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The Impact of Firms' GVC Participation on Wages*

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Abstract

The expansion of global value chains (GVCs) has reshaped labor markets in developed countries, influencing both wage levels and inequality. By linking the "Basic Survey of Japanese Business Structure and Activities" with the "Basic Survey on Wage Structure," this study employs the Mincer model to empirically examine the effects of a firm's GVC participation on workers' wages. The results indicate that GVC participation is associated with higher wages across nearly all worker characteristics, with both direct and indirect GVC firms offering wage premiums relative to non-GVC firms. Moreover, GVC participation appears to mitigate the wage inequality between male and female workers, non-production and production workers, and non-routine and routine workers. However, these benefits are not distributed evenly. Cognitive and regular workers experience greater wage gains, whereas manual and non-regular workers face lower wage growth, leading to a widening wage gap. This finding aligns with the Stolper-Samuelson theorem because Japan, a developed country, specializes in capital- and skill-intensive production while offshoring labor-intensive tasks. These findings have significant implications for Japan's labor market, where wage inequality persists despite prolonged wage stagnation. As many Japanese firms are likely to engage in GVCs and many GVC firms faced with shrinking domestic markets intensify their participation in GVCs, the wage disparity between cognitive and manual workers, as well as between regular and non-regular workers, may further intensify. To cope with this problem, policies should focus on reskilling and upskilling manual and non-regular workers to ensure that they benefit from globalization.

Keywords: GVC, labor market, wages, wage inequality
JEL classification: D31, E24, F14, F16, J31

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1. Introduction

One of the most significant features of globalization is the expansion of global value chains (GVCs) driven by trade liberalization and technological advancements. Multinational corporations (MNCs) in developed countries play a pivotal role in shaping GVCs by fragmenting production into specialized tasks and distributing them across locations through foreign direct investment (FDI). Specifically, labor-intensive tasks have been outsourced to developing countries with lower wages, whereas capital- and skill-intensive activities have remained in developed countries with a highly skilled workforce.

Earlier studies primarily examined the determinants and benefits of GVC participation. In particular, both theoretical and empirical research highlight its positive impact on productivity. Theoretical research suggests that firms engaged in GVCs benefit from a more refined international division of labor, increased competition, and knowledge spillovers, all of which contribute to productivity enhancement (Baldwin & Robert-Nicoud, 2014; Grossman & Rossi-Hansberg, 2008; Li & Liu, 2014). Empirical evidence supports this view, demonstrating that GVC participation leads to significant productivity gains for firms (Baek & Urata, 2023; Del Prete et al., 2017; Montalbano et al., 2018; Urata & Baek, 2022). For firms in developed countries, GVC participation enhances efficiency, reduces costs, and enables specialization in high-value-added activities. Firms in developing countries benefit from access to international markets, advanced technologies, and foreign investment. These firm-level productivity gains contribute to broader industrial productivity growth and ultimately drive economic growth.

Despite the benefits of GVC participation, their expansion is increasingly seen as a factor contributing to rising income inequality. The expansion of GVCs contributed to narrowing the intercountry income inequality between developed and developing countries by fostering economic growth in developing economies. However, as people focus on within-country wage inequality, which directly affects their lives, this perception is fueling anti-globalization sentiments, driving the rise of protectionist policies and economic nationalism, especially in developed countries. Against this backdrop, research on the impact of GVC participation on workers' wages and wage inequality increased. However, owing to data limitations, most studies are confined to analyses at the industry level, and firm-level analyses typically overlook worker heterogeneity by relying on firms' average wages. Consequently, the effect of GVC participation on wages and wage inequality at the worker level remains unclear.

Furthermore, firms can participate in GVCs not only directly through exports and imports but also indirectly by procuring from or supplying direct GVC firms. Given this, a comprehensive analysis of firm-level GVC participation should account for both direct and indirect forms of GVC engagement.

To address this gap in the previous research, this study considers both firm- and worker-level heterogeneity using employer-employee matched data, with a particular focus on Japan, a developed country that played a leading role in shaping GVCs in East Asia. Additionally, by incorporating inter-firm transaction data to measure indirect GVC participation, this study provides a comprehensive analysis of the impacts of direct and indirect GVC participation on workers' wages and wage inequality.

The remainder of this paper is organized as follows. Section 2 reviews the literature on wage inequality and the role of GVC participation. Section 3 describes the methodology and the data used in the analysis. Section 4 presents the empirical results on the patterns of wages and GVC participation. Section 5 reports our estimation results. Section 6 concludes with a summary of key findings and policy implications.

2. Literature Review

This section provides a brief overview of the literature on wage inequality. We then review recent empirical studies that examine the impact of GVC participation on wages and wage inequality.

Discussions on wage inequality date back to the 1980s, when concerns arose about the impact of manufacturing decline in developed economies, particularly in the U.S. During this period, economists debated whether trade or other structural factors were responsible for the rising wage inequality. The Stolper-Samuelson theorem, rooted in the Heckscher-Ohlin trade model, predicts that trade liberalization will increase wage inequality in skill-abundant countries, such as the U.S., by raising the relative wages of skilled workers. However, Lawrence et al. (1993) challenge this view by showing that the prices of skill-intensive goods did not rise as expected, suggesting that factors beyond trade, such as technological advancement, played a more significant role in increasing wage inequality. By the 1990s and early 2000s, research increasingly attributed rising wage disparities to skill-biased technological changes (SBTC). Berman et al. (1993) provide empirical evidence that the demand for skilled labor in U.S. manufacturing rose because of technological advancements rather than trade. Krueger (1993) further demonstrates that computer adoption significantly increases the skill premium, reinforcing the SBTC hypothesis. Autor et al. (2003) expand this framework, arguing that the automation of routine tasks contributes to labor market polarization.

