956
	Between	0.0529	0.0628	0.0733	0.0564	0.004	0.044
Industry+Size	Within	0.1825	0.2108	0.2643	0.2238	0.041	0.511
	Between	0.0721	0.0998	0.1322	0.1117	0.040	0.489
Establishment	Within	-	-	0.1494	0.1309		
	Between	-	-	0.2471	0.2046		
Fixed Wage							
Total		0.1940	0.2288	0.3007	0.2525	0.059	
Industry	Within	0.1598	0.1897	0.2516	0.2178	0.058	0.992
	Between	0.0342	0.0391	0.0491	0.0347	0.000	0.008
Industry+Size	Within	0.1512	0.1722	0.2257	0.1929	0.042	0.713
	Between	0.0428	0.0566	0.0750	0.0596	0.017	0.287
Establishment	Within	-	-	0.1308	0.1169		
	Between	-	-	0.1699	0.1356		

Notes. This table shows contributions of changes in within- and between-variances to changes in wage variances. The difference between total wages and fixed wages concerns whether bonuses are included. Industry (two-digit), industry-size (two-digit and five categories), and establishments are treated as groups. The list of included industries is in Table A1 in appendix. The numbers of establishments and workers used in this figure are 55,504 (2006-2015) and 6,601,829 (1994-2015), respectively.

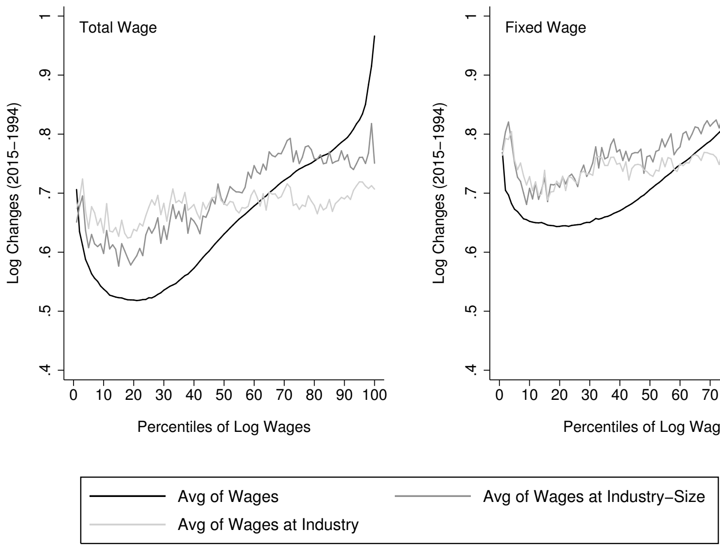
and 2015, while the variance between industry-size groups contributes 48.9%. Although this pattern is commonly observed for fixed wages, the magnitudes of the contributions of between-inequality (0.8% at the industry level and 28.7% at the industry-size level) are much smaller due to the absence of the effects of bonuses.

3.2 Distributional Changes of Wages

The variance in log real hourly wages, a simple statistic for inequality, cannot capture the distributional features of wages. To determine which percentiles cause the increased wage inequality between 1994 and 2015, I calculate the wage differences between the two years by wage percentiles. Specifically, I first group the samples into 100 wage percentile bins per year. Then, I calculate the average of log wages and of the mean wages of the industry, and then do the same for the industry-size groups for each percentile. Finally, I calculate the differences of each average value between 1994 and 2015 by wage percentile.

Figure 2 shows the distributional changes in wages between 1994 and 2015. The left plot is for total wages and the right one is for fixed wages. Three phenomena revealed through the comparison between the two plots are worth mentioning. First, the upward slopes of wages (shown by the black line, labeled "Avg of Wages") observed in both plots (except for the range below about the 20% percentile) indicate that workers at the upper distribution earn more than those at the bottom. Moreover, the upward slope is much steeper for total wages than for fixed wages, indicating that bonuses make the wage distribution more dispersed. Second, the comovement between the average of wages (shown by the black lines) and the average of wages at the industry-size level (shown by the dark gray lines, labeled "Avg of Wages at industry-size") is much stronger for total wages

Figure 2: Changes in Average of Log Wages across Wage Percentiles (1994 vs. 2015)



Notes. This figure shows the distributional changes in wages between 1994 and 2015. The left plot is for total wages and the right one is for fixed wages. X-axis is 100 wage percentile bins per year. Y-axis is log changes of average of wages and of the mean wages of the groups at the corresponding bins between 1994 and 2015. The list of included industries is in Table A1 in appendix.

than for fixed wages. The correlations between the two lines are 0.892 and 0.684, respectively. This means that the bonus differential between industry-size groups is a crucial factor in the widening wage gaps among workers. Third, the gap between the average of wages at the industry-size level and the average of wages at the industry level (shown by the dark and thin gray lines respectively) is broader when bonuses are considered. This shows that the changes in bonuses by wage percentile between the two years are attributable to the bonus differentials between establishment sizes rather than those among industries, as shown in Figure 1 and Table 2.

4 Does Sorting Matter?

Does the rising wage inequality between industry-size groups come mainly from sorting effects or pure group effects? This section answers this question. The sorting effects would cause the differentials in labor quality to lead to wage inequality between groups. If the sorting effects explain most of the trend in between-inequality, the contribution of industry-size effects to wage inequality would come not from their own characteristics but from the differences in labor quality.

4.1 Trends in the Variances of Residuals

Using the WSS data, I estimate the following augmented Mincer–type wage equation for the 1994–2015 period based on Barth et al. (2016)'s model:

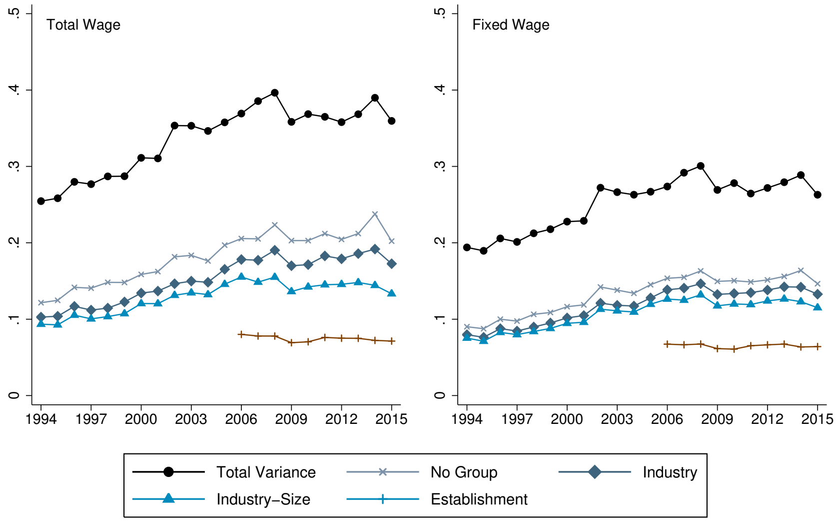
$$w_{i,g} = x_{i,g}b + \varphi_g(i) + u_{i,g}, \text{ with } \ E(u_{i,g}|x_{i,g}, \varphi_g) = 0 \tag{7}$$

In this equation, $w_{i,g}$ is a vector of log real hourly wages for worker i in group g; $x_{i,g}$ is a set of independent variables for worker characteristics (years of schooling, experience and its square [Mincer], union participation, occupation dummies [nine categories], and interaction terms for each variable with gender); and $\varphi_g(i)$ is a vector of dummy variables for group g shared by workers employed in group g. The residual $u_{i,g}$ captures unobserved factors such as worker-group match effects, unobservable worker characteristics, and purely transitory wage fluctuations. To allow the prices of worker characteristics to vary over time, all models are fitted separately by year.

One way to observe how the effect of each group contributes to wage inequality is to compare the trends in residuals estimated by different groups. I conduct four regressions using equation (7) for several groups: no group (worker characteristics only), industry, industry-size, and establishment. The four regressions have the same independent variables for worker characteristics, but the group dummies are different. Owing to data constraints, the regressions using establishment dummies are conducted from 2006 to 2015. The regression results at industry and industry-size level are in Table A3 and A4 in appendix.

Figure 3 plots the weighted variances of residuals estimated by the four regressions. The top line (marked with circles) of the figure is the trend of the weighted variance of log wages shown in the earlier section. The second line (marked with X) is the variance of the residuals from equation (7) with no group dummies. Although worker characteristics explain a large portion of the total variance, the trend in the residual variance is similar to the trend in the total variance of wages. This indicates that the changes in wage inequality cannot be fully accounted for by worker characteristics only. The third line (marked with diamonds) and fourth line (marked with triangles) are the variances of the residuals from the models with two-digit industry

Figure 3: Trends in the Variance of Residuals by Groups



Notes. This figure shows the trends of the weighted variances of residuals estimated by the four regressions using equation (7) for several groups. The difference between total wages and fixed wages concerns whether bonuses are included. "No Group," "Industry," "Industry-Size," and "Establishment" denote the variances of the estimated residuals using the worker characteristics (W.C.) only, W.C. + industry dummies, W.C. + industry–size dummies, and W.C. + Establishment dummies as regressors, respectively.

dummies and industry-size dummies, respectively. One notable feature of these two lines is the difference between each line and the second line. The difference between the second line and third line is stable over time, suggesting that the contributions of between-inequality at the industry level to changes in wage inequality are limited. By contrast, the difference between the second line and the fourth line increases over time. This reveals that size effects dominate the impact of industry-size groups on wage inequality trends. The last line shows a substantial contribution of establishment heterogeneity in explaining both the levels and changes in wage inequality. The contribution of establishment heterogeneity to wage inequality levels can be measured by the difference between the second line and the last line. The flat shape of this line means that the trends that are not explained by industry-size group effects are attributable to establishment heterogeneity.

Finally, the most important feature observed in Figure 3 is the difference between the left panel, for total wages, and the right panel, for fixed wages. Although the phenomena explained above are observed in both panels, the industry and industry-size group effects observed in the left panel for total wages seem to make a large contribution to wage inequality. As mentioned, this phenomenon denotes that bonuses have played an important role in the contribution of between-inequality to overall wage inequality. To add such interpretation, the difference between two panels implies that the substantial contribution of the bonuses to between-inequality has not came from worker characteristics. The fact that the amount of bonuses that is paid by employers are less related to the observed labor quality provides a possibility that it would be more related to firm-side factors unless sorting effects dominate the effects of between-inequality on trends in wage inequality.

4.2 Full Variance Decomposition

In the previous section, by observing the estimated residuals trend by group, I confirm the large contribution of between-inequality at the industry-size level to the rising trends in wage inequality. As mentioned, this large contribution comes from two components: pure effects and sorting effects. I decompose between-group variance into these two effects using equations (8) and (9) formed by taking the variance of equation (7), where ρ $(=Cov(xb, \bar{xb}_g)/Var(xb))$ is the worker–worker segregation index across groups suggested by Kremer and Maskin (1996), and $\rho_\varphi(= Cov(xb, \varphi)/Var(xb))$ is a worker-group segregation index: [16]

$$
\begin{aligned}
Var(w) &= Var(xb) + Var(\varphi) + 2Cov(xb, \varphi) + Var(u) &(8)\\
&= \underbrace{\underbrace{Var(xb)(\rho + 2\rho_\varphi)}_{\text{sorting effect}} + \underbrace{Var(\varphi)}_{\text{group effects}}}_{\text{Between-group variance}} + \underbrace{Var(xb)(1-\rho)}_{\text{Within-group variance}} + Var(u) &(9)
\end{aligned}
$$

Here, ρ shows the sorting effect by worker characteristics. If a firm employs workers randomly by observed characteristics, then $\rho = 0$. When a firm hires observably similar workers, ρ will be close to 1. Similarly, ρ_φ captures the sorting effect between observed worker characteristics and group wage premiums. If the observably more qualified workers are hired in groups with higher wages, then ρ_φ will be close to 1.[17] The values of interest in equation (9) are the extent of the ratio of

[16] Barth et al. (2016) treated Var(u) as within-group variance. If establishment effects are completely controlled by group dummies, Var(u) can be treated as within-group variance, as in Barth et al. (2016). In this paper, however, since only industry or industry-size effects are controlled, establishment effects that are not captured by industry or industry-size effects remain error terms. Thus, Var(u) is not included in within-group variance.

[17] Since the worker-group segregation index, ρ_φ, comes from the covariance term in equation (8), the difference between equations (8) and (9) concerns whether to consider the worker-worker segregation index. If the worker-worker segregation index has a negligible quantity, we can measure the sorting effects using the covariance term in equation (8). The estimated worker-worker segregation index is 0.133, 0.186, and 0.175 in 1994, 2008, and 2015, respectively. I consider that these figures are not negligible.

group effects to overall variance, $Var(\varphi)/Var(w)$, and its trend over time.

