Assessing the Causal Impact of Global Value Chain Participation on Total Factor Productivity in Indian Manufacturing: Firm-Level Evidence Using PSM-DiD

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Abstract

This study examines the impact of Global Value Chain (GVC) participation on the Total Factor Productivity (TFP) of Indian manufacturing firms. Using firm-level data from the CMIE Prowess database for the period 2006–2015, we classify firms as GVC participants if they engage in both importing and exporting activities. To address potential endogeneity and selection bias, we employ a Propensity Score Matching (PSM) approach combined with a Difference-in-Differences (DiD) estimation, accounting for staggered treatment adoption and allowing for treatment effect heterogeneity. Our analysis reveals limited and heterogeneous productivity effects of GVC participation, with notable improvements observed only for specific firm cohorts. While some firms derive gains, these benefits are neither uniform nor guaranteed. The findings underscore the importance of reducing trade frictions, enhancing firm-level capabilities, and providing supportive policy frameworks to translate GVC participation into meaningful productivity improvements.

1 INTRODUCTION

During the past decade, India's exports have remained largely static, only recently showing signs of growth, while imports have increased consistently. Despite the steady growth of the Indian economy, trade, a crucial driver of growth, has been underused in the past 15 years. The annual export of goods, a key contributor to job creation in the manufacturing sector, remained at approximately $ 300 billion per year, only to increase to $ 452 billion in 2022[1]. Notably, India's trade as a percentage of GDP has seen a significant decline, dropping from 56 percent in 2011 to 40 percent in 2019, the year before the COVID-19 pandemic. Although India's trade has shown signs of recovery since 2021, primarily due to increased demand and price effects, maintaining these levels will be challenging, as it is expected that trade recovery will slow further due to the ongoing Israel-Palestine conflict and the Russia-Ukraine crisis.

The trade dispute between the United States (US) and China, coupled with the COVID-19 pandemic, has exposed severe vulnerabilities in the production networks of many essential products, necessitating a reconfiguration of supply chains. This has opened opportunities for India to integrate into the major global value chains (GVCs). Previously, US-based Multinational Corporations (MNCs) had established bases in China to leverage their infrastructure, skills, and low factor costs, allowing the US to manufacture goods at competitive prices and export globally. Consequently, a large proportion of the global production of steel, consumer durables, textiles and clothing, shoes, and electronics was concentrated in China. However, the trade dispute and the controversy surrounding the handling of the COVID-19 pandemic by China led to the imposition of tariffs on imports from China, causing many multinationals to look for alternative locations to manufacture these goods and diversify their supply sources to reduce their risks. This led to the creation and movement of GVCs to more favorable countries. In light of this, the leaders of the Quad—Australia, India, Japan, and the US—emphasized the need for reliable and resilient supply chains at their virtual summit in March 2021[2].

Shifting of the GVCs presents a compelling opportunity for the Indian economy; however, it remains a missed opportunity. While the Indian government and the industry prioritize efforts to play a vital role in shifting the GVC dynamics, the share of manufacturing in India's GDP, which could have created more jobs, particularly in labour-intensive manufacturing, an opportunity for India to integrate into GVCs, has remained stagnant at about 17 %[3]for the past four decades. It is evident that out of the 56 US firms shifting their bases out of China due to trade tensions, only three companies relocated to India, while the majority moved to Vietnam and Thailand[4]. Thus, India needs to embed itself into GVCs through a specialized focus on labour-intensive "network products" for which the production processes of MNEs, such as IT hardware, electricals, and electronics, are globally fragmented. This involves integrating Assembly in India into the Make in India initiative[5].

Indian firms seeking to integrate into GVCs encounter substantial obstacles, including the need to meet quality standards, a lack of institutional backing, and insufficient information. Companies that cater to multiple markets often duplicate production processes to comply with various standards or certification systems, which results in a significant cost for producers[6]. Institutional support is frequently lacking in terms of infrastructure, market access, and production subsidies[7]. Furthermore, companies often report inadequate information about markets, partners, EXIM rules, and trade finance. To facilitate integration into GVCs, India needs to ensure consistency and stability in its trade policies, which can be achieved through a predictable tariff regime and increased engagement in Free Trade Agreements (FTAs). When developing countries enter GVCs, they often focus on low-skilled and low-value-added activities and find it challenging to upgrade their activities due to competition, thus reaping limited benefits. Therefore, India must enhance the value-add in production, facilitate the transfer of knowledge and technology, address market failures, and ensure the equitable distribution of economic benefits[8].

While it is recognized that the Indian economy will benefit from the enhanced GVC participation of Indian manufacturing firms, it is crucial to understand its impact on productivity. Productivity is an efficiency indicator that can be improved through technology transfer, better management practices, and access to larger markets. Understanding the impact on productivity helps assess whether firms benefit from GVC integration by examining improvements in efficiency and competitiveness.

2 LITERATURE REVIEW

The interplay between GVC participation and total factor productivity (TFP) has emerged as a critical area of research in understanding firm-level efficiencies. TFP has been the cornerstone of growth theory, and the discussion around it dates back to Solow's seminal paper "Technical Change and the Aggregate Production Function." ([9] In it, he introduced the idea that production could not be explained in entirety by the input factors capital and labour but is a function of technical change, which he explains as any kind of shift, such as improvement in the education of the labour force or speedups, amongst others. This "Technical Change" we know today as total factor productivity.

Over time, the literature has shifted from single-input production models to multi-input models, which better capture the complexities of modern production systems. This transition aligns with the advancements in understanding how multiple factors contribute to output accounted by the cobb-douglas production function. The more common method of estimating TFP is the residual method, which accounts for the contributions of inputs within a Cobb-Douglas production framework [10][11]. The approach allows TFP to be treated as the residual in log-transformed equations, accounting for shocks and unobservable variables impacting the production, aligning with Solow's initial definition of 'any kind of shift'.

Multiple studies have examined the impact of GVC participation on TFP across different countries. The Asian Development Bank's flagship GVC integration flagship report using its Input-Output database highlighted the drivers and benefits of GVC Participation of Indian firms, focusing on infrastructure, trade facilitation, and institutional quality. Sectors like pharmaceutical and electronics demonstrated productivity growth due to deep GVC involvement, leveraging vertical specialization and backward linkages. The studied concluded that India's GVC participation is constrained by labour market rigidity, insufficient trade facilitation, and regulatory bottlenecks, limiting the scope of TFP improvements[12].

Another study on India by Banga utilized a two-stage empirical strategy combining propensity score matching (PSM) and the generalized method of moments (GMM) to assess the impact of GVC embeddedness on TFP. The findings indicated a positive impact of GVC participation on TFP of Indian manufacturing firms, particularly the network product industries. Vertical specialization—a measure of GVC embeddedness—further amplified productivity gains[13]. Other studies following a similar methodology of measuring TFP on firm level data, reported varying impacts. While Canadian firms showed strong productivity gains from GVC participation [14], Japanese firms experienced moderate improvements.

Urata and Baek (2022) examined the productivity effects for Japanese firms over the period 1994–2018. Using PSM-DID methods, their study found that the impact of GVC participation on productivity is generally positive but not consistently strong with only 35% coefficients positive. In particular, the study highlights a learning effect, where productivity gains accumulate over time as firms adapt to new technologies and management practices [15].

Using PSM DiD method, Del Prete et al., use World Bank's Enterprise database finds that firms in Egypt and Morrocco that enter GVCs perform better ex ante and show additional productivity gains ex post [16].

Despite coverage of impact of GVC integration on the total factor productivity, gaps remain in understanding the relationship in India using firm-level data. Despite some literature discussing this research topic [13] the focus has remained on defining the GVC and using different indices. Additionally, allocation of inputs in the production closely mirrors each other in the manufacturing sector, resulting in potential correlation. This examination of the "correlation" is widely written about in the literature, as early as by (Marschak, Andrews; 1944)[17]. In their study, they highlighted the inherent complexities in modelling the interdependent system of decisions that govern a firm's production.