Meanwhile, Feenstra (1998) introduces offshoring as an additional factor, suggesting that globalization and technological change jointly shape wage inequality. Krugman (2008) revisits the trade-wage nexus, emphasizing that the rise in vertical specialization and offshoring intensified wage disparities. In the 2010s, the "China Shock" fundamentally reshaped the debate by shifting attention back to trade. Autor et al. (2013) demonstrates that rising Chinese imports led to significant job losses and wage declines in the U.S. manufacturing sector, challenging the assumption that labor markets adjust smoothly to trade shocks. Acemoglu et al. (2016) further highlight that increased import penetration from China had a widespread labor market effect, not only through direct job losses in exposed industries, but also via input–output linkage and local demand spillovers, underscoring the limitations of traditional industry-level adjustment mechanisms. These mechanisms assume a fully inelastic labor supply, no labor market frictions, and full employment, under which reallocation effects would offset trade-induced shocks. However, labor market imperfections hinder such reallocation, preventing employment from returning to pre-shock levels.

More recently, research shifted to examining the role of GVCs in shaping wage inequality. While earlier studies primarily examined industry- and firm-level dynamics, analyses at the worker level are limited. Even among studies on GVCs, many have been conducted at the country or industry level using GVC variables derived from international input–output tables, as well as country- or industry-level income and Gini coefficients, and their findings on the impact of GVC participation on wages and wage inequality are mixed.

Turning to country- and industry-level studies, Carpa et al. (2022) analyze data from 39 developing countries between 1995 and 2016, finding that increased GVC participation contributes to reducing income inequality in the long run. However, in the short term, GVC-related trade can negatively impact income distribution, although these adverse effects are mitigated as labor market adjustments occur. Lopez-Gonzalez et al. (2015) examine 40 OECD and emerging economies from 1995 to 2009 and report that GVC participation does not directly affect wage inequality. However, its effects vary by country: wage inequality tends to be narrow in developing countries, whereas it often widens in developed countries. Ndubuisi and Owusu (2022) examine 45 developed and developing countries from 2000 to 2015 and find that GVC participation generally raises wages. However, the effects vary by country and labor market conditions. In developed countries, GVC participation and upstream specialization lead to higher wages across all wage segments. By contrast, in developing countries, while GVC participation increases wages, upstream specialization puts downward pressure on wages, particularly for low-wage workers.

Shifting the focus to firm-level studies, Lu et al. (2019) analyze Chinese firm-level data from 2000 to 2006 and found that GVC participation raises firms' average wages. This effect is more pronounced in capital-intensive and foreign-invested firms. Additionally, the relationship between GVC embedment and wages is U-shaped, with the marginal wage effect initially declining and subsequently increasing. Wang et al. (2021) examine the impact of GVC participation on wage inequality using Chinese firm-level data from 2000 to 2006. They find that, while GVC participation itself has an ambiguous effect on wage inequality, firms moving upstream within GVCs experience a widening wage gap between skilled and unskilled workers. Firms higher upstream tend to employ more skilled workers and pay higher wages, which contributes to rising wage inequality.

A review of the existing studies reveals several limitations in understanding the relationship between GVC participation and wages. Most studies rely on country- or industry-level data, while firm-level studies primarily use firm-level worker characteristics. This approach makes it difficult to capture the precise effects of GVC participation on individual wages, and may lead to misleading conclusions. Given these constraints, a more comprehensive approach that accounts for firm- and worker-level heterogeneity is necessary. To address these gaps, this study uses employer-employee matched data to examine the impact of GVC participation on wages and wage inequality. Furthermore, rather than focusing solely on direct GVC participation, this study incorporates inter-firm transaction data to capture indirect GVC participation, which previous studies did not analyze. By leveraging detailed inter-firm relationships, this study systematically identifies firms that do not engage in GVC but are connected to GVC networks through transactions with GVC firms. This novel approach to measuring indirect GVC participation makes a significant contribution to the literature as it broadens the scope of analysis beyond direct GVC participation and enables a more comprehensive assessment of the relationship between GVC participation and wages, as well as wage inequality.

3. Methodology and Data

In this section, we present the estimation method, variables, and data used in the analysis. To examine the impact of firms' GVC participation on wages and wage inequality, we employ the Mincer wage equation to analyze an employer-employee dataset. The estimation is based on the following specification:

$$\begin{aligned} lnWage_{icspt} = {} & \beta_0 + \beta_1 Schooling_{icspt} + \beta_2 Exp\_years_{icspt} + \beta_3 Exp\_years^2_{icspt} + \beta_4 X_{icspt} \\ & + \beta_5 DGVC_{cspt} + \beta_6 INDGVC_{cspt} + \beta_7 Z_{cspt} + u_{spt} + \epsilon_{icspt}, \end{aligned} \tag{1}$$

where $lnWage_{icspt}$ represents the logarithm of real hourly wages for worker i in firm c, sector s, prefecture p, and year t. We calculate hourly wages by adding one-twelfth of the annual bonus and other special payments to the cash salary and then dividing by the total working hours. $Schooling_{icspt}$ denotes the number of years of education completed by the worker, whereas Exp_years_{icspt}captures the total work experience in terms of the number of years of employment. To account for the nonlinear relationship between experience and wages, we include Exp_years^2, the squared term of total work experience. This specification reflects the common pattern in which wages increase with experience, but at a diminishing rate over time.

X_{icspt} represents the following worker characteristics. *Female*, a dummy variable that equals 1 for female workers and 0 for male workers, captures gender-related wage differences. *Non_reg_worker*, a dummy variable that equals 1 for non-regular workers and 0 for regular (permanent) workers, allows us to examine wage disparities based on employment stability. *Prod_workers*, a dummy variable that takes the value of 1 for production workers and 0 for non-production workers, distinguishes between those engaged in direct production activities and those in other roles, such as managers, researchers, and engineers. Finally, the *Routine* and *Manual* dummy variables represent job task attributes[1]. *Routine* takes the value of 1 for workers in routine-task occupations and 0 for those in non-routine occupations. Similarly, *Manual* equals 1 for workers in manual-task occupations and 0 for workers in cognitive-task occupations. The classification of routine versus non-routine tasks captures the degree of automation exposure, as routine tasks are more susceptible to technological advancements and automation, whereas non-routine tasks require greater adaptability and problem-solving skills, making them less prone to machine displacement. Meanwhile, the distinction between manual and cognitive tasks not only reflects differences in task complexity, but is also relevant in the GVC context, as manual tasks tend to be more labor-intensive and are often outsourced to developing countries where labor costs are lower. By contrast, cognitive tasks, which typically require higher skill levels and involve knowledge-intensive activities, are less likely to be relocated abroad. By incorporating these classifications, we can analyze how job task characteristics influence wage determination and how firms' GVC participation affects the demand for different types of labor.

