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Posted Date: March 18th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-9143061/v1

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Additional Declarations: The authors declare no competing interests.

RIF quantile-band decompositions: An application to gender ear nings gaps among the self-employed and paid employees

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January 2026

Abstract

This paper provides the first comparative analysis of gender earnings gaps in self-employment and paid employment in South Korea. Using data from the 2023 Korean Working Conditions Survey, we introduce a simple extension of the recentered influence function (RIF) framework to decompose gender gaps in monthly earnings among low-, middle-, and high earners. By averaging RIFs within quantile bands, we address the instability of single-quantile estimates caused by distributional bunching and obtain mo re stable inference. We find that gender gaps are larger among paid employees than among the self-employed—contrary to findings for other countries—particularly among l ow earners. In paid employment, these larger gaps among low earners are driven by composition effects related to work hours and industrial segmentation. In self-employm ent, gender gaps are flatter across the distribution, with composition effects increasing at higher earnings levels, partly reflecting gender differences in business scale.

JEL Classification: I31, J22, J16, J28

Keywords: Gender earnings gaps, Self-employment, Decomposition analysis, Quantile decompositions, South Korea

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Acknowledgement: We appreciate the valuable comments from Jungeun Elly Kim of Keio University and Soo Jung Kim of Seoul National University, which greatly improved our paper.

1. Introduction

Are gender earnings gaps larger in paid employment or in self-employment? This question has been largely overlooked, despite its importance for understanding the sources of gender inequality and the role of alternative work arrangements in shaping economic opportunity. A common view in the literature is that gender gaps are larger in self-employment than in paid employment, as documented by Hundley (2000) for the United States (US) and Lechmann and Schnabel (2012) for Germany. Theoretically, however, the predicted direction of this comparison is ambiguous. Self-employment may reduce exposure to employer discrimination but increase exposure to customer discrimination or unequal access to credit. It may allow earnings to more closely reflect effort but make it more difficult to balance household production and market work.

These competing mechanisms are also likely to operate differently across the earnings distribution—that is, among low-, middle-, and high earners. To our knowledge, a distributional perspective has not yet been applied to gender gaps in self-employment. A key practical challenge is that estimated gaps are often unstable across adjacent quantiles due to distributional bunching of earnings, so inferred gender gaps may differ sharply depending on whether, for example, the 10^{th} or 11^{th} quantile is considered. This sensitivity can lead to misleading conclusions. Accordingly, one goal of this study is to introduce a simple extension of the recentered influence function (RIF) decomposition of Firpo et al. (2009), moving from specific quantiles to quantile bands, while analyzing gender earnings gaps across both the earnings distribution and employment types.

South Korea provides an especially salient context in which to revisit this comparison and to apply this distributional framework. In 2023, the share of self-employment in total employment was 23% in Korea, well above the OECD average of 17%, and far higher than in other major economies such as the United States (6%), Germany (9%), and Japan (10%).[2] Self-employment is also widespread for both genders: the self-employment rate was 26% for men and 20% for women in 2023.[3] Korea is also notable

[2] The self-employed include workers who work for themselves and unpaid family workers. OECD Data, Gender Wage Gap. URL: https://www.oecd.org/en/data/indicators/gender-wage-gap.html.

[3] Statistics Korea Microdata Integrated Service (MDIS), Economically Active Population Survey (EAPS). URL: https://mdis.mods.go.kr/dwnlSvc/ofrSurvSearch.do?curMenuNo=UI_POR_P9240

for exhibiting some of the largest gender gaps among paid employees in the OECD—for example, a 29% gender gap in the median wage, compared to the OECD average of 11%.[4] Despite the combination of high self-employment and large employee wage gaps, to the best of our knowledge no study has examined gender earnings gaps in self-employment in Korea, nor provided a systematic comparison of gender gaps across employment type s.

This paper addresses that gap. Using the 2023 Korean Working Conditions Survey (KWCS)—the largest nationally representative Korean survey that reports earnings for both the self-employed and paid employees—we provide a comparative analysis of gender earnings gaps across employment types. The KWCS is uniquely suited to this purpose; while the EAPS has comparable sample sizes, it does not report earnings for the self-employed. We analyze gender gaps in net monthly earnings in self-employment and paid employment and assess how their magnitude varies across the earnings distribution. We then decompose the gaps into structural effects and composition effects using a simple extension of the RIF framework from individual quantiles to quantile bands.

We find that gender earnings gaps in Korea are significantly smaller in self-employment than in paid employment across the entire earnings distribution. Among the self-employed, gender gaps are relatively stable across low-, middle-, and high earners and are driven primarily by structural effects. Composition effects become more important moving up the earnings distribution, with gender differences in the presence of employees emerging as a key contributor. Among paid employees, by contrast, gender gaps are much larger for low earners. Composition effects—especially gender differences in work hours and industrial segregation—account for most of the gender gap among lo w earners, while structural effects become more important among higher earners. These patterns highlight substantial heterogeneity in both the size and sources of gender earnings gaps across employment types and the earnings distribution in Korea, underscoring the value of a distributional approach that goes beyond mean comparisons.

The remainder of the paper is organized as follows. Section 2 reviews the related literature and provides context. Section 3 describes the data. Section 4 outlines the

[4] OECD Data, Gender Wage Gap. URL: https://www.oecd.org/en/data/indicators/gender-wage-gap.html.

quantile-band RIF decomposition framework. Section 5 presents the results, and Section 6 discusses the implications of the findings for researchers and policymakers.

2. Literature review and context

An important but largely overlooked question in gender inequality research is whether gender earnings gaps are larger in paid employment or in self-employment, and why. To the best of the authors' knowledge, only two studies have made such comparisons, both finding larger gender earnings gaps in self-employment than in paid employment: Hundley (2000) for the United States and Lechmann and Schnabel (2012) for Germany.

Evidence from the United States emphasizes household specialization as a key mechanism. Using longitudinal data, Hundley (2000) shows that the earnings consequences of family circumstances differ sharply by gender in self-employment: self-employed women's earnings decline with marriage, family size, and housework hours, while self-employed men's earnings increase with marriage and family size. Walker (2009) similarly finds that women's housework effort contributes to their lower earnings among the self-employed, while preferences for flexible hours do not strongly support a simple "women choose self-employment for flexibility" story. Together these studies imply that self-employment may magnify the earnings effects of gendered household responsibilities.

Cross-country comparisons also suggest that self-employment is not automatically equalizing. For Australia, Eastough and Miller (2004) report a large gender earnings gap among the self-employed and argue that policy focused only on employee wage-setting institutions will not close overall gender disparities. They highlight liquidity constraints as a plausible channel that could limit women's self-employment earnings potential. For Germany, Lechmann and Schnabel (2012) find both raw and unexplained gender earnings gaps are higher in self-employment than in paid employment. Differences in working hours account for a nontrivial share of the self-employment gap, and family background affects male and female earnings differently, while segregation effects are not robust. These patterns are consistent with the idea that self-employment relocates constraints—from firms to families, time, and financing—rather than removing them.

Korea is an especially relevant case because self-employment is large and highly heterogeneous. Ryoo and Choi (1999) show that Korea's high self-employment share reflects historical and institutional factors, with both higher-skill "entrepreneurial" and lower-skill "subsistence" segments, and that industry shifts—especially toward wholesale/retail and accommodation/food—drive changes in its size. Cheon (2003) finds that higher unemployment raises self-employment entry and that correlates differ by gender: human capital matters positively for men, experience matters negatively for wo men, and entrepreneurial networks matter for both. Institutional factors also matter: Kim (2022) shows that demographics explain the rise in self-employment up to 2001, while post-2002 declines are driven by institutions, notably minimum wage increases—changes that can reshape gender composition and earnings positions. Also, Sung (2001), finds that childcare-related factors influence women's employment participation but do not significantly determine choosing self-employment over paid employment

Direct evidence on gender earnings gaps within Korean self-employment is limited. Ahn (2025) argues that Korea's self-employment market is in a structural transition driven by demographic change, shifting consumption, and digitalization rather than a temporary downturn. Despite this transition, the sector remains large by OECD standards and is rapidly aging, raising concerns that poorly prepared older entrants into low-barrier sectors may face asset depletion and debt. Kim (2025) stresses the need to account for within-sector heterogeneity and notes that existing work focuses more on entry, exit, and vulnerability rather than earnings. Comparative evidence (Choi and Jeong, 2007) suggests larger unexplained components among the self-employed, especially in services.

3. Data: Self-employed and paid employees in Korea

To analyze gender earnings gaps among both the self-employed and paid employees, we use data from the most recent wave (2023) of the Korean Working Conditions Survey (KWCS). The KWCS is a nationally representative survey of workers aged 15 or older, modeled on the European Working Conditions Survey. It covers all employed persons—including the self-employed, paid employees, unpaid family workers, and workers temporarily on leave—drawn from a stratified sample of 50,000 households.

The 2023 wave includes 50,195 respondents, which we restrict to the self-employed and paid employees. Workers in agriculture, forestry, and fishing are dropped due to the seasonality of earnings and those in utilities, public administration, household services, and extraterritorial organizations are dropped due to the small number of self-employed in these industries. To reduce the influence of outliers, we trim the top and bottom 1 percent of the earnings distribution separately for self-employed men, self-employed women, paid-employed men, and paid-employed women. In line with Lechmann and Schnabel (2012), we also exclude individuals reporting fewer than 10 or more than 100 weekly working hours.[5] Our final sample consists of 10,818 self-employed workers (5,769 men and 5,049 women) and 23,010 paid employees (10,787 men and 12,223 women). Sample weights are used in all analyses.

Our main outcome variable is net monthly earnings. The KWCS reports average monthly earnings over the past three months after taxes and social security contributions. We express earnings in thousands of Korean won[6] and use the natural logarithm in analyses. Table 1 shows that mean earnings are higher among the self-employed than among paid employees for both men and women, but gender earnings gaps are larger among paid employees (0.37 log points) than among the self-employed (0.25 log points).[7] Gender *earnings* gaps tend to be larger than gender *wage* gaps among paid employees (such as the 29% gap reported in the introduction), due to gender differences in work hours. Consistent with this interpretation, Appendix Table A1 shows that after controlling for weekly work hours, the gender earnings gap among paid employees declines from 0.37 to 0.25 log points, while that among the self-employed remains at 0.25 log points.

We focus on gender gaps across the earnings distribution. Figure 1(a) and 1(b) show that substantial bunching in earnings at specific levels gives rise to large fluctuations in gender gaps across adjacent quantiles. For example, the earnings gap among paid employees at 9th quantile is 0.69 log points but that the 10th quantile is 0.51 log points. This means that the choice of a specific quantile can be somewhat arbitrary and can also

[5] The above exclusions have no significant effect on estimates of earnings and gender earnings gaps.

[6] In 2023, 1,000 KRW was approximately worth 0.80 USD.

[7] These correspond to earnings gaps of approximately 45% (= $e^{0.37} - 1$) and 28% (= $e^{0.25} - 1$). The gaps estimated without the above exclusions are almost identical at 0.38 and 0.25 log points.

lead to misleading inferences. In fact, this pattern is not only true for earnings but also for hourly wages, as shown in Appendix Figure A1. To address this issue, we focus on averages of quantiles within broader bands (5^{th}–14^{th} quantile, 15^{th}–24^{th} quantile, etc.), which produce the more stable patterns shown in Figures 1(c) and 1(d).

