The Conditional Upstreamness Premium: Global Value Chain Intensity and Firm Performance in Indian Manufacturing.

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Abstract

We investigate whether the productivity premium of firm upstreamness in GVCs depends on a firm's depth of integration, using panel data on Indian manufacturing firms, 2000-2015. We construct a firm-level upstreamness index, classify these firms across four levels of GVC intensity and estimate total factor productivity, instrumenting upstreamness with a shift-share IV strategy. Our findings reveal that firms' upstreamness raises productivity, but the effect strengthens with GVC intensity: firms in the lower tier show minimal gains, but deeply integrated firms gain more. Mechanism analysis indicates that upstreamness translates into productivity gains via in-house R&D and royalty payments. Results are robust to alternative TFP estimators, dynamic specifications, and contributes to the discussion on how firms escape low-level GVC traps.

Keywords: Global Value Chains, Upstreamness, Total Factor Productivity

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1 Introduction

The organization of Global Value Chains (GVC hereafter)[2] has undergone a fundamental transformation since the emergence of modern GVCs in the 1980s. Instead of simply integrating into these trade networks, firms have shifted their focus towards securing more advantageous positions. Empirical literature shows that GVC firms carry a productivity premium of over 20 percent compared to purely domestic firms (Manghnani et al., 2021). While this holds true from an aggregate perspective, these firms differ considerably in terms of value-creating tasks they undertake. Specifically, the smile curve[3] hypothesis posits that upstream stages, such as innovation, design, and core component manufacturing, capture higher margins compared to downstream assembly activities (Meng et al., 2020; Rungi & Del Prete, 2018). For emerging economies, this implies potential advantages in moving upstream. However, whether all firms can actually capture these gains or whether the benefits accrue only to those already deeply embedded in GVC networks remains an open and underexplored question. In a world where the majority of firms in developing nations engage in modest importing and exporting without deep embeddedness in GVC networks, does moving upstream actually improve firm performance? Or does this upstreamness-productivity premium only emerge beyond a certain threshold, leaving the majority in a low-level trap? These questions carry significant policy relevance given that more than 70 percent of global trade takes place in intermediate goods (World Bank, 2020).

Upstream firms show higher stability and performance compared to firms positioned closer to the final consumers (Gao et al., 2025; Ju & Yu, 2015; Mahy et al., 2022; Yang & Inui, 2025). These firms specialize in high-value-added activities, which require substantial innovation and R&D, further enhancing their technological competence and bargaining power (Antràs et al., 2012; Antràs & Chor, 2013; Koopman et al., 2014; Xu et al., 2024). In addition, firms engaging in upstream activities often control key intellectual property and encounter limited competition. Moreover, upstream activities capture a large share of value added since the outputs of upstream firms serve as essential inputs for numerous downstream firms (Miller & Temurshoev, 2017).

[2] "*GVC consists of a series of stages involved in producing a product or service that is sold to consumers, with each stage adding value, and with at least two stages being produced in different countries. A firm participates in a GVC if it produces at least one stage in a GVC* " (Antràs, 2020)

[3] The term 'Smile Curve' effect was coined by Stan Shih, the founder of Acer, in the early 1990s as a tool to analyze value distribution in the IT industry (Shih, 1996).