The key variables in this study are *DGVC* (Direct GVC) and *INDGVC* (Indirect GVC). A GVC firm is defined as a firm that engages in both exporting and importing, following Antràs (2020), who argues that GVC consists of a series of stages involved in producing a product or service that is sold to consumers with each stage adding value, and with at least two stages being produced in different countries. Based on this observation he states that when a given firm in a given country both imports and exports, it is natural to conclude that this firm participates in GVC. Based on this definition, we define firms engaging in both direct exports and direct imports as direct GVC firms. Furthermore, firms can participate in GVCs indirectly by supplying to exporters or procuring from importers. Based on these observations, we include separate dummy variables for direct and indirect GVC participation, *DGVC* and *INDGVC*, respectively, to examine the impact of GVC participation at different levels of engagement on wages. Consequently, we classify all firms into three categories: direct, indirect, and non-GVC firms.

Z_{cspt} denotes the following set of firm-level control variables that capture firm characteristics. *Age_f* is the number of years since the firm's establishment. *Foreign_share_f* is the proportion of foreign ownership in terms of paid-in capital in the firm. *lnScale_f* represents firm size measured as the logarithm of the number of employees. *lnTFP*[2] represents total factor productivity. u_{spt} denotes the sector–prefecture–year fixed effect used to minimize the risk of omitted variable bias.

To examine how firms' GVC participation affects workers' wages and contributes

[1] Using the occupational information database from the Japanese version of O-NET, we extract the items used in Autor et al. (2003) and apply their methodology to construct the variables for *Routine*, *Manual*, *Non-Routine Cognitive*, *Routine Cognitive*, *Routine Manual*, and *Non-Routine Manual*, as Table A1 shows.

[2] Given the limitations of an unbalanced panel dataset with missing values, we adopt the Levinsohn and Petrin (2003) method, which allows for a larger number of observations to estimate the production function than alternative estimation methods. Value-added is (total sales – intermediate input) / output deflator), while intermediate input is {cost of sales – (wages + rent + depreciation)} / intermediate input deflator}. We measure labor as the number of employees multiplied by the sectoral average working hours from the JIP database (RIETI).

to wage inequality, we estimate Equation (2), which includes an interaction term between worker characteristics and the two GVC variables. This specification allows us to analyze whether the effect of GVC participation on wages differs across worker groups. In this model, among workers in non-GVC firms, those without characteristic X receive a baseline wage of β_0, while those with the characteristic X earn wage $(\beta_0 + \beta_4)$. Thus, β_4 captures the wage difference associated with characteristic X within the non-GVC group. In comparison, workers in direct GVC firms without characteristic X earn wage $(\beta_0 + \beta_5)$, while those with the characteristic earn wage $(\beta_0 + \beta_4 + \beta_5 + \beta_7)$. Therefore, $\beta_4 + \beta_7$ represents the wage difference associated with characteristic X within the direct GVC group. Similarly, in indirect GVC firms, workers without characteristic X earn wage $(\beta_0 + \beta_6)$, and those with the characteristic earn wage $(\beta_0 + \beta_4 + \beta_6 + \beta_8)$. Accordingly, $\beta_4 + \beta_8$ captures the wage difference associated with characteristic X within the indirect GVC group. Specifically, we examine: (1) wage differences among non-GVC firms, direct GVC firms, and indirect GVC firms for workers with the same characteristics; (2) wage inequality within each type of GVC firm based on worker characteristics; and (3) whether within-group wage inequality differs across non-GVC firms, direct GVC firms, and indirect GVC firms. By incorporating these comparisons, this study provides a comprehensive assessment of how GVC participation is associated with variations in wage structures.

$$\begin{aligned} lnWage_{icspt} = \beta_0 &+ \beta_1 Schooling_{icspt} + \beta_2 Exp\_years_{icspt} + \beta_3 Exp\_years^2_{icspt} + \beta_4 X_{icspt} \\ &+ \beta_5 DGVC_{cspt} + \beta_6 INDGVC_{cspt} + \beta_7 X_{icspt} \times DGVC_{cspt} + \beta_8 X_{icspt} \times INDGVC_{cspt} \\ &+ \beta_9 Z_{cspt} + u_{spt} + \epsilon_{icspt} \end{aligned} \quad (2)$$

The analysis covers the period from 2019 to 2021 and focuses on 32 manufacturing sectors. The data[3] used in this study are derived from the following sources. Data on wages and worker characteristics are obtained from the Basic Survey on Wage Structure (BSWS) conducted by Japan's Ministry of Health, Labour and Welfare (MHLW). Firm-level data, including direct export and import activities, are sourced from the Basic Survey of Japanese Business Structure and Activities (BSJBSA) administered by Japan's Ministry of Economy, Trade and Industry (METI). We link the BSWS to the BSJBSA using the corporate identification number, which has been available in the BSWS since 2018 and in the BSJBSA since 2016[4]. We construct the indirect GVC variables using transaction data from Tokyo Shoko Research (TSR). The TSR dataset consists of four components: (1) firm-level information, including capital, number of employees, sales, and other characteristics (2007–2022); (2) inter-firm relationships, which record up to 24 major suppliers and 24 major customers per firm (2007–2022); (3) trade data showing whether a firm engages in exporting

[3] Following Tanaka (2022), we exclude part-time workers because of the lack of education information, a key variable in the wage function. Given Japan's lifetime employment system, wages drop sharply after age 60. Thus, we exclude workers aged 60 and above from the analysis.

