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# Employer Size and Wage Inequality: Rent-Sharing Role of Performance Pay*

Sang-yoon Song**

*This study analyzes employer contributions to size–wage effects via heterogeneous rent-sharing behaviors and compensation for capital dependency. Mainly attributed to differences in performance pay between small and large employers, the increasing size–wage effect has substantially contributed to a growing wage inequality since 1994, even after factoring in observed and unobserved worker characteristics. Analysis of the sources of increasing size–wage effects in terms of firm-side factors reveal that more active rent-sharing behaviors and compensation for capital dependency of large employers that use performance pay translate into the increasing size–wage effect. These results show that, unlike in the United States, the labor market in Korea associates performance pay more with employer characteristics than with worker characteristics.*

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Keywords: Wage Inequality, Performance Pay, Employer Size, Industry, Labor Productivity, Capital-to-Labor Ratio, Rent-Sharing Behavior

## I. Introduction

The size–wage effect, namely, the positive association between employer size and employee wages, plays an important role in wage inequality (e.g., Brown and Medoff, 1989; Krueger and Summers, 1988; Moore, 1911; Oi and Idson, 1999; Bayard and Troske, 1999; Lluis, 2009; Pedace, 2010). In a standard competitive labor market model, one possible explanation for this inequality is the difference in labor quality across employer sizes. Although this employee factor identifies one of the possible sources of size–wage effects, empirical evidence shows a large

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** Economist, Economic Research Institute, The Bank of Korea, 55, Namdaemun-ro, Jung-gu, Seoul, Korea. Phone: 82-2-759-5478, E-mail: sy.song@bok.or.kr

contribution of employer characteristics (e.g., Blanchower et al., 1996; Arai, 2003; Faggio et al., 2010; Card, Heining, and Kline, 2013; Song et al., 2015; Barth et al., 2016).

In line with previous research, the present study has two objectives. First, we investigate the contribution of size–wage effects to changes in wage inequality in the Korean labor market. This growing inequality originates primarily from the increasing size–wage effects, which in turn are mainly affected by the growing performance pay differences between small and large employers. Second, analysis of the sources of increasing size-wage effects reveals two firm-side factors, namely, heterogeneous rent-sharing behaviors (i.e., association between labor productivity and wages) and compensation for capital dependency (i.e., association between labor-to-capital ratio and wages) between small and large employers. These two factors are the major sources of the increasing size-wage effects and strongly associated with performance pay differences between small and large employers.

Using comprehensive and representative worker-level data from 1994 to 2015 (Wage Structure Survey), we show that changes in wage inequality between industry-size groups contribute significantly to changes in overall wage inequality.[1] Moreover, these changes result predominantly from increasing size–wage effects that are amplified by the growing performance pay differences between small and large employers. Using firm-level balance sheet and worker-level data at the industry-size-year level, a counterfactual analysis is carried out using the methodology of Machado and Mata (2005). Increasing size–wage effects are found largely attributable to firm-side factors such as active rent-sharing behaviors and compensation for capital dependency of large employers.

The main results of the empirical analysis are as follows. First, changes in wage inequality between industry-size groups contribute significantly to changes in the overall wage inequality even when controlling for observed and unobserved worker characteristics. Furthermore, the high wages of large employers (size–wage effect) serve as the main factor of the wage inequality across industry-size groups. Second, the size–wage effect is largely attributed to performance pay differences between small and large employers. The contribution of wage inequality between industry-size groups to the overall wage inequality decreases from 44.03% to 29.35% when performance pay is not considered. This large decline shows that performance pay differentials between industry-size groups play important roles in explaining their wage inequality trends. Third, investigation of firm-side factors that account for changes in wage inequality between industry-size groups show that heterogeneous rent-sharing behaviors and compensation for capital dependency of employers are

[1] We use “wage inequality between industry-size groups” to refer to the dispersion in average wages of industry-size groups. Specifically, two industries and two sizes (i.e., large and small firms) indicate four industry-size groups. Under this assumption, “wage inequality between industry-size groups” means the dispersion in average wages of those four groups.

the main elements of the growing wage inequality between industry-size groups. Moreover, these results are more apparent when wages include performance pay, and imply that firms use performance pay to share their rents with workers and compensate for heavy capital dependency.

The present study complements recent empirical works on wage determination and inequality. Blanchower et al. (1996) provide theoretical background for the relation between wages and employer rent-sharing behavior. A simple wage equation is derived using the wage bargaining model. In addition, blending microeconomic data on wages with industrial data empirically demonstrates a positive association between wages and employer rent-sharing behavior. Using Swedish data on workers matched to employer balance sheets, Arai (2003) shows that wages are positively correlated with the capital-to-labor ratio and with employer profits. Barth et al. (2016) report that wage variances among establishments contributes 65% of the increased variance in earnings from 1992 to 2007 in the United States (US). Lemieux et al. (2009) demonstrate the importance of performance pay in explaining wage inequality using data from Panel Study of Income Dynamics. The authors focus on the contributions of performance pay to wage inequality within firms by comparing performance-pay and non-performance-pay jobs. Compensation for performance-pay jobs is more closely associated with worker characteristics, and changes in returns to skill due to technological changes induce more firms to offer performance pay in the US. Concerning methodology, Machado and Mata (2005) observe the marginal effects of firm-side factors on wage inequality using quantile regression and the integral transformation theorem. The present study builds up on this research.

The remainder of this paper is organized as follows. Section 2 describes the data and two types of wages used in this study. Section 3 presents the results of a variance decomposition using the augmented Mincer-type wage equation to observe the contribution of wage inequality between industry-size groups to the overall wage inequality. Section 4 discusses the distributional changes in industry-size group effects over time. Section 5 describes the investigation of the effects of firm-side factors on wage inequality trends between industry-size groups. Finally, Section 6 concludes the paper.

# II. Data Description

## 2.1. Data

The Wage Structure Survey (WSS) dataset is the largest worker-level dataset in Korea and includes 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. WSS data include monthly wages, hours worked, and 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+).[2] Since 2006, this dataset has also been providing establishment identifiers that can be used to observe the effects of establishment-level heterogeneity on wage inequality.

Usage of this dataset to study wage inequality presents two advantages. First, total monthly wages can be decomposed into regular wages, overtime wages, and performance pay. The provision of performance pay allows us to identify its effects on wage inequality. Second, WSS is gathered by establishment-level surveys and is thus relatively free of measurement error. Given that the survey is implemented using employer payroll, measurement errors are much smaller than in individual-level surveys.

The critical limitation of the WSS dataset for studying wage inequality is that self-employed, non-regular, and other workers in firms with fewer than 10 employees cannot be considered due to the survey design and data consistency. This limitation may lead to a biased evaluation of the overall wage inequality in Korea, and thus the results have to be interpreted for regular workers in firms with over 10 employees. Another limitation is that, as the WSS comprises cross-sectional data, unobserved heterogeneity among workers cannot be controlled for. To address this concern and check the robustness of the results derived from the WSS data, we use the Korean Labor and Income Panel Study (KLIPS) data that have longitudinal features and provide information on workers similar to that provided by the WSS for 1998–2015. Unfortunately, the KLIPS data provide information on only 5,000 regular employees each year and is thus less representative. However, given that the wage inequality (measured by the variance in log real hourly wages) in the two datasets shows similar rising trends, using the KLIPS to check the robustness of the WSS results shows no apparent problems.

To simultaneously observe the effects of worker characteristics and firm-side factors on wage inequality, employee and employer data must be merged into one dataset. For this reason, we also use the Korea Enterprise Database (KED) that offers data on financial statements and the number of regular workers in Korean firms. KED covers the period 2000–2015 and 50% of Korean firms.[3] Unlike other available firm-level balance sheet data, KED is useful for studying wage inequality because of its inclusion of many small firms with fewer than 50 regular employees. Unfortunately, as the employee-level datasets (WSS and KLIPS) and employer-

[2] 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.