Table 3 and 4 show the results of a full variance decomposition for total wages and fixed wages using equation (9). When industries are treated as groups, the share of the change in variance of total wages between 1994 and 2015 is largely explained by the change in variance of the residuals (66.53%). Moreover, the change in variance between industries explains just 11.33% of the change in the variance of total wages. These results indicate that observed worker characteristics and employer industry affiliation cannot fully account for the trend in the variance of total wages. By contrast, the contribution of the residual decreases to 37.94% when industry-size is treated as groups. Furthermore, what dominates the increased variance in total wages is the increased inequality between industry-size groups (62.2%), which is attributable mainly to group effects, not sorting effects. The group effects account for the bulk of the between-group variance (0.4403/0.662=66.5%), and, while the variance in total wages decreases from 0.3956 to 0.3596 between 2008 and 2015, the variance between industry-size groups increases from 0.0803 to 0.0828. The decreasing variance in total wages is due to within and residual variances. This means that, though wage inequality shows a decreasing trend between 2008 and 2015, the group effects at the industry-size level are increasing since 1994, and the decreasing trend of between-inequality

Table 3: The Results of A Full Variance Decomposition (Total Wages)

Group	Variance	1994	2002	2008	2015	2008-1994 Change	2008-1994 Share	2015-1994 Change	2015-1994 Share
Total		0.2546	0.3535	0.3965	0.3596	0.1419	1.0000	0.1050	1.0000
Industry	Between	0.0529	0.0834	0.0733	0.0734	0.0205	0.1442	0.0205	0.1950
	Group effect	0.0225	0.0426	0.0375	0.0344	0.0149	0.1051	0.0119	0.1133
	Sorting effect	0.0303	0.0408	0.0359	0.0389	0.0055	0.0391	0.0086	0.0818
	Within	0.0990	0.1237	0.1329	0.1136	0.0339	0.2391	0.0147	0.1397
	Residual	0.1028	0.1465	0.1903	0.1726	0.0875	0.6167	0.0699	0.6653
Industry+Size	Between	0.0722	0.1264	0.1370	0.1375	0.0649	0.4571	0.0653	0.6220
	Group effect	0.0365	0.0641	0.0803	0.0828	0.0438	0.3085	0.0462	0.4403
	Sorting effect	0.0356	0.0623	0.0567	0.0547	0.0211	0.1485	0.0191	0.1817
	Within	0.0890	0.0957	0.1044	0.0888	0.0154	0.1089	-0.0001	-0.0014
	Residual	0.0935	0.1314	0.1551	0.1333	0.0616	0.4341	0.0398	0.3794

Notes. This table shows the results of a full variance decomposition for total wages (bonuses+fixed wages) using the WSS data and equation (9). The sorting effects include the worker-worker segregation effect ($Var(xb) * \rho$) and worker-group segregation effect ($2 * Var(xb) * \rho_{\varphi}$) where ρ shows the sorting effect by worker characteristics and ρ_{φ} captures the sorting effect by the associastion between observed worker characteristics and group wage premiums.

Table 4: The Results of A Full Variance Decomposition (Fixed Wages)

Group	Variance	1994	2002	2008	2015	2008-1994		2015-1994	
						Change	Share	Change	Share
Total		0.1940	0.2721	0.3007	0.2629	0.1066	1.0000	0.0689	1.0000
Industry	Between	0.0342	0.0564	0.0491	0.0452	0.0148	0.1392	0.0110	0.1595
	Group effect	0.0124	0.0255	0.0197	0.0164	0.0072	0.0678	0.0040	0.0577
	Sorting effect	0.0218	0.0310	0.0294	0.0288	0.0076	0.0713	0.0070	0.1018
	Within	0.0801	0.0947	0.1052	0.0850	0.0251	0.2355	0.0049	0.0715
	Residual	0.0797	0.1210	0.1464	0.1327	0.0667	0.6253	0.0530	0.7691
Industry+Size	Between	0.0412	0.0743	0.0758	0.0718	0.0346	0.3247	0.0307	0.4449
	Group effect	0.0181	0.0359	0.0376	0.0383	0.0195	0.1830	0.0202	0.2935
	Sorting effect	0.0231	0.0384	0.0382	0.0335	0.0151	0.1418	0.0104	0.1514
	Within	0.0776	0.0847	0.0929	0.0760	0.0153	0.1438	-0.0016	-0.0229
	Residual	0.0753	0.1131	0.1319	0.1151	0.0567	0.5315	0.0398	0.5781

Notes. This table shows the results of a full variance decomposition for fixed wages using the WSS data and equation (9). The sorting effects include the worker-worker segregation effect ($Var(xb) * \rho$) and worker-group segregation effect ($2 * Var(xb) * \rho_{\varphi}$) where ρ shows the sorting effect by worker characteristics and ρ_{φ} captures the sorting effect by the associastion between observed worker characteristics and group wage premiums.

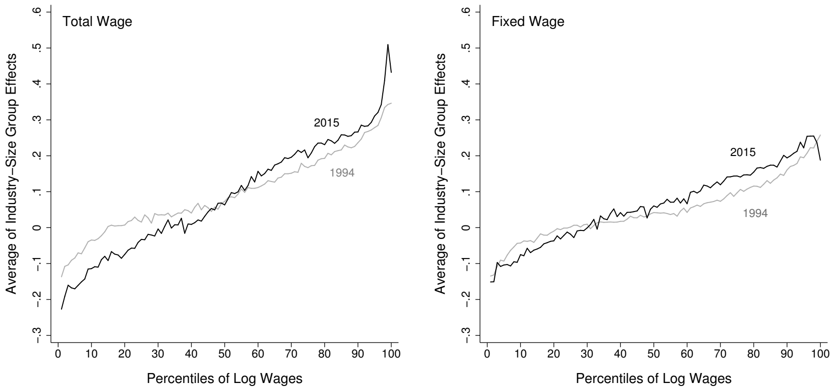
between 2008 and 2015 observed in the simple variance decomposition of section 3 is induced not by group effects but by other effects, such as worker characteristics and residuals.

Two interesting features are captured by comparing between the results for total wages and fixed wages. First, the share of the variance between industry-size groups from 1994 to 2015 drops steeply from 62.2% to 44.49% when bonuses are not included in wages, while the decreased share of the variance between industries is smaller from 19.5% to 15.95%. This implies that, even after worker characteristics are controlled for, the effects of bonuses on wage inequality trend come mainly from the difference in bonuses between establishment sizes. Second, the large drop in the variance between industry-size groups is attributable to drop in the share of group effects from 44.04% to 29.35%, while the change in the share of sorting effects is modest. This reveals that the differences in bonuses between industry-size groups depend not on differences of labor quality between them but on their own characteristics.

4.3 Distributional Changes in Group Wage Premiums

Figure 4 plots the average of industry-size group effects in 1994 and 2015 by 100 wage percentiles. The upward slopes observed in all lines indicate that wages and industry-size wage premiums are positively correlated regardless of the year or type of wages. According to these

Figure 4: Estimated Group Effect by Wage Percentiles (Industry–size Level)



Notes. This figure plots the average of industry-size group effects in 1994 and 2015 by 100 wage percentiles using the WSS data. The difference between total wages and fixed wages concerns whether bonuses are included. The average of group effects are calculated by the estimates of $\varphi_g(i)$ in regression equation (7). See Table A5-A8 in appendix for the results of the estimated wage premiums by industry-size groups, separately estimated by years and the types of wages.

two panels, the rising inequality between industry-size groups is derived from three distributional factors: the deterioration of group effects at the bottom 50%, the increase of group effects at the top 50%, and the soaring group effects at the top 5% of the wage distribution. Thus, we can conclude that the increasing wage polarization between industry-size groups is a main factor in the rising wage inequality, and the more polarized group wage premiums in 2015 are induced by the bonus differentials between groups.

The changes in group wage premiums by wage percentiles between 1994 and 2015 illustrated in Figure 4 can be decomposed into two effects: composition effects and wage premium effects. The composition effects mean the effects of changes in workers' group compositions within wage percentiles on the difference in the group wage premiums. Although the estimated group wage premiums are totally same between two years, if workers employed by groups where wage premiums are low are more concentrated at the bottom 50% of total wages in 2015, the estimated group wage premiums under the support of total wages can be more polarized. In contrast, if the workers' group compositions within wage perncetiles are totally same between two years, then the results shown in Figure 4 are mainly affected by the wage premium effects that come from the estimated group wage premiums more dispersed in 2015. The two effects can be expressed by simple equations as follows:[18]

$$\bar{\varphi}_t^p = \frac{1}{n_t^p}\left(\sum_{g=1}^{k}\hat{\varphi}_{g,t}n_{g,t}^p\right) = \sum_{g=1}^{k}\hat{\varphi}_{g,t}\theta_{g,t}^p \quad \text{where} \quad n_t^p = \sum_{g=1}^{k} n_{g,t}^p \tag{10}$$

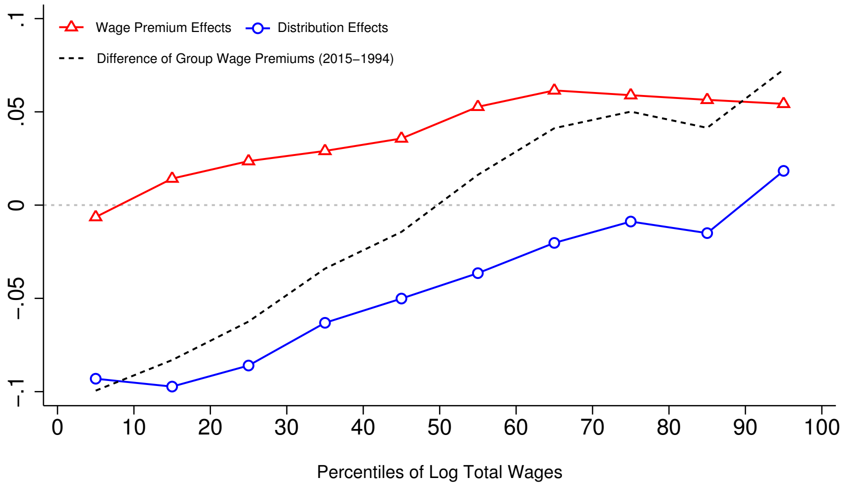
$$\triangle\,\bar{\varphi}^p = \bar{\varphi}_{t+1}^p - \bar{\varphi}_t^p = \sum_{g=1}^{k}\left(\hat{\varphi}_{g,t+1}\theta_{g,t+1}^p - \hat{\varphi}_{g,t}\theta_{g,t}^p\right) \tag{11}$$

$$\triangle\,\bar{\varphi}^p = \underbrace{\sum_{g=1}^{k}(\frac{\theta_{g,t+1}^p + \theta_{g,t}^p}{2})(\hat{\varphi}_{g,t+1} - \hat{\varphi}_{g,t})}_{\text{Wage Premium Effects}} + \underbrace{\sum_{g=1}^{k}(\frac{\hat{\varphi}_{g,t+1} + \hat{\varphi}_{g,t}}{2})(\theta_{g,t+1}^p - \theta_{g,t}^p)}_{\text{Composition Effects}} \tag{12}$$

where $\bar{\varphi}_t^p$ is the estimated group wage premiums averaged at wage percentile p and period t; $\hat{\varphi}_{g,t}$ is the estimated group wage premiums of group g at period t; n_t^p and $n_{g,t}^p$ are the number of workers at wage

[18] This decomposition has been used in the literatures on poverty to decompose the changes in poverty measures into population shift effects and group effects (e.g. urban and rural). See Son (2003), Khan et al. (2003) and Heshmati (2004) for details.

Figure 5: Wage Premium Effects and Composition Effects by Wage Percentiles



Notes. This figure plots 'wage premium effects' and 'composition effects' by wage percentiles calculated by equation (12). The line marked with triangles is the wage premium effects; the line marked with circles is the distribution effects; and the dash line shows the difference of average group wage premiums by 10 wage percentiles between 1994 and 2015.

percentile p and the number of workers employed by group g at wage percentile p and period t, respectively; $\theta^p_{g,t}$ is the share of workers employed by group g within wage percentile p at period t; and k is the number of industry-size groups.

Figure 5 plots the two effects by wage percentiles calculated by equation (12). The line marked with triangles is the wage premium effects; the line marked with circles is the composition effects; and the dashed line shows the difference of average group wage premiums by wage percentiles between 1994 and 2015. The sum of composition effects and wage premium effects equals to the difference of average group wage premiums. The results reveal that the deterioration of

Table 5: The Changes in Wage Premiums and Worker Distribution by Establishment Size

Total Wages	Size	Year				Changes
		1994	2002	2008	2015	('15-'94)
Premiums	Size 1: 10–29	-0.052	-0.112	-0.167	-0.188	-0.135
	Size 2: 29–99	-0.051	-0.056	-0.146	-0.127	-0.076
	Size 3: 100–299	0.015	0.016	-0.047	-0.028	-0.044
	Size 4: 299–499	0.052	0.114	0.162	0.114	0.062
	Size 5: 500+	0.190	0.207	0.360	0.405	0.215
Bottom 50%	Size 1: 10–29	2.86%	10.02%	17.56%	18.78%	+15.92%p
	Size 2: 29–99	11.34%	16.00%	21.84%	24.69%	+13.35%p
	Size 3: 100–299	24.52%	28.98%	36.52%	29.24%	+4.72%p
	Size 4: 299–499	24.70%	20.77%	9.21%	10.63%	-14.06%p
	Size 5: 500+	36.58%	24.23%	14.86%	16.65%	-19.93%p
Top 50%	Size 1: 10–29	1.57%	3.97%	8.35%	7.52%	+5.95%p
	Size 2: 29–99	5.95%	7.71%	12.17%	12.96%	+7.00%p
	Size 3: 100–299	17.06%	19.39%	29.16%	19.94%	+2.88%p
	Size 4: 299–499	21.46%	22.22%	13.45%	12.75%	-8.71%p
	Size 5: 500+	53.96%	46.71%	36.87%	46.82%	-7.13%p

Notes. This table shows the changes in wage premiums and workers' compositions at the bottom 50% and at the top 50% of total wages by establishmnet size categories. The wage premiums of the industry-size level are estimated by equation (7), and the reported wage premiums in this table are calculated by averaging them into size level.

group effects at the bottom 50% of the wage distribution is mainly attributable to composition effects, and the increase of them at the top 50% is due primarily to wage premium effects. These results imply that the considerable effects of changes in the group wage premiums on changes in wage dispersion between 1994 and 2015 come from the increased wage premium of groups where workers at the top 50% of wage distribution are employed.