We argue that the upstream-productivity linkage need not hold uniformly across firms, and that a firm's depth of GVC integration determines whether upstreamness translates into measurable gains. The current firm-level literature has largely estimated the upstreamness-productivity relationship as a single average effect (Mahy et al., 2022; Ju & Yu 2015). However, these studies did not test whether this relationship varies with a firm's depth of GVC integration. Therefore, whether the upstreamness premium is homogeneous across firms, or conditional on integration intensity, remains an open empirical question. Our theoretical argument rests on two mechanisms. First, we draw on absorptive capacity theory (Cohen & Levinthal, 1990) to argue that upstream firms require absorptive capacity to convert this positional advantage into productivity. Firms that are deeply integrated into GVC have acquired this knowledge through repeated international transactions and familiarity with foreign technology. If this mechanism holds, we would expect upstreamness to strengthen R&D spillovers, royalty transfers and quality upgrading primarily through these repeated buyer-supplier interactions since upstream firms are expected to meet the strict international standards and compliance (Xu et al., 2024). They are also required to supply intermediary goods to downstream firms with specific technical requirements. Additionally upstream firms gain priority access to global technology markets direct linkages with international buyers and multinational suppliers (Gereffi et al., 2005). We therefore treat R&D investment and royalty payments as candidate empirical channels through which upstreamness could be converted into firm performance, and test this directly in Section 4. Second, we posit that moving upstream often requires substantial upfront investment such that only firms with sufficient export scale and transaction frequency can sustain the transition. These high entry costs may act as a natural barrier for firms with shallow GVC participation. Together, these two conjectures motivate our central hypothesis: upstreamness-productivity premium accrues primarily to firms with deep GVC integration, while firms with marginal GVC participation derive comparatively little benefit from upstream repositioning. We test this hypothesis formally in Section 3.

This question has important policy implications for emerging economies. Advanced countries from Western Europe, North America, and East Asia continue to dominate the capital-intensive segments of GVCs, while labor-rich economies are often confined to lower-value-added assembly activities (Tajoli & Felice, 2018; Baldwin, 2016), perpetuating a low-level GVC trap[4].

[4] Emerging economies characterized by minimal capital and abundant unskilled labor, are often concentrated in low-value-added assembly stages in GVC: Examples include the poor working conditions in Bangladesh apparel industry

Consequently, moving into more upstream, higher-value segments has become a central development objective. Nevertheless, certain emerging economies from East Asia has broken this pattern. China's transition from assembly-oriented production to high-value manufacturing, together with Taiwan's emergence as global leader in semi-conductor production through TSMC, illustrates successful upgrading in GVCs. India, however, by contrast, presents a strikingly different trajectory, making it an interesting setting to analyze whether upstream positioning translated into higher firm productivity.

As a labor-abundant economy, India exhibits moderate backward GVC participation, ranging between 10-15 percent (Sharma & Arora, 2023; Veeramani & Dhir, 2022)[5]. However, the relatively low level of forward participation (Domestic Value Added) suggests that Indian manufacturing remain stuck in downstream assembly stages. This pattern creates two interrelated challenges. First, even though backward participation has supported absorption of India's vast labor force, it may limit firms from enjoying the productivity gains from moving upstream. Second, even among Indian manufacturing firms that engage in international trade, most participate marginally as one-way or occasional two-way traders rather than as deeply embedded GVC participants[6]. This concentration in low-intensity trading positions makes India an appropriate setting for testing whether productivity gains from upstream positioning emerge only beyond a certain threshold of GVC integration. Therefore, limited upstream positioning and shallow GVC integration highlight both the challenges and the opportunities facing Indian manufacturing.

Despite these clear pathways for emerging economies to escape the low-level GVC trap, there are notable gaps in the GVC positioning literature. First, the majority of the GVC literature focuses on GVC participation rather than position (Banga, 2022; Chakrabarty & Chanda, 2021; Lu et al., 2018; Reddy & Sasidharan, 2021; Sasidharan & Reddy, 2021), and the firm-level empirical literature on upstreamness remains limited[7]. Furthermore, most GVC positioning studies work at the country-industry level (Amendolagine et al., 2019; Huang & Zhang, 2023; Ndubuisi

and the prevalence of sweat shop labor in parts of Thailand (Wilhelm et al., 2025). We do not investigate whether firms persist in upstream positions over time. Instead, we examine whether the productivity returns to upstream positioning depend on the depth of GVC integration at a given point in time.