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

level dataset (KED) have no common public employer identifier, a linked employer-employee dataset cannot be constructed. However, data on industry (two-digit), establishment size (five categories), and year can be used to link employee- and employer-level data. We first average the WSS and KED into industry-size levels per year using the provided weights and number of employees, respectively, and then combine these to construct longitudinal data at the industry-size level.[4] Although the combined dataset cannot observe inequality between firms, the inequality between industry-size groups and its sources can be captured using worker- and firm-side variables aggregated in industry-size-year cells.

For the main analysis, samples comprise regular workers aged between 20–60 years, but exclude those who work fewer than 10 days per month and who earn less than the minimum hourly wage. In addition, we exclude the agriculture industry and several industries in the service sector, such as education, health, and social work (e.g., hospital). Arts-, sports-, and recreation-related services (e.g., creativity and art-related services), membership organizations, repair, other personal services (e.g., labor and religious organizations), and extraterritorial organizations are likewise excluded. The association between wages and establishment characteristics are not likely to be meaningful in the above industries.[5]

The Korean government has revised its industry classification twice, in 2000 and 2007 (i.e., 8th and 9th Korea Standard Industry Classification [KSIC], respectively), since 1994. Given that the recent revision provides more detailed classifications, we aggregate several industries for time-series consistency over the analysis periods.[6] The manipulation of industry classification applies equally to all datasets (i.e., WSS, KLIPS, KED).

## 2.2. Two Types of Wages

This study uses two types of real (adjusted by CPI, 2015=100) hourly wages, namely, fixed and total wages, defined as follows:

[4] One possible criticism of this process is that the WSS provide establishment-level data while the KED provides firm-level data. Given that 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 over five regular employees total 68,989 and 65,059 in the manufacturing sector, respectively. Firms with over two establishments constitute conglomerates, such as Samsung and Hyundai, which have over 500 employees. The biases induced by combining establishment-and firm-level data are not sufficiently large to contaminate the main results of this study.

[5] According to unreported results using all industries, the main results are not sensitive to the exclusion of several service industries.

[6] For instance, the food and beverage industries belong to the same industry under the two-digit classification in the 7th and 8th KSIC but are separated in the 9th KSIC. Thus, to maintain classification consistency, we integrate these industries after 2007.

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

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

As mentioned in Section 2.1, regular wage, overtime wage, and working hours provided in the WSS data are monthly (based on the June of each year). However, performance pays are yearly, and are thus divided by 12 to obtain the monthly data. The difference between the two types of wages determines the inclusion of performance pay; the difference in their variance can therefore be interpreted as the effects of performance pay on wage inequality.

To better understand the role of performance pay in our analysis, we describe its definition in detail. According to the Korea Ministry of Employment and Labor, the performance pay in the WSS is the sum of two types, namely, fixed and variable wages: the former is defined as a customary performance pay for all workers (e.g., regular bonus) and the latter is paid to workers on a temporary and indefinite basis depending on employer profits (e.g., irregular bonus and incentive). As such, the amount of employee performance pay is affected by employer profits. Thus, we judge that the performance pay in the WSS is a suitable measure for assessing the effects of employer performance and rent-sharing behavior on employee wages.

Table 1 shows the contribution of performance pay to wage inequality across industries and sizes by comparing two types of real (adjusted by CPI, 2015=100) hourly wages, fixed and total. The weighted standard deviations (weighted SD) are calculated using the weights provided in WSS data. Two results are noteworthy. First, the weighted SD of industry average wages and the log wage differences between size 1 (10–29) and size 5 (500+) are larger for total wages than for fixed wages in all years. This result indicates that performance pay is a factor in wage inequality increases. Second, although the differences in weighted SD of industry average wages between total and fixed wages are relatively stable, the wage differences between size 1 and 5 increases over time. This finding raises the possibility that employer size is a more influential factor than employer industry in explaining the effects of performance pay on wage inequality increases.

Under the results in Table 1, another question then emerges: Are the above-mentioned employer-side effects on wage inequality attributable to the interaction between the returns (observable and unobservable) of worker characteristics, performance pay, and the sorting effects of these characteristics across industries and sizes, or are they purely the effects of industry-size groups? We answer this question in the next section.

**[Table 1]** Comparison of Two Types of Wages by Industry and Establishment Size

| Industry and Size | Average of (log real hourly) Wages | | | | | |
|---|---|---|---|---|---|---|
| | 1994–1997 | | 2003–2007 | | 2013–2015 | |
| | Total | Fixed | Total | Fixed | Total | Fixed |
| **Industry (one-digit)** | | | | | | |
| Mining and quarrying | 0.1151 | −0.0771 | 0.4183 | 0.2155 | 0.5758 | 0.4338 |
| Manufacturing | −0.1401 | −0.3706 | 0.2543 | 0.0440 | 0.5181 | 0.3305 |
| Electricity, Gas, Steam, and Water Supply | 0.2438 | −0.0498 | 0.8775 | 0.6060 | 1.0617 | 0.8283 |
| Construction | 0.0723 | −0.1052 | 0.3315 | 0.2141 | 0.7153 | 0.6205 |
| Wholesale and Retail Trade | −0.0600 | −0.2674 | 0.3802 | 0.1916 | 0.4353 | 0.3155 |
| Accommodation and Food Service Activities | −0.1897 | −0.3718 | −0.0414 | −0.1701 | −0.0395 | −0.0744 |
| Transportation | −0.1121 | −0.2846 | 0.2733 | 0.0966 | 0.4226 | 0.2865 |
| Financial and Insurance Activities | 0.3333 | −0.0303 | 0.8413 | 0.5100 | 0.9911 | 0.7464 |
| Real Estate Activities and Renting and Leasing | −0.4398 | −0.6158 | 0.0526 | −0.0851 | 0.2689 | 0.2028 |
| **Weighted SD** | 0.1585 | 0.1284 | 0.1891 | 0.1552 | 0.1843 | 0.1559 |
| **Establishment Size (Five Categories)** | | | | | | |
| Size 1: 10−29 | −0.1573 | −0.3169 | 0.1792 | 0.0443 | 0.3680 | 0.2737 |
| Size 2: 30−99 | −0.1962 | −0.3767 | 0.1853 | 0.0278 | 0.3748 | 0.2666 |
| Size 3: 100−299 | −0.1119 | −0.3357 | 0.3008 | 0.0826 | 0.4491 | 0.2879 |
| Size 4: 300−499 | 0.0288 | −0.2446 | 0.4628 | 0.1974 | 0.6682 | 0.4532 |
| Size 5: 500+ | 0.1629 | −0.1751 | 0.7041 | 0.3560 | 1.0759 | 0.7168 |
| **Size 5 - Size 1** | 0.3202 | 0.1418 | 0.5249 | 0.3117 | 0.7079 | 0.4432 |

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 and fixed wages determines the inclusion of performance pay. The weighted standard deviations (weighted SD) are calculated using the worker weights provided in the WSS data.