Table 5 shows the changes in wage premiums and workers' compositions at the bottom 50% and at the top 50% of total wages by establishmnet size. The wage premiums of sizes are calculated by averaging industry-size wage premiums estimated by equation (7) into size level. The group wage premiums between establishment size have become more dispersed as time goes by, and this may affect the wage premium effects illustrated in Figure 5. The phenomenon shown at Figure 5 that the deterioration of group effects at the bottom 50% of wage distribution are dominantly affected by compostion effects may, to some degree, come from changes in size distribution: shares of small establishments (size 1-3) are increased between 1994 and 2015. In contrast, although the shares of small ones are also increased at the top 50%, the extent of the increase is smaller than it is at the bottom 50%. This may lead to, to some degree, the dominant role of the wage premium effects at the top 50%.

4.4 Effects of Unmeasured Worker Heterogeneity

One plausible criticism of the findings from the cross-sectional data is the effect of unmeasured heterogeneity across workers on between-inequality. It could be argued that, if we do not control for unobserved worker characteristics, the variance between groups could display large biases. Specifically, the group effects of regression equation (7), $\varphi_g(i)$, may capture the average level of workers' unmeasured characteristics as well as the wage premium of each group. Thus, if there are systematic differences in unobserved heterogeneity across groups and if they dominate the between-inequality, the estimated group effects shown in Table 3 would be attributable not to the pure group effect, but to the sorting effects from unobserved worker heterogeneity.

Krueger and Summers (1988) suggest two possible strategies for addressing this problem. The first approach considers alternative models in which some control variables for labor quality are ruled out in order to observe the effects of the excluded variables on the group effects. If wage differentials across industry-size groups are significantly affected by workers' unmeasured heterogeneity, then the variance between groups would vary according to the excluded control variables. Table 6 shows the pure group effects (Var($\varphi_g(i)$) estimated from the alternative models using the WSS data. Here, model 1 includes years of schooling only; model 2 includes experience, its square, and the variables in model 1; model 3 includes interaction terms for the variables used in model 2 with woman, occupation dummies (nine categories), and the variables used in model 2; and the full model is the same as that reported in Table 3. The results show that the shares of between-variances are stable regardless of model specification, namely 45.29% in model 1 and 44.03% in the full model. The last column shows the correlation of the coefficients for the group effects estimated in models 1 to 3 with the full model. The estimated coefficients for the group effects are highly correlated across the models irrespective of labor quality control.

The second approach is to analyze the longitudinal data. Using the KLIPS data, I estimate wage equation (13), in which the term α_i

Table 6: Alternative Models of Control for Labor Quality (Industry–size level, Total Wage)

Variance		1994	2015	2015–1994 Change	2015–1994 Share	Correlations of Coefficients
Total		0.2546	0.3596	0.1050	1.0000	-
	Model 1	0.0526	0.1002	0.0476	0.4529	0.9268
Group Effect	Model 2	0.0494	0.1052	0.0557	0.5307	0.9748
$(= Var(\varphi_g(i))$	Model 3	0.0375	0.0886	0.0511	0.4862	0.9965
	Full Model	0.0365	0.0803	0.0462	0.4403	-

Notes. This table shows the results of variance decompositions using the equation (9) to explore the effects of labor quality on group effects. Model 1 includes years of schooling only; model 2 includes experience, its square, and the variables in model 1; model 3 includes interaction terms for the variables used in model 2 with woman, occupation dummies (nine categories), and the variables used in model 2; and the full model is the same as that reported in Table 3. The last column shows the correlation of the coefficients for the group effects estimated in models 1 to 3 with the full model.

is added to equation (7) to control for workers' unmeasured heterogeneity within two intervals: 1998-2003 and 2004-2008.[19]

$$w_{i,g} = \alpha_i + x_{i,g}b + \varphi_g(i) + u_{i,g} \tag{13}$$

The independent variables in regression equation (13) are the same as those in equation (7). Workers with fewer than three observations within a period are dropped. The variance decomposition for equation (13) can be expressed as follows:

$$\begin{aligned} Var(w) &= Var(\alpha) + Var(xb) + Var(\varphi) \\ &+ 2cov(\alpha, xb) + 2cov(\alpha, \varphi) + 2cov(xb, \varphi) + Var(u) \end{aligned} \tag{14}$$

[19]Since the equation has two sources of unobserved heterogeneity, the firm and the workers, it has been called a "two-way fixed effect" model. To estimate this equation, I use the modified zigzag algorithm introduced by Guimaraes et al. (2010). This method is relatively easy on computer memory but requires a longer estimation time. See Guimaraes et al. (2010) for details.

Table 7: The Effects of Unobserved Characteristics of Workers (Industry–Size Level)

Variance	Period 1 (1998–2003)	Period 2 (2004–2008)	Change (P2-P1)	Share
Total ($= Var(w)$)	0.2969	0.3377	0.0409	1.0000
Between ($= Var(\bar{w}_g)$)	0.0897	0.1299	0.0402	0.9833
Within ($= Var(w - \bar{w}_g)$)	0.2071	0.2078	0.0007	0.0167
A. Controlling the Unobserved Characteristics of Workers				
$Var(xb)$	0.0345	0.0336	-0.0009	-0.0231
$Var(\alpha)$	0.2163	0.2235	0.0072	0.1755
$Var(\varphi)$	0.0317	0.0539	0.0222	0.5426
$\sum 2 * (Cov(\cdot))$	-0.0292	-0.0065	0.0226	0.5532
$Var(u)$	0.0435	0.0334	-0.0102	-0.2483
B. Uncontrolling the Unobserved Characteristics of Workers				
$Var(xb)$	0.1021	0.1055	0.0035	0.0844
$Var(\varphi)$	0.0472	0.0692	0.0220	0.5374
$2 * Cov(xb, \varphi)$	0.0200	0.0389	0.0189	0.4612
$Var(u)$	0.1275	0.1242	-0.0034	-0.0830
The number of observations	6,319	5,854	-	-

Notes. This table compares the results of various variance decompositions: a simple variance decomposition and two full variance decomposition(controlling and uncontrolling the unobserved characteristics of workers) using the KLIPS data. The models in part A and part B are estimated by the equation (13) and (7), and variance decompositions are implemented by the equation (14) and (8), respectively.

My interest in equation (14) is whether the variance in group effects, $Var(\varphi)$, is still meaningful in explaining the trends in wage inequality, even after controlling for unmeasured worker heterogeneity, α_i. Table 7 shows the results of a simple variance decomposition using equation (4) and two full variance decompositions using equations (14) and (7). The results of the simple variance decomposition show that the changes in between-variances at the industry-size level dominate the changes in wage variance (98.33%). The second part of Table 7 (labeled "A") shows the results of the variance decomposition using equation (14). Although the levels in the variances of estimated worker heterogeneity substantially explains wage differentials among workers in all periods (72.85% [=0.2163/0.2969] in period 1 and 66.18% [=0.2235/ 0.3377] in period 2), the contribution of their changes to wage variances changes is much smaller than the contribution of their changes to group effects. The third part of Table 7 (labeled "B") shows the results of a variance decomposition using equation (7) where unobserved worker heterogeneity is not controlled for. The contribution of changes in group effects is similar to the result shown in the second part of Table 7 (i.e., 54.26% and 53.74%), indicating that the contribution of group effects to wage variance trends is robust to the unobserved worker characteristics.

The results of the two approaches discussed above suggest that the findings of the cross-sectional analysis are robust to the effects of worker heterogeneity on wage inequality trends.

5 Firm–side Factors and Between–Inequality of Wages

I have shown that changes in between-inequality explain a large portion of the changes in wage inequality. In this section, I investigate the relation between firm-side factors and the between-inequality of wages using the merged data from the WSS and KED introduced in section 2.1. Owing to the limited time period covered by the KED, the analysis period of this section covers 2000 to 2015.

Previous studies discuss two issues concerning the estimation of firm-side effects on wage determination and inequality. The first is how to control for the effects of human capital on wage inequality. Unless the differentials in human capital among groups are controlled for, the effects of firm-side factors on wage inequality can be overestimated. Blanchflower et al. (1996) adopted two strategies to address this problem: they averaged out human capital variables at the worker-level to those at the industry-level, and they conducted two-stage regressions of wage equations. They took the coefficients of group dummies in the first stage and used them to form the dependent variable in the second stage. Barth et al. (2016) used variables calculated by averaging the estimated values, $x_{i,g}b$, in wage equation (7) into firm-level values. To observe the effects of worker characteristics on wage inequality at the industry-size level, I adopt Barth et al. (2016)'s strategy.

The second issue is the reverse causality between wages and firm-side variables, particularly productivity-related (or profit-related) variables. The employment of highly qualified workers, which implies greater remuneration, can lead to greater labor productivity for employers. There are two ways to address this problem: adopting lagged variables of labor productivity, or finding good instrumental variables. Carlsson et al. (2014) and Guiso et al. (2005) utilized the lag variable of labor productivity to address the endogeneity problem. Other studies, such as Barth et al. (2016) and Card et al. (2014), took the labor productivity of the same industry outside the region of the observed employer as the instrument. In this analysis, the former method (i.e., using the lagged variables) is adopted. Since Korea is small compared to countries such as the U.S. or Portugal, which previous studies have analyzed, the instruments are not likely to be exogenous. Moreover, Blanchflower et al. (1996) suggested that shocks to labor productivity (or profit) might take time to be passed on in wages. This is acceptable for the wage-setting system used for Korean workers because one year's wage usually depends on the previous year's performance.

The analysis years, 2000 to 2015, are divided into two comparable periods: 2000–2008 and 2009–2015. From section 3, we know that, if worker characteristics are controlled for, between-variance at the industry-size level has an increasing trend between 2000 and 2015 in spite of the decreasing wage variance trend after 2008. Thus, this section seeks to identify what kinds of firm-side factors make between-inequality more dispersed between the two periods. To decompose the changes in between-inequality into covariate effects ("quantity effects") and coefficient effects ("price effects") between the two periods, I use Machado and Mata (2005)'s method based on quantile regression. While traditional wage decomposition methods such as the Oaxaca decomposition hinge on the effects of covariates and coefficients at a mean level (Oaxaca, 1973), Machado and Mata (2005)'s method allows us to factor in heterogeneous effects of firm-side factors along with wage distribution and to observe the marginal effect of each variable on changes in wage inequality by calculating counterfactual variances.

5.1 Firm–side Factors

Labor Productivity

The main variable in this analysis is labor productivity per worker. In previous studies, the estimated coefficient on labor productivity has been referred to as "rent-sharing elasticity" or the "rent-sharing parameter." The measure of labor productivity per worker used in this study is the value-added per worker. The value-added per worker in firm j, with employees n_j, labor cost LC_j, profit P_j, tax-related cost TC_j, financial cost FC_j, and depreciation D_j can be calculated as follows:

$$\frac{\text{value-added}_j}{n_j} = \frac{\mathrm{LC}_j + \mathrm{P}_j + \mathrm{TC}_j + \mathrm{FC}_j + \mathrm{D}_j}{n_j}. \tag{15}$$

The original definition of value-added is the value of the total output less the value of intermediate goods. Because value-added is distributed among several costs and the profit in balance sheets, I calculate it using equation (15). The measures for labor productivity most widely used in the literature are sales per worker and value-added per worker. As Card et al. (2016) pointed out, since sales per worker can be affected by intermediate inputs and services that are purchased rather than produced in-house, I choose value-added per worker as a proxy for labor productivity. [20]

Capital–to–Labor Ratio

Several recent studies have shown the positive and significant effects of the capital–labor ratio on wages (e.g., Arai, 2003; Leonardi, 2007).[21] The research shows that the capital-to-labor ratio reflects the role of technology in the evolution of wage inequality. The fact that technology is embodied in physical capital implies that labor costs are a minor part of firms' costs; thus, firms with high capital-to-labor ratios may be more favorable to high wage demands. Moreover, since high capital-to-labor ratios may also reflect the high fixed costs required for a new firm's entry, workers employed in firms with high capital-to-labor ratios are paid more. In light of efficiency wages, as pointed out by Akerlof and Yellen (1986), if high capital-to-labor ratios lead to increases in turnover costs or poor performance costs, firms with high capital-to-labor ratios will pay more to evade them. The capital-to-labor ratio used in this study is calculated as tangible assets (e.g.,

[20] Card et al. (2016) showed biases in the two measures of labor productivity using a simple linear technology equation. According to their simple model, value added per worker can be a valid index of TFP when the average quality of human capital is controlled for.