[4] The matching rate between these two datasets is approximately 57% based on individual records in the wage data (BSWS).

or importing (2019–2022); and (4) corporate identification numbers (2018–2022). From the inter-firm relationship data, each firm can report up to 24 suppliers and 24 customers. However, many firms transact with more than 24 partners; therefore, the dataset may not include all business relationships. To address this limitation, we also use information reported by other firms, specifically cases in which a firm is listed as a trading partner by others. By combining both reporting directions, we identify firms that do not directly trade internationally, but transact with firms that do. We classify these firms as indirect exporters (if they sell to exporting firms) or importers (if they buy from importing firms). We classify firms that engage in both indirect exporting and importing as indirect GVC firms. Finally, we pool the TSR data from 2018 to 2022 that include corporate identification numbers, to construct a concordance table between TSR firm IDs and corporate identifiers. Similarly, we pooled the BSJBSA data from 2016 to 2021 to create a concordance table between BSJBSA firm IDs and corporate identifiers. Using these matched corporate numbers, we merge the TSR and BSJBSA datasets[5].

4. Empirical Patterns of Wages and GVC Participation

In this section, we present stylized facts on the relationships between GVC participation, productivity, wages, and worker characteristics. Figure 1 shows the distribution of TFP across firms based on GVC participation in 2019. Direct GVC firms show the highest productivity levels, followed by indirect GVC firms, whereas non-GVC firms display the lowest productivity. This pattern suggests that firms more deeply integrated into GVCs tend to be more productive. Similarly, Figure 2 shows the distribution of real wages based on GVC participation in 2019. As with TFP, the density curves suggest that wages tend to be highest for direct GVC firms followed by indirect GVC firms, whereas non-GVC firms exhibit the lowest wage levels. This pattern suggests that higher productivity enhances profitability by allowing firms to offer higher wages to workers. Notably, firms engaged in direct GVC participation tend to achieve greater productivity and pay higher wages than those with indirect GVC participation or firms that do not participate in GVCs. This finding reinforces the notion that deeper integration into GVCs is linked to greater economic advantages for both firms and workers.

=== Figure 1 & 2 ===

Table 1 presents the average wages (Japanese yen per hour) of workers according to their experience, education, sex, employment type, and occupation from 2019 to 2021. Several patterns emerge from the data. First, wages generally increase with experience,

[5] Because some corporate identification numbers changed over time or were reassigned to different firms, we exclude duplicated corporate numbers from the concordance tables. Thus, the matching rate between the TSR and BSJBSA datasets is 87.78%.

peaking in the 30-39 years category before declining for workers with 40 or more years of experience. Wages tend to rise with higher educational attainment, with workers holding a 16-year education consistently earning the highest wages. Gender-based wage differences are evident, with male workers earning consistently higher wages than female workers in all years. Regular employees receive significantly higher wages than non-regular employees, reflecting the wage premium associated with stable employment contracts. In terms of occupational classification, non-production workers earn higher wages than production workers. Among the task-based occupational classifications in Occupation (B), non-routine cognitive workers receive the highest wages, followed by routine manual, routine cognitive, and non-routine manual workers. This pattern reflects differences in wage structures across various job tasks.

=== Table 1 ===

5. Estimation Results

We estimate Equations (1) and (2) using OLS for Japanese manufacturing firms from 2019 to 2021. Table 2 shows that the key worker characteristics consistently demonstrate statistically significant effects on wages. These results remain robust regardless of whether we include firm-fixed effects (Columns 1–3) or firm-level control variables (Columns 4–9). *Schooling* and *experience* (*Exp_years)* positively correlate with wages, whereas the negative and significant coefficient of *Exp_years_sq* suggests diminishing returns on experience. The results also indicate significant wage disparities according to sex and employment type. The negative and significant coefficient for *Female* suggests a gender wage gap, while the negative coefficients for *Non_reg_worker* and *Prod_workers* reflect lower wages for non-regular and production workers than for their counterparts. The firm-level controls in Columns 4–6 show that larger firms (*lnScale_f*), firms with higher foreign ownership (*Foreign_share_f*), and more productive firms (*lnTFP*) tend to pay higher wages. Columns 7–9 introduce GVC participation, in which both *DGVC* and *INDGVC* are positively and significantly associated with wages. This implies that firms engaged in GVCs tend to pay higher wages than non-GVC firms. Moreover, the coefficient of *DGVC* is larger than that of *INDGVC*, suggesting that the wage premium is greater for firms directly participating in GVCs than for those involved indirectly.

=== Table 2 ===

Table 3 shows the relationship between task characteristics and wages, focusing on routine and manual occupations. The results show that routine workers (those performing repetitive, rule-based tasks) earn significantly higher wages than their non-routine counterparts, as the positive and statistically significant coefficient for *Routine* indicates. By contrast, manual workers (those engaged in physical, labor-intensive tasks) receive lower wages than cognitive workers, as reflected in the negative and statistically significant coefficient for *Manual*. The results indicate that non-routine cognitive workers, who engage in complex cognitive tasks that require problem-solving and analytical skills, earn the highest wages among all occupational groups. The positive and statistically significant coefficient (Column 5) confirms this wage advantage. Furthermore, when we use non-routine cognitive workers as the reference group (Column 4), all other occupational categories show negative and statistically significant coefficients, reinforcing the finding that they earn lower wages than non-routine cognitive workers. By contrast, non-routine manual workers who perform physically demanding but less repetitive tasks receive significantly lower wages, as indicated by the negative and statistically significant coefficients (Columns 4 and 6). Among routine workers, those in routine cognitive occupations earn higher wages than routine manual and non-routine manual workers, as Columns 4 and 7 show. This result suggests that while routine cognitive workers do not earn as much as non-routine cognitive workers, they receive a wage premium over manual jobs. By contrast, in Column 4, routine manual workers who engage in repetitive physical tasks earn lower wages than non-routine cognitive and routine cognitive workers. However, they earn higher wages than non-routine manual workers, who perform physically demanding but less repetitive tasks, and receive the lowest wages among all occupational groups, as the consistently negative and statistically significant coefficients indicate. Given the dominance of routine cognitive workers in the manufacturing sector,[6] we further distinguish between *Routine Cognitive (Univ)* and *Routine Cognitive (NoUniv)* workers based on their educational attainment. The results show that *Routine Cognitive (Univ)* workers—those with a university degree—earn a wage premium, as reflected in the positive and statistically significant coefficient. By contrast, *Routine Cognitive (NoUniv)* workers—those with less than a university degree—receive significantly lower wages, highlighting the role of education, even within routine cognitive occupations.