Thus, this paper aims to bridge such gaps, we use firm level data and use modified version of Levinsohn and Petrin's approach [18] to calculate total factor productivity accounting for productivity and unobserved shocks. Additionally, to address the self selection bias - where the higher productivity companies 'self-select' themselves into the GVC, we deploy propensity score matching. The matched dataset is then used in Diff-in-Diff, where we use group time average treatment effect (ATTGT) proposed by Callaway and Anna [19]. Since different firms enter GVC at different time periods, this identification strategy is crucial allowing for treatment effect heterogeneity and dynamics. Additionally, it allows for to utilize "not-yet treated units" as controls. Since our GVC participation assumption (as we talk about it below) is that a firm once integrated into GVC, remains GVC firm for rest of the timeline, Callaway and Anna's paper posits the similar approach for treated.

3 DATA

The data for this study were sourced from the Centre for Monitoring Indian Economy (CMIE) Prowess, a comprehensive proprietary database that documents the financial performance of Indian companies. The primary source of information for this database is the annual reports of these companies. CMIE Prowess provides data on both listed and unlisted firms.

For this analysis, data on Indian manufacturing companies (18,060 companies) was extracted, focusing on key variables for the ten-year period from 2006 to 2015. The selection of this time frame was primarily driven by the limited availability of data on the variables of interest after 2015. The collected data encompassed variables including Sales, Change in stock of finished goods, Change in stock of work-in-progress and semi-finished goods, Raw materials, stores and spares, Purchase of finished goods, Power and fuel, Salaries and wages, Net fixed assets, Gross fixed assets, Total assets, Current assets (including short-term investments, loans and advances), Export of goods (FOB), Export of services, Import of raw materials (CIF), Import of stores and spares (CIF), Import of finished goods (CIF), Import of capital goods (CIF), Gross fixed assets depreciation during the year, Current liabilities, and Short-term borrowings.

It is crucial to note that these variables are time series (2006-2015). The study also extracted Company Name, Incorporation Year, and Industry Code as static variables. Given the focus on manufacturing firms, CMIE Prowess employs five-digit National Industry Classification (NIC) codes to classify companies into various sub-manufacturing sectors. To determine the corresponding industry names, the NIC 2008 classification was used, narrowing the focus to the first two levels of codes to identify 23 key manufacturing subsectors.

As mentioned, while CMIE Prowess reports industry codes up to 5 digits, this study focused on broad industry categories to avoid unnecessary complications. For instance, the focus was on Manufacturing of Food Products (10) rather than specific subcategories like Beef Slaughtering, Preparation (10102). Given the 10-year time horizon of the analysis, companies reporting data for less than four years were filtered out. This approach ensured minimal skewness and outliers in the sales data, ultimately leaving a refined database of 10,699 manufacturing companies.

3.1 Variable Calculation Methods

3.1.1 Estimation of Real Capital Stock

This section details the methodology adopted for estimating the real capital stock for the firms, based on the modified Perpetual Inventory Method (PIM), a version of which is used by a few studies in literature[13],[11].

The Gross Fixed Capital Formation (GFCF) data was sourced from the Ministry of Statistics and Programme Implementation (MOSPI)[20]. Since CMIE Prowess does not report data on GFCF at firm level, to calculate firm level capital stock, GFCF of the manufacturing sector (as a whole) was used to calculate the π, g , Implicit Price Deflator, amongst others as mentioned below. The adjustments included:

- Post-2011-12 Data: GFCF data from 2011-12 to 2014-15 was obtained at 2011-12 prices[21].
- Pre-2011-12 Data: MOSPI reports GFCF data before 2011-12 at 2004-05 prices[22]. For the period 2006-07 to 2010-11, these figures were converted to 2011-12 prices using the price indices

The price deflator for a given year is calculated as:

$$\text{Price Deflator (Year } i) = \frac{\text{Price Index of 2004-05 (Year } i)}{\text{Price Index of 2004-05 (2011-12)}} \tag{1}$$

The price deflator was then multiplied by the current prices of 2006-07 to 2010-11 to estimate constant prices at the 2011-12 level.

For each year, the implicit price deflator was computed to align current and constant prices using the formula:

$$\text{Implicit Price Deflator} = \frac{\text{GFCF}_{\text{Current Prices}}}{\text{GFCF}_{\text{Constant Prices}}} \tag{2}$$

The real GFCF growth rate for each sector was estimated using the exponential growth model

$$\ln(S_t) = \alpha + g \cdot t$$

Where,

- S_t is the real GFCF in year t,
- g is the estimated growth rate,
- α is a constant

The inflation rate(π) was estimated using the Compound Annual Growth Rate (CAGR) of the implicit price deflators over time (t to $t+10$, where $t = 2006$). And the firms were categorized based on their incorporation year to determine the vintage of capital stock:

- *Companies Incorporated Before 1980:* The initial year of capital was set to 1980, with $T = 32$.Primarily also because MOSPI does not have data on GFCF prior to 1979-1980

- *Companies Incorporated Between 1981 and 2011:* The vintage was calculated as the difference between the incorporation year and the base year (2012)
- *Companies Incorporated in 2012 or Later:* These companies were assumed to have $T = 0$, as their vintage starts from their incorporation year

Thus, the Gross Fixed Assets in Real Terms (GFARC) for each company and year were calculated using:

$$\text{GFARC}_t = \text{Gross Fixed Assets} \cdot \frac{(1+g)^t}{(1+\pi)^t} \tag{3}$$

where,

- g is the sector-wide growth rate,
- π is the inflation rate,
- t is the time elapsed since the base year

For firms incorporated before 2006, the benchmark year capital stock (K_{BM}) was calculated using data from 2006. Here we have subtracted the accumulated depreciation from the GFARC in 2006, to calculate the benchmark year capital (when it was acquired/purchased):

$$K_{\text{BM}} = \text{GFARC}_{2006} - \text{Acc Dep}_{2006} \tag{4}$$

For firms incorporated after 2006, the benchmark year capital stock (K_{BM}) was calculated using data from the firm's year of incorporation (YOI):

$$K_{\text{BM}} = \text{GFARC}_{\text{YOI}} - \text{Acc Dep}_{\text{YOI}} \tag{5}$$

Then we set K_{BM} as the initial value for the capital stock, on which we will then apply PIM:

$$K_{\text{i1}} = K_{\text{BM}} \tag{6}$$

For each subsequent year:

$$K_t = K_{t-1} \cdot (1-\delta) + (\text{Net Block}_t - \text{Net Block}_{t-1}) \tag{7}$$

where,

- δ: Economic Depreciation rate (assumed to be 5% for all firms across years). It is consistent with the literature using PIM and assuming the economic rate of depreciation[13]
- Net Block$_t$: Real (constant price) net block for year t, where net block is:

  Gross Fixed Assets$_t$ - Acc Depreciation$_t$

3.1.2 Estimation of Output and Input Variables

This subsection details the calculation and proxies used for the calculation of output variable and input variables, labour, materials, electricity. With calculation of capital stock detailed in 3.1.1. Sales was used as a proxy to calculate Output, which was further adjusted for change in inventory and purchase of finished goods using the following equation:

$$\begin{aligned} \text{Output} = \text{Sales} + \Delta\text{Stock of Finished Goods} + \Delta\text{Stock of Semifinished} \\ + \text{WIP Goods} - \text{Purchases of Final Goods} \end{aligned} \tag{8}$$

Two different Wholesale Price Index (WPI) series were applied to deflate sales. For the years 2013–2015, WPI indices with the 2011–12 base year were used, whereas for 2006–2013, WPI indices with the 2004–05 base year were utilized. A conversion factor was calculated similar to 1. The conversion factor was then multiplied by the WPI 2004–05 levels to adjust the sales data for the years 2006–2012.

Similarly, expenses on raw materials were used for material input, while expenses on power and fuel served as a proxy for electricity input. As manufacturing companies were analyzed, electricity was identified as a key input. The deflation of raw materials, power, and fuel followed the same methodology as the deflation of sales, with adjustments made using the WPI Fuel at 2011 levels. The data on price levels were sourced from the MOSPI Price and Quantum Indices reports[22][21].