[21] Leonardi (2007) showed the important role of the capital-to-labor ratio in explaining the residual wage inequality in the U.S. from 1970 to 2002. He called the wage premium induced by differentials in capital-to-labor ratios across firms a "capital intensity premium."

equipment and plants) divided by the number of employees.

Other Factors

The control variables used to reduce the biases in estimating the effects of labor productivity and the capital–labor ratio on wage inequality are alternative wages at the industry-year level and averaged worker characteristics at the industry-size-year level. First, alternative wages are the average wage of the (two-digit) industry of each year that would affect the average wage of industry-size groups through several paths, such as bargaining power of workers and demand-supply conditions. Since the average wages of two-digit industries are affected by within-group wage levels, the wages in the industry's group are not included when calculating the average wages of the industries.[22] Second, worker characteristics are (as mentioned) represented by averaging the values of $x_{i,g}b$ estimated separately by years in equation (7) into industry-size-year level.

5.2 Results I: Firm–side Factors and Wage Determination

Prior to decomposing wage inequality using quantile regression, the effects of firm-side factors on mean wages are estimated using the OLS method as the basic results. Consider the following regression

[22]For instance, the alternative wage of industry A of size category 1 (10–29 employees) is the average wage of the groups including industry A of size categories 2 to 5.

equation:

$$w_{g,t} = \beta LP_{g,t-1} + \gamma CL_{g,t} + \delta AW_{g,t} + \eta WC_{g,t} + \mu_i + \theta_t + \epsilon_{g,t}, \quad (16)$$

where $w_{g,t}$ is a vector of average log real hourly wages for industry-size group g in period t from the WSS data; $LP_{g,t-1}$ and $CL_{g,t}$ are vectors of log real labor productivity per worker of the previous year (lag 1) and of the capital-to-labor ratio for industry-size group g in period t from the KED, respectively; $AW_{g,t}$ and $WC_{g,t}$ are vectors of log real alternative wages and worker characteristics of group g in period t, respectively; μ_i are two-digit industry dummies used to control for the unobserved characteristics of industries; θ_t are year dummies representing the economy condition of each year; $\epsilon_{g,t}$ is an unobserved time-varying errors.

Table 8 reports the estimation results using regression equation (16). While the estimation of the rent-sharing parameter is 0.330 when not considering the other factors (model [1]), adding worker characteristics to model (1) reduces it to 0.162. This result implies that about half of the positive effect of labor productivity on wages is due to the sorting of workers across industry-size groups. Thus, the difference in the coefficient of labor productivity per worker between models (1) and (2) is not due to the rent-sharing behaviors of employers but to the compensation for workers' quality. The rent-sharing parameter is further reduced to 0.059 when the capital-to-labor ratio and alterna-

Table 8: The Effect of Firm–side Factors on Wage Determination: Industry–Size level

Dep. Var: log hourly wages	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
			Total Wage			**Fixed Wage**	
L1.Labor Productivity	0.330***	0.162***	0.122***	0.059**	0.076***	0.048**	0.053***
Per Worker	(0.039)	(0.037)	(0.032)	(0.027)	(0.011)	(0.019)	(0.019)
Capital-to-Labor Ratio			0.039***	0.044***	0.081***	0.025***	0.051***
			(0.015)	(0.013)	(0.006)	(0.009)	(0.018)
Alternative Wages				0.546***	0.154***	0.621***	0.282**
				(0.085)	(0.049)	(0.076)	(0.134)
Worker Characterisitcs		1.318***	1.326***	0.770***	1.131***	0.575***	0.878***
		(0.069)	(0.070)	(0.090)	(0.045)	(0.084)	(0.152)
Constant	-2.508***	-1.534***	-1.528***	-1.036***	-1.486***	-0.685***	-0.944***
	(0.360)	(0.315)	(0.303)	(0.273)	(0.092)	(0.172)	(0.198)
Industry Dummies (2-digit)	No	No	No	No	Yes	No	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.261	0.669	0.679	0.745	0.795	0.798	0.829
Number of observations	2,320	2,320	2,320	2,320	2,320	2,320	2,320

Notes. Labor Productivity is measured by the value-added per worker. Its lagged values are used so as to reduce endogeneity problems. Capital-to-labor ratio is calculated as tangible assets (e.g., equipment and plants) divided by the number of employees. Alternative wages are the average wage of the (two-digit) industry except for own size group. The worker characteristics are the average of $x_{i,g}b$ from equation (7) at the industry-size level. Year dummies are included in all models. Standard errors clustered by two–digit industry are in parentheses. *, ** and *** indicate the 10%, 5% and 1% significance level, respectively.

tive wages are included. As expected, the capital-to-labor ratio and alternative wages have positive and significant effects on wages (model [4]).[23]

Model (5) adds two-digit industry dummies to Model (4), allowing the estimated coefficients in model (5) to be interpreted as the effects of within-industry and between-sizes of firm-side factors. The rent-sharing parameter increases from 0.059 to 0.076 when industry dummies are added, indicating that the significant and positive effects of labor productivity on wages via firms' rent-sharing behaviors are more clearly observed among firm sizes than among industries. Next, the coefficient of the capital-to-labor ratio increases from 0.044 to 0.081, implying that the positive correlation between the capital–labor ratio and wages is also much stronger among sizes than among industries.

Models (6) and (7) show the results for fixed wages. All model specifications are the same as in models (4) and (5) for total wages. As expected, the rent-sharing parameters are reduced compared to the results for total wages, implying that paying bonuses is one way in which employers exhibit rent-sharing behavior. The coefficients of the capital–labor ratio also decrease compared to the results for total wages. Moreover, the declines in the coefficients of the capital-to-labor ratio are even larger than for labor productivity. That the effects of

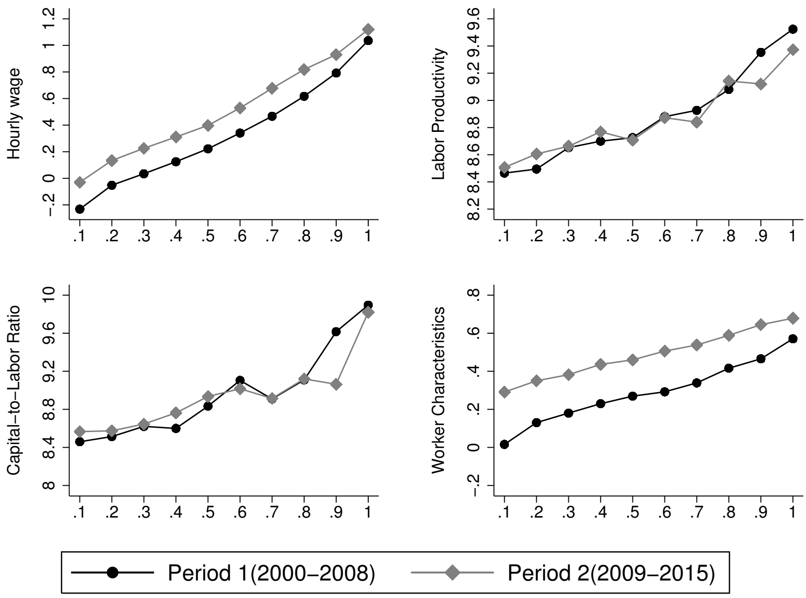
[23]Card et al. (2016) summarized the estimation results for rent-sharing parameters in previous studies, revealing that they were estimated in the range of 0.05 to 0.15. In light of the results of previous studies, the estimated rent-sharing parameters shown in Table are reliable.

the capital-to-labor ratio are sensitive to bonuses, even more sensitive than is labor productivity, indicates that, although firms with higher capital-to-labor ratios are more favorable to demands for higher wages for several reasons (such as minor labor costs, the advantages of high fixed costs, and reduced turnover costs), the wage premiums from heavy capital dependency are also associated with the performance of workers and firms. Alternative wages appear to be more sensitive to fixed wages than to total wages. This means that wage gaps between groups via different bargaining power of workers and demand-supply mismatches of labor are reflected more strongly in fixed wages than in total wages.

5.3 Results II: Marginal Effects of Firm–side Factors on Between–Inequality

In the previous section, I show the significant effects of the study's variables on wage determination. This final section explores the sources of the changes in between-inequality between the two periods (2000-2008 and 2009-2015). Changes in wage inequality have to be captured according to changes in wage distribution. The analysis in the previous section cannot be extended to an analysis of the entire wage distribution. Beyond the traditional decomposition methods, in this section, I adopt the methods of Machado and Mata (2005) based on quantile regression and a simulation technique to investigate the marginal

Figure 6: Firm–side Factors by Wage Quantiles and Periods



Notes. This figure provides information on the variables by 10% quantile of total wages averaged at the industry-size level (x-axis) and two periods. X-axis means 10 quantiles of the average wages at industry–size level. Labor productivity is measured by the value–added per worker. Capital–to–labor ratio is calculated by tangible assets (e.g. equipment and plants) divided by the number of employees. Worker characteristics are the average of $x_{i,g}b$ from equation (7) at the industry-size level. The detailed information on the variables is in section 5.1.

effects of each variable on changes in between-inequality.

5.3.1 Covariates Effects on Between–Inequality

Figure 6 provides information on the variables by 10% quantile of total wages averaged at the industry-size level (x-axis) and two periods (shown by the black lines marked with circles [2000–2008] and the gray lines marked with diamonds [2009–2015]). From these figures, we can see roughly which covariates affect the changes in between-inequality. The first plot shows that the decrease in between-inequality between the two periods is attributable to industry-size groups placed at the top 30% of average wages. They show a smaller increase in wages than do the other wage quantiles. I have already shown in section 4.2 (the full variance decomposition) that the between-industry decrease is induced by worker characteristics. Although between-inequality shows decreasing trends between 2009 and 2015 in the simple variance decomposition, it shows a continuous increase since 1994 if worker characteristics and sorting effects are controlled for. The last plot for worker characteristics supports these results, showing that the difference between the two lines narrows at the top 30% wage quantile.

The second plot for labor productivity provides two important results. First, regardless of the period, labor productivity has upward slopes under the support of wage quantiles. This shows that wages and labor productivity are positively correlated, as predicted by efficiency wage models. Second, while labor productivity is similar at the bottom 80% wage quantile between the two periods, it decreases at the top 20% of wages in the second period. This means that the difference in labor productivity between the bottom 80% and top 20% wage quantiles is smaller in period 2 than in period 1, suggesting that those changes may cause between-inequality to be less dispersed. The third plot for the capital-to-labor ratio shows that the differences in ratios between the two periods are minor, except for the 90% quantile.

5.3.2 Coefficient Effects on Between–Inequality

The next step is to estimate for prices of covariates using quantile regression and evaluate their contributions to changes in between-inequality. Given a vector of covariates, z, let $Q_\theta(w|z)$ for $\theta \in (0,1)$ denote the θth quantile of the distribution of the log hourly average wages at the industry-size level. The conditional quantiles can be modeled by equation (17) where $\beta(\theta)$ is a vector of the quantile regression coefficients.

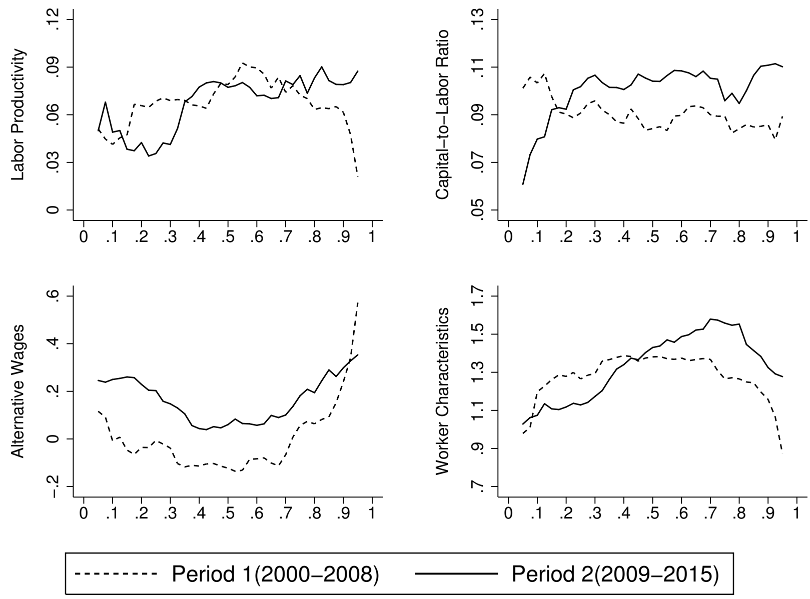
$$Q_\theta(w|z) = z'\beta(\theta) \tag{17}$$

$\beta(\theta)$ can be estimated by minimizing equation (17) in $\beta(\theta)$ using linear programming methods (Koenker and Basset, 1987):

$$\sum_{i:w_i \geq z_i'\beta}^{n} \theta|w_i - z_i'\beta(\theta)| + \sum_{i:w_i < z_i'\beta}^{n} (1-\theta)|w_i - z_i'\beta(\theta)| \tag{18}$$

Figure 7 shows the coefficient estimates, $\hat{\beta}$, by 2.5% wage quantile. The dotted lines represent period 1 (2000–2008), and the solid lines represent period 2 (2009–2015). The changes in coefficients for labor productivity decrease at the bottom quantiles between the two periods, while they increase at the upper quantiles. This implies that the changes in labor productivity prices cause between-inequality to become more dispersed. The estimated coefficients for the capital-to-

Figure 7: The Estimate Results of Quantile Regression by Periods (Total Wages)



Notes. This figure shows the coefficient estimates, $\hat{\beta}$, using equation (18). The regressions are implemented for every 2.5% wage quantiles. X-axis means 2.5% quantiles of the average wages at the industry–size level.

labor ratio show the opposite shapes between the two periods. While wages and the coefficients are negatively correlated at period 1, they are positively correlated at period 2. This may be a factor that increases between-inequality. The coefficients for worker characteristics are crossed at about the 50% wage quantile, and the differences between the two lines are greatest in the top quantiles. This may also cause between-inequality to become more dispersed. Figure A2 in appendix shows the coefficient estimates for fixed wages. When not considering bonuses, the changes in coefficients of labor productivity are modest in the overall distribution of wages, implying that bonuses workers are paid and rent-sharing behavior of employers are highly associated.