=== Table 3 ===

Table 4 shows wage differences across non-GVC, indirect GVC, and direct GVC firms, as well as within-group wage inequality by worker characteristics.

To begin with gender wage differences, the results show that both male and female workers earn higher wages in GVC firms, including both direct GVC firms and indirect GVC firms, relative to non-GVC firms. The we observe the highest wages in direct GVC firms. Across all GVC groups, male workers consistently outearn female workers, indicating a persistent gender wage gap. The within-group gender wage gap is identical (0.298) in both direct and indirect GVC firms, whereas it is slightly larger in non-GVC firms (0.302). These findings suggest that, although GVC participation leads to wage increases for both male and

[6] Routine cognitive workers account for 89% of the dataset.

female workers, the relative gain is greater for female workers, thereby narrowing the gender wage gap compared to the non-GVC case.

By contrast, when comparing regular and non-regular workers, regular workers earn the highest wages in direct GVC firms (6.136), followed by indirect GVC (6.117) and non-GVC firms (6.092). However, non-regular workers earn the highest wages in non-GVC firms (5.600), followed by direct GVC (5.591) and indirect GVC firms (5.569). Across all GVC groups, regular workers consistently earn more than non-regular workers. The wage gap is the smallest in non-GVC firms (0.492) and similarly large in indirect and direct GVC firms (0.547 and 0.544, respectively), indicating that GVC participation is associated with increased wage disparity between regular and non-regular workers.

Turning to occupational classification, both non-production and production workers earn the highest wages in direct GVC firms, followed by indirect GVC and non-GVC firms. Within each GVC type, non-production workers consistently earn more than production workers. The wage gap between these two groups is the largest for non-GVC firms (0.101), followed by indirect GVC firms (0.094) and direct GVC firms (0.089). This pattern suggests that greater GVC participation is associated with a modest reduction in the wage disparity between non-production and production workers.

For task-based the classification, both non-routine and routine workers earn higher wages in GVC-participating firms relative to non-GVC firms, with the highest wages observed in direct GVC firms, followed by indirect and non-GVC firms. In non-GVC and indirect GVC firms, routine workers earn significantly higher wages than non-routine workers do, as indicated by the negative and statistically significant wage gaps. However, for direct GVC firms, the wage gap is not statistically significant. The wage gap between routine and non-routine workers is the largest in non-GVC firms (-0.036), followed by indirect GVC firms (-0.021). In direct GVC firms, the difference becomes statistically insignificant, suggesting that greater GVC engagement may help reduce the wage disparities associated with task routineness.

Focusing on another dimension of the task-based classification (cognitive versus manual work), cognitive workers earn the highest wages in direct GVC firms, followed by indirect and non-GVC firms. Manual workers, on the other hand, earn the highest wages in indirect GVC firms, followed by direct GVC and non-GVC firms. Across all GVC groups, cognitive workers consistently earn higher wages than manual workers. The wage gap between cognitive and manual workers is statistically significant in non-GVC (0.036) and direct GVC firms (0.041), with a larger gap observed in direct GVC firms. This pattern suggests that participation in direct GVCs may amplify wage disparities between cognitive and manual occupations, with cognitive workers benefiting more from GVC participation. This finding aligns with the earlier result that gender wage disparities are smaller in GVC firms as female workers are employed in cognitive occupations.

=== Table 4 ===

6. Concluding Remarks

This study investigates the impact of firms' participation in GVC on workers' wages and wage inequality in Japan. Using employer-employee data from 2019 to 2021, we analyze both direct and indirect GVC participation across 32 manufacturing sectors.

The empirical findings indicate that GVC participation is associated with higher wages for workers across all characteristics except for non-regular workers. Both direct and indirect GVC firms offer wage premiums relative to non-GVC firms. This premium is generally larger for direct GVC firms than for indirect GVC firms across all worker characteristics, with the exception of manual workers. These results suggest that deeper integration into global production networks enhances firm productivity and profitability, leading to higher employee wages.

Although GVC participation generally leads to higher wages, its impact on wage inequality varies depending on worker characteristics. GVC participation reduces wage inequality between male and female workers, non-production and production workers, and non-routine and routine workers. By contrast, it widens the wage gap between regular and non-regular workers, as well as between cognitive and manual workers. This pattern is consistent with the Stolper-Samuelson theorem. As a developed country, Japan specializes in high-value-added, capital-, and skill-intensive production, whereas labor-intensive tasks are increasingly offshored to lower-wage countries. Consequently, workers with higher skills or more stable employment, such as cognitive and regular workers, enjoy greater wage gains in GVC-participating firms, whereas manual and non-regular workers are relatively disadvantaged. This finding suggests that GVC participation reinforces skill- and contract-based wage inequalities.

These results have important implications for Japan’s labor market, where wage inequality remains evident during the period of prolonged wage stagnation. The wage structure of GVC firms reflects Japan’s industrial composition, in which high-skilled work retains value domestically, while lower-skilled production processes are increasingly outsourced. With major Japanese firms are leading efforts to raise wages in recent years, particularly since 2024, GVC firms, which are predominantly large and export-oriented, are likely to be at the forefront of these wage adjustments. However, this may further amplify disparities between cognitive and manual workers, as well as between regular and non-regular workers, reinforcing skill-based wage inequality because GVC firms, faced with shrinking domestic markets, are likely to expand their GVC operations. Therefore, to leverage the benefits of GVC participation while mitigating rising inequality, policies should prioritize workforce development, particularly by reskilling and upskilling manual and non-regular workers to adapt to shifting labor demands.