For labour input calculation, Chawla (2012)[10] inspired the Annual Survey of Industries (ASI)-based approach was used. A dataset that included total emoluments and the number of persons engaged in industries classified under NIC 2008 codes for each year from 2006 to 2015 was created. This information was sourced from the ASI reports for the respective years[23]. The average industry wage was then calculated as:

$$\text{Average Industry Wage} = \frac{\text{Total Emoluments}}{\text{Total Persons Engaged}} \tag{9}$$

3.1.3 Total Factor Productivity Calculation

To calculate Total Factor Productivity (TFP), a modified version of (Levinsohn, Petrin; 2003)[18] production function estimation approach was utilized to address the issue of simultaneity bias in the production function estimation, where intermediate inputs are used as a proxy control for the correlation between the inputs used and the productivity shocks. The underlying rationale is that the intermediary inputs are not typically state variables and are likely to respond to productivity shocks more smoothly [18].

Starting from the version of Cobb-Douglas production function:

$$Y_{it} = F(L_{it}, K_{it}, M_{it}, E_{it}, \Omega_{it}) \tag{10}$$

where K_{it} is the real capital, L_{it} is the labor input, and Eit is the power and fuel inputs, M_{it} is the material input. Taking the log-linear approximation:

$$\ln Y_{it} = \beta_0 + \beta_l \ln L_{it} + \beta_k \ln K_{it} + \beta_e \ln E_{it} + \beta_m \ln M_{it} + \ln u_{it} \tag{11}$$

The error term u_{it} is assumed to be composed of two additive components: a transmitted component Ω_{it} and an independent and identically distributed (i.i.d.) component ηt. The critical distinction between Ω_{it} and ηt is that the transmitted component Ω_{it} is a state variable, meaning it influences the firm's decision-making processes, while the i.i.d. component ηt has no impact on the firm's decisions[18]

Using the material input to estimate the productivity shocks.

$$\ln M_{it} = \alpha_0 + \alpha_1 \ln K_{it} + \alpha_2 \ln L_{it} + \alpha_3 \ln E_{it} + \epsilon_{it} \tag{12}$$

The residuals from this regression, ϵ_{it}, are used as a proxy for unobservable productivity shocks

(Ω_{it}) captures the productivity shocks:

$$\Omega_{it} = \ln M_{it} - \widehat{\ln M}_{it} \tag{13}$$

We assume that productivity shocks follow a Markov process, so a shock in the current will lead to change in input demand, thus expressed as:

$$\Omega_{it+1} = f(\Omega_{it}) + \eta_{it} \tag{14}$$

The lagged value of Ωit, denoted as Ω_{it-1}, is used to account for the serial dependence of these shocks.

The production function, thus, is estimated by incorporating the proxy for productivity shocks (Ω_{it}) to control for unobservable factors:

$$\ln Y_{it} = \beta_0 + \beta_L \ln L_{it} + \beta_K \ln K_{it} + \beta_E \ln E_{it} + \beta_\Omega \Omega_{it} + \nu_{it} \tag{15}$$

Where $\ln Y_{it}$ is the logarithm of output, and the coefficients β_L, β_K, and β_E represent the elasticities of output with respect to labor, capital, and power and fuel, respectively.

Total Factor Productivity (TFP) is computed as the residual from the production function, expressed as:

$$\ln \mathrm{TFP}_{it} = \ln Y_{it} - \tilde{\beta}_L \ln L_{it} - \tilde{\beta}_K \ln K_{it} - \tilde{\beta}_E \ln E_{it} \tag{16}$$

This provides a measure of firm-level productivity.

3.1.4 Global Value Chain Status

Based on their simultaneous engagement in importing and exporting, firms are categorized as GVC or Non-GVC firms. Specifically, a firm is considered a GVC firm if, in a given year, it reports positive values for imports (import of stores and spares, import of finished goods, or import of capital goods) and exports (export of goods or export of services). If a firm engages in only one of these activities, it is categorized as Non-GVC for that year. To ensure consistency in data handling and account for potential reporting errors, once a firm transitions to being a GVC firm, it is assumed to remain a GVC firm for all subsequent years. This approach is in line with the body of literature [19][13].

3.2 Causal Methods

3.2.1 Propensity Score Matching

Propensity score matching estimation was used, in which treated, i.e., GVC firms (binary value 1) were matched with the control, i.e., non-GVC firms (binary value 0) along firm-level characteristics before evaluating the impact of GVC participation on the firms. The rationale behind using PSM estimations was to create a counterpart with similar characteristics for treated firms among the control firms that have a similar probability of participating in the GVC. Thus, propensity scores were estimated using logistics regression, defined as the probability that a firm participates in the GVC given its observed covariates. The covariates included lagged measures of TFP, firm size, and firm age. Additionally, industry-specific indicator variables were introduced to control for heterogeneous sectoral effects ensuring that the treatment assignment is driven by measured characteristics rather than latent attributes. After calculating the propensity scores, treated firms were matched with control firms using a nearest-neighbour matching. The effectiveness of matching was evaluated through the balancing test and the balance of covariates was observed before and after the process. The standardized mean difference was used as a diagnostic measure to quantify the discrepancy between treated and control firms.

$$\text{Propensity Score Matching} = \frac{1}{N}\sum_{i\in \text{GVC1}}\left(Y_{i,t+s}(1) - \sum_{j\in \text{GVC0}} W\left(P(X_{i,t-1}), P(X_{j,t-1})\right) Y_{j,t+s}(0)\right) \tag{17}$$

where:

- GVC1 and GVC0 represent the treated group (GVC firms) and the matched control group (non-GVC firms), respectively.
- $Y_{i,t+s}(1)$: TFP when firm i is in the GVC.
- $Y_{j,t+s}(0)$: Counterfactual outcome, when firm j does not participate in GVC.
- $P(X_{i,t-1})$: Propensity score estimated using pre-treatment (before participating in GVC) covariates (X_{t-1}).
- $W\left(P(X_{i,t-1}), P(X_{j,t-1})\right)$: Matching weight based on the similarity of propensity scores for treated and control firms (using k-neighbour estimates).

- N: Number of treated firms in GVC1.

3.2.2 Difference-in-Difference

This section employs a difference-in-differences (DiD) estimator influenced by the framework proposed by Callaway and Sant'Anna (2020)[19], where I have integrated it with the propensity-score-matched sample. Unlike classical DiD methods that assume all treated units receive the intervention at the same time, this approach accommodates staggered adoption—firms enter GVC participation at differing points in time, forming multiple "cohorts" of treatment initiation. By leveraging this variation, the model capture not only the average effect of treatment but also how these effects evolve across different entry years.

The matched dataset, which aligns treated and control firms based on similar baseline characteristics, provides the foundation for this analysis. After PSM, each treated firm is assigned to a cohort corresponding to the year it first transitions into the treated state (the year it entered GVC). Firms that have not yet transitioned in that same period serve as control units, dynamic counterfactual as time progresses. This structure allows the identification strategy to remain robust even when treatment timing differs significantly across firms, reducing reliance on the restrictive assumption of uniform treatment timing[19].

Consider a firm i observed over multiple time periods t, with G_i denoting the specific year when it enters GVC participation. We define potential outcomes $Y_{it}(1)$ and $Y_{it}(0)$ to represent, respectively, the firm's productivity outcome (here, $\ln TFP$) if it were treated or untreated at time t using matched sample. The DiD estimator hinges on observed changes in outcomes before and after treatment, contrasted against the not-yet-treated controls, to identify the average treatment effect on the treated (ATT):

$$\text{ATT}_{g,t} = E[Y_{it}(1) - Y_{it}(0) \mid G_i = g].$$

We have used three different types of aggregation to calculate the average effect, i.e., cohort aggregation calculates the average effects of the treatment across cohorts, and time aggregation calculates the effect of treatment across time. We also use event aggregation to calculate the average effect across positive relative periods. Since we use ATTGT, to ensure its validity, we consider the standard assumption of parallel trends and staggered treatment adoption (firm gaining the GVC status retains it thereafter. For this analysis, we use the differences package in Python developed by Bernardo Dionisi.

