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GVCs, Skill Bias, and Wage Inequality in India

Saloni Khurana

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WPS No. EC-25-77

GVCs, Skill Bias, and Wage Inequality in India*

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Abstract

This paper studies the impact of global value chain (GVC) integration on wage inequality in India from 1999 to 2018, combining individual-level wage data with industry-level GVC indicators from the OECD TiVA database. Using a two-way fixed effects framework, we show that backward linkages, the dominant mode of India's GVC participation, consistently increase wage inequality in urban sectors. A one percentage point rise in backward linkages raises high-skilled wages in urban manufacturing by 0.8%, while reducing wages for low- and medium-skilled workers by 0.9% and 0.6%, respectively, relative to high-skilled wages, thus increasing wage inequality. In urban services, low-skilled wages decline by 1.4% relative to high-skilled counterparts. These effects reflect capital-skill complementarity and task routineness. In contrast, forward linkages are associated with more inclusive wage effects, particularly in labor-intensive manufacturing. We further show that higher domestic value added in exports (DVAX), a measure often omitted in standard GVC analysis is associated with rising wages across all skill groups and declining inequality, helping to explain the wage compression observed in rural and some urban sectors.

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The results show the distributional asymmetries of GVC participation and the role of domestic production depth in shaping labor market outcomes.

JEL Codes: J31, F16, O15

Keywords: GVC, wage inequality, India, skills

1. Introduction

Global trade today is no longer confined to the simple exchange of final goods between nations. A growing share of trade now involves intermediate goods and services that cross borders multiple times before final assembly and consumption. As Feenstra & Hanson (1996) observed, this production fragmentation leads to "double counting" in trade statistics, since both components and finished products, for example, automobile parts and assembled vehicles traded between the United States and Canada are recorded separately. Such measures obscure the actual value added by each country and mask the underlying structure of production that defines global value chains (GVCs).

Participation in GVCs reconfigures the allocation of labor and capital across national boundaries by embedding domestic production into internationally segmented value chains. This structural shift raises distributional concerns, particularly regarding factor rewards. Feenstra & Hanson (1996) shows that the United States increasingly imports intermediate goods at downstream stages of production, which intensifies demand for skilled labor in final processing and raises skill premia. In line with the Heckscher-Ohlin and RicardoViner frameworks, Feenstra (2015) argues that firms in capital-abundant economies, facing higher relative costs for low-skilled labor, outsource labor-intensive tasks such as assembly to labor-abundant economies like China, India and Vietnam, optimizing production across borders.

However, the wage effects of GVC participation in developing countries remain theoretically indeterminate and empirically context dependent. The trade-in-tasks framework developed by Grossman & Rossi-Hansberg (2008) suggests that offshoring can raise demand for low-skilled labor by reallocating routine-intensive tasks to lower-wage economies. However, this mechanism assumes that such tasks are readily executable by the receiving workforce. In practice, as noted by Raei et al. (2019), GVCs frequently involve the transfer of production-specific technology and organizational know-how, which may not be easily absorbed by workers in low-skilled occupations. Moreover, tasks considered low-skilled in advanced economies may still require substantial human capital in developing country settings, limiting their accessibility. As a result, the incidence of wage gains depends not only on the nature of offshored tasks but also on the elasticity of substitution between skill groups and the absorptive capacity of the domestic labor force.

Understanding these effects is particularly important for economies that are actively integrating into global production networks but still exhibit deep internal labor market inequalities. **This paper examines how GVC integration affects wage inequality across sectors and skill levels in India, a country that reflects many of the structural characteristics of other emerging economies, including high labor informality, sectoral heterogeneity, and rapid trade liberalization. We ask whether deeper GVC participation narrows wage gaps by raising demand for low-skilled labor, or whether it amplifies inequality by increasing returns to skilled and capital-complementary.**

Most existing literature focuses narrowly on formal sector employment (e.g.: Sasidharan et al. (2024)), overlooking the large informal segment that characterizes production in many developing countries. Our analysis extends this scope by including all paid employees within industries, both formal and informal. This approach captures a more complete picture of labor market adjustment in GVC-linked sectors. For instance, in labor-intensive industries such as textiles, leather, and footwear, informal wage workers[2] in India constitute over 80 percent of employment and are directly affected by shifts in global demand and outsourcing strategies. By accounting for this broader labor force, the paper provides insights that are directly relevant not only for India but also for other developing economies facing similar structural constraints and integration pathways.

In India, GVC participation has steadily increased since the late 1990s. Between 1998 and 2018, the country's overall GVC participation rose from 24 percent to 32.9 percent. This increase has been primarily driven by stronger backward linkages, with the share of foreign inputs in exports rising from 10.4 percent to 19.9 percent over the same period. However, the evolution of wage inequality has followed a more complex and asymmetric trajectory. Rural wage inequality declined by 7 percentage points between 1999 and 2018, largely due to faster wage growth among low-skilled workers compared to medium- and high-skilled counterparts. In contrast, urban wage inequality initially widened, driven by rising returns to high-skilled labor, and stabilized at levels significantly higher than in the rural sector. Post-2011, this trend reversed, with low-skilled wage growth outpacing that of medium- and high-skilled labor.

[2] Informal wage workers are defined as those paid employees without a written job contract.

This paper explores whether these diverging patterns of wage inequality across skill levels in manufacturing and services[3] can be linked to India's changing position in global production networks. Specifically, it examines whether rising backward GVC participation contributes to wage convergence by altering the relative demand for different categories of labor across sectors.

This paper employs a two-way fixed effects model to estimate the impact of GVC participation on wage inequality, exploiting GVC-variation across industries, and years. The dependent variable is the log of real wages, measured at the individual level. Wage inequality is examined through skill categories defined by occupational classifications. Since wage levels may also influence an industry's integration into global production networks, through mechanisms such as labor cost competitiveness or upgrading decisions, we mitigate potential endogeneity by using the lagged value of industry-level GVC participation as the key explanatory variable. Our analysis distinguishes between two forms of GVC integration: backward linkages, where industries rely on foreign inputs for export production, and forward linkages, where domestic industries supply intermediate goods used in other countries' exports.

We find that GVC participation has no significant impact on rural areas. The most prominent effects appear in urban manufacturing and services, driven largely by backward linkages. This occurs because GVC-integrated firms and the necessary infrastructure are concentrated in urban centers, enabling greater use of imported intermediate inputs and deeper integration into global production networks.

In urban manufacturing, a one percentage point rise in GVC exposure increases wages for high-skilled workers by 0.6 percent, while low-skilled and medium-skilled workers earn 0.7 percent and 0.4 percent less, respectively, relative to high-skilled workers. As expected from theories linking GVC participation to capital-intensive production, we further examined the effects by distinguishing between capital- and labor-intensive sectors. In capital-intensive urban manufacturing, low-skilled workers earn 1.1 percent less and medium skilled workers 0.6 percent less than high-skilled workers. In capital-intensive services, backward linkages reduce low-skilled wages by 1.4 percent relative to high-skilled wages. These effects are consistent

[3] In the agriculture sector, where 90 percent of workers are in low-skilled occupations and 80 percent have low levels of education, the distribution of workers is highly compressed at the lower end of the wage and skill spectrum. Given this limited variation in worker characteristics, it is not possible to meaningfully examine differences in wage inequality within the agriculture sector due to GVC participation.

with skill biased upgrading, where imported technologies and compliance standards increase the demand for skilled labor. In contrast, forward linkages in labor-intensive manufacturing raise wages across the distribution, with gains of 1.7 percent for low-skilled and 1.0 percent for medium-skilled workers.

Next, we examine heterogeneity by employment type to understand how GVC participation affects formal and informal workers differently. Among formal workers, backward linkages increase the skill premium, while forward linkages tend to reduce it. In contrast, informal workers are largely excluded from GVC-related gains. Backward linkages reduce their wages, particularly at the lower end of the skill distribution, and forward linkages yield weak or statistically insignificant effects. Given that these dynamics typically contribute to rising wage inequality, we explored potential moderating factors that could account for the observed declines in average wages.

First, we assess the role of routine task intensity (RTI). Occupations with higher RTI show lower wage returns from GVC participation, especially in urban services, which is consistent with automation and offshore outsourcing substituting routine labor. Second, we consider the impact of domestic value-added in exports (DVAX). Higher DVAX raises wages across all skill levels, with particularly equitable effects observed in urban manufacturing and rural services.

To ensure that our results are not confounded by industry-specific trends over time, we include industry-year fixed effects. The findings remain robust. Additionally, we test the framework using educational attainment as an alternative to occupational skill classification. The results remain broadly consistent, reinforcing the validity of the primary analysis. Finally, to rule out spurious correlations, we conduct placebo tests using low-GVC sectors. If the observed effects were driven by unrelated trends, we would expect significant impacts even in these sectors. However, the absence of statistically significant effects in low-GVC industries confirms that the wage outcomes are indeed attributable to GVC integration.

The literature increasingly links GVC participation with rising wage inequality. The dominant explanation emphasizes SBTC, where exposure to global markets pushes firms to adopt productivity-enhancing, often capital-intensive, technologies that disproportionately reward skilled labor (Feenstra & Hanson 1996; Acemoglu & Autor 2011; Shingal 2015; Carpa & Mart´ınez-Zarzoso 2022). However, some recent literature shows that SBTC does not fully

explain the observed variation across countries and sectors. The nature of task specialization within GVCs matters (Lewandowski et al. 2023). High-income economies typically retain high-value-added roles, such as R&D, branding, and logistics, while lower-income countries undertake low skill, routine activities like assembly or raw material processing (Timmer et al. 2014). This is also explained by the trade-in-tasks model by Grossman & Rossi-Hansberg (2008), showing that the effect of offshoring on domestic wages depends on the task type: offshoring of low-skill tasks can raise wages for unskilled workers in host countries, but upgrading can eventually favor skilled labor, reversing initial gains.

Empirical evidence confirms this heterogeneity. In the United States and Western Europe, increased GVC exposure has raised the relative demand for skilled workers, contributing to labor market polarization (Fays et al. 2023). In contrast, in countries like Vietnam and Thailand, the effects are more mixed. Vietnam's integration through textile and electronics exports initially boosted wages for low-skilled labor, but gains became concentrated among skilled, urban workers as the country moved up the value chain (Kabeer & Trˆan 2006). Thailand experienced a similar duality: while foreign input reliance in manufacturing raised average wages, the benefits accrued disproportionately to male, skilled workers in capital-intensive industries (Korwatanasakul et al. 2020).

Despite a growing body of literature on global value chains, there remains a clear gap in understanding how GVC participation affects wage inequality paid workers in India. Existing work largely focuses on productivity or trade performance (Banga 2016; Chawla & Kumar 2023), or explores firm-level dynamics in organized manufacturing (Sasidharan et al. 2024). These data sources, while valuable, tend to overlook a large segment of the workforce–particularly informal workers–who play a significant role in GVC-linked production but are excluded from official surveys. As a result, the distributional effects of GVCs remain incompletely understood, especially in sectors beyond organized manufacturing.

For example, Sasidharan et al. (2024) use ASI plant-level data to examine the impact of GVC participation on employment and wages in the manufacturing sector. Their findings suggest that GVC integration increases employment for both skilled and unskilled workers, with particularly strong effects for female and unskilled labor. However, they also report a widening wage gap between skilled and unskilled workers, especially in high-technology industries. While informative, such studies cannot capture wage heterogeneity within industries or assess

impacts on informal labor, which constitutes a substantial share of employment in India's GVC-linked sectors.