# III. Variance Decomposition

## 3.1. Augmented Wage Equation

To carry out a variance decomposition that considers worker characteristics and sorting effects, we estimate the following augmented Mincer-type wage equation for the 1994–2015 period based on the model in Barth et al. (2016):

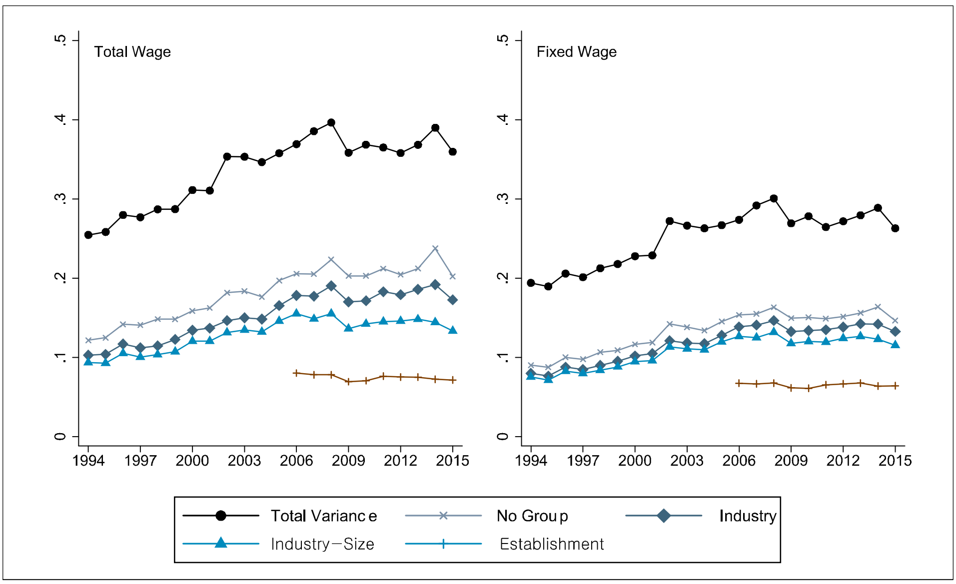
$$w_{i,g} = x_{i,g} b + \varphi_g(i) + u_{i,g}\text{, with } E(u_{i,g} \mid x_{i,g}, \varphi_g) = 0\text{,} \tag{3}$$

where $w_{i,g}$ 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 education, 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 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 returns of worker characteristics to vary over time, all models are fitted separately by year.

One method to observe how the effect of each group contributes to wage inequality is to compare the trends in residuals estimated by different groups. Four regressions using Equation (3) are thus carried out: no group (worker characteristics only), industry, industry-size, and establishment. The four regressions have the same independent variables for worker characteristics but different group dummies. Owing to data constraints, the regressions using establishment dummies are carried out for 2006–2015.

**[Figure 1]** 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 (3) for several groups. The difference between total and fixed wages determines the inclusion of performance pay. "No Group," "Industry," "Industry-Size," and "Establishment" denote the variances of the estimated residuals using the worker characteristics (WC) only, WC + industry dummies, WC + industry-size dummies, and WC + Establishment dummies as regressors, respectively.

Figure 1 plots the weighted variances of the residuals estimated by the four regressions. The first line (marked with circles) at the top of the figure is the trend of the weighted variance of log wages. The second line (marked with Xes) is the variance of the residuals from Equation (3) with no group dummies. Although worker characteristics explain a large portion of the total variance, the trend in the residual variance is similar to that in the total wage variance. This result indicates that worker characteristics and their returns cannot fully account for the changes in wage inequality. The third line (marked with diamonds) and fourth line (marked with triangles) are the variances of residuals from the models with two-digit industry and industry-size dummies, respectively. In these last two lines, one notable feature is the difference between each line and the second line. The difference between the second and third lines is stable over time, suggesting limited contributions of wage inequality between industry-size groups to changes in overall wage inequality. By contrast, the difference between the second and fourth lines increases over time. This result reveals that size effects dominate the impact of industry-size groups on wage inequality trends. The fifth line shows a substantial contribution of establishment heterogeneity in explaining the levels and changes in wage inequality. The fifth line is lower than the other lines, indicating that establishment heterogeneity largely affects wage inequality. Furthermore, the fifth line is less variable than the fourth line, implying that establishment heterogeneity can be partly accounted for the wage inequality trend that is unexplained by wage differentials.

Finally, the most important feature observed in Figure 1 is the difference between the left panel, total wages and the right panel, fixed wages. Although both panels demonstrate the phenomena explained above, the industry and industry-size group effects in the left panel for total wages appear to largely contribute to wage inequality. This result denotes that performance pays play an important role in the contribution of wage inequality between industry-size groups to the overall wage inequality. To add such interpretation, the difference between two panels implies that the substantial contribution of performance pay to wage inequality between industry-size groups does not come from worker characteristics. The fact that the amount of performance pay from employers is less related to the observed labor quality provides the possibility of its relation more to firm-side factors, unless the sorting effects dominate the effects of wage inequality between industry-size groups on the overall wage inequality.

### 3.2. Does Sorting Matter?

In the previous section, by observing the estimated residuals trend by group, we confirm the large contribution of wage inequality between industry-size groups to the rising trends in overall wage inequality. This large contribution comes from two components, group and sorting effects. We decompose the between-group variance into these two effects using Equations (4) and (5) formed by taking the variance of Equation (3), where $\rho$ 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:

$$Var(w) \;=\; Var(xb)+Var(\varphi)+2Cov(xb,\varphi)+Var(u) \tag{4}$$

$$= \underbrace{\underbrace{Var(xb)(\rho+2\rho_{\varphi})}_{\text{sorting effect}} + \underbrace{Var(\varphi)}_{\text{groug effect}}}_{\text{Between-group variance}} + \underbrace{Var(xb)(1-\rho)}_{\text{Within-group variance}} + Var(u)\,. \tag{5}$$

$\rho(=Cov(xb,\overline{xb}_g)/Var(xb))$ is calculated by dividing the covariance between the worker characteristics and its intra-establishment averages by their variance. This value shows the sorting effect of worker characteristics. If a firm employs random workers by observed characteristics, then $\rho=0$. If a firm hires observably similar workers, then $\rho$ is closer to 1. Similarly, $\rho_{\varphi}$ captures the sorting effect between the observed worker characteristics and group wage premiums. If the observably more qualified workers are hired in groups with higher wages, then $\rho_{\varphi}$ is also close to 1.[7] The values of interest in Equation (5) are the extent of the ratio of group effects to the overall variance, $Var(\varphi)/Var(u)$ and its trend over time.[8]

Table 2 shows the results of full variance decomposition for total and fixed wages using Equation (5). When industries are treated as groups, the change in the variance of residuals (66.53%) largely explains the share of the change in the variance of total wages between 1994 and 2015. Moreover, the change in the variance between industries explains only 11.33% of the change in the variance of total wages. These results indicate that the observed worker characteristics and employer industry affiliation cannot fully account for the trend in the variance of total wages. By contrast, when the industry-size is treated as groups, the contribution of the residual decreases to 37.94%. Furthermore, the increased variance in total wages is dominated by the increased inequality between industry-size groups (62.2%), which is attributable mainly to the group effects and not the sorting effects. The group effects account for majority of the between-group variance (0.4403/0.662=66.5%), and between 2008 and 2015. The variance in total wages decreases from 0.3956 to 0.3596, but increases from 0.0803 to 0.0828 between industry-size groups. This means that although wage inequality shows a decrease from 2008 to 2015, the group effects at the industry-size level are consistently increasing since 1994. In addition, the decreasing trend of wage inequality between industry-size groups between 2008 and 2015 is induced not by group effects but by

[7] Given that the worker–group segregation index, $\rho_{\varphi}$, comes from the covariance term in Equation (4), the difference between Equations (4) and (5) determines whether to consider the worker–worker segregation index. If this index has a negligible quantity, we can measure the sorting effects using the covariance term in Equation (4). The estimated worker–worker segregation index is 0.133, 0.186, and 0.175 in 1994, 2008, and 2015, respectively. We consider that these figures are not negligible.

[8] Barth et al. (2016) treated $Var(u)$ as within-group variance, if establishment effects are completely controlled by group dummies. However, only industry or industry-size effects are controlled in this study, and thus establishment effects that are not captured by industry or industry-size effects remain error terms. $Var(u)$ is then excluded in within-group variance.

others, such as worker characteristics and residuals.

**[Table 2]** Results of Variance Decompositions

| Group | Variance | 1994 | 2001 | 2008 | 2015 | 2008–1994 Change | 2008–1994 Share | 2015–1994 Change | 2015–1994 Share |
|---|---|---|---|---|---|---|---|---|---|
| Total Wages | | | | | | | | | |
| 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 |
| Fixed Wages | | | | | | | | | |
| 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 full variance decomposition for two types of wages using the WSS data and Equation (5). The difference between total and fixed wages determines the inclusion of performance pay. The sorting effects include the worker–worker segregation effect $(Var(xb)*\rho)$ and worker–group segregation effect $(2*Var(xb)*\rho_{\varphi})$ where the sorting effect $\rho$ shows that of worker characteristics and $\rho_{\varphi}$ shows that of the association between observed worker characteristics and group wage premiums.

