

Global Value Chain Participation and Skill Demand: Evidence from Chinese Manufacturing Firms

Jiawei Ma

p2626244@mpu.edu.mo

MPI GTR Center: Macao Polytechnic University Gaming Teaching and Research Center

<https://orcid.org/0009-0000-6423-3039>

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Table of Contents

Corresponding author. Email: P2626244@mpu.edu.mo

ORCID: 0009-0000-6423-3039

Faculty of Management Sciences, Macao Polytechnic University, Macao, China

Highlights

- GVC participation raises firm skill demand by 10% of mean
- IV-2SLS confirms causal effect with first-stage $F=586.37$
- Technology upgrading is dominant mechanism (3.3% mediation)
- Foreign firms and high-tech industries benefit most
- Findings robust to alternative measures and specifications

Abstract

This paper examines the causal effect of global value chain (GVC) participation on firm-level skill demand using comprehensive micro-data from China. Merging the China Industrial Enterprise Database with the China Customs Trade Database, we construct a panel of 56,151 firm-year observations from 3,000 manufacturing enterprises over 2000–2020. We employ the Koopman–Wang–Wei (2014) framework to decompose GVC participation into forward and backward linkages and combine two-way fixed effects regression with a Bartik-style instrumental variable to address endogeneity.

We document four main findings. First, GVC participation significantly raises skill demand: a one-standard-deviation increase in GVC participation increases the skilled labor share by approximately 10 percent relative to the mean (two-way FE coefficient = 0.2121, $p < 0.01$). Second, IV-2SLS estimation confirms the causal interpretation

(coefficient = 0.2433, $p < 0.01$; first-stage $F = 586.37$), with the IV estimate exceeding the OLS estimate

1. Introduction

The past three decades have witnessed a profound transformation in the structure of global production. What once were tightly integrated manufacturing processes confined within national borders have become increasingly fragmented and dispersed across countries, giving rise to what is now commonly referred to as global value chains (GVCs) [Gereffi & Fernandez-Stark, 2016]. This phenomenon—characterized by the sequential fragmentation of production stages across multiple countries, each contributing intermediate inputs, assembly services, or design and marketing functions—has fundamentally reshaped the landscape of international trade and labor markets worldwide [Antras & Chor, 2022]. Today, approximately 70 percent of world trade involves transactions along GVCs, with multinational enterprises orchestrating complex networks of suppliers, manufacturers, and distributors spanning dozens of countries [World Bank, 2020]. The implications of this structural transformation extend far beyond the realm of trade statistics; they penetrate deeply into labor market dynamics, altering the composition of employment, the structure of wages, and, critically, the demand for different types of skills across firms, industries, and economies [Baldwin, 2016]. Understanding how GVC participation shapes firms' skill demand has become an urgent priority for researchers and policymakers alike, particularly as concerns about inequality, workforce displacement, and the future of work intensify in an era of accelerating globalization and technological change.

The expansion of GVCs has been driven by a confluence of factors: dramatic reductions in trade costs and transportation times, rapid advances in information and communication technologies, and substantial liberalization of trade and investment policies across both developed and developing economies [Grossman & Rossi-Hansberg, 2008]. These developments have enabled firms to unbundle their production processes geographically, retaining skill-intensive activities—such as research and development, product design, and strategic management—in their home countries while relocating labor-intensive stages to locations with abundant low-cost

labor [Baldwin & Venables, 2013]. This “slicing up” of the value chain has created new opportunities for specialization and efficiency gains but has also generated significant distributional consequences, particularly for workers with different levels of human capital [Helpman, 2018]. The displacement of routine tasks through offshoring and automation has contributed to labor market polarization in advanced economies, with employment opportunities contracting in the middle of the skill distribution while expanding at both the top and the bottom [Autor et al., 2003; Goos et al., 2014]. In developing countries, integration into GVCs has been associated with structural transformation and skill upgrading, though the magnitude and distribution of these benefits remain subjects of active debate [Kee & Tang, 2016; Kummritz, 2016].

A substantial body of literature has examined the relationship between international trade and skill demand, consistently finding that trade liberalization and increased import competition tend to raise the relative demand for skilled labor within firms and industries [Goldberg & Pavcnik, 2007]. The canonical Stolper-Samuelson theorem predicts that trade openness increases the relative returns to the factor of production that is relatively abundant in a given country, implying that skill-abundant economies will experience rising demand for skilled labor following trade integration [Feenstra, 2004]. Complementing this trade-based explanation, a parallel literature on skill-biased technological change (SBTC) argues that technological advancements—particularly in computing and information technology—have disproportionately increased the productivity of skilled workers, thereby raising their relative demand [Acemoglu & Autor, 2011; Katz & Murphy, 1992]. More recently, researchers have recognized that these two channels are deeply intertwined: trade integration may itself induce firms to adopt more skill-intensive technologies, creating a feedback loop between globalization and technological upgrading [Bustos, 2011; Lileeva & Trefler, 2010]. Despite the richness of this literature, existing empirical evidence has predominantly relied on country-level or industry-level data, which, while informative about aggregate trends, may mask substantial heterogeneity at the firm level and cannot directly illuminate the microeconomic mechanisms through which GVC participation alters firms’ labor demand decisions [Topalova, 2010; Autor et al., 2013].

This paper addresses a critical gap in the literature by examining how firms' participation in global value chains affects their demand for skilled labor using detailed micro-level data. Specifically, we ask: How does GVC participation at the firm level influence the structure of skill demand? Does integration into global production networks systematically tilt firms' employment composition toward high-skill workers? And if so, what are the underlying mechanisms driving this relationship? To answer these questions, we construct a comprehensive firm-level dataset covering 3,000 enterprises across a broad spectrum of manufacturing and service industries, spanning the period from 2000 to 2020, yielding a total of 56,151 firm-year observations. This extensive panel structure allows us to exploit both cross-sectional variation across firms and temporal variation within firms, providing a rich empirical foundation for identifying the effects of GVC participation on skill demand.

Our analysis yields several important findings. First, we document a strong positive relationship between GVC participation and firms' demand for skilled labor. Specifically, our baseline ordinary least squares (OLS) estimates indicate that a one-standard-deviation increase in GVC participation is associated with a 0.2121 increase in the share of high-skilled employees within the firm, an effect that is statistically significant at the 1 percent level. This result is robust to the inclusion of firm fixed effects, year fixed effects, and a comprehensive set of time-varying firm-level controls, suggesting that the relationship is not merely driven by unobserved firm heterogeneity or common macroeconomic trends. Second, we decompose GVC participation into its forward and backward components and find that both dimensions contribute positively to skill demand, with backward GVC participation—reflecting firms' use of imported intermediate inputs—exhibiting a particularly pronounced effect. This decomposition is theoretically meaningful because forward and backward linkages operate through different economic mechanisms: backward participation primarily exposes firms to foreign intermediate inputs and technologies embedded in those inputs, while forward participation connects firms to downstream global markets, potentially inducing quality upgrading and more stringent skill requirements [Koopman et al., 2014; Wang et al., 2017].

Third, to address the potential endogeneity of GVC participation—arising from omitted variable bias, reverse causality, or simultaneity between firms' GVC engagement and skill structure decisions—we employ an instrumental variable (IV)

strategy using an industry-level Bartik-style instrument constructed from initial GVC participation patterns and subsequent sectoral growth in global value chain integration. Our two-stage least squares (2SLS) estimates yield a coefficient of 0.2433 on GVC participation, slightly larger than the OLS estimate, suggesting that OLS estimates may understate the true causal effect. The first-stage F-statistic of 586.37 strongly rejects concerns about weak instrument bias, providing confidence in the reliability of our causal identification. The fact that the IV estimate exceeds the OLS estimate is consistent with the interpretation that firms facing negative productivity shocks may simultaneously reduce GVC participation and cut back on skilled employment, generating a downward bias in the OLS estimates [Nunn & Qian, 2014].

Fourth, and perhaps most importantly, we systematically investigate the microeconomic mechanisms through which GVC participation reshapes firms' skill demand. Our analysis identifies three distinct channels: technology upgrading, task specialization, and capital deepening. First, GVC participation appears to stimulate firms' investment in research and development (R&D), with our estimates showing that GVC engagement raises R&D intensity by 3.3 percentage points. Access to international markets and exposure to global best practices likely increase the returns to innovation, inducing firms to allocate more resources toward R&D activities, which are inherently skill-intensive [Aghion et al., 2018]. Second, GVC participation facilitates the import of specialized intermediate inputs, which increase by 1.2 percentage points among participating firms. This greater reliance on imported intermediates allows firms to specialize in higher value-added stages of production that demand more skilled labor, consistent with the predictions of recent theories of trade in tasks [Grossman & Rossi-Hansberg, 2008]. Third, GVC participation is associated with increased capital intensity (0.2 percentage points), suggesting that firms engaged in global production networks may adopt more automated production processes that substitute for low-skill labor while complementing high-skill labor in supervisory, maintenance, and programming roles [Acemoglu & Restrepo, 2020].

Finally, our heterogeneity analysis reveals that the skill-upgrading effects of GVC participation are substantially stronger for foreign-invested enterprises and firms operating in high-technology industries. Foreign firms, which typically possess superior managerial practices, stronger global networks, and greater technological capabilities, appear better positioned to leverage GVC integration for skill upgrading

[Javorcik, 2014]. Similarly, firms in technology-intensive sectors experience amplified effects, consistent with the hypothesis that GVC participation and technological sophistication are complementary forces in driving structural transformation toward skill-intensive production [Yeaple, 2005]. These findings carry significant policy implications: while GVC integration can be a powerful engine for skill upgrading, its benefits are not uniformly distributed across all types of firms, and targeted policies may be needed to ensure that domestic enterprises and firms in traditional sectors can also capitalize on the skill-upgrading potential of global production networks.

This paper makes three primary contributions to the literature. **Contribution 1:** To the best of our knowledge, this study provides the first comprehensive evidence on the causal effect of firm-level GVC participation on skill demand using a large panel dataset with detailed firm-level information. By moving beyond country-level and industry-level analyses, we are able to directly link firms' GVC engagement decisions to their labor demand outcomes, opening a window into the microeconomic foundations of how globalization reshapes labor markets [Bernard et al., 2007; Mayer et al., 2016]. While existing studies have documented correlations between trade openness and skill upgrading at the aggregate level, our firm-level approach allows us to control for unobserved heterogeneity across firms, track within-firm changes over time, and directly test the microeconomic mechanisms that mediate the relationship between GVC integration and labor demand. The granularity of our data—spanning 3,000 firms over two decades—enables us to capture the substantial heterogeneity in how firms respond to GVC participation, which is entirely masked in aggregate analyses. **Contribution 2:** Our use of an instrumental variable strategy provides credible causal identification of the effect of GVC participation on skill demand, addressing a methodological limitation that has plagued much of the existing literature on trade and labor markets. The strength of our instruments, evidenced by a first-stage F-statistic of 586.37, and the consistency between OLS and IV estimates lend considerable confidence to our findings and distinguish this study from prior correlational analyses [Nunn & Qian, 2014]. **Contribution 3:** Our systematic investigation of the mechanisms through which GVC participation affects skill demand—technology upgrading, task specialization, and capital deepening—provides a nuanced understanding of why and how global production integration reshapes

firms' labor demand, offering actionable insights for managers and policymakers seeking to harness the benefits of GVC participation while mitigating potential adverse distributional consequences. By decomposing the total effect into these three distinct channels, we are able to speak to multiple theoretical traditions simultaneously and provide guidance for policy interventions that target specific mechanisms.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and develops our theoretical framework and testable hypotheses. Section 3 describes the data sources, variable construction, and empirical strategy. Section 4 presents our main results, robustness checks, and causal identification. Section 5 investigates the underlying mechanisms. Section 6 examines heterogeneous effects across firm types and industries. Section 7 concludes with a discussion of the implications of our findings for policy and future research.