Our paper addresses these limitations by using nationally representative individual-level data from the National Sample Survey (NSS) and the Periodic Labor Force Survey (PLFS), which include both formal and informal workers across a range of sectors. This allows us to examine how GVC integration affects wage inequality not only between industries but also within them, across different skill groups and employment types.

We link these worker-level datasets with industry-level GVC participation metrics from the OECD Trade in Value Added (TiVA) database. This enables us to assess whether industries more integrated into global production networks exhibit greater wage inequality between low-, medium-, and high-skilled workers. Unlike previous studies that focus narrowly on manufacturing, we examine GVC effects across both manufacturing and services, incorporating industry heterogeneity into the analysis.

In doing so, our paper makes several key contributions to the literature on globalization and labor market inequality. First, it provides the first nationally representative, individual-level analysis of how GVC participation affects wage inequality in India, a rapidly integrating but structurally segmented developing economy. Second, it disaggregates the analysis across formal and informal employment, capital- and labor-intensive sectors, and backward versus forward GVC linkages, offering a comprehensive view of heterogeneity in global integration's effects. Third, it introduces two important moderating channels: routine task intensity (RTI), which captures variation in tasks' susceptibility to offshoring and automation, and domestic value added in exports (DVAX), which reflects the extent to which export value is generated locally rather than through imported inputs.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data sources and variable construction. Section 4 presents descriptive trends. Section 5 outlines the empirical strategy. Section 6 presents the main findings and explores heterogeneity. Section 7 explores two other main channels – RTI, and DVAX – to explain changes in wages. Section 8 concludes and draws implications for labor market policy.

2. Existing Studies

Extensive research has investigated the labor market impacts of GVCs in developed economies, focusing on cross-country analyses and firm-level data. A foundational study by Feenstra &

Hanson (1996) found how offshoring-an integral component of GVCs-contributed to a relative increase in demand for skilled labor in the United States, exacerbating wage inequality. This trend is similarly observed across other advanced economies, However, Gonzalez et al. (2015) argued that the effect of offshoring on wage inequality is contingent upon the nature of the tasks being relocated. Gonzalez et al. (2015) found that while greater backward GVC participation in OECD countries generally correlates with lower overall wage inequality, the nature of offshoring tasks plays a crucial role. Specifically, offshoring low-skilled tasks can help reduce wage inequality by boosting wages for lower-skilled workers, whereas offshoring high-skilled tasks tends to widen the wage gap. This nuanced view aligns with the trade-in-tasks model proposed by Grossman & RossiHansberg (2008), which conceptualizes offshoring acts as a form of labor-augmenting technological change, enhancing productivity and wages for specific workers whose tasks are offshored.

A key driver of rising wage inequality in the context of GVCs is skill-biased technological change. Integration into GVCs incentivizes firms to adopt advanced technologies that bolster productivity but disproportionately increase the demand for high-skilled labor, thereby widening wage gaps (Grossman & Rossi-Hansberg 2008). This phenomenon is further amplified by Foreign Direct Investment (FDI), which facilitates the transfer of advanced technology and capital, primarily benefiting high-skilled workers (Carpa & Mart´ınez-Zarzoso 2022). Additionally, economic upgrading-where countries ascend to higher value-added segments within GVCs tends to favor skilled labor, leaving low-skilled workers concentrated in lower-value roles, which deepens inequality (Lewandowski et al. 2023).

Empirical studies substantiate these mechanisms. Kummritz (2016) showed that increased GVC integration enhances labor productivity across countries, yet these gains are unevenly distributed, often favoring skilled workers and contributing to wage disparities. However, these productivity gains are not uniformly distributed, often disproportionately benefiting skilled workers and contributing to wage disparities. Lee & Yi (2018) extended this analysis by using a multi-country general equilibrium trade model to show that global integration shocks, such as China's entry into the WTO, can increase the skill premium-by 1.8% in China and nearly 1% in the U.S.-thereby widening wage disparities between skilled and unskilled workers.

The hierarchical nature of GVCs further entrenches income disparities. Aguiar de Medeiros & Trebat (2017) emphasized that GVCs concentrate high value-added activities in developed countries, allowing Transnational Corporations (TNCs) to capture significant rents through

intellectual property rights and financial mechanisms, thereby skewing the distribution of value-added in favor of capital and high-skilled labor. This results in a decline in value-added shares for low-skilled labor, particularly in developing countries, where low-skilled labor experienced a 6.3% decline in value-added, contrasting with a 5% increase for high-skilled labor in wealthy nations. Cai et al. (2023) found that an increase in a country's GVC position generally reduces domestic income inequality by increasing the labor share in national income. A 1% increase in GVC position was associated with a 0.22% rise in labor share. However, this reduction in overall inequality is counterbalanced by a simultaneous increase in the wage gap between skilled and unskilled labor, particularly in advanced economies, where the gap widened by 1.96%.

Fays et al. (2023) found that firm-level upstreamness in the Belgian manufacturing sector leads to wage increases, particularly in high-tech and knowledge-intensive sectors, where high-wage workers from developed countries benefit the most. However, significant disparities exist even within these sectors. Workers from developed countries experienced a greater wage-upstreamness elasticity (0.021) compared to those from developing countries (0.020).

Unlike in developed economies, where GVC participation typically exacerbates wage disparities, the effects in developing economies vary significantly, reflecting the diverse economic structures and levels of industrialization. Workers in traded sectors often enjoy higher wages compared to those in non-traded sectors, a phenomenon observed in several developing countries. For instance, in Bangladesh, GVC participation in the garment sector led to wage increases for workers due to heightened labor demand in export sectors (Kabeer & Mahmud 2004). Similar effects were observed in Vietnam, where the participation in GVCs has driven up wages in manufacturing sectors (Kabeer & Trˆan 2006). In Kenya, export-oriented agricultural sectors benefited from GVC participation, resulting in wage premiums for workers in these industries (McCulloch & Ota 2002). In India, workers in the manufacturing sector experienced wage increases due to GVC integration, reflecting the sector's pivotal role in global production networks (Banga 2016).

In Thailand, greater industry integration with GVCs resulted in higher wages and a greater skill premium, particularly in manufacturing sectors where foreign inputs played a significant role. Korwatanasakul et al. (2020) found that GVC participation significantly increased monthly wages, with forward and backward linkages contributing to wage increases by 15.3% and 12.1%, respectively. Moreover, Paweenawat & Liao (2021) reported that higher GVC

participation in Thailand led to an increased skill premium, which widened wage disparities between high-skilled and low-skilled workers (Paweenawat & Liao 2021).

In Malaysia, Abd Rahman et al. (2022) found the exacerbation of wage inequality due to GVC participation, particularly in trade with Transpacific Partnership Agreement (TPPA) countries. The study reported a Theil index of 0.139 for wage inequality among high-skilled workers, compared to lower indices of 0.058 and 0.050 for trade with BRICS and ASEAN countries, respectively. The analysis revealed that the Chinese ethnic group, heavily represented in high-skilled jobs, benefited disproportionately from TPPA trade, with a Theil index of 0.065 compared to 0.059 for Malays and 0.015 for Indians, further highlighting the uneven distribution of GVC-related gains (Abd Rahman et al. 2022).

GVC participation also intersects with issues of gender and regional inequality. In some cases, GVCs offer more inclusive job opportunities for rural, female, and low-skilled workers, potentially mitigating wage inequality. For example, in Thailand, GVC participation was associated with improved labor market outcomes for women and workers in rural areas, partly due to the expansion of manufacturing sectors that employed a significant proportion of female and rural labor (Paweenawat & Liao 2021). However, this positive impact is not uniform across all sectors or regions. Some studies have stressed that GVC participation can reinforce existing gender and regional disparities, particularly when high-wage jobs are concentrated in urban areas or in sectors traditionally dominated by men (Korwatanasakul et al. 2020).

The long-term and short-term effects of GVC participation on wage inequality also differ. Carpa & Mart´ınez-Zarzoso (2022) found that in the long run, backward GVC participation decreased inequality in developing countries by integrating these economies into global production networks. Specifically, a 1 percentage point increase in FVA was associated with a 2-3 percentage point reduction in the Gini coefficient, signaling a decrease in income inequality. However, the short-term effects showed an increase in inequality, as the initial phase of GVC integration often benefited higher-skilled workers and firms with better access to international markets.

In China, Lu et al. (2024) examined the effects of GVC participation on wages, employment, and labor productivity across 31 Chinese provinces from 2012 to 2017. The study found that GVC participation negatively impacted both employment and labor productivity, particularly in backward linkages, with a 1.015% decrease in employment and a 1.073% decrease in labor productivity for every 1% increase in GVC participation. On the other hand, provincial value

chains (PVCs) were found to have a positive effect on employment and labor productivity, suggesting that domestic value chains might mitigate some of the negative impacts of GVCs.

Research on GVCs in India has primarily focused on employment outcomes, often neglecting the nuanced impacts on wage inequality. Recent studies, such as Sasidharan et al. (2024), have made strides by using plant-level data to examine the effects of GVC participation on wage disparities within the manufacturing sector. However, much of the existing literature emphasizes the role of value-added trade and backward linkages in shaping employment patterns, leaving significant gaps in our understanding of how GVC integration affects wage distribution across different segments of the workforce. While Sasidharan et al. (2024) have made a recent attempt to uncover this relationship using a firm-level database, the supply side of workers still remains underexplored. In India, GVC participation contributed to a 12% wage increase in manufacturing sectors, showing the pronounced impact of GVCs in driving wage growth in these industries (Banga 2016).

Gasiorek et al. (2020) demonstrate the substantial role of value-added trade in employment generation in India, noting that export-related jobs nearly doubled from 37.9 million in 1995 to 75.3 million in 2011, accounting for 16% of total employment. Similarly, Banga (2016) focuses on the negative impact of increased backward linkages on employment growth in non-manufacturing industries, though forward linkages were found to have an insignificant effect. These findings suggest that while GVC participation can drive job creation, the quality and distribution of these jobs, particularly in terms of wage outcomes, remain critical areas for further exploration.

Vashisht & Dubey (2019) shifts the focus to the impact of international trade on wage inequality within the Indian manufacturing sector, employing a dynamic panel covering 49 industries from 1989 to 2018. His analysis reveals that trade liberalization, especially import liberalization, has significantly widened wage inequality, with the effects varying depending on the direction of trade. Notably, imports from developed countries are linked to greater wage disparities, while exports to developing countries tend to reduce inequality by increasing demand for unskilled labor. These insights underscore the complex relationship between GVC participation and wage dynamics, suggesting that the benefits of GVC integration are not evenly distributed across all segments of the workforce.

Building on these findings, Lewandowski et al. (2023) provide a broader perspective by examining the role of GVCs in shaping worker tasks and wage inequality across 47 countries

at different stages of development. Their study emphasizes the importance of RTI in moderating the impact of GVC participation on wage inequality. Interestingly, their results indicate that in low and middle-income countries, GVC participation may actually decrease wage inequality, a phenomenon not universally observed in more developed economies. This points to the need for context-specific analysis when examining the effects of GVC integration on wage outcomes.