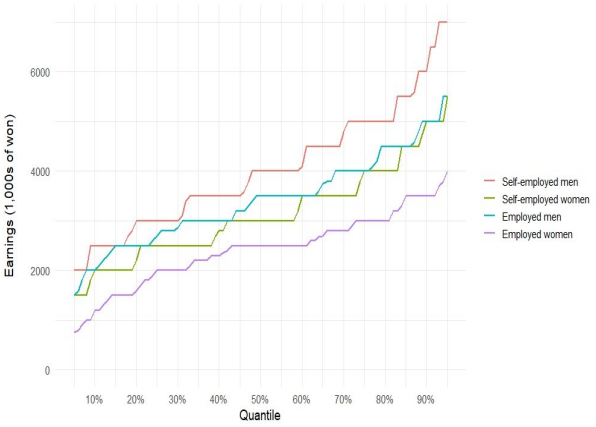
Table 1. Mean and standard deviation by employment type and gender

	Self-employed			Paid employees		
	Men	Women	Difference	Men	Women	Difference
Net monthly earnings (1,000s of won)	4,109 (1,602)	3,181 (1,200)	927	3,431 (1,178)	2,426 (918)	1,005
Log net monthly earnings	8.25 (0.39)	7.99 (0.38)	0.25	8.07 (0.41)	7.70 (0.48)	0.37
Age	53.3 (10.9)	51.3 (11.3)	2.02	44.3 (12.8)	43.2 (13.2)	1.03
Married (dummy)	0.88	0.80	0.08	0.70	0.67	0.02
Children (dummy)	0.81	0.77	0.04	0.58	0.58	0.00
Middle school or less (dummy)	0.04	0.06	-0.02	0.03	0.05	-0.02
High school (dummy)	0.44	0.45	-0.01	0.30	0.31	-0.02
College (2-3 years) (dummy)	0.21	0.21	-0.01	0.21	0.25	-0.04
University or more (dummy)	0.32	0.28	0.04	0.47	0.39	0.08
Weekly work hours	48.9 (10.3)	47.9 (10.7)	1.04	42.0 (7.68)	38.4 (8.99)	3.65
Log weekly work hours	3.86 (0.25)	3.84 (0.27)	0.03	3.72 (0.22)	3.61 (0.30)	0.11
Years of tenure	12.4 (8.92)	9.48 (7.80)	2.94	7.26 (6.84)	4.66 (4.87)	2.60
On-the-job training (dummy)	0.09	0.07	0.02	0.30	0.26	0.05
Presence of employees (dummy)	0.34	0.23	0.10	-	-	-
Firm size: 1-4 workers (dummy)	0.92	0.97	-0.05	0.15	0.26	-0.11
Firm size: 5-9 workers (dummy)	0.06	0.02	0.04	0.19	0.24	-0.05
Firm size: 10+ workers (dummy)	0.03	0.01	0.01	0.66	0.50	0.16
Occupation (8 dummies)	Fig. 2(a)	Fig. 2(a)	Fig. 2(a)	Fig. 2(a)	Fig. 2(a)	Fig. 2(a)
Industry (14 dummies)	Fig. 2(b)	Fig. 2(b)	Fig. 2(b)	Fig. 2(b)	Fig. 2(b)	Fig. 2(b)
Sample size	5,769	5,049		10,787	12,223	

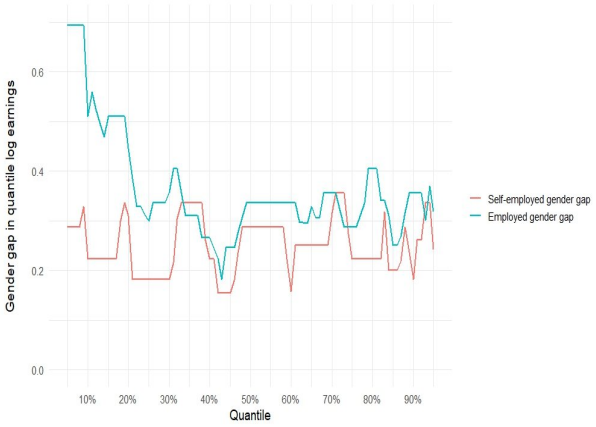
Note: All statistics are calculated using sample weights. Standard deviations of continuous variables are reported in parentheses.

Figure 1. Net monthly earnings and gender gaps across quantiles and quantile bands

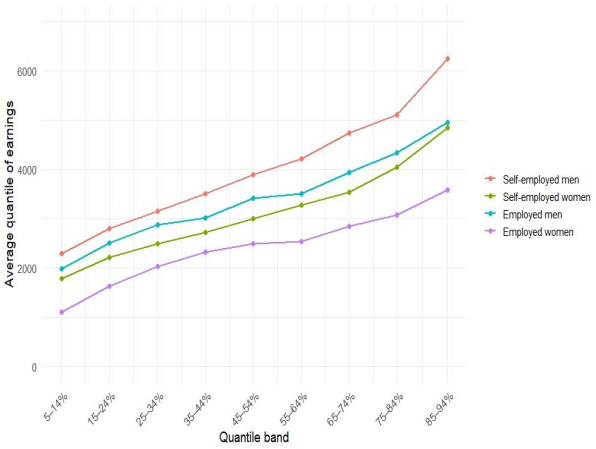
(a) Earnings across quantiles



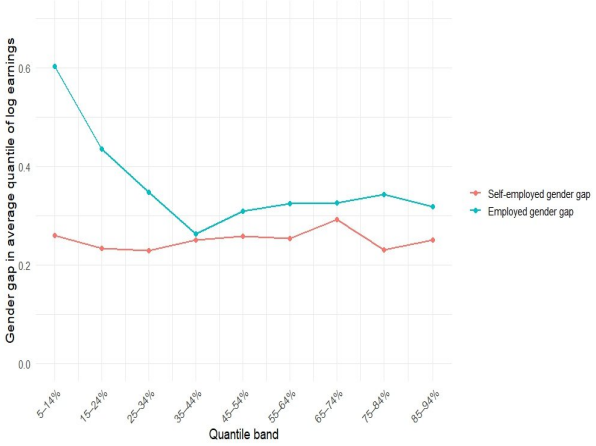
(b) Gender gaps in quantile log earnings



(c) Average quantiles of earnings within quantile bands



(d) Gender gaps in average quantiles of log earnings



Note: The bottom and top 5% of earners are excluded in the figures to mitigate the influence of outliers.

According to Figure 1(d), gender earnings gaps among paid employees are larger than those among the self-employed across the earnings distribution. This pattern also holds for hourly wages, as shown in Appendix Figure A1. Among the self-employed, gen der earnings gaps fluctuate within a narrow range of 0.23 to 0.29 log points across the quantile bands. In contrast, those among paid employees vary widely, ranging from 0.26 to 0.60 log points. The gaps among paid employees are particularly large at the bottom of the earnings distribution—around 0.60 log points—suggesting a pronounced sticky-floor

effect.[8] As shown in Appendix Figure A1, this pattern does not hold for hourly wages, suggesting that differences in working hours may drive the sticky floor in earnings.

The explanatory variables used in our decomposition analyses include demographic characteristics, human capital measures, and job attributes as listed in Table 1. We select a relatively parsimonious set of covariates to improve comparability between the self-employed and paid employees. First, we include age and age squared, which also serve as a rough proxy for work experience in the absence of direct measures. In addition, we include dummy variables indicating whether the respondent is married and whether they have children. The self-employed and men are more likely to be older, married, and have children than paid employees and women. These patterns may reflect life-cycle and selection effects, if individuals enter self-employment later in their working lives, and if older married women with children are more likely to exit the labor force. Finally, gender differences across these variables are also larger among the self-employed.

We also consider educational attainment with four categories: middle school or less, high school, college (2–3 years), and university or more. The self-employed are more likely to be high school graduates, whereas paid employees are more likely to be university graduates. This pattern is consistent with the idea that educational credentials are more important in paid employment. Women are more likely to be college graduates, while men are more likely to be university graduates, which is consistent with human capital theory predicting lower educational investment among women when expected labor market attachment is weaker. Finally, the gender difference in the share of university graduates is twice as large among paid employees (0.08) than among the self-employed (0.04).

Our focus on monthly earnings, rather than hourly wages, reflects our interest in the role of work hours in gender earnings gaps. We use weekly work hours, which are log-transformed in the analyses. On average, the self-employed and men work longer weekly hours than paid employees and women. One plausible explanation is that the self-employed work longer hours because their earnings are more directly tied to output, while women work shorter hours due to greater nonmarket responsibilities that constrain their

[8] We use the term "sticky floor" in a neutral sense, without implying a specific mechanism, as any larger gap may reflect discrimination or gender differences in job characteristics.

labor supply. Finally, gender differences in weekly hours is only 1.04 hours among the self-employed but 3.65 hours among paid employees, possibly reflecting the much higher prevalence of part-time work among women in paid employment.

We include measures of tenure in the current job, measured in years, and tenure squared. On average, tenure is lower for paid employees and women, possibly reflecting greater job mobility in paid employment and higher labor market exit rates among women related to marriage and childbirth. However, the gender difference in tenure is larger among the self-employed (2.94 years) than among paid employees (2.60 years). We include an indicator for participation in on-the-job training (OJT) during the past 12 months. OJT is more common for paid employees and men, consistent with the greater relevance of firm-specific training in paid employment and with employers' incentives to invest in workers with longer expected tenure. The gender difference in OJT participation is larger among paid employees (0.05) than among the self-employed (0.02).

For the self-employed, we include an indicator for having employees. 34 percent of men and 23 percent of women have employees, implying a gender gap of 0.10 (after r ounding). To capture firm size, we distinguish between firms with 1–4 workers, 5–9 workers, and 10 or more workers. We adopt this broad categorization to facilitate comparisons with paid employees, as only a small share of the self-employed operate in firms with 10 or more workers. It is important to note that firm size differs from the number of employees, as self-employed individuals without employees may work alongside others. The self-employed are more likely to work in micro firms (1–4 workers), possibly reflecting the prevalence of small family businesses in Korea. In paid employment, women are much more likely to work in micro firms, which contributes to the larger gender difference in firm size among paid employees than the self-employed.

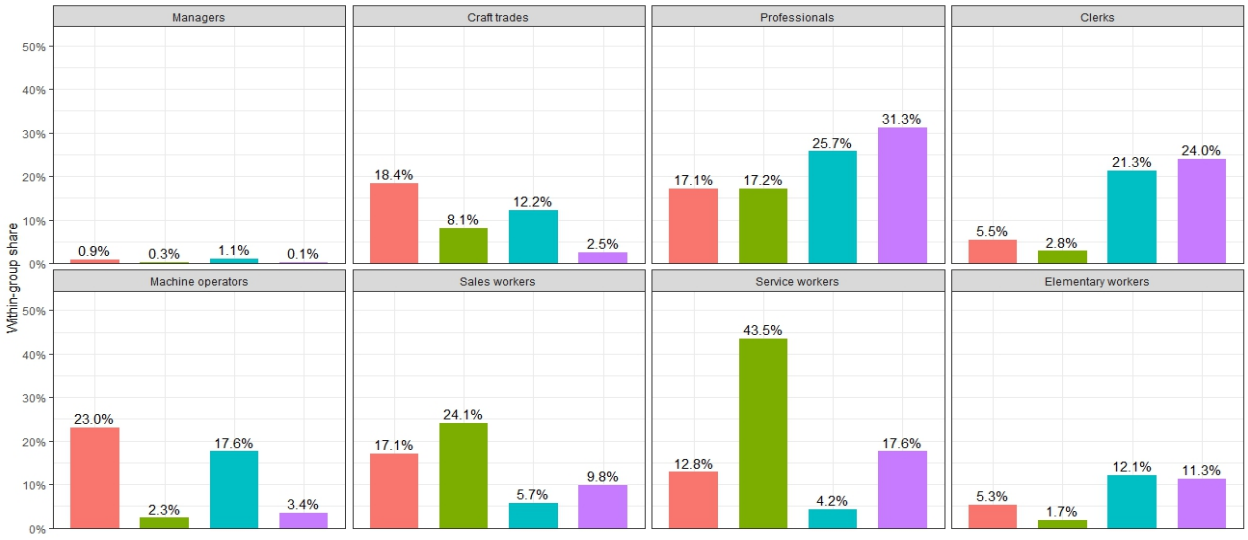
Finally, we include eight occupational categories and fourteen industrial categories.[9] Although more detailed classifications would be desirable, they would create sparse cells and increases the risk of common support violations and multicollinearity.

[9] Occupations are classified according to the Korean Standard Classification of Occupations (KSCO), which is based on the International Standard Classification of Occupations (ISCO-08), while industries are classified using the Korean Standard Industrial Classification (KSIC), which is based on the International Standard Industrial Classification (ISIC Rev. 4).