2. Literature Review and Hypothesis Development

2.1 Global Value Chain Participation and Labor Markets

The concept of global value chains emerged from the broader literature on the international fragmentation of production, which recognizes that modern manufacturing and service delivery frequently involve the geographic dispersion of multiple production stages across different countries [Gereffi et al., 2005; Baldwin, 2016]. Unlike traditional trade, which was primarily characterized by the exchange of final goods between countries, GVC trade involves the cross-border flow of intermediate inputs, components, and services that are assembled, processed, and re-exported multiple times before reaching final consumers [Johnson & Noguera, 2012]. This fundamental restructuring of production has profound implications for labor markets, as it alters the skill content of tasks performed in different locations, the distribution of employment across occupations, and the returns to different types of human capital [Helpman, 2018]. Understanding these labor market effects requires a synthesis of insights from multiple strands of the economics literature, including international trade, labor economics, and the economics of technological change.

Early theoretical contributions to the GVC literature emphasized the role of trade costs and factor price differences in driving the geographic fragmentation of production. Grossman and Rossi-Hansberg [2008] developed an influential framework in which reductions in offshoring costs—analogueous to reductions in transportation or communication costs—can generate productivity gains by allowing firms to relocate specific tasks to locations where they can be performed more cheaply. In their model, the effects on domestic labor markets depend critically on the type of tasks being offshored: offshoring of low-skill tasks creates a “productivity effect” that benefits all workers by lowering production costs and expanding output, but also generates a “labor-supply effect” that reduces the relative demand for low-skill workers in the offshoring country. The net effect on relative wages and employment is generally ambiguous and depends on the relative strength of these competing forces.

Subsequent work by Baldwin and Venables [2013] extended this framework to distinguish between “snake” and “spider” patterns of production fragmentation, highlighting how the sequential nature of some supply chains creates complex interdependencies between stages that have important implications for the location of employment and the distribution of value added.

The empirical literature on GVCs and labor markets has grown rapidly in recent years, spurred by the development of new data sources and methodologies for measuring value chain participation. Kee and Tang [2016] used Chinese firm-level data to examine how processing trade—a prominent form of GVC participation in developing countries—affected domestic value added in exports. They found that Chinese firms increased their domestic content over time, a process they termed “depth of trade liberalization,” which was accompanied by upgrading in product quality and, implicitly, in the skill intensity of production. Kummritz [2016] used the World Input-Output Database (WIOD) to examine the labor market effects of GVC participation across multiple countries, finding that increased participation in GVCs was associated with shifts in employment toward non-routine cognitive tasks and away from routine manual tasks. Timmer et al. [2014] used international input-output data to trace the allocation of workers across tasks within GVCs, documenting that high-skill workers are increasingly concentrated in pre- and post-production stages (research, design, marketing), while developing-country workers remain concentrated in manufacturing stages with lower skill requirements.

More recent studies have employed firm-level data to examine the microeconomic channels through which GVC participation affects labor demand. Bas [2012] examined the relationship between import liberalization and firms' skill upgrading in Indonesia, finding that input tariff reductions induced firms to increase the skill intensity of their workforce by importing higher-quality intermediate goods. Feng et al. [2016] studied the effects of processing trade liberalization on firm-level innovation and productivity in China, documenting that access to imported intermediates stimulated R&D investment and technology adoption. Hallak et al. [2021] examined how Argentine firms responded to import liberalization by adjusting their workforce composition, finding significant increases in the demand for skilled workers among firms that expanded their use of imported inputs. These studies collectively suggest that GVC participation—whether through the import of intermediates or the export of processed goods—tends to raise firms' demand for skilled labor, though the specific mechanisms and magnitudes vary across institutional contexts and types of GVC engagement.

Despite this growing body of evidence, several important gaps remain. First, most existing firm-level studies have focused on specific channels—such as imported intermediates or processing trade status—rather than providing a comprehensive analysis of overall GVC participation that encompasses both backward and forward linkages. Second, causal identification remains a significant challenge, as firms' decisions to participate in GVCs and their skill demand choices may be jointly determined by unobserved firm characteristics. Third, the literature has paid relatively less attention to the heterogeneous effects of GVC participation across different types of firms and industries, which is critical for understanding the distributional consequences of global production integration. Our paper addresses each of these gaps by providing a comprehensive, causally identified analysis of GVC participation's effects on skill demand using rich firm-level data and exploiting exogenous variation in GVC participation through an instrumental variable strategy.

2.2 Trade Liberalization and Skill Demand

The relationship between international trade and the demand for skilled labor has been a central focus of international and labor economics for several decades, motivated by the striking empirical regularity that trade liberalization episodes in both developed

and developing countries have been accompanied by increases in the employment share and relative wages of skilled workers [Goldberg & Pavcnik, 2007]. This section reviews the key theoretical and empirical contributions to this literature, highlighting the mechanisms through which trade integration affects skill demand and identifying the unresolved questions that our analysis seeks to address.

The classical Heckscher-Ohlin framework provides a foundational lens for understanding the relationship between trade and factor returns. In its two-factor, two-good formulation, the Stolper-Samuelson theorem predicts that an increase in the relative price of the skill-intensive good—induced, for instance, by trade liberalization in a skill-abundant country—will raise the relative return to skilled labor while reducing the return to unskilled labor [Feenstra, 2004]. Conversely, in countries abundant in unskilled labor, opening to trade should compress the skill premium by raising the relative demand for unskilled workers. While this framework offers clear predictions, empirical tests have yielded mixed results: in many developing countries, trade liberalization has been associated with increased skill premiums, contrary to the Stolper-Samuelson prediction [Hanson & Harrison, 1999; Attanasio et al., 2004]. These anomalies have motivated the development of richer theoretical frameworks and empirical strategies that can account for the pervasive skill-upgrading effects of trade across diverse country contexts.

The skill-biased technological change (SBTC) hypothesis emerged as a leading alternative explanation for rising skill demand, positing that exogenous advances in technology—particularly in computing and information technology—have disproportionately raised the productivity of skilled workers, thereby increasing their relative demand [Katz & Murphy, 1992; Berman et al., 1994]. In its canonical formulation, SBTC shifts the relative labor demand curve outward for skilled workers, causing both the employment share and relative wages of skilled workers to increase. However, subsequent research has recognized that technological change is not purely exogenous but may itself be shaped by trade and globalization forces. Bustos [2011] developed a theoretical model in which trade liberalization induces firms to adopt more skill-intensive technologies by raising the output of exporting firms and thereby increasing the returns to technology upgrading. Empirically, she found that Argentine firms in industries facing larger tariff reductions exhibited greater technology upgrading, providing direct evidence for the technology-mediated channel of trade-

induced skill demand. Lileeva and Trefler [2010] similarly documented that Canadian firms induced to export by the Canada-U.S. Free Trade Agreement increased their productivity, innovation, and technology investment relative to non-exporting firms.

The integration of trade and technology channels has been further advanced by the literature on trade in tasks and offshoring. Autor et al. [2003] argued that the declining costs of automating routine tasks and offshoring routine activities have contributed to labor market polarization, with employment contracting in routine occupations (both cognitive and manual) while expanding in non-routine occupations at both ends of the skill distribution. Grossman and Rossi-Hansberg [2008] formalized the “trade in tasks” framework, in which reductions in offshoring costs generate productivity gains analogous to factor-augmenting technological change, with distributional consequences that depend on the relative importance of productivity, labor-supply, and relative-price effects. Goos et al. [2014] provided comprehensive cross-country evidence for the polarization hypothesis, documenting that routine-biased technological change has been the dominant force driving employment shifts across European countries, though trade has played a contributing role.

In developing countries, the literature has documented a similarly strong relationship between trade liberalization and skill upgrading. Pavenik [2003] found that Chilean firms in industries facing larger tariff reductions experienced significant productivity gains and increases in skill intensity. Amiti and Cameron [2012] examined the effects of tariff liberalization on Indonesian firms, finding that imported inputs raised the skill premium while output tariffs reduced it, highlighting the importance of decomposing trade liberalization into its input and output dimensions. Topalova [2010] studied the effects of India’s trade liberalization on poverty and inequality, finding that districts more exposed to tariff cuts experienced slower poverty reduction, partly due to adverse labor market effects for low-skill workers. Collectively, these studies suggest that trade liberalization tends to raise skill demand even in countries abundant in unskilled labor, a finding that has motivated the development of heterogeneous firm models and task-based frameworks that can generate skill-upgrading predictions consistent with the empirical evidence [Melitz, 2003; Yeaple, 2005].

Despite the richness of this literature, several important limitations motivate our analysis. First, most existing studies have focused on the effects of tariffs, trade

volumes, or export status on skill demand, rather than directly examining GVC participation as a distinct form of international engagement with potentially unique labor market implications. Second, the causal identification of trade effects on skill demand remains challenging, with most studies relying on difference-in-differences strategies or firm fixed effects that may not fully address endogeneity concerns. Third, the microeconomic mechanisms linking trade to skill upgrading—particularly the roles of technology adoption, input specialization, and capital investment—remain incompletely understood at the firm level. Our paper contributes to addressing these limitations by directly examining the causal effect of firm-level GVC participation on skill demand and systematically investigating the underlying mechanisms.

2.3 Theoretical Framework and Hypothesis Development

To guide our empirical analysis, we develop a simple theoretical framework that links GVC participation to firms' skill demand through three distinct channels: technology upgrading, task specialization, and capital deepening. This framework builds on the heterogeneous firm literature initiated by Melitz [2003] and extended by Yeaple [2005], as well as the task-based trade models of Grossman and Rossi-Hansberg [2008].

Consider a representative firm that produces output Y using a production function that combines capital K , skilled labor L_s , and unskilled labor L_u :

$$Y = F(K, L_s, L_u) = A \cdot K^\alpha \cdot L_s^{\beta_s} \cdot L_u^{\beta_u}$$

where A represents total factor productivity (TFP), and α , β_s , and β_u are the output elasticities of capital, skilled labor, and unskilled labor, respectively. We assume constant returns to scale in the production factors, such that $\alpha + \beta_s + \beta_u = 1$. The firm's decision problem involves choosing optimal levels of K , L_s , and L_u to maximize profits, taking factor prices and productivity as given.

GVC Participation and Technology Upgrading. When a firm participates in a global value chain—whether by importing intermediate inputs or exporting processed goods—it gains access to foreign markets, international knowledge spillovers, and exposure to global best practices. This enhanced access raises the returns to innovation and technology adoption because larger market sizes increase the profitability of introducing new products or processes, and because competitive

pressure from global markets creates incentives for continuous improvement [Aghion et al., 2018]. Formally, GVC participation can be modeled as increasing firms' incentives to invest in R&D, which augments the productivity parameter A . Since R&D activities are inherently skill-intensive—requiring scientists, engineers, and technically trained personnel—the induced technology upgrading raises the relative demand for skilled labor. Empirically, we expect GVC participation to increase firms' R&D intensity, which in turn raises the share of skilled workers in total employment. This channel is consistent with the SBTC literature but endogenizes the technology decision as a response to GVC engagement rather than treating it as exogenous [Bustos, 2011].

GVC Participation and Task Specialization. Global value chains enable firms to specialize in specific stages of production while sourcing intermediate inputs from other countries that specialize in complementary stages [Grossman & Rossi-Hansberg, 2008]. When a firm increases its backward GVC participation by importing specialized intermediate inputs, it effectively outsources the production of certain components or tasks to foreign suppliers. This outsourcing allows the firm to reallocate its domestic labor toward more skill-intensive activities such as product design, quality control, coordination of global suppliers, and marketing. Similarly, forward GVC participation—connecting the firm to downstream global markets—may expose it to more demanding international buyers who require higher product quality, better compliance with international standards, and more sophisticated after-sales services, all of which increase the demand for skilled labor [Javorcik, 2014]. In terms of our production framework, task specialization increases the relative productivity of skilled workers (β_s/β_u) because the tasks retained domestically tend to be those with higher skill requirements, while the offshored or outsourced tasks tend to be more routine and less skill-intensive. We therefore expect GVC participation to increase firms' reliance on imported intermediate inputs and to simultaneously raise the skill intensity of their domestic workforce.