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Table 1. Average Wages by Worker Characteristics (2019–2021)

Year	2019	2020	2021
Experience (Years)			
0-9	1,493	1,568	1,508
10-19	1,947	2,023	1,940
20-29	2,412	2,433	2,313
30-39	2,681	2,730	2,592
40+	1,824	1,983	1,955
Education (Years)			
9	1,609	1,695	1,581
12	1,826	1,894	1,790
14	1,907	1,964	1,871
16	2,421	2,430	2,342
Gender			
Male	2,119	2,186	2,090
Female	1,388	1,479	1,411
Employment Type			
Regular Employee	2,093	2,154	2,058
Non-Regular Employee	1,262	1,372	1,302
Occupation (A)			
Non-Production Worker	-	2,257	2,301
Production Worker	-	1,632	1,691
Occupation (B)			
Non-routine Cognitive	1,793	2,433	3,408
Non-routine Manual	1,606	2,258	2,113
Routine Cognitive	1,692	2,690	2,521
Routine Manual	1,764	2,881	2,761

Source: Author's compilation.

Note: Wages are hourly wages in Japanese yen.

Table 2. Baseline Estimation (1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Schooling	0.054***	0.042***	0.032***	0.055***	0.044***	0.033***	0.057***	0.045***	0.033***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Exp_years	0.036***	0.035***	0.030***	0.036***	0.035***	0.030***	0.036***	0.035***	0.030***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exp_years_sq	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Age_f				-0.000***	-0.000***	-0.001***	-0.000***	-0.001***	-0.001***
				[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Foreign_share_f				0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
				[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
lnScale_f				0.016***	0.021***	0.023***	0.078***	0.072***	0.064***
				[0.004]	[0.004]	[0.004]	[0.003]	[0.003]	[0.003]
lnTFP				0.153***	0.125***	0.103***			
				[0.007]	[0.006]	[0.008]			
DGVC							0.044***	0.035***	0.038***
							[0.008]	[0.007]	[0.008]
INDGVC							0.029***	0.015**	0.028***
							[0.008]	[0.007]	[0.009]
Female		-0.203***	-0.222***		-0.214***	-0.232***		-0.218***	-0.237***
		[0.002]	[0.003]		[0.003]	[0.003]		[0.003]	[0.003]
Non_reg_worker		-0.440***	-0.311***		-0.439***	-0.308***		-0.444***	-0.312***
		[0.005]	[0.007]		[0.005]	[0.007]		[0.005]	[0.007]
Prod_workers			-0.090***			-0.095***			-0.099***
			[0.003]			[0.004]			[0.004]
Constant	6.479***	6.720***	6.810***	6.372***	6.596***	6.676***	5.891***	6.206***	6.366***
	[0.015]	[0.015]	[0.018]	[0.031]	[0.029]	[0.034]	[0.020]	[0.020]	[0.023]
Number of obs.	337,257	337,257	114,404	329,982	329,982	112,851	335,005	335,005	113,921
Sector FE	Yes	Yes	Yes	No	No	No	No	No	No
Province FE	Yes	Yes	Yes	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	No	No	No	No	No	No
Firm FE	Yes	Yes	Yes	No	No	No	No	No	No
Sector × Prefecture × Year FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-sq.	0.643	0.757	0.764	0.579	0.709	0.712	0.564	0.699	0.703

Source: Author's compilation.

Notes: This table reports the results obtained using the OLS estimation. DGVC and INDGVC indicate direct and indirect GVC participation, respectively. ***, **, and * indicate 1%, 5%, and 10% levels of statistical significance, respectively. Standard errors clustered by firm are reported in parentheses.

Table 3. Baseline Estimation (2)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Schooling	0.049***	0.049***	0.049***	0.049***	0.050***	0.049***	0.049***	0.050***	0.028***	0.047***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Exp_years	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***	0.035***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Exp_years_sq	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Female	-0.312***	-0.311***	-0.311***	-0.312***	-0.309***	-0.312***	-0.311***	-0.309***	-0.305***	-0.308***
	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]	[0.004]
Age_f	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Foreign_share_f	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
lnScale_f	0.074***	0.074***	0.074***	0.074***	0.074***	0.074***	0.074***	0.074***	0.074***	0.074***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
DGVC	0.035***	0.036***	0.035***	0.035***	0.036***	0.036***	0.035***	0.036***	0.035***	0.036***
	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]
INDGVC	0.018**	0.018**	0.018**	0.018**	0.017*	0.018**	0.018**	0.017*	0.017*	0.017*
	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]	[0.009]
Routine	0.022	0.067***								
	[0.014]	[0.007]								
Manual	-0.049***		-0.063***							
	[0.014]		[0.007]							
Non-routine Cognitive					0.063***					
					[0.024]					
Non-routine Manual				-0.136***		-0.075***				
				[0.025]		[0.007]				
Routine Cognitive				-0.061**			0.059***			
				[0.024]			[0.007]			
Routine Manual				-0.100***				-0.036**		
				[0.028]				[0.015]		
Routine Cognitive (Univ)									0.108***	
									[0.005]	
Routine Cognitive (NoUniv)										-0.016***
										[0.005]
Constant	6.151***	6.102***	6.172***	6.236***	6.154***	6.172***	6.112***	6.155***	6.420***	6.204***
	[0.025]	[0.023]	[0.022]	[0.033]	[0.022]	[0.022]	[0.023]	[0.022]	[0.024]	[0.028]
Number of obs.	237,592	237,592	237,592	237,592	237,592	237,592	237,592	237,592	237,592	237,592
Sector × Prefecture × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-sq.	0.618	0.617	0.618	0.618	0.617	0.618	0.617	0.617	0.619	0.617

Source: Author's compilation.

Notes: This table reports the results obtained using the OLS estimation. DGVC and INDGVC indicate direct and indirect GVC participation, respectively. ***, **, and * indicate 1%, 5%, and 10% levels of statistical significance, respectively. Standard errors clustered by firm are reported in parentheses.