Comparison of the results for the total and fixed wages captures two interesting features. First, the share of the variance between industry-size groups from 1994 to 2015 sharply decreases from 62.2% to 44.49% when wages exclude performance pay, while the share of the variance between industries has a smaller decline from 19.5% to 15.95%. This result implies that even after the worker characteristics are controlled for, the effects of performance pay on the trends of wage inequality come mainly from its differences between establishment sizes. Second, the large decline in the variance between industry-size groups is attributable to that of the share of group effects from 44.03% to 29.35%, while the share of sorting effects has a modest change. This reveals that performance pay differences between industry-size groups depend not on the assortment of workers between groups but on the characteristics of industry-size groups.

### 3.3. Effects of Unobserved Worker Heterogeneity

One plausible criticism of the findings from cross-sectional data is the effect of unmeasured heterogeneity across workers on the wage inequality between industry-size groups. If the unobserved worker characteristics are not controlled for, the variance between groups can display large biases.[9] Specifically, the group effects of regression Equation (3), $\varphi_g(i)$, may capture the average level of unmeasured worker characteristics, as well as the pure wage effect of each group. Thus, if systematic differences in unobserved heterogeneity exist across groups, and if these differences dominate the inequality among industry-size groups, then the estimated group effects shown in Table 2 is attributable not to the pure group effect but to the sorting effects from unobserved worker heterogeneity.

The robustness of the results derived from the cross-sectional data are derived using two strategies. First, as suggested by Krueger and Summers (1988), we consider alternative models in which several control variables for labor quality are ruled out to observe their influence on the group effects. If the wage differentials across industry-size groups are significantly affected by unmeasured worker heterogeneity, then the variance between groups change according to the excluded control variables. Table A2 in the appendix shows the contribution of group effects $(Var(\varphi_g(i))$ estimated from the alternative models to the wage variances using the WSS data. The results show that the shares of between-variances are stable regardless of model specification: 45.29% in model 1 (including years of education only) and 44.03% in the full model between 1994 and 2015. The last column shows the correlation of coefficients for the group effects estimated in the alternative and the full models. The estimated coefficients for group effects are highly correlated across models, irrespective of the control variables.

Second, we analyze the longitudinal data. Using the KLIPS data, we estimate wage Equation (6), where $\alpha_i$ is added to Equation (3) to control for unmeasured worker heterogeneity within two periods: 1998–2003 and 2004–2008.

$$w_{i,g} = \alpha_i + x_{i,g}b + \varphi_g(i) + u_{i,g}\ . \tag{6}$$

[9] Recent studies on wage inequality using large longitudinal worker datasets report that unobserved worker heterogeneity contributes significantly to changes in wage inequality in the US and Germany (e.g., Card, Heining, and Kline, 2013; Song et al., 2015).

The independent variables in Equation (6) are the same as those in Equation (3). The dependent variable, $w_{i,g}$, is the same as the total wage defined in Section 3.1. Workers with fewer than three observations within a period are excluded from the analysis. The variance decomposition for Equation (6) can be expressed as follows:

$$\begin{aligned} Var(w) &= Var(\alpha) + Var(xb) + Var(\varphi) \\ &+ 2\operatorname{cov}(\alpha, xb) + 2\operatorname{cov}(\alpha, \varphi) + 2\operatorname{cov}(xb, \varphi) + Var(u)\,. \end{aligned} \tag{7}$$

Our interest in Equation (7) is whether the variance in the group effects at the industry-size level, $Var(\varphi)$, remains meaningful in explaining the trends in wage inequality even after controlling for unmeasured worker heterogeneity, $\alpha_i$. Table 3 shows the results of the variance decomposition using Equation (7). Although the levels in the variances of estimated worker heterogeneity substantially explain the wage differentials 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 changes to wage variances (17.55%) is much smaller than that of changes to group effects (54.26%).

In summary, the results of the two abovementioned approaches suggest that findings of the cross-sectional analysis are robust to the effects of unobserved worker heterogeneity on wage inequality trends.

**[Table 3]** Effects of the Unobserved Worker Characteristics (Industry-Size Level, KLIPS)

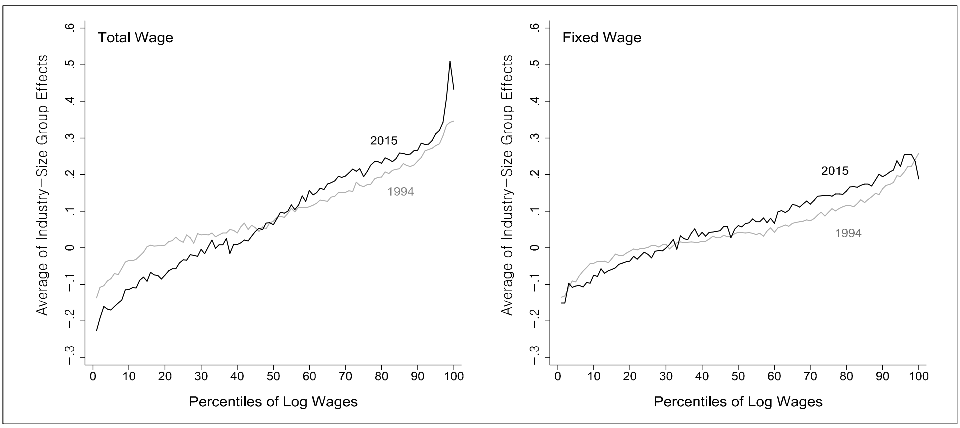
| Variance | Period 1 (1998–2003) | Period 2 (2004–2008) | Change (P2−P1) | Share |
|---|---|---|---|---|
| Total $(= Var(w))$ | 0.2969 | 0.3377 | 0.0409 | 1.0000 |
| Variance Decomposition | | | | |
| $Var(xb)$ | 0.0345 | 0.0336 | −0.0009 | −0.0231 |
| $Var(\alpha)$ | 0.2163 | 0.2235 | 0.0072 | 0.1755 |
| $Var(\varphi)$ | 0.0317 | 0.0539 | 0.0222 | 0.5426 |
| $2*(Cov(\alpha,xb)+Cov(\alpha,\varphi)+Cov(xb,\varphi))$ | −0.0292 | −0.0065 | 0.0226 | 0.5532 |
| $Var(u)$ | 0.0435 | 0.0334 | −0.0102 | −0.2483 |
| Number of observations | 6,319 | 5,854 | - | - |

Notes: This table shows the result of variance decomposition using KLIPS data. The wage equation is estimated by Equation (6), and variance decompositions are implemented by Equation (7).

## IV. Distributional Changes in Industry-size Group Effects

The variance in the estimated group effects cannot capture their distributional features. To observe the group effects at industry-size levels along with the wage distribution between 1994 and 2015, we plot the average industry-size group effects in that period by 100 wage percentiles in Figure 2. The upward slopes in all lines indicate that wages and the industry-size group effects are positively correlated regardless of the year or type of wages. According to the left panel (total wages), the rising inequality between industry-size groups is derived from three distributional factors: deterioration of group effects at the bottom 50%, increase in group effects at the top 50%, and the soaring group effects at the top 5% of the wage distribution. In the right panel (fixed wages), the effects of the first factor are relatively small, and those of the third factor disappear. These results reveal that the greater polarization of group effects in 2015 than in 1994 is caused largely by the performance pay differences between industry-size groups.[10]

**[Figure 2]** 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. The difference between total and fixed wages concerns whether performance pay is included or not. The average of group effects is calculated by estimates of $\varphi_g(i)$ in regression Equation (3).