GVC Participation and Capital Deepening. Participation in global value chains may also induce firms to invest in more capital-intensive and automated production technologies. Two factors drive this channel. First, connecting to global markets may increase firms' access to foreign capital goods and embodied technologies, enabling them to adopt production processes that are more mechanized and less reliant on

manual labor [Amiti & Cameron, 2012]. Second, to remain competitive in global markets, firms may need to achieve greater precision, consistency, and scale in their production, which often requires investment in automated equipment and advanced machinery [Acemoglu & Restrepo, 2020]. Capital and skill are typically complements in modern production technologies: automated equipment requires skilled workers for programming, operation, maintenance, and quality control, while unskilled workers perform tasks that are more easily automated. In our production function, this capital-deepening channel operates by increasing the capital-labor ratio $K/(L_s + L_u)$, and because capital is more complementary to skilled labor than to unskilled labor, the increased capital intensity disproportionately raises the demand for skilled workers. We therefore expect GVC participation to increase firms' capital intensity, with the associated automation shifting the employment structure toward more skilled labor.

Hypotheses. Based on this theoretical framework, we derive three testable hypotheses that guide our empirical analysis:

H1: GVC participation increases firms' demand for skilled labor. This is the central prediction of our framework. GVC participation raises the relative demand for skilled workers through the combined effects of technology upgrading, task specialization, and capital deepening. We test this hypothesis using our baseline regression specification, which relates firms' skilled labor share to their GVC participation index. A positive and statistically significant coefficient on GVC participation would provide support for H1.

H2: The effect of GVC participation on skill demand is stronger in technology-intensive industries. If the skill-upgrading effects of GVC participation operate partly through technology upgrading and innovation, then these effects should be more pronounced in industries where technological change is more rapid and where the scope for innovation is greater. Technology-intensive industries are characterized by higher baseline R&D intensity, more rapid product cycles, and greater complementarity between GVC participation and technological upgrading [Yeaple, 2005]. We test this hypothesis by interacting GVC participation with industry-level technology intensity and examining whether the interaction term is positive and statistically significant.

H3: Export intensity amplifies the skill demand effect of GVC participation.

Firms that are more deeply integrated into global markets through exports may have greater exposure to international competition and knowledge spillovers, which can amplify the incentives for skill upgrading. Export-intensive firms are likely to face more demanding international buyers, greater competitive pressure, and larger potential markets for innovative products, all of which strengthen the link between GVC participation and skill demand [Bustos, 2011; Lileeva & Trefler, 2010]. We test this hypothesis by examining whether the effect of GVC participation on skill demand varies with firms' export intensity, expecting a positive interaction between GVC participation and export orientation.

These hypotheses provide a structured framework for interpreting our empirical results. In the following sections, we describe our data and empirical strategy, present our main findings, and conduct detailed analyses of the mechanisms and heterogeneous effects that underlie the aggregate relationship between GVC participation and firms' skill demand.

3 Data and Empirical Strategy

3.1 Data Sources and Sample Selection

This study examines the relationship between global value chain (GVC) participation and skill demand using a comprehensive firm-level panel dataset spanning the period 2000–2020. The empirical analysis integrates data from two primary administrative sources in China: the China Industrial Enterprise Database (CIED) and the China Customs Trade Database (CCTD). These datasets have been widely employed in the international trade literature and are recognized as among the most comprehensive sources of firm-level information for a developing economy (Brandt et al., 2012; Yu, 2015).

China Industrial Enterprise Database. The CIED is compiled by the National Bureau of Statistics of China (NBS) and covers all state-owned enterprises (SOEs) and non-state-owned enterprises with annual sales exceeding 5 million RMB (approximately 600,000 USD). This database provides detailed information on firm characteristics, including employment structure, financial accounts, fixed assets,

industrial output, and innovation inputs. Critically for our purposes, the CIED reports the number of employees by educational attainment category, which serves as the basis for constructing our skill demand measure. Specifically, we utilize the distinction between workers with college education or above (classified as high-skilled workers) and those with education below the college level (classified as low-skilled or medium-skilled workers), following the convention established in the labor economics literature (Acemoglu & Autor, 2011).

China Customs Trade Database. The CCTD, administered by the General Administration of Customs of the People’s Republic of China (GACC), records detailed transaction-level trade data at the firm-product-destination level. The database covers the universe of Chinese import and export transactions, providing information on product classification (at the 8-digit HS code level), trade values and quantities, source and destination countries, and trade regime (processing trade versus ordinary trade). This granular trade information enables us to construct precise measures of GVC participation by decomposing firms’ trade flows according to the positioning of traded goods within global production networks.

Data Merging Procedure. We merge the CIED and CCTD using a two-step matching procedure. In the first step, we match records across the two databases using firms’ unique identifiers: the legal person registration code and the enterprise organization code, which are common to both administrative systems. Following the methodology of Brandt et al. (2012), we implement a fuzzy matching algorithm to address potential inconsistencies in firm identification codes arising from data entry errors or administrative reclassifications. The second step employs firm name matching as a complement to identifier-based merging, using string similarity metrics to capture matches missed by the primary procedure. This dual approach yields a match rate consistent with the established literature, approximately 55–60% of manufacturing firms in the CIED being successfully linked to trade records in the CCTD.

Sample Selection Criteria. We apply the following selection criteria to construct our analysis sample. First, we restrict the sample to the period 2000–2020, which encompasses China’s accession to the World Trade Organization (2001) and the subsequent two decades of deepening trade integration. Second, we retain only firms

with valid and non-missing information on all key variables of interest: skill demand (share of high-skilled workers), GVC participation measures, and control variables. Third, following standard practice in the literature, we exclude observations with obviously erroneous or implausible values—for instance, firms reporting negative employment, negative value added, or missing industrial classification codes. Fourth, we winsorize all continuous variables at the 1st and 99th percentiles to mitigate the influence of extreme outliers. Fifth, we require firms to appear in the sample for at least two consecutive years, ensuring the panel structure necessary for fixed-effects estimation.

After applying these selection criteria, our final balanced panel comprises **56,151 firm-year observations** spanning **3,000 unique manufacturing enterprises** over the 21-year period from 2000 to 2020. The sample exhibits substantial variation both across firms and within firms over time, providing sufficient statistical power to identify the effects of GVC participation on skill demand.

3.2 Variable Definitions

3.2.1 Dependent Variable: Skill Demand

Our primary outcome variable is **skill demand**, measured as the share of high-skilled employees in total firm employment. Following the task-based framework of Acemoglu and Autor (2011), we classify workers with college-level education or higher as high-skilled labor, and those with education below the college level as non-high-skilled labor. Formally:

$$\text{Skill Demand}_{it} = \frac{L_{it}^H}{L_{it}^H + L_{it}^L}$$

where L_{it}^H denotes the number of high-skilled workers (college-educated and above) and L_{it}^L denotes the number of non-high-skilled workers in firm i at time t . This measure captures the intensive margin of skill demand within the firm and has been widely adopted in the literature on international trade and labor markets (Helpman et al., 2010; Han et al., 2012).

The skill demand measure ranges from 0.05 to 0.81 in our sample, with a mean of 0.243 and a standard deviation of 0.138, indicating considerable heterogeneity in skill utilization across Chinese manufacturing firms. The relatively low mean value reflects the broad composition of China's manufacturing workforce during our sample period, though we document a clear upward trend over time consistent with ongoing structural transformation.

3.2.2 Core Explanatory Variable: GVC Participation

We construct three complementary measures of GVC participation based on the decomposition framework pioneered by Koopman et al. (2014) and widely adopted in the GVC literature (Wang et al., 2013; Kee & Tang, 2016).

Forward Participation (GVC-FP): This captures the extent to which a firm's exports contain domestic value added that is subsequently re-exported by the importing country—effectively measuring the firm's role as an upstream supplier in global production networks. Formally:

$$\text{GVC-FP}_{it} = \frac{\text{Exports of Intermediate Goods}_{it} \times \text{Foreign Absorption Share}}{\text{Total Exports}_{it}}$$

Intuitively, a higher forward participation indicates that the firm specializes in producing intermediate inputs that are further processed abroad before reaching final consumers.

Backward Participation (GVC-BP): This measures the foreign value added content embedded in a firm's exports, reflecting the firm's reliance on imported inputs in its production process:

$$\text{GVC-BP}_{it} = \frac{\text{Foreign Value Added in Exports}_{it}}{\text{Total Exports}_{it}}$$

A higher backward participation indicates greater integration into global production networks through the sourcing of foreign intermediates.

Total GVC Participation (GVC-Total): The sum of forward and backward participation, capturing the overall degree of GVC engagement:

$$\text{GVC-Total}_{it} = \text{GVC-FP}_{it} + \text{GVC-BP}_{it}$$

Our primary analysis employs GVC-Total as the key explanatory variable, with separate analyses for GVC-FP and GVC-BP to disentangle the directional mechanisms through which different modes of GVC integration affect skill demand. The firm-level GVC measures are computed using data from the World Input-Output Database (WIOD) and the OECD Trade in Value Added (TiVA) database, combined with firm-specific trade flow information from the CCTD. The GVC-Total measure has a mean of 0.302 (standard deviation 0.156), with GVC-FP averaging 0.137 and GVC-BP averaging 0.165, suggesting that Chinese manufacturing firms are somewhat more intensively engaged in backward linkages than forward linkages during our sample period.

3.2.3 Control Variables

To mitigate concerns about omitted variable bias, we include a comprehensive set of time-varying firm-level control variables:

Firm Size ($\ln L_{it}$). The natural logarithm of total employment. Larger firms may have different skill structures due to economies of scale, scope for specialization, and organizational complexity (Brown & Medoff, 1989). Mean value: 5.02.

Capital Intensity ($\ln(K/L)_{it}$). The natural logarithm of the ratio of fixed capital stock to total employment. Capital-skill complementarity implies that more capital-intensive firms may demand relatively more skilled labor (Griliches, 1969; Krusell et al., 2000). Mean value: 4.06.

Total Factor Productivity (TFP). We estimate firm-level TFP using the augmented Olley-Pakes approach (Olley & Pakes, 1996), controlling for endogeneity in input choices and firm exit decisions. More productive firms may self-select into skill-intensive production modes (Mayer et al., 2014). Mean value: 3.04.

Export Intensity. The ratio of export value to total sales revenue, capturing the direct exposure to international markets beyond GVC participation per se. Firms with higher export intensity may face different competitive pressures and quality requirements that influence skill demand (Verhoogen, 2008). Mean value: 0.219.

3.2.4 Mechanism Variables

To investigate the channels through which GVC participation affects skill demand, we construct the following mechanism variables:

R&D Intensity. The ratio of research and development expenditure to total sales revenue, capturing the firm's investment in technological upgrading. Mean value: 0.053.

Patent Stock. The natural logarithm of cumulative patent applications (invention and utility model patents) plus one, measuring the stock of technological knowledge accumulated by the firm. Mean value: 1.16.

Intermediate Imports Share. The ratio of imported intermediate inputs to total intermediate inputs, capturing the firm's reliance on foreign-sourced inputs and the associated technology spillovers. Mean value: 0.178.

3.2.5 Heterogeneity Classification Variables

We classify firms along three dimensions to examine heterogeneous treatment effects:

Ownership Structure. SOEs (State-Owned Enterprises), privately-owned domestic firms, and foreign-invested enterprises (FIEs), coded as 1, 2, and 3 respectively.

Technology Intensity. Based on the OECD classification of manufacturing industries by R&D intensity: high-technology (e.g., electronics, pharmaceuticals), medium-technology (e.g., machinery, chemicals), and low-technology (e.g., textiles, food processing), coded as 1, 2, and 3 respectively.

Geographic Location. Coastal region firms (eastern provinces with preferential trade policies) versus inland region firms, coded as 1 and 2 respectively.

3.3 Descriptive Statistics

Table 1 presents the descriptive statistics for the key variables used in our empirical analysis. The sample comprises 56,151 firm-year observations from 3,000 manufacturing enterprises over the period 2000–2020.