4 RESULTS

4.1 Overview of Global Value Chain Participation and Productivity Trends

Figure 1 shows a clear convergence between the number of Global Value Chain (GVC) firms and Non-GVC firms over time. In 2006, Non-GVC firms substantially outnumbered GVC firms, with counts of 1053 versus 730, respectively. By 2015, however, this gap had narrowed considerably, as GVC firms grew to 906 while Non-GVC firms declined to 878. This shift suggests a gradual, economy-wide move toward greater participation in global production networks. Table 2 reinforces this point. It reveals that, for certain industries—such as *Coke and Refined Petroleum Products*—the proportion of GVC firms rose significantly, from about 31.7% in 2006 to 50% in 2015. This pattern indicates that, over time, more firms across various sectors are embracing international production linkages, potentially altering competitive dynamics and market structure.

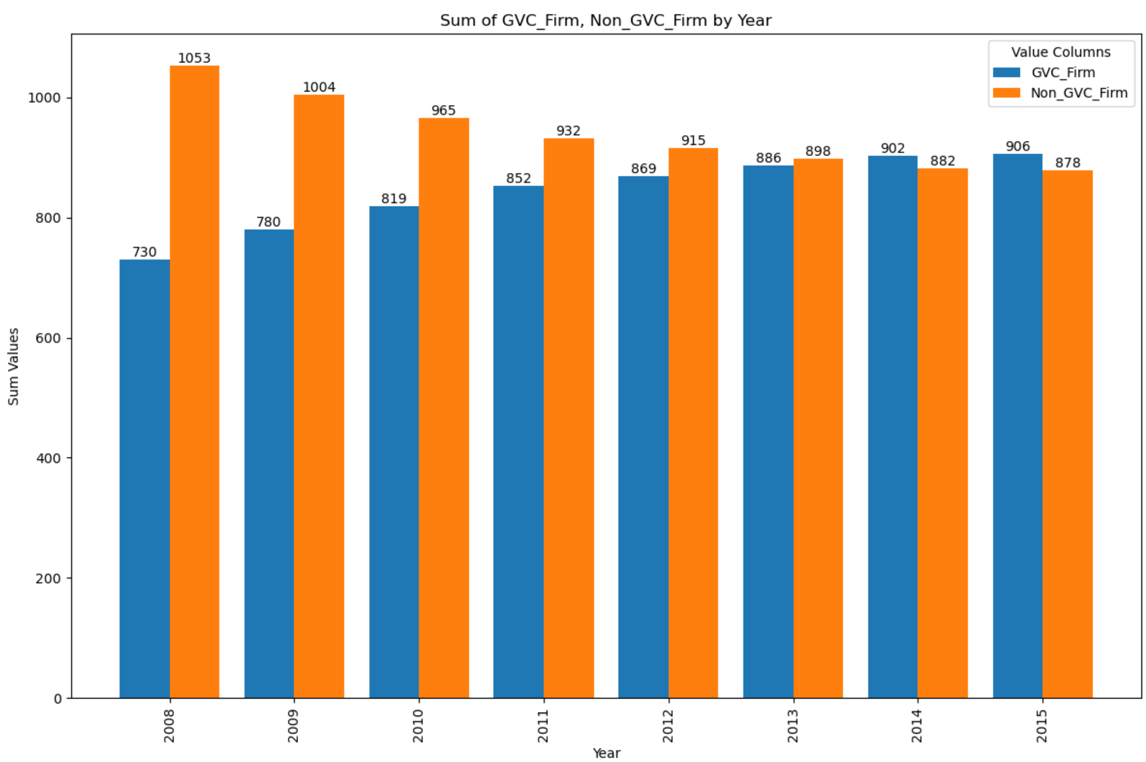
Turning to productivity, Table 1 presents the estimation of Total Factor Productivity (TFP). The regression model explains over 95% of output variation, and the coefficients for labor, capital, and energy inputs are all statistically significant at the 1% level. These high levels of significance and the relatively large coefficients for traditional inputs underscore the importance of factor accumulation and efficient resource use. At the same time, they highlight that changes in productivity—reflected in the residual—also play a substantial role.

Industry-specific differences in productivity emerge from Figure 2. Capital-intensive and technologically advanced sectors, such as *Coke and Refined Petroleum Products* (mean lnTFP = 5.4), generally outperform less capital-intensive ones like *Leather and Leather Products* (3.4) and *Wood and Wood Products* (3.2). This variation underlines how industry-specific factors, such as technology adoption, production complexity, and capital intensity, influence overall productivity levels.

In Figures 4 and 3, we see that GVC firms typically exhibit slightly higher productivity than their Non-GVC counterparts. Across years, density plots show GVC firms' TFP distributions shifted modestly to the right of Non-GVC firms. Similarly, mean and median TFP values for GVC firms remain about 0.5 log points above those of Non-GVC firms. Yet, the overall differences are not strikingly large. Non-GVC firms have also seen gradual TFP improvements over time, suggesting that while GVC participation is associated with some productivity advantages, it is not a panacea. Many Non-GVC firms appear capable of making incremental gains, perhaps through learning effects, incremental upgrades in production methods, or spillovers from broader industry trends.

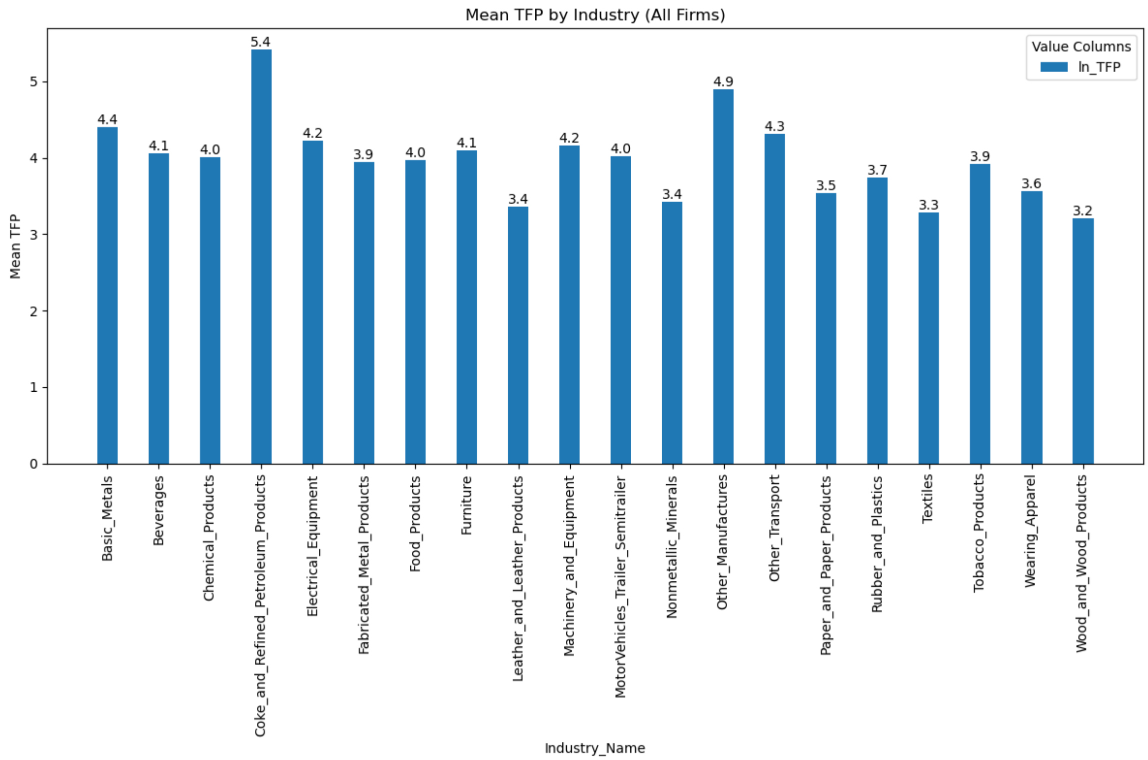
In sum, the steady increase in GVC participation aligns with modest productivity differentials, implying that while global integration can offer some benefits, other factors—such as factor inputs, industry characteristics, and ongoing improvements within Non-GVC firms—also shape productivity outcomes.