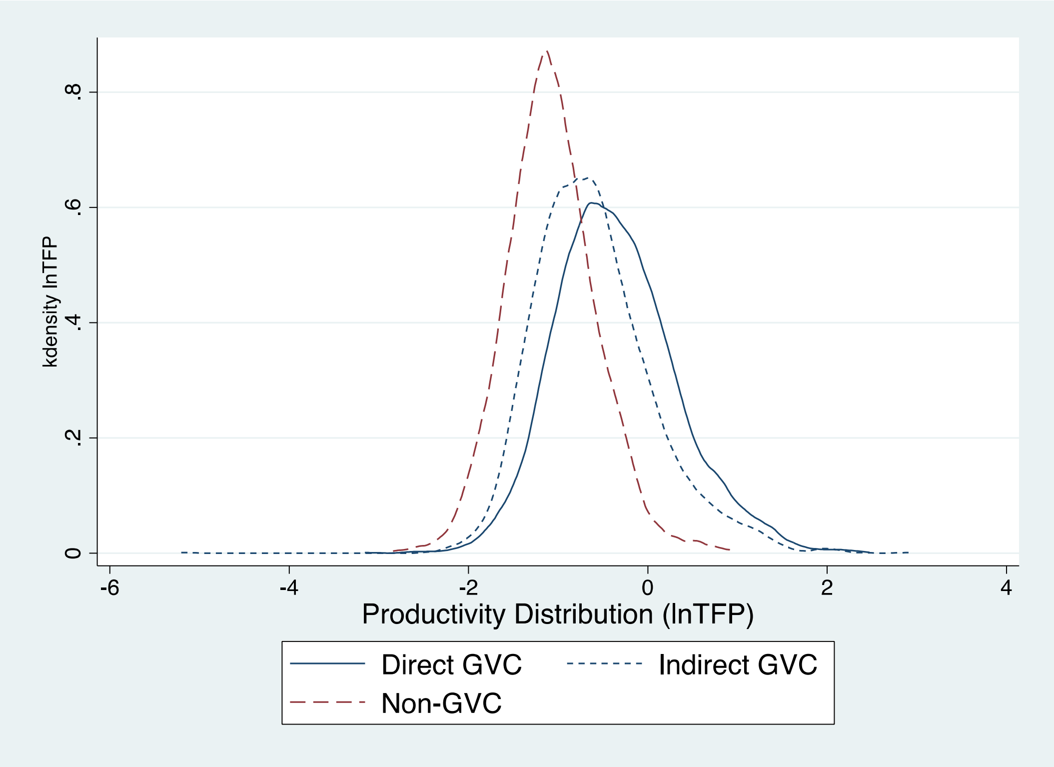
Table 4. Wage Differences by GVC Participation

	Non-GVC	Indirect GVC	Direct GVC
Male	6.087***	6.109***	6.125***
	[0.019]	[0.021]	[0.021]
Female	5.785***	5.811***	5.826***
	[0.020]	[0.022]	[0.022]
Male – Female	0.302	0.298	0.298
	[0.005]	[0.007]	[0.005]
Regular Worker	6.092***	6.117***	6.136***
	[0.019]	[0.020]	[0.022]
Non-Regular Worker	5.600***	5.569***	5.591***
	[0.022]	[0.023]	[0.024]
Regular Worker – Non-Regular Worker	0.492	0.547	0.544
	[0.008]	[0.010]	[0.011]
Non-Production Worker	6.091***	6.128***	6.131***
	[0.024]	[0.029]	[0.027]
Production Worker	5.989***	6.033***	6.042***
	[0.024]	[0.027]	[0.026]
Non-Production Worker – Production Worker	0.101***	0.094***	0.089***
	[0.006]	[0.007]	[0.006]
Non-Routine	5.921***	5.958***	5.978***
	[0.026]	[0.027]	[0.029]
Routine	5.957***	5.980***	5.997***
	[0.022]	[0.025]	[0.026]
Non-Routine – Routine	-0.036**	-0.021*	-0.018
	[0.014]	[0.012]	[0.014]
Cognitive	5.960***	5.981***	6.000***
	[0.022]	[0.024]	[0.026]
Manual	5.923***	5.963***	5.958***
	[0.025]	[0.027]	[0.028]
Cognitive – Manual	0.036***	0.018	0.041***
	[0.013]	[0.012]	[0.012]

Source: Author's compilation.

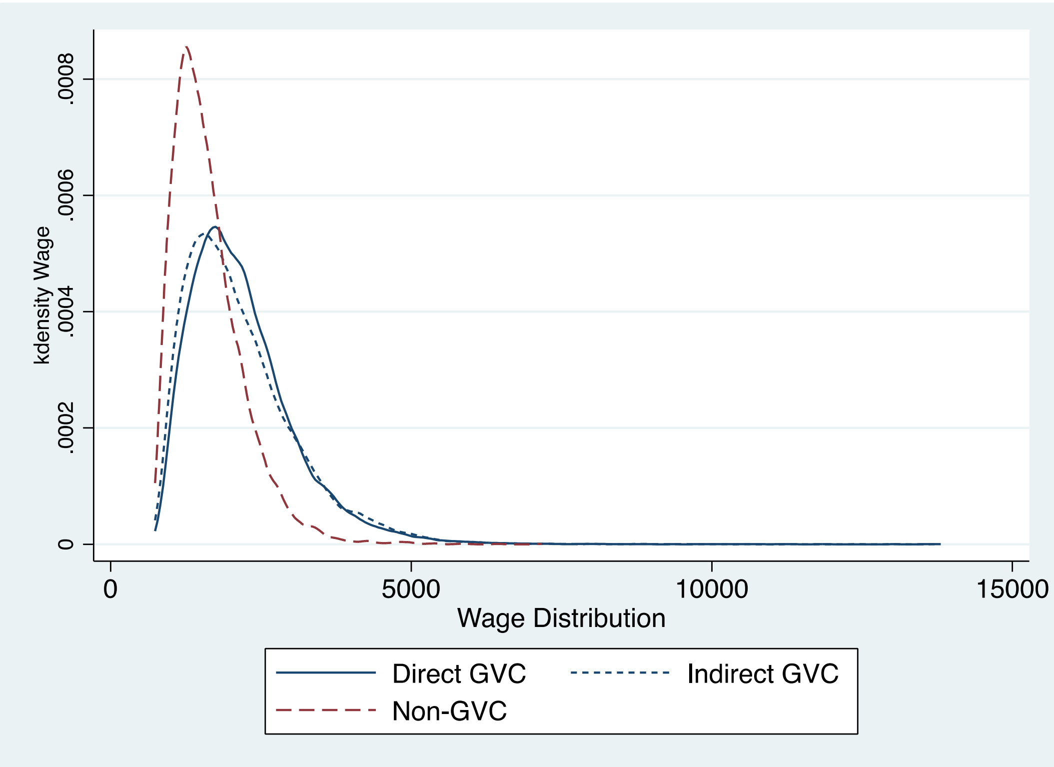
Note: The reported values are computed as log hourly wages in Japanese yen, based on linear combinations of the estimated coefficients in Equation (2). They represent the wages predicted by worker characteristics, controlling for the other variables in Equation (2). For the original estimation results, refer to Table A2. The description of Equation (2) explains the derivation of each coefficient. For example, when characteristic X in Equation (2) is a dummy for female (1 for female, 0 for male), the coefficient β_0 = 6.087 represents the wage of male workers in non-GVC firms. The sum $\beta_0 + \beta_4$ = 5.785 represents the wage of female workers in non-GVC firms, and their difference β_4 = 0.302 indicates the gender wage gap within non-GVC firms. Similarly, the wage of male workers in indirect GVC firms is $\beta_0 + \beta_6$ = 6.109, and that of female workers is $\beta_0 + \beta_4 + \beta_6 + \beta_8$ = 5.811, resulting in a gender wage gap of $\beta_4 + \beta_8$ = 0.298. Lastly, in direct GVC firms, the estimated wage is $\beta_0 + \beta_5$ = 6.125 for male workers and $\beta_0 + \beta_4 + \beta_5 + \beta_7$ = 5.826 for female workers. Therefore, $\beta_4 + \beta_7$ = 0.298 represents the gender wage gap within direct GVC firms. The statistical significance and standard errors for the sum of coefficients are calculated using a linear combination test. ***, **, and * indicate 1%, 5%, and 10% levels of statistical significance, respectively. Standard errors clustered by firm are reported in parentheses.