Table 1: Descriptive Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Dependent Variable					
Skill Demand	56,151	0.243	0.138	0.050	0.810
GVC Participation Measures					
GVC-Total	56,151	0.302	0.156	0.012	0.784
GVC-Forward	56,151	0.137	0.089	0.003	0.521
GVC-Backward	56,151	0.165	0.102	0.008	0.612
Control Variables					
Firm Size (ln L)	56,151	5.020	1.245	2.303	9.210
Capital Intensity (ln K/L)	56,151	4.060	1.387	0.693	8.517
TFP	56,151	3.040	0.876	0.412	6.230
Export Intensity	56,151	0.219	0.174	0.001	0.893
Mechanism Variables					
R&D Intensity	56,151	0.053	0.041	0.000	0.312
Patent Stock (ln)	56,151	1.160	1.324	0.000	6.785
Intermediate Imports	56,151	0.178	0.156	0.000	0.745
Heterogeneity Variables					
Ownership (1=SOE, 2=Private, 3=FIE)	56,151	2.143	0.762	1	3
Tech Level (1=High, 2=Medium, 3=Low)	56,151	2.106	0.687	1	3
Region (1=Coastal, 2=Inland)	56,151	1.342	0.475	1	2

Notes: This table reports descriptive statistics for the main variables used in the empirical analysis. The sample consists of 56,151 firm-year observations from 3,000 Chinese manufacturing firms over the period 2000–2020. Continuous variables are winsorized at the 1st and 99th percentiles.

Several patterns emerge from the descriptive statistics. First, the skill demand variable exhibits substantial variation across firms, with a coefficient of variation of approximately 0.57, suggesting meaningful heterogeneity in skill utilization patterns within Chinese manufacturing. Second, the GVC participation measures reveal that backward linkages (mean 0.165) are quantitatively more important than forward linkages (mean 0.137) on average, consistent with China’s role as an assembly and processing hub in East Asian production networks during much of our sample period.

The correlation structure between the key variables (reported in Appendix Table A.1) reveals a positive and statistically significant unconditional correlation of 0.342 between GVC-Total and Skill Demand, providing preliminary suggestive evidence of a positive association between global value chain integration and skill-intensive employment. Notably, the two components of GVC participation exhibit a moderate positive correlation of 0.287, indicating that firms engaged in forward GVC linkages are also somewhat more likely to participate in backward linkages, though the two dimensions capture distinct aspects of GVC integration.

3.4 Empirical Strategy

Our empirical analysis proceeds in three stages. We first estimate the baseline relationship between GVC participation and skill demand using a two-way fixed effects panel regression. We then address potential endogeneity concerns through an instrumental variables (IV) approach. Finally, we investigate the underlying mechanisms using a mediation analysis framework.

3.4.1 Baseline Model

We specify the following two-way fixed effects panel regression model:

$$\text{Skill}_{it} = \alpha + \beta \cdot \text{GVC}_{it} + \boldsymbol{\gamma}'\mathbf{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where: - Skill_{it} denotes the share of high-skilled workers in firm i at time t ; - GVC_{it} denotes the measure of GVC participation (GVC-Total, GVC-Forward, or GVC-Backward) for firm i at time t ; - $\mathbf{X}_{it}$ is a vector of time-varying firm-level control variables including firm size, capital intensity, total factor productivity, and export intensity; - μ_i represents firm fixed effects, absorbing all time-invariant heterogeneity across firms such as geographical location, industry affiliation, and historical organizational factors; - λ_t represents year fixed effects, capturing common macroeconomic shocks, business cycle fluctuations, and secular trends in skill demand; - ε_{it} is the idiosyncratic error term, clustered at the firm level to account for within-firm serial correlation.

The coefficient of primary interest is β , which captures the causal effect of GVC participation on skill demand under the assumption of strict exogeneity conditional on

the fixed effects and control variables. A positive and statistically significant β would indicate that deeper GVC integration is associated with increased demand for high-skilled labor, consistent with the hypothesis that global production networks foster skill-biased technological change and organizational upgrading.

3.4.2 Instrumental Variables Estimation

While the fixed effects specification controls for time-invariant confounders, the coefficient β may still suffer from endogeneity bias arising from three sources: reverse causality (firms with higher skill intensity may self-select into GVC participation), omitted time-varying confounders (e.g., changes in managerial quality or organizational practices), and measurement error in the GVC participation variables. To address these concerns, we employ an instrumental variables (IV) strategy using a Bartik-style shift-share instrument.

Instrument Construction. Following the methodology of Bartik (1991) and its modern applications in the international trade literature (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022), we construct our instrument as follows:

$$IV_{it} = \sum_j s_{ij,t_0} \cdot \Delta GVC_{-i,jt}$$

where s_{ij,t_0} denotes firm i 's initial share in industry j (measured at the base year $t_0 = 2000$), and $\Delta GVC_{-i,jt}$ denotes the change in industry-level GVC participation excluding firm i 's contribution. This instrument exploits variation in GVC participation driven by industry-level trends that are plausibly exogenous to individual firm decisions, while weighting these trends by each firm's initial industry composition.

The first-stage regression takes the form:

$$GVC_{it} = \pi_0 + \pi_1 \cdot IV_{it} + \boldsymbol{\pi}_2' \mathbf{X}_{it} + \mu_i + \lambda_t + \nu_{it}$$

and the second-stage regression is:

$$\text{Skill}_{it} = \alpha + \beta_{IV} \cdot \widehat{GVC}_{it} + \boldsymbol{\gamma}' \mathbf{X}_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where $\widehat{GVC}_{it}$ denotes the fitted values from the first-stage regression.

The validity of our IV strategy depends on two key assumptions. First, the relevance condition requires that the instrument is sufficiently correlated with the endogenous GVC variable. We assess this through the first-stage F-statistic, which substantially exceeds the conventional threshold of 10 (Stock & Yogo, 2005). Second, the exclusion restriction requires that the instrument affects skill demand only through its effect on GVC participation, and not through alternative channels. We provide detailed discussion and supporting evidence for the exclusion restriction in Section 3.5.

3.4.3 Mechanism Analysis: Mediation Framework

To investigate the channels through which GVC participation affects skill demand, we implement a mediation analysis following the Baron-Kenny (1986) approach, adapted for the panel data setting. We identify three candidate mechanisms suggested by the theoretical literature: **technological upgrading** (captured by R&D intensity and patent stock), **automation** (proxied by capital intensity and technology adoption), and **task specialization** (measured by intermediate input sourcing patterns).

The mediation framework decomposes the total effect of GVC participation on skill demand into a direct effect and an indirect effect operating through the mediator M_{it} . We estimate the following system of equations:

Path a (GVC $\rightarrow$ Mediator):

$$M_{it} = \delta_0 + \delta_1 \cdot \text{GVC}_{it} + \delta_2' \mathbf{X}_{it} + \mu_i + \lambda_t + \eta_{it}$$

Path b (Mediator $\rightarrow$ Skill | GVC):

$$\text{Skill}_{it} = \theta_0 + \kappa \cdot M_{it} + \rho \cdot \text{GVC}_{it} + \theta_1' \mathbf{X}_{it} + \mu_i + \lambda_t + \zeta_{it}$$

The indirect (mediated) effect is computed as $\hat{\delta}_1 \times \hat{\kappa}$, and the total effect is $\hat{\beta} = \hat{\rho} + \hat{\delta}_1 \times \hat{\kappa}$. We assess the statistical significance of the indirect effect using the Sobel-Goodman test (Sobel, 1982; MacKinnon et al., 2002) and report the proportion of the total effect mediated through each channel.

3.5 Identification Strategy

3.5.1 Potential Sources of Endogeneity

The consistent estimation of β in Equation (1) requires that GVC participation be uncorrelated with the error term after conditioning on firm fixed effects, year fixed effects, and the observed control variables. However, several sources of endogeneity may threaten this assumption.

Reverse Causality. Firms with higher baseline skill intensity may possess comparative advantages in participating in GVCs, particularly in skill-intensive segments of global production networks (Antràs & Chor, 2022). If more skilled firms self-select into GVC participation, OLS estimates would overstate the causal effect of GVC integration on skill demand. Conversely, firms experiencing adverse skill shocks may reduce their GVC engagement, generating downward bias.

Omitted Variables. Time-varying firm-level characteristics such as management quality, organizational capital, or entrepreneurial ability may simultaneously influence both GVC participation decisions and skill demand. While our control variables capture observable determinants of firm behavior, unobserved heterogeneity in management practices and dynamic capabilities remains a potential source of omitted variable bias (Bloom & Van Reenen, 2007).

Measurement Error. Our firm-level GVC measures, constructed by combining WIOD/TiVA industry-level data with firm-specific trade information, may contain classical measurement error that attenuates the OLS estimates toward zero.

3.5.2 Instrument Validity: Relevance and Exclusion

Relevance Condition. The Bartik instrument satisfies the relevance condition because industry-level GVC trends reflect aggregate forces—such as trade policy changes, transportation cost reductions, and foreign demand shocks—that shape the GVC participation opportunities available to individual firms but are not under the control of any single firm. The first-stage F-statistic substantially exceeds conventional thresholds, providing strong empirical support for instrument relevance.

Exclusion Restriction. The exclusion restriction requires that our instrument affects skill demand solely through GVC participation and not through alternative channels.

We argue for the plausibility of this restriction on several grounds. First, the instrument is constructed using *leave-out* industry-level GVC trends, ensuring that firm-specific shocks do not contaminate the instrument. Second, we control flexibly for firm fixed effects and year fixed effects, absorbing both time-invariant firm heterogeneity and common macroeconomic trends. Third, the initial industry shares s_{ij,t_0} are measured in the base year (2000), predating the GVC changes that generate identifying variation, thereby mitigating concerns about dynamic endogeneity of the shares.

Nevertheless, we acknowledge that the exclusion restriction is fundamentally untestable. To provide supporting evidence, we conduct two falsification exercises. First, we regress pre-determined firm characteristics (2000 values) on future values of the instrument and verify that the instrument does not predict baseline skill levels. Second, we implement an over-identification test using alternative instrument constructions based on different base years, finding consistent estimates across specifications. These results, combined with the strong first-stage relationship, lend credibility to our IV estimates as informative upper bounds on the causal effect of GVC participation on skill demand.

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4. Empirical Results

This section presents the core empirical findings of our analysis. We begin with the baseline regression results documenting the relationship between GVC participation and firms' skill demand, proceed to address endogeneity concerns through instrumental variable estimation, and conclude with a discussion of the economic significance and implications of our findings.

4.1 Baseline Regression Results

Table 2 reports the baseline regression results examining the effect of GVC participation on firm-level skill demand. We present four specifications with progressively richer sets of controls and fixed effects to assess the robustness of the estimated relationship.

Table 2: Baseline Regression Results

	(1) OLS	(2) OLS+Ctrl	(3) Firm FE	(4) Two-way FE
GVC Total	0.5386*** (0.0080)	0.2209*** (0.0060)	0.3616*** (0.0035)	0.2121*** (0.0026)
Firm Size		0.0233*** (0.0006)	0.0169*** (0.0004)	0.0088*** (0.0003)
Capital Intensity		0.0167*** (0.0007)	0.0139*** (0.0004)	0.0058*** (0.0003)
TFP		0.0387*** (0.0007)	0.0251*** (0.0005)	0.0068*** (0.0004)
Export Intensity		0.4941*** (0.0079)	0.1618*** (0.0039)	0.0386*** (0.0028)
Firm FE	No	No	Yes	Yes
Year FE	No	No	No	Yes
Observations	56,151	56,151	56,151	56,151
R-squared	0.1905	0.4890	0.3487(Within)	0.2529(Within)

Note: Dependent variable is firm-level skill demand. Clustered robust standard errors at the firm level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Column (1): Unconditional Correlation. The simplest specification in Column (1) regresses skill demand on GVC participation without any controls or fixed effects. The estimated coefficient on GVC participation is 0.5386, statistically significant at the 1 percent level (standard error = 0.0080). This raw correlation suggests a strong positive association between GVC integration and firms' demand for skilled labor: a one-unit increase in GVC participation is associated with a 0.54 percentage point increase in the skill share. While this estimate is informative about the unconditional relationship, it likely captures both the causal effect of GVC participation and the confounding influence of observable and unobservable firm characteristics that correlate with both GVC engagement and skill intensity. The R-squared of 0.1905 indicates that GVC participation alone explains approximately 19 percent of the variation in skill demand across firms.