Despite the growing body of research, there remains a paucity of studies that directly address the impact of GVC participation on wage inequality at the worker level in India. Most existing studies rely on firm level data, which may overlook the differential effects on various segments of the workforce. For instance, Sasidharan et al. (2024) used plant-level data from the Annual Survey of Industries (ASI) to explore how GVC participation influences employment and wage inequality in the Indian manufacturing sector. They found that GVC integration significantly boosts employment for both skilled and unskilled workers, with more pronounced effects on unskilled and female workers. However, the wage gap between skilled and unskilled workers has widened, particularly in high-tech sectors, suggesting that GVC participation may exacerbate existing wage inequalities. Our paper seeks to fill this gap by employing individual-level data to examine the impact of GVC participation on wage inequality in various sectors of India.

Very few studies have directly examined wages, and those that have primarily focused on the manufacturing sector, often overlooking other key industries. Our paper addresses these gaps by analyzing wage inequality from the worker's perspective across a diverse range of industries. By incorporating sectoral classifications with industry-level heterogeneity, we provide a nuanced understanding of how GVC integration impacts wages in various sectors beyond manufacturing. Furthermore, we investigate capital-skill complementarity to examine how the interplay between capital intensity and skill levels influences wage disparities.

Using RTI at the occupation level, we explore how the routineness of tasks mediates the relationship between GVC integration and wage inequality.

3. Data

3.1 Wage Inequality

The analysis uses wage data sourced from the National Sample Survey Employment and Unemployment Survey (NSS EUS) for the years 1999-2000, 2004-2005, 2007-2008, 2009-

2010, and 2011-2012, as well as the Periodic Labor Force Survey (PLFS) rounds for 2017-2018 and 2018-2019. These are referred to as the 1999, 2004, 2007, 2009, 2011, 2017, and 2018 datasets. The NSS and PLFS datasets offer detailed data on workers, including variables such as age, education, employment status, wages, industry affiliation, and occupation. However, they do not include information on employer characteristics. The data is repeated cross-sectional in nature, meaning that the individuals surveyed in each round are different, and no longitudinal tracking of workers is conducted. The sample is restricted to the working-age population, defined as individuals aged 15 to 59 years. All paid workers, including casual and salaried employees based on daily status, are considered in the analysis. Wages are winsorized at the top and bottom 1%.

The data provide occupational information for each worker based on National Classification of Occupations (NCO) codes, which are mapped to the International Standard Classification of Occupations (ISCO) to ensure consistency in skill categorization. In our analysis, we classify workers in major groups 1, 2, and 3 as high skilled (managers, professionals, and technicians), groups 4, 5, 7, and 8 as medium-skilled (clerical support, service and sales workers, craft and related trades workers, and plant and machine operators), and groups 6 and 9 as low-skilled (skilled agricultural workers and those in elementary occupations). This occupational classification is used to analyze wage inequality by comparing how wages differ across low-, medium-, and high-skilled workers[4].

3.2 GVC exposure

GVC data are sourced from the Trade in Value Added (TiVA) database (2021), which provides a detailed decomposition of gross exports into domestic value-added (DVA), foreign value-added (FVA), and double counted components across 45 industries, disaggregated by exporting industry and country. Covering 45 industries, TiVA captures both forward and backward linkages in GVCs, providing a comprehensive view of value creation across stages of production. The decomposition methodology, based on Borin & Mancini (2019), ensures consistency by aligning sectoral value-added with the total GDP embodied in a country's exports. This approach accounts for intermediate goods that cross borders multiple times, preventing overestimation of export value by appropriately

[4] Given the industrial structure, where over 90 percent of employment in sectors such as mining and agriculture consists of low-skilled workers, these sectors are excluded from the primary scope of our analysis. Our objective is to examine wage inequality across low-, medium-, and high-skilled workers, which requires sufficient occupational heterogeneity within sectors. The limited variation in skill levels and wage dispersion in mining and agriculture constrains our ability to identify meaningful differences in wage outcomes across skill groups.

classifying value-added at different stages and identifying double counted components. For instance, when a product is processed by one industry and subsequently re-exported by another, its value is treated as 'value-added' during the initial export and 'double-counted' upon re-export. This methodology preserves additivity across sectors and bilateral trade flows, enabling accurate aggregation of value-added components by industry and trade partners. Consequently, the refined approach offers granular insight into how industries and countries contribute to GVCs, supporting a more precise analysis of value distribution across international production networks.

The framework developed by Borin & Mancini (2019) improves upon earlier methodologies, including the Vertical Specialization index by Hummels et al. (2001) and the decomposition by Koopman et al. (2014). Although these earlier approaches advanced the measurement of backward linkages by quantifying the foreign content of exports, they fell short in addressing forward linkages-where domestic intermediates are incorporated into other countries' exports-and in accounting for double counting, which arises from multiple cross-border movements of intermediate goods. Unlike previous methods, Borin & Mancini (2019) decompose gross exports into four distinct components: domestic value-added, domestic double-counted, foreign value-added, and foreign double-counted, ensuring consistent additivity across sectors and bilateral trade partners. This decomposition yields a comprehensive measure of GVC participation by accurately capturing forward linkages (domestic value embedded in foreign re-exports) and backward linkages (foreign intermediates in domestic exports), while mitigating overestimation due to repeated cross-border flows.

The 45 industries from the TiVA (2021) database are mapped to the National Industrial Classification (NIC) codes used in the NSS and PLFS datasets. TiVA industries adhere to the International Standard Industrial Classification of All Economic Activities, Revision 4 (ISIC Rev. 4), which aligns with the NIC 2008 classification. Since the employment data in NSS and PLFS is reported at various NIC levels, crosswalks between NIC 2008, NIC 2004, and NIC 1998 are applied to ensure consistency across classification systems. The measures of backward linkage, forward linkage, and GVC participation rate are defined using the following formulas:

$$BL_{st} = FVA_{st} * 100/GEXP_{st} \dots (1)$$

$$FL_{st} = (DVA_{st} - DAVAX_{st}) * 100/GEXP_{st} \dots (2)$$

$$GVC\ Participation_{st} = BL_{st} + FL_{st} \dots (3)$$

Here, s represents industry, t represents year, BL denotes backward linkage, FL represents forward linkage, DVA refers to domestic value-added, FVA stands for foreign value-added, and DAVAX represents DVA consumed in a foreign country. These metrics collectively capture the extent of GVC integration by measuring the foreign content in exports (backward linkage) and the domestic content embedded in other countries' exports (forward linkage).

4. Background

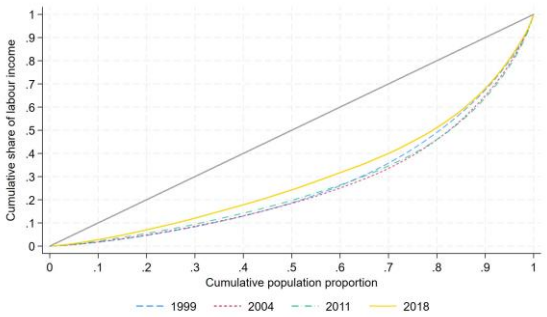
4.1 Stylized Facts: Wage Inequality in India

Figure 1 shows the Lorenz curves depicting wage inequality, with a noticeable shift towards the 45-degree equality line over time, particularly by 2018 (Panel (a)), indicating a substantial reduction in wage inequality between 1999 and 2018[5]. Panel (b) illustrates the trajectories of wage inequality in India's manufacturing and services sectors over the period 1999 to 2018. In manufacturing, the Gini index declined markedly from 43.9 in 1999 to 34.5 in 2018, with the most substantial reduction occurring after 2009. This sustained signals structural changes within the sector. In contrast, the services sector maintained persistently higher levels of wage inequality throughout the period. Inequality peaked at 48.7 in 2009 before declining to 40.8 in 2018, representing a net reduction of 5.1 percentage points. However, the decline in services was less pronounced and less consistent than in manufacturing. These trends align with the wage growth patterns shown in Figure A.1 of the Appendix. In rural areas, particularly after 2009, low-skilled workers experienced faster wage growth than high-skilled workers, contributing to a narrowing wage gap. In contrast, the urban sector saw a reversal in wage growth patterns only after 2011, when low-skilled wages began rising more rapidly than high-skilled wages, following a decade of widening inequality, helping to explain the persistent but moderating disparities observed in urban services.

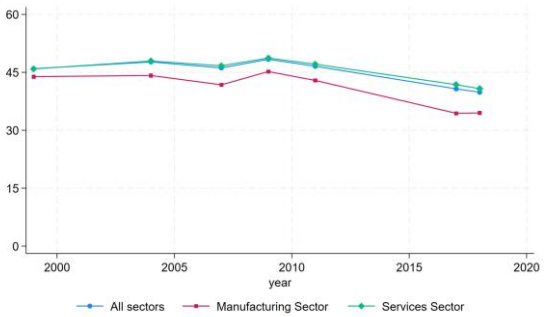
[5] While our findings show a decline in wage inequality, other studies, such as Bharti *et al.* (2024), attribute the rise in overall inequality to increasing wealth concentration, with the top 1% holding 40.1% of total wealth. This analysis focuses exclusively on wage inequality.

Fig. 1 Wage Inequality (1999–2018)

(a) Lorenz Curve



(b) Gini Coefficient



Notes: This comprises data from India's manufacturing and services sectors for the years 1999, 2004, 2007, 2009, 2011, 2017, and 2018.
Source:Authors' calculations based on NSS and PLFS database.

Table 1 shows substantial wage disparities across rural and urban areas, sectors, and skill levels, with the clearest evidence of wage inequality concentrated in urban manufacturing and services. On average, urban workers earn significantly more than rural workers. The average wage in urban services (Rs 601) is approximately 1.3 times higher than in urban manufacturing (Rs 449) and about 1.7 times higher than in rural services (Rs 352). Within both rural and urban contexts, services command a wage premium over manufacturing, by a factor of 1.3 in rural areas and roughly 1.3 in urban areas as well.

Skill-based wage gaps are even more pronounced. In urban manufacturing, high-skilled workers earn Rs 1153, which is 4 times the wage of low-skilled workers (Rs 289) and 3.1 times that of medium-skilled workers (Rs 378). In urban services, high-skilled workers earn Rs 1043, which is 3.6 times the wage of low skilled workers (Rs 290) and 2.2 times that of medium-skilled workers (Rs 477). Similar but smaller gaps are observed in rural areas. In rural manufacturing, high-skilled workers earn Rs 606, which is 2.6 times the wage of low-skilled workers (Rs 231) and 2.1 times that of medium-skilled workers (Rs 287). In rural services, high-skilled workers earn Rs 616, which is 2.5 times the wage of low-skilled workers (Rs 245) and 2.0 times that of medium-skilled workers (Rs 313). This indicates wage inequality is most severe in urban manufacturing and services, primarily driven by large skill-based wage differentials. This likely reflects the concentration of high-productivity firms and capital-intensive activities in urban manufacturing and services.

