Do Indian Manufacturing Firms Gain from Global Value Chain Participation?

By Girish Sharma*

This paper investigates the productivity effects of global value chain (GVC) participation among Indian manufacturing firms using firm-level panel data (2013–2024). I pursue two goals: (i) estimation of total factor productivity at the firm level; and (ii) causal impacts of GVC participation on TFP, incorporating heterogeneous treatment timing using a staggered DiD framework. While aggregate ATT estimates are statistically significant, dynamic post-treatment effects are weak and sensitive to trend violations. Cohort analysis suggests more recent entrants benefit more, though results are imprecise. Descriptive analysis reveals that firm-level TFP tends to decline year-on-year after GVC entry. I then explore size heterogeneity; point estimates indicate higher ATT for small firms, but the results are volatile and statistically insignificant. I conclude with a discussion of policy implications, recommendations, and potential extensions to this study.

The question of whether firms benefit from participating in global value chains (GVCs) is central to trade and industrial policy in emerging economies. GVCs - cross-border production systems that enable firms to specialize in specific stages of production - offer potential productivity gains through exposure to international markets, access to advanced technologies, and knowledge exchange with global buyers and suppliers. In India, where manufacturing has long been a comparative advantage due to low labor costs, the sector's contribution to GDP has remained at 13–15% over the past four decades [Bank, 2023].

This paper investigates whether Indian manufacturing firms gain from GVC participation. I begin

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by deriving a theoretical framework for firm-level total factor productivity (TFP) and estimating TFP following [Olley and Pakes, 1996] and [Levinsohn and Petrin, 2003] methodology. To identify the causal effect of GVC entry on productivity, I apply a staggered difference-in-differences design in the spirit of [Callaway and Sant'Anna, 2021]. In Section IV, I present average treatment effect on treated and dynamic event-study estimates, which show no statistically significant post-treatment effects. Aggregating treatment effects across cohorts and calendar years yields a positive and statistically significant average ATT. However, this result warrants caution: pre-treatment trends differ significantly from zero, and a power analysis of the pre-trend test indicates high sensitivity to violations with a slope greater than 0.007. Sensitivity checks following [Rambachan and Roth, 2023] show that the post-treatment ATT remains statistically significant only if violations are less than half the magnitude of the largest pre-trend deviation.

I also examine heterogeneity by firm size. While ATT estimates are higher for small firms, these effects are not statistically significant. Descriptive statistics show that GVC firms tend to be larger, exhibit greater R&D intensity, and have higher average TFP than non-GVC firms. Yet, cohort-level plots reveal a decline in productivity following GVC entry, suggesting that gains may not persist over time. The paper concludes that India's integration into GVCs is both incomplete and uneven. Policy recommendations include prioritizing network products, strengthening pharmaceutical manufacturing, enforcing compliance standards through public procurement, reducing trade costs, and maintaining a stable policy regime.

I. Background Literature

This study reviews three bodies of literature that provide the theoretical and methodological foundations for examining productivity gains from participation in global value chains (GVCs).

The first strand concerns the measurement of firm-level productivity using total factor productivity (TFP). The measurement of TFP has been central to growth theory since Solow [1957]'s seminal work, 'Technical Change and the Aggregate Production Function.' Over time, this theoretical industrial organization (IO) literature has evolved from single-input to multi-input empirical production models using the Cobb-Douglas production framework. The most common approach to estimating TFP is the residual method, which accounts for input contributions within this framework.

However, firm-level TFP estimation faces significant challenges. Olley and Pakes, 1996, addressed two key sources of bias: simultaneity and endogeneity. The former arises from the correlation between input choices (capital and labor) and productivity shocks, while the latter stems from the fact that productivity shocks are unobserved to the econometrician. To address these issues, they employed investment as a proxy for productivity shocks, allowing for control over the correlation between inputs and the unobserved factors. However, this methodology risks truncating a substantial portion of the dataset, particularly because unlisted plants in developing countries often do not report investment data.

To overcome this limitation, especially in cases where investment data are unavailable, as is common in firm-level datasets, [Levinsohn and Petrin, 2003] proposed using intermediate inputs as proxies for productivity shocks. This approach effectively addresses simultaneity bias without relying on investment figures.

With the availability of detailed product-level data, recent IO literature has raised concerns about the use of revenue-based production functions [De Loecker et al., 2016]; [Goldberg et al., 2010]. Since revenue equals price times quantity, productivity changes may reflect price shifts rather than genuine efficiency gains. This has led to calls for quantity-based production functions that disentangle price effects from true productivity improvements. While this literature is advancing - particularly with the availability of 8-digit product specifications data - such data remains noisy. Inconsistencies in product classification and sector definitions often require manual concordances [Goldberg et al., 2010].

The second strand of the literature examines how participation in GVCs affects firm productivity beyond the context of India. There is a broad consensus on defining GVC participation using firm-level data - specifically, firms that simultaneously import and export products or services are considered GVC participants [Banga, 2022]; [Urata and Baek, 2022]. While this proxy measure does not fully capture the nuance of input–output exchanges, it remains a practical and widely accepted approach.

The literature on the impact of GVC participation on TFP beyond India reports varying outcomes. Although Canadian companies exhibited strong productivity gains from GVC involvement [**?**], Japanese firms showed more moderate improvements. Urata and Baek 2022 analyzed the productivity effects of GVC participation among Japanese companies over the period 1994-2018. Using propensity score matching combined with a difference-in-differences (PSM-DID) approach, they conducted 110 estimations by converting the participation timeline into a 2×2 DID framework, comparing two base years against each year from 1994 to 2018. However, only 35% of the average treatment effects were found to be statistically significant [Urata and Baek, 2022].

Despite growing interest in the impact of GVC integration on TFP, there remains limited literature exploring this relationship within the Indian context using firm-level data. In India, a few empirical studies have laid the groundwork by employing the Levinsohn-Petrin (LP) methodology to estimate firm-level productivity prior to assessing the effects of GVC participation. For instance, Goldar et al. [2019], using an LP estimation with a value-added specification, report a negative and statistically significant impact of tariffs on TFP. Meanwhile, Banga [2022] applies a system generalized method of moments (GMM) framework to assess the productivity effects of GVC participation, documenting productivity gains up to three times higher for Indian firms integrated into global value chains.

However, both studies share common methodological approaches that may introduce measurement errors. Specifically, they rely on the perpetual inventory method to estimate capital stock vintage, assuming uniform economic depreciation rates across firms. Additionally, they use average industry-wide wages to approximate labor input. As Petrin and Levinsohn [2012] point out, relying on sector-level indices as proxies for firm-level variables—or to deflate nominal values—can generate measurement errors when firm-level prices diverge from industry averages. Moreover, Collard-Wexler and De Loecker [2016] demonstrates that the perpetual inventory method may introduce up to 40% measurement error in capital stock estimation. This could potentially explain the negative capital coefficients often observed in production function estimates.

This study addresses several limitations prevalent in the existing literature. First, most research estimates firm-level TFP at the aggregate manufacturing sector level, with limited attention to sub-industries such as food and beverages, textiles and apparel, pharmaceuticals, etc. Ignoring this sub-classification may mask or distort sector-specific effects in TFP estimation, particularly given the heterogeneity in operations and resource allocation across manufacturing segments.

Second, there is a noticeable gap in empirical work examining the impact of GVC participation on firm productivity using post-2015 Indian data. This is especially salient given the reconfiguration of global supply chains in the last decade and significant macroeconomic and policy shifts such as the implementation of the Goods and Services Tax (GST), demonetization, and the COVID-19 pandemic.

Third, challenges remain in defining the GVC treatment variable. While existing studies often define GVC participation as the simultaneous import and export of goods, resembling bilateral trade-firms in GVCs are better conceptualized as nodes within a global production network.[1] Relaxing the import-export of finished goods criterion broadens firm inclusion under the GVC label. Leveraging the Prowess IQ database, which provides finer line-item classifications distinguishing raw material from finished goods trade, I refine the definition to include firms that simultaneously import and export intermediate goods and services.

Fourth, existing Indian studies overlook the heterogeneity in GVC entry timing. Canonical DiD frameworks are ill-suited for firm-level analyses of GVC participation, as entry is not a discrete exogenous shock and firms join GVCs at varying points in time unless multiple year-by-year comparisons are made like Urata and Baek [2022] study on Japenese firms.

Moreover, much of the Indian literature is dominated by descriptive assessments and policy analyses, lacking rigorous firm-level empirical evaluations.

This research addresses key gaps in the literature by (a) refining TFP estimation to sector level and advancing empirical analysis in India context post-2015; (b) constructing firm-level TFP variables with careful attention to measurement errors identified in prior studies; and (c) applying causal inference techniques -specifically staggered DiD methods consistent with recent econometric developments—to estimate the impact of GVC participation on TFP, accounting for heterogeneous treatment timing across firms.

By tackling these methodological and empirical challenges, this study contributes to both the empirical literature on TFP measurement and if GVC participation affects firm productivity in the Indian manufacturing sector.

[1] For example, Samsung sources raw materials from Southeast Asian countries, assembles products in India and Bangladesh, and sells globally with major markets in the European Union and the United States. All countries in this multi-stage value network are participants in the GVC, which differs from conventional two-country trade flows.

II. Data

I use firm-level panel data from the Prowess IQ database maintained by the Centre for Monitoring Indian Economy (CMIE), a proprietary source that compiles audited financial statements of both listed and unlisted Indian firms. Unlike the Annual Survey of Industries (ASI), which is primarily designed for macro-level industrial monitoring and has historically been released as repeated cross-sections, Prowess enables the construction of a continuous panel dataset. It also provides more detailed financial variables essential for productivity analysis, including disaggregated sales, assets, wage bills, and material costs.

A key advantage of Prowess IQ is its coverage and the ability to track firm dynamics over time. I construct an unbalanced panel of 11,052 manufacturing firms over the fiscal years 2013–2024. Firm identifiers are consistent across years, and I restrict the sample to firms with non-missing data on key production inputs and outputs required for estimating total factor productivity.

CMIE classifies firms using both the official National Industrial Classification (NIC) system (up to 5-digit level) and a proprietary 11-digit internal classification. For consistency with existing literature and ease of interpretation, I aggregate industries at the 2-digit NIC level to define sectors, and at the 4-digit level to define industries. Table 1 provides an illustrative example.