Column (2): Controlling for Firm Characteristics. Column (2) augments the specification by including a set of firm-level control variables: firm size (log of employment), capital intensity (log of capital-labor ratio), total factor productivity (TFP, log), and export intensity (export sales ratio). The inclusion of these controls substantially attenuates the GVC coefficient from 0.5386 to 0.2209, yet the estimate remains highly significant (standard error = 0.0060, $p < 0.01$). This reduction suggests that approximately 59 percent of the unconditional correlation between GVC participation and skill demand can be attributed to the confounding effects of firm size, technology, productivity, and export orientation. Larger, more capital-intensive, more productive, and more export-oriented firms tend to participate more intensively in GVCs and simultaneously demand more skilled labor.

The coefficients on the control variables carry expected signs and are precisely estimated. Firm size exhibits a positive and significant coefficient of 0.0233 (standard error = 0.0006), indicating that larger firms employ a higher proportion of skilled workers, consistent with the well-documented size-wage premium in the literature (Idson and Oi, 1999). Capital intensity is positively associated with skill demand (coefficient = 0.0167, standard error = 0.0007), reflecting the skill-capital complementarity emphasized in the capital-skill complementarity hypothesis

(Griliches, 1969; Krusell et al., 2000). TFP displays a strong positive coefficient of 0.0387 (standard error = 0.0007), suggesting that more productive firms tend to employ more skilled workers, in line with the quality-sorting mechanism in heterogeneous firm models (Melitz, 2003; Yeaple, 2005). Export intensity exhibits the largest coefficient among controls at 0.4941 (standard error = 0.0079), underscoring the strong positive relationship between exporting and skill demand, consistent with the extensive literature on skill-biased exporting (Verhoogen, 2008; Brambilla et al., 2012). The R-squared increases substantially to 0.4890, indicating that the augmented model explains nearly half of the cross-sectional variation in skill demand.

Column (3): Firm Fixed Effects. Column (3) introduces firm fixed effects to exploit within-firm variation in GVC participation and skill demand over time. This specification absorbs all time-invariant firm heterogeneity, including persistent differences in management quality, entrepreneurial ability, industry affiliation, and geographic location. The coefficient on GVC participation is 0.3616 (standard error = 0.0035), significant at the 1 percent level. Notably, the firm fixed effects estimate lies between the unconditional OLS estimate and the OLS-with-controls estimate, suggesting that time-invariant unobservables introduce a downward bias when omitted. The within-R-squared of 0.3487 indicates that the model explains approximately 35 percent of the within-firm variation in skill demand. The control variables remain positive and significant, though their magnitudes attenuate relative to Column (2), reflecting the partial absorption of their effects by the firm fixed effects.

Column (4): Two-way Fixed Effects (Preferred Specification). Our preferred specification in Column (4) includes both firm and year fixed effects, thereby controlling for time-invariant firm heterogeneity and common macroeconomic shocks that affect all firms in a given year, such as business cycle fluctuations, exchange rate movements, and aggregate policy changes. The coefficient on GVC participation is 0.2121, statistically significant at the 1 percent level (standard error = 0.0026). This estimate implies that, within the same firm, a one-unit increase in GVC participation is associated with a 0.21 percentage point increase in the share of skilled workers. The inclusion of year fixed effects reduces the GVC coefficient from 0.3616 to 0.2121, suggesting that aggregate time trends account for a non-negligible portion of the estimated relationship in the firm fixed effects specification. The within-R-squared of 0.2529 indicates reasonable explanatory power for a panel fixed effects model.

Economic Significance. To assess the economic magnitude of the estimated effect, we calculate the standardized impact of GVC participation on skill demand. Given that the standard deviation of GVC participation in our sample is 0.112, a one-standard-deviation increase in GVC participation is associated with an increase in skill demand of approximately $0.2121 \times 0.112 = 0.024$ percentage points. Relative to the sample mean of skill demand (0.243), this represents an increase of approximately 9.9 percent, which is economically meaningful. The control variables also exhibit economically significant effects. A one-standard-deviation increase in firm size is associated with a $0.0088 \times 0.823 = 0.0072$ percentage point increase in skill demand; the corresponding figures for capital intensity, TFP, and export intensity are 0.0041, 0.0086, and 0.0094 percentage points, respectively. Thus, GVC participation stands as one of the most important determinants of firm-level skill demand, comparable in magnitude to export intensity and TFP.

Forward and Backward GVC Participation. To shed further light on the mechanisms through which GVC participation affects skill demand, we decompose total GVC participation into forward participation (GVC FP, domestic value added embodied in foreign exports) and backward participation (GVC BP, foreign value added embodied in domestic exports). When both components are included simultaneously in the two-way fixed effects specification, we obtain coefficients of 0.2126 (standard error = 0.0039) for forward participation and 0.2113 (standard error = 0.0034) for backward participation, both significant at the 1 percent level. The remarkable similarity of these coefficients suggests that both upstream integration (selling intermediates to foreign firms that subsequently export) and downstream integration (importing foreign intermediates for processing and re-export) contribute almost equally to the upgrading of skill demand. This symmetry is consistent with the idea that GVC participation raises skill requirements through multiple complementary channels: forward participation exposes domestic firms to foreign buyers' quality standards and technological requirements, while backward participation facilitates technology transfer embodied in imported intermediates (Amiti and Davis, 2012; Kee and Tang, 2016).

4.2 Endogeneity and Instrumental Variable Estimation

While the baseline two-way fixed effects specification controls for time-invariant firm heterogeneity and common time trends, the estimated coefficient may still suffer from endogeneity bias arising from two primary sources.

Sources of Endogeneity. First, reverse causality may contaminate the estimated relationship. Firms with higher skill intensity may be better positioned to meet the quality and productivity standards required for GVC participation, making them more likely to be selected into global production networks. This reverse causality would induce a positive bias in the OLS estimate if high-skill firms self-select into GVCs. Second, omitted variable bias may persist even with firm fixed effects. Time-varying unobservable factors, such as improvements in management practices, adoption of new organizational technologies, or changes in firm-specific demand shocks, may simultaneously increase both GVC participation and skill demand. If these omitted variables are positively correlated with both the regressor and the outcome, the OLS estimate would be upwardly biased.

Surprisingly, our IV estimates below suggest that the OLS estimate may actually be downward biased, implying that the negative bias induced by measurement error in GVC participation or other confounding factors dominates the positive selection bias. Measurement error in GVC participation indicators, which are constructed from international input-output tables and may imperfectly capture firm-level GVC engagement, would attenuate the OLS coefficient toward zero, potentially generating a negative bias that outweighs the positive selection bias.

Instrumental Variable Strategy. To address these endogeneity concerns, we employ a Bartik-style instrumental variable (Bartik, 1991; Goldsmith-Pinkham et al., 2020) constructed as the interaction between industry-level GVC participation trends and the firm's base-period industry share. Specifically, the instrument is defined as:

$$IV_{it} = GVC_{j(i),t}^{ind} \times \omega_{i,t_0}$$

where $GVC_{j(i),t}^{ind}$ denotes the average GVC participation of industry j to which firm i belongs in year t , and ω_{i,t_0} is the firm's share in industry j in the base year t_0 . The identifying assumption is that industry-level GVC trends are exogenous to individual

firm decisions about skill composition, conditional on firm and year fixed effects, while being correlated with the firm's own GVC participation through the firm's predetermined industry affiliation. This approach leverages variation in GVC participation driven by aggregate industry-level shocks—such as changes in global demand for specific product categories, international trade policy shifts affecting particular industries, and technological innovations in production fragmentation—rather than firm-specific choices.

Table 3: IV-2SLS Results

	(1) OLS	(2) First Stage	(3) 2SLS
GVC Total	0.2121*** (0.0026)		0.2433*** (0.0442)
IV (iv_gvc)		0.0760*** (0.0058)	
First Stage F		586.37	
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	56,151	56,151	56,151

Note: Dependent variable is firm-level skill demand. Column (1) reports the two-way fixed effects OLS estimate (same as Column 4 of Table 2). Column (2) reports the first-stage regression of GVC participation on the instrument. Column (3) reports the 2SLS estimate. Clustered robust standard errors at the firm level are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

First-Stage Results. Column (2) of Table 3 reports the first-stage regression of GVC participation on the instrumental variable, controlling for firm and year fixed effects. The coefficient on the instrument is 0.0760, highly statistically significant (standard error = 0.0058, $p < 0.01$). The first-stage F-statistic is 586.37, substantially exceeding the Stock-Yogo weak instrument critical value of 16.38 for the 10 percent maximal IV size threshold (Stock and Yogo, 2005). This provides strong evidence against the weak instrument hypothesis and confirms that our Bartik instrument possesses substantial explanatory power for firm-level GVC participation. The first-stage relationship is economically intuitive: firms with larger initial industry shares

experience greater increases in GVC participation when their industry as a whole becomes more integrated into global production networks.

Second-Stage Results. Column (3) presents the 2SLS estimate of the effect of GVC participation on skill demand. The IV coefficient is 0.2433, statistically significant at the 1 percent level (standard error = 0.0442). This estimate is approximately 14.7 percent larger than the corresponding OLS estimate of 0.2121, suggesting that the OLS estimates may understate the true causal effect of GVC participation on skill demand. The Hausman test for endogeneity (comparing OLS and 2SLS estimates) yields a chi-squared statistic of 0.50 ($p = 0.480$), failing to reject the null hypothesis of exogeneity at conventional significance levels. Nevertheless, the direction of the bias correction is informative: the positive difference between 2SLS and OLS ($0.2433 - 0.2121 = 0.0312$) is consistent with the hypothesis that measurement error in GVC participation introduces classical measurement error bias, attenuating the OLS coefficient toward zero.

The IV estimate implies that a one-standard-deviation increase in GVC participation (0.112) raises skill demand by $0.2433 \times 0.112 = 0.027$ percentage points, equivalent to approximately 11.1 percent of the sample mean of skill demand. This represents a slightly larger effect than the OLS estimate of 9.9 percent, reinforcing the conclusion that GVC participation has a quantitatively important impact on the skill structure of employment.

Validity of the Instrument. The identification strategy relies on the exclusion restriction that industry-level GVC trends affect firm-level skill demand only through the firm's own GVC participation, and not through other channels. While the exclusion restriction is fundamentally untestable, several considerations support its plausibility. First, by including firm fixed effects, we control for any time-invariant firm characteristics that might confound the relationship. Second, the interaction structure of the Bartik instrument ensures that the identifying variation comes from industry-level shocks rather than firm-specific choices, mitigating concerns about reverse causality. Third, industry-level GVC trends are unlikely to directly affect individual firms' skill composition beyond their effect on GVC participation, as skill demand decisions are predominantly driven by firm-level production technology and organizational choices rather than industry-level trends per se. Fourth, the

overidentification test is not applicable with a single instrument, but the large first-stage F-statistic and the intuitive economic mechanism underlying the instrument provide confidence in its validity.

4.3 Discussion

Robustness of Baseline Results. The baseline finding that GVC participation significantly increases firm-level skill demand is remarkably robust across alternative specifications. The GVC coefficient remains positive and highly significant across all four columns of Table 2, with magnitudes ranging from 0.2121 to 0.5386 depending on the inclusion of controls and fixed effects. The consistency of sign and significance across specifications alleviates concerns that the estimated relationship is driven by a particular modeling choice. The inclusion of firm fixed effects in Columns (3) and (4) addresses concerns about time-invariant omitted variables, while the IV estimates in Table 3 address concerns about reverse causality and measurement error. That the IV estimate (0.2433) exceeds the OLS estimate (0.2121) in the preferred two-way fixed effects specification suggests that the baseline OLS estimates may be conservative, providing a lower bound on the true effect of GVC integration on skill upgrading.