Table 1 Summary Statistics: Average Wages of Workers

	(1) Rural-Manu	(2) Rural-Serv	(3) Urban-Manu	(4) Urban-Serv
Wages	268.036	352.298	449.332	601.399
	(200.1)	(303.1)	(432.3)	(555.4)
Low-Skilled workers	231.400	244.648	289.463	289.796
	(129.7)	(133.1)	(193.4)	(215.7)
Medium-Skilled workers	263.978	339.661	377.994	476.839
	(182.9)	(257.8)	(290.1)	(382.4)
High-Skilled workers	606.429	616.418	1152.532	1043.324
	(442.9)	(470.3)	(712.2)	(699.3)
Low-Educated workers	202.974	236.407	264.762	278.810
	(115.2)	(136.7)	(163.5)	(193.3)
Medium-Educated workers	290.673	356.640	390.661	467.630
	(182.4)	(270.9)	(287.8)	(369.3)
High-Educated workers	535.415	674.761	932.000	1025.401
	(370.7)	(460.2)	(659.8)	(669.3)
Observations	25209	136268	45118	179363

Notes: Average wages of paid workers in the manufacturing and service sector are provided in the table with their standard deviation in parentheses.

Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017 and 2018.

4.2 Stylized Facts: GVC Involvement of India

Figure 2a presents India's participation in GVC, disaggregated into backward and forward linkages as a share of total exports. Between 1998 and 2018, India's GVC participation grew moderately, increasing from 24% to 32.90%, largely driven by the expansion of backward linkages, which rose from 10.42% to 19.92%, while forward linkages remained stable around 12.9%. This trend is further illustrated in Figure 2b, where backward and forward linkages are indexed at 100 in 1998. Forward linkages experienced a modest increase of approximately 10% until 2008, after which they plateaued, remaining at levels comparable to 1998. In contrast, backward linkages nearly doubled by 2008, reflecting the era of 'hyper-globalization', followed by a slight decline in 2009 due to the subprime crisis (Chawla & Kumar 2023). Post-crisis, backward participation surged, peaking in 2012 at nearly 2.5 times its 1998 level before declining until 2016. Comparatively, during this period, Asian economies such as Viet Nam, the Republic of Korea, the Philippines, and Taipei, China, achieved notable improvements in GVC participation. India, however, experienced a relative decline, attributed to rigid labor markets, a preference for domestic demand over export-driven growth, lower quality standards,

and challenges in FDI attraction (Banga 2022). More recently, there has been a slight resurgence in India's backward participation rate.

Table 2 presents summary statistics for GVC participation and wage variables. GVC exposure is highest in the manufacturing sector, where backward linkages (BL) dominate, reflecting the sector's reliance on foreign inputs. While, the services sector exhibits a mix of both BL and FL, indicating its dual role in global production networks, integrating foreign inputs while also contributing to downstream activities.

Figure 3 shows backward (Panel a) and forward (Panel b) linkages across 45 industries from 1998 to 2018. In agriculture and forestry, domestic value-added has remained dominant, accounting for nearly 80% of exports. In manufacturing, GVC participation has been more prominent, particularly in sectors such as coke and refined petroleum products, which exhibited the highest GVC participation at 69% in 2018, driven by a sharp increase in backward linkage from 23% to 59%. This reflects India's dependence on crude oil imports, which are refined domestically and exported as petroleum products, generating $86.28 billion in FY 2023 and making India the world's second-largest petroleum exporter[6]. Other manufacturing industries, such as basic metals and chemicals, also showed significant GVC participation, with over 50% of their exports reliant on backward linkages. However, the slower growth of India's manufacturing sector and its limited ability to fully capitalize on Free Trade Agreements (FTAs) have constrained deeper integration into GVCs. Increased imports of finished goods and slower domestic skill development have further limited the sector's ability to enhance its GVC role. These challenges have coincided with global trade deceleration and a declining trend in GVCs as many countries move toward localized production due to economic uncertainties and geopolitical tensions, further impacting India's potential to expand its GVC presence.

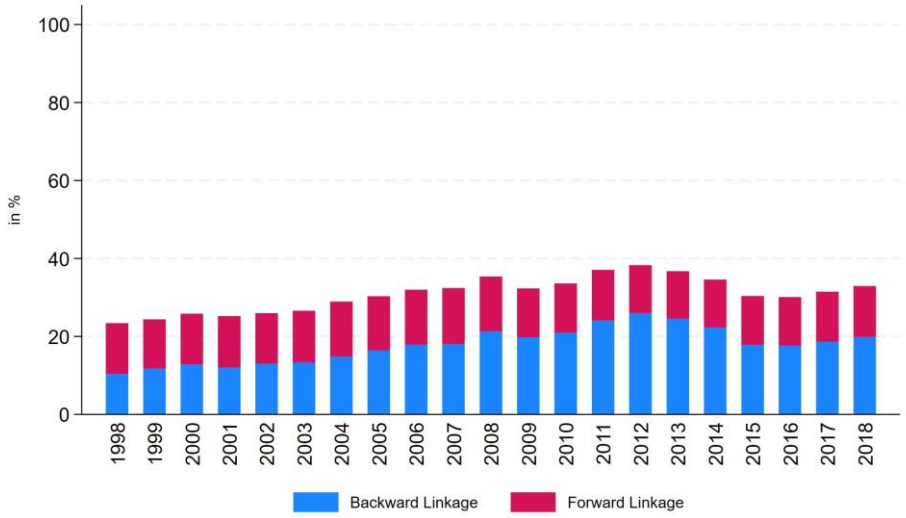
In the service sector, GVC participation remains lower, with industries such as education and arts, entertainment, and recreation reporting participation rates of just 5% and 10% in 2018, respectively. However, water transport stands out, with 44% GVC participation, split between 27% backward linkage and 17% forward linkage, highlighting India's strategic role in global maritime logistics. Additionally, India's IT and business process outsourcing (BPO) sectors play a central role in service-oriented GVCs, contributing significantly through the export of software development, data processing, and technical support. These industries enable global

[6] https://www.nbr.org/publication/oil-for-india/

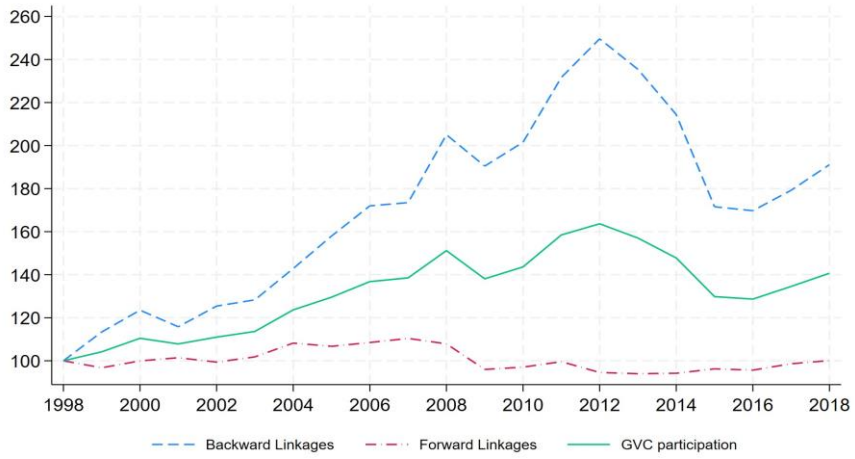
companies like Microsoft and IBM to function efficiently, underscoring the importance of human capital and digital capabilities in India's integration into global markets.

Fig. 2 Patterns of GVC-related trade from 1998 to 2018

(a) Share of backward and forward linkages in exports



(b) Indexed backward linkages, forward linkages, and GVC participation to 1999.



Source: TiVA (2021)

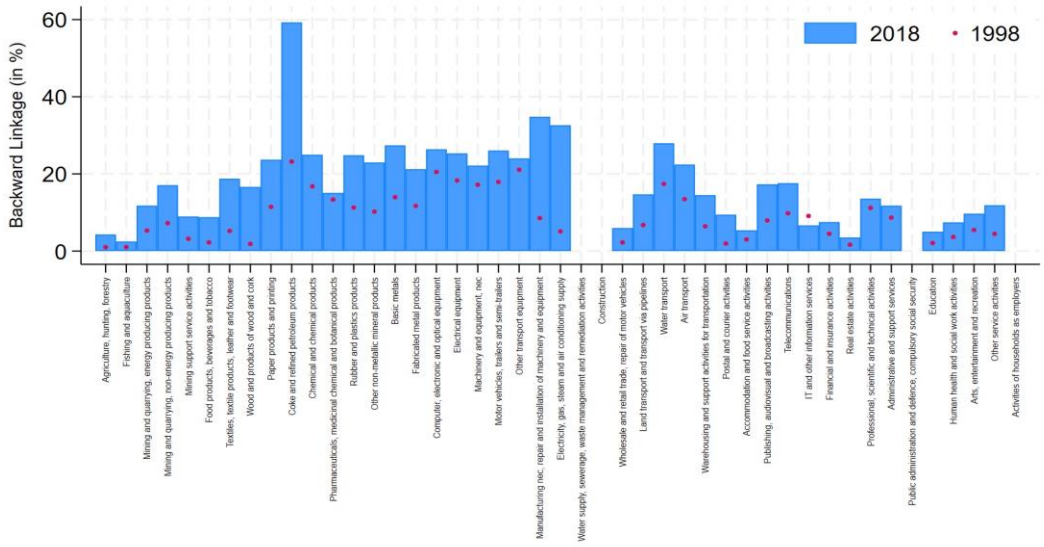
Table 2 Summary Statistics- GVC-related Variables

	(1) Manufacturing	(2) Services
GVC	28.579	9.795
	(9.981)	(11.99)
BL	17.675	4.541
	(8.441)	(5.486)
FL	10.904	5.255
	(4.568)	(7.686)
DVAX	82.068	50.111
	(8.504)	(45.66)
Observations	70327	315631

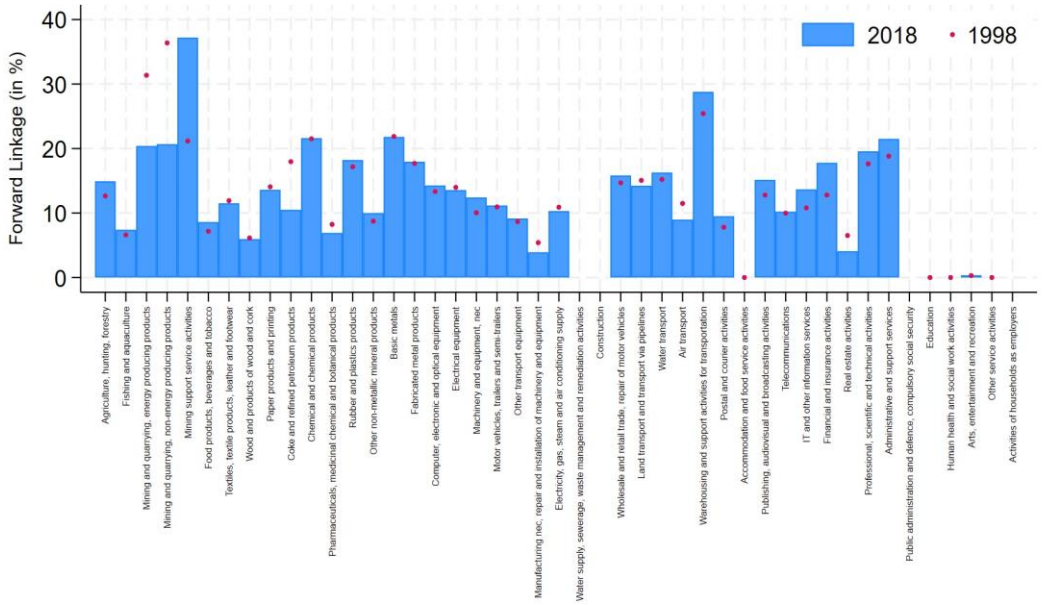
Notes: Average GVC-related trade variables by different categories are provided in the table with their standard deviation in parentheses. GVC refers to GVC related trade. BL refers to the Backward Linkage, FL refers to the Forward Linkage, and DVAX refers to the proportion of DVA absorbed abroad.
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017

Fig. 3 Growth in GVC-related trade by Industry, 1998 vs 2018

(a) Backward Linkages



(b) Forward Linkages



Source: TiVA (2021)

5. Empirical Strategy

This analysis focuses on workers employed in industries integrated into GVCs. Specifically, we utilize industry-level GVC participation metrics and link them to individual-level wage data. In doing so, we investigate how GVC integration influences wage inequality in various industries and skill levels. Industries with higher GVC exposure are expected to exhibit differential wage outcomes due to skill-biased technological changes and structural shifts associated with GVC participation.