5.3.3 Marginal Effects of Covariates and Coefficients on Changes in Between–Inequality

Changes in between-inequality come from both the changes in covariates shown in Figure 6 and the changes in their coefficients shown in Figure 7. To observe the marginal effects of the covariates and coefficients on changes in between-inequality, I need to estimate the conditional distribution of wages given z, and the marginal density of wages.

I follow two of Machado and Mata (2005)'s methods. The first is generating the conditional distribution of wages given z. Under the assumption that the conditional quantile function defined in equation (17) is correctly specified at a sufficiently large number of points θ, the conditional distribution of wages can be simulated using the estimated parameters $\hat{\beta}(\theta)$ and probability integral transformation theorem: if U is a uniform random variable on [0,1], then $F^{-1}(U)$ has distribution F. Thus, if $\theta_1, \theta_2, ...\theta_m$ are drawn from a uniform (0,1) distribution, the corresponding m estimates of the conditional quantiles of wages at z, $\{z'\hat{\beta}(\theta_i)\}_{i=1}^{m}$, constitute a random sample from the (estimated) conditional distribution of wages given z.

The second is estimating the marginal density of wages through a procedure of integrating z out. In OLS, z can be integrated out easily using the law of iterated expectations, but it does not work in quantile regression since $Q_\theta(w) \neq E_z[Q_\theta(w|z)]$. To address this problem, Machado and Mata (2005) suggest the following simulation-based technique.

- Generate a random sample of size k from a uniform distribution U[0,1]: $\theta_1, ..., \theta_k$
- For each θ_k and at time t, estimate the QR coefficients $\hat{\beta}^t(\theta_k)$.
- Generate a random sample of size k with replacement from the empirical distribution of covariates (that is, from the rows of covariates), denoted by $\{z_i^*(t)\}_{i=1}^k$
- Using the random sample of covariates and the estimated QR coefficients, calculate a random sample of size k that are from the desired distribution: $\{w_i^*(t) = z_i^{*'}(t)\hat{\beta}^t(\theta_i)\}_{i=1}^k$

This procedure is essentially equivalent to numerically integrating the estimated conditional quantile function over the distribution of z and θ. Using this technique, I can calculate the marginal effects of the covariates and coefficients on wage variance. Suppose that only one covariate is changed and the other covariates and all coefficients are unchanged between the two periods. Then, the counterfactual variance can be expressed as the variance of $x_2\hat{\gamma}_1(\theta) + d_1\hat{\rho}_1(\theta)$ where x_2 is the changed covariate from the value of period 1 to period 2; $\hat{\gamma}_1(\theta)$

is the estimated coefficient of the changed covariate at period 1; d_1 is a set of unchanged covariates; and $\hat{\rho}_1(\theta)$ is a set of coefficients for the unchanged covariates. Finally, we can interpret the difference in variance between $x_1\hat{\gamma}_1(\theta) + d_1\hat{\rho}_1(\theta)$ and $x_2\hat{\gamma}_1(\theta) + d_1\hat{\rho}_1(\theta)$ as the marginal contribution of changes in covariate x to between-inequality.

Table 9 presents the actual and counterfactual variances of wages. *Raw* and *Estimated* in the first part of Table 9 indicate the variances of wages calculated from the data and the variances of predicted wages, $w_i^*(t)$, with $k = 5000$, respectively. The numbers in brackets are 95% bootstrap confidence intervals for variances looked for through 10,000 iterations of bootstrap sampling. The wage variances from the data at periods 1 and 2 are 0.1449 and 0.1262 and the estimated variances are 0.131 and 0.1169, respectively. The differences in the two variances between the data and the estimated variances reflect variances explained by residuals. The estimated variances explain a large portion of the variances from the data: about 90.4% (= 0.131/0.1449) at period 1 and 92.6% (= 0.1169/0.1262) at period 2.

The numbers in *Covariate Effects* and *Coefficient Effects* in the second part of Table 9 show the counterfactual variances calculated under the assumptions of changes in covariates and coefficients separately. *Aggregate* indicates that all covariates (or all coefficients) are changed from the values of period 1 to those of period 2. The results show that the aggregate effect of the covariates is a factor that

Table 9: The Counterfactual Variances by Covariates and Coefficients Effects

Actual and Estimated Variances				
	Raw		Estimated	
	Total	Fixed	Total	Fixed
Period 1 (2000-2008)	0.1449	0.1023	0.131 [0.1262 ; 0.1359]	0.0901 [0.0868 ; 0.0936]
Period 2 (2009-2015)	0.1262	0.0834	0.1169 [0.1129 ; 0.121]	0.0766 [0.074 ; 0.0791]

(Estimated) Counterfactual Variances				
x or γ	Covariate Effects $(= var(x_2\hat{\gamma}_1(\theta) + d_1\hat{\rho}_1(\theta))$		Coefficients Effects $(= var(x_1\hat{\gamma}_2(\theta) + z_1\hat{\rho}_1(\theta)))$	
	Total	Fixed	Total	Fixed
Aggregate	0.1056	0.0704	0.1517	0.0998
	[0.102 ; 0.1093]	[0.0681 ; 0.0728]	[0.1461 ; 0.1574]	[0.0962 ; 0.1035]
Labor Productivity	0.117	0.0827	0.1879	0.0926
	[0.1127 ; 0.1216]	[0.0796 ; 0.0859]	[0.1803 ; 0.1957]	[0.0891 ; 0.0961]
Capital–to–Labor Ratio	0.1221	0.0855	0.1808	0.1136
	[0.1174 ; 0.1269]	[0.0823 ; 0.0888]	[0.174 ; 0.1878]	[0.1093 ; 0.118]
Alternative Wages	0.1373	0.0678	0.158	0.0879
	[0.1324 ; 0.1423]	[0.0653 ; 0.0704]	[0.1523 ; 0.1639]	[0.0846 ; 0.0913]
Worker Characteristics	0.0888	0.0547	0.1503	0.1088
	[0.0854 ; 0.0923]	[0.0525 ; 0.0568]	[0.1445 ; 0.1562]	[0.1043 ; 0.1134]
Industry Dummies	-	-	0.1472	0.1057
	-	-	[0.1419 ; 0.1527]	[0.1016 ; 0.1099]

Notes. This table provides the actual and counterfactual variances of two types of wages at the industry-size level. *Raw* and *Estimated* in the first part of this table indicate the variances of wages calculated from the data and the variances of predicted wages, $w_i^*(t)$, with $k = 5000$, respectively. $var(x_2\hat{\gamma}_1(\theta) + d_1\hat{\rho}_1(\theta))$ in the second part means the counterfactual variance where x_2 is the changed covariate from the value of period 1 to period 2; $\hat{\gamma}_1(\theta)$ is the estimated coefficient of the changed covariate at period 1; d_1 is a set of unchanged covariates; and $\hat{\rho}_1(\theta)$ is a set of coefficients for the unchanged covariates. *Aggregate* means that all covariates (or all coefficients) are changed from values of period 1 to ones of period 2. The numbers in brackets are 95% bootstrap confidence intervals for variances looked for through 10,000 iterations of bootstrap sampling.

decreases the wage variance from 0.131 to 0.1056. The decreases of dispersions in labor productivity and worker characteristics between the two periods contribute significantly to alleviating the between-inequality. The changes in labor productivity cause the wage variance to go from 0.131 to 0.117, and the changes in worker characteristics decrease it to 0.0888. These results are in line with the observations in Figure 6. In contrast to the covariate effects, the aggregate effect of the coefficients is a factor that increases the wage variance from 0.131 to 0.1517. Among the estimated coefficients, the changes in the coefficients of labor productivity and the capital-to-labor ratio are main factors in widening the between-inequality from 0.131 to 0.1897 and to 0.1808, respectively.

The directions of the effects of the covariates and coefficients in fixed wages on between-inequality are similar to those for total wages. The magnitudes of the effects are, however, quite different. In particular, the effect of changes in the coefficients of labor productivity is much weaker: the wage variance increases only from 0.0910 to 0.0926 for fixed wages. The capital-to-labor ratio shows a pattern similar to that of labor productivity.

Overall, the findings indicate that between-inequality has consistently increased since 1994 despite a decreasing wage inequality trend between 2009 and 2015 when worker characteristics are controlled for due to changes in the coefficients of firm-side factors between the

2000–2008 and 2009–2015 periods. Changes in the coefficients of labor productivity and the capital-to-labor ratio are main factors in the rising wage inequality between industry-size groups. These results are even more clearly observed when bonuses are included in wages. This means that paying bonuses provides a channel through which firms share their rents with workers and compensate for capital dependency. This employer behavior translates into a widening wage distribution.

6 Conclusion

This study attempts to determine why wage inequality has increased in Korea over the last two decades. Although the observed (by econometricians) and unobserved characteristics of workers have explained levels of wage inequality, their effects on wage inequality trends are limited. Rather, industry affiliation and employer size underlie much of the increase in wage inequality. Among industry and employer size, the increased size-wage premiums play a more important role in explaining the increasing wage inequality, while industry-wage premiums are relatively stable over time.

On the distributional side, the rising inequality between industry-size groups is caused by three factors: the deterioration of group effects at the bottom 50% of wage distribution, the increase of them at the top 50%, and their soaring group effects at the top 5% of the wage distribution. The increasing polarization between industry-size groups is therefore a main distributional factor in their rising inequality.

One novel feature of this study is its consideration of bonuses' contributions to wage inequality. I show that the bonus is a factor that makes between-inequality more dispersed. When bonuses are included in wages, the changes in between-inequality at the industry-size level account for 44.03% of the changes in wage inequality between 1994 and 2015 after observed worker characteristics and sorting effects are controlled for, while they account for 29.35% when bonuses are not considered. Within-inequality is relatively stable regardless of whether bonuses are considered.

Furthermore, using a merged set of worker-level and firm-level balance sheet data at the industry-size-year level, I examine the sources of changes in between-inequality between the 2000–2008 and 2009–2015 periods. To overcome the drawbacks of the OLS mean-level approach, I adopt the methodology of Machado and Mata (2005) based on quantile regression and a simulation technique to estimate the marginal effects of covariates and coefficients on changes in between-inequality. The results show that the increasing between-inequality is attributable to changes in the coefficients. Changes in the coefficients of labor productivity ("rent-sharing parameters") and the capital-to-labor ratio are the main factors in the rising between-inequality. Firms paying higher wages have been more willing to share their rents with workers and compensate for capital dependency since 2009. These results are much more clearly observed when bonuses are included in wages.

Paying bonuses may allow firms to respond more flexibly to their performance and wage-setting strategy. As fixed wages are contracted, they cannot be easily adjusted for several reasons, such as wage rigidity and labor union influence. Bonuses are more easily adjustable. The results of this paper that 1) bonuses affect between-inequality more than within-inequality and 2) compensation for labor productivity and capital dependency is closely linked to bonuses show that the role of bonuses in the Korean labor market differs from the role they play in the US and UK markets, which Lemieux et al. (2009) and Bryan and Bryson (2016) studied to examine the connection between performance pay and worker characteristics.

Finally, beyond the problem of inequality, it is necessary to consider the effects of bonuses on labor market efficiency. Lemieux et al. (2009) pointed out that performance pay can reflect workers' marginal productivity more accurately than fixed wage schedules can; this could make job-matching more efficient even if wages' within-inequality becomes more dispersed. By contrast, if the effects of bonuses or performance pay are captured chiefly in between-inequality rather than within-inequality—as in the case of Korea—bonuses could have negative effects on both labor market efficiency and wage disparities. In this situation, productive workers might be concentrated in already productive firms in order to receive compensation equal to their abilities, widening wage and labor productivity inequality between employers. This could act as a barrier to consistent growth among productive firms.