Figure 1: Number of GVC and Non GVC firms



Source: Author's Computation.

Figure 2: Mean TFP by Industry



Source: Author's Computation.

Table 1: LP Estimation Coefficients

	Output (Y)
const	3.9937***
	(0.0147)
Labour (L)	0.3772***
	(0.0023)
Capital (K)	0.2508***
	(0.0023)
Power_Fuel (E)	0.2401***
	(0.0019)
R-squared	0.9592
R-squared Adj.	0.9592

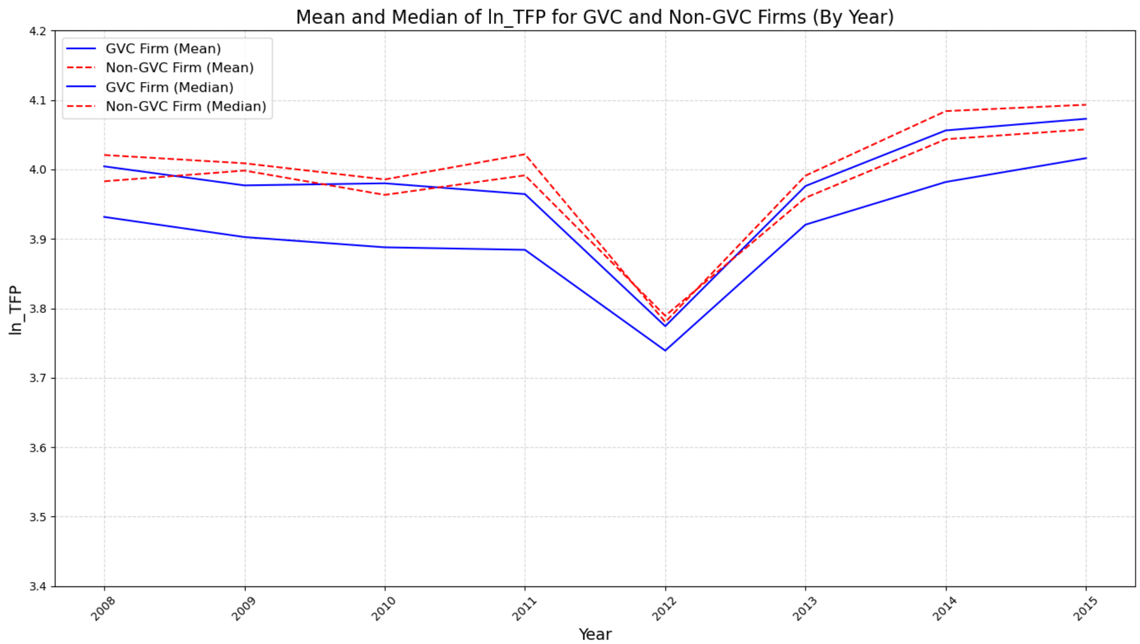
Standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$
All coefficients of log real variables

Table 3: Summary Statistics of Log TFP by Industry.

Industry Name	**Mean ln(TFP)**	**Max ln(TFP)**	**Min ln(TFP)**
Basic Metals	4.40	6.75	-0.60
Beverages	4.06	6.45	0.92
Chemical Products	4.01	6.79	-0.02
Coke and Refined Petroleum Products	5.42	7.01	2.35
Electrical Equipment	4.22	6.27	0.42
Fabricated Metal Products	3.94	7.30	2.51
Food Products	3.97	6.56	0.22
Furniture	4.09	4.68	3.54
Leather and Leather Products	3.36	4.61	0.83
Machinery and Equipment	4.15	6.32	1.72
Motor Vehicles, Trailers, Semitrailers	4.03	6.10	1.87
Nonmetallic Minerals	3.43	5.20	1.75
Other Manufactures	4.90	8.24	1.94
Other Transport	4.32	5.63	-0.48
Paper and Paper Products	3.54	6.18	1.60
Rubber and Plastics	3.74	5.87	1.99
Textiles	3.28	6.40	-1.08
Tobacco Products	3.92	4.79	2.90
Wearing Apparel	3.57	5.71	0.30
Wood and Wood Products	3.20	4.63	1.47

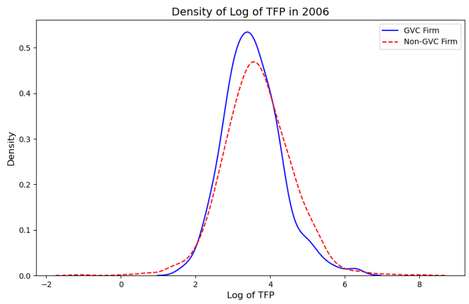
Source: Author's Computation.

Figure 3: Comparison of Mean and Median Log TFP for GVC and Non-GVC Firms.

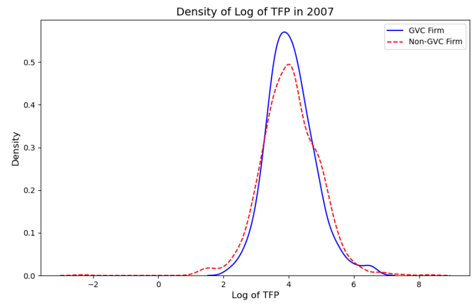


Source: Author's Computation.

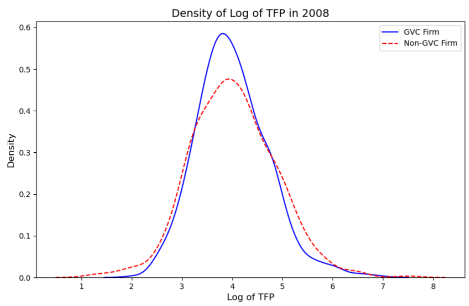
Figure 4: TFP Distribution by GVC Status