The empirical strategy employed in this paper involves a two-way fixed effects approach to examine the impact of differential temporal and industrial variation in the growth of GVC on wage inequality. One potential source of endogeneity in this model is reverse causality, where higher wages may lead to increased GVC participation as participation in GVCs often exposes firms and workers to new technologies and practices, enhancing their skills and capabilities (Ndubuisi & Owusu 2022). To address this issue, GVC participation from the previous year is used in the model, as it is less influenced by current wage levels and less subject to endogeneity as suggested by Ebenstein et al. (2014). This approach helps to get an unbiased estimate of the causal effect of GVC participation on wages in the current year. The model is specified as follows:

$$log(W_{ist}) = \beta_0 + \beta_1 * GVCs_{(t-1)} + \beta_2 * LowSkill_{ist} + \beta_3 * MedSkill_{ist} +$$

$$\beta_4 * LowSkill_{ist} * GVC_s(t-1) + \beta_5 * MedSkill_{ist} * GVC_s(t-1) + \beta_6 X_{ist} + \beta_7 S_{st} + D_d + T_t + I_s + \epsilon_{ist} \quad \dots (4)$$

In equation 4, $log(W_{ist})$ represents the log of daily real wage of worker i in industry s in year t; $GVC_s(t-1)$ denotes the GVC participation of industry s in the previous year; $LowSkill_{ist}$ indicates whether the worker is low-skilled, and $MedSkill_{ist}$ indicates whether the worker is medium-skilled, with high-skilled workers serving as the reference group. X_{ist} includes worker-specific characteristics such as age, education, religion, social group, marital status, and gender. S_{st} is a control variable that represents the share of industry s's GSDP in the total GSDP of the state for year t.

The model has district fixed effects (D_d) to account for unobserved heterogeneity in local labor market conditions, infrastructure, and amenities that might differentially impact wages across districts. These include variations in local labor demand and supply, as well as the quality of infrastructure and public services. Year fixed effects (T_t) are included for unobserved factors that vary over time, such as macroeconomic conditions like economic growth, inflation, and unemployment rates. Industry fixed effects (I_s) capture unobserved industry-level factors affecting wages, including industry-specific productivity shocks driven by technological advancements and industry-specific labor demand and skill requirements.

The regression specifications are estimated separately for the rural and urban sector of manufacturing and services. Standard errors are clustered at the industry-year levels to account for potential within-group correlation.

The key coefficients of interest, β_4 and β_5, capture the interaction between the GVC participation and the levels of skills of the workers. β_4 represents the interaction for low-skilled workers, and β_5 for medium skilled workers, with high-skilled workers as the reference group. These interaction terms examine whether GVC participation differentially affects wages between skill groups. A positive coefficient suggests that GVC participation increases the wage premium for a given skill group relative to highly skilled worker, thus reducing wage inequality. While a negative coefficient indicates that GVCs exacerbate wage inequality by reducing wages for lower-skilled workers relative to high-skilled workers.

6. Results

Table 3 shows the estimated effects of GVC participation on wages across sectors in India. The results show a clear asymmetry in how global integration affects different segments of the labor

market. The most pronounced and statistically robust effects are concentrated in urban sectors, particularly manufacturing and services (Column 2 and 4), while rural sectors remain largely unaffected (Column 1 and 3).

In urban manufacturing (Column 2), a 1 percentage point rise in GVC participation is associated with a 0.6 percent increase in daily wages for high-skilled workers. For low- and medium-skilled workers, the corresponding gains are 0.7 and 0.4 percentage points lower, respectively, relative to high-skilled workers. This suggests that firms participating in global production chains disproportionately reward technical and supervisory roles, intensifying the wage hierarchy within the sector. Using average wages from Table 1, high-skilled workers in urban manufacturing earn around Rs 1153 per day, while low-skilled workers earn roughly Rs 289. This gap, amounting to Rs 864, reflects a large baseline disparity. The estimated coefficients imply that a 1 percentage point increase in GVC reduces the relative wage of low-skilled workers by about 0.7 percent, narrowing the gap slightly. In absolute terms, the gap falls by just Rs 2, from Rs 864 to approximately Rs 862. The overall effect on wage inequality is directionally progressive, but quantitatively limited.

A similar, though more regressive, pattern emerges in urban services (Column 4). Although the coefficient on GVC for high-skilled workers is not statistically distinguishable from zero, low- and medium-skilled workers earn 0.7 and 0.5 percent less, respectively, relative to high-skilled workers following a 1 percentage point increase in GVC participation. Here, the wage structure is already polarized. High-skilled workers earn about Rs 1043 per day, compared to Rs 290 for low-skilled workers. A differential of Rs 753 at baseline means that any further erosion in the relative position of low-skilled workers reinforces existing disparities. In this context, GVC participation in services appears to displace routine tasks, while offering no measurable gains to low-skilled labor. The result is a widening of inequality through compression at the lower end of the distribution rather than expansion at the top.

By contrast, rural sectors remain weakly connected to global production systems, and the estimated effects are either statistically insignificant or small in magnitude. In rural manufacturing (Column 1), the wage effects across skill groups are negligible, suggesting limited transmission of GVC-related gains to local labor markets. In rural services (Column 3), high-skilled workers experience a statistically significant 1.2 percent decline in wages, while low- and medium-skilled workers see no meaningful change. This results in a mild compression of wage differentials, though not enough to imply any substantive redistribution.

This asymmetry is further contextualized by the baseline wage structure reported in Table 1. Urban service middle-skilled workers already earn significantly more than urban manufacturing middle-skilled workers, with average wages in urban services reaching Rs 477 compared to Rs 377 in urban manufacturing. Consequently, even when percentage gains are similar across manufacturing and service sectors, the absolute returns are much larger in urban service areas, especially for middle-skill workers.

These results point to a central conclusion: GVC participation amplifies existing labor market hierarchies. The integration into global production networks tends to reinforce the advantages of skilled labor in urban settings while bypassing large segments of the rural and low-skilled workforce. This finding is consistent with Lewandowski et al. (2023), who show that in developing countries, upgrading within GVCs may eventually shift gains from low-skilled to high-skilled labor, reinforcing skill-based wage disparities. It also complements Vashisht & Dubey (2019), who find that trade liberalization in Indian manufacturing widened wage inequality through rising returns to education and skills.

While GVC participation influences wages overall, its impact may depend on the mode of integration. Sectors linked through backward linkages, by importing foreign inputs, may experience different wage dynamics than those connected through forward linkages, by supplying intermediates for other countries' exports.

Table 3 Effect of GVC Participation on Wage Inequality Across Skill Levels

	Manufacturing		Services	
	Rural	Urban	Rural	Urban
	(1)	(2)	(3)	(4)
Low × GVC	-0.005	-0.007***	0.001	-0.007***
	(0.00)	(0.00)	(0.00)	(0.00)
Medium × GVC	-0.001	-0.004**	0.001	-0.005***
	(0.00)	(0.00)	(0.00)	(0.00)
GVC	0.005	0.006***	-0.012***	-0.004
	(0.00)	(0.00)	(0.00)	(0.00)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
R-Squared	0.576	0.610	0.500	0.604
Clusters	119	119	161	161
Observations	24107	43554	132738	173202

*Notes: The dependent variable is the log of real daily wages. GVC denotes the percentage share of GVC-related trade in gross exports. Low and Medium represent workers with low and medium skill levels, classified based on their occupational categories, with high-skilled workers as the reference group. Control variables include age group, sex, marital status, social group, education, religion, sector categories, and the share of industrial GSDP in state GSDP. The regression also accounts for district fixed effects, year effects, and industry fixed effects. Standard errors (in parentheses) are clustered at the year and industry levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*
Source: Wages and Employment data are from 55th, 61st, 64th, 66th and 68th Employment-Unemployment NSS rounds and 1st and 2nd PLFS rounds. GVC-related trade data is from TiVA (2021) database.

These distinctions matter because they reflect different positions in global production networks and potentially different implications for labor markets. We explore this heterogeneity in the next section.

6.1 Heterogeneity by forward and backward linkages

To understand whether the nature of GVC integration matters for wage inequality, Table 4 distinguishes between backward linkages (BL), where industries rely on foreign inputs, and forward linkages (FL), where industries supply intermediate goods for other countries' exports. These two forms of integration represent distinct positions in global production networks, with different implications for labor demand and skill use. The expectation is that backward linkages, which often require adapting to imported technologies and more advanced inputs, would create greater demand for skilled labor, whereas forward linkages may reflect lower value-added activities with more limited skill differentiation.

The results largely confirm this expectation. In both urban manufacturing and urban services, backward linkages are strongly associated with rising wage inequality. A one percentage point increase in backward linkages raises wages for high-skilled workers in urban manufacturing by 0.8 percent, while low- and medium skilled workers earn 0.9 and 0.6 percent less, respectively, relative to high-skilled workers. In urban services, backward linkages are linked to a 1.4 percent decline in wages for low-skilled workers and a 0.6 percent decline for medium-skilled workers, with no significant change for the high-skilled. These patterns reinforce earlier findings in Table 3 and show that sectors integrated through imported inputs tend to favor more skilled workers, likely due to their ability to complement foreign capital, adapt to global quality standards, and manage technologically complex tasks. This is aligned with the capital-skill complementarity thesis explored by Sasidharan et al. (2024) in the Indian context, where backward GVC integration disproportionately benefits high-skilled formal workers in high-

tech industries. It also echoes Carpa & Mart´ınez-Zarzoso (2022) who show that the short-run effects of backward GVC integration may exacerbate inequality in developing economies.

In contrast, forward linkages do not exhibit significant or consistent effects across sectors. Most coefficients are small and statistically insignificant, indicating limited impact on wage structures. The only notable exception is a 0.5 percent wage decline for medium-skilled workers in urban services, relative to high-skilled workers. This further shows that forward integration plays a weaker role in shaping wage outcomes. Importantly, these findings gain greater relevance in light of the broader trend: India's GVC participation has grown primarily through backward linkages, which have increased steadily over the past two decades.