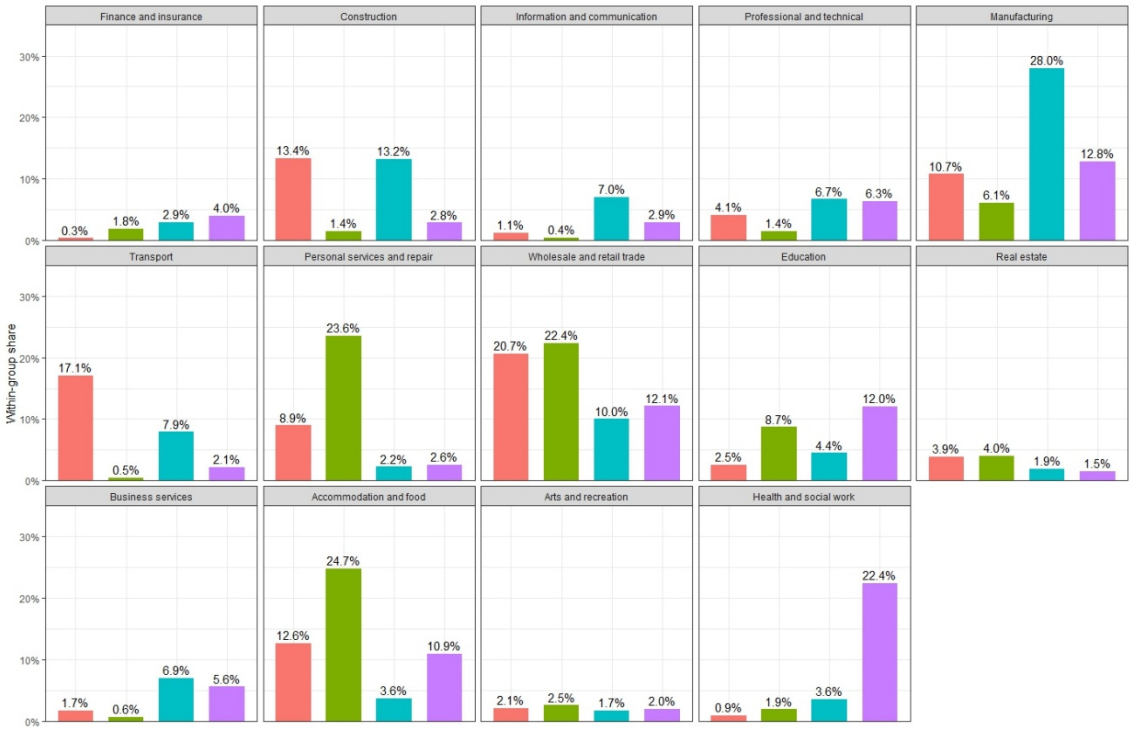
Figures 2(a) and 2(b) show the distributions of workers across occupational categories a nd industrial categories by employment type and gender.

Figure 2: Occupational and industrial category shares by employment type and gender

(a) Occupational categories



(b) Industrial categories



Note: Categories are ordered from those with the highest average earnings, on the left, to those with the lowest, on the right.

Men in both self-employment and paid employment are overrepresented in craft trades (e.g., food processing and automobile mechanics) and machine-operator occupations (e.g., automobile driving and laundry services), as well as in transport (e.g., land transport and transport via pipelines), construction (e.g., specialized construction a ctivities), manufacturing (e.g., manufacturing of food products and manufacturing of m otor vehicles), and information and communication industries (e.g., publishing activitie s), although the last applies only to men in paid employment.

Women in both self-employment and paid employment are overrepresented in service occupations (e.g., cooks and hairdressing) and sales occupations (e.g., retail sales workers), as well as in accommodation and food (e.g., food and beverage service activities) and education industries. In addition, women in self-employment are overrepresented in personal services and repair (e.g., maintenance and repair services of personal and household goods) industries, while women in paid employment are overrepresented in health and social work (e.g., social work activities) industries.

4. Method: From means to quantiles to quantile bands

We propose a method to decompose gender gaps in earnings within quantile bands, extending recentered influence function (RIF) decompositions (Firpo et al., 2009), which focus on earnings at specific quantiles. Both approaches build on Oaxaca–Blinder (OB) decompositions (Blinder, 1973; Oaxaca, 1973), which focus on mean earnings. This meth od assumes that each gender g∈{m,f} has a conditional mean earnings function:

$$E_g(Y|X) = B_g X \tag{1}$$

where Y denotes wages, X covariates, and β the returns to covariates. By the law of iterated expectations, $E(Y) = E_X[E(Y|X)] = E(\beta X) = \beta E(X)$, so the gender gap in mean earnings can be written as:

$$\begin{aligned} E(Y_m) - E(Y_f) &= \beta_m E(X_m) - \beta_f E(X_f) \\ &= \beta_m E(X_m) - \underbrace{\beta_m E(X_f)}_{counterfactual} + \underbrace{\beta_m E(X_f)}_{counterfactual} - \beta_f E(X_f) \end{aligned} \tag{2}$$

$$= \underbrace{\beta_m[E(X_m) - E\left(X_f\right)]}_{composition\ effect} + \underbrace{[\beta_m - \beta_f]E\left(X_f\right)}_{structural\ effect}.$$

By adding and subtracting the counterfactual term $\beta_m E\left(X_f\right)$, the gender gap in mean earnings is decomposed into a part ascribed to gender differences in covariates X (the composition effect) and a part ascribed to gender differences in returns to covariates β (the structural effect).[10] The counterfactual $\beta_m E\left(X_f\right)$, which uses men's coefficients as the reference group, and the alternative counterfactual $\beta_f E(X_m)$, which uses women's co efficients as the reference group, can yield different results; therefore, both are used and compared as a sensitivity check.[11] Coefficients β_g are estimated via separate OLS regressions for men and women, and $E\left(X_g\right)$ are computed as sample averages.

In addition to aggregate structural effects and composition effects, detailed composition effects for each covariate j can be estimated, such as $\beta_{m,j}[E\left(X_{m,j}\right) - E\left(X_{f,j}\right)]$ when using men's coefficients as the reference group and $\beta_{f,j}[E\left(X_{m,j}\right) - E\left(X_{f,j}\right)]$ when using women's coefficients as the reference group. When estimating detailed composition effects for dummy variables with several categories, the results can be sensitive to the omitted base category. To address this issue, Gardeazabal and Ugidos (2004) propose a recentering approach that subtracts the average of the category coefficients so that they sum to zero, making the decomposition results invariant to the choice of base categories.

The above method was extended to gender gaps in quantile earnings, rather than mean earnings, by Firpo et al. (2009) using recentered influence function (RIF) regressions. Their method involves estimating the RIF for some quantile of interest, defi ned for the τ^{th} quantile Q_τ as

[10] The composition effect is often referred to as the "explained" or "endowment" effect, while the structural effect is often referred to as the "unexplained" or "discrimination" effect. We avoid the term "discrimination" because differences in returns to covariates need not reflect discrimination, and discrimination may also operate through differences in covariates themselves, making the label potentially misleading.

[11] Using the alternative, the decomposition is $E\left(Y_m\right) - E\left(Y_f\right) = \beta_f[E\left(X_m\right) - E\left(X_f\right)] + [\beta_m - \beta_f]E\left(X_m\right)$.

$$RIF(Y,Q_\tau) = Q_\tau + \frac{\tau - 1\{Y \le Q_\tau\}}{f_Y(Q_\tau)} \tag{3}$$

where $1\cdot$ is the indicator function and $f_Y(\cdot)$ is the density of Y at Q_τ. The RIF has the property that its expectation equals the statistic of interest, i.e. $\mathbb{E}[RIF(Y,Q_\tau)] = Q_\tau$. Therefore, regressing $RIF(Y,Q_\tau)$ on covariates X via OLS yields coefficients δ_τ that provide a first-order approximation to the marginal effects of X on the unconditional quantile Q_τ. These coefficients can then be used in an OB–type decomposition such as

$$\begin{aligned} & Q_\tau(Y_m) - Q_\tau\left(Y_f\right) \approx \delta_{\tau,m} E(X_m) - \delta_{\tau,f} E\left(X_f\right) \\ &= \delta_{\tau,m} E(X_m) - \delta_{\tau,m} E\left(X_f\right) + \delta_{\tau,m} E\left(X_f\right) - \delta_{\tau,f} E\left(X_f\right) \\ &= \underbrace{\delta_{\tau,m}[E(X_m) - E\left(X_f\right)]}_{composition\ effect} + \underbrace{[\delta_{\tau,m} - \delta_{\tau,f}]E\left(X_f\right)}_{structural\ effect}. \end{aligned} \tag{4}$$

As illustrated in the previous section, gender gaps can vary substantially across adjacent quantiles. To overcome this, we implement RIF decompositions for quantile bands, defined as averages of quantiles within a given range (e.g., 5^{th}–14^{th} quantiles),

$$\overline{Q}_T \equiv \frac{1}{K}\sum_{k=1}^{K} Q_{Tk} \tag{5}$$

where $T = \{\tau_1, \dots, \tau_k\}$ denotes the set of quantiles included in the band and k indexes the quantiles. Specifically, we estimate the RIF for each quantile within a band and then average the resulting RIFs as

$$\overline{RIF}(Y) \equiv \frac{1}{K}\sum_{k=1}^{K} RIF(Y,Q_{Tk}). \tag{6}$$

This averaged RIF is subsequently used as the dependent variable in OLS regressions and the same decomposition described above. The validity of this approach follows directly from the defining property of the RIF, namely that its expectation equals the associated unconditional statistic. By the linearity of expectations,

$$\mathbb{E}[\overline{RIF}(Y)] = E\left[\frac{1}{K}\sum_{k=1}^{K} RIF(Y,Q_{Tk})\right] = \overline{Q}_T. \quad (7)$$

The two major assumptions of decompositions are common support and conditional independence. The common support assumption requires that group membership $g \in \{m,f\}$ cannot be perfectly predicted by any value of $X = x$; that is, $0 < Pr[D_g = 1 \mid X = x] < 1$. To help satisfy this, we use a parsimonious set of covariates with broad categories for variables such as occupations. The conditional independence assumption requires that unobserved factors are independent of gender after conditioning on X; that is, $D_g \perp \varepsilon \mid X$. This allows the construction of counterfactual wage distributions and identification in aggregate but not detailed decompositions.

Seeing as the conditional independence assumption may not hold in practice, our estimates of structural effects and composition effects should be interpreted as descriptive rather than causal, as is generally the case in gender gap decompositions. Despite this limitation, Fortin et al. (2010) emphasize that decomposition methods remain useful for assessing the contribution of different covariates in an accounting sense, and for identifying which covariates are quantitatively important.

5. Results: Gender earnings gaps across employment types

5.1. Aggregate decompositions

Table 2 reports the aggregate decomposition estimates for gender earnings gaps among the self-employed (columns 1–3) and paid employees (columns 4–6), using the 5^{th}-14^{th}, 45^{th}-54^{th}, and 85^{th}–94^{th} quantile bands to represent low-, middle-, and high earners. Estimates using men as the reference group are reported in rows 4-7, and those using women as the reference group are reported in rows 8-11. The structural effects and composition effects, defined in Equation (4), are computed using the covariate means in Table 1 and regression coefficients for men and women in Appendix Tables A2 and A3.

Table 2. Aggregate decompositions of gender gaps across quantile bands

	Self-employed			Paid employees		
	5-14th Q	45-54th Q	85-94th Q	5-14th Q	45-54th Q	85-94th Q
Raw earnings gap	0.259*** (0.016)	0.259*** (0.011)	0.252*** (0.016)	0.603*** (0.033)	0.310*** (0.006)	0.318*** (0.019)
RIF earnings gap	0.282*** (0.008)	0.265*** (0.009)	0.257*** (0.016)	0.625*** (0.030)	0.288*** (0.005)	0.282*** (0.016)
Estimation error	0.022	0.006	0.005	0.022	-0.022	-0.036
Structural effect (m)	0.225*** (0.014)	0.178*** (0.012)	0.143*** (0.020)	0.145*** (0.028)	0.193*** (0.006)	0.215*** (0.006)
Composition effect (m)	0.057*** (0.011)	0.087*** (0.012)	0.114*** (0.019)	0.480*** (0.024)	0.095*** (0.005)	0.067*** (0.005)
Structural effect (m, %)	80%	67%	56%	23%	67%	76%
Composition effect (m, %)	20%	33%	44%	77%	33%	24%
Structural effect (f)	0.290*** (0.036)	0.226*** (0.020)	0.161*** (0.037)	0.158*** (0.022)	0.227*** (0.005)	0.196*** (0.020)
Composition effect (f)	-0.008 (0.036)	0.039** (0.019)	0.096*** (0.032)	0.468*** (0.031)	0.060*** (0.004)	0.087*** (0.007)
Structural effect (f, %)	103%	85%	63%	25%	79%	70%
Composition effect (f, %)	-3%	15%	37%	75%	21%	30%
Sample size	10,818	10,818	10,818	23,010	23,010	23,010

Note: Standard errors, obtained from 500 bootstrap replications, are reported in parentheses. Statistical significance levels are denoted as follows: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.10$. The estimation error captures the discrepancy between raw earnings gaps calculated using log wages and those calculated using the RIF of log wages, arising from the estimation of earnings densities when computing the RIFs.