[5] China's foreign value-added (FVA) share of exports is approximately 16–20 percent whereas India peaks around 37 percent which indicates a higher reliance on imported inputs.

[6] Refer: Fig.1 GVC intensity by sector

[7] Firm-level studies in the context of upstreamness cover broad areas such as trade policy uncertainty, technology transfer, firm survival, and digitalization (Gu et al., 2026; Yan et al., 2024; Yang & Inui, 2025; Zhang et al., 2026)

& Owusu, 2022; Thakur & Sharma, 2025), which means firm-level heterogeneity is largely left unexamined. The works of Ju & Yu (2015) and Mahy et al. (2022) are most closely related to our study in analyzing firm-level upstreamness and productivity. While, these studies focus on China and Belgium, our research builds upon their baseline by studying how this upstreamness premium is conditional on GVC integration intensity of firms. Furthermore, we specifically examine an emerging economy context that is predominantly locked in backward GVC participation[8].

Given this backdrop, we examine the relationship between firm-level upstreamness and productivity in the Indian manufacturing and assess whether this relationship varies with the intensity of GVC integration. We use the Indian manufacturing sector as an empirical testing ground for these relationships. We use rich firm-product-level data obtained from CMIE PROWESS, comprising 32,644 firm-year observations spanning 2000 to 2015. Following Chor et al. (2021) and Herkenhoff et al. (2024), we construct a firm-level GVC position index by combining industry-level upstreamness from the OECD TiVA with granular firm-product-level information on Indian firms. We classify GVC firms into five distinct intensity categories: (i) High; (ii) Intermediate; (iii) Limited; (iv) Marginal-two-way traders and (v) Marginal-one-way traders[9]. We use panel fixed effects to estimate the baseline model. To establish causality, we estimate 2SLS using Bartik-style shift-share instruments. Finally, we examine the role of R&D expenditure and royalty payments as the primary mechanisms through which the upstreamness-productivity linkage operates.

This study makes three contributions to the existing literature. First, we contribute to the literature by developing and testing conditionality perspective: the productivity premium associated with upstream positioning is not universal but accrues primarily to firms with deep GVC integration. Drawing on absorptive capacity theory (Cohen & Levinthal, 1990) and transaction cost arguments (Gereffi et al., 2005), we derive a threshold prediction that the upstreamness-productivity premium intensifies after crossing a critical GVC intensity threshold and firms operating below this point only derive marginal benefits from GVC upgradation. Second, we address a critical gap in the growing literature on GVC position and firm performance, which has

[8] In the Indian context, recent research on upstreamness includes studies examining corporate social responsibility, investigating the impact of foreign environmental regulations regarding emissions (Herkenhoff et al. 2024; Semrau 2026)

9 This classification follows Manghnani et al. (2021) with some minor changes. We provide detailed explanation of the construction of this variable in section 2.2

predominantly focused on developed economies, by offering evidence from an emerging market context. India's manufacturing sector provides a uniquely demanding empirical setting for testing the threshold hypothesis. With 64.5 percent of firms operating below the proposed integration threshold, India offers sufficient variation in both the treatment (upstreamness) and the moderator (GVC intensity) to identify the threshold non-parametrically. A finding of marginal premium below the threshold and a highly positive premium above it is far more credible when the majority of the sample lies in the no-premium region, which mitigate concerns of spurious aggregate correlation. We adapt the firm-level upstreamness methodology of Antràs et al. (2012), Chor et al. (2021), and Herkenhoff et al. (2024) to a data-scarce emerging market setting, demonstrating its applicability beyond the high-income contexts for which it was originally developed and providing a replicable template for GVC positioning research in similar economies. Most of the studies in Indian context focus predominantly on GVC participation (Reddy & Sasidharan, 2024; Sasidharan & Reddy, 2021) using a dummy variable approach by classifying firms as GVC participants, if they export and import simultaneously. However, a limitation of this measure is that it ignores the trade intensity since a binary indicator does not capture variation in trade intensity. Therefore, we measure GVC through a spectrum of five levels of intensity following the approach by Manghnani et al. (2021)[10]. Finally, by decomposing the upstreamness-productivity relationship into internal innovation (R&D) and external technology transfer (royalties) channels, we show that these mechanisms operate differently across the GVC intensity spectrum. R&D investment appears to be an important channel for deeply integrated GVC firms, whereas royalty-based technology acquisition remains relevant across a broad range of integration levels. These findings provide more granular evidence on the mechanisms through which GVC positional upgrading translates into firm performance.