Table 1—Sample Sector and Industry Classifications

NIC Code	**Description**
10	Food Products (sector)
1010	Processing and Preserving of Meat (industry)
1050	Dairy Products (industry)
1074	Macaroni, Noodles, Couscous (industry)

Note: For NIC 10, there are a total of 18 industries, but only a subset are listed in the table.

Further, I construct a sector-level concordance by aggregating related industries. For example, the Food Products and Beverages sectors are grouped together, as are Wood Products and Furniture. The full concordance is documented in table A1.

I construct the core variables for production function estimation and firm characteristics using methods mentioned in table 2:

Table 2—Variable Construction

Variable	Method
Output	Sales + Δ finished and WIP goods − Purchase of finished goods.
Capital	Gross fixed assets.
Labour	Total wage bill (salaries, wages, bonuses, etc.).
Materials	Raw material expenses + power and fuel + stores and spares consumed.
R&D Intensity	= 1 if (R&D Expenses / Total Sales) > 0; 0 otherwise.
Foreign Share	= 1 if (foreign promoter shareholding) > 10%; 0 otherwise.
Size	Total tangible and intangible assets.
GVC Status	= 1 if:
	(i) export of goods **or** services > 0; **and** (ii) import of capital **or** raw materials > 0.

Note: All variables are derived from firm-level financial statements compiled in the CMIE Prowess database and deflated to 2012 prices using two-digit sector-level wholesale price deflators, rather than a single deflator for the entire manufacturing sector. CMIE Prowess reports R&D expenditure only for firms where such spending constitutes at least 1% of annual sales. Accordingly, missing values are treated as indicative of firms that are not R&D-intensive.

III. Research Design

A. *Total Factor Productivity: Theoretical Model*

The TFP model draws from the broader IO literature on production function estimation, with methodological steps closely following Olley and Pakes [1996] and Levinsohn and Petrin [2003]. The key distinction lies in the construction of variables and model modifications that incorporate two primary inputs - labor (l) and capital (k) in Olley and Pakes's model and alongside a composite materials input (m), which serves as a proxy for unobserved productivity shocks Levinsohn and Petrin [2003].

Using a Cobb-Douglas production function:

$$Y_t = F(L_t, K_t, M_t, \Omega_t; \beta)$$

Here β is a vector of coefficients of interest; $\beta \in \beta_k, \beta_l, \beta_m$. The log-linear specification is:

$$y_t = \beta_0 + \beta_l l_t + \beta_k k_t + \beta_m m_t + \varepsilon_t$$

where $\varepsilon_t = \omega_t + \eta_t$, representing the firm's productivity (i.e., an unobserved state variable) and an i.i.d. error component, respectively.

The material demand function is modeled as:

$$m_t = m(\omega_t, k_t)$$

Assuming the monotonicity condition holds (will prove below), this function is invertible and allows recovery of ω_t:

$$\omega_t = m_t^{-1}(m_t, k_t)$$

To invert the material demand function and recover ω_t, the mapping $\omega_t = m_t^{-1}(m_t, k_t)$ must be increasing in m_t conditional on k_t. In simple terms, if the monotonicity condition holds, then given any observed level of k_t, an increase in m_t implies a higher ω_t [Levinsohn and Petrin, 2003].

From Figure 1, plotted over three time periods (2013–2016, 2017–2019, and 2020–2024),[2] which reflect major economic cycles shaping the Indian manufacturing industry, the monotonicity condition appears to hold. Across all three periods, ω_t increases with m_t for given levels of k_t, supporting the assumption of invertibility of the material demand function.

Substituting the expression for ω_t into the production function yields:

$$y_t = \beta_l l_t + \phi_t(m_t, k_t) + \eta_t$$

where,

$$\phi_t(m_t, k_t) = \beta_0 + \beta_k k_t + \beta_m m_t + m_t^{-1}(m_t, k_t)$$

is a composite term that can be estimated nonparametrically. To identify β_l, take expectations conditional on m_t and k_t:

$$E[y_t \mid m_t, k_t] = \beta_l E[l_t \mid m_t, k_t] + \phi_t(m_t, k_t)$$

[2]These time periods respectively correspond to Pre-GST, Pre-Covid-19, and Covid-19 and Post.

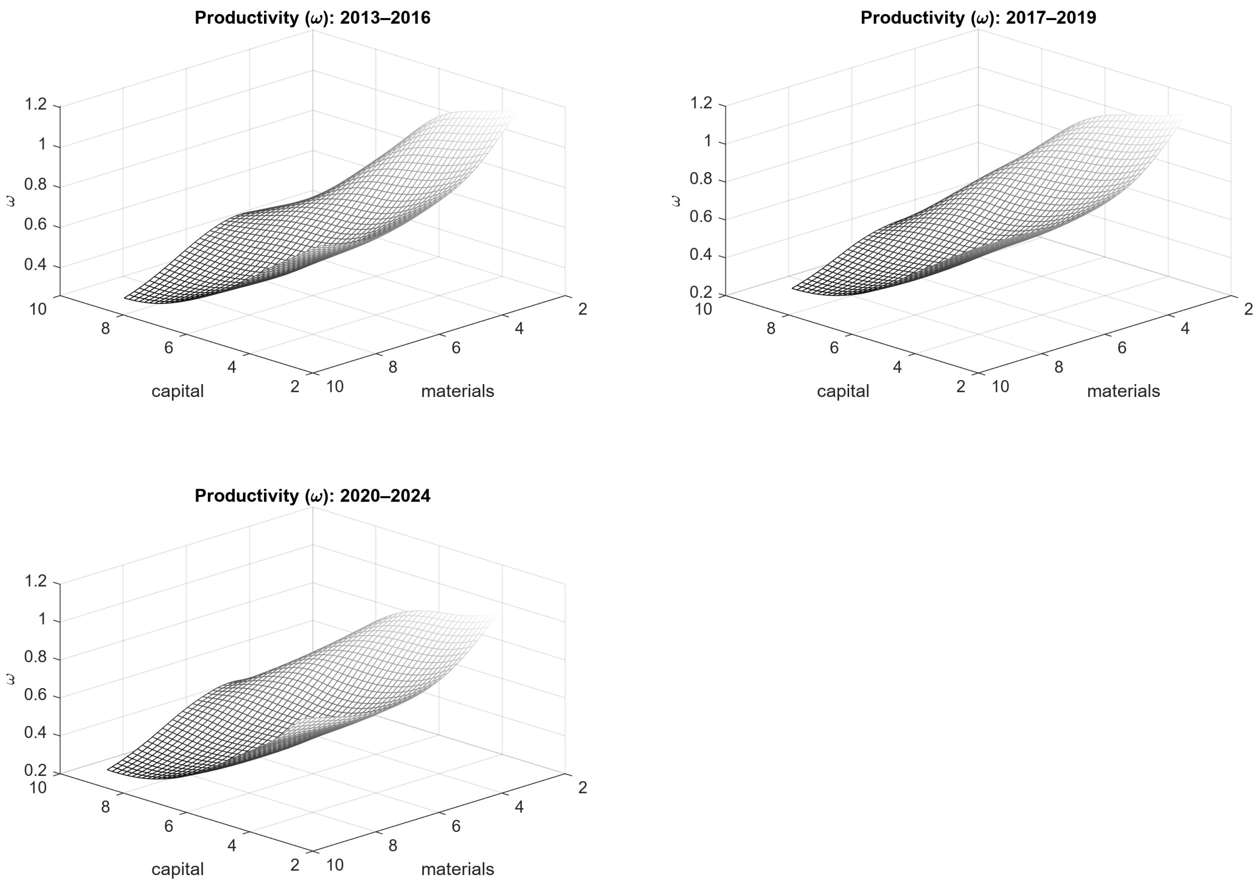

FIGURE 1. NONPARAMETRIC ESTIMATE OF PRODUCTIVITY ω_t AS A FUNCTION OF m_t AND k_t

Note: This figure plots $\omega_t = m_t^{-1}(m_t, k_t)$ using locally estimated scatterplot smoothing (LOESS). The vertical axis measures the estimated TFP (ω_t), the right axis measures composite materials (m_t), and the left axis measures capital stock (k_t).

Subtracting the conditional expectation from the original production function gives:

$$y_t - E[y_t \mid m_t, k_t] = \beta_l(l_t - E[l_t \mid m_t, k_t]) + \eta_t$$

Given mean independence of l_t from η_t conditional on m_t and k_t, this expression provides a consistent estimator of β_l.

Following Olley and Pakes [1996], suppose productivity evolves according to a first-order Markov process:

$$\omega_t = E[\omega_t \mid \omega_{t-1}] + \xi_t$$

Then, taking output net of labor and substituting the Markov structure:

$$y_t^* = \beta_0 + \beta_k k_t + \beta_m m_t + E[\omega_t \mid \omega_{t-1}] + \eta_t^*$$

where $\eta_t^* = \xi_t + \eta_t$.

Since k_t is chosen prior to the realization of ω_t, it is uncorrelated with the innovation ξ_t. Likewise, lagged material inputs m_{t-1} are uncorrelated with η_t^*. Thus, using moment conditions:

$$E[m_{t-1} \cdot \eta_t^*] = 0$$

identification of β_k and β_m is achieved.

Although $E[\omega_t \mid \omega_{t-1}]$ is not separately identified from β_0, the coefficients of interest, β_k, β_l, and β_m, are recoverable without imposing further assumptions on constants.

B. GVC Impact on TFP: Estimation Model

This paper estimates the causal effect of GVC participation on firm productivity using a staggered DiD framework [Callaway and Sant'Anna, 2021]. Traditional DiD models assume that all treated units are exposed to the intervention simultaneously. In contrast, GVC participation varies substantially in timing: firms enter at different points, forming distinct treatment cohorts. By leveraging this staggered timing, I estimate cohort-specific treatment effects and track how effects evolve across entry years.

Each treated firm is assigned to a cohort based on the first year of GVC entry. Firms that have not yet received treatment in a given year serve as controls for that period. This structure allows for the estimation of dynamic treatment effects while relaxing the restrictive assumption of uniform treatment timing.