The raw gender earnings gaps among low-, middle-, and high earners in self-employment are 0.259, 0.259, and 0.252 log points, respectively, while the corresponding gaps in paid employment are 0.630, 0.310, and 0.318 log points. These estimates indicate that gender earnings gaps in Korea are smaller among the self-employed than among paid employees. The differences across employment type, −0.343 (SE = 0.036), −0.051 (SE = 0.012), and −0.066 (SE = 0.018), are statistically significant based on standard errors computed from 500 bootstrap replications. This pattern contrasts with evidence for the US (Hundley, 2000) and Germany (Lechmann and Schnabel, 2012) where gender gaps are larger in self-employment than paid employment. In addition, our estimates su ggest that gender gaps among the self-employed are stable across the earnings distribution, whereas those among paid employees are substantially larger among low earners.

For the self-employed, structural effects—the part of the gap attributed to gender differences in *coefficients*—decrease from 0.225 to 0.178 and 0.143 log points as one mo ves from low- to middle- and high earners, accounting for 80%, 67%, and 56% of the res pective gender earnings gaps. Composition effects—the part of the gap attributed to gen der differences in *covariates*—increase from 0.057 to 0.087 and 0.114 log points, corres ponding to 20%, 33%, and 44% of the respective gaps. Thus, although structural effects are larger than composition effects across the distribution, the size of composition effects and their share of the gap increase moving up the distribution. In other words, differences in observable characteristics between self-employed men and women become more important among higher earners. When estimated using women as the reference group, composition effects are smaller, but the overall patterns remain unchanged.[12]

For paid employees, the opposite pattern emerges. Structural effects increase from 0.145 to 0.193 and 0.215 log points across low-, middle-, and high earners, accounting for 23%, 67%, and 75% of the respective gaps. In contrast, composition effects decrease from 0.480 to 0.095 and 0.067 log points, corresponding to 77%, 33%, and 24% of the gaps. T hus, unlike among the self-employed, both the size of composition effects and their share of the gap among paid employees, decrease moving up the distribution. In other words, differences in observed characteristics between men and women in paid employment be come less important among higher earners. These patterns also hold when using women as the reference group.[13] Finally, the composition effects of 0.480 or 0.468 log points su ggests that the large gender earnings gap among low earners in paid employment is driven primarily by composition effects rather than structural effects.

For Germany, Lechmann and Schnabel (2012) find that composition effects are si milar, implying that larger structural effects drive the larger gender gap in mean earning s among the self-employed. In contrast, for Korea we find that the larger gender earning s gap among paid employees relative to the self-employed are driven by larger compositi on effects for low earners, larger structural effects for high earners, and somewhat

[12] When using women as the reference group, structural effects are 0.290, 0.226, and 0.161 log points (103%, 85%, and 63%) and composition effects are –0.008, 0.039, and 0.096 log points (–3%, 15%, and 37%).

[13] When using women as the reference group, structural effects are 0.158, 0.227, and 0.196 log points (25%, 79%, and 70%) and composition effects are 0.468, 0.060, and 0.087 log points (75%, 21%, and 31%).

ambiguous contributions of the two effects among middle earners. These findings highlight substantial heterogeneity in the roles of structural effects and composition effects across both employment types and earnings distributions, underscoring the limitations of focusing on a single summary statistic such as the mean.

Although instability in individual quantile estimates may limit fully distributional approaches, our simple extension of the RIF decomposition to quantile bands provides a robust framework for analyzing distributional heterogeneity in earnings gaps. Appendix Table A4 shows considerable variation in earnings gaps and decomposition results across proximate quantiles. It compares gaps and decomposition results for individual quantiles within the 85th–94th quantile band to those for the quantile band as a whole. The band-level results are essentially the averages of the corresponding individual-quantile estimates. While researchers could run decompositions at each individual quantile and then average the results within the band, estimating the average RIF within the band and conducting a single decomposition is computationally simpler and yields equivalent estimates.

5.2. Detailed composition effects

The previous section showed that composition effects increase across the earnings distribution among the self-employed but decrease among paid employees, and that the large gender gap among low earners in paid employment is driven by composition effects. In this section, we explain these patterns by examining the detailed composition effects reported in Tables 3 and 4. These effects are estimated as $\beta_{m,j}[E(X_{m,j}) - E(X_{f,j})]$ when using men as the reference group and $\beta_{f,j}[E(X_{m,j}) - E(X_{f,j})]$ when using women as the reference group. The former measures how much smaller the gender gap would be if men had women's covariate distribution, holding their wage structure constant, while the latter measures the corresponding reduction if women had men's covariate distribution.

For the self-employed, several factors contribute to the larger composition effects a s we move up the earnings distribution. When men are used as the reference group, gender differences in occupations, the presence of employees, and firm size[14] have larger

[14] This is driven by a large share of self-employed women working in micro firms (1-4 workers).

effects among higher earners. Specifically, the detailed composition effects are 0.047, 0.027, and 0.019 log points, respectively, corresponding to 18%, 11%, and 7% of the gender earnings gap among high earners in self-employment. Together, this implies that if self-employed men had the same occupations, presence of employees, and firm size as self-employed women, the gap among high earners would be roughly 0.093 log points s maller. When women are used as the reference group, gender differences in the presence of employees remain important (0.026 log points), whereas differences in occupations and firm size are no longer economically or statistically significant. Industrial segregation now has an estimated effect of 0.036 log points; however, it is not statistically significant.

The differences across reference groups reflect gender-specific associations between earnings and both occupation and firm size, as shown in Appendix Tables A2 and A3. Among high-earning self-employed men, working as a machine operator is positively associated with earnings, whereas no comparable association is observed for women. Similarly, among high-earning self-employed men, working in micro firms (1–4 workers) is negatively associated with earnings. The former pattern likely reflects the use of broad occupational categories, within which detailed occupations differ by gender. This limitation is unavoidable when the number of observations within detailed occupations for each gender is insufficient to permit meaningful comparisons and to satisfy the common support assumption. Lechmann and Schnabel (2012) report a similar pattern for Germany, finding that segregation across professions and firm size matters when men are used as the reference group but not when women are used. These findings highlight that the estimated effects of segregation often depend on the choice of counterfactual.

Lower down the earnings distribution of the self-employed, gender differences in t he presence of employees also matters under both reference groups for low earners (0.010 or 0.012 log points) and middle earners (0.023 or 0.015 log points), although its contribution is smaller than that for high earners. When men are used as the reference g roup, industrial segregation contributes 0.030 log points for low earners and 0.023 log points for middle earners, while tenure contributes 0.012 log points for low earners and 0.015 log points for middle earners. When women are used as the reference group, occupational segregation shows a sizeable negative effect of -0.047 among low earners, i mplying that segregation reduces gender gaps among low earners in self-employment.

Table 3. Detailed decompositions of gender gaps across quantile bands (reference group = men)

	Self-employed			Paid employees		
	5-14th Q	45-54th Q	85-94th Q	5-14th Q	45-54th Q	85-94th Q
Raw earnings gap	0.259***	0.259***	0.252***	0.603***	0.310***	0.318***
	(0.016)	(0.011)	(0.016)	(0.033)	(0.006)	(0.019)
RIF earnings gap	0.282***	0.265***	0.257***	0.625***	0.288***	0.282***
	(0.008)	(0.009)	(0.016)	(0.030)	(0.005)	(0.016)
Estimation error*	0.022	0.006	0.005	0.022	-0.022	-0.036
Structural effect	0.225***	0.178***	0.143***	0.145***	0.193***	0.215***
	(0.014)	(0.012)	(0.020)	(0.028)	(0.006)	(0.006)
Composition effect	0.057***	0.087***	0.114***	0.480***	0.095***	0.067***
	(0.011)	(0.012)	(0.019)	(0.024)	(0.005)	(0.005)
- Total age	-0.010***	-0.007*	-0.001	0.019***	0.006***	0.002
	(0.004)	(0.004)	(0.008)	(0.005)	(0.002)	(0.001)
- Age	0.045**	0.042**	0.023	0.115***	0.034***	0.011**
	(0.020)	(0.021)	(0.047)	(0.029)	(0.009)	(0.005)
- Age sq	-0.054**	-0.049**	-0.025	-0.096***	-0.028***	-0.009**
	(0.019)	(0.019)	(0.041)	(0.026)	(0.008)	(0.004)
- Married	0.003	0.005*	-0.004	0.002	0.001	-0.000
	(0.002)	(0.003)	(0.004)	(0.001)	(0.001)	(0.001)
- Children	-0.001	-0.001	0.003	-0.000	0.000	0.000
	(0.001)	(0.002)	(0.003)	(0.001)	(0.000)	(0.001)
- Education	0.010***	0.006***	0.005***	0.014***	0.009***	0.008***
	(0.002)	(0.001)	(0.002)	(0.004)	(0.001)	(0.001)
- Middle school	0.007***	0.003**	0.002***	0.007***	0.002***	0.001***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
- High school	-0.001	0.000	0.000	-0.001	0.001*	0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
- College (2-3 years)	-0.001	0.000	-0.000	-0.007***	-0.002***	0.000
	(0.002)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)
- University or more	0.005**	0.004***	0.003**	0.014***	0.008***	0.006***
	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)

- Log weekly work hours	0.004**	0.003*	0.002	0.246***	0.009***	0.001
	(0.002)	(0.002)	(0.002)	(0.014)	(0.001)	(0.002)
- Total tenure	0.012***	0.015***	0.006	0.025***	0.038***	0.039***
	(0.004)	(0.003)	(0.006)	(0.005)	(0.002)	(0.003)
- Tenure	0.043***	0.035***	0.006	0.050***	0.067***	0.041***
	(0.009)	(0.007)	(0.013)	(0.010)	(0.004)	(0.006)
- Tenure sq	-0.030***	-0.020***	-0.000	-0.025***	-0.029***	-0.002
	(0.007)	(0.004)	(0.011)	(0.007)	(0.003)	(0.004)
- On-the-job training	0.000	0.001*	0.003***	0.000	0.001***	0.001***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
- Presence of employees	0.010***	0.023***	0.027***	-	-	-
	(0.002)	(0.003)	(0.005)			
- Firm size	0.001**	0.007***	0.019***	0.026***	0.011***	0.008***
	(0.001)	(0.002)	(0.005)	(0.006)	(0.001)	(0.001)
- Firm size: 1-4 workers	0.001*	0.004***	0.013***	0.017**	0.004***	0.002***
	(0.000)	(0.001)	(0.003)	(0.004)	(0.001)	(0.001)
- Firm size: 5-9 workers	0.000	0.002**	0.004	-0.003***	0.000	0.001**
	(0.000)	(0.001)	(0.003)	(0.001)	(0.000)	(0.000)
- Firm size: 10+ workers	0.000	0.000	0.002*	0.013***	0.006***	0.005***
	(0.000)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
- Occupations	-0.004	0.012	0.047***	0.045***	-0.002	-0.012***
	(0.009)	(0.010)	(0.018)	(0.009)	(0.003)	(0.003)
- Industries	0.030***	0.023***	0.008	0.103***	0.022***	0.021***
	(0.009)	(0.008)	(0.016)	(0.018)	(0.004)	(0.004)
Sample size	10,818	10,818	10,818	23,010	23,010	23,010

Note: Standard errors, obtained from 500 bootstrap replications, are reported in parentheses. Statistical significance levels are denoted as follows: *** for p < 0.01, ** for p < 0.05, and * for p < 0.10. * The estimation error captures the discrepancy between raw earnings gaps calculated using log wages and those calculated using the RIF of log wages, arising from the estimation of earnings densities when computing the RIFs.