The changes in group effects by wage percentile between 1994 and 2015 can be decomposed into two additional effects: composition and wage premium. The former reflects how the changes in worker group compositions within the wage percentiles affect the differences in the group effects, and the latter reflects how industry-size wage premiums affect differences in the group effects for the two years. Although the group wage premiums are identical, the estimated group effects under the support of total wages is more polarized if workers employed by groups with low

[10] Figure 2 shows a large difference between the two panels: the shape of group effects at the top 5% of the wage distribution. Although the group effects peak at the top 5% in the left panel, they fall in the right panel. This result means that the wages of high-wage workers (top 5%) are affected by performance pay in 2015 more than in 1994. Other studies likewise demonstrate this phenomenon. Lemieux et al. (2009) shows that the impact of performance pay is highly concentrated at the top of the wage distribution, and the impact increases in the early 1990s than in the late 1970s.

wage premiums are concentrated at the bottom 50% of total wages in 2015. By contrast, if the industry-size group composition of workers within wage percentiles is identical for the two years, then the wage premium effects mainly affect the phenomenon in Figure 2. The two effects can be expressed within the simple equations below:

$$\bar{\varphi}_t^p = \frac{1}{n_t^p}\left(\sum_{g=1}^{k}\hat{\varphi}_{g,t}n_{g,t}^p\right) = \sum_{g=1}^{k}\hat{\varphi}_{g,t}\theta_{g,t}^p \quad \text{where} \quad n_t^g = \sum_{g=1}^{k} n_{g,t}^p \tag{8}$$

$$\Delta\bar{\varphi}^p = \bar{\varphi}_{t+1}^p - \bar{\varphi}_t^p = \sum_{g=1}^{k}(\hat{\varphi}_{g,t+1}\theta_{g,t+1}^p - \hat{\varphi}_{g,t}\theta_{g,t}^p) \tag{9}$$

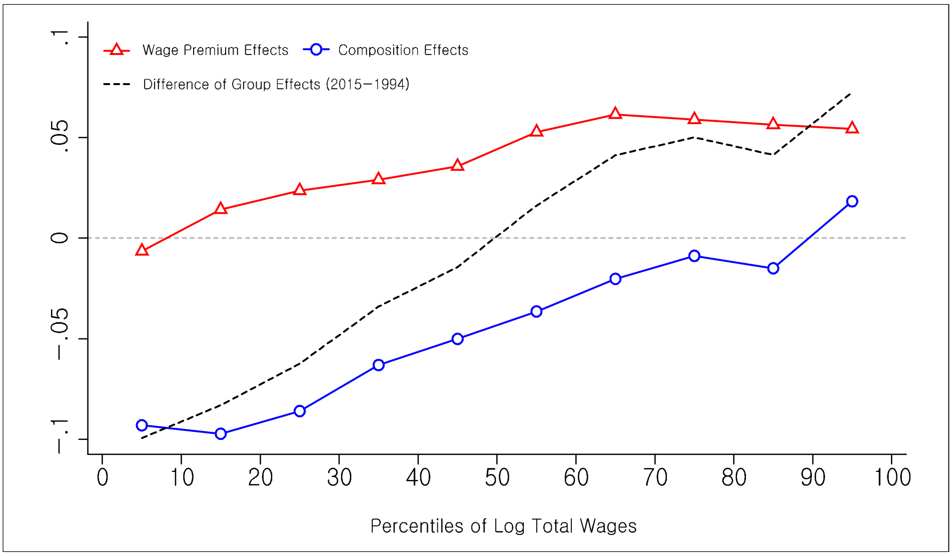
$$= \underbrace{\sum_{g=1}^{k}\left(\frac{\theta_{g,t+1}^p + \theta_{g,t}^p}{2}\right)(\hat{\varphi}_{g,t+1} - \hat{\varphi}_{g,t})}_{\text{Wage Premium Effects}} + \underbrace{\sum_{g=1}^{k}\left(\frac{\hat{\varphi}_{g,t+1} + \hat{\varphi}_{g,t}}{2}\right)(\theta_{g,t+1}^p - \theta_{g,t}^p)}_{\text{Composition Effects}}, \tag{10}$$

where $\bar{\varphi}_t^p$ is the estimated group effects averaged at wage percentile $p$ and period $t$; $\hat{\varphi}_{g,t}$ is the estimated group effects of group $g$ at period $t$; $n_t^p$ and $n_{g,t}^p$ are the number of workers at wage percentile $p$ and the number of workers employed by group $g$ at wage percentile $p$ and period $t$, respectively; $\theta_{g,t}^p$ 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.[11]

Figure 3 illustrates the results of the decomposition using Equation (10). The wage premium effects are marked with triangles, the composition effects is marked with circles, and the difference in the average group effects between 1994 and 2015 by 10 wage percentiles is the dashed line. The sum of the composition and wage premium effects equals the difference in the average group effects. Figure 3 reveals that the decrease in group effects at the bottom 50% of wage distribution is attributable mainly to composition effects, while the increase at the top 50% is due primarily to wage premium effects. The fact that the composition effects are more influential than the wage premium effects at the bottom 50% of wage distribution implies that workers in low-wage industry-size groups are more concentrated at the bottom 50% of the wage distribution in 2015 than in 1994. Furthermore, the fact that wage premium effects are more influential at the top 50% implies that the industry-size groups with workers at the top 50% of wage distribution pay more wage premiums.

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

**[Figure 3]** Wage Premium Effects vs. Composition Effects




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

## V. Firm-side Factors and Wage Inequality

The previous sections show that changes in wage inequality between industry-size groups explain a large portion of the changes in overall wage inequality. In this section, we investigate the relation between firm-side factors and wage inequality between industry-size groups using the merged data from the WSS and KED introduced in Section 2.1. Given the limited time period covered by the KED, the analysis period covers 2000 to 2015.

Previous studies discussed two issues concerning the estimation of firm-side effects on wage determination and inequality. The first issue is how to control for the effects of human capital on wage inequality. Unless the human capital differences among groups are controlled for, the effects of firm-side factors on wage inequality may be overestimated. Blanchower et al. (1996) addressed this problem using two strategies, namely, averaged human capital variables at the worker level to those at the industry level and two-stage regressions of wage equations. The coefficients of group dummies in the first stage are used to form the dependent variables in the second stage. Barth et al. (2016) used variables calculated by averaging the estimated values, $x_{i,g}b$, in wage Equation (3) into firm-level values. This strategy is adopted to observe the effects of worker characteristics on wage inequality at the industry-size level.

The second issue is the reverse causality between wages and firm-side variables, particularly productivity-related (or profit-related) variables. Hiring highly qualified workers, which implies greater remuneration, can lead to greater labor productivity for employers. This problem can be addressed in two ways, namely, adopting lagged variables of labor productivity or finding good instrumental variables. Carlsson et al. (2014) and Guiso et al. (2005) utilize the lag variable of labor productivity to address the endogeneity problem. Barth et al. (2016) and Card et al. (2014), among others, consider labor productivity of the same industry outside the region of the observed employer as the instrument. In the present analysis, the former method is adopted. Korea is small compared with countries such as the US that are analyzed in previous studies, and thus the instruments are not likely to be exogenous. Moreover, Blanchower et al. (1996) suggest that shocks to labor productivity (or profit) may take time to be passed on in wages. This lag is acceptable for the wage-setting system used for Korean workers because an annual wage usually depends on the performance of the previous year.

The analysis years, 2000–2015, are divided into two comparable periods, namely, 2000–2008 and 2009–2015. From Section 3, we know that if worker characteristics are controlled for, the between-variance at the industry-size level increases in 2000–2015 despite the decreasing wage variance after 2008. Thus, this section seeks to identify the firm-side factors that further disperse wage inequality between industry-size groups between the two periods. To decompose the changes in wage inequality between industry-size groups into covariate effects ("quantity effects") and coefficient effects ("price effects") between the two periods, we use the methodology of Machado and Mata (2005) based on quantile regression. While traditional wage decomposition methods, such as that of Oaxaca, hinge on the effects of covariates and coefficients at a mean level (Oaxaca, 1973), the method of Machado and Mata (2005) can factor in heterogeneous effects of firm-side factors along with wage distribution and observe the marginal effect of each variable on the changes in wage inequality by calculating counterfactual variances.