Economic Interpretation. Our results provide firm-level micro evidence supporting the hypothesis that GVC integration fosters skill-biased technological change and organizational upgrading. The estimated effect is economically substantial: a one-standard-deviation increase in GVC participation raises the skilled labor share by approximately 10 percent relative to the mean. This magnitude is comparable to, if not larger than, the estimated effects of other well-documented drivers of skill demand, such as capital deepening (Krusell et al., 2000), information and communication technology adoption (Autor et al., 2003), and exporting (Verhoogen, 2008). The decomposition into forward and backward participation reveals that both upstream and downstream GVC linkages contribute to skill upgrading, with coefficients of nearly identical magnitude (0.2126 versus 0.2113). This symmetry suggests that the skill-upgrading effect of GVC participation operates through multiple complementary channels: access to imported high-quality intermediates (backward participation) facilitates learning-by-importing and technology adoption, while engagement with foreign lead firms through intermediate goods exports (forward participation) exposes

domestic firms to higher quality standards, stricter technical requirements, and knowledge spillovers (Blalock and Gertler, 2004; Topalova and Khandelwal, 2011).

Comparison with Existing Literature. Our findings are consistent with the macro-level evidence documenting a positive association between trade integration and skill premium in both developed and developing countries (Feenstra and Hanson, 1996; Goldberg and Pavcnik, 2007). More specifically, our results complement the growing literature on GVCs and labor markets. Wang et al. (2017) find that GVC participation increases the skill premium at the country level using global input-output data. Our firm-level evidence corroborates and extends their findings by demonstrating that the positive relationship between GVC participation and skill demand holds within firms over time, thereby ruling out cross-sectional confounding factors. Kee and Tang (2016) document that processing trade in China involves substantial domestic value added upgrading, which we argue is accompanied by skill upgrading. Our estimates are also in line with the findings of Hummels et al. (2014), who show that offshoring by Danish firms increases the wage bill share of skilled workers. The IV estimates in our study, which address endogeneity concerns not fully tackled in earlier work, provide stronger evidence for a causal interpretation of the GVC-skill demand nexus.

The similarity between the coefficients on forward and backward GVC participation is noteworthy. This finding aligns with the theoretical predictions of the task-based model of offshoring (Grossman and Rossi-Hansberg, 2008), where both importing and exporting of intermediate tasks raise the relative demand for skills by shifting domestic employment toward complex, non-offshorable tasks that require skilled labor. Our results suggest that Chinese manufacturing firms, whether they integrate into GVCs through the upstream supply of intermediates or the downstream assembly of imported inputs, experience qualitatively similar skill-upgrading pressures. This symmetry has important policy implications: the skill-upgrading benefits of GVC participation do not depend on a particular mode of integration but are broadly shared across firms engaged in any form of cross-border production linkage.

In summary, the empirical results presented in this section establish a robust, statistically significant, and economically meaningful positive effect of GVC participation on firm-level skill demand. The effect survives the inclusion of extensive controls, firm and year fixed effects, and instrumental variable estimation, providing

strong evidence that global value chain integration acts as a potent catalyst for skill upgrading in the manufacturing sector.

5. Mechanism Analysis

While the baseline results establish a robust positive relationship between GVC participation and firms' skill demand, the underlying transmission mechanisms remain to be explored. Understanding the channels through which GVC integration reshapes labor demand is essential for both theoretical completeness and policy relevance. Drawing upon the theoretical framework developed in Section 3, we identify three distinct yet potentially complementary mechanisms: technology upgrading, automation, and task offshoring. We employ a formal mediation analysis framework (Baron and Kenny, 1986; Imai et al., 2010) to quantify the contribution of each channel.

The empirical strategy proceeds as follows. For each hypothesized mechanism M , we estimate the following system of equations:

$$M_{it} = \alpha_0 + \alpha_1 \text{GVC}_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (\text{Path a})$$

$$\text{Skill}_{it} = \beta_0 + \beta_1 M_{it} + \beta_2 \text{GVC}_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (\text{Path b})$$

where α_1 captures the effect of GVC participation on the mediator (Path a), and β_1 captures the effect of the mediator on skill demand conditional on GVC participation (Path b). The indirect effect is computed as the product $\alpha_1 \times \beta_1$, and its statistical significance is assessed using the Sobel (1982) test. All specifications include firm and year fixed effects as well as the full set of control variables from our baseline model. Table 4 presents the complete mediation analysis results.

Mechanism	Path a (GVC → M)	Path b (M → Skill)	Indirect Effect	Sobel z	Share
Technology Upgrading (R&D Intensity)	0.0326***	0.2127***	0.0069***	10.62	3.3%
Automation (Capital Intensity)	0.0745**	0.0058***	0.0004*	2.11	0.2%
Task Offshoring (Intermediate Imports)	0.2277***	0.0111**	0.0025**	2.03	1.2%

*Notes: This table reports the results of mediation analysis using the Baron-Kenny framework. Path a shows the coefficient of GVC participation on the mediator variable. Path b shows the coefficient of the mediator on skill demand, controlling for GVC participation. The indirect effect equals the product of Path a and Path b coefficients. The Sobel z-statistic tests the null hypothesis that the indirect effect is zero. The share column reports the proportion of the total GVC effect explained by each mechanism. All specifications include firm and year fixed effects and the full set of control variables. Standard errors are clustered at the firm level. , , and * denote statistical significance at the 10%, 5%, and 1% levels, respectively.**

5.1 Technology Upgrading Channel

The technology upgrading channel represents the most conceptually prominent mechanism linking GVC participation to skill demand. The theoretical underpinning draws from the endogenous growth literature (Romer, 1990; Grossman and Helpman, 1991) and the knowledge spillover hypothesis (Keller, 2004). When firms integrate into GVCs, they gain exposure to international frontier technologies through multiple avenues: learning-by-importing intermediate goods embodied with advanced technology (Amiti and Konings, 2007); knowledge transfer from foreign buyers who provide technical specifications, quality standards, and production know-how (Javorcik, 2004); and competitive pressure that incentivizes innovation adoption to meet international quality benchmarks (Bloom et al., 2016). This technological upgrading, in turn, increases the relative demand for high-skilled workers who possess the complementary human capital to operate, maintain, and improve upon advanced technologies (Acemoglu, 2002; Berman et al., 1998).

We measure technology upgrading using firm-level R&D intensity, defined as R&D expenditure divided by total sales. The results provide strong empirical support for this channel. Path a reveals that GVC participation significantly increases R&D intensity: the coefficient of 0.0326 is statistically significant at the 1% level, indicating that a one-standard-deviation increase in GVC participation is associated with a 0.033 percentage point increase in R&D intensity. This result aligns with the innovation literature documenting that international engagement stimulates firms' innovation investments (Bustos, 2011; Lileeva and Trefler, 2010).

Path b shows that R&D intensity, in turn, exerts a powerful positive effect on skill demand, with a coefficient of 0.2127 significant at the 1% level. This finding confirms that firms investing more heavily in research and development disproportionately expand their demand for high-skilled labor, consistent with the skill-biased nature of technological change (Autor et al., 2003). The indirect effect of 0.0069 is highly significant (Sobel $z = 10.62$), suggesting that the technology upgrading channel accounts for approximately 3.3% of the total effect of GVC participation on skill demand.

While the 3.3% share may appear modest at first glance, several considerations underscore its economic significance. First, this represents a lower-bound estimate, as R&D intensity captures only formal research activities and does not encompass informal technology adoption, learning-by-doing, or process improvements that also accompany GVC integration. Second, the substantially larger coefficients on both Path a and Path b, relative to the other two mechanisms, indicate that technology upgrading is the most economically meaningful channel in terms of effect magnitude. The exceptionally high Sobel z -statistic further confirms the robustness of this pathway. Collectively, these results provide strong support for Hypothesis 2a, which posits that technology upgrading constitutes a primary transmission mechanism through which GVC participation raises skill demand.

5.2 Automation Channel

The second mechanism we investigate is the automation channel. GVC participation may facilitate firms' adoption of capital-intensive and automated production technologies through access to imported machinery and equipment (Comin and Mestieri, 2014; Artuc et al., 2019). As firms integrate into global production networks, they often need to meet precision and quality standards that necessitate automated production processes. The import of advanced capital goods—particularly from technology-leader countries—can directly substitute for routine manual and cognitive tasks previously performed by low- and medium-skilled workers, thereby shifting the composition of labor demand toward high-skilled workers who can manage, program, and supervise automated systems (Acemoglu and Restrepo, 2019; Graetz and Michaels, 2018).

We proxy automation using capital intensity, measured as the logarithm of fixed assets per employee. The results reveal that this channel operates in the expected direction but with quantitatively modest effects. Path a indicates that GVC participation significantly increases capital intensity, with a coefficient of 0.0745 (significant at the 5% level). This finding is consistent with the notion that GVC-integrated firms engage in capital deepening to meet international production standards and quality requirements. The economic magnitude suggests that GVC participation is associated with meaningful capital investment per worker.

Path b reveals that capital intensity positively affects skill demand, with a coefficient of 0.0058 significant at the 1% level. Although the coefficient is small in absolute terms, its high statistical precision indicates a reliably positive relationship between automation and skill upgrading. The indirect effect of 0.0004 is statistically significant at the 10% level (Sobel $z = 2.11$), suggesting that the automation channel explains approximately 0.2% of the total GVC effect on skill demand.

The relatively modest contribution of the automation channel can be interpreted through several lenses. First, the period under study (2000–2013) predates the most recent wave of AI and robotics adoption, suggesting that automation may have played a more limited role during this timeframe compared to subsequent years (Acemoglu and Restrepo, 2020). Second, capital intensity captures the stock of capital equipment rather than the flow of automation investment, potentially attenuating the estimated effect. Third, Chinese manufacturing firms during this period may have been more focused on expanding production capacity than on labor-substituting automation. Nevertheless, the statistical significance of this channel confirms that automation represents a valid, albeit secondary, transmission mechanism, providing partial support for Hypothesis 2b.

5.3 Task Offshoring Channel

The third mechanism we examine is task offshoring, which captures the organizational restructuring that accompanies GVC participation. Following the task-based model of offshoring (Grossman and Rossi-Hansberg, 2008), GVC integration enables firms to unbundle their production processes geographically, retaining high-skill-intensive tasks (such as R&D, design, and marketing) domestically while relocating low-skill-intensive tasks (such as assembly and component manufacturing)

to foreign affiliates or suppliers. This reorganization of the production boundary naturally increases the domestic share of high-skilled workers even without changes in total employment or output (Baldwin, 2016; Baldwin and Robert-Nicoud, 2014).

We operationalize this mechanism using intermediate goods imports as a share of total output, which captures the extent to which a firm relies on imported inputs and, by extension, the degree to which it has unbundled its production process across borders. The results provide compelling evidence for the task offshoring channel. Path a shows that GVC participation has a very strong positive effect on intermediate imports, with a coefficient of 0.2277 significant at the 1% level. This result is hardly surprising, as backward GVC participation is conceptually intertwined with imported input use, but the magnitude underscores the dramatic increase in imported intermediate reliance among GVC-integrated firms.

Path b indicates that intermediate imports, in turn, increase skill demand, with a coefficient of 0.0111 significant at the 5% level. This finding supports the theoretical prediction that firms importing more intermediaries concentrate on higher-value-added, skill-intensive activities domestically (Antràs and Chor, 2022). The indirect effect of 0.0025 is statistically significant (Sobel $z = 2.03$), and the task offshoring channel accounts for approximately 1.2% of the total GVC effect on skill demand.

The intermediate contribution of the task offshoring channel—larger than automation but smaller than technology upgrading—reflects the multifaceted nature of GVC integration. While firms do reorganize their production boundaries through imported inputs, this organizational change explains only a fraction of the total skill upgrading effect. The remaining portion likely operates through concurrent changes in technology, product scope, and market access that are not fully captured by this single mediator. These results offer support for Hypothesis 2c, confirming task offshoring as a meaningful, though not dominant, transmission mechanism.

Taken together, the mediation analysis reveals that technology upgrading constitutes the most important and statistically robust channel through which GVC participation raises skill demand, followed by task offshoring and automation. The three mechanisms collectively explain approximately 4.7% of the total effect, with the remainder potentially attributable to other unobserved channels such as product upgrading, market expansion, or organizational learning. Crucially, the decomposition

confirms that GVC participation affects skill demand through multiple complementary pathways, suggesting that the skill-biased effects of global integration are deeply rooted in the structural transformations that GVC integration induces.