Our empirical results show that upstreamness significantly raises firm-level productivity, and this relationship is entirely conditional on a firm's depth of GVC integration. The results reveal a step-like pattern where the effect of this relationship intensifies along with the intensity of GVC participation. Marginal GVC firms, which constitute 64.5 percent of the total sample, show only limited productivity benefits from upstream positioning. The positive upstreamness-productivity relationship emerges significantly only beyond the limited GVC threshold. This category

[10] Goldar & Goldar (2026) use a similar classification to study GVC participation and firm productivity in the Indian context.

comprises firms that either engage in intensive import or export activities or that are part of a major business group. Beyond this threshold, the relationship stabilize, and marginal benefits are saturated among the intermediate and high GVC categories. Finally, mechanism analysis reveals that the upstreamness-productivity linkage operates through two distinct channels: within-firm R&D investment and royalty-based external technology acquisition. Critically, both channels are highly active only among firms that have crossed the limited GVC threshold, consistent with the absorptive capacity argument developed above.

The remainder of the paper is organized as follows. Section 2 describes data, variables and the empirical strategy. Section 3 reports the econometric results. Section 4 provides robustness checks. Section 5 outlines the mechanism analysis. Section 6 concludes the study.

2 Data, variables, and empirical strategy

2.1 Data Sources

Our empirical analysis integrates data from two complementary sources to construct a panel for Indian manufacturing firms covering the period 2000-2015. We restrict our study period till 2015 for two major reasons. First, this avoids the measurement discrepancies introduced by large-scale additions to the PROWESS database in subsequent years. Second, this controls our estimates from the macroeconomic shocks of the 2016 Indian demonetization and the 2020 global pandemic.

We use the PROWESS database provided by the Centre for Monitoring Indian Economy (CMIE) as our primary data source. PROWESS is India's most comprehensive corporate database covering 110,324 companies (5,713 listed and 104,611 unlisted). It provides detailed financial information on firms operating in the manufacturing, utilities, and financial sectors. PROWESS is particularly well suited for our study for three critical reasons. First, unlike the Annual Survey of Industries (ASI)[11], PROWESS provides a detailed breakdown of foreign exchange earnings and expenditures. Specifically, it distinguishes between imports of raw materials, capital goods, stores and finished goods, while also reporting export earnings. This level of detail is essential for our GVC classification. Second, PROWESS contains granular product-level information on sales values and quantities[12]. This enables us to map individual products to their corresponding

[11] The Annual Survey of Industries (ASI), conducted by the Ministry of Statistics and Programme Implementation (MoSPI), is the principal source of industrial statistics in India.

[12] According to the Companies Act of 1956, Indian firms are required to disclose their product level information on capacities, production scale and sales in their annual reports.

industries and construct firm specific upstreamness measure. Third, the database provides the variables required for calculating TFP, including information on sales, exports, imports, employee compensation, gross fixed assets (GFA), and expenditure on power and fuel. Overall, firms covered by PROWESS account for more than 70 percent of economic activity in India's organized manufacturing sector (Topalova & Khandelwal, 2011). Consequently, the database has been widely used in studies examining firm performance in India (Banga, 2022; De Loecker et al., 2016; Herkenhoff et al., 2024; Reddy & Sasidharan, 2021; Topalova & Khandelwal, 2011).