To assess selection into GVC participation—that is, whether firms' observed characteristics predict GVC entry, which relates to the Conditional Parallel Trends (CPT) assumption—I estimate a logit model conditioning on pre-treatment (lagged) covariates. Specifically,

$$\Pr(\text{GVC}_i = 1) = F\left(\omega_{t-2} + \omega_{t-1} + \rho_{t-1} + \xi_{t-1} + \alpha_i + \delta_s + \gamma_t\right)$$

Here, total factor productivity (TFP) is denoted by ω, R&D intensity by ρ, firm size by ξ, firm age by α_i, sector fixed effects by δ_s, and year fixed effects by γ_t.[3]

To test the positivity assumption that every firm has a non-zero probability of entering GVCs conditional on its pre-participation characteristics, I estimate propensity scores based on the logit specification above and inspect their distribution to confirm common support.

Additionally, I invoke the strong overlap assumption, which ensures that the conditional probability of treatment is bounded away from one. [4] This condition is essential for maintaining the validity of treated vs. control comparisons. To assess it, I examine whether the estimated propensity scores are adequately bounded away from unity.

The identification strategy relies on the conditional parallel trends assumption[5] that conditional on observable characteristics, untreated firms (i.e., those not yet treated) serve as valid counterfactuals for treated firms. Formally, for each (s,t) with $t \geq g$ and $s \geq t$, and for treatment cohort g:

$$\mathbb{E}[Y_t(\infty) - Y_{t-1}(\infty) \mid X, G_g = 1] = \mathbb{E}[Y_t(\infty) - Y_{t-1}(\infty) \mid X, D_s = 0, G_g = 0]$$

This assumption allows for group-specific trends and facilitates comparison between treated and not-yet-treated firms conditional on covariates [Callaway and Sant'Anna, 2021].

I implement the doubly robust estimator proposed by Callaway and Sant'Anna [2021]:

$$\text{ATT}^{\text{ny}}_{g,t} = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{p_{g,t}(X)(1-D_t)}{1-p_{g,t}(X)} \Big/ \mathbb{E}\left[\frac{p_{g,t}(X)(1-D_t)}{1-p_{g,t}(X)}\right]\right)\left(Y_t - Y_{g-1} - m^{\text{ny}}_{g,t}(X)\right)\right]$$

[3]Except for ρ, all variables are in logarithmic form, and all covariates are lagged by at least one year.
[4]Formally, for some

$$\varepsilon > 0, \quad \mathbb{P}(G = 2 \mid X) < 1 - \varepsilon$$

[5]To evaluate covariate balance between GVC and non-GVC firms, I conducted joint t-tests on pre-treatment characteristics. The results revealed statistically significant differences, suggesting the presence of selection bias. Consequently, I employed the conditional parallel trends assumption, which allows for differences in covariates to be accounted for when constructing valid counterfactuals for treated units, reinforcing the robustness of the identification strategy under non-random treatment timing.

Where the conditional outcome expectation for not-yet-treated units is:

$$m^{\text{ny}}_{g,t}(X) = \mathbb{E}\left[Y_t - Y_{g-1} \mid X, D_t = 0, G_g = 0\right]$$

To assess the plausibility of conditional parallel trends, I conduct a joint Wald test of the pre-treatment ATT estimates. Specifically, the null hypothesis being evaluated is:

$$H_0 : \text{ATT}_{g,t} = 0 \quad \text{for all } t < g \tag{1}$$

Further I conduct several robustness tests including power analysis of pre-trend tests by [Roth, 2022] and sensitivity analysis of parallel trend violation by [Rambachan and Roth, 2023].

Threat to identification

A key challenge in applying a staggered DiD framework to firm-level panel data on Indian firms is the issue of left-censoring of treatment status, where some firms may have entered GVC participation prior to the start of the observation window. In this dataset, which begins in 2013, an unusually high number of firms appear as GVC participants in the initial year. This spike likely reflects left-truncation rather than a genuine surge in GVC entry in 2013.

To address this concern, I restrict the sample to firms identified as non-GVC participants in 2013. From 2014 onward, I track these firms to determine their transition into GVC. Treatment is defined as the first year a firm enters GVC status, conditional on it being untreated in 2013. Firms not yet treated serve as controls, while treated firms are grouped into cohorts based on their entry year.

This sampling strategy ensures well-defined pre-treatment periods for each treated unit and mitigates the misclassification of long-term participants as new entrants. Moreover, it avoids the confounding effects of left-censoring, strengthening the validity of the staggered DiD design. Once a firm enters GVC participation, it is assumed to remain treated in all subsequent years, reflecting the persistent nature of global integration.

IV. Result and Discussion

The results are presented in five subsections. First, I report the TFP estimation and the corresponding production function coefficients, as detailed in Section III.A. Second, I provide descriptive statistics of key firm-level TFP variables and GVC participation status. Third, I present the results from the logit model used to evaluate potential confounding in treatment assignment and selection into GVCs.

Fourth, I report empirical causal estimates following the framework outlined in Section III.B. This includes: (i) an assessment of pre-treatment trends and identification validity; (ii) estimates of aggregated ATTs; (iii) dynamic treatment effects across cohorts; and (iv) sensitivity analyses related to violations of pre-trend assumptions.

Finally, I extend the analysis to explore firm size heterogeneity in the treatment effects, offering insights into if GVC participation impacts firms differently depending on their size.

A. Total Factor Productivity Estimates

The sectoral production function estimates in Table 3 highlight considerable heterogeneity across manufacturing sub-industries. In all sectors, the materials coefficient emerges as the most dominant input, displaying the highest elasticity and achieving statistical significance at the 99% level. This finding reinforces the essential role of intermediate inputs in driving manufacturing output, which is consistent with prior literature [Levinsohn and Petrin, 2003].

Beyond the material inputs, divergent patterns in capital and labor intensity characterize different sectors. For instance, industries such as Metals and Machinery exhibit elevated capital elasticities, indicative of production processes heavily reliant on physical assets and equipment. Conversely, sectors like Pharmaceuticals and Wood & Paper reveal a greater dependence on labor inputs. This labor intensity suggests that human capital and specialized skills are more crucial to the value creation process in these sectors, with Pharmaceuticals serving as a prime example of skill-biased production. This is also consistent which placement of Indian firms in these sector's value chain processes - assembling and packaging.

Table 3—Sectoral Production Function Estimates

Sector	logl	logk	logm
Chemicals	0.203***	0.084***	0.985***
	(0.009)	(0.027)	(0.036)
Electronics	0.219***	0.090**	0.933***
	(0.009)	(0.038)	(0.051)
Food & Beverages	0.218***	0.169***	0.866***
	(0.008)	(0.052)	(0.059)
Machinery	0.253***	0.154***	0.849***
	(0.013)	(0.045)	(0.083)
Metals	0.142***	0.192***	1.000***
	(0.006)	(0.034)	(0.019)
Other Manufacturing	0.198***	0.147**	0.939***
	(0.022)	(0.070)	(0.152)
Pharmaceuticals	0.394***	0.089**	0.796***
	(0.018)	(0.037)	(0.063)
Textiles	0.204***	0.077**	0.980***
	(0.009)	(0.036)	(0.039)
Transport	0.146***	0.087*	0.979***
	(0.011)	(0.049)	(0.036)
Wood & Paper	0.266***	0.182**	0.914***
	(0.028)	(0.079)	(0.111)

Each row reports estimated input elasticities of labor (logl), capital (logk), and materials (logm) by sector. Bootstrapped Standard errors in parentheses. *, **, *** indicates significance level of 10, 5, and 1 percent respectively.

B. *Firms' Profile and GVC Participation*

Figure 2 illustrates the evolving landscape of GVC participation among Indian manufacturing firms from 2013 to 2024, shaped significantly by a sequence of industrial policy shocks. A sharp decline in GVC participation follows key reforms, most notably demonetization in 2016 and the implementation of the GST) in 2017, highlighting the vulnerability of firms operating within globally interlinked production systems to abrupt regulatory changes[Riyazahmed, 2022].

Demonetization, the withdrawal of high-denomination Indian currency, led to immediate liquidity shortages that disrupted working capital flows and stalled transactions of Indian firms across domestic supply chains. For GVC-participating firms, these effects were amplified due to their reliance on tightly coordinated production timelines and complex logistics across domestic and international partners [Sharma, 2017].

The subsequent rollout of GST, although intended to streamline India's tax structure and reduce logistics costs, introduced a significant compliance burden—particularly for small and medium enterprises (SMEs) embedded in backward linkages. Requirements such as updated invoicing systems, input tax credit documentation, and sector-specific reporting posed challenges to firms unaccustomed to centralized tax regimes. Importantly, many firms were still recovering from the liquidity shock of demonetization when the GST transition began, resulting in compounded disruption.

Finally, the onset of the COVID-19 pandemic further exacerbated the decline in GVC participation by triggering widespread global supply chain interruptions, prolonging recovery and reshaping firms' strategic engagement with international production networks.

Table 4 reinforces that GVC-participating firms, on average across years, outperform non-GVC firms across multiple input dimensions, including output, capital stock, labor employment, and material usage. The disparities in capital and labor metrics reveals that GVC firms typically operate at larger scales and employ more workers, suggesting they potentially have the capacity to leverage economies of scale.

Moreover, GVC firms demonstrate significantly higher R&D expenditure and increased levels of foreign ownership. Both indicators point toward superior access to advanced technologies and global markets. For example, the average R&D spending among GVC firms is nearly double that of non-GVC firms, underscoring their greater capacity for innovation and strategic collaboration across borders.

However these are not causal claims, as these differences may underscore the possibility of self-selection into GVCs - firms with superior productive capabilities and external linkages may be more likely to participate, especially if they are able to absorb entry-related costs and meet international standards Melitz [2003]. Conversely, smaller firms with limited capital and innovation capacity face greater frictions, particularly during periods of external shocks. As the data shows, average productivity advantage of GVC firms may be partially explained by selection on observables such as size, capital investment, and technological maturity.

C. Selection into GVCs

To assess potential selection into GVC participation, I conduct mean-difference tests on key pre-treatment covariates, comparing firms that eventually enter GVCs with those that remain non-GVC throughout the sample period. Table 5 presents results from two-sample t-tests, which reveal statistically significant differences across multiple dimensions.