Table 4. Detailed decompositions of gender gaps across quantile bands (reference group = women)

	Self-employed			Paid employees		
	5-14th Q	45-54th Q	85-94th Q	5-14th Q	45-54th Q	85-94th Q
Raw earnings gap	0.259*** (0.016)	0.259*** (0.011)	0.252*** (0.016)	0.603*** (0.033)	0.310*** (0.006)	0.318*** (0.019)
RIF earnings gap	0.282*** (0.008)	0.265*** (0.009)	0.257*** (0.016)	0.625*** (0.030)	0.288*** (0.005)	0.282*** (0.016)
Estimation error*	0.022	0.006	0.005	0.022	-0.022	-0.036
Structural effect	0.290*** (0.036)	0.226*** (0.020)	0.161*** (0.037)	0.158*** (0.022)	0.227*** (0.005)	0.196*** (0.020)
Composition effect	-0.008 (0.036)	0.039** (0.019)	0.096*** (0.032)	0.468*** (0.031)	0.060*** (0.004)	0.087*** (0.007)
- Total age	-0.006* (0.004)	0.001 (0.003)	0.004 (0.005)	0.019*** (0.005)	0.001 (0.001)	0.005*** (0.002)
- Age	0.028 (0.022)	0.027* (0.016)	0.009 (0.030)	0.080*** (0.027)	0.005 (0.003)	0.020*** (0.007)
- Age sq	-0.034 (0.022)	-0.026* (0.015)	-0.005 (0.029)	-0.061** (0.025)	-0.004 (0.003)	-0.015** (0.006)
- Married	0.000 (0.002)	-0.003 (0.002)	-0.002 (0.004)	0.000 (0.002)	0.000 (0.000)	-0.000 (0.001)
- Children	-0.002 (0.002)	-0.001 (0.002)	-0.000 (0.003)	0.000 (0.002)	0.000 (0.001)	-0.000 (0.000)
- Education	0.005*** (0.001)	0.004*** (0.001)	0.004*** (0.002)	0.008*** (0.002)	0.005*** (0.001)	0.011*** (0.001)
- Middle school	0.004*** (0.001)	0.001*** (0.000)	0.002*** (0.000)	0.004*** (0.001)	0.001*** (0.000)	0.001*** (0.000)
- High school	-0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	-0.000 (0.001)	0.000 (0.000)	0.001*** (0.000)
- College (2-3 years)	-0.001 (0.001)	0.000 (0.000)	-0.000 (0.000)	-0.003* (0.002)	-0.001*** (0.000)	0.000 (0.000)

- University or more	0.003***	0.002***	0.003***	0.008***	0.004***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
- Log weekly work hours	0.008**	0.004**	0.003	0.407***	0.023***	0.004***
	(0.003)	(0.002)	(0.002)	(0.023)	(0.001)	(0.001)
- Total tenure	0.007	0.008***	0.010*	-0.008	0.020***	0.061***
	(0.005)	(0.003)	(0.005)	(0.006)	(0.001)	(0.004)
- Tenure	0.034***	0.025***	0.026***	0.023	0.043***	0.053***
	(0.013)	(0.007)	(0.012)	(0.016)	(0.003)	(0.007)
- Tenure sq	-0.028**	-0.016***	-0.017*	-0.031	-0.023***	0.007
	(0.012)	(0.005)	(0.010)	(0.013)	(0.002)	(0.007)
- On-the-job training	-0.000	0.001	0.002	-0.001	-0.001***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)
- Presence of employees	0.012***	0.015***	0.026***	-	-	-
	(0.002)	(0.002)	(0.004)			
- Firm size	-0.001	0.004*	0.007	0.014***	0.007***	0.012***
	(0.002)	(0.002)	(0.005)	(0.005)	(0.001)	(0.002)
- Firm size: 1-4 workers	-0.001	0.001	0.002	0.005*	0.003***	0.002***
	(0.002)	(0.001)	(0.003)	(0.003)	(0.000)	(0.001)
- Firm size: 5-9 workers	0.001	0.003**	0.007*	0.000	0.000	0.001***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.000)	(0.000)
- Firm size: 10+ workers	-0.001	0.000	-0.002	0.008***	0.004***	0.008***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
- Occupations	-0.043**	-0.013	0.009	-0.020	-0.010***	-0.024***
	(0.019)	(0.011)	(0.021)	(0.017)	(0.003)	(0.005)
- Industries	0.012	0.021	0.036	0.048***	0.015***	0.019***
	(0.031)	(0.019)	(0.029)	(0.014)	(0.003)	(0.006)
Estimation error	0.022	0.006	0.005	0.022	-0.022	-0.036
Sample size	10,818	10,818	10,818	23,010	23,010	23,010

Note: Standard errors, obtained from 500 bootstrap replications, are reported in parentheses. Statistical significance levels are denoted as follows: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.10$. The estimation error captures the discrepancy between raw earnings gaps calculated using log wages and those calculated using the RIF of log wages, arising from the estimation of earnings densities when computing the RIFs.

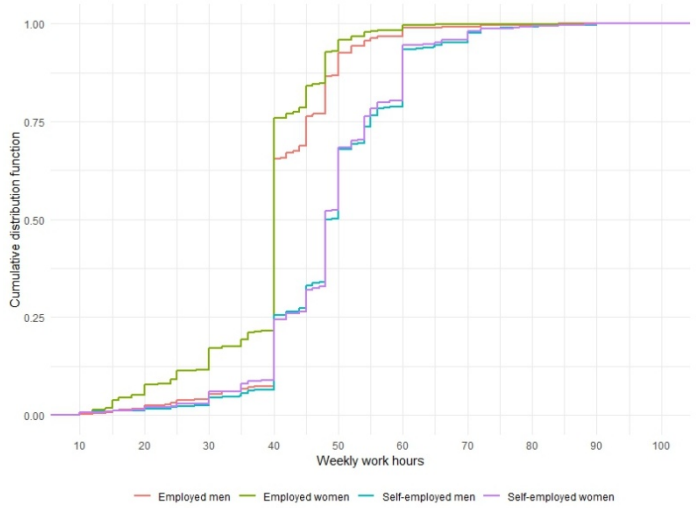
To summarize, we find that the increase in composition effects as one moves up the earnings distribution of the self-employed is primarily driven by gender differences in the presence of employees, occupations, and firm size. The first two also matter among low and middle earners, alongside gender differences in industries and tenure. With the exception of the presence of employees, however, these effects all depend on the reference group. Finally, differences in age, marital status, parental status, educational attainment, weekly work hours, and on-the-job training (OJT) appear to play no economically signifi cant role in gender earnings gaps among the self-employed in Korea. The limited role of work hours contrasts sharply with the findings of Lechmann and Schnabel (2012) for Ge rmany, who report that hours account for one quarter to one third of the gender gap in mean earnings among the self-employed. We return to this difference below.

For paid employees, the large composition effect—and thus gender earnings gap—among low earners is primarily driven by gender differences in weekly work hours. The estimated effect sizes are 0.246 and 0.407 log points when using male and female as the reference groups, respectively, accounting for 39% and 65% of the gender earnings gap. These effects reflect both a gender gap in average weekly work hours of 3.65 hours and a particularly strong associations between work hours and monthly earnings among low e arners, especially for women in paid employment. These patterns suggest that earnings for lower-paid employees are more closely tied to work hours. No doubt many of these workers are in part-time employment. In contrast, earnings for higher-paid employees and the self-employed may plausibly depend relatively more on performance.

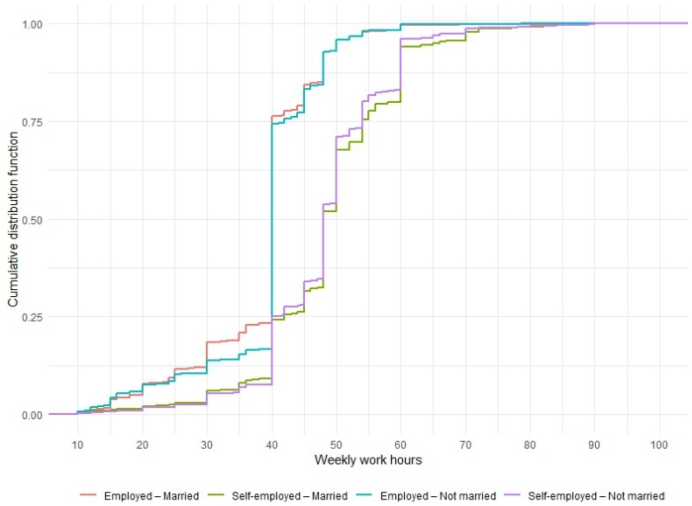
The importance of work hours in gender gaps among paid employees contrasts sharply with their insignificant role among the self-employed in Korea. Evidence from the U.S. (Hundley, 2000; Walker, 2009) and Germany (Lechmann and Schnabel, 2012) shows that work hours account for a substantial portion of the gender earnings gap in self-employment. Hundley (2000) argues that women in the US select into self-employment to better balance market work and household production, whereas men choose self-employment to pursue higher earnings. In Korea, Figure 3(a) shows that women working fewer hours are more likely to be in paid employment than in self-employment, while Figures 3(b–d) indicate that women in part-time employment are more likely to be married, have children, and be younger than 30 or older than 60.

Figure 3. Cumulative distributions of weekly work hours by employment status

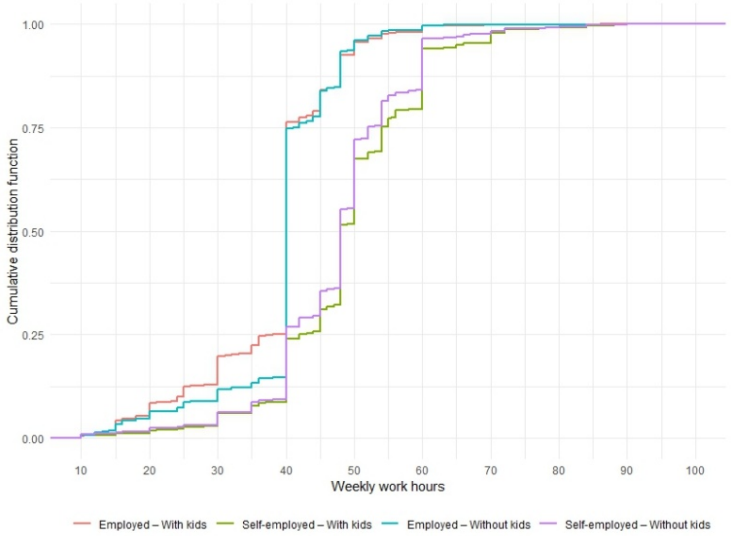
(a) by employment status and gender



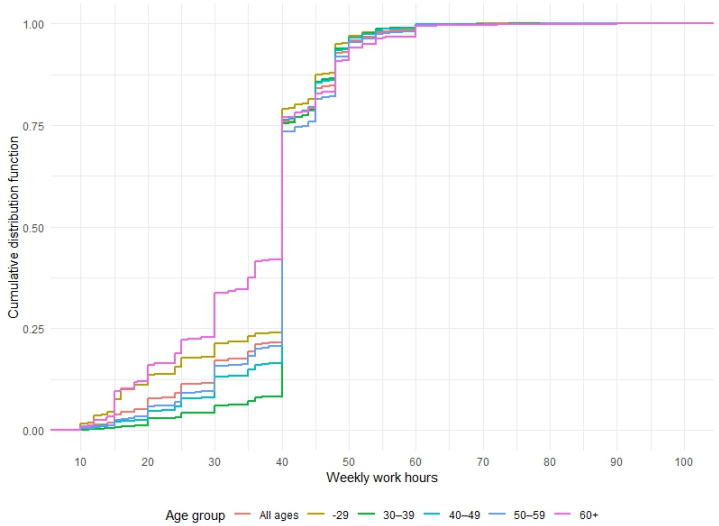
(b) by employment status and marital status (only women)



(c) by employment status and parental status (only women)



(d) by age group (only women in paid employment)



These patterns highlight the need to better understand the drivers of selection acr oss employment types. They also show that, although gender differences in demographic characteristics—such as age, marital status, and parental status—may have small or stati stically insignificant direct effects, they can influence gender earnings gaps indirectly through other composition effects (e.g., via gender differences in work hours or tenure). Moreover, demographic characteristics may affect gender earnings gaps through structural effects (e.g., differences in returns to work hours or tenure). This underscores the importance of a nuanced interpretation of decomposition results, particularly when assessing the roles of individual covariates when potential interactions exist.

Other factors contributing to the larger composition effects among low earners in paid employees include industry and age. The estimated effect of industrial segregation is 0.103 log points (17% of the gap) when men are used as the reference group and 0.048 log points (8% of the gap) when women are used as the reference group, while the effect of age is 0.019 log points, regardless of reference group. Comparing across employment types, industrial segregation plays a much larger role in gender gaps among low earners in paid employment than in self-employment. When men are used as the reference grou p, occupational segregation, firm size,[15] and education[16] also contribute 0.045, 0.026, an d 0.014 log points, respectively, to the larger composition effect among low earners. Co mparing across employment types, occupational segregation plays a larger role in gende r gaps among low earners in paid employment but high earners in self-employment, although this pattern holds only when men are used as the reference group.

Higher up the earnings distribution, gender differences in tenure become more important, with estimated effects of 0.038 and 0.039 log points among middle and high earners (13% and 14% of the gaps) when men are used as the reference group, and 0.020 and 0.046 log points (7% and 16% of the gaps) when women are used. Thus, while tenure matters more among low and middle earners in self-employment, it matters more among middle and high earners in paid employment. Indeed, gender differences in tenure are t he single most important composition effect among middle and higher earners in paid e

[15] This is driven by the larger share of women in micro-firms and men in firms with 10 or more workers.