## 5.1. Firm-side Factors

The main variables in this analysis are labor productivity per worker and capital-to-labor ratio, adjusted by Producer Price Index (PPI) (2010=100). In this study, the measure of labor productivity is the value-added per worker.[12] The capital-to-labor ratio is calculated as tangible assets (e.g., equipment and plants) divided by

[12] The most widely used measures for labor productivity are sales per worker and value-added per worker. Card et al. (2016) show biases in the two measures of labor productivity using a simple linear technology equation. According to their model, value added per worker can be a valid index of Total Factor Productivity (TFP) when the average quality of human capital is controlled for.

the number of employees.[13] The control variables used to reduce the biases in estimating the effects of labor productivity and capital-to-labor ratio on wage inequality are the alternative wages at the industry-year level and the averaged worker characteristics at the industry-size-year level. First, alternative wages are the average of the (two-digit) industry of each year that affect the average wage of the industry-size groups through several paths, such as worker bargaining power and demand-supply conditions. Second, worker characteristics are (as mentioned) represented by averaging the values of $x_{i,g}b$ estimated separately by year in Equation (3) into the industry-size-year level.

## 5.2. Effects of Firm-side Factors on Wage Determination

Before wage inequality is decomposed using quantile regression, the effects of firm-side factors on the mean wages are estimated using the ordinary least squares (OLS) method as the basic results. Consider the following regression equation:

$$w_{g,t} = \beta LP_{g,t-1} + \gamma CL_{g,t} + \delta AW_{g,t} + \eta WC_{g,t} + \mu_{ind} + \theta_t + \varepsilon_{g,t}, \tag{11}$$

where $w_{g,t}$ is a vector of the 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; $\mu_{ind}$ are two-digit industry dummies used to control for unobserved industry characteristics; $\theta_t$ are year dummies representing the economic conditions of each year; and $\varepsilon_{g,t}$ is an unobserved time-varying error.

Table 4 reports the estimation results using regression Equation (11). All regressions are weighted using the WSS to capture the composition of industry-size groups. The rent-sharing parameter is estimated at 0.428 when other factors are not considered (model [1]), adding worker characteristics to model (1) reduces the estimation to 0.296. This result implies that approximately 30% of the positive effect

[13] Recent studies show the positive and significant effects of the capital-to-labor ratio on wages (e.g., Arai, 2003; Leonardi, 2007). This 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 business costs; thus, firms with high capital-to-labor ratios may be more favorable to high wage demands. Moreover, given that high capital-to-labor ratios may also reflect high fixed costs required for a new firm entry, workers employed in firms with high capital-to-labor ratios are paid more. In light of efficiency wages, as pointed out by Salop (1979) and Akerlof and Yellen (1986), if high capital-to-labor ratios lead to increases in turnover or poor performance costs, which firms with high capital-to-labor ratios avoid through high payments.

of labor productivity on wages is due to the sorting of workers across industry-size groups. The rent-sharing parameter further decreases to 0.143 at the inclusion of the capital-to-labor ratio and alternative wages, which have positive and statistically significant effects on wages (model [4]) as expected.[14]

**[Table 4]** Effect of Firm-side Factors on Wage Determination: Industry-Size level

| Dep. Var: log hourly wages | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Total Wages | | | | | Fixed Wages | |
| L1. Labor Productivity | 0.428*** | 0.296*** | 0.216*** | 0.143*** | 0.089*** | 0.093*** | 0.054** |
| Per Worker | (0.043) | (0.052) | (0.040) | (0.038) | (0.016) | (0.026) | (0.023) |
| Capital-to-Labor Ratio | | | 0.082*** | 0.097*** | 0.160*** | 0.059*** | 0.100*** |
| | | | (0.031) | (0.028) | (0.011) | (0.018) | (0.021) |
| Alternative Wages | | | | 0.480*** | -0.056 | 0.583*** | 0.034 |
| | | | | (0.112) | (0.088) | (0.092) | (0.111) |
| Worker Characteristics | | 1.185*** | 1.243*** | 0.767*** | 1.217*** | 0.546*** | 1.032*** |
| | | (0.093) | (0.076) | (0.131) | (0.065) | (0.096) | (0.124) |
| Constant | -3.420*** | -2.689*** | -2.717*** | -2.215*** | -2.244*** | -1.366*** | -1.362*** |
| | (0.383) | (0.429) | (0.393) | (0.418) | (0.118) | (0.254) | (0.242) |
| Industry Dummies (2-digit) | No | No | No | No | Yes | No | Yes |
| Year Dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.340 | 0.666 | 0.711 | 0.746 | 0.855 | 0.806 | 0.881 |
| 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 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 its own size group. Worker characteristics are the average of $x_{i,g}b$ from equation (3) at the industry-size level. Year dummies are included in all models. All regressions are weighted using the WSS. Standard errors clustered by two-digit industry are in parentheses. *, **, and *** indicate the 10%, 5%, and 1% significance levels, respectively.

Equation (5) adds two-digit industry dummies to Equation (4), allowing the estimated coefficients to be interpreted as the effects of the within-industry and between-sizes of firm-side factors. The rent-sharing parameter decreases from 0.143 to 0.089 when industry dummies are added. However, this modest decline indicates that the significant and positive effects of labor productivity on wages via firm rent-sharing behaviors are larger among employer sizes than among industries. Next, contrary to the rent-sharing parameter, the coefficient of capital-to-labor ratio increases from 0.097 to 0.160. This result implies that the positive correlation between capital-to-labor ratio and wages is also much stronger among sizes than

[14] Card et al. (2016) summarize the estimation results for rent-sharing parameters, revealing their estimation in the range of 0.05 to 0.15. In light of those previous results, the estimated rent-sharing parameters in Table 4 are reliable.

among industries.

Equations (6) and (7) show the results for fixed wages. All model specifications are the same as in Equations (4) and (5) for total wages. As expected, the rent-sharing parameters decrease compared with total wages, implying that employers use performance pay as a method to exhibit rent-sharing behavior. The coefficients of capital-to-labor ratio also decrease compared with the results for total wages and are even larger than those for labor productivity when industry dummies are included. The fact that the effects of capital-to-labor ratio are sensitive to performance pay, even more than 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, advantages of high fixed costs, and reduced turnover costs), the wage premiums from heavy capital dependency are also associated with employee and employer performance. Alternative wages appear to be more sensitive to fixed than to total wages. Thus, the wage inequality between groups via different worker bargaining powers and the labor demand-supply mismatches are reflected more strongly in fixed wages than in total wages.

## 5.3. Effects of Firm-side Factors on Wage Inequality Among Industry-Size Groups

The previous section shows the significant effects of the study variables on wage determination. In this final section, we explore the sources of the changes in wage inequality between industry-size groups between the two periods (2000–2008 and 2009–2015). These changes have to be captured according to the changes in wage distribution. The analysis in the previous section cannot be extended to the entire wage distribution. In this section, beyond the traditional decomposition methods, we adopt the method of Machado and Mata (2005) based on quantile regression and a simulation technique to investigate the marginal effects of each variable on the changes in wage inequality between industry-size groups.