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Table A1: The Number of Workers by Two–digit Industries – WSS

Industry (two-digit)	Number of Workers
Mining and Quarrying	
Coal, Crude Petroleum and Natural Gas	50,252
Metal Ores	4,258
Non-metallic Minerals, Except Fuel	32,244
Manufacturing	
Food and Beverages	297,120
Tobacco	33,290
Textiles, Except Apparel	206,798
Wearing apparel, Clothing Accessories and Fur Articles	155,041
Tanning and Dressing of Leather, Luggage and Footwear	67,898
Wood and Cork; Except Furniture	48,740
Pulp and Paper	91,580
Printing and Reproduction of Recorded Media	117,880
Coke, Hard-coal, Lignite Fuel and Refined Petroleum	74,054
Chemicals, Except Pharmaceuticals, Medicinal Chemicals	327,946
Rubber and Plastic	211,512
Other Non-metallic Mineral Products	159,737
Basic Metal Products	189,830
Fabricated Metal Products, Except Machinery and Furniture	169,469
Electronic Components (Computer, Radio, and so on)	605,651
Medical, Precision and Optical Instruments, Watches and Clocks	89,076
Motor Vehicles, Trailers and Semitrailers	323,993
Other Transport Equipment	216,309
Furniture; Other manufacturing	95,340
Electricity, Gas, Steam and Water Supply	
Electricity, gas, steam and air conditioning supply	181,356
Water Supply	26,300
Construction	
General Construction; Special Trade Construction	300,086
Wholesale and Retail Trade	
Sale of Motor Vehicles and Parts	55,764
Wholesale Trade and Commission Trade, Except of Motors	356,431
Retail Trade, Except Motor Vehicles and Motorcycles	330,384
Accommodation and Food Service Activities	
Accommodation; Food and beverage service activities	234,402
Transportation	
Land Transport ; Transport Via Pipelines	520,962
Water Transport	55,394
Air Transport	62,312
Telecommunications	164,710
Financial and Insurance Activities	
Financial Institutions, Except Insurance and Pension	253,864
Insurance and Pension Funding	162,636
Activities Auxiliary to Financial Service and Insurance	135,195
Real Estate Activities and Renting and Leasing	
Real Estate Activities	167,265
Renting and leasing; except real estate	26,750
Total	6,601,829

Notes. The number of workers are the sum of workers between 1994 and 2015.

Table A2: The Number of Establishments by Two–digit Industries – KED

Industry (two-digit)	Number of Establishments
Mining and quarrying	
Coal, Crude Petroleum and Natural Gas	175
Metal Ores	58
Non-metallic Minerals, Except Fuel	1,805
Manufacturing	
Food and Beverages	26,982
Tobacco	72
Textiles, Except Apparel	20,187
Wearing apparel, Clothing Accessories and Fur Articles	11,452
Tanning and Dressing of Leather, Luggage and Footwear	4,219
Wood and Cork; Except Furniture	5,126
Pulp and Paper	9,065
Printing and Reproduction of Recorded Media	10,662
Coke, Hard-coal, Lignite Fuel and Refined Petroleum	1,194
Chemicals, Except Pharmaceuticals, Medicinal Chemicals	32,143
Rubber and Plastic	27,764
Other Non-metallic Mineral Products	22,943
Basic Metal Products	19,817
Fabricated Metal Products, Except Machinery and Furniture	42,783
Electronic Components (Computer, Radio, and so on)	41,900
Medical, Precision and Optical Instruments, Watches and Clocks	18,549
Motor Vehicles, Trailers and Semitrailers	26,976
Other Transport Equipment	10,247
Furniture; Other manufacturing	14,641
Electricity, gas, steam and water supply	
Electricity, gas, steam and air conditioning supply	1,534
Water Supply	38
Construction	
General Construction; Special Trade Construction	181,493
Wholesale and retail trade	
Sale of Motor Vehicles and Parts	10,809
Wholesale Trade and Commission Trade, Except of Motors	201,671
Retail Trade, Except Motor Vehicles and Motorcycles	16,724
Accommodation and food service activities	
Accommodation; Food and beverage service activities	3,948
Transportation	
Land Transport ; Transport Via Pipelines	13,054
Water Transport	3,019
Air Transport	172
Telecommunications	1,700
Financial and insurance activities	
Financial Institutions, Except Insurance and Pension	126
Insurance and Pension Funding	24
Activities Auxiliary to Financial Service and Insurance	281
Real estate activities and renting and leasing	
Real Estate Activities	12,298
Renting and leasing; except real estate	2,377
Total	798,028

Notes. The number of establishments are the sum of establishments between 2000 and 2015.

Table A3: The Estimation Results of the Augmented Mincer-type Wage Equation: Using Two–Digit Industry Dummies

Type of Wages	Total Wage				Fixed Wage			
Dependent Variable: ln(wages)	1994	2002	2008	2015	1994	2002	2008	2015
Basic Variables								
Years of schooling	0.041***	0.056***	0.077***	0.077***	0.038***	0.055***	0.075***	0.067***
Experience	0.060***	0.067***	0.064***	0.056***	0.051***	0.058***	0.056***	0.048***
Experience^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
Union	0.114***	0.260***	0.274***	0.299***	0.025***	0.120***	0.107***	0.127***
Interactions with Woman								
Woman * Years of schooling	-0.002***	0.004***	0.005***	0.008***	-0.005***	0.002***	0.003***	0.006***
Woman * Experience	-0.038***	-0.037***	-0.036***	-0.029***	-0.033***	-0.032***	-0.031***	-0.025***
Woman * Experience^2	0.001***	0.001***	0.001***	0.000***	0.001***	0.001***	0.000***	0.000***
Woman * Union	0.079***	0.039***	0.112***	0.007	0.074***	0.045***	0.122***	0.039***
Occupation Dummies								
Technicians and Associate Professionals	-0.194***	-0.078***	0.002	-0.341***	-0.247***	-0.080***	-0.004	-0.355***
Clerks	-0.255***	-0.170***	-0.134***	-0.439***	-0.292***	-0.176***	-0.150***	-0.430***
Service Workers	-0.298***	-0.313***	-0.347***	-0.616***	-0.345***	-0.281***	-0.326***	-0.572***
Sale Workers	-0.379***	-0.298***	-0.287***	-0.599***	-0.390***	-0.266***	-0.279***	-0.576***
Skilled Agricultural, Forestry, and Fishery	-0.452***	-0.586***	-0.522***	-0.750***	-0.462***	-0.509***	-0.470***	-0.723***
Craft and Related Trades Workers	-0.428***	-0.348***	-0.338***	-0.589***	-0.430***	-0.326***	-0.328***	-0.589***
Plant, Machine Operators and Assemblers	-0.465***	-0.398***	-0.439***	-0.666***	-0.459***	-0.375***	-0.421***	-0.645***
Elementary Occupations	-0.656***	-0.556***	-0.598***	-0.780***	-0.652***	-0.508***	-0.542***	-0.741***
Constant	-0.850***	-1.014***	-1.056***	-0.666***	-0.883***	-1.067***	-1.112***	-0.580***
Industry Dummies (two-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.5964	0.5857	0.5201	0.52	0.5891	0.5554	0.5131	0.4952
N	300,567	240,099	349,056	318,538	300,567	240,099	349,056	318,538

Notes. This table shows the weighted regression results from the augmented Mincer type wage equation, described in equation (7) of section 4.1, using the WSS (Worker Structure Survey) data. Industry dummies at two–digit level are included in all models. Two types of (log real hourly) wages are used for dependent variables. Hourly fixed wage is regular wage per hour plus overtime wage per hour. Hourly total wage is hourly fixed wage plus hourly bonus. The bonus includes performance pay and non–production pay. The omitted occupation for estimation is Professionals. Standard errors are not reported because most of them are less than 0.00. *** denotes significance at 1%.

Table A4: The Estimation Results of the Augmented Mincer-type Wage Equation: Using Industry–Size Dummies

Type of Wages	Total Wage				Fixed Wage			
Independent Variable: ln(wages)	1994	2002	2008	2015	1994	2002	2008	2015
Basic Variables								
Years of schooling	0.038***	0.050***	0.070***	0.065***	0.037***	0.051***	0.070***	0.059***
Experience	0.058***	0.065***	0.064***	0.057***	0.050***	0.057***	0.056***	0.048***
Experience^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
Union	0.020***	0.128***	0.117***	0.134***	-0.012***	0.049***	0.013***	0.033***
Interactions with Woman								
Woman * Years of schooling	-0.005***	0.002***	0.002***	0.004***	-0.007***	0.001	0.001***	0.004***
Woman * Experience	-0.034***	-0.034***	-0.030***	-0.025***	-0.030***	-0.031***	-0.027***	-0.023***
Woman * Experience^2	0.001***	0.001***	0.000***	0.000***	0.001***	0.000***	0.000***	0.000***
Woman * Union	0.093***	0.060***	0.152***	0.056***	0.087***	0.063***	0.148***	0.065***
Occupation Dummies								
Technicians and Associate Professionals	-0.254***	-0.066***	0.047***	-0.347***	-0.276***	-0.071***	0.022***	-0.351***
Clerks	-0.286***	-0.147***	-0.085***	-0.394***	-0.311***	-0.161***	-0.120***	-0.395***
Service Workers	-0.316***	-0.309***	-0.315***	-0.600***	-0.351***	-0.276***	-0.308***	-0.570***
Sale Workers	-0.402***	-0.265***	-0.237***	-0.527***	-0.397***	-0.243***	-0.252***	-0.521***
Skilled Agricultural, Forestry, and Fishery	-0.490***	-0.564***	-0.500***	-0.691***	-0.482***	-0.501***	-0.450***	-0.673***
Craft and Related Trades Workers	-0.451***	-0.338***	-0.277***	-0.565***	-0.441***	-0.317***	-0.290***	-0.564***
Plant, Machine Operators and Assemblers	-0.484***	-0.388***	-0.385***	-0.624***	-0.463***	-0.365***	-0.388***	-0.612***
Elementary Occupations	-0.681***	-0.535***	-0.535***	-0.745***	-0.660***	-0.497***	-0.504***	-0.712***
Constant	-0.736***	-0.885***	-0.979***	-0.502***	-0.831***	-0.987***	-1.054***	-0.483***
Industry–Size Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.6328	0.6284	0.6089	0.6292	0.6121	0.5844	0.5612	0.5622
N	300,567	240,099	349,056	318,538	300,567	240,099	349,056	318,538

Notes. This table shows the weighted regression results from the augmented Mincer type wage equation, described in equation (7) of section 4.1, using the WSS (Worker Structure Survey) data. Industry–size group dummies at two–digit level and five categories (10–29, 30–99, 100–299, 300–499, and 500+) are included in all models. Two types of (log real hourly) wages are used for dependent variables. Hourly fixed wage is regular wage per hour plus overtime wage per hour. Hourly total wage is hourly fixed wage plus hourly bonus. The bonus includes performance pay and non–production pay. The omitted occupation for estimation is Professionals. Standard errors are not reported because most of them are less than 0.00. *** denotes significance at 1%.

Table A5: The Estimated Group Wage Premiums (Total Wage, Year=1994)

Industry	Size Categories				
	10–29	30–99	100–299	300–499	500+
Mining and Quarrying					
Coal, Crude Petroleum and Natural Gas	-0.1401	0.0480	0.1290	0.0481	0.4139
Metal Ores	-0.2625	0.0376	-0.0249	-	-
Non-metallic Minerals, Except Fuel	-0.0172	0.0160	0.0753	0.1665	-
Manufacturing					
Food and Beverages	-0.0934	-0.1891	-0.0324	-0.0821	-0.0601
Tobacco	-0.0162	-	0.1391	-	0.4211
Textiles, Except Apparel	-0.1673	-0.0923	-0.1421	-0.0937	-0.0212
Wearing apparel, Clothing Accessories and Fur Articles	-0.1223	-0.1270	-0.1672	-0.2397	-0.0163
Tanning and Dressing of Leather, Luggage and Footwear	-0.2276	-0.1595	-0.1992	-0.1330	-0.3104
Wood and Cork; Except Furniture	0.0384	-0.1268	-0.1214	-0.1842	-0.0139
Pulp and Paper	-0.1568	-0.1803	0.1287	0.0888	0.0898
Printing and Reproduction of Recorded Media	-0.1193	-0.2477	-0.1282	0.2114	0.2029
Coke, Hard-coal, Lignite Fuel and Refined Petroleum	-0.0915	0.1612	0.2826	0.3833	0.5659
Chemicals, except pharmaceuticals, medicinal chemicals	-0.1125	-0.1274	0.1322	0.1522	0.2027
Rubber and Plastic	-0.1468	-0.0819	0.0733	0.0352	0.0150
Other Non-metallic Mineral Products	-0.2284	-0.1378	-0.0614	0.0567	0.1849
Basic Metal Products	-0.1112	-0.1114	-0.0706	-0.0183	0.2094
Fabricated Metal Products, Except Machinery and Furniture	-0.0971	-0.1173	-0.0582	0.0527	0.2450
Electronic Components (Computer, Radio, and so on)	-0.2579	-0.2140	-0.0698	0.0081	0.2086
Medical, Precision, Optical Instruments, Watches	-0.0820	-0.1458	0.0854	0.0757	0.0588
Motor Vehicles, Trailers and Semitrailers	-0.1963	0.0067	0.0665	-0.0508	0.2044
Other Transport Equipment	-0.0653	-0.0248	0.0673	-0.1136	0.3047
Furniture; Other manufacturing	-0.1896	-0.2073	-0.1485	-0.1125	-0.0966

Notes. This table shows the group wage premiums estimated by the wage equation (7) using the WSS data at the industry–size level.