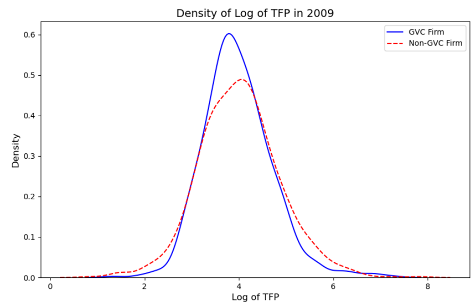
(a) Log of TFP in 2006



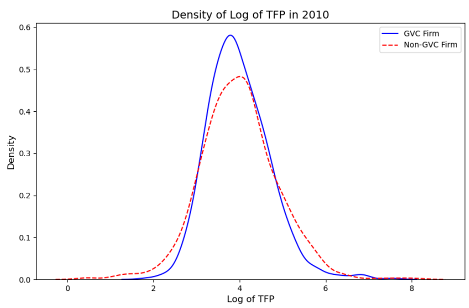
(b) Log of TFP in 2007



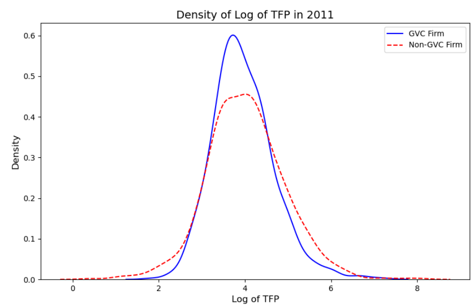
(c) Log of TFP in 2008



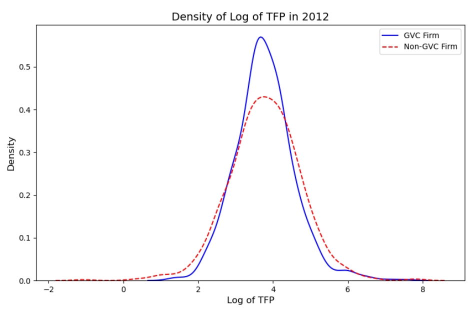
(d) Log of TFP in 2009



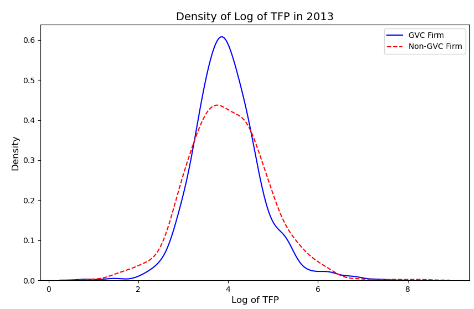
(e) Log of TFP in 2010



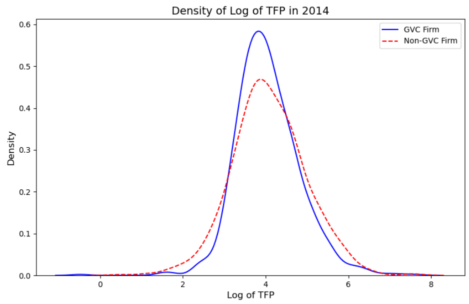
(f) Log of TFP in 2011



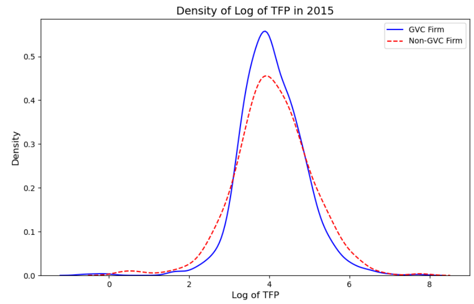
(g) Log of TFP in 2012



(h) Log of TFP in 2013



(i) Log of TFP in 2014



(j) Log of TFP in 2015

Source: Author's Computation.

4.2 Causal Inference

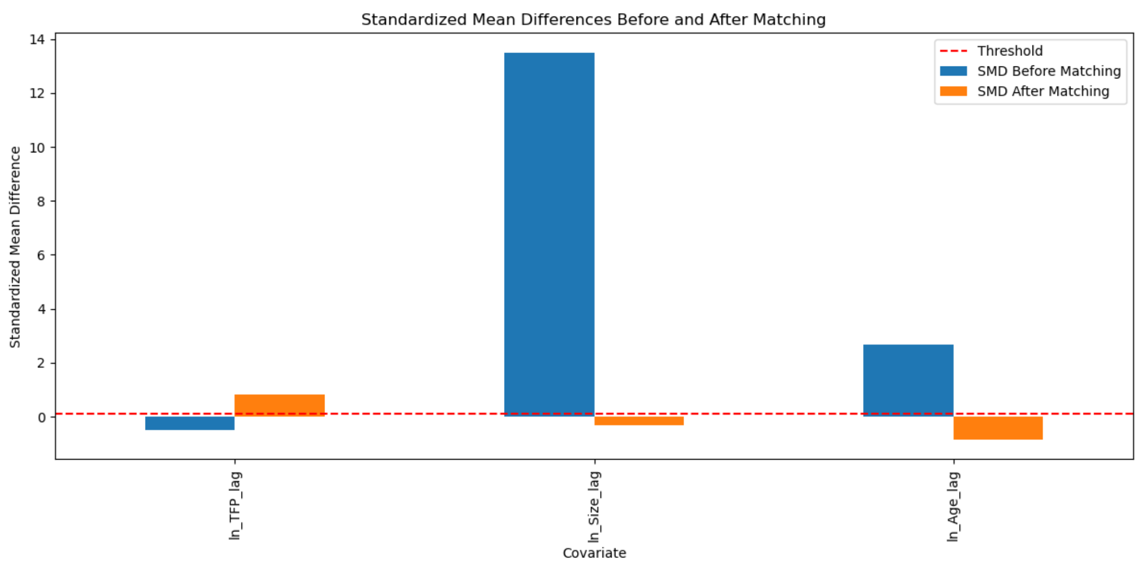
The analysis presented here focuses on understanding whether participation in GVCs leads to measurable improvements in firm-level productivity. After applying Propensity Score Matching combined with a Difference-in-Differences (PSM-DiD) design, we find that the matched sample exhibits strong covariate balance. In particular, the standardized mean differences before and after matching (5) show that initially large imbalances in certain covariates—such as firm size—are substantially reduced. This improvement in balance suggests that the matched sample is more suitable for isolating the effect of GVC participation from other confounding factors.

Turning to the time-specific results (8 and 5, the Average Treatment Effects on the Treated (ATT) estimated for each year are generally small and often statistically indistinguishable from zero. The early years, such as 2009 and 2010, show modest positive ATT values (around 0.08–0.09), but the associated confidence intervals include zero, indicating we cannot conclusively state that GVC participation raised productivity in a statistically significant way. Over the subsequent years, the estimates fluctuate around zero. The largest positive point estimate emerges in 2015 (ATT = 0.102), suggesting a possible delayed benefit, but even this estimate has a confidence interval that includes zero, signaling caution in interpreting it as a definitive impact.

Cohort-specific estimates 9 and 4 offer a complementary perspective. The 2009 cohort stands out with a positive and statistically significant ATT (0.236), meaning firms that joined GVCs in that year appear to have experienced notable productivity gains relative to their matched controls. In contrast, cohorts entering in later years often show negative or negligible effects. This heterogeneity could reflect varying initial conditions, differences in the global economic environment at the time of entry, or the nature of the GVC relationships formed by different cohorts. The 2014 cohort, for instance, shows a relatively large positive point estimate (0.363), but with wide confidence intervals that include zero, making it unclear whether this is a true outlier or just sampling variability. The event study analysis 7 examines productivity patterns relative to the exact year of GVC integration. The results suggest that before treatment, treated and control firms follow similar productivity trends, thereby supporting the parallel trends assumption. Following GVC participation, the ATT estimates remain close to zero for most relative periods, indicating that, on average, there is no strong or immediate shift in productivity. While a slight upward movement appears in later post-treatment periods, it does not translate into robust statistical significance.

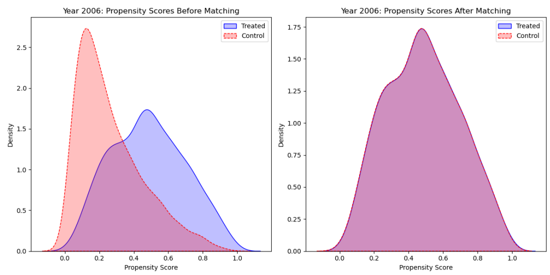
Overall, these results imply that any productivity benefits from GVC participation are limited, uncertain, and may depend heavily on when and under what conditions firms enter GVCs.

Figure 5: Standardized Mean Difference

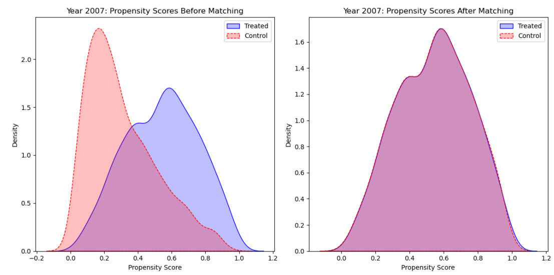


Source: Author's Computation.