### 5.3.1. Three Steps

We follow the three steps used by Machado and Mata (2005). The first step is to carry out a quantile regression. Given a vector of covariates, $z$, let $Q_\theta(w \mid z)$ for $\theta \in (0,1)$ denote the $\theta$th quantile of the distribution of log hourly average wages at the industry-size level. The conditional quantiles can be modeled with Equation (12), where $\beta(\theta)$ is a vector of the quantile regression coefficients. $\beta(\theta)$ can be estimated by minimizing Equation (13) using linear programming methods (Koenker and Basset, 1978):

$$Q_\theta(w \mid z) = z'\beta(\theta) \tag{12}$$

$$\sum_{i:w_i \geq z_i'\beta}^{n} \theta \,|\, w_i - z_i'\beta(\theta) \,| + \sum_{i:w_i < z_i'\beta}^{n} (1-\theta) \,|\, w_i - z_i'\beta(\theta) \,| . \tag{13}$$

Figure A1 in the appendix shows the coefficient estimates, $\hat{\beta}$, by 2.5% wage quantiles. 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, whereas the changes increase at the upper quantiles. This result implies that changes in the rent-sharing parameter further disperse the wage inequality between industry-size groups. The estimated coefficients for the capital-to-labor ratio show opposite shapes for the two periods. Wages and the coefficients are negatively correlated at period 1 but are positively correlated at period 2. This result may be a factor that increases the wage inequality between industry-size groups. The coefficients for worker characteristics are crossed at approximately the 50% wage quantile, and the differences between the two lines are greatest in the top quantiles. In addition, wage inequality between industry-size groups may become more dispersed. Figure A2 in the appendix shows the coefficient estimates for fixed wages. When performance pay is not considered, the changes in coefficients of labor productivity are modest in the overall distribution of wages, implying that employee performance pays and employer rent-sharing behaviors are highly associated.

The second step is to generate the conditional distribution of wages given $z$. Under the assumption that the conditional quantile function defined in Equation (12) is correctly specified at a sufficiently large number of points $\theta$, the conditional wage distribution 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 $\theta_1, \theta_2, \ldots \theta_m$ are drawn from a uniform (0,1) distribution, then the corresponding $m$ estimates of the conditional wage quantiles at $z$, $\{z'\hat{\beta}(\theta_i)\}_{i=1}^{m}$, constitute a random sample from the (estimated) conditional wage distribution given $z$.

The third step is to estimate the marginal wage density by integrating $z$. In OLS, $z$ can be easily integrated using the law of iterated expectations, but does not work in quantile regressions because $Q_\theta(w) \neq E_z[Q_\theta(w \,|\, z)]$. To address this problem, Machado and Mata (2005) suggest the simulation-based technique. The three steps and the simulation-based technique can be summarized as follows:

- Generate a random sample of size $k$ from a uniform distribution $U[0,1]$: $\theta_1, \ldots, \theta_k$
- For each $\theta_k$ and at time $t$, estimate the QR coefficients $\hat{\beta}^t(\theta_k)$.
- Generate a random sample of size $k$ with a 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 $k$ from the desired distribution: $\{w_i^*(t) = z_i^{*\prime}(t)\hat{\beta}^t(\theta_i)\}_{i=1}^k$

According to Autor et al. (2005), this procedure is essentially equivalent to numerically integrating the estimated conditional quantile function over the distribution of $z$ and $\theta$. Using this technique, we can calculate the marginal effects of the covariates and coefficients on wage inequality between industry-size groups. Suppose that only one covariate changes 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; $\hat{\gamma}_i(\theta)$ 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, the difference in the variance between $x_1\hat{\gamma}_1(\theta) + d_1\hat{\rho}_1(\theta)$ and $x_2\hat{\gamma}_1(\theta) + d_1\hat{\rho}_1(\theta)$ can be interpreted as the marginal contribution of the changes in covariate $x$ to the wage inequality between industry-size groups.

### 5.3.2. Marginal Effects of Covariates and Coefficients

Table 5 presents the actual and counterfactual variances of the average wages of industry-size groups. *Raw* and *Estimated* in the first part of Table 5 indicate the variances of wages calculated from the data and of the predicted wages, $w_i^*(t)$, with $k = 5{,}000$, respectively. The numbers in the brackets are 95% bootstrap confidence intervals for the variances identified 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 the explanation of the residuals. The estimations explain a large portion of the variances from the data: approximately 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 5 show the counterfactual variances separately calculated under the assumptions of changes in the covariates and coefficients. *Aggregate* indicates that all covariates (or all coefficients) change from the values of period 1 to those of period 2. The results show that the aggregate effect of covariates is a factor that decreases the wage inequality between industry-size groups from 0.131 to 0.1056. The decreases in dispersions in labor productivity and worker characteristics between the two periods considerably contribute to alleviating the wage inequality between industry-size groups. The changes in labor productivity reduce the wage inequality between the industry-size groups from 0.131 to 0.117, and the changes in worker characteristics decrease to 0.0888. In contrast to the covariate effects, the aggregate effect of coefficients increases the wage variance from 0.131 to 0.1517. Among the estimations, the changes in the coefficients of labor productivity and capital-to-labor ratio are the main factors in increasing the wage inequality between industry-size groups from 0.131 to 0.1897 and to 0.1808, respectively. The directions of the covariate and coefficient effects in fixed wages on wage inequality between industry-size groups are similar to those for total wages. Their magnitudes are, however, quite different. In particular, the effect of changes in the coefficients of labor productivity is much weaker: 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.

**[Table 5]** Counterfactual Variances by the Covariate and Coefficient 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 $\gamma$ | Covariate Effects $(=\mathrm{var}(x_2\hat{\gamma}_1(\theta)+d_1\hat{\rho}_1(\theta))$ | | Coefficient Effects $(=\mathrm{var}(x_1\hat{\gamma}_2(\theta)+z_1\hat{\rho}_1(\theta))$ | |
| | 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. In the second part, $\mathrm{var}(x_2\hat{\gamma}_1(\theta)+d_1\hat{\rho}_1(\theta))$ means the counterfactual variance where $x_2$ is the changed covariate from the values 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) change from values of period 1 to period 2. The numbers in brackets are 95% bootstrap confidence intervals for variances identified through 10,000 iterations of bootstrap sampling.

Overall, the findings indicate that wage inequality between industry-size groups has consistently increased since 1994, despite a decreasing trend of the overall wage inequality 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 rent-sharing parameters and coefficients of capital-to-labor ratio are the main factors in the rising wage inequality between industry-size groups. These results are even more apparent when wages include performance pays. Thus, performance pays provide a channel through which firms share their rents with workers and compensate for capital dependency. This employer behavior translates into a widening wage distribution.

These results can be supported by the efficiency wage theory of Shapiro and Stiglitz (1984), Akerlof and Yellen (1986), and Salop (1979). According to Shapiro and Stiglitz (1984), higher wages can impose a larger penalty for shirking. This penalty motivates employees to exert more efforts. Given that large firms face higher monitoring costs than small firms, paying higher wages is a more efficient way for large firms to elicit more effort from employees and minimize the monitoring costs. Variations of rent-sharing behaviors of large firms between periods 1 and 2 can be understood in terms of the process of pursuing greater efficiency via paying for performance. In addition, the variation of capital-to-labor ratio coefficients and its effects on wage inequality between the two periods can be understood using the logic of Shapiro and Stiglitz (1984), Akerlof and Yellen (1986), and Salop (1979).

# VI. Conclusion

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

The novel feature of this study is its consideration of performance pay contributions to wage inequality. Performance pay is found to cause the further dispersion of wage inequality between industry-size groups. When wages include performance pay, the changes in wage inequality between industry-size groups account for 44.03% of the changes in the overall wage inequality between 1994 and 2015 after observed worker characteristics and sorting effects are controlled for. These changes account for 29.35% when performance pay is not considered. This result is robust to unobserved worker characteristics.

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

Overall, this study describes the unique roles of performance pay in wage inequality. Unlike Lemieux et al. (2009) and Bryan and Bryson (2016) who examine the connection between performance pay and worker characteristics, the present study shows that performance pay affects wage inequality between industry-size groups. This phenomenon flows from the heterogeneity of rent-sharing behaviors and compensation for capital dependency across industry-size groups. The results imply that the effects of performance pay on wage determination and inequality vary according to employer wage-setting strategies and business environment.