Table A5–1: The Estimated Group Wage Premiums (Total Wage, Year=1994)

Industry	Size Categories				
	10–29	30–99	100–299	300–499	500+
Electricity, gas, steam and water supply					
Electricity, gas, steam and air conditioning supply	0.0550	0.1047	0.1892	0.2259	0.1552
Water Supply	-	-	-	-	0.1941
Construction					
General Construction; Special Trade Construction	-0.0073	0.0174	0.0939	0.1273	0.2223
Wholesale and retail trade					
Sale of Motor Vehicles and Parts	-0.0888	-0.0355	0.1160	-	0.2460
Wholesale Trade and Commission Trade, Except of Motors	-0.0431	-0.0621	0.1972	0.0135	0.2358
Retail Trade, Except Motor Vehicles and Motorcycles	-0.1359	0.0013	-0.0780	0.0129	0.1415
Accommodation and food service activities					
Accommodation; Food and beverage service activities	-0.2049	-0.1400	-0.0241	-0.0229	0.2306
Transportation					
Land Transport ; Transport Via Pipelines	-0.3887	-0.2099	-0.2121	-0.1105	-0.1126
Water Transport	-0.1327	0.1207	-0.0261	0.0660	0.1616
Air Transport	-0.0002	0.1187	0.1139	-	0.4693
Telecommunications	0.2088	0.2061	0.3022	0.1918	0.3567
Financial and insurance activities					
Financial Institutions, Except Insurance and Pension Funding	0.3236	0.2501	0.3417	0.6187	0.5220
Insurance and Pension Funding	0.2921	0.2352	0.4446	0.2645	0.2699
Activities Auxiliary to Financial Service and Insurance	0.3961	0.3155	0.3454	0.5046	0.5690
Real estate activities and renting and leasing					
Real Estate Activities	-0.3098	-0.3153	-0.0100	-0.1467	-0.2463
Renting and leasing; except real estate	0.1016	0.0005	0.3920	0.2879	0.9441

Notes. This table shows the group wage premiums estimated by the wage equation (7) using the WSS data at the industry–size level.

Table A6: The Estimated Group Wage Premiums (Total Wage, Year=2015)

Industry	Size Categories				
	10–29	30–99	100–299	300–499	500+
Mining and Quarrying					
Coal, Crude Petroleum and Natural Gas	-	0.4762	0.3814	0.4704	0.4851
Metal Ores	-0.4855	-0.1592	-	-	-
Non-metallic Minerals, Except Fuel	-0.2032	-0.0578	-	-	-
Manufacturing					
Food and Beverages	-0.2972	-0.1460	-0.0802	0.1485	-0.0560
Tobacco	-	0.0237	0.3122	0.0943	0.4474
Textiles, Except Apparel	-0.2626	-0.3062	-0.1620	0.0099	0.1247
Wearing apparel, Clothing Accessories and Fur Articles	-0.2601	-0.2156	-0.1746	0.0826	0.2730
Tanning and Dressing of Leather, Luggage and Footwear	-0.1807	-0.3136	-0.1923	-	-
Wood and Cork; Except Furniture	-0.2686	-0.2715	-0.0795	0.1866	-0.2152
Pulp and Paper	-0.1597	-0.1504	0.0660	0.2532	0.4378
Printing and Reproduction of Recorded Media	-0.1566	-0.0583	-0.2215	-	-
Coke, Hard-coal, Lignite Fuel and Refined Petroleum	-0.0998	-0.0018	0.4285	-	0.5800
Chemicals, except pharmaceuticals, medicinal chemicals	-0.1345	-0.0382	0.1728	0.1481	0.2811
Rubber and Plastic	-0.2360	-0.1530	-0.0601	0.1089	0.1858
Other Non-metallic Mineral Products	-0.2230	-0.1235	-0.0360	0.1199	0.5302
Basic Metal Products	-0.1684	-0.1401	0.0900	-0.1640	0.2951
Fabricated Metal Products, Except Machinery and Furniture	-0.2041	-0.1640	-0.0893	0.0221	0.3540
Electronic Components (Computer, Radio, and so on)	-0.1693	-0.0991	-0.1472	0.2233	0.6892
Medical, Precision, Optical Instruments, Watches	-0.0869	-0.1289	-0.0620	0.1394	0.2278
Motor Vehicles, Trailers and Semitrailers	-0.2291	-0.1789	-0.0217	0.0437	0.3670
Other Transport Equipment	-0.1795	-0.1301	-0.1433	0.1487	0.3528
Furniture; Other manufacturing	-0.2818	-0.1228	-0.0812	0.2630	0.6039

Notes. This table shows the group wage premiums estimated by the wage equation (7) using the WSS data at the industry–size level.

Table A6–1: The Estimated Group Wage Premiums (Total Wage, Year=2015)

Industry	Size Categories 10–29	30–99	100–299	300–499	500+
Electricity, gas, steam and water supply					
Electricity, gas, steam and air conditioning supply	0.2582	0.3101	0.3335	0.2596	0.4063
Water Supply	0.0935	0.0412	0.1187	-	0.1050
Construction					
General Construction; Special Trade Construction	-0.4735	-0.1728	0.0297	0.0577	0.3511
Wholesale and retail trade					
Sale of Motor Vehicles and Parts	0.2016	0.1923	0.1719	-	-
Wholesale Trade and Commission Trade, Except of Motors	-0.0720	0.0576	0.1022	0.3645	0.3589
Retail Trade, Except Motor Vehicles and Motorcycles	-0.2429	-0.1885	-0.1204	-0.0942	0.1390
Accommodation and food service activities					
Accommodation; Food and beverage service activities	-0.2343	-0.2515	-0.0933	-0.0159	0.3861
Transportation					
Land Transport ; Transport Via Pipelines	-0.3535	-0.4404	-0.3210	-0.1025	0.0167
Water Transport	-0.1071	-0.0040	0.1696	0.3455	0.2067
Air Transport	0.1228	0.0157	0.0433	0.2748	0.2852
Telecommunications	-0.0033	0.1311	0.1339	0.0231	0.0696
Financial and insurance activities					
Financial Institutions, Except Insurance and Pension Funding	0.2150	0.2213	0.2169	0.1692	0.2936
Insurance and Pension Funding	0.1331	-0.0150	0.2543	0.3230	0.3395
Activities Auxiliary to Financial Service and Insurance	0.1927	0.3700	0.0942	0.4144	0.2926
Real estate activities and renting and leasing					
Real Estate Activities	-0.4235	-0.3640	-0.1105	-0.0356	0.0774
Renting and leasing; except real estate	-0.2447	-0.2398	0.1754	-	-

Notes. This table shows the group wage premiums estimated by the wage equation (7) using the WSS data at the industry–size level.

Table A7: The Estimated Group Wage Premiums (Fixed Wage, Year=1994)

Industry	Size Categories 10–29	30–99	100–299	300–499	500+
Mining and Quarrying					
Coal, Crude Petroleum and Natural Gas	-0.0930	0.1644	0.1334	0.1107	0.4247
Metal Ores	-0.1753	0.1636	0.0198	-	-
Non-metallic Minerals, Except Fuel	0.0833	0.0656	0.0244	-0.0252	-
Manufacturing					
Food and Beverages	-0.0250	-0.1714	-0.0860	-0.0936	-0.1084
Tobacco	-0.0737	-	0.1178	-	0.3193
Textiles, Except Apparel	-0.0754	-0.0444	-0.0986	-0.0865	-0.0747
Wearing apparel, Clothing Accessories and Fur Articles	-0.0201	-0.0512	-0.1463	-0.2344	-0.0409
Tanning and Dressing of Leather, Luggage and Footwear	-0.0914	-0.0898	-0.1688	-0.1510	-0.3172
Wood and Cork; Except Furniture	-0.0155	-0.0202	-0.1212	-0.1911	-0.0567
Pulp and Paper	-0.1098	-0.0998	0.0793	-0.0342	0.0037
Printing and Reproduction of Recorded Media	-0.0015	-0.1536	-0.0632	0.1103	0.1203
Coke, Hard-coal, Lignite Fuel and Refined Petroleum	-0.0878	0.1264	0.1759	0.2231	0.3772
Chemicals, except pharmaceuticals, medicinal chemicals	-0.0521	-0.0904	0.0553	0.0758	0.0966
Rubber and Plastic	-0.0540	-0.0362	0.0381	-0.0119	-0.0471
Other Non-metallic Mineral Products	-0.1497	-0.0970	-0.0976	-0.0229	0.0736
Basic Metal Products	-0.0638	-0.0737	-0.0952	-0.0939	0.0663
Fabricated Metal Products, Except Machinery and Furniture	0.0064	-0.0658	-0.0717	0.0210	0.1651
Electronic Components (Computer, Radio, and so on)	-0.2095	-0.1625	-0.0801	-0.0499	0.0952
Medical, Precision, Optical Instruments, Watches	0.0521	-0.1098	0.0154	0.0086	-0.0537
Motor Vehicles, Trailers and Semitrailers	-0.0852	0.0175	0.0141	-0.0619	0.0623
Other Transport Equipment	0.0348	0.0711	0.0205	-0.1665	0.1814
Furniture; Other manufacturing	-0.1567	-0.1575	-0.1228	-0.1390	-0.1263

Notes. This table shows the group wage premiums estimated by the wage equation (7) using the WSS data at the industry–size level.

Table A7–1: The Estimated Group Wage Premiums (Fixed Wage, Year=1994)

Industry	Size Categories				
	10–29	30–99	100–299	300–499	500+
Electricity, gas, steam and water supply					
Electricity, gas, steam and air conditioning supply	0.0033	0.0959	0.1437	0.0978	0.1624
Water Supply	-	-	-	-	0.1083
Construction					
General Construction; Special Trade Construction	0.0894	0.0843	0.0892	0.1152	0.1656
Wholesale and retail trade					
Sale of Motor Vehicles and Parts	-0.0044	0.0426	-0.0153	-	0.0771
Wholesale Trade and Commission Trade, Except of Motors	-0.0058	-0.0240	0.1381	-0.0354	0.1019
Retail Trade, Except Motor Vehicles and Motorcycles	-0.0808	0.0028	-0.0498	-0.0405	0.0377
Accommodation and food service activities					
Accommodation; Food and beverage service activities	-0.1018	-0.0506	0.0433	-0.0301	0.1610
Transportation					
Land Transport ; Transport Via Pipelines	-0.2297	-0.1005	-0.1257	-0.0364	-0.0580
Water Transport	-0.0708	0.0646	-0.0625	0.0522	0.0923
Air Transport	0.0151	0.0851	0.0867	-	0.4281
Telecommunications	0.2401	0.1769	0.2373	0.1258	0.2832
Financial and insurance activities					
Financial Institutions, Except Insurance and Pension Funding	0.2321	0.1248	0.2285	0.5331	0.4119
Insurance and Pension Funding	0.2367	0.1368	0.3215	0.1904	0.1512
Activities Auxiliary to Financial Service and Insurance	0.2681	0.1987	0.2561	0.3690	0.4669
Real estate activities and renting and leasing					
Real Estate Activities	-0.2824	-0.2786	-0.0204	-0.1602	-0.2073
Renting and leasing; except real estate	0.0905	0.0865	0.3734	0.1893	0.8666

Notes. This table shows the group wage premiums estimated by the wage equation (7) using the WSS data at the industry–size level.