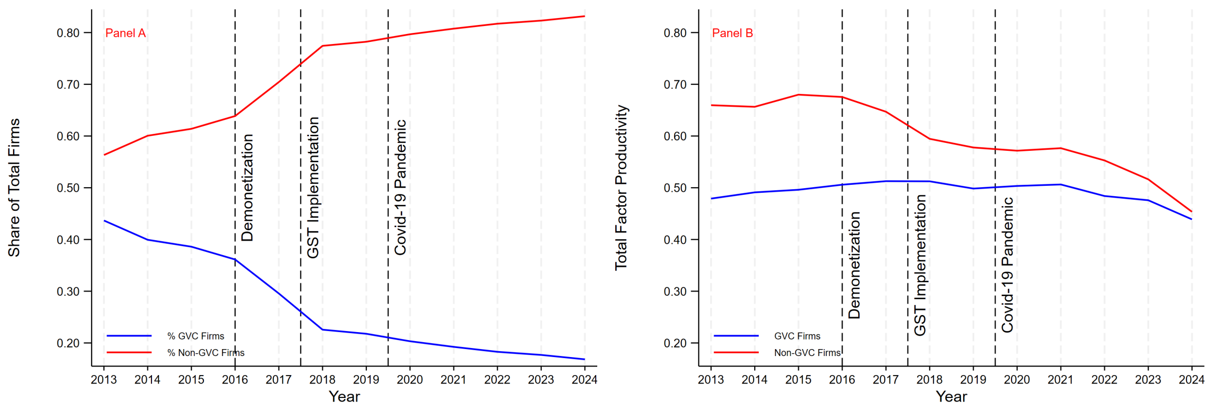

Figure 2. GVC Status and Productivity by Year

Note: Panel A shows the composition of total firms in the panel by GVC participation status, over the period 2013–2024. Panel B displays the average total factor productivity (TFP, in logs) for GVC and non-GVC firms over the same period. India's fiscal year runs from April to March; year labels refer to fiscal years.

On average, GVC entrants have lower lagged TFP, are larger in size, and are more likely to be classified as large firms relative to non-GVC peers. Additionally, they tend to be slightly younger and more likely to be R&D intensive. These differences suggest that GVC entry is related to firm-level observables, underscoring the importance of conditioning on covariates when estimating treatment effects. This is further revealed by the logit model, illustrated in Figure 3, which estimates the likelihood of GVC participation based on lagged firm-level characteristics. The coefficients—reported in log-odds units - indicate that R&D intensity, firm size, and firm age have statistically significant effects on GVC entry. In contrast, lagged TFP variables are significant at 90% confidence interval (See A2 for different model specification). Sector and year fixed effects are included in the model specification, with full results documented in table A2.

Based on the results, all covariates are lagged to minimize concerns of reverse causality [Sant'Anna and Zhao, 2020]; [HK, 2023]; [Athey and Imbens, 2006]; [Wooldridge, 2021], and are incorporated into both the propensity score estimation and the doubly robust DiD framework to ensure valid counterfactual comparisons.

D. Empirical Estimation Results

Validity of positivity and overlap assumption for conditional PTA

Figure A2 presents the distribution of estimated propensity scores for treated (GVC entrants) and untreated (non-GVC) firms, based on a logit model of GVC participation. The mirrored histogram

Table 4—Summary Statistics of Key Variables

	All	GVC Firms	Non GVC Firms
Output	6.83	7.36	6.64
	(1.86)	(1.45)	(1.95)
Capital	5.96	6.54	5.75
	(1.91)	(1.55)	(1.98)
Labour	4.04	4.76	3.78
	(1.81)	(1.37)	(1.87)
Materials	6.37	6.84	6.21
	(1.90)	(1.53)	(1.99)
RD	0.16	0.26	0.13
	(0.37)	(0.44)	(0.34)
Foreign Firms	0.02	0.03	0.02
	(0.15)	(0.18)	(0.13)

Note: All reported data are expressed in logs and in 2012 prices (INR millions), except for dummy variables

Source: Variables are calculated based on CMIE panel data from 2013–2024

Table 5—Mean Difference Test

	NonGVC	GVC	Diff. (NonGVC - GVC)	Standard Error	Observations
TFP_{t-1}	0.6	0.5	0.13***	(0.00)	64454
TFP_{t-2}	0.6	0.5	0.12***	(0.00)	55806
Age_{t-1}	2.9	3.0	-0.07***	(0.01)	64445
Foreign $\text{Firm}_{(t-1)}$	0.0	0.0	0.00**	(0.00)	64454
Firm $\text{Size}_{(t-1)}$	6.1	7.2	-1.05***	(0.01)	64454
R&D $\text{Intensity}_{(t-1)}$	0.1	0.2	-0.10***	(0.00)	64454

Note: The table presents two-sample t-tests between lagged covariates of GVC and Non GVC firms. TFP, Age, Firm Size are in log forms, Foreign Firms and R&D Intensity are dummies. *, **, *** indicates significance level of 10, 5, and 1 percent respectively. With the exception of the Foreign Firms dummy, the mean differences in lagged covariates between GVC and Non-GVC firms are statistically significant. For standardized mean difference test, refer Appendix

compares the density of observations across the range of predicted treatment probabilities.

The figure reveals substantial overlap in support between treated and untreated firms, indicating that most values of the propensity score include firms from both groups. This supports the positivity assumption, which requires that each unit has a nonzero probability of receiving either treatment status, conditional on observed covariates.

Furthermore, the distributions are bounded away from 0 and 1, with no excessive mass at the extremes. This supports the strong overlap assumption, ensuring that estimated treatment effects are not unduly driven by firms with near-certain treatment or non-treatment status.

Thus, the distribution shown in Figure A2 provides evidence in favor of covariate adjustment

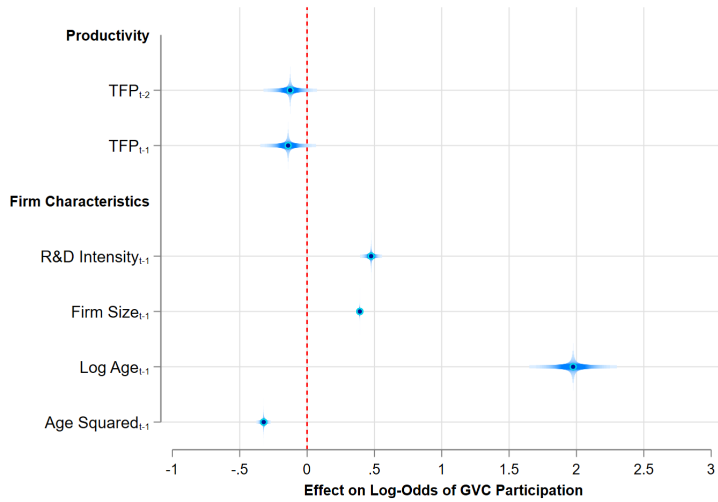

FIGURE 3. GVC STATUS AND PRODUCTIVITY BY YEAR

Note: Logit coefficient estimates are presented with 95% confidence intervals. Coefficients are reported in log-odds units. Lagged firm characteristics, including age, size, and R&D intensity, are statistically significant at the 5% level. Productivity-related variables are not statistically distinguishable from zero. Sector and year fixed effects are included in the model. Full model specifications are reported in the appendix

strategies such as doubly robust DiD. It also reinforces the plausibility of the conditional parallel trends assumption by showing once controlled for covariates the treated and untreated firms similar on observable characteristics across most of the propensity score's support.[6]

PRE-TREATMENT TRENDS AND IDENTIFICATION

I begin by testing the parallel trends assumption using pre-treatment event-time ATT estimates in the joint test (see Section III). A joint significance test rejects the null hypothesis that all pre-treatment coefficients equal zero ($\chi^2(27) = 60.97$, $p = 0.0002$)[7], indicating statistically significant violations of parallel trends at the 95% confidence level. See Figure 4, Panel A, for the corresponding pre-treatment ATT coefficients.

To assess the credibility of the parallel trends assumption, I implement the pre-trend robustness check proposed by [Roth, 2022], which quantifies how large a linear violation in trends must be to be reliably detected. With a power threshold set at 80%, the minimum detectable linear deviation corresponds to a slope of 0.007. Hence, linear trend violations smaller than this threshold would

[6]Note that I did not perform formal matching, as [Callaway and Sant'Anna, 2021]'s doubly robust inverse probability weighting estimator jointly estimates the propensity score and the outcome regression. Propensity scores were calculated using a logit model to validate the balance of covariates fed into the DiD estimator.
[7]Inference is based on wild bootstrap standard errors clustered at the firm level, with 999 repetitions.

likely remain undetected in the pre-trend test conducted above. This threshold suggest that the test is reasonably sensitive and given the rejection of the null in the joint test, the observed deviations exceed this threshold and may compromise identification [8].

Figure 4 (Panel B) illustrates a linear pre-trend violation (red line) in the estimated event-time ATT coefficients. The dashed blue line represents the expected trajectory of the estimated coefficients assuming the violation was not detected. That is, the event study results we would observe if the true underlying process followed the red trend but the test failed to identify it.

Notably, the actual post-treatment ATT estimates diverge from both the red and dashed blue lines, indicating that they do not conform to the pattern implied by the trend violation. This suggests that the observed post-treatment effects are unlikely to be driven by this minor pre-trend deviation, despite the formal test rejecting the null. Taken together, the slope magnitude and the visible divergence in the graph, these patterns lend support to the practical credibility of the identification strategy, even in the presence of a formally detected PTA violation.

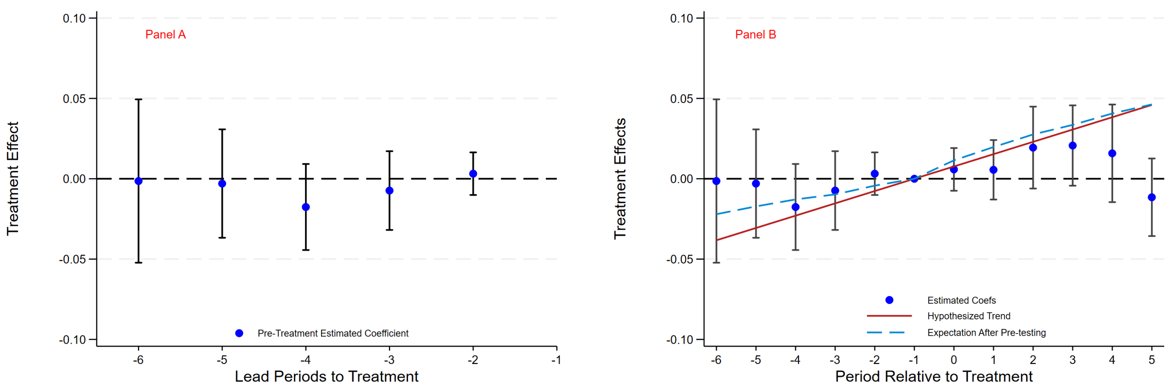

Figure 4. Testing Parallel Trend Assumption

Note: Panel A: Pre-treatment ATT estimates using the doubly robust estimator with 95% confidence interval.
Panel B: Power analysis for parallel trend violations, showing the estimated coefficients, hypothesized trend, and expectation after pre-testing. Please note that the coefficients within the window (-6 5) are used for brevity.