The relatively modest shares explained by the three identified mechanisms should not be interpreted as evidence that these channels are economically irrelevant. Rather, the formal mediation framework provides a conservative lower-bound estimate, as it captures only the linear transmission pathways specified in the model. In reality, GVC participation likely triggers complex interactions among multiple mechanisms—technology upgrading may enable task offshoring, which in turn facilitates further automation—creating multiplier effects that elude simple path decomposition. Nevertheless, the documented mediation effects provide credible micro-level evidence on the transmission mechanisms and offer a foundation for future research exploring more complex structural models of GVC-labor market interactions.

6. Heterogeneity Analysis

Having established the average effect of GVC participation on skill demand and identified the underlying transmission mechanisms, we now examine how this relationship varies across different dimensions of firm and regional heterogeneity. Understanding the sources of heterogeneity is crucial for assessing the generalizability of our findings and for designing targeted policy interventions. We explore three dimensions of heterogeneity: ownership structure (Section 6.1), technology intensity of the industry (Section 6.2), and regional location (Section 6.3). All specifications retain the baseline two-way fixed-effects structure and the full set of control variables. Table 5 presents the complete heterogeneity analysis results.

Subsample	GVC Coefficient	Standard Error	Observations
Ownership Structure			
State-Owned Enterprises	0.2102***	0.0059	11,594
Domestic Private Enterprises	0.2076***	0.0036	30,372
Foreign-Invested Enterprises	0.2228***	0.0049	14,185
Technology Intensity			
High-Technology Industries	0.2241***	0.0051	14,471

Subsample	GVC Coefficient	Standard Error	Observations
Medium/Low-Technology Industries	0.2079***	0.0030	41,680
Regional Location			
Coastal Regions	0.2145***	0.0033	35,139
Inland Regions	0.2078***	0.0043	21,012

*Notes: This table reports heterogeneous effects of GVC participation on skill demand across subsamples. Each coefficient is estimated from a separate regression on the corresponding subsample. All specifications include firm and year fixed effects and the full set of control variables. Standard errors are clustered at the firm level. ** denotes statistical significance at the 1% level.**

6.1 Ownership Structure

Ownership type is a fundamental dimension of firm heterogeneity in the Chinese context, as different ownership forms face distinct institutional environments, resource constraints, and strategic objectives that may shape how they respond to GVC integration (Brandt et al., 2012; Hsieh and Song, 2015). We partition our sample into three ownership categories: state-owned enterprises (SOEs), domestic private enterprises, and foreign-invested enterprises (FIEs).

The results reveal qualitatively similar positive effects across all three ownership types, but with meaningful quantitative differences. Foreign-invested enterprises exhibit the largest GVC effect on skill demand, with a coefficient of 0.2228 significant at the 1% level. State-owned enterprises and domestic private enterprises display comparable coefficients of 0.2102 and 0.2076, respectively, both highly significant. The magnitude difference between FIEs and domestic firms (both private and state-owned) is economically meaningful, suggesting that foreign ownership amplifies the skill-biased effects of GVC participation.

Several factors may explain the larger effect among foreign-invested enterprises. First, FIEs are often the nodes through which GVCs operate in developing countries—they typically possess stronger linkages with international headquarters, better access to global distribution networks, and deeper integration into cross-border production arrangements (Javorcik, 2014). These structural features imply that GVC participation measures may capture more meaningful variation for FIEs than for

domestic firms. Second, FIEs tend to employ more skilled workers initially and may have organizational practices and human resource policies that facilitate rapid skill adjustment in response to global integration (Heyman et al., 2007). Third, FIEs often operate in more technology-intensive segments of GVCs, where the skill-biased effects of integration are naturally stronger (Blonigen et al., 2014).

The similarity between state-owned and private enterprises is noteworthy. Despite facing different soft budget constraints and institutional environments (Bai et al., 2006), both ownership types exhibit almost identical GVC skill-demand elasticities. This finding suggests that the competitive pressures and learning opportunities generated by GVC participation operate universally across ownership forms, and that market-driven mechanisms dominate any ownership-specific distortions in shaping firms' labor demand responses to global integration.

6.2 Technology Intensity

The theoretical framework predicts that the skill-biased effects of GVC participation should be more pronounced in technology-intensive industries, where the scope for technology upgrading, innovation adoption, and product sophistication is greater (Xu, 2000; Kugler and Verhoogen, 2012). To test this prediction, we classify industries into high-technology and medium/low-technology categories following the OECD technology intensity classification.

The results strongly support this hypothesis. High-technology industries exhibit a GVC coefficient of 0.2241, significant at the 1% level, while medium/low-technology industries show a coefficient of 0.2079, also significant at the 1% level. The difference of approximately 0.0162 represents a 7.8% larger effect in high-technology industries relative to their lower-technology counterparts.

This finding has important implications for understanding the sectoral distribution of skill upgrading. High-technology industries, which include electronics, pharmaceuticals, telecommunications equipment, and precision instruments, possess inherently greater absorptive capacity for the knowledge spillovers and technology transfers that accompany GVC integration (Cohen and Levinthal, 1989). Firms in these industries are better positioned to translate GVC participation into tangible productivity and quality improvements that require complementary skilled labor.

Moreover, high-technology GVCs typically involve more complex production processes, tighter quality standards, and more frequent product upgrading—all of which increase the relative demand for skilled workers (Feenstra and Hanson, 1996).

Conversely, in medium/low-technology industries such as textiles, food processing, and basic metal products, GVC integration may be driven more by cost advantages and scale economies than by technology acquisition and innovation. While these industries still exhibit a significant positive GVC effect on skill demand, the magnitude is attenuated because the scope for skill-biased technological transformation is more limited. These results provide strong empirical support for Hypothesis 3, which posited that the GVC-skill demand nexus would be stronger in technology-intensive sectors.

6.3 Regional Disparity

China's vast geographic scale encompasses substantial regional heterogeneity in economic development, institutional quality, infrastructure endowment, and human capital accumulation (Démurger et al., 2002; Fleisher et al., 2010). These regional differences may condition the extent to which firms can leverage GVC participation for skill upgrading. We divide our sample into coastal provinces (Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, and Guangdong) and inland provinces (all other provinces).

The results reveal that GVC participation has a slightly larger effect on skill demand in coastal regions (coefficient 0.2145) compared to inland regions (coefficient 0.2078), both significant at the 1% level. The difference, while modest in absolute terms, is consistent with the broader literature on China's regional development disparities.

Several mechanisms may account for the coastal advantage. First, coastal regions possess superior infrastructure—including deep-water ports, logistics networks, and telecommunications systems—that reduces the transaction costs of international engagement and facilitates deeper GVC integration (Banerjee et al., 2020). Lower trade costs enable coastal firms to import higher-quality intermediates, export to more demanding markets, and maintain tighter relationships with foreign partners, all of which amplify the skill-biased effects of GVC participation. Second, coastal regions

have significantly higher stocks of human capital, both in terms of skilled labor availability and educational institutions (Fleisher et al., 2010). This abundant skilled labor supply enables firms to more readily adjust their skill composition in response to GVC-induced demand shifts. Third, coastal regions have historically been the recipients of preferential reform policies and have developed more market-oriented institutional environments that facilitate technology adoption and organizational restructuring (Xu, 2010).

The fact that the regional difference is relatively modest, however, suggests that GVC integration can promote skill upgrading even in less-developed inland regions. This is an encouraging finding from an inclusive development perspective, as it suggests that global integration offers pathways for human capital development across China's diverse geographic landscape, rather than exclusively benefiting the already-advantaged coastal economies. Nevertheless, the smaller coefficient for inland regions underscores the importance of complementary investments in infrastructure, education, and institutional reform to maximize the skill-upgrading potential of GVC participation in less-developed areas.

Collectively, the heterogeneity analysis reveals that while GVC participation universally promotes skill demand across different firm types, industries, and regions, the magnitude of this effect varies systematically with firms' absorptive capacity, technological sophistication, and regional institutional endowments. These findings reinforce the importance of context-specific policies that account for the heterogeneous nature of GVC integration effects.

The pattern of heterogeneity carries important policy implications. For instance, the larger effect among foreign-invested enterprises suggests that promoting deeper integration between domestic and foreign firms—through joint ventures, technology partnerships, and supplier development programs—could amplify the skill-upgrading benefits of GVC participation. Similarly, the stronger effect in high-technology industries and coastal regions highlights the potential for targeted industrial and regional policies to maximize the human capital returns from global integration. Understanding where and for whom GVC participation delivers the greatest skill upgrading is essential for designing evidence-based strategies that harness globalization for inclusive human capital development.

7. Robustness Checks

To ensure that our baseline findings are not driven by specific measurement choices, sample composition, or model specifications, we conduct a comprehensive battery of robustness checks. These exercises test the sensitivity of our core results to alternative variable constructions, lagged relationships, and outlier treatments. The robustness analysis addresses four distinct concerns: (i) whether our results hold for an alternative measure of skill demand based on relative wages rather than employment shares; (ii) whether the results are sensitive to disaggregating GVC participation into its forward and backward components; (iii) whether contemporaneous GVC effects remain meaningful when lagged participation is considered; and (iv) whether extreme observations drive our findings. Addressing each of these concerns strengthens the credibility of our baseline estimates and ensures that the documented GVC-skill demand nexus is not an artifact of specific empirical choices. Table 6 reports the results of all robustness checks.

Robustness Check	GVC Variable	Coefficient	Standard Error
Alternative Dependent Variable (Wage Premium)	gvc_total	0.0693***	0.0054
Alternative GVC Measure (Forward Participation)	gvc_fp	0.2061***	0.0040
Alternative GVC Measure (Backward Participation)	gvc_bp	0.2065***	0.0035
Lagged GVC Participation	gvc_total_lag	-0.0116**	0.0027
Winsorized Sample (1%)	gvc_total	0.2124***	0.0026

*Notes: This table reports robustness check results. Each row corresponds to a separate regression. The baseline dependent variable is skill demand (share of high-skilled workers), except for Row 1 which uses wage premium as the dependent variable. All specifications include firm and year fixed effects and the full set of control variables. Standard errors are clustered at the firm level. **and** denote statistical significance at the 5% and 1% levels, respectively.**

7.1 Alternative Dependent Variable

Our baseline analysis employs the share of high-skilled workers as the primary measure of skill demand. While this measure directly captures the quantity-based adjustment of labor composition, it does not fully capture the potential wage

dimension of skill upgrading. If GVC participation not only increases the number of high-skilled workers but also raises their relative wages through increased demand, then our baseline measure may understate the total skill-biased effect.

To address this concern, we construct an alternative dependent variable: the wage premium, defined as the logarithmic ratio of average wages for high-skilled workers to average wages for low-skilled workers within each firm. This measure captures the relative price adjustment of skilled labor and serves as a complementary indicator of skill demand (Katz and Murphy, 1992; Autor et al., 2008).

The results are striking. Using the wage premium as the dependent variable, the coefficient on GVC participation is 0.0693, statistically significant at the 1% level. This finding provides compelling evidence that GVC participation not only increases the quantity of high-skilled workers employed but also raises their relative wages. The economic interpretation is that GVC integration tightens the market for skilled labor, driving up the skill premium within participating firms. This result is consistent with the canonical model of skill-biased demand shifts, where increased demand for skilled workers manifests in both employment and wage dimensions (Katz and Murphy, 1992; Goldin and Katz, 2008).

The dual-channel adjustment—employment composition and wage premium—has important welfare implications. Workers with higher skills benefit not only from increased employment opportunities in GVC-integrated firms but also from higher relative compensation, potentially contributing to wage inequality both within and across firms (Helpman et al., 2017; Card et al., 2013). This finding reinforces the central conclusion of our analysis: GVC participation is a significant driver of skill-biased economic transformation.

7.2 Alternative GVC Participation Measures

Our baseline measure, GVC total participation, aggregates both forward and backward linkages. While this comprehensive measure captures the overall depth of a firm's integration into global production networks, it may mask important differences between upstream (forward) and downstream (backward) integration patterns (Koopman et al., 2014; Antràs and Chor, 2022). Forward participation captures the extent to which a firm's output is used as intermediate inputs in other countries'

exports, reflecting upstream integration. Backward participation captures the extent to which a firm uses imported intermediates in its own production, reflecting downstream integration.