Our initial sample comprised an unbalanced panel of 501,432 firm year observations over the period 2000–2015. We excluded observations with missing data on sales, GFA, compensation to employees and intermediate inputs. After applying these filters and merging the data with product-level information, the final sample comprised of 32,644 firm-year observations. A necessary implication of our data construction is that the estimation sample is restricted to firms with observed international trade activity, as both firm upstreamness and GVC-intensity classification are defined only for firms that import and/or export. As shown in Table A.1, this restriction excludes 23,872 firm-year observations from the broader PROWESS manufacturing sample. Consequently, our estimates should be interpreted as characterizing the relationship between upstreamness–productivity among firms that already participate in international trade, rather than among Indian manufacturing firms as a whole. This restriction directly follows from the research question, since a firm's position in the GVC is not well defined in the absence of cross-border transactions. Accordingly, our analysis identifies intensive-margin effects of GVC positioning conditional on trade participation, rather than the determinants of firm's entry into international trade. Firms are classified according to the National Industrial Classification (NIC) 2008, and the analysis is restricted to manufacturing sectors (see Appendix Table A.1 for complete steps involve in data cleaning and sample construction).

To compute upstreamness measures, we use the OECD Trade in Value-Added (TiVA) 2021 database. The TiVA database provides inter-country input-output (ICIO) tables covering 45 industries (ISIC Rev. 4) across 66 countries for the period 1995-2023 (Mancini et al., 2024)[13]. Although databases such as World Input Output Database (WIOD) and Eora provide broader country coverage, TiVA's harmonized input–output framework, methodological consistency, and

[13] This data is available following: https://www.tradeconomics.com/position/. This database is developed by Mancini et al. (2024). For our purpose, we use the upstreamness measure based on OECD TiVA.

regular updates make it particularly suitable for our analysis.

2.2 GVC Classification

Following Manghnani et al. (2021) and Meyer (2019), we classify GVC firms into 5 categories. This classification identifies five different modes of GVCs based on firms that meet specific criteria for intensive exporting, importing, and international linkages. A firm is classified as an intensive exporter if its export intensity exceeds 66% (Two-thirds of output). Similarly, intensive importer firms should have an import intensity of more than 33% (Importing one-third of intermediary inputs). Finally, a firm should either be owned by a foreign group or should be part of a major Indian business group to fulfill the linkage criteria. Based on these three criteria, we classify our sample firms as:

(i) *High/ Triple GVC*: includes domestic or foreign firms that are deeply integrated. They must fulfil all three core conditions of intensive exporting, intensive importing, and international linkages simultaneously. (ii) *Intermediate/Dual GVC firms*: those actively participating in GVC through significant trade linkages or is part of an international trade linkage. Here, the firms should meet at least two out of three core conditions. (iii) *Limited/ Single GVC*: This classification is for either domestic or foreign firms which have limited engagement in GVC by fulfilling only one of the three core conditions. (iv) *Marginal GVC/ Two-way traders*: in this category, we relax the intensive import and export criteria. Firms having a positive import and export intensity are part of this group, meaning their export share is less than 66% and import share is less than 33%. These are also the domestic firms that are not part of any major business groups. These firms also should be importing and exporting simultaneously (Two- way traders). (v) *Marginal GVC/ One-way traders*: Firms belonging to this category satisfy marginal GVC criterion and engage in either importing or exporting[14].

This classification ensures that GVC participation is not binary but exists along a spectrum. This allows us to examine how integration depth moderates the firm upstreamness productivity relationship. In Indian context Goldar & Goldar (2026) used a similar classification following

[14] For the category 4 and 5, we slightly modify Manghnani et al. (2021) and Meyer (2019) framework. Instead of assigning a group for domestic firms, which is irrelevant when it comes to upstreamness, we include an additional classification as 'Marginal GVC' (two way and one way trading firms). In addition, the low GVC category from the original paper is renamed as 'Limited GVC' to better reflect its interpretation in the present context.