[16] This is driven by the larger share of men with a university degree or more and women with a middle school diploma or less.

mployment. The greater importance of tenure among higher-earning paid employees likely reflects seniority-based pay and promotion systems in Korea. Given that tenure appears to matter more in paid employment, a natural question for future research is whether these tenure effects influence selection patterns across employment types.

Industrial segregation also matters higher up the earnings distribution with estimated effects of 0.022 and 0.021 log points among middle and high earners when men are used as the reference group, and 0.015 and 0.019 log points when women are used. Work hours play a nonnegligible role among middle earners in paid employment with an estimated effect size of 0.023 log points when women are used as the reference g roup. In contrast, occupational segregation may reduce gender earnings gaps among high earners in paid employment, with estimated effects of −0.012 log points when men are used as the reference group and −0.024 log points when women are used. When men are used as the reference group, the results suggest that occupational segregation widens gender gaps among low earners but narrows them among high earners in paid employm ent, highlighting an important heterogeneity across the earnings distribution.

To summarize, we find that the large composition effect—and thus gender earnings gap—among low earners in paid employment are primarily driven by gender differences in work hours and industrial segregation. Industrial segregation remains important higher up the earnings distribution, alongside gender differences in tenure. While demographic characteristics—age, marital status, and parental status—have little direct effect, they likely exert indirect effects by influencing work hours and variables, such as tenure. Other factors, including gender differences in firm size and education, also play a role in explaining the earnings gaps. Finally, we find evidence that occupational segregation may narrow gender earnings gaps among high earners in paid employment.

5.3. Occupational and industrial segregation

In this final section, we examine the detailed composition effects for specific occupational categories and industrial categories shown in Tables 5 and 6. We also use the regression coefficients reported in Appendix Tables A2 and A3 to discuss possible explanations for differences in estimated effects across reference groups.

Among the self-employed, occupational segregation contributes −0.043 log points to the gender earnings gap among low earners when women are used as the reference group, but 0.047 log points among high earners when men are used as the reference group. Industrial segregation contributes 0.030 and 0.023 log points to the gender earnings gaps among low and middle earners when men are used as the reference group. Thus, all estimates of segregation effects for the self-employed depend on the reference group.

The negative effect of occupational segregation on gender earnings gaps among low earners (−0.043 log points) reflects the overrepresentation of self-employed women in service occupations (−0.013 log points), which are positively associated with earnings among low-earning women, and of self-employed men in machine-operator occupations (−0.023 log points), which are negatively associated with earnings among low-earning women. The effect of machine-operator occupations, however, is not statistically significant. These associations do not hold for self-employed men, which may reflect either gender differences in occupational returns or in detailed occupations within broad occupational categories. A closer examination of detailed occupations aligns with the latter interpretation. Among self-employed women in service occupations, 51% are cooks and 42% are hairdressers, whereas among self-employed men in services, 70% are cooks and 12% work in food and beverage services. Such differences in detailed occupational distributions may contribute to the sensitivity of the results across reference groups.

The positive effect of occupational segregation on gender earnings gaps among high earners (0.047 log points) reflects the overrepresentation of self-employed men in machine-operator occupations (0.017 log points), which are positively associated with earnings among high-earning men, and of self-employed women in sales and service occupations (0.011 and 0.019 log points), which are negatively associated with earnings among high-earning men, although the effect of service occupations is not statistically significant. The positive association between machine-operator occupations and earnings does not hold for women. A closer examination of detailed occupations within machine-operator categories reveals that among self-employed female machine operators, 69% are laundry machine operators, whereas among self-employed male machine operators, 55% are automobile drivers. Thus, once again, differences in detailed occupational distributions may contribute to the sensitivity of the results across reference groups.

Finally, the positive effects of industrial segregation on gender earnings gaps among low and middle earners (0.030 and 0.023 log points) reflect the overrepresentation of self-employed men in construction industries (0.010 and 0.012 log points), which are positively associated with earnings among low- and middle-earning men, and in transport industries (0.010 log points), which are positively associated with earnings among low-earning men, as well as the overrepresentation of self-employed women in personal services and repair industries (0.011 log points), which are negatively associated with earnings among middle-earning men. These associations tend to be weaker or statistically insignificant for women. Compared with self-employed men, self-employed women are more likely to work in generalized construction, warehousing and support activities for transportation, and other personal services within the above broad industrial categories.

Turning to paid employees, occupational segregation contributes 0.045 log points to the gender earnings gap among low earners when men are the reference group, but −0.012 and −0.024 log points to the gender earnings gap among high earners when men and women are used as the reference groups, respectively. Industrial segregation contributes 0.103, 0.022, and 0.021 log points to the gaps among low-, middle-, and high earners when men are the reference group, and 0.047, 0.015, and 0.019 log points when women are the reference group. Overall, segregation effects among paid employees are more robust to the choice of reference group than those among the self-employed.

The positive effect of occupational segregation on gaps among low earners (0.045 log points) reflects the overrepresentation of male paid employees in craft trades and machine-operator occupations (0.018 and 0.015 log points), which are positively associated with earnings among low-earning men, as well as the overrepresentation of female paid employees in service occupations (0.019 log points), which are negatively associated with earnings among low-earning men. For women, none of these associations are statistically significant, which may reflect gender differences in occupational returns or heterogeneity within broad occupational categories. Supporting the latter interpretation, within craft trades 17% of men are automobile mechanics, whereas 39% of women are food processing workers. Within services, 11% of men are guards and security workers, compared with 31% of women in caregiving and health services.

Table 5. Detailed composition effects for occupations and industries (reference group = men)

	Self-employed			Paid employees		
	5-14th Q	45-54th Q	85-94th Q	5-14th Q	45-54th Q	85-94th Q
Occupations	-0.004	0.012	0.047***	0.045***	-0.002	-0.012***
	(0.009)	(0.010)	(0.018)	(0.009)	(0.003)	(0.003)
Managers	-0.000	0.000	0.001	0.001***	0.001***	0.002***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Professionals	0.000	0.000	0.000	-0.009***	-0.003***	-0.003**
	(0.001)	(0.001)	(0.004)	(0.002)	(0.001)	(0.001)
Clerks	-0.000	0.002***	0.002	-0.004***	0.000	0.001*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Service workers	-0.002	-0.003	0.019	0.019***	0.008***	0.004***
	(0.007)	(0.008)	(0.013)	(0.007)	(0.001)	(0.001)
Sales workers	0.000	0.006***	0.011***	0.008***	0.000	0.000
	(0.001)	(0.002)	(0.003)	(0.001)	(0.000)	(0.000)
Craft trades	0.001	0.001	-0.004	0.018***	0.003***	-0.006***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
Machine operators	-0.003	0.006	0.017***	0.015***	-0.009***	-0.010***
	(0.003)	(0.005)	(0.010)	(0.003)	(0.001)	(0.002)
Elementary workers	0.001	0.000	0.002	-0.003	-0.001	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)
Industries	0.030***	0.023***	0.008	0.103***	0.022***	0.021***
	(0.009)	(0.008)	(0.016)	(0.018)	(0.004)	(0.004)
Manufacturing	0.000	0.001	0.001	0.021***	0.003***	0.001
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)
Construction	0.010***	0.012***	0.003	0.017***	0.006***	0.001
	(0.002)	(0.003)	(0.005)	(0.003)	(0.001)	(0.001)
Wholesale and retail trade	-0.000	-0.001	-0.001	-0.001*	0.000	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Transport	0.010**	-0.008*	-0.025***	0.007**	0.002**	-0.001
	(0.005)	(0.005)	(0.010)	(0.003)	(0.001)	(0.001)
Accommodation and food	-0.002	0.002	0.013**	0.033***	-0.007***	-0.005***
	(0.003)	(0.004)	(0.006)	(0.005)	(0.001)	(0.001)
Information and communication	0.000	0.000	-0.001	0.003	0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.003)	(0.001)	(0.001)
Finance and insurance	-0.000	0.000	-0.002	-0.002***	-0.001***	-0.002***
	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)

Real estate	-0.000	0.000	0.000	-0.001***	0.000**	-0.000*
	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)
Professional and technical	0.001*	0.001	0.004	0.000	0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)
Business services	-0.001	0.000	-0.002***	0.001	-0.000**	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Education	0.004	0.006*	0.002	0.000	0.005***	0.006***
	(0.005)	(0.004)	(0.009)	(0.005)	(0.002)	(0.002)
Health and social work	0.001	-0.001	-0.006	0.023***	0.013***	0.021***
	(0.001)	(0.001)	(0.005)	(0.013)	(0.003)	(0.002)
Arts and recreation	0.001	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Personal services and repair	0.006*	0.011***	0.022***	0.000	0.000	-0.000
	(0.003)	(0.003)	(0.006)	(0.000)	(0.000)	(0.000)

Note: Standard errors, obtained from 500 bootstrap replications, are reported in parentheses. Statistical significance levels are denoted as follows: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.10$.

Table 6. Detailed composition effects for occupations and industries (reference group = women)

	Self-employed			Paid employees		
	5-14th Q	45-54th Q	85-94th Q	5-14th Q	45-54th Q	85-94th Q
Occupations	-0.043**	-0.013	0.009	-0.020	-0.010***	-0.024**
	(0.019)	(0.011)	(0.021)	(0.017)	(0.003)	(0.005)
Managers	0.001	0.001	0.001	0.001	0.001***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)
Professionals	-0.000	0.000	-0.000	-0.013***	-0.003***	-0.005**
	(0.002)	(0.002)	(0.004)	(0.005)	(0.001)	(0.002)
Clerks	0.001	-0.001	0.001	-0.002	-0.001***	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.001)
Service workers	-0.013*	-0.007	0.015	0.006	0.006***	-0.003
	(0.007)	(0.006)	(0.011)	(0.006)	(0.001)	(0.003)
Sales workers	0.001	0.004**	0.013***	0.008***	0.000	0.001
	(0.002)	(0.002)	(0.004)	(0.001)	(0.000)	(0.001)
Craft trades	-0.006**	0.000	-0.003	-0.009	-0.004***	-0.002
	(0.003)	(0.002)	(0.004)	(0.008)	(0.001)	(0.003)
Machine operators	-0.023	-0.009	-0.016	-0.010	-0.008***	-0.016***
	(0.016)	(0.009)	(0.017)	(0.008)	(0.002)	(0.004)
Elementary workers	-0.003	0.000	-0.002	-0.000	-0.001	-0.000
	(0.004)	(0.002)	(0.002)	(0.002)	(0.000)	(0.001)
Industries	0.012	0.021	0.036	0.048***	0.015***	0.019***
	(0.031)	(0.019)	(0.029)	(0.014)	(0.003)	(0.006)
Manufacturing	0.003	-0.001	-0.002	0.005	0.000	0.000
	(0.002)	(0.001)	(0.002)	(0.005)	(0.001)	(0.002)
Construction	0.015**	0.008	0.001	0.013**	0.002	-0.002
	(0.004)	(0.005)	(0.010)	(0.005)	(0.001)	(0.002)
Wholesale and retail trade	-0.000	0.000	-0.002	0.000	0.000**	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)
Transport	0.003	0.003	0.016	-0.003	0.002	-0.002*
	(0.029)	(0.017)	(0.024)	(0.005)	(0.001)	(0.001)
Accommodation and food	0.000	0.003	-0.003	0.022***	0.000	-0.001
	(0.003)	(0.003)	(0.005)	(0.004)	(0.000)	(0.001)
Information and communication	-0.002	0.000	0.000	-0.002	0.000	0.002
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Finance and insurance	-0.003***	-0.001**	-0.003***	-0.002***	-0.001***	-0.002***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)

Real estate	-0.000	0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Professional and technical	-0.002	0.002	0.007	0.000	0.000	0.000
	(0.002)	(0.002)	(0.005)	(0.000)	(0.000)	(0.001)
Business services	-0.002	0.000	-0.000	0.003*	0.000**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)
Education	0.001	0.000	0.011*	-0.008	0.003***	0.005**
	(0.004)	(0.003)	(0.006)	(0.005)	(0.001)	(0.002)
Health and social work	-0.000	0.000	0.002	0.020***	0.009***	0.020***
	(0.001)	(0.001)	(0.002)	(0.006)	(0.001)	(0.002)
Arts and recreation	0.000	0.000	0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.003)	(0.001)	(0.000)
Personal services and repair	-0.001	0.006*	0.006	0.000	0.000	-0.000
	(0.005)	(0.003)	(0.006)	(0.000)	(0.000)	(0.000)

Note: Standard errors, obtained from 500 bootstrap replications, are reported in parentheses. Statistical significance levels are denoted as follows: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.10$.