Average Treatment Effects

Table A2 presents the ATT estimated using the doubly robust estimator with covariate adjustment, where firms not yet treated were taken as the control group. Panel A reports dynamic ATT

[8] In the next sections, I conduct sensitivity analyses to assess the implications of pre-trend violations. These analyses help guard against dismissing the estimated treatment effect by bounding permissible post-treatment deviations based on information from the pre-treatment period.

estimates, which, although increasing post-GVC entry, remain statistically indistinguishable from zero at the 95% confidence level.[9]

Since the primary objective of this paper is to assess whether GVC participation affects firm productivity, rather than learning by doing (see [Urata and Baek, 2022] for related mechanisms such as learning and knowledge transfer), I focus on aggregated treatment effects derived using weights and parameters detailed in Appendix A3. These aggregated estimates retain power than event-time dynamics.

To further examine heterogeneity, Panel B of Table A3 presents ATT estimates disaggregated by year of GVC entry cohort. Using the parameter defined in Equation (A1), I compute cohort-specific average treatment effects. Among the eight cohorts, only the 2021 and 2023 cohorts exhibit statistically significant effects at the 95% confidence level.

Although point estimates appear larger for later cohorts, potentially suggesting stronger treatment effects, definitive comparisons are not advisable. The wide confidence intervals, many of which include zero, indicate imprecision, and any claim about differential effects across cohorts would lack robustness unless restricted to contrasts between the 2021 and 2023 cohorts.

Therefore, rather than relying solely on these cohort-wise ATT estimates, I also present a descriptive plot in Figure A.A2, which tracks the mean TFP of each cohort over time.

Panel C of Table A3 reports ATT estimates disaggregated by calendar year, while Panel D aggregates treatment effects across all groups and time periods. The ATT estimates in Panel D reveal a statistically significant positive association between GVC participation and firm-level total factor productivity. This suggests that, on average, entry into GVC leads to productivity improvements, even though the precise timing and cohort-specific impacts remain heterogeneous and somewhat imprecise. However, the aggregation across all cohorts and periods also has limitation as it disproportionately put more weight on firm's from earlier cohort (as discussed in [Callaway and Sant'Anna, 2021].

[9]The estimated event study coefficients, shown in Panel B of Figure 4, depict the dynamic pattern of treatment effects relative to GVC entry, with confidence intervals that overlap zero in most post-treatment periods.

Sensitivity to Pre-trend Violations

To assess the robustness of the estimates to potential violations of the parallel trends assumption, I implement the sensitivity analysis framework proposed by Rambachan and Roth [2023]. Their methodology formalizes the intuition that pre-treatment dynamics offer meaningful guidance for bounding post-treatment violations, particularly under the assumption that such deviations evolve gradually over time.

Given that the average treatment effect is estimated using firm-level data, I apply the $\Delta\text{RM}(\bar{M})$ restriction, which allows for post-treatment deviations from the counterfactual trajectory to differ from those in the pre-treatment period, but only within a bounded range. Specifically, this restriction constrains the magnitude of post-treatment violations to be no greater than $\bar{M}$ times the maximum deviation observed before treatment.

This specification is especially appropriate in my context, where firms entering GVCs experience shocks such as regulatory changes or compliance costs, e.g., due to GST reforms or volatile global input prices, that differ from pre-entry dynamics, but are unlikely to represent sharp discontinuities. I construct 95% robust confidence intervals over a range of $\bar{M} \in [0, 2.5]$ (Figure 5). At $\bar{M} = 0$, the robust interval already includes zero, indicating a statistically significant deviation prior to treatment. As $\bar{M}$ increases, the interval expands, and by $\bar{M} = 0.5$, it consistently includes zero. This pattern suggests that the causal interpretation of the dynamic event study coefficients is sensitive to modest violations of the parallel trends assumption. In other words, the ATT remains statistically significant only under the assumption that post-treatment deviations are less than half (or in fact lower than that) the magnitude of the most extreme pre-treatment trend.

Taken together, this sensitivity analysis tempers the strength of causal claims derived from the event study plot. While the main specification, based on aggregated ATT, yields a statistically significant effect, the dynamic event study coefficients show violations of the identifying assumption. Thus, I would recommend interpreting these coefficients and GVC's impact on TFP as suggestive rather than causal definite to avoid overinterpretation.

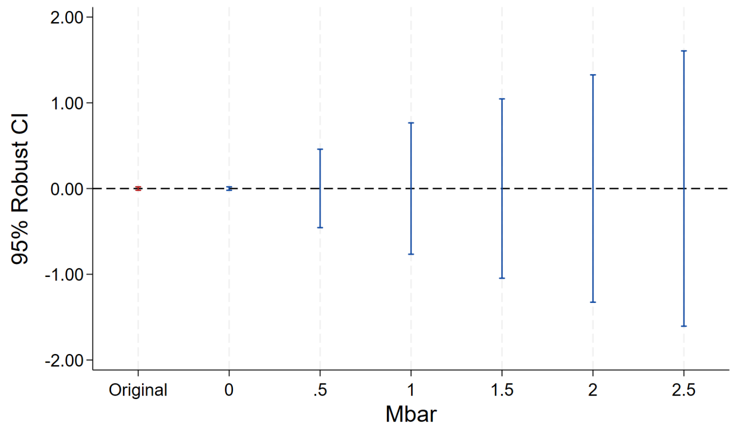

Figure 5. Sensitivity Analysis

E. Size Heterogeneity Analysis

Understanding how the impact of GVC participation varies across firm size is particularly important in the Indian context, where approximately 63 million formal and informal micro, small, and medium enterprises (MSMEs) coexist alongside large manufacturing firms [Aftab, 2023]. These two segments occupy markedly different starting points in terms of global value chain integration.

Seminal trade literature suggests that only firms exceeding a certain productivity threshold can absorb the fixed costs associated with exporting and importing [Melitz, 2003]. Accordingly, larger and typically more productive firms tend to self-select into GVCs. They often benefit from greater financial reserves and dedicated R&D units, allowing them to meet the regulatory and quality standards required for global market access.

By contrast, smaller firms face significant barriers to GVC entry. Survey evidence indicates that financial constraints particularly those resulting in reduced R&D and innovation budgets lower the likelihood of GVC participation by 7–8 percentage points [Reddy and Sasidharan, 2020]. These firms also tend to lack robust information networks and the infrastructure needed to engage meaningfully in international production systems.

To study firm size heterogeneity, I classify firms as either small or large based on the log of total real assets, averaged over the pre-treatment period (2013–2015). Firms with pre-entry size at or below the sample median are designated as small, while those above the median are considered large. This classification captures differences in the operational capacity, proxied through total assets (including intangible components such as patents, goodwill, and intellectual property that may influence the firm's ability to engage in GVCs).

Importantly, by using pre-treatment size median helps avoid bias, since firm classification should not influenced by treatment intself (GVC entry).[10]

Panel A of Table A4 shows that small firms are, on average, more productive than large ones (0.776 vs. 0.439 in log TFP). This could reflect unobserved differences in structure and incentives—for example, small firms often operate with leaner teams, flatter hierarchies, and benefit from targeted support programs by the Indian government, such as capital subsidies and the MUDRA Yojana.[11]

In contrast, large firms show higher R&D intensity (0.156 vs. 0.053) and deeper participation in innovation-related activities. This also suggests they tend to be older. Testing pre-treatment parallel trends using the joint significance test reveals violations for small firms ($p = 0.12$), but a strong rejection for large firms ($p < 0.001$). The divergence among small firms may reflect persistent differences in trajectories, e.g., only the dynamic small firms might self-select into GVCs, while the control group remains relatively stagnant.

Panel C of Table A4 presents the aggregated ATT coefficients across cohorts and calendar periods, estimated using (A3). Figure 6 illustrates the corresponding event study coefficients. The aggregated ATT is positive for small firms (0.0187) and nearly zero for large firms (-0.0007), though neither estimate is statistically significant. The 95% confidence interval for small firms spans from -0.0173 to 0.0547, while for large firms it ranges from -0.0165 to 0.0150. Notably, the wider interval for small firms points to greater uncertainty, likely driven by underlying heterogeneity. While the null of no effect is not rejected, the bounds cautiously allow us to rule out large negative impacts, given the proximity of the lower bound to zero.

[10]See seminal discussions on the use of pre-treatment covariates as subgroup identifiers and controls in TWFE models, staggered ATT designs, and canonical 2×2 DiD frameworks: Sant'Anna and Zhao [2020]; HK [2023]; Athey and Imbens [2006]; Wooldridge [2021].

[11]MUDRA Yojana provides collateral-free loans to micro and small enterprises. Other credit schemes include Stand-Up India and the Credit Guarantee Trust Fund for Micro and Small Enterprises.