Figure 6: Propensity Score Distributions Before and After Matching

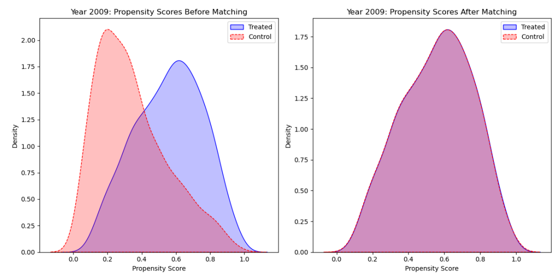


(a) Before and After Matching (2006)

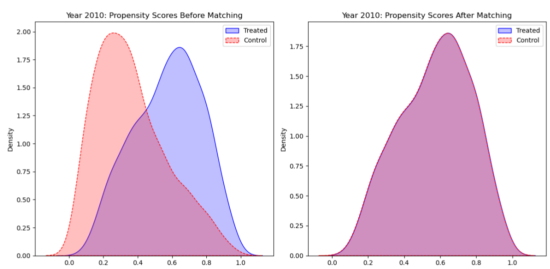


(b) Before and After Matching (2007)

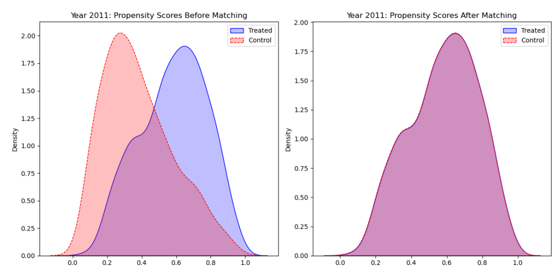
(c) Before and After Matching (2008)



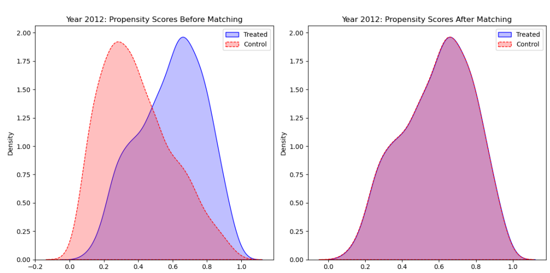
(d) Before and After Matching (2009)



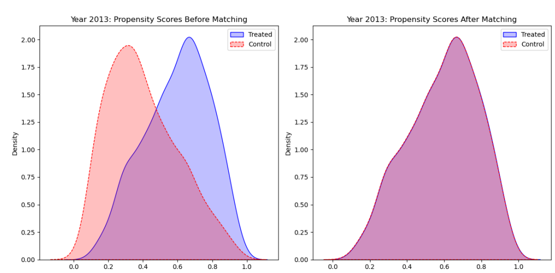
(e) Before and After Matching (2010)



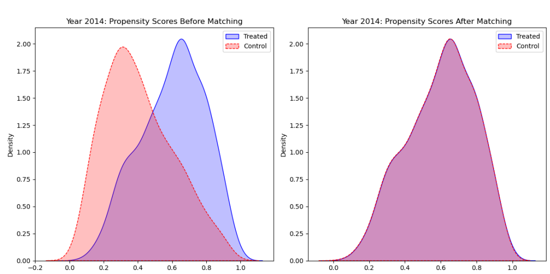
(f) Before and After Matching (2011)



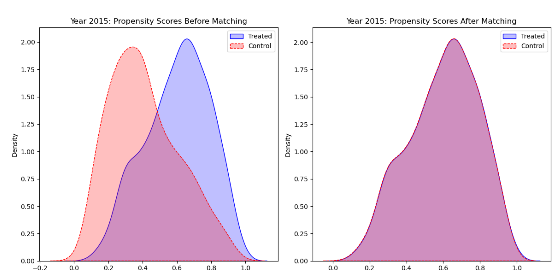
(g) Before and After Matching (2012)



(h) Before and After Matching (2013)



(i) Before and After Matching (2014)



(j) Before and After Matching (2015)

Table 4: Cohort-Specific ATT Estimates

Cohort	**ATT**	**Std. Error**	**Lower Bound**	**Upper Bound**	**Zero Not in C.I.**
2009	0.236	0.097	0.046	0.427	*
2010	-0.044	0.154	-0.347	0.258	
2011	-0.006	0.131	-0.264	0.251	
2012	-0.285	0.156	-0.590	0.021	
2013	-0.129	0.108	-0.342	0.083	
2014	0.363	0.201	-0.032	0.757	
2015	-0.040	0.711	-1.434	1.355	

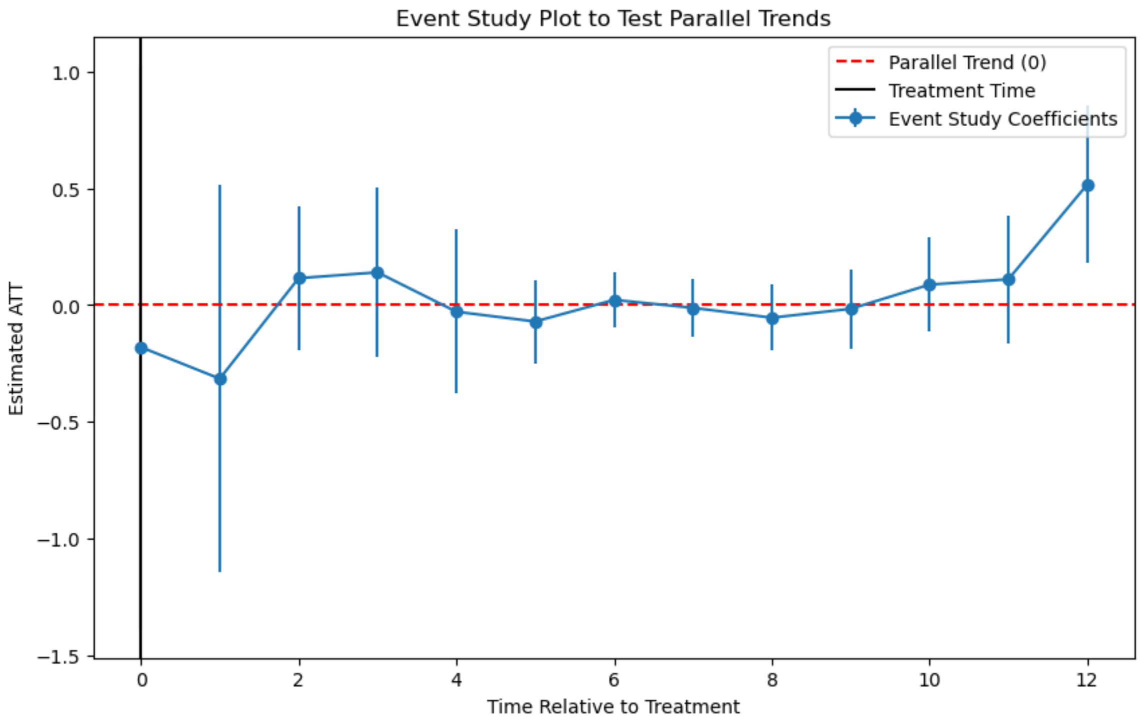
Source: Author's Computation.

Table 5: Time-Specific ATT Estimates

Time	**ATT**	**Std. Error**	**Lower Bound**	**Upper Bound**	**Zero Not in C.I.**
2009	0.086	0.089	-0.089	0.261	
2010	0.085	0.083	-0.077	0.248	
2011	0.035	0.087	-0.134	0.205	
2012	-0.010	0.088	-0.182	0.163	
2013	-0.049	0.081	-0.207	0.109	
2014	0.020	0.092	-0.160	0.200	
2015	0.102	0.112	-0.117	0.322	

Source: Author's Computation.