The role of micro, small and medium enterprises (MSMEs) in the economic and social development of India is well established. As per the NSSO survey 2015-16, the total number of MSMEs in India are around 6.30 crore (which is 98.50% of all the industrial units in India) employing over 111 million persons. With almost 51 percent of the MSMEs based in rural areas, the sector contributes towards the economic empowerment and social inclusion of the marginalized through the generation of employment. It is the second largest employer after agriculture. The MSME sector accounts for 45 % of total industrial production, 40% of total exports and contributes 30% of the country's GDP. The figure1.4 shows the trend in growth of MSME exports is in line with the total exports of the country. The MSME exports grew by 4.19% in 2014-15, which declined to -5.85 % in 2015-16. During the same period, total exports also declined from -1.29% to -15.49%. During 2016-17 and 2017-18 there was positive growth in case of both MSME exports and total exports.

Table 4 Effect of GVC Participation on Wage Inequality: Heterogeneity by Backward and Forward Linkages

	Manufacturing		Services	
	(1) Rural	(2) Urban	(3) Rural	(4) Urban
Low × BL	-0.002	-0.009***	-0.001	-0.014***
	(0.00)	(0.00)	(0.01)	(0.00)
Medium × BL	0.001	-0.006***	-0.001	-0.006**
	(0.00)	(0.00)	(0.01)	(0.00)
BL	0.003	0.008***	-0.012**	-0.003
	(0.00)	(0.00)	(0.01)	(0.00)
Low × FL	-0.011	0.001	0.001	-0.002
	(0.01)	(0.00)	(0.00)	(0.00)
Medium × FL	-0.006	0.003	0.002	-0.005**
	(0.01)	(0.00)	(0.00)	(0.00)
FL	0.016	0.002	-0.005	0.002
	(0.01)	(0.01)	(0.01)	(0.01)

District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
R-Squared	0.576	0.611	0.500	0.605
Clusters	119	119	161	161
Observations	24107	43554	132738	173202

*Notes: The dependent variable is the log of real daily wages. GVC denotes the percentage share of GVC-related trade in gross exports. Low and Medium represent workers with low and medium skill levels, classified based on their occupational categories, with high-skilled workers as the reference group. Control variables include age group, sex, marital status, social group, education, religion, sector categories, and the share of industrial GSDP in state GSDP. The regression also accounts for district fixed effects, year effects, and industry fixed effects. Standard errors (in parentheses) are clustered at the year and industry levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*
Source: Wages and Employment data are from 55th, 61st, 64th, 66th and 68th Employment-Unemployment NSS rounds and 1st and 2nd PLFS rounds. GVC-related trade data is from TiVA (2021) database.

6.2 Heterogeneity: Labor and Capital Intensity

To further explore how GVC participation influences wage inequality, we classify industries into labor-intensive and capital-intensive categories. This classification is based on the ratio of total employment (in thousands) to capital stock (Rs. crores, constant 2011–12 prices), using data from the India KLEMS database. Industries with a ratio above 1.2 are identified as labor-intensive, while those below 0.9 are deemed capital-intensive. For industries in the intermediate range (0.9-1.2), classification is based on the dominant factor income share, labor income share indicates labor-intensive, capital income share indicates capital-intensive sectors. Examples include textiles and construction as labor-intensive, and chemicals, machinery, and professional services as capital-intensive (see Appendix Table A.1 for the full classification). Since earlier results (Tables 3 and 4) show that the rural sector is minimally affected by GVC integration, we restrict the analysis here to urban sectors and omit rural results for brevity.

Table 5 Effect of Backward and Forward Linkage on Wage Inequality: Heterogeneity by Labor- and Capital-Intensive Industry in Urban Sector

	Labor Intensive		Capital Intensive	
	(1) Urban Manu	(2) Urban Services	(3) Urban Manu	(4) Urban Services
Low × BL	-0.004	-0.013***	-0.011***	-0.014***
	(0.01)	(0.00)	(0.00)	(0.01)
Medium × BL	-0.008	-0.003	-0.006***	-0.007**
	(0.01)	(0.00)	(0.00)	(0.00)
BL	0.010	-0.003	0.007*	-0.003
	(0.01)	(0.00)	(0.00)	(0.00)
Low × FL	0.017	-0.002	0.006	-0.004
	(0.02)	(0.00)	(0.01)	(0.00)

Medium × FL	0.001	-0.005**	0.005	-0.006**
	(0.02)	(0.00)	(0.00)	(0.00)
FL	0.071***	0.015**	-0.002	-0.008
	(0.02)	(0.01)	(0.01)	(0.01)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
R-Squared	0.535	0.541	0.649	0.611
Clusters	21	77	98	84
Observations	18847	113565	24666	59635

*Notes: The dependent variable is the log of real daily wages. BL and FL denote the percentage share of Backward and Forward Linkage-related trade in gross exports, respectively. Low and Medium represent workers with low and medium skill levels, classified based on their occupational categories, with high-skilled workers as the reference group. Control variables include age group, sex, marital status, social group, religion, sector categories, and the share of industry GSDP in state GSDP. The regression also accounts for district fixed effects, year effects, and industry fixed effects. Standard errors in parentheses are clustered at the state and industry levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Source: Wages and Employment data are from 55th, 61st, 64th, 66th and 68th Employment-Unemployment NSS rounds and 1st and 2nd PLFS rounds. GVC-related trade data is from TiVA (2021) database.*

As shown in Table 5, and consistent with prior findings, the effects of GVC participation are stronger, and more unequal, in capital-intensive urban industries. In manufacturing, backward linkages are associated with a 0.7 percent wage gain for high-skilled workers, while low- and medium-skilled workers see wage declines of 1.1 and 0.6 percent, respectively. This effect is even more pronounced in services, where low-skilled wages fall by 1.4 percent and medium-skilled by 0.7 percent, with high-skilled workers largely unaffected. These results align with the capital-skill complementarity hypothesis, which posits that technological upgrading and GVC integration disproportionately benefit skilled labor in capital-rich sectors. As firms become more globally embedded, high-skilled workers are better positioned to operate complex systems, interface with international markets, and meet global production standards, capturing the majority of wage gains. Similar patterns are observed by Korwatanasakul et al. (2020) in Thailand, where foreign input reliance raised skill premiums in capital-intensive manufacturing. In India, Banga (2016) also reports that backward linkages in capital-intensive industries reduce employment elasticity and shift income gains toward skilled labor.

By contrast, wage effects in labor-intensive urban industries are more balanced. Backward linkages exhibit weaker and largely insignificant effects, while forward linkages show more inclusive patterns, particularly in manufacturing. A one percentage point rise in forward linkages increases wages by 7.1 percent for high-skilled workers but also raises wages for low-

skilled (1.7 percent) and medium-skilled (0.1 percent) workers. This suggests that forward integration can reduce wage inequality when it stimulates broad-based labor demand through downstream services such as logistics and retail. However, this inclusive pattern is less evident in labor-intensive services, where wage gains are concentrated among high-skilled workers and limited for others. Taken together, the results show that GVC participation in capital-intensive sectors intensifies wage inequality, while forward integration in labor-intensive sectors offers a more equitable, though context dependent, distribution of gains.

6.3 Heterogeneity: Formal and Informal Workers

To understand how GVC participation interacts with domestic labor institutions, we examine its differential effects on formal and informal workers in urban sectors. Formal employment is defined by eligibility for Provident Fund (PF) benefits, a standard criterion in India denoting legal protections, contractual security, and greater likelihood of firm-level upgrading. Informal workers, by contrast, lack such protections and are typically concentrated in low-productivity segments with limited access to training or capital. This distinction is analytically important, as the ability to benefit from GVC integration depends not only on skill level or sector, but also on institutional access to the channels through which globalization generates productivity gains.

The results shown in Table 6 show that formal manufacturing workers disproportionately capture the benefits of GVC participation, particularly through backward linkages. A one percentage point increase in backward integration raises wages for high-skilled formal workers by 0.8 percent but reduces wages for low and medium-skilled formal workers by 1.0 and 0.6 percent relative to high-skilled formal workers, respectively. This pattern is consistent with GVCs rewarding tasks that require capital-skill complementarity, such as technology management, compliance, and quality oversight, roles predominantly held by formal high-skilled workers. Informal manufacturing workers, by contrast, experience no wage gains at the top and wage losses at the bottom, reflecting their exclusion from these productivity-enhancing functions. The results suggest that wage inequality in globally integrated manufacturing is driven by dynamics unfolding largely within the formal segment.

Table 6 Effect of Backward and Forward Linkage on Wage Inequality: Heterogeneity by Formal and Informal Worker in Urban Sector

	Formal Worker		Informal Worker	
	(1) Urban Manu	(2) Urban Services	(3) Urban Manu	(4) Urban Services
Low × BL	-0.010***	-0.005	-0.006*	-0.013***
	(0.00)	(0.00)	(0.00)	(0.00)
Medium × BL	-0.006***	-0.005**	-0.005*	-0.007*
	(0.00)	(0.00)	(0.00)	(0.00)
BL	0.008***	-0.002	0.005	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)
Low × FL	0.017***	-0.005**	-0.003	-0.005*
	(0.01)	(0.00)	(0.01)	(0.00)
Medium × FL	0.010***	-0.001	-0.003	-0.009***
	(0.00)	(0.00)	(0.01)	(0.00)
FL	-0.010	-0.014	0.003	0.010
	(0.01)	(0.01)	(0.01)	(0.01)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
R-Squared	0.619	0.422	0.529	0.514
Clusters	102	138	102	138
Observations	10125	58752	18340	56852

*Notes: The dependent variable is the log of real daily wages. BL and FL denote the percentage share of Backward and Forward Linkage-related trade in gross exports, respectively. Low and Medium represent workers with low and medium skill levels, classified based on their occupational categories, with high-skilled workers as the reference group. Control variables include age group, sex, marital status, social group, religion, sector categories, and the share of industry GSDP in state GSDP. The regression also accounts for district fixed effects, year effects, and industry fixed effects. Standard errors in parentheses are clustered at the state and industry levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Source: Wages and Employment data are from 55th, 61st, 64th, 66th and 68th Employment-Unemployment NSS rounds and 1st and 2nd PLFS rounds. GVC-related trade data is from TiVA (2021) database.*

A different pattern emerges in forward-linked integration. In formal manufacturing, forward linkages lead to wage gains across all skill groups, 1.7 percent for low-skilled and 1.0 percent for medium-skilled workers, indicating a more inclusive wage effect. This may reflect the labor-absorbing nature of downstream activities like distribution, logistics, and final-stage assembly, which create formal employment opportunities beyond managerial roles. In services, the effects are weaker but directionally similar: forward linkages raise wages for low-skilled formal workers by 0.5 percent relative to high-skilled workers, while backward linkages have no significant impact. These findings suggest that the structure of GVC engagement matters: backward integration tends to reinforce skill-biased inequality, while forward integration,

especially in labor-intensive segments, can generate broader wage gains, at least where formal labor markets are well developed.

Among informal workers, however, GVC participation delivers limited benefits and, in many cases, worsens wage outcomes. In informal manufacturing and services, backward linkages are consistently associated with wage declines for low- and medium-skilled workers, while high-skilled wages remain unchanged. Forward linkages offer only marginal, statistically insignificant gains for low-skilled workers. This reflects both occupational segmentation and institutional exclusion: informal workers are concentrated in low-value, routine tasks and lack access to the firm-level upgrading or employment protections that mediate GVC gains. As a result, GVC participation, particularly through backward linkages, tends to reinforce, rather than bridge, the dualism of India's urban labor market, disproportionately benefiting formal high-skilled workers while leaving informal labor behind.