The negative effect of occupational segregation on gender earnings gaps among high earners (−0.012 or −0.024 log points) holds regardless of the reference group. These effects are driven primarily by the overrepresentation of male paid employees in machine-operator occupations (−0.010 or −0.016 log points), which are negatively associated with earnings among high-earning men and women in paid employment. Taken together with the preceding results, this finding illustrates how occupational segregation can have differing effects across the earnings distribution and employment types. For example, th e overrepresentation of men in machine-operator occupations may widen gender gaps a mong low earners in paid employment and high earners in self-employment (using men as the reference group) but narrow the gap among high earners in paid employment.

Finally, industrial segregation has positive effects on gender earnings gaps across the earnings distribution (0.103, 0.022, and 0.021 log points when using men as the reference group, or 0.047, 0.015, and 0.019 log points when using women as the reference group). These effects are driven largely by the overrepresentation of female paid employees in health and social work industries (0.023, 0.013, and 0.021 log points when using men as the reference group, or 0.020, 0.009, and 0.020 log points when using wo men as the reference group), which are negatively associated with earnings across the distribution, particularly among low and high earners. Within this category, 33% of employed men work are in social work and 67% in health, compared with 55% of employed women in social work and 45% in health. Among low earners, the overrepresentation of women in accommodation and food services (0.033 or 0.022 log points) and of men in construction (0.017 or 0.013 log points) are also important. Finally, the overrepresentation of men in manufacturing contributes positively (0.021 log points) to gaps, but only when men are used as the reference group.

6. Discussion and Conclusion

Are gender earnings gaps larger in paid employment or in self-employment, and through which mechanisms do the gaps arise? We provide the first systematic comparison of gender earnings gaps in Korea across these two employment forms using a unified decomposition framework. Methodologically, we refine existing approaches by averaging RIFs over quantile bands, which reduces sensitivity to arbitrary quantile choices, and yields more transparent distributional inference in the presence of earnings bunching.

We document three main findings. First, gender gaps in net monthly earnings are consistently larger among paid employees than among the self-employed across the entire distribution, with the largest gaps concentrated at the bottom of the paid-employment earnings distribution. In contrast, gaps among the self-employed are relatively stable across earnings levels. This indicates that Korea's most severe gender inequality is concentrated among low-paid employees rather than driven by self-employment.

Second, the mechanisms underlying these gender gaps differ sharply by employment type and earnings level. Among the self-employed, structural effects dominate across the distribution, while composition effects become increasingly important at higher earnings levels. In paid employment, composition effects are largest among low earners and decline with earnings, explaining much of the gender gap among low earners. As a result, gender differences in observed characteristics matter most for high earners in self-employment but for low earners in paid employment.

Third, the relevant characteristics differ across employment types. Among the self-employed, gender differences in employing workers—reflecting business scale—are the only detailed composition effect that is robust across reference groups and increase in importance at higher earnings levels. Other factors, including firm size, tenure, and occupational and industrial segregation, contribute to the gap but are sensitive to the choice of reference group. Among paid employees, by contrast, gender differences in weekly work hours explain the majority of the gap among low earners and remain important among middle earners. Industrial segregation contributes across the entire ea rnings distribution, while tenure differences matter among middle and high earners.

These findings have important implications for both research and policy. For researchers, analyses should move beyond means and single quantiles toward quantile bands to improve stability and transparency. Better data are also key, including larger samples that support detailed occupations and industries and richer measures of key drivers of self-employment earnings, such as starting capital, experience, and business scale. In addition, analyses across employment types would benefit from modeling selection into paid employment versus self-employment, as gendered sorting on observed and unobserved characteristics likely shapes both entry and earnings outcomes.

In paid employment, the most urgent problem is concentrated at the bottom of the earnings distribution and closely linked to women's concentration in low-hour, low-earn ing jobs. Policies that reduce the earnings penalty associated with short-hours may therefore have the largest effects. These findings align with recent policy initiatives to curb excessive working hours (Jung, 2025), introduce a statutory "right to disconnect", and reduce annual working hours toward the OECD average by 2030 (Park, 2025; Jung, 2025). Korea has also expanded parental leave and financial support for families (Kim, 2025), including tax-free employer childcare support of up to KRW 200,000 per month per child and tax-free reduced-hours childcare benefits.[17] Our results suggest these policies could be sharpened by focusing more directly on low-paid women with short hours.

In self-employment, policies that treat "self-employment promotion" as a uniform goal risk pushing women into low-return segments with limited scalability. Instead, the results support policies that enable scaling—through better access to finance, markets, and business networks—and that facilitate transitions from low-return occupations and industries into higher-return segments. More broadly, the contrast between sectors implies that gender inequality cannot be addressed by a single lever: paid employment is characterized by inequality concentrated at the lower end of the distribution linked to work hours, as well as industrial segmentation across the earnings distribution, whereas self-employment is shaped by gender differences in business scale. Much remains to be done to better understand these mechanisms and uncover additional ones.

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Appendix

Table A1. Pooled OLS regressions on monthly earnings by employment type

	Self-employed			Paid employees		
	Pooled (1)	Pooled (2)	Pooled (3)	Pooled (1)	Pooled (2)	Pooled (3)
Female	-0.252*** (0.009)	-0.247*** (0.009)	-0.178*** (0.008)	-0.370*** (0.008)	-0.253*** (0.006)	-0.172*** (0.005)
Age			0.023*** (0.004)			0.033*** (0.002)
Age squared/100			-0.027*** (0.004)			-0.035*** (0.002)
Married			-0.001 (0.016)			0.022*** (0.007)
Children			-0.024 (0.015)			-0.025*** (0.007)
High school			0.246*** (0.022)			0.095*** (0.013)
College (2-3 years)			0.303*** (0.024)			0.168*** (0.015)
University or more			0.338*** (0.025)			0.237*** (0.015)
Log weekly work hours		0.175*** (0.020)	0.197*** (0.020)		1.074*** (0.017)	0.805*** (0.015)
Years of tenure			0.013*** (0.001)			0.024*** (0.001)
Tenure squared/100			-0.030*** (0.004)			-0.044*** (0.004)
On-the-job training			0.063*** (0.016)			0.011*** (0.005)
Presence of employees			0.221*** (0.010)			-
Firm size: 5-9 workers			0.146*** (0.025)			0.048*** (0.007)
Firm size: 10+ workers			0.105*** (0.038)			0.097*** (0.008)
Occupations (7)		Yes			Yes	
Industry (13)		Yes			Yes	
Intercept	8.246*** (0.007)	7.571*** (0.080)	6.633*** (0.137)	8.070*** (0.005)	4.078*** (0.065)	4.102*** (0.060)
Adjusted squared	0.08	0.10	0.33	0.15	0.49	0.72
Sample size	10,818	10,818	10,818	23,010	23,010	23,010

Note: Robust standard errors in parentheses. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.10.

Table A2. RIF quantile-band regression coefficients for log monthly earnings (men)

	Self-employed			Paid employees		
	5-14th Q	45-54th Q	85-94th Q	5-14th Q	45-54th Q	85-94th Q
Age	0.022***(0.007)	0.021***(0.006)	0.012(0.012)	0.111***(0.009)	0.033***(0.002)	0.011***(0.002)
Age squared/100	-0.027***(0.007)	-0.024***(0.006)	-0.012(0.011)	-0.120***(0.009)	-0.036***(0.002)	-0.012***(0.002)
Married	0.033(0.026)	0.061**(0.030)	-0.054(0.044)	0.070***(0.026)	0.042***(0.012)	-0.013(0.013)
Children	-0.014(0.023)	-0.030(0.026)	0.077**(0.037)	-0.099(0.025)	0.031***(0.011)	0.084***(0.015)
Education						
Middle school or less	-0.367***(0.050)	-0.136***(0.137)	-0.093***(0.024)	-0.392***(0.073)	-0.103***(0.013)	-0.063***(0.011)
High school	0.092***(0.019)	-0.006(0.010)	-0.016(0.015)	0.036(0.029)	-0.033***(0.007)	-0.021***(0.006)
College (2-3 years)	0.134***(0.019)	0.045***(0.013)	0.031(0.021)	0.170***(0.031)	0.036***(0.008)	-0.000(0.008)
University or more	0.141***(0.019)	0.097***(0.013)	0.079***(0.022)	0.186***(0.033)	0.100***(0.008)	0.084***(0.008)
Log weekly work hours	0.150***(0.034)	0.096***(0.026)	0.086**(0.038)	2.264***(0.090)	0.087***(0.014)	0.010(0.016)
Years of tenure	0.015***(0.003)	0.012***(0.002)	0.002(0.004)	0.019***(0.004)	0.026***(0.002)	0.016***(0.002)
Tenure squared/100	-0.036***(0.008)	-0.024***(0.005)	0.000(0.009)	-0.046(0.015)	-0.053***(0.005)	-0.004(0.009)
On-the-job training	0.007(0.018)	0.067***(0.020)	0.148***(0.051)	0.008(0.018)	0.021***(0.008)	0.025***(0.001)
Presence of employees	0.102***(0.012)	0.230***(0.016)	0.268***(0.029)	-	-	-
Firm size						
1-4 workers	-0.015*(0.009)	-0.083***(0.019)	-0.241***(0.053)	-0.150***(0.029)	-0.037***(0.006)	-0.015**(0.006)
5-9 workers	0.008(0.008)	0.053**(0.022)	0.099(0.066)	0.068***(0.020)	-0.003(0.006)	-0.017***(0.006)
10+ workers	0.007(0.012)	0.029(0.031)	0.142*(0.083)	0.081**(0.020)	0.040***(0.005)	0.032***(0.006)
Occupations						
Managers	-0.007(0.041)	-0.092(0.067)	0.156(0.193)	0.149***(0.046)	0.088***(0.023)	0.190***(0.057)
Professionals	-0.009(0.020)	0.048*(0.026)	-0.089*(0.054)	0.163***(0.025)	0.059***(0.009)	0.045***(0.016)
Clerks	-0.009(0.018)	0.068**(0.024)	0.059(0.065)	0.130***(0.023)	0.016*(0.008)	-0.035***(0.012)
Service workers	0.007(0.027)	0.010(0.029)	-0.062(0.049)	-0.142*(0.075)	-0.062***(0.016)	-0.031*(0.016)

Sales workers	-0.001(0.015)	-0.086***(0.022)	-0.157***(0.043)	-0.206***(0.040)	0.010(0.012)	-0.007(0.016)
Craft trades	0.012(0.015)	0.009(0.018)	-0.039(0.041)	0.182***(0.028)	0.027**(0.012)	-0.063***(0.015)
Machine operators	-0.016(0.019)	0.031(0.021)	0.081*(0.046)	0.103***(0.025)	-0.060***(0.011)	-0.074***(0.013)
Elementary workers	0.023(0.027)	0.013(0.031)	0.051(0.060)	-0.379***(0.047)	-0.077***(0.012)	-0.025**(0.012)
Industries						
Manufacturing	0.006(0.024)	0.013(0.024)	0.022(0.054)	0.138***(0.020)	0.022***(0.008)	0.004(0.011)
Construction	0.084***(0.017)	0.102***(0.023)	0.025(0.048)	0.164***(0.028)	0.061***(0.011)	0.007(0.015)
Wholesale and retail trade	0.018(0.015)	0.078***(0.021)	0.037(0.042)	0.049*(0.028)	0.009(0.011)	-0.013(0.011)
Transport	0.059**(0.027)	-0.048*(0.026)	-0.148***(0.052)	0.124***(0.047)	0.039***(0.014)	-0.010(0.015)
Accommodation and food	0.016(0.028)	-0.016(0.030)	-0.108*(0.056)	-0.453***(0.089)	0.093***(0.017)	0.072***(0.017)
Information and communication	0.060*(0.032)	0.023(0.071)	-0.174*(0.102)	0.083*(0.044)	-0.009(0.016)	-0.003(0.026)
Finance and insurance	0.025(0.073)	0.020(0.073)	0.116(0.222)	0.143***(0.025)	0.069***(0.015)	0.203***(0.042)
Real estate	0.038(0.028)	-0.044(0.032)	-0.062(0.049)	-0.190**(0.078)	-0.055***(0.016)	-0.024*(0.013)
Professional and technical	0.050(0.031)	0.046(0.035)	0.142(0.090)	0.108**(0.053)	0.019(0.014)	0.009(0.024)
Business services	-0.056(0.066)	-0.002(0.048)	-0.222***(0.074)	0.067(0.045)	-0.037(0.013)	-0.023(0.015)
Education	-0.067(0.061)	-0.102**(0.049)	-0.025(0.099)	-0.003(0.047)	-0.072***(0.015)	-0.086***(0.022)
Health and social work	-0.079(0.076)	0.107**(0.044)	0.640***(0.243)	-0.123**(0.062)	-0.068***(0.017)	-0.113***(0.015)
Arts and recreation	-0.113*(0.061)	-0.102**(0.045)	-0.095*(0.053)	-0.105(0.084)	-0.075***(0.028)	-0.031(0.029)
Personal services and repair	-0.042(0.026)	-0.075***(0.022)	-0.150***(0.040)	-0.003(0.045)	0.002(0.018)	0.008(0.023)
Intercept	6.578*** (0.212)	7.283***(0.183)	8.254***(0.314)	-3.555***(0.321)	6.840***(0.063)	8.048***(0.070)
Adjusted R squared	0.15	0.24	0.16	0.53	0.37	0.18
Sample size	5,769	5,769	5,769	10,787	10,787	10,787

Note: Standard errors, obtained from 500 bootstrap replications, are reported in parentheses. Statistical significance levels are denoted as follows: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.10$. Coefficients for dummy variables with more than two levels (education, firm size, occupation, and industry) are recentered by subtracting the average of their category coefficients, making them invariant to the choice of base category.