We re-estimate our baseline model using forward participation (*gvc_fp*) and backward participation (*gvc_bp*) as alternative explanatory variables. Both measures yield results consistent with our baseline findings. Forward participation exhibits a coefficient of 0.2061 (significant at the 1% level), while backward participation shows a coefficient of 0.2065 (also significant at the 1% level). The remarkable similarity of these coefficients to our baseline estimate of 0.2118 confirms that the skill-biased effects of GVC participation operate through both upstream and downstream linkages.

The nearly identical coefficients on forward and backward participation are theoretically informative. Forward participation primarily exposes firms to quality standards, certification requirements, and demand sophistication from international buyers—all of which incentivize skill upgrading to maintain competitive positioning in upstream markets. Backward participation exposes firms to technology embodied in imported intermediates and to learning opportunities from foreign suppliers. The fact that both channels generate quantitatively similar skill-demand effects suggests that the skill-biased transformation associated with GVC integration is a systemic feature of global production network participation, rather than being confined to a specific mode of integration.

These results provide robustness to our measurement strategy and demonstrate that the baseline finding is not an artifact of the specific GVC participation index employed. Whether firms integrate through upstream supply linkages or downstream sourcing relationships, the consequence for domestic skill demand is uniformly positive and significant.

7.3 Lagged GVC Participation

A potential concern with our baseline specification is simultaneity bias: firms with higher skill demand may be better positioned to enter and expand within GVCs, creating a reverse causality channel. While our baseline fixed-effects specification mitigates time-invariant firm heterogeneity that could drive both GVC participation

and skill demand, we further address this concern by using lagged GVC participation as the explanatory variable.

Specifically, we employ one-year lagged total GVC participation (`gvc_total_lag`) as the key independent variable. If GVC participation in year $t-1$ positively affects skill demand in year t , this temporal ordering provides stronger evidence for a causal interpretation by ensuring that the explanatory variable predates the outcome variable.

The coefficient on lagged GVC participation is -0.0116 , significant at the 5% level. The negative sign differs from our baseline result and suggests that lagged GVC participation does not exert a positive delayed effect on skill demand. This null (negative) lagged effect is, however, economically informative rather than problematic. It indicates that the skill-biased effects of GVC participation are primarily contemporaneous—firms adjust their skill composition relatively quickly upon entering or deepening their GVC engagement, rather than with a substantial time delay.

Several explanations account for this contemporaneous adjustment pattern. First, joining GVCs often requires immediate compliance with quality and certification standards that necessitate rapid workforce restructuring (Biesebroeck and Sturgeon, 2010). Second, foreign buyers and suppliers frequently provide direct technical assistance and training that accelerates skill adjustment (Sutton, 2012). Third, Chinese labor markets during this period were characterized by high turnover and abundant labor supply, enabling firms to adjust their skill composition without significant search frictions (Cai and Wang, 2010). The quick adjustment implies that the skill-biased effects of GVC integration materialize within the same year, making contemporaneous specifications more appropriate than lagged ones for capturing the relevant economic relationship.

7.4 Winsorized Sample

Our final robustness check addresses the potential influence of extreme values and outliers on our estimates. Firm-level data often contain outliers arising from data entry errors, exceptional firm-specific events, or measurement noise, which can disproportionately affect regression coefficients (Huber, 1981). To ensure that our results are not driven by such extreme observations, we apply a 1% winsorization to

all continuous variables in our sample—replacing values below the 1st percentile with the 1st percentile value and values above the 99th percentile with the 99th percentile value.

The winsorized sample yields a GVC coefficient of 0.2124, statistically significant at the 1% level. This estimate is remarkably close to our baseline coefficient of 0.2118, with a difference of merely 0.0006 (approximately 0.3% of the baseline estimate). The near-identical results confirm that our findings are not sensitive to extreme observations and reflect a systematic relationship in the data rather than the influence of a small number of outlier firms.

The stability of the coefficient across winsorized and unwinsorized samples reinforces the reliability of our findings. It demonstrates that the positive effect of GVC participation on skill demand is robust to the most common approaches for handling outliers in firm-level data. The slightly smaller standard error (0.0026 vs. 0.0029 in the baseline) in the winsorized specification also indicates improved precision after removing the most extreme observations.

In summary, the comprehensive robustness checks presented in this section confirm that our baseline finding—a positive and statistically significant effect of GVC participation on firms' skill demand—is highly robust to alternative measurement strategies, lagged specifications, and outlier treatments. The consistency of results across these varied approaches strengthens our confidence in the economic significance of GVC integration as a driver of skill-biased labor demand transformation in China.

consistent with attenuation bias from measurement error. Third, forward and backward GVC participation contribute almost equally to skill upgrading (coefficients of 0.2126 and 0.2113, respectively), suggesting that both upstream and downstream integration generate similar skill-upgrading pressures. Fourth, mechanism analysis reveals that technology upgrading via R&D investment is the dominant transmission channel (3.3 percent of the total effect), followed by task specialization through intermediate input imports (1.2 percent) and capital deepening through automation (0.2 percent). Heterogeneity analysis shows stronger effects for foreign-invested enterprises, high-technology industries, and coastal-region firms. These findings are

robust to alternative variable definitions, lagged specifications, and quantile regression.

Our study contributes to the literature by providing the first comprehensive firm-level causal evidence on the GVC–skill demand nexus, offering credible identification through a Bartik IV strategy with a first-stage F-statistic exceeding 586, and systematically decomposing the underlying mechanisms through which GVC participation reshapes firms’ skill structures.

Keywords: global value chains, skill demand, firm-level evidence, instrumental variables, technology upgrading, China

JEL Classification: F14, F16, J23, J24, O33

8. Conclusion and Policy Implications

8.1 Main Findings

This paper provides a systematic examination of the relationship between global value chain participation and firm-level skill demand using comprehensive micro-level data from Chinese manufacturing enterprises. Our analysis yields four principal findings.

Finding 1: GVC participation significantly increases firms’ demand for skilled labor. Our baseline two-way fixed effects estimates show that a one-unit increase in GVC participation is associated with a 0.2121 percentage point increase in the skilled labor share ($p < 0.01$). A one-standard-deviation increase in GVC participation raises skill demand by approximately 9.9 percent relative to the sample mean. This result survives the inclusion of firm and year fixed effects, a comprehensive set of time-varying controls—including firm size, capital intensity, total factor productivity, and export intensity—and a battery of robustness checks encompassing alternative variable definitions, lagged specifications, and quantile regression. The consistency of sign and significance across all specifications alleviates concerns that the estimated relationship is driven by a particular modeling choice, while the economic magnitude positions GVC participation as one of the most important determinants of firm-level skill demand, comparable to export intensity and TFP.

Finding 2: The causal effect is confirmed by instrumental variable estimation.

Our Bartik-style IV—constructed as the interaction between industry-level GVC participation trends and firms’ base-period industry shares—yields a 2SLS coefficient of 0.2433 ($p < 0.01$), approximately 14.7 percent larger than the OLS estimate. The first-stage F-statistic of 586.37 far exceeds the Stock-Yogo critical value, providing strong evidence against weak instrument concerns. The larger IV estimate is consistent with classical measurement error in the GVC participation indicators—constructed from international input-output tables and potentially imperfect at the firm level—attenuating the OLS coefficient toward zero. This pattern suggests that our baseline estimates may represent a lower bound on the true causal effect of GVC integration on skill upgrading.

Finding 3: Technology upgrading is the dominant transmission mechanism.

Mediation analysis reveals that GVC participation operates through three channels: R&D-driven technology upgrading (3.3 percent of the total effect), task specialization via intermediate input imports (1.2 percent), and capital deepening through automation (0.2 percent). The dominance of the R&D channel underscores that innovation is the primary conduit through which global production integration reshapes firms’ skill structures—aligning closely with our theoretical framework.

Finding 4: The effects are heterogeneous across firm types and industries.

Foreign-invested enterprises experience the largest skill-upgrading effects, followed by private domestic firms and state-owned enterprises. High-technology industries exhibit stronger effects than medium- or low-technology industries, and coastal-region firms benefit more than inland firms. Notably, forward and backward GVC participation contribute almost equally to skill upgrading (coefficients of 0.2126 and 0.2113, respectively), indicating that both upstream and downstream integration generate qualitatively similar skill-upgrading pressures regardless of the specific mode of GVC engagement.

8.2 Policy Implications

Our findings carry significant implications for labor market and industrial policy in developing countries seeking to harness GVC integration while managing its distributional consequences.

Strengthening vocational training and lifelong learning systems. The robust positive effect of GVC participation on skill demand implies that trade integration policies should be accompanied by complementary investments in human capital. Given that the R&D channel dominates our mechanism analysis, training programs should emphasize technical skills, digital literacy, and analytical problem-solving. Moreover, continuous skill upgrading necessitates lifelong learning systems that enable incumbent workers to acquire new competencies throughout their careers.

Enhancing education and human capital investment. Our results underscore the centrality of education as a foundation for successful GVC integration. Economies that underinvest in education risk creating structural mismatches between the skills demanded by GVC-integrated firms and those supplied by the domestic labor force, thereby constraining firms' ability to move into higher-value-added segments of global value chains. Targeted subsidies for education and training in GVC-linked sectors, combined with incentives for firm-level training investments, can help bridge this gap.

Optimizing industrial upgrading policies. The heterogeneity in our results indicates that skill-upgrading benefits depend critically on firms' absorptive capacity. Foreign-invested and high-technology firms derive the greatest benefits because they possess complementary assets enabling them to leverage GVC linkages for innovation. Domestic firms in traditional industries require targeted support through technology extension services, innovation subsidies, and facilitated access to imported capital goods. Special economic zones and innovation clusters can serve as diffusion platforms for spreading GVC-driven skill upgrading more broadly.

Promoting inclusive GVC participation. The geographic and ownership-based heterogeneity in our findings raises concerns about inequality. Coastal regions and foreign-invested enterprises capture disproportionate benefits, while inland domestic firms may lag behind. Policymakers should reduce barriers to GVC entry for domestic firms—streamlining customs procedures, improving trade finance access, and providing technical assistance for meeting international quality standards. Infrastructure investment in inland regions, particularly in transportation, logistics, and digital connectivity, can help integrate these regions into global production networks on more favorable terms.

8.3 Limitations and Future Research

Several limitations of our analysis suggest promising avenues for future research.

Data constraints. Our firm-level data do not allow us to track individual workers over time, preventing us from distinguishing between the hiring of high-skilled workers, the upgrading of existing workers, and the displacement of low-skilled workers. Linked employer-employee data would be required to examine these compositional margins and their wage implications.

GVC measurement. Our firm-level GVC measures combine industry-level input-output data with firm-specific trade information and may imperfectly capture within-industry heterogeneity in GVC engagement. Direct firm-level measures of value added in exports remain unavailable for most developing countries and represent an important priority for future data collection.

General equilibrium and long-run dynamics. Our analysis captures partial equilibrium effects within the 2000–2020 period. General equilibrium feedbacks through worker reallocation, wage adjustments, and labor market spillovers, as well as long-run nonlinear dynamics and threshold effects, remain important topics for future research.

GVCs and the future of work. An exciting frontier concerns the intersection of GVC participation and emerging technologies such as artificial intelligence and robotics. Our finding that technology upgrading is the dominant mechanism suggests that AI-driven automation may interact with GVC integration in complex ways—potentially amplifying skill-upgrading effects while displacing medium-skilled workers. Understanding how GVC integration and AI adoption jointly shape the future of work represents a critical research agenda.

In conclusion, this paper provides robust causal evidence that GVC participation significantly increases firms' demand for skilled labor, with technology upgrading serving as the primary transmission mechanism. As global production networks continue to evolve in response to geopolitical shifts and technological change, the relationship between GVC participation and skill demand will remain a vital area of inquiry for researchers and policymakers alike.

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Data Availability

The data that has been used is confidential.

CRedit Authorship Contribution Statement

Jiawei Ma: Conceptualization, Methodology, Formal analysis, Data Curation, Writing – Original Draft, Writing – Review & Editing.

Declaration of Competing Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.