7. Discussion

7.1 Impact of Domestic Value Added in Exports

The evidence thus far points to rising wage inequality within globally integrated sectors, particularly in urban manufacturing and services, where GVC participation disproportionately benefits high-skilled workers. However, this sectoral pattern contrasts with the broader trend observed in Figure 1, which shows a steady decline in wage inequality over the study period. This divergence suggests that factors beyond GVC integration are influencing the distribution of wages, and that the net effect of trade on inequality is more complex than the GVC channel alone would imply.

One such factor is the domestic value-added content of exports (DVAX), which captures the share of export value generated through local factor inputs and ultimately absorbed by foreign consumers. Unlike backward or forward GVC linkages, DVAX reflects the extent to which production processes supporting exports are anchored domestically. In the Indian context, the DVAX share is substantial, approximately 80 percent of manufacturing exports and 50 percent of services exports consist of domestically produced value. This high degree of domestic retention implies that a significant portion of export-driven income remains within the domestic economy.

The labor market implications of DVAX differ markedly from those of GVC positioning. While GVC participation often entails specialization in narrowly defined tasks, frequently

favoring capital or skill-intensive functions, high DVAX is typically associated with greater local sourcing, broader participation of domestic firms, and more inclusive use of labor across skill levels. This is especially true in upstream activities such as input production and intermediate goods processing, which tend to be more labor-intensive and geographically dispersed. As a result, export growth driven by increased DVAX is more likely to generate widespread labor demand and diffuse the gains from trade more evenly.

In this framework, DVAX not only reflects deeper domestic integration into trade, but also serves as a transmission mechanism through which trade-related income is distributed across the labor force. Its rise may therefore help explain the observed decline in wage inequality despite the regressive effects of GVC participation in certain sectors. For instance, if a manufacturing firm expands exports by increasing domestic sourcing of inputs, rather than relying on imported intermediates, it creates employment opportunities across a wider range of occupations and regions, including for lower-skilled workers. Similarly, in services, higher domestic content in exports such as software, education, or professional support services can extend the wage benefits of trade to mid- and lower-skill occupations involved in production, delivery, and client management.

Table 7 estimates how changes in the domestic value-added content of exports (DVAX) affect relative wage outcomes across skill groups. In urban manufacturing, the results point to a modest compression in wage inequality. A higher share of domestic value added is associated with lower wages for high-skilled workers (-0.7 percent), while low- and medium-skilled workers experience small but statistically significant gains relative to the high-skilled baseline (0.9 and 0.6 percent, respectively). This stands in contrast to the earlier results on GVC participation in the same sector, where high-skilled workers gained disproportionately, and low-skilled workers earned 0.7 percent less relative to them. The reversal here suggests that when manufacturing export production is more locally embedded, drawing on domestic inputs rather than imported intermediates, wage growth is more evenly distributed. One plausible mechanism is that domestic value retention increases labor demand across a wider range of functions, including upstream inputs, logistics, and low-skill support services, thereby raising relative returns for less-skilled workers.

The pattern in services differs. In both rural and urban services, DVAX is positively associated with high-skilled wages (1.5 and 1.0 percent), while interaction terms for low- and medium-skilled workers are negative (-0.002 to -0.001). This indicates that although DVAX raises the

service sector's wages overall, the gains are concentrated among high-skilled workers, widening the wage gap. This finding aligns with the task structure of tradable services, where value creation is often concentrated in non-routine cognitive, technical, and managerial roles. Compared to the GVC participation effects in services, where backward linkages also increased inequality, DVAX follows a similar direction, but through a different mechanism: domestic value retention amplifies returns to skill rather than purely reflecting foreign input intensity. These sectoral differences imply that the equity effects of deeper integration depend not only on trade intensity but also on how production is organized. When domestic value-added growth is distributed across multiple layers of the supply chain, inequality may fall; when it is captured by specialized high-skill functions, wage differentials are likely to widen.

Table 7 Effect of domestic value-added trade in exports on wage inequality

	Manufacturing		Services	
	(1) Rural	(2) Urban	(3) Rural	(4) Urban
Low × DVAX	0.004	0.009***	-0.002***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
Medium × DVAX	0.000	0.006***	-0.002***	-0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
DVAX	-0.003	-0.007***	0.015***	0.010***
	(0.00)	(0.00)	(0.00)	(0.00)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
R-Squared	0.576	0.611	0.501	0.604
Clusters	119	119	161	161
Observations	24107	43554	132738	173202

*Notes: The dependent variable is the log of real daily wages. DVAX denotes the percentage share of domestic value-added trade in gross exports. Low and Medium represent workers with low and medium skill levels, classified based on their occupational categories, with high-skilled workers as the reference group. Control variables include age group, sex, marital status, social group, religion, sector categories, and the share of industry GSDP in state GSDP. The regression also accounts for district fixed effects, year effects, and industry fixed effects. Standard errors in parentheses are clustered at the industry-year levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*
Source: Wages and Employment data are from 55th, 61st, 64th, 66th and 68th Employment-Unemployment NSS rounds and 1st and 2nd PLFS rounds. Domestic value-added trade data is from TiVA (2021) database.

These patterns reinforce a broader theoretical insight: the nature of trade integration, its depth, composition, and domestic linkages, determines its distributive consequences. While backward-linked GVC participation may yield productivity gains, these are often concentrated in capital-intensive, skill-biased segments. In contrast, higher DVAX reflects greater domestic

embeddedness of manufacturing export activity, which in turn supports more inclusive labor absorption and wage growth. This supports Banga (2016), who argues that higher domestic value retention in exports enhances employment and wage outcomes in India's manufacturing sector, particularly for less skilled labor, by strengthening domestic supply chains and multiplier effects.

7.2 Role of RTI as a Moderator

An increasingly influential strand of the globalization and labor economics literature emphasizes the role of routine task intensity (RTI) in mediating the wage and employment effects of trade and technological change. RTI captures the extent to which occupations consist of repetitive, codifiable tasks that can be easily automated or outsourced. Occupations with high RTI, typically associated with clerical, assembly line, and low-skill service roles, are more substitutable by machines or offshore labor. In contrast, low RTI occupations tend to require non-routine cognitive or interpersonal skills that are harder to replicate or displace. Following Fern´andez-Mac´ıas & Bisello (2022), we compute RTI at the 3-digit ISCO-88 occupation level, allowing for variation in task content across the skill distribution.

This distinction is particularly salient in the context of GVC participation, which fragments production across borders based on task decomposability and cost advantages. In theory, routine-intensive tasks are more mobile and thus more likely to be relocated to developing economies such as India, where labor is abundant and less costly. However, whether this mobility translates into wage compression or employment gains depends on both the nature of the sector and the position within the value chain. RTI, therefore, serves as a critical intermediary variable, potentially shaping not just the direction but also the distribution of GVC-induced wage effects.

Empirical results reported in Table 8 suggest that the moderating role of RTI varies sharply across sectors. In both rural and urban manufacturing, GVC participation continues to favor high-skilled labor, but the interaction with RTI is either statistically insignificant or weakly positive. This implies that the routine content of jobs does not substantially alter the distributional effects of GVCs in manufacturing. One possible explanation lies in the heterogeneous composition of manufacturing in India. While low-end segments engage in labor-intensive, routine assembly, high-end segments, particularly in formal, export-oriented firms, are increasingly capital- and technology-intensive. As a result, technological upgrading

and global integration in manufacturing apply across the task spectrum, muting the relative influence of RTI on wage outcomes.

By contrast, in urban services, RTI plays a more pronounced and economically meaningful role. The interaction between RTI and GVC participation is negative, and RTI itself is strongly associated with lower wages. This suggests that GVC integration in routine-intensive service segments, such as business process outsourcing, data entry, or call center operations, exerts downward pressure on wages, particularly for low skilled workers. These sectors are highly exposed to cost-based competition and automation, with firms increasingly substituting labor through digital technologies or offshoring to lower-cost environments. This is consistent with Lewandowski et al. (2023), who demonstrate that the routine intensity of tasks moderates GVC effects in developing countries, where high-RTI sectors face wage stagnation due to limited upgrading potential. The findings reflect a broader structural vulnerability of routine service employment in globally integrated settings. Unlike manufacturing, where upgrading can generate complementary demand for local labor, service sectors characterized by high RTI are more prone to displacement rather than diffusion of gains. Consequently, GVC participation in these areas exacerbates wage inequality, not by skewing returns upward, but by eroding the wage floor.

Table 8 Effect of GVC on Wage Inequality: Role of RTI as a Moderator

	Manufacturing		Services	
	(1) Rural	(2) Urban	(3) Rural	(4) Urban
Low × GVC	-0.009**	-0.006**	0.001	-0.006***
	(0.00)	(0.00)	(0.00)	(0.00)
Medium × GVC	-0.003	-0.003*	0.001	-0.005***
	(0.00)	(0.00)	(0.00)	(0.00)
GVC	0.005	0.006***	-0.013***	-0.004*
	(0.00)	(0.00)	(0.00)	(0.00)
Country RTI ISCO-88 (3-digit)	-0.060	-0.019	-0.055**	-0.125***
	(0.04)	(0.03)	(0.03)	(0.03)
Country RTI ISCO-88 (3-digit) × GVC	0.002*	-0.000	0.000	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
R-Squared	0.576	0.611	0.501	0.607
Clusters	119	119	161	161
Observations	24106	43553	132704	173192

*Notes: The dependent variable is the log of real daily wages. GVC denotes the percentage share of GVC-related trade in gross exports. Low and Medium represent workers with low and medium skill levels, classified based on their occupational categories, with high-skilled workers as the reference group. Control variables include age group, sex, marital status, social group, education, religion, sector categories, and the share of industrial GSDP in state GSDP. The regression also accounts for district fixed effects, year effects, and industry fixed effects. Standard errors (in parentheses) are clustered at the year and industry levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.*
Source: Wages and Employment data are from 55th, 61st, 64th, 66th and 68th Employment-Unemployment NSS rounds and 1st and 2nd PLFS rounds. GVC-related trade data is from TiVA (2021) database.

7.3 Robustness

To strengthen our findings, we do a series of robustness checks that address three core identification concerns: unobserved sector-specific heterogeneity, potential mis-classification of skill, and spurious correlation arising from structural wage dynamics unrelated to GVC integration. These exercises are designed not only to test the sensitivity of our estimates but also to clarify the economic mechanisms through which GVCs shape wage inequality. Across specifications, the results remain consistent with our core conclusion: GVC participation disproportionately raises wages for high-skilled workers, reinforcing wage differentials in globally integrated sectors.

Our first robustness exercise introduces industry-by-year fixed effects to absorb unobserved, time-varying shocks that may influence wage structures independently of GVC participation. These could include changes in domestic industrial policy, sector-specific technological adoption, or fluctuations in global demand unrelated to the value chain position. By conditioning on these shocks, we isolate the component of wage variation attributable to differential GVC exposure across skill groups. As shown in Table 9, the main inequality patterns persist, especially in urban manufacturing and services, where global integration is deepest. The only attenuation appears in rural services, where coefficients shrink and lose precision, likely reflecting the low intensity and indirect nature of GVC exposure in fragmented rural labor markets. This specification helps rule out omitted variable bias from unobserved sector-level dynamics, reinforcing that the wage effects we observe are not driven by extraneous macro shocks.