Table A8: The Estimated Group Wage Premiums (Fixed Wage, Year=2015)

Industry	Size Categories				
	10–29	30–99	100–299	300–499	500+
Mining and Quarrying					
Coal, Crude Petroleum and Natural Gas	-	0.3943	0.3969	0.5529	0.4293
Metal Ores	-0.3586	-0.1027	-	-	-
Non-metallic Minerals, Except Fuel	-0.1362	-0.0224	-	-	-
Manufacturing					
Food and Beverages	-0.2010	-0.0976	-0.0825	0.1088	-0.0668
Tobacco	-	-0.0594	0.2937	0.3194	0.4174
Textiles, Except Apparel	-0.1659	-0.2314	-0.0719	0.1082	-0.0141
Wearing apparel, Clothing Accessories and Fur Articles	-0.1386	-0.1004	-0.1314	0.1715	0.3058
Tanning and Dressing of Leather, Luggage and Footwear	-0.0839	-0.2009	-0.1693	-	-
Wood and Cork; Except Furniture	-0.1833	-0.2155	0.0070	0.2279	-0.1931
Pulp and Paper	-0.0833	-0.1055	-0.0505	0.0899	0.1807
Printing and Reproduction of Recorded Media	-0.0366	0.0315	-0.1619	-	-
Coke, Hard-coal, Lignite Fuel and Refined Petroleum	-0.0140	-0.0704	0.1402	-	0.3881
Chemicals, except pharmaceuticals, medicinal chemicals	-0.0384	-0.0424	0.0994	0.1531	0.2016
Rubber and Plastic	-0.1470	-0.1192	-0.0707	0.0473	0.0201
Other Non-metallic Mineral Products	-0.1328	-0.0963	-0.0873	-0.0248	0.2469
Basic Metal Products	-0.1357	-0.1836	-0.0321	-0.1865	0.0855
Fabricated Metal Products, Except Machinery and Furniture	-0.1304	-0.1064	-0.0882	-0.0726	0.2115
Electronic Components (Computer, Radio, and so on)	-0.0683	-0.0305	-0.1112	0.0688	0.4251
Medical, Precision, Optical Instruments, Watches	-0.0433	-0.0362	0.0669	0.1485	0.1428
Motor Vehicles, Trailers and Semitrailers	-0.1548	-0.1439	-0.0486	-0.0474	0.1487
Other Transport Equipment	-0.0842	-0.0748	-0.1343	0.1258	0.1563
Furniture; Other manufacturing	-0.1690	-0.0862	-0.1482	0.1590	0.3163

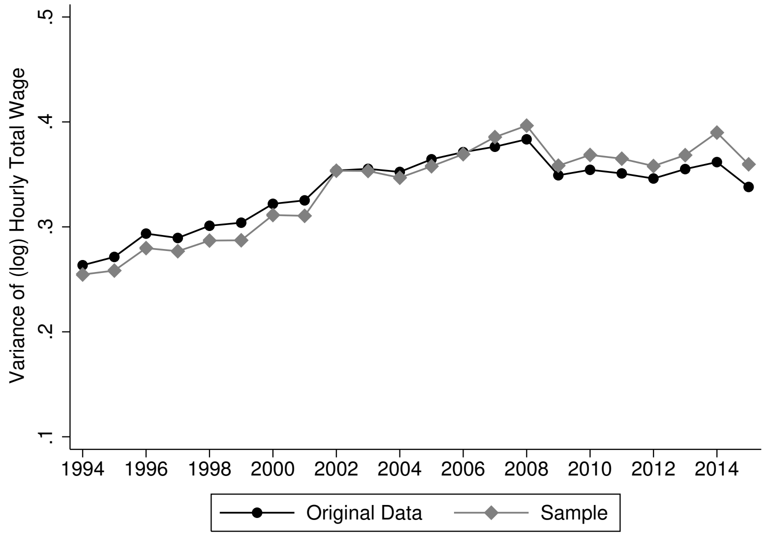
Notes. This table shows the group wage premiums estimated by the wage equation (7) using the WSS data at the industry–size level.

Table A8-1: The Estimated Group Wage Premiums (Fixed Wage, Year=2015)

Industry	Size Categories				
	10–29	30–99	100–299	300–499	500+
Electricity, gas, steam and water supply					
Electricity, gas, steam and air conditioning supply	0.3132	0.3205	0.2557	0.2179	0.4187
Water Supply	0.1764	0.1372	0.1471	-	0.1188
Construction					
General Construction; Special Trade Construction	-0.3476	-0.0873	0.0741	0.1288	0.3966
Wholesale and retail trade					
Sale of Motor Vehicles and Parts	-0.0696	0.2289	0.1994	-	-
Wholesale Trade and Commission Trade, Except of Motors	-0.0167	0.0917	0.1416	0.3132	0.2537
Retail Trade, Except Motor Vehicles and Motorcycles	-0.1719	-0.1516	-0.1173	-0.1003	0.1280
Accommodation and food service activities					
Accommodation; Food and beverage service activities	-0.1474	-0.1757	-0.0769	-0.2176	0.0852
Transportation					
Land Transport ; Transport Via Pipelines	-0.2441	-0.3147	-0.2143	-0.0422	0.1130
Water Transport	-0.0649	0.0798	0.1379	0.5235	0.3572
Air Transport	0.1202	-0.0423	-0.1369	-0.0405	0.2555
Telecommunications	0.0621	0.0596	0.1437	0.0228	0.1264
Financial and insurance activities					
Financial Institutions, Except Insurance and Pension Funding	0.1339	0.1713	0.2410	0.1952	0.1949
Insurance and Pension Funding	0.1007	0.0343	0.2864	0.2741	0.3156
Activities Auxiliary to Financial Service and Insurance	0.1014	0.2958	0.0433	0.2574	0.2951
Real estate activities and renting and leasing					
Real Estate Activities	-0.3157	-0.2714	-0.0349	0.0499	0.1563
Renting and leasing; except real estate	-0.1311	-0.1568	0.2659	-	-

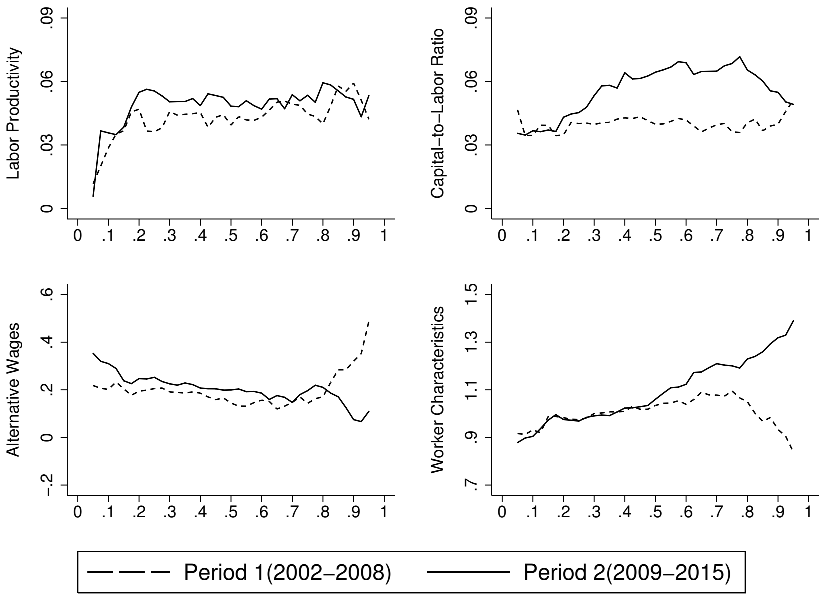
Notes. This table shows the group wage premiums estimated by the wage equation (7) using the WSS data at the industry–size level.

Figure A1: The Comparison of Variances of (log) Hourly Total Wages between Original Data and Sample Data



Notes. Original data means the data before the manipulation of industry. The number of observations and industries of the original data between 1994 and 2015 are 10,612,699 and 83, respectively. Sample means the data after the manipulation of industry. The number of observations and industries of the sample data in the same period are 6,601,829 and 37, respectively. Although about a half of industries and 40% of workers in the original data are deleted by sample restriction, the trends in variances of log real hourly total wage are similar.

Figure A2: The Estimated Results of Quantile Regression by Periods (Fixed Wages)



Notes. This figure shows the coefficient estimates, $\hat{\beta}$, using equation (18). The regressions are implemented for every 2.5% wage quantiles. X-axis means 2.5% quantiles of the average wages at the industry–size level.

국문초록

사업체 규모, 산업과 임금 불평등: 보너스와 수익 배분의 역할을 중심으로

본 논문에서는 고용노동부의 임금구조부문 자료(WSS), 한국노동패널(KLIPS) 및 기업 재무제표 자료(KED)를 이용하여 기업 측면의 요인이 우리나라 임금 불평등에 미친 영향에 대해 다룬다. 분석기간은 1994년부터 2015년까지다.

본 논문에서 밝히고자 하는 것은 크게 두 가지다. 먼저, 산업과 기업규모 간 임금격차가 노동자의 임금 불평등에 미친 영향을 분석한다. 대표성을 가지고 있는 고용노동부 자료를 주로 이용하되, 시간에 따라 변하지 않는 노동자들의 특성을 통제하기 위해 한국노동패널을 보조적으로 활용한다. 다음으로, 기업 재무제표 자료와 고용노동부 임금구조부문 자료를 연계하여 산업 및 기업규모 간 임금격차의 원인을 분석한다. 산업 및 기업규모 간 노동생산성의 차이, 수익 공유의 정도 차이, 자본 의존도 차이, 자본 의존에 대한 보상 차이 등이 주요 관심 변수다.

이러한 두 가지 주제를 연구함에 있어 주요 변수인 임금은 고정임금과 총임금 두 가지 종류를 고려한다. 총임금에는 고정임금에 더하여 보너스가 포함되며, 보너스는 성과급과 복지 차원의 비생산임금(non-production pay)의 합으로 정의한다. Lemieux et al. (2009)은 미국 노동시장에서 성과급이 임금 불평등에 부정적인 영향을 미친다고 보고하였는데 이러한 결과가 우리나라에도 적용되는지, 아니라면 미국과 우리

나라의 차이점은 무엇인지를 파악하는 것이 두 가지 종류의 임금을 함께 관찰하는 이유다.

주요 결과는 다음과 같다. 첫째, 1994년 이후 우리나라 임금 불평등의 지속적인 악화는 산업 간 임금격차보다 기업규모 간 임금격차에 더 큰 영향을 받았다. 임금방정식을 추정한 후 임금의 분산을 집단 내 분산과 집단 간 분산으로 분해하여 보면 산업 간 임금격차는 임금 불평등 상승분의 11.33%를 설명하는 데에 그친 반면, 산업과 기업규모를 동시에 고려할 경우 이들 간 임금격차는 임금 불평등 상승분의 44.03%를 설명하는 것으로 나타났다. 이는 기업규모가 산업 대비 임금 불평등에 더 큰 영향을 미치고 있음을 보여준다. 산업 및 기업규모 간 노동자들의 인적자본 차이(학력, 경력 등)는 임금 불평등의 절대적인 수준에는 큰 영향을 미쳤으나, 추이의 변화에는 영향력이 크지 않았다.

둘째, 산업 및 기업규모 간 임금격차의 상승은 고정임금 뿐 아니라 보너스의 차이에도 큰 영향을 받은 것으로 나타났다. 고정임금만을 고려하면 산업-규모 간 임금격차는 임금 불평등 상승분의 29.35%만을 설명하는 데에 그쳤으며, 이는 앞에서 말한 44.03% 보다 약 14.68%p 낮은 수치다. 또한 보너스는 산업-규모 내 임금격차보다 산업-규모 간 임금격차에 더 큰 영향을 미쳤는데, 이는 미국의 사례를 분석한 Lemieux et al. (2009)과 다른 결과다. 이는 성과급의 역할이 미국과 우리나라에서 다를 가능성을 제기한다.

셋째, 노동자들의 관측되지 않는 속성이 산업-규모 간 임금격차 추이에 미친 영향은 크지 않았다. 한국노동패널을 이용하여 노동자의 고정효과를 통제한 후 임금의 집단 간 분산과 집단 내 분산 추이를 관찰한

결과, 노동자들의 미관측 속성은 임금 불평등 수준에 매우 큰 영향을 미쳤으나 추이에는 영향을 미치지 못하였다. 반면 횡단면 자료에서 관측된 산업 및 기업규모 간 임금격차가 임금 불평등 추이에 미친 영향력은 크게 달라지지 않았다. 횡단면 자료와 종단면 자료를 함께 이용하여 도출된 위의 결과들은 기업규모 간 임금 및 보너스 격차가 1994년 이후 우리나라 임금 불평등을 악화시킨 주요인이라는 것을 보여준다.

넷째, 고용노동부 임금구조부문 자료와 기업 재무제표 자료를 연계하여 산업-규모 간 임금격차의 원인을 분석한 결과, 이는 산업-규모 간 수익 공유 정도의 차이와 자본 의존에 대한 보상 차이에 큰 영향을 받은 것으로 나타났다. Machado and Mata (2005)의 방법론을 이용하여 반사실적 분포(counterfactual distribution)를 추정하였는데, 산업-규모 간 수익 공유 파라미터(rent-sharing parameter)의 차이는 산업-규모 평균임금의 분산을 0.131에서 0.1879까지 상승시켰으며, 자본 의존에 대한 보상 차이의 경우 산업-규모 평균임금의 분산을 0.1808까지 상승시킨 것으로 추정되었다. 이는 산업-규모 간 이질적인 수익 공유와 자본 의존에 대한 보상이 임금 불평등에 큰 영향력을 행사하고 있음을 시사한다.

다섯째, 위에서 보인 결과들은 보너스가 임금에 포함될 때에만 유의한 것으로 나타났다. 고정임금만을 가지고 동일한 분석을 진행한 결과 산업-규모 간 이익 공유의 차이와 자본 의존에 대한 보상 차이가 유의미하지 않았으며, 이는 기업들이 보너스를 수익 공유 및 자본 의존에 대한 보상 수단으로 활용하고 있음을 보여준다.

본 연구에서는 우리나라 임금 불평등이 산업 및 기업규모 간 이질적인 특성에 상당 부분 영향을 받고 있다는 결과를 보였으나, 이들이 왜

이질적인지는 다루지 못하였다. 우리나라 임금 불평등에 대한 심도 깊은 이해를 위해서는 기업 간 노동생산성의 격차가 어디에서 비롯되는지, 노동생산성이 유사한 기업일지라도 왜 어떤 기업은 다른 기업 대비 수익을 노동자들에게 더 많이 분배하는지 등의 질문들에 대한 해답을 찾아 나가야 할 것이다. 또한 본 논문에서 보인 기업규모 간 임금 불평등 악화가 대기업과 중소기업 간의 관계(원하청 관계, 수직적 상하관계 등)에서 비롯되는 것은 아닌지 점검해 볼 필요가 있다.

주요어: 임금 불평등, 보너스, 사업체 규모, 산업, 노동생산성, 자본-노동 비율, 수익 공유 행동

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