Figure 1. TFP Distribution by GVC Participation in 2019



Source: Authors' compilation.

Figure 2. Wage Distribution by GVC Participation in 2019



Source: Authors' compilation.

Note: Wages are hourly wages in Japanese yen.

Appendix

Table A1. Task Classification

Ocuppation	Task	Japanese O-NET Occupational Information
Non-routine Cognitive	4.A.2.a.4 Analyzing data/information	Analyzing information and data (Job Content)
	4.A.2.b.2 Thinking creatively	Thinking creatively (Job Content)
	4.A.4.a.1 Interpreting information for others	Explaining the meaning of information to others (Job Content)
	4.A.4.a.4 Establishing and maintaining personal relationships	Building and maintaining relationships (Job Content)
	4.A.4.b.4 Guiding, directing and motivating subordinates	Supervising, instructing, and motivating subordinates (Job Content)
	4.A.4.b.5 Coaching/developing others	Coaching and developing others (Job Content)
Routine Cognitive	4.C.3.b.7 Importance of repeating the same tasks	Repeating the same task (Job Characteristics)
	4.C.3.b.4 Importance of being exact or accurate	Precision and accuracy (Job Characteristics)
	4.C.3.b.8 Structured v. Unstructured work (reverse)	Structuring tasks (Job Characteristics)
Routine Manual	4.C.3.d.3 Pace determined by speed of equipment	Performing tasks based on machine speed (Job Characteristics)
	4.A.3.a.3 Controlling machines and processes	Controlling machinery and the manufacturing process (Job Content)
	4.C.2.d.1.i Spend time making repetitive motions	Performing repetitive tasks (Job Characteristics)
Non-Routine Manual	4.A.3.a.4 Operating vehicles, mechanized devices, or equipment	Operating and driving vehicles (Job Content)
	4.C.2.d.1.g Spend time using hands to handle, control or feel objects, tools or controls	Performing manual tasks involving objects, tools, and control devices (Job Characteristics)
	1.A.2.a.2 Manual dexterity	
	1.A.1.f.1 Spatial orientation	

Source: Author’s compilation based on Autor et al. (2003) and the Japanese O-NET.

Table A2. Wage Differences by GVC Participation

	(1)	(2)	(3)	(4)	(5)
Schooling	0.052***	0.048***	0.044***	0.055***	0.055***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Exp_years	0.034***	0.036***	0.032***	0.036***	0.036***
	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Exp_years_sq	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Age_f	-0.000***	-0.001***	-0.000**	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Foreign_share_f	0.001***	0.001***	0.001***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
lnScale_f	0.073***	0.076***	0.067***	0.080***	0.081***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
DGVC	0.037***	0.044***	0.040***	0.056***	0.040***
	[0.008]	[0.007]	[0.010]	[0.021]	[0.010]
INDGVC	0.021***	0.025***	0.036***	0.037*	0.021**
	[0.008]	[0.008]	[0.012]	[0.020]	[0.010]
Female	-0.303***				
	[0.005]				
DGVC × Female	0.004				
	[0.008]				
INDGVC × Female	0.005				
	[0.008]				
Non_reg_worker		-0.492***			
		[0.009]			
DGVC × Non_reg_worker		-0.052***			
		[0.014]			
INDGVC × Non_reg_worker		-0.055***			
		[0.013]			
Prod_workers			-0.102***		
			[0.006]		
DGVC × Prod_workers			0.012		
			[0.009]		
INDGVC × Prod_workers			0.007		
			[0.009]		
Routine				0.036**	
				[0.015]	
DGVC × Routine				-0.017	
				[0.020]	
INDGVC ×Routine				-0.014	
				[0.020]	
Manual					-0.036***
					[0.014]
DGVC × Manual					-0.005
					[0.018]
INDGVC ×Manual					0.018
					[0.018]
Constant	6.088***	6.092***	6.092***	5.922***	5.960***
	[0.019]	[0.020]	[0.025]	[0.026]	[0.023]
Number of obs.	335,005	335,005	113,921	237,592	237,592
Sector × Prefecture × Year FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-sq.	0.632	0.667	0.581	0.548	0.549

Source: Author's compilation.

Notes: This table reports the results obtained using the OLS estimation. DGVC and INDGVC indicate direct and indirect GVC participation, respectively. ***, **, and * indicate 1%, 5%, and 10% levels of statistical significance, respectively. Standard errors clustered by firm are reported in parentheses.