Table 9 Robustness: Effect of GVC on wage inequality (including industry-year fixed effects)

	Manufacturing		Services	
	(1)	(2)	(3)	(4)

	Rural	Urban	Rural	Urban
Low × GVC	-0.005*	-0.007***	-0.000	-0.007***
	(0.00)	(0.00)	(0.00)	(0.00)
Medium × GVC	-0.002	-0.004**	-0.001	-0.005***
	(0.00)	(0.00)	(0.00)	(0.00)
District FE	✓	✓	✓	✓
Industry-Year FE	✓	✓	✓	✓
wave	✓	✓	✓	✓
R-Squared	0.582	0.615	0.506	0.608
Clusters	119	119	160	161
Observations	24107	43554	132737	173202

*Notes: The dependent variable is the log of real daily wages. GVC refers to the percentage share of GVC-related trade in gross exports. Other controls include age-group, sex, marital status, social group, religion, sector categories, and share of industrial GSDP in state GSDP. Standard errors in parentheses are clustered at industry-year level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.*
Source: Wages and Employment data are from the 55th, 61st, 64th, 66th, and 68th Employment-Unemployment NSS rounds, and the 1st and 2nd PLFS rounds. GVC-related trade data is from the TiVA (2021) database.

Second, we test the robustness of our results to alternative measures of skill, substituting educational attainment for occupation-based classification. This addresses a common concern in labor economics: that occupation may proxy for firm or industry affiliation rather than underlying human capital, while education may fail to capture actual job content or task complexity. Table 10 shows that although the magnitude of inequality effects weakens slightly under the education-based approach, the direction and statistical significance remain consistent. This attenuation is expected, education levels provide a coarse proxy for productivity, particularly in developing economies where over-qualification, underemployment, and informal credentials blur the mapping between schooling and labor market outcomes. Nevertheless, the persistence of results confirms that our estimates are not an artifact of classification method, but reflect substantive differences in how workers are rewarded in GVC-integrated sectors.

Third, we implement a placebo test on low-GVC sectors, defined as those at or below the median level of global integration. This exercise targets the possibility that observed inequality effects are generated not by GVC participation per se, but by sector-specific wage structures or long-run shifts unrelated to trade. If our estimates were capturing a generic structural transformation or endogenous sorting of workers across industries, we would expect similar patterns in low-GVC sectors. Yet as reported in Table 11, the interaction terms between GVC exposure and skill levels in these sectors are small, imprecise, and statistically insignificant.

This null result serves as a falsification test: it rules out mechanical correlations between skill and wages unrelated to trade exposure and strengthens the claim that GVC participation is the relevant treatment driving observed inequality.

Table 10 Robustness: Effect of GVC on wage inequality (changing measurement of wage inequality)

	Manufacturing		Services	
	(1) Rural	(2) Urban	(3) Rural	(4) Urban
Low × GVC	0.001	-0.005***	0.004*	-0.006***
	(0.00)	(0.00)	(0.00)	(0.00)
Medium × GVC	-0.001	-0.005***	0.004**	-0.005***
	(0.00)	(0.00)	(0.00)	(0.00)
GVC	0.003	0.006***	-0.013***	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
R-Squared	0.566	0.574	0.493	0.588
Clusters	119	119	161	161
Observations	24188	43681	133796	174257

*Notes: The dependent variable is the log of real daily wages. GVC refers to the percentage share of GVC-related trade in gross exports. Other controls include age-group, sex, marital status, social group, religion, sector categories, and share of industrial GSDP in state GSDP. Standard errors in parentheses are clustered at the industry-year level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.*
Source: Wages and Employment data are from the 55th, 61st, 64th, 66th, and 68th Employment-Unemployment NSS rounds, and the 1st and 2nd PLFS rounds. GVC-related trade data is from the TiVA (2021) database.

Table 11 Placebo: Effect of GVC on wage inequality in Low GVC engaged sector

	Urban Manu (1)	Urban Services (2)
	(0.04)	(0.01)
Low × GVC	0.003	-0.006
	(0.02)	(0.01)
Medium × GVC	-0.002	0.000
	(0.02)	(0.00)
GVC	-0.049	-0.004
District FE	✓	✓
Year FE	✓	✓
Industry FE	✓	✓
R-Squared	0.649	0.601
Clusters	10	73
Observations	5016	109607

Notes: The dependent variable is the log of real daily wages. GVC refers to the percentage share of GVC-related trade in gross exports. Other controls include age-group, sex, marital status, social group, religion,

*sector categories, and share of industrial GSDP in state GSDP. Standard errors in parentheses are clustered at the industry-year level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.*
Source: Wages and Employment data are from the 55th, 61st, 64th, 66th, and 68th Employment-Unemployment NSS rounds, and the 1st and 2nd PLFS rounds. GVC-related trade data is from the TiVA (2021) database.

8. Conclusion

This paper studies how GVC participation affects wage inequality in India using nationally representative worker-level data linked with sector-level trade metrics. The analysis shows that GVC integration raises the relative wages of high-skilled workers, particularly in urban manufacturing and capital-intensive services. In urban manufacturing, a one percentage point increase in GVC exposure is associated with a 0.6 percent increase in wages for high-skilled workers, while low- and medium-skilled workers earn 0.7 percent and 0.4 percent less, respectively, relative to high-skilled workers. In urban services, the distribution is even more skewed, with low-skilled workers earning 1.4 percent less. These patterns are consistent with skill biased effects of trade and technology, where global engagement raises demand for non-routine, capital complementary labor.

To assess whether certain structural conditions moderate these effects, the paper examines two mechanisms: domestic value-added in exports (DVAX) and routine task intensity (RTI). DVAX measures the extent to which export value is produced within the local economy. Where DVAX is higher, such as in urban manufacturing and rural services, wage gains are more equally distributed across skill groups. This suggests that deeper domestic production linkages can reduce the inequality associated with global integration. RTI captures task-level exposure to automation and offshoring. In urban services, where many occupations are routine-intensive, GVC participation is associated with lower relative wages for these jobs. This indicates that task structure shapes how workers are positioned within global production.

These findings suggest that wage inequality under GVC participation is not only a function of trade exposure but of how production is organized and who is employed in globally connected sectors. Inequality tends to rise when integration is capital-intensive and routine-based but falls when production is more embedded domestically and spreads across a broader range of tasks. Policy efforts that promote domestic value creation, support upgrading of task content, and expand access to informal employment could improve the distributional outcomes of global integration.

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Appendix

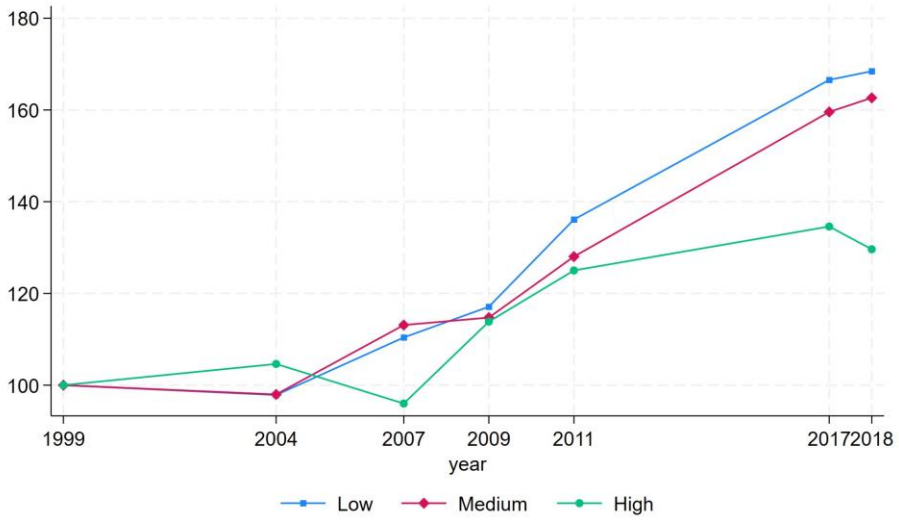
Table A.1 Classification of Industries by Capital and Labor Intensity

Capital-Intensive Industries	Labor-Intensive Industries
Food products, beverages and tobacco	Textiles, textile products, leather and footwear

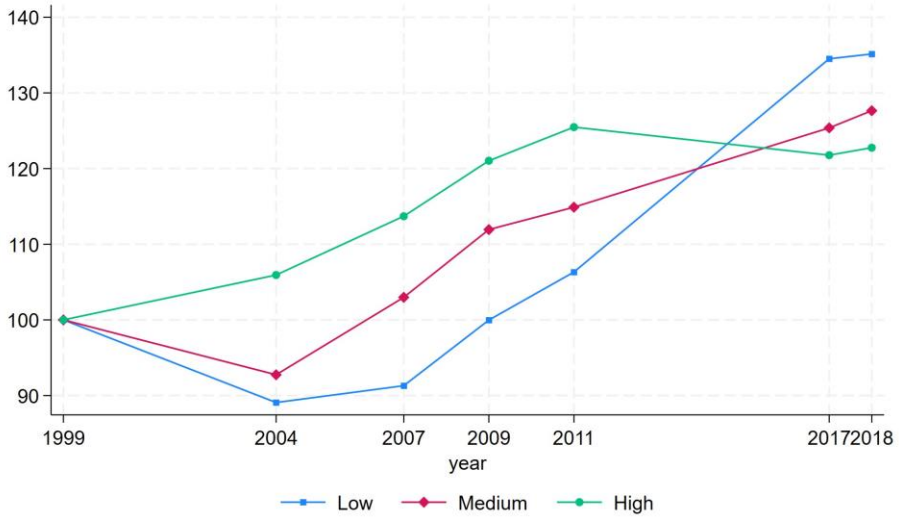
Paper products and printing	Wood and products of wood and cork
Coke and refined petroleum products	Manufacturing nec, repair and installation of machinery and equipment
Chemical and chemical products	Water supply, sewerage, waste management and remediation activities
Pharmaceuticals, medicinal chemical and botanical products	Construction
Rubber and plastics products	Wholesale and retail trade; repair of motor vehicles
Other non-metallic mineral products	Land transport and transport via pipelines
Basic metals	Water transport
Fabricated metal products	Air transport
Computer, electronic and optical equipment	Warehousing and support activities for transportation
Electrical equipment	Accommodation and food service activities
Machinery and equipment, nec	Education
Motor vehicles, trailers and semi-trailers	Human health and social work activities
Other transport equipment	Textiles, textile products, leather and footwear
Electricity, gas, steam and air-conditioning supply	Arts, entertainment and recreation
Postal and courier activities	
Publishing, audiovisual and broadcasting activities	
Telecommunications	
IT and other information services	
Financial and insurance activities	
Real estate activities	
Professional, scientific and technical activities Administrative and support service activities Public administration and defence; compulsory social security	
Other service activities	
Activities of households as employers	

Fig. A.1 Growth in Average Wages of Low, Medium and High Skilled Workers (1999–2018)

(a) Rural Sector



(b) Urban Sector



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