Figure 7: Event Study Plot

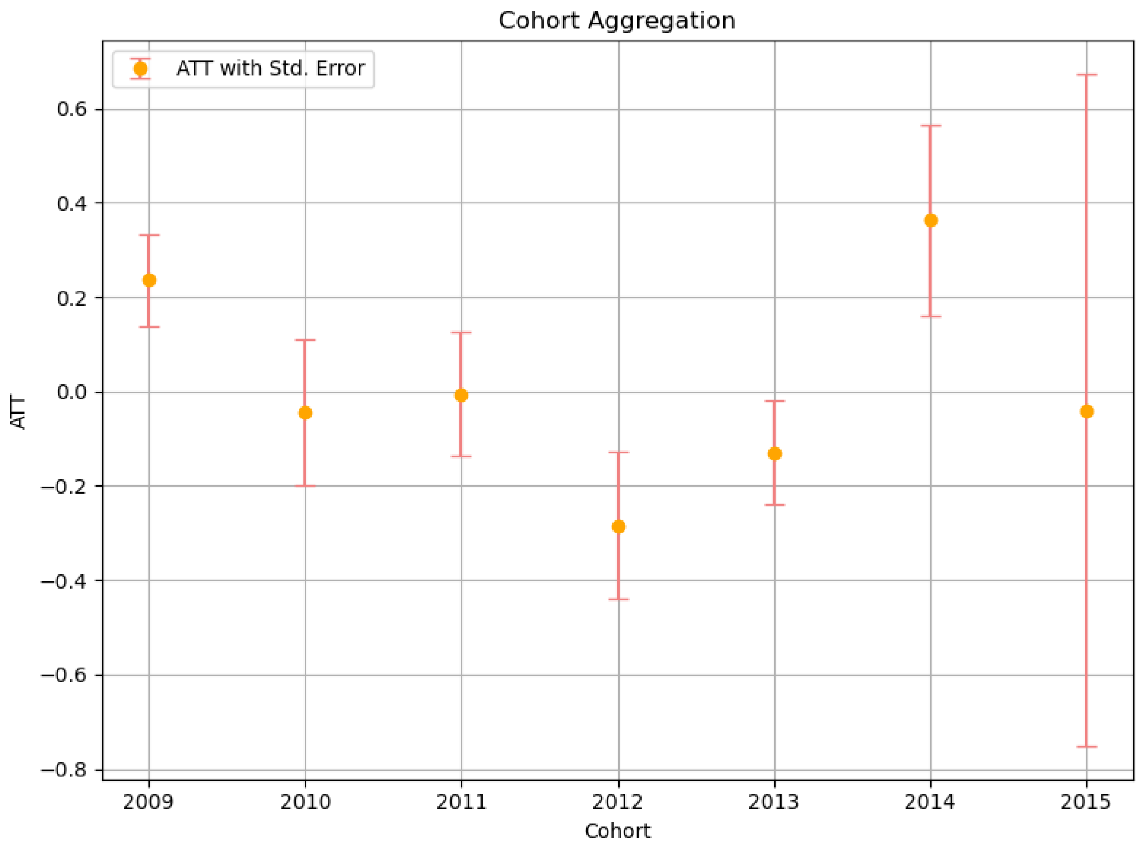


Source: Author's Computation.

Figure 8: Time Aggregation Results

Source: Author's Computation.

Figure 9: Cohort Aggregation Results



Source: Author's Computation.

5 CONCLUSION AND DISCUSSION

The results of our empirical analysis indicate that while the number of Indian firms participating in GVCs has grown steadily over the years, the direct productivity gains from GVC integration appear limited and statistically inconclusive for most cohorts and time periods. Despite a modest productivity advantage observed for some early cohorts and certain industries, these benefits do not robustly materialize across the board. This is infact in tandem with the evaluation of Japanese firms by [15], where only 35% of the coefficients were significant. Our findings are in contrast with [13] who also studied the impact on Indian manufacturing companies and concludes positive impact.

However, their study primarily focus on building a GVC embeddedness index and deploy GMM, which relies on valid instruments and its effectiveness on second-order autocorrelation. Further, we deploy staggered DiD allowing for multiple time period treatment, which is often the case in practice as not all firms receive treatment in the same year.

In light of these findings, the broader discussion on challenges and policy directions for fostering deeper GVC integration must acknowledge that merely increasing participation in global production networks is not guaranteed to yield immediate or substantial productivity improvements.

Indian firms encounter multiple hurdles when attempting to integrate more meaningfully into GVCs, including compliance with complex international standards, inadequate institutional support, and insufficient information. The empirical results, however, suggest that addressing these obstacles is necessary but not sufficient for ensuring productivity gains. High tariffs, regulatory uncertainty, and cumbersome border procedures increase the cost of intermediate inputs and raise overall production expenses, but the observed productivity differences between GVC and Non-GVC firms remain modest even when some firms do integrate. This implies that improving trade facilitation and reducing trade costs—while crucial—will not automatically translate into significantly higher total factor productivity without accompanying measures to enhance firm-level capabilities.

Our results reinforce the idea that integrating into GVCs frequently places developing-country firms in lower-value-added segments. Without effective strategies to upgrade product quality, adopt advanced technologies, and scale production competitively, firms may remain stuck performing low-skill tasks, thus realizing only limited benefits. Industry-level disparities in TFP are apparent, with high-performing industries—often capital-intensive and technologically advanced—showing relatively greater potential for gains. Yet, the overall weak relationship between GVC participation and productivity improvements underscores that structural shifts, skill enhancement, and technological catch-up are essential for translating GVC presence into tangible performance upgrades.

To make GVC participation more beneficial, India needs consistent and predictable trade policies, engagement in value-enhancing trade agreements, and the development of high-quality infrastructure. These interventions should be coupled with concerted efforts to upgrade firm capabilities, enhance workforce skills, and promote innovation. Policies supporting MSMEs—central to India's manufacturing ecosystem—should extend beyond credit access to include technical assistance, quality certification support, and incentives for technology adoption. As our analysis suggests, meaningful productivity gains require addressing deeper, more systemic challenges related to knowledge transfer, skill development, and industrial upgrading.

In essence, the limited productivity impacts observed in our results highlight the importance of a holistic approach. Reducing trade frictions, improving infrastructure, and fostering a stable policy environment are necessary precursors, but India must also focus on strategic interventions that empower firms to move up the value chain. This includes strengthening labor and education policies, encouraging the adoption of advanced technologies, and building resilient supply chains. By doing so, the potential long-term gains from GVC integration can be realized more fully, transforming modest initial impacts into sustained productivity growth and broader economic development

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Table 2: Percentage of GVC and Non-GVC Firms for Selected Years Across Industries.

Industry Name	**2008**		**2011**		**2015**	
	GVC	Non-GVC	GVC	Non-GVC	GVC	Non-GVC
Basic Metals	29.7%	70.3%	32.8%	67.2%	36.7%	63.3%
Beverages	31.0%	69.0%	35.7%	64.3%	50.0%	50.0%
Chemical Products	39.8%	60.2%	47.3%	52.7%	50.0%	50.0%
Coke and Refined Petroleum Products	47.8%	52.2%	60.9%	39.1%	60.9%	39.1%
Electrical Equipment	48.0%	52.0%	52.0%	48.0%	52.9%	47.1%
Fabricated Metal Products	42.2%	57.8%	50.6%	49.4%	53.0%	47.0%
Food Products	21.9%	78.1%	31.3%	68.7%	34.1%	65.9%
Furniture	33.3%	66.7%	66.7%	33.3%	66.7%	33.3%
Leather and Leather Products	75.0%	25.0%	81.2%	18.8%	87.5%	12.5%
Machinery and Equipment	53.4%	46.6%	61.6%	38.4%	63.7%	36.3%
Motor Vehicles, Trailers, Semitrailers	55.0%	45.0%	66.4%	33.6%	68.5%	31.5%
Nonmetallic Minerals	37.7%	62.3%	41.5%	58.5%	41.5%	58.5%
Other Manufactures	57.9%	42.1%	63.2%	36.8%	65.8%	34.2%
Other Transport	53.3%	46.7%	53.3%	46.7%	60.0%	40.0%
Paper and Paper Products	29.7%	70.3%	40.6%	59.4%	42.2%	57.8%
Rubber and Plastics	49.7%	50.3%	56.4%	43.6%	60.4%	39.6%
Textiles	38.8%	61.2%	43.5%	56.5%	47.6%	52.4%
Tobacco Products	33.3%	66.7%	33.3%	66.7%	33.3%	66.7%
Wearing Apparel	55.6%	44.4%	60.0%	40.0%	62.2%	37.8%
Wood and Wood Products	42.9%	57.1%	42.9%	57.1%	42.9%	57.1%

Source: Author's Computation.