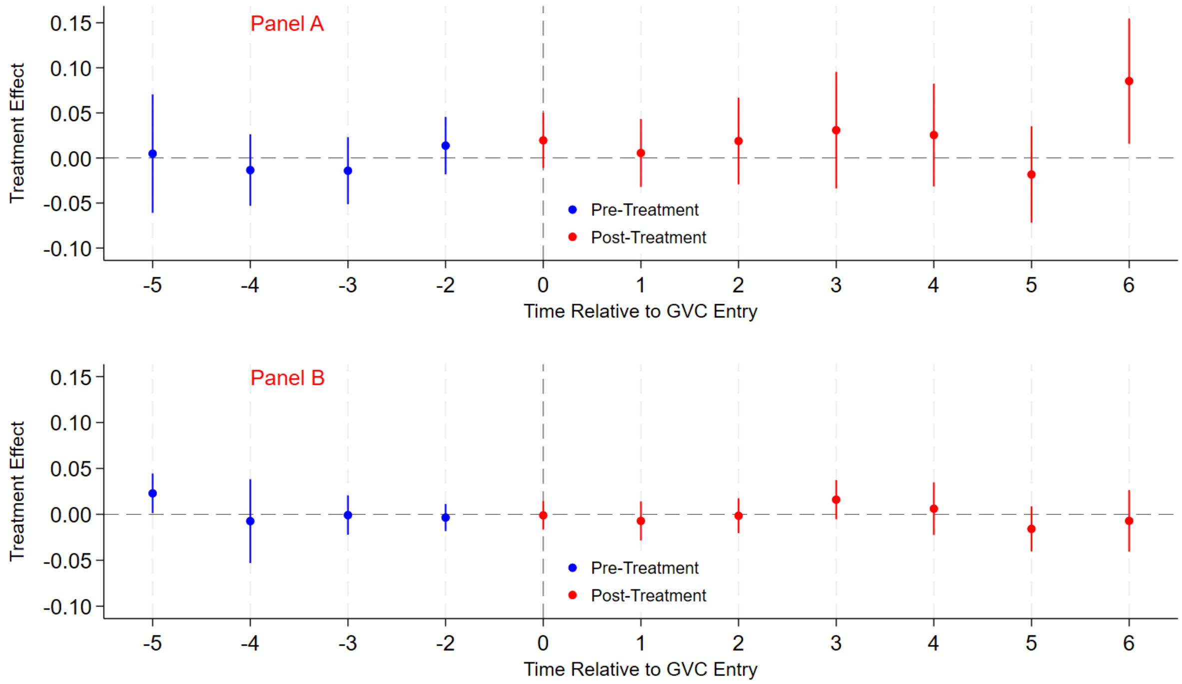

Figure 6. Dynamic Average Treatment Plot

Note: This figure shows dynamic treatment effects of GVC participation on firm-level log TFP, estimated separately for small firms (Panel A) and large firms (Panel B), using the doubly robust estimator of Callaway and Sant'Anna [2021]. Pre-treatment coefficients (in blue) test for violations of the parallel trends assumption, while post-treatment effects (in red) capture average treatment effects relative to the year of GVC entry. Confidence intervals are bootstrapped with 500 repetitions. Firm size is based on the median log real assets over 2013–2015. See Appendix X for aggregation details

V. Policy Implications

The shifting of GVCs presents a compelling opportunity for the Indian economy, but it remains a missed opportunity. Even though the Indian manufacturing firms and the Government are prioritizing efforts to integrate in GVC dynamics, the share of manufacturing value added in India GDP has remained reduced from 15% in 2013 to 13% in 2023 and has remaine in this range for the past four decades [Bank, 2023]. Interestingly, during the reconfiguration of GVCs and 56 US firms shifting their bases out of China due to trade tensions, only three firms relocated to India, while the majority moved to Vietnam and Thailand. Thus, India needs to embed itself into GVCs through a specialised focus on "network products" for which the production processes are globally fragmented such as IT hardware, electricals, electronics, amongst others. Essentially, this involves integrating Assembly in India into the Make in India initiative.

Indian firms aiming to integrate into global value chains (GVCs) face substantial challenges, including meeting quality standards, a lack of coordinated institutional support, and limited access to critical information. Institutional assistance - such as infrastructure development, market access, and production-related subsidies—remains inadequate. Additionally, firms frequently report insufficient knowledge regarding market dynamics, trade partners, export-import (EXIM) regulations, and trade finance mechanisms. To enable greater GVC integration, India must prioritize policy consistency and stability. This can be achieved through a predictable tariff structure and deeper engagement in Free Trade Agreements (FTAs). In many cases, developing countries enter GVCs by participating in low-skill, low-value-added activities and struggle to move up the value chain due to competitive pressures, resulting in limited economic gains [Ray and Miglani, 2020]. Therefore, it is essential for India to increase the value-added component of its production, facilitate the transfer of technology and expertise, correct market inefficiencies, and promote the equitable distribution of economic benefits.

Reducing trade costs is a critical component of India's integration into the GVCs. Currently, India's applied tariffs on intermediate goods are significantly higher than those in East and Southeast Asian economies, raising production costs for both domestic consumption and exports. To enhance competitiveness, it is essential to lower tariffs on intermediate inputs. Although India has reduced its average tariff rate from approximately 70 percent in the early 1990s, tariffs remain relatively high [Peiris et al., 2022]. Overall, the cost of importing into India is nearly twice as high as in China and other major manufacturing hubs [Peiris et al., 2022].

India, with its inherent strengths as a production and supply destination, is well-positioned to build a resilient GVC network. Its strategic location - providing access to diverse trade routes by land and sea, and proximity to key Asian markets - makes it an attractive hub. To capitalize on this advantage, India must foster a conducive market environment for domestic manufacturers and attract investment from leading global firms. GVC integration is especially vital for India's pharmaceutical sector, as reflected by its relatively high labor coefficient values in table 3. In capital-intensive industries, the challenge lies in keeping pace with emerging technologies and achieving large-scale competitive manufacturing, even when domestic production infrastructure exists. More broadly, India's GVC-linked manufacturing exports remain less diversified than the global average.

The highest levels of integration are observed in sectors such as coke and petroleum, chemicals, primary and fabricated metals, and transport equipment.

Firm-level resilience is essential for maintaining systemic stability. To minimize disruptions in value chains, improvements in supply chain management, enhanced trade facilitation, and diversification of supply sources are necessary. The Government of India could leverage public procurement as a strategic tool to promote best practices by requiring companies to adopt sustainable methods as a condition for participating in government projects. Additionally, implementing unified logistics and transportation standards would help alleviate bottlenecks and ensure smoother movement of goods across the country.[12]

VI. Conclusion

This paper analyzes whether Indian manufacturing firms experience productivity gains from participating in GVCs. Using firm-level panel data and a staggered DiD framework, I estimate TFP and assess the impact of GVC entry over time. While the aggregated average treatment effect on the treated is positive and statistically significant, dynamic event-study estimates show no robust post-entry effects. Violations of the parallel trends assumption in the pre-treatment period - alongside power analysis and sensitivity checks - suggest caution in interpreting the results causally.

Exploring firm size heterogeneity reveals that small firms show higher ATT estimates, although confidence intervals remain wide and statistically inconclusive. Descriptive patterns suggest that GVC firms tend to be larger, more R&D intensive, and more productive, but these differences may reflect selection on observables rather than treatment effects.

Taken together, the findings point to incomplete and uneven integration of Indian firms into GVCs. While some firms may benefit from international production linkages, broader gains are constrained by policy uncertainty, regulatory burdens, and firm-level capacity gaps. Targeted support for sectors with global fragmentation, such as electronics and pharmaceuticals, and improved trade infrastructure and logistics, are essential for India to realize the productivity potential of GVCs.

[12] India has centralized public procurement tool enlisting tender and prerequisites which could you be used to formalize certain best practices including mandatory spend on R&D, compulsory compliance training, etc. https://eprocure.gov.in/eprocure/app

Extending the analysis to include earlier periods (e.g., pre-2000s) would allow examination of long-run GVC effects and structural shifts. Additionally, employing alternative estimators such as the imputation-based approach developed by Borusyak, Jaravel, and Spiess (2021) can offer robustness under different identifying assumptions. Finally, exploring treatment effect heterogeneity by R&D intensity and foreign shareholding—two key dimensions of global competitiveness—remains an important avenue beyond the scope of the current paper.

REFERENCES

Anya Aftab. Small Business, Big Impact: Empowering Women SMEs for Success, January 2023. URL `https://www.ifc.org/en/stories/2024/small-business-big-impact`.

Susan Athey and Guido W. Imbens. Identification and Inference in Nonlinear Difference-in-Differences Models. *Econometrica*, 74(2):431–497, 2006. ISSN 1468-0262. doi: 10.1111/j.1468-0262.2006.00668.x. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1468-0262.2006.00668.x`. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1468-0262.2006.00668.x.

Karishma Banga. Impact of global value chains on total factor productivity: The case of Indian manufacturing. *Review of Development Economics*, 26(2):704–735, 2022. ISSN 1467-9361. doi: 10.1111/rode.12867. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/rode.12867`.

World Bank. World Bank Open Data, 2023. URL `https://data.worldbank.org`.

Brantly Callaway and Pedro H. C. Sant'Anna. Difference-in-Differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230, December 2021. ISSN 0304-4076. doi: 10.1016/j.jeconom.2020.12.001. URL `https://www.sciencedirect.com/science/article/pii/S0304407620303948`.

Allan Collard-Wexler and Jan De Loecker. Production Function Estimation and Capital Measurement Error, July 2016. URL `https://www.nber.org/papers/w22437`. Issue: 22437 Series: Working Paper Series.

Jan De Loecker, Pinelopi K. Goldberg, Amit K. Khandelwal, and Nina Pavcnik. Prices, Markups, and Trade Reform. *Econometrica*, 84(2):445–510, 2016. ISSN 1468-0262. doi: 10.3982/ECTA11042. URL `https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA11042`.

Bishwanath Goldar, Isha Chawla, and Smruti Ranjan Behera. Trade liberalization and productivity of Indian manufacturing firms. *Indian Growth and Development Review*, 13(1):73–98, June 2019. ISSN 1753-8254. doi: 10.1108/IGDR-10-2018-0108. URL `https://www.emerald.com/insight/content/doi/10.1108/igdr-10-2018-0108/full/html`.

Pinelopi K. Goldberg, Amit K. Khandelwal, Nina Pavcnik, and Petia Topalova. Multiproduct Firms and Product Turnover in the Developing World: Evidence from India. *The Review of Economics and Statistics*, 92(4):1042–1049, 2010. URL `https://ideas.repec.org//a/tpr/restat/v92y2010i4p1042-1049.html`. Publisher: MIT Press.

Nick HK. Controls in Difference-in-Differences Don't Just Work, April 2023. URL `https://nickchk.substack.com/p/controls-in-difference-in-differences`.