Table A3. RIF quantile-band regression coefficients for log monthly earnings (women)

	Self-employed			Paid employees		
	5-14th Q	45-54th Q	85-94th Q	5-14th Q	45-54th Q	85-94th Q
Age	0.014***(0.005)	0.014***(0.004)	0.005(0.007)	0.077***(0.010)	0.005***(0.001)	0.019***(0.002)
Age squared/100	-0.017***(0.005)	-0.013***(0.004)	-0.003(0.006)	-0.076***(0.010)	-0.005***(0.002)	-0.018***(0.002)
Married	0.001(0.017)	-0.045***(0.016)	-0.032(0.026)	0.014(0.034)	0.014**(0.007)	-0.019(0.015)
Children	-0.059***(0.018)	-0.037**(0.017)	-0.011(0.029)	-0.069**(0.034)	-0.036***(0.007)	-0.028*(0.015)
Education						
Middle school or less	-0.224***(0.028)	-0.076***(0.013)	-0.092***(0.022)	-0.204***(0.067)	-0.061***(0.008)	-0.049***(0.009)
High school	0.064***(0.012)	-0.019***(0.007)	-0.010(0.011)	0.022(0.030)	-0.015***(0.004)	-0.049***(0.005)
College (2-3 years)	0.092***(0.013)	0.034***(0.010)	0.036**(0.016)	0.077**(0.032)	0.019***(0.005)	-0.012(0.008)
University or more	0.068***(0.015)	0.061***(0.010)	0.066***(0.018)	0.104***(0.035)	0.057***(0.005)	0.109***(0.008)
Log weekly work hours	0.309***(0.041)	0.138***(0.020)	0.105***(0.032)	3.742***(0.084)	0.208***(0.007)	0.033***(0.010)
Years of tenure	0.012***(0.003)	0.008***(0.002)	0.009***(0.003)	0.009(0.006)	0.017***(0.001)	0.021***(0.002)
Tenure squared/100	-0.033***(0.008)	-0.020***(0.004)	-0.020***(0.007)	-0.057**(0.023)	-0.043***(0.004)	0.014(0.012)
On-the-job training	-0.004(0.026)	0.040***(0.019)	0.106***(0.037)	-0.015(0.025)	-0.011**(0.005)	0.026**(0.012)
Presence of employees	0.114***(0.011)	0.146***(0.013)	0.259***(0.028)	-	-	-
Firm size						
1-4 workers	0.022(0.030)	-0.027**(0.018)	-0.035(0.042)	-0.048**(0.024)	-0.023***(0.004)	-0.020***(0.006)
5-9 workers	0.026(0.025)	0.069***(0.025)	0.167**(0.069)	-0.003(0.020)	-0.001(0.003)	-0.029***(0.006)
10+ workers	-0.049(0.052)	-0.042(0.027)	-0.132**(0.053)	0.051***(0.018)	0.025***(0.004)	0.050***(0.006)
Occupations						
Managers	0.113*(0.069)	0.145***(0.045)	0.227(0.180)	0.137*(0.072)	0.119***(0.018)	0.064(0.161)
Professionals	0.037(0.037)	-0.009(0.034)	0.122*(0.073)	0.237***(0.043)	0.057***(0.007)	0.090***(0.027)
Clerks	0.050(0.037)	-0.039(0.029)	0.040(0.063)	0.088***(0.029)	0.051***(0.006)	0.004(0.025)
Service workers	0.043*(0.025)	0.024(0.018)	-0.048(0.043)	-0.043(0.055)	-0.045***(0.008)	0.022(0.026)

Sales workers	-0.009(0.028)	-0.061**(0.024)	-0.183***(0.055)	-0.198***(0.046)	-0.006(0.008)	-0.022(0.026)
Craft trades	-0.063*(0.035)	-0.005(0.025)	-0.026(0.047)	-0.097(0.099)	-0.041***(0.013)	-0.017(0.033)
Machine operators	-0.112*(0.064)	-0.041(0.029)	-0.079(0.057)	-0.072(0.060)	-0.056***(0.014)	-0.112***(0.030)
Elementary workers	-0.079(0.085)	-0.014(0.039)	-0.055(0.054)	-0.052(0.057)	-0.079***(0.008)	-0.028(0.025)
Industries						
Manufacturing	0.073(0.048)	-0.022(0.034)	-0.037(0.056)	0.036(0.034)	0.002(0.006)	0.002(0.017)
Construction	0.128***(0.033)	0.067(0.050)	0.012(0.091)	0.122**(0.059)	0.017(0.012)	-0.020(0.022)
Wholesale and retail trade	0.015(0.031)	0.009(0.025)	0.105*(0.058)	-0.003(0.043)	-0.018***(0.007)	0.010(0.013)
Transport	0.019**(0.148)	0.016(0.081)	0.094(0.140)	-0.054(0.081)	0.037**(0.016)	-0.042(0.026)
Accommodation and food	-0.004(0.035)	-0.028(0.025)	0.021(0.047)	-0.301***(0.061)	0.003(0.007)	0.009(0.012)
Information and communication	-0.219*(0.195)	-0.033(0.089)	0.069(0.224)	-0.043(0.047)	0.011(0.013)	0.045(0.037)
Finance and insurance	0.228***(0.037)	0.073*(0.038)	0.186*(0.073)	0.211***(0.032)	0.063***(0.007)	0.216***(0.026)
Real estate	0.045(0.047)	-0.032(0.038)	-0.128(0.076)	0.070(0.068)	-0.008(0.012)	-0.009(0.018)
Professional and technical	-0.094(0.107)	0.089(0.060)	0.258(0.186)	0.012***(0.032)	0.026***(0.009)	0.096***(0.028)
Business services	-0.176(0.146)	0.019(0.074)	-0.022(0.077)	0.215***(0.062)	-0.030***(0.011)	-0.067***(0.012)
Education	-0.016(0.047)	-0.004(0.035)	-0.184***(0.071)	0.106**(0.045)	-0.034***(0.008)	-0.065***(0.018)
Health and social work	0.028(0.048)	-0.041(0.043)	-0.217**(0.092)	-0.104***(0.038)	-0.048***(0.006)	-0.104***(0.012)
Arts and recreation	-0.037*(0.061)	-0.073*(0.037)	-0.114**(0.045)	-0.182(0.188)	-0.046**(0.019)	-0.077***(0.028)
Personal services and repair	0.008(0.036)	-0.040(0.024)	-0.043(0.045)	-0.084(0.075)	0.025*(0.013)	0.006(0.020)
Intercept	5.944*** (0.193)	7.107***(0.117)	7.883***(0.191)	-8.402***(0.232)	6.937***(0.031)	7.529**(0.054)
Adjusted R squared	0.15	0.13	0.13	0.62	0.39	0.23
Sample size	5,049	5,049	5,049	12,223	12,223	12,223

Note: Standard errors, obtained from 500 bootstrap replications, are reported in parentheses. Statistical significance levels are denoted as follows: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.10$. Coefficients for dummy variables with more than two levels (education, firm size, occupation, and industry) are recentered by subtracting the average of their category coefficients, making them invariant to the choice of base category.

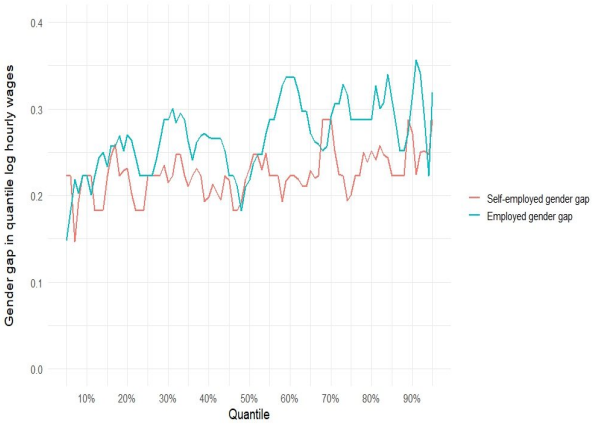
Table A4. Comparison of RIF quantile vs. RIF quantile-band decompositions (reference = men)

	Self-employed										
	85th Q	86th Q	87th Q	88th Q	89th Q	90th Q	91st Q	92nd Q	93rd Q	94th Q	85-94th Q
Raw earnings gap	0.201***	0.201***	0.219***	0.288***	0.237***	0.182***	0.262***	0.262***	0.336***	0.336***	0.252***
	(0.008)	(0.016)	(0.041)	(0.025)	(0.043)	(0.027)	(0.039)	(0.019)	(0.032)	(0.024)	(0.016)
RIF earnings gap	0.213***	0.212***	0.160***	0.231***	0.281***	0.331***	0.272***	0.286***	0.284***	0.304***	0.257***
	(0.020)	(0.020)	(0.019)	(0.039)	(0.134)	(0.024)	(0.021)	(0.017)	(0.034)	(0.070)	(0.016)
Estimation error	0.012	0.011	-0.059	-0.057	0.044	0.149	0.010	0.024	-0.052	-0.032	0.005
Structural effect	0.130***	0.128***	0.062***	0.096***	0.146***	0.197***	0.143***	0.157***	0.176***	0.197***	0.143***
	(0.024)	(0.022)	(0.023)	(0.039)	(0.035)	(0.034)	(0.026)	(0.023)	(0.035)	(0.063)	(0.020)
Composition effect	0.084***	0.084***	0.099***	0.134***	0.134***	0.134***	0.129***	0.129***	0.107***	0.107***	0.114***
	(0.023)	(0.020)	(0.019)	(0.021)	(0.019)	(0.023)	(0.026)	(0.020)	(0.020)	(0.027)	(0.019)
Structural effect (%)	61%	60%	39%	42%	52%	60%	53%	55%	62%	65%	56%
Composition effect (%)	39%	40%	62%	58%	48%	40%	47%	45%	38%	35%	44%
Sample size	10,818	10,818	10,818	10,818	10,818	10,818	10,818	10,818	10,818	10,818	10,818

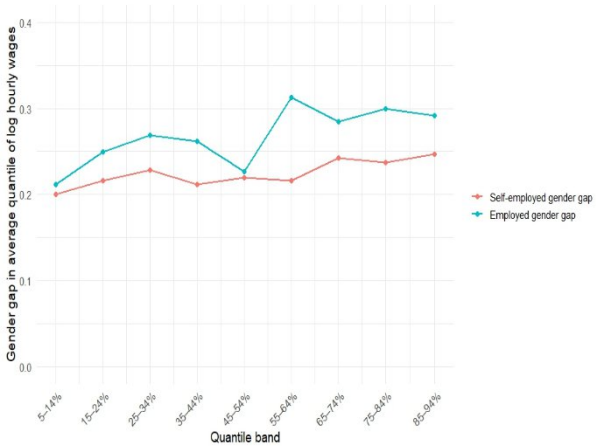
Note: Standard errors, obtained from 500 bootstrap replications, are reported in parentheses. Statistical significance levels are denoted as follows: *** for $p < 0.01$, ** for $p < 0.05$, and * for $p < 0.10$. The estimation error captures the discrepancy between raw earnings gaps calculated using log wages and those calculated using the RIF of log wages, arising from the estimation of earnings densities when computing the RIFs.

Figure A1. Net wages and gender gaps across quantiles and quantile bands

(a) Gender gaps in quantile log hourly wages



(b) Gender gaps average quantile of log hourly wages



Note: The bottom and top 5% of earners are excluded in the figures to mitigate the influence of outliers.