Finally, beyond the problem of inequality, considering the effects of performance pay from various angles is necessary. Lemieux et al. (2009) point out that performance pay can reflect marginal worker productivity more accurately than fixed wage schedules, and thus allow for more efficient job-matching even if wage inequality further disperses within industry-size groups or between establishments. By contrast, if the effects of performance pay are captured chiefly in wage inequality between industry-size groups or between establishments, as in the case of Korea, performance pay can have negative effects on both labor market efficiency and wage disparities. Moreover, in this situation, productive workers might congregate in already productive firms to receive more compensation. This scenario can lead to consistent wage gaps between already productive and potentially productive employers, and act as a barrier to new businesses and innovations.

**[Table A1]** Analyzed Industries and the Number of Observations − WSS and KED

| Industry (two-digit) | Number of Workers (WSS Data) | Number of Firms (KED Data) |
|---|---|---|
| **Mining and Quarrying** | | |
| Coal, Crude Petroleum, and Natural Gas | 50,252 | 175 |
| Metal Ores | 4,258 | 58 |
| Non-metallic Minerals, Except Fuel | 32,244 | 1,805 |
| **Manufacturing** | | |
| Food and Beverages | 297,120 | 26,982 |
| Tobacco | 33,290 | 72 |
| Textiles, Except Apparel | 206,798 | 20,187 |
| Wearing apparel, Clothing Accessories and Fur Articles | 155,041 | 11,452 |
| Tanning and Dressing of Leather, Luggage and Footwear | 67,898 | 4,219 |
| Wood and Cork, Except Furniture | 48,740 | 5,126 |
| Pulp and Paper | 91,580 | 9,065 |
| Printing and Reproduction of Recorded Media | 117,880 | 10,662 |
| Coke, Hard-coal, Lignite Fuel, and Refined Petroleum | 74,054 | 1,194 |
| Chemicals, Except Pharmaceuticals and Medicinal Chemicals | 327,946 | 32,143 |
| Rubber and Plastic | 211,512 | 27,764 |
| Other Non-metallic Mineral Products | 159,737 | 22,943 |
| Basic Metal Products | 189,830 | 19,817 |
| Fabricated Metal Products, Except Machinery and Furniture | 169,469 | 42,783 |
| Electronic Components (Computer, Radio, and others) | 605,651 | 41,900 |
| Medical, Precision, Optical Instruments, Watches | 89,076 | 18,549 |
| Motor Vehicles, Trailers, and Semitrailers | 323,993 | 26,976 |
| Other Transport Equipment | 216,309 | 10,247 |
| Furniture and Other manufacturing | 95,340 | 14,641 |
| **Electricity, Gas, Steam, and Water Supply** | | |
| Electricity, Gas, Steam, and Air Conditioning Supply | 181,356 | 1,534 |
| Water Supply | 26,300 | 38 |
| **Construction** | | |
| General Construction; Special Trade Construction | 300,086 | 181,493 |
| **Wholesale and Retail Trade** | | |
| Sale of Motor Vehicles and Parts | 55,764 | 10,809 |
| Wholesale and Commission Trade, Except of Motors | 356,431 | 201,671 |
| Retail Trade, Except Motor Vehicles and Motorcycles | 330,384 | 16,724 |
| **Accommodation and Food Service Activities** | | |
| Accommodation; Food and Beverage Service Activities | 234,402 | 3,948 |
| **Transportation** | | |
| Land Transport and Transport Via Pipelines | 520,962 | 13,054 |
| Water Transport | 55,394 | 3,019 |
| Air Transport | 62,312 | 172 |
| Telecommunications | 164,710 | 1,700 |
| **Financial and Insurance Activities** | | |
| Financial Institutions, Except Insurance and Pension | 253,864 | 126 |

| | | |
|---|---|---|
| Funding | | |
| Insurance and Pension Funding | 162,636 | 24 |
| Activities Auxiliary to Financial Service and Insurance | 135,195 | 281 |
| **Real Estate Activities and Renting and Leasing** | | |
| Real Estate Activities | 167,265 | 12,298 |
| Renting and leasing; Except Real Estate | 26,750 | 2,377 |
| Total | 6,601,829 | 798,028 |

Notes: The number of workers from the WSS is the sum of workers between 1994 and 2015. The number of firms from the KED is the sum of firms between 2000 and 2015.

**[Table A2]** Contribution of Industry-Size Effects: Alternative Models for Labor Quality

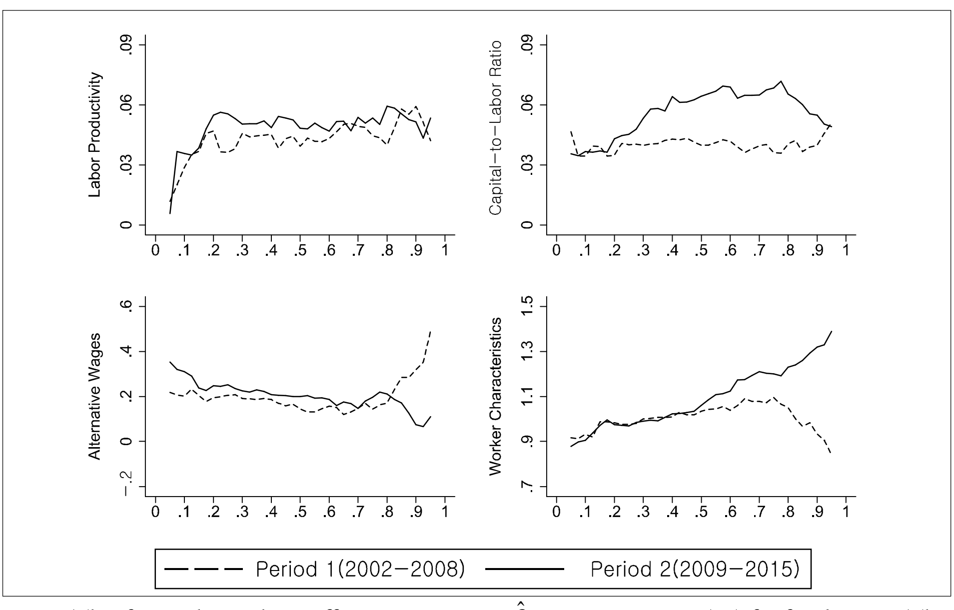
| Variance | | 1994 | 2008 | 2015 | 2008–1994 | | 2015–1994 | | Correlations |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | Change | Share | Change | Share | of Coefficients |
| Total | | 0.2546 | 0.3965 | 0.3596 | 0.1419 | 1.0000 | 0.1050 | 1.0000 | - |
| Group Effect $(=Var(\varphi_g(i))$ | Model 1 | 0.0526 | 0.1014 | 0.1002 | 0.0488 | 0.3437 | 0.0476 | 0.4529 | 0.9268 |
| | Model 2 | 0.0494 | 0.1052 | 0.1052 | 0.0558 | 0.3931 | 0.0557 | 0.5307 | 0.9748 |
| | Model 3 | 0.0375 | 0.0866 | 0.0886 | 0.0490 | 0.3454 | 0.0511 | 0.4862 | 0.9965 |
| | Full Model | 0.0365 | 0.0803 | 0.0828 | 0.0438 | 0.3085 | 0.0462 | 0.4403 | - |

Notes: This table shows the results of variance decompositions using Equation (7) 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 2. The last column shows the correlation of coefficients for the group effects estimated in Models 1–3 with the full model.

**[Figure A1]** Estimate Results of Quantile Regression by Periods (Total Wages)


Notes: This figure shows the coefficient estimates, $\hat{\beta}$, using Equation (13). The regressions are implemented for every 2.5% wage quantiles. The X-axis indicates 2.5% quantiles of the average wages at the industry-size level.

**[Figure A2]** Estimated Results of Quantile Regression by Periods (Fixed Wages)




Notes: This figure shows the coefficient estimates, $\hat{\beta}$, using Equation (13) for fixed wages. 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.

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