James Levinsohn and Amil Petrin. Estimating Production Functions Using Inputs to Control for Unobservables. *The Review of Economic Studies*, 70(2):317–341, April 2003. ISSN 0034-6527. doi: 10.1111/1467-937X.00246. URL `https://doi.org/10.1111/1467-937X.00246`.

Marc J. Melitz. The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica*, 71(6):1695–1725, 2003. ISSN 1468-0262. doi: 10.1111/1468-0262.00467. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/1468-0262.00467`.

G. Steven Olley and Ariel Pakes. The Dynamics of Productivity in the Telecommunications Equipment Industry. *Econometrica*, 64(6):1263–1297, 1996. ISSN 0012-9682. doi: 10.2307/2171831. URL `https://www.jstor.org/stable/2171831`.

Shanaka J. Peiris, Weicheng Lian, Pragyan Deb, Patrick Blagrave, and Naihan Yang. Chapter 9 Boosting Trade and Value Chain Participation to Sustain Growth in South Asia. March 2022. ISBN 978-1-5135-8721-9. URL `https://www.elibrary.imf.org/display/book/9781513587219/CH009.xml`. Section: South Asia's Path to Resilient Growth.

Amil Petrin and James Levinsohn. Measuring aggregate productivity growth using plant-level data. *The RAND Journal of Economics*, 43(4):705–725, 2012. ISSN 1756-2171. doi: 10.1111/1756-2171.12005. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/1756-2171.12005`. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1756-2171.12005.

Ashesh Rambachan and Jonathan Roth. A More Credible Approach to Parallel Trends. *Review of Economic Studies*, 90(5):2555–2591, September 2023. ISSN 0034-6527, 1467-937X. doi: 10.1093/restud/rdad018. URL `https://academic.oup.com/restud/article/90/5/2555/7039335`.

Saon Ray and Smita Miglani. India's GVC integration: An analysis of upgrading efforts and facilitation of lead firms. February 2020.

Ketan Reddy and Subash Sasidharan. Driving small and medium-sized enterprise participation in global value chains: Evidence from India. *ADBI Working Paper Series*, (118), January 2020.

K Riyazahmed. Impact OF GST On Indian Companies - A Panel Data Analysis. October 2022.

Jonathan Roth. Pretest with Caution: Event-Study Estimates after Testing for Parallel Trends. *American Economic Review: Insights*, 4(3):305–322, September 2022. ISSN 2640-205X. doi: 10.1257/aeri.20210236. URL `https://www.aeaweb.org/articles?id=10.1257/aeri.20210236`.

Pedro H. C. Sant'Anna and Jun Zhao. Doubly robust difference-in-differences estimators. *Journal of Econometrics*, 219(1):101–122, November 2020. ISSN 0304-4076. doi: 10.1016/j.jeconom.2020.06.003. URL `https://www.sciencedirect.com/science/article/pii/S0304407620301901`.

SP Sharma. Impact of Demonetization on Economy, Businesses and People. January 2017.

Robert M. Solow. Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, 39(3):312–320, 1957. ISSN 0034-6535. doi: 10.2307/1926047. URL `https://www.jstor.org/stable/1926047`.

Shujiro Urata and Youngmin Baek. Impacts of firm's GVC participation on productivity: A case of Japanese firms. *Journal of the Japanese and International Economies*, 66:101232, December 2022. ISSN 0889-1583. doi: 10.1016/j.jjie.2022.101232. URL `https://www.sciencedirect.com/science/article/pii/S0889158322000417`.

Jeffrey M. Wooldridge. Two-Way Fixed Effects, the Two-Way Mundlak Regression, and Difference-in-Differences Estimators, August 2021. URL `https://papers.ssrn.com/abstract=3906345`.

Appendix

A1. Sector Concordance

To ensure consistency and maintain enough sample size within sectors, a concordance was built. This concordance harmonizes firm-level sector classifications by aggregating 22 CMIE manufacturing categories into 10 broader sectors. The grouping is informed by underlying similarities in the products of the finer digit NIC codes. For instance, the "Food, Beverage & Tobacco" sector combines closely related sub-industries Food, Beverages, and Tobacco.

Table A1—Sector Concordance to Broad Aggregates

Aggregated Sector	**Original CMIE Sector Names**
Food, Beverage & Tobacco	Food products, Beverages, Tobacco products
Textiles & Apparel	Textiles, Wearing apparel, Leather and related products
Transport Equipment	Motor vehicles, trailers, Other transport equipment
Metals	Basic metals, Fabricated metal products
Wood, Paper & Furniture	Paper and paper products, Wood and of products of wood and cork, Furniture
Other Manufacturing & Media	Other manufacturing, Reproduction of recorded media
Chemicals, Plastics & Petroleum	Rubber and plastics products, Chemicals and chemical products, Coke and refined petroleum products
Pharmaceuticals	Basic pharmaceutical products
Machinery	Machinery and equipment n.e.c.
Electronics & Equipment	Computer, electronic and optical products, Electrical equipment, Other non-metallic mineral products

This concordance groups detailed manufacturing sector codes into 10 broad categories based on similarities at the 4-digit product level (see Table 1 for example).

Treatment Effects Aggregation

I used partial aggregations given by Callaway and Sant'Anna [2021] to summarize the average treatment effects and pin-point treatment effect heterogeneity.

Aggregation of the treatment effects for each cohort across all periods. Intuitively, this captures how the treatment effect evolves over time for firms in each cohort—for example, tracking the average treatment effects of firms that entered in 2016, 2017, and subsequent years using the following parameter from Callaway and Sant'Anna, 2021:

$$\theta_{group}(\tilde{g}) = \frac{1}{T - \tilde{g} + 1} \sum_{t=\tilde{g}}^{T} ATT(\tilde{g}, t) \tag{A1}$$

The parameter used to get aggregate treatment effect by calendar, which is the average of treatment effects of groups that have adopted treatment by that calendar year is:

$$\theta_{calendar}(\tilde{t}) = \sum_{g \in \mathcal{G}} 1\{\tilde{t} \geq g\} \cdot P(G = g \mid G \leq \tilde{t}) \cdot ATT(g,t) \tag{A2}$$

The estimate of treatment effect for all cohorts across all period is given by the parameter:

$$\theta_{\text{aggregate}} := \frac{1}{\kappa} \sum_{g=2}^{\tau} \sum_{t=2}^{\tau} 1\{g \leq t\} \cdot ATT(g,t) \cdot P(G = g \mid C \neq 1) \tag{A3}$$

A2. Logit Model Specifications

TABLE A2—LOGIT COEFFICIENTS BY DIFFERENT SPECIFICATIONS

	(1)	(2)	(3)	(4)
Treated				
TFP_{t-2}	0.084	-0.145**	0.099	-0.122*
	(0.062)	(0.072)	(0.062)	(0.073)
TFP_{t-2}	0.088	-0.167**	0.095	-0.142*
	(0.068)	(0.083)	(0.069)	(0.083)
R&D Intensity$_{(t-1)}$	0.562***	0.452***	0.582***	0.476***
	(0.069)	(0.073)	(0.070)	(0.074)
Firm Size$_{(t-1)}$	0.426***	0.396***	0.420***	0.392***
	(0.020)	(0.024)	(0.021)	(0.024)
Age$_{t-1}$	1.720***	1.739***	1.622***	1.645***
	(0.228)	(0.244)	(0.233)	(0.249)
Age Squared$_{t-1}$	-0.289***	-0.287***	-0.277***	-0.275***
	(0.040)	(0.043)	(0.041)	(0.044)
Year Effects	No	No	Yes	Yes
Sector effects	No	Yes	No	Yes

This table reports logit regression coefficients estimating across different model specification, varying in the inclusion of sector and year fixed effects. Positive and statistically significant coefficients on R&D intensity, firm size, and firm age across specifications indicate that increases in these variables are associated with higher log odds of GVC entry. Once sector and year fixed effects are introduced (column 4), coefficients on lagged TFP become negative and statistically significant, suggesting that conditional on time and sector firms with higher productivity in earlier year exhibit a lower propensity to enter GVCs. *, **, *** indicates confidence level of 90, 95, and 99 percent respectively clustered at firm level.

Table A3—ATT Estimates by Aggregation Type

	ATT	SE	t-stat	95% CI Lower	95% CI Upper
Dynamic ATT					
T-7	-0.126	0.038	-3.335	-2.020	1.769
T-6	-0.001	0.027	-0.052	-1.357	1.354
T-5	-0.003	0.017	-0.173	-0.874	0.868
T-4	-0.018	0.013	-1.319	-0.687	0.652
T-3	-0.007	0.013	-0.569	-0.657	0.642
T-2	0.003	0.007	0.480	-0.327	0.333
T+0	0.006	0.007	0.863	-0.333	0.345
T+1	0.006	0.011	0.528	-0.524	0.536
T+2	0.019	0.014	1.424	-0.665	0.703
T+3	0.021	0.013	1.619	-0.621	0.662
T+4	0.016	0.016	0.973	-0.801	0.832
T+5	-0.012	0.012	-0.963	-0.612	0.589
T+6	0.153	0.024	6.262	-1.076	1.383
T+7	-0.209	0.002	-115.082	-0.300	-0.118
ATT by Group					
G2016	-0.020	0.016	-1.198	-0.062	0.023
G2017	0.031	0.015	2.142	-0.007	0.069
G2018	0.001	0.015	0.042	-0.039	0.041
G2019	0.009	0.019	0.452	-0.041	0.058
G2020	0.037	0.020	1.792	-0.017	0.090
G2021	0.056	0.021	2.657	0.001	0.110
G2022	0.049	0.020	2.384	-0.005	0.102
G2023	0.058	0.015	3.940	0.020	0.096
ATT by Calendar Period					
T2016	-0.027	0.017	-1.560	-0.071	0.017
T2017	-0.020	0.013	-1.556	-0.053	0.013
T2018	-0.009	0.016	-0.549	-0.049	0.031
T2019	-0.006	0.012	-0.522	-0.036	0.024
T2020	0.003	0.012	0.216	-0.028	0.034
T2021	0.005	0.013	0.354	-0.028	0.037
T2022	0.011	0.012	0.918	-0.019	0.041
T2023	0.100	0.013	7.711	0.067	0.132
ATT all Group and Period Aggregate	0.018	0.008	2.381	0.003	0.033

This table reports the ATT estimates using the doubly robust estimator by Callaway and Sant'Anna, 2021 with covariates with wild bootstrap standard errors. Panel A presents dynamic event-time ATTs relative to GVC entry (T=0). Panel B shows cohort-specific estimates by first year of GVC participation following estimator in equation (A1). Panel C displays calendar-year-specific estimates calculated using equation (A2). Panel D reports the aggregate ATT across all groups and periods, see equation (A3). 95% confidence intervals are based on uniform inference across treatment periods.

Table A4—Descriptive and Empirical Statistics by Firm Size

Descriptive Statistics	TFP	R&D Intensity	Age	Observations	
Small Firms	0.7764	0.0532	23	28,340	
Large Firms	0.4398	0.1560	26	30,554	
Pre-treatment Trend Test	χ^2	df	p-value		
Small Firms	35.7893	27	0.1200		
Large Firms	53.3039	23	0.0003***		
ATT all Group and Period Aggregate	Coefficient	SE	t-stat	95% CI Lower	95% CI Upper
Small Firms	0.01870	0.0185	1.01	-0.0173	0.0547
Large Firms	-0.0007	0.0078	-0.09	-0.0165	0.0150

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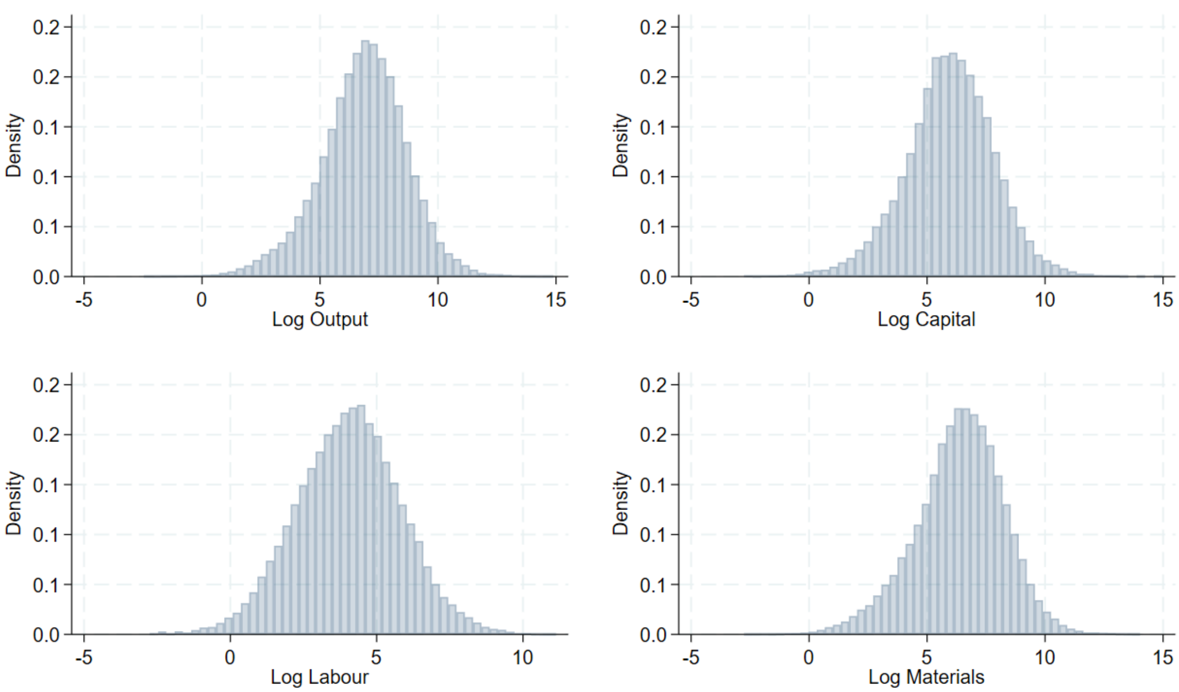

Figure A1. Density Plots of TFP Variables

Source: Author's Calculation.

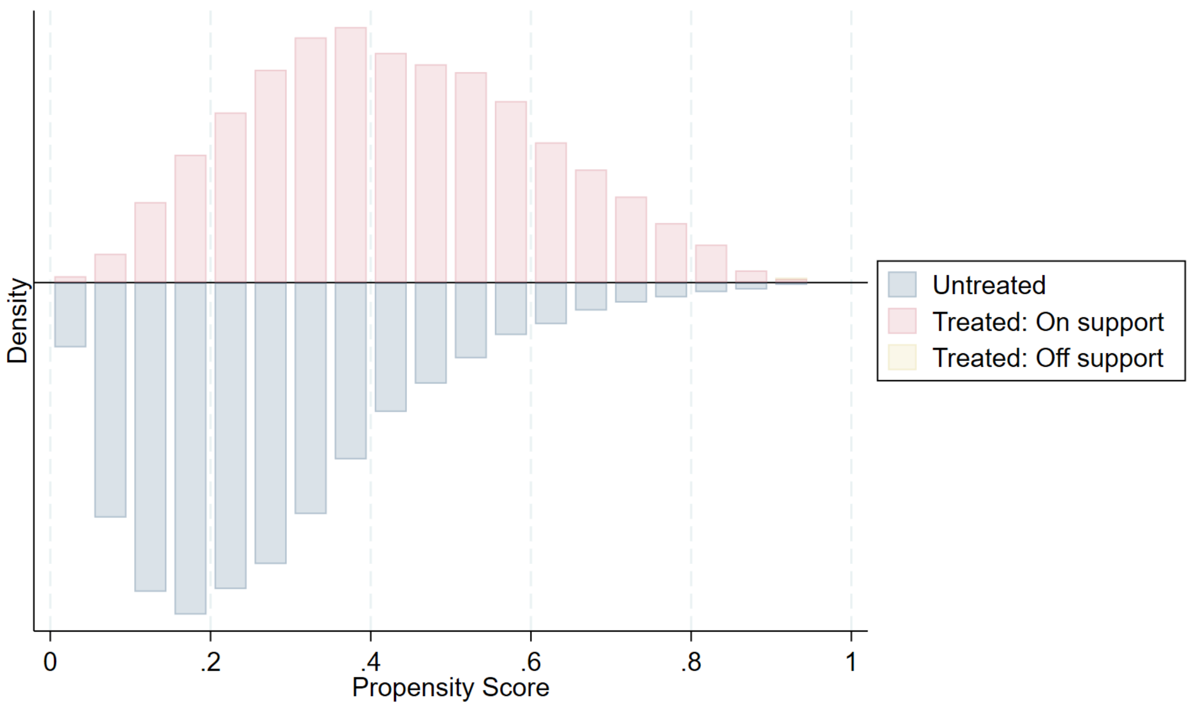

Figure A2. Common Support of Treatment and Control Group

Note: The plot shows the estimated propensity score distribution for treated and untreated firms. The plot verifies the positivity and overlap assumptions by showing substantial common support and scores bounded away from 0 and 1, enabling credible comparisons across groups.

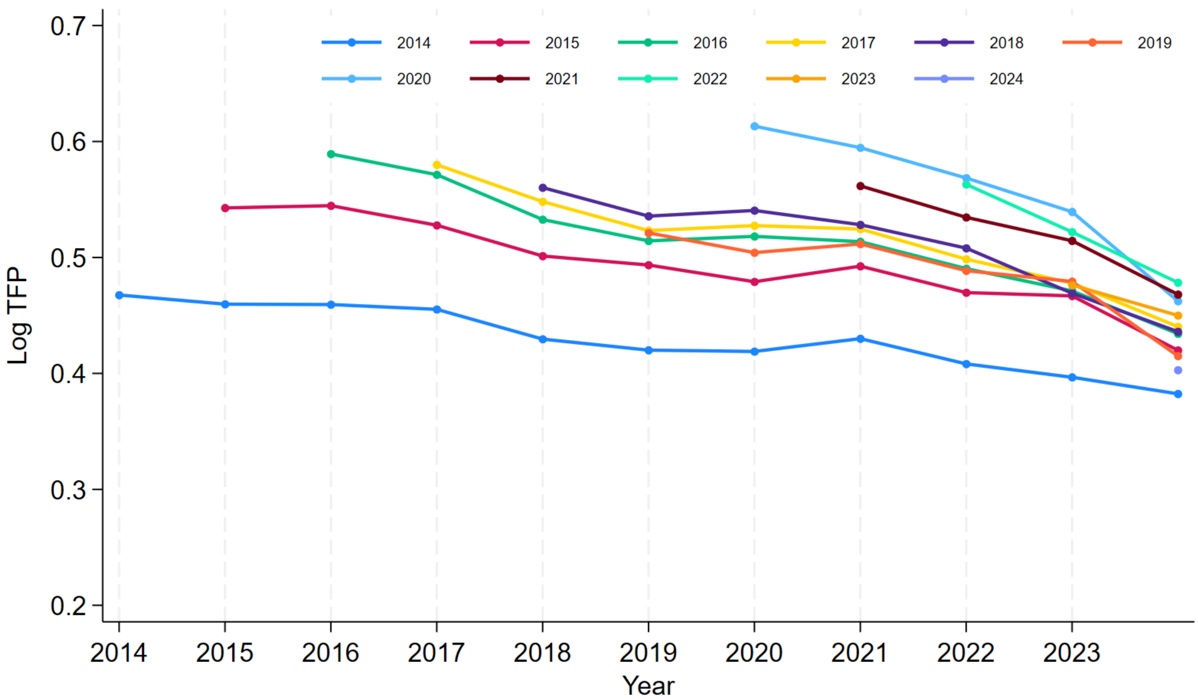

Figure A3. Mean Total Factor Productivity Evolution by Treatment Cohort

Note: The figure plots the average log TFP of treated firms, grouped by their entry year into GVCs. Each trajectory reflects the mean productivity path of a specific entry cohort, defined under the "once treated, always treated" assumption. The average TFP at the time of entry typically hovers between 0.5 and 0.6 across cohorts. A declining trend is observed in subsequent years, with trajectories gradually converging over time. The similar plot with median TFP was also analyzed, which exhibited the same trends except for the y-scale hence the plot was skipped for brevity. However, this figure is purely descriptive and should not be interpreted as evidence of a causal impact of GVC participation on TFP. Rather, it illustrates the evolution of firm-level productivity post-entry.