Manghnani et al., (2021)

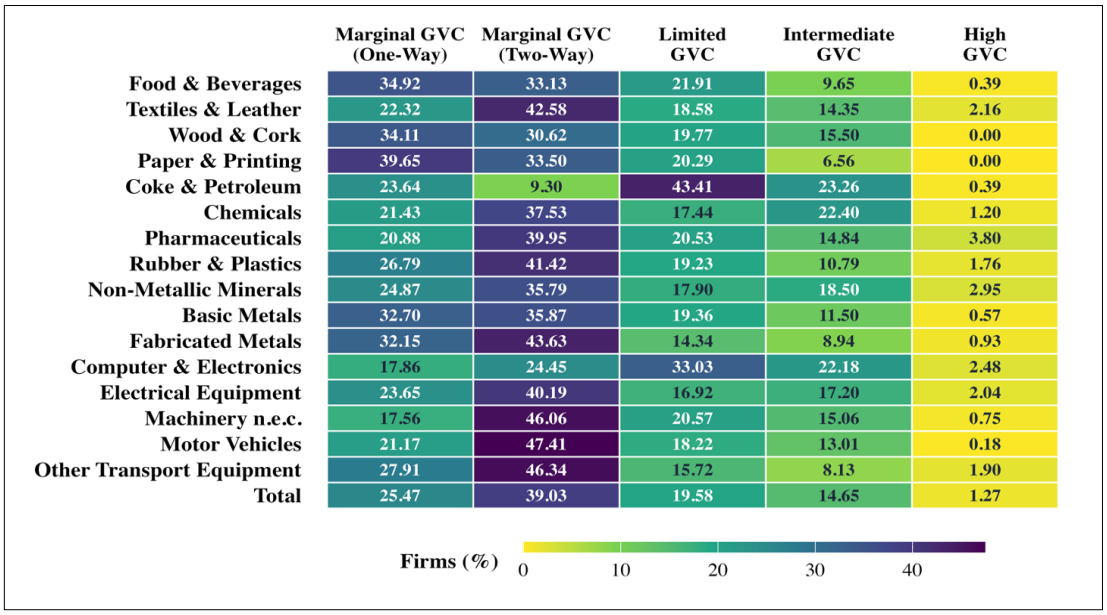


Fig. 1: GVC intensity by sector

Fig. 1 shows the GVC integration across Indian manufacturing industries. In our sample, 64.5% of sample firms fall into the Marginal GVC category, while only 1.27% of firms are classified as High GVC firms. From the figure, we observe substantial sectoral heterogeneity in GVC integration with technology-intensive sectors exhibiting deeper integration than traditional industries. Pharmaceutical sector records highest share of firms in High GVC category (3.80%), followed by the computer & electronics, electrical equipment. These patterns suggest that knowledge-intensive production is associated with high degree of GVC integration. However, motor vehicle industries show a contrasting picture. Although, 47.41% are two-way traders, but only 0.18% of firms qualify as High GVC category. This indicates that extensive import and export activities alone do not guarantee strategic embedding. While these firms participate in GVC networks, but they appear to be concentrated in assembly-oriented activities (Marginal GVC) characterized by arm's length transactions rather than network integration. Traditional manufacturing sectors exhibit even shallower level of GVC integration. Firms in the Textiles, Leather, Food & Beverages industries are mainly concentrated in the Marginal GVC category. Also, the pronounced sectoral heterogeneities evident from Fig. 1 provides strong motivation for our empirical strategy by incorporating an interaction term that allow upstreamness to vary by GVC intensity.

2.3 Variable Description

2.3.1 Total factor productivity (TFP)

We measure firm performance using TFP at the firm level. Unlike other partial productivity or accounting measures[15], TFP isolates the efficiency gains attributable to factor accumulation. This allows us to assess whether upstream positioning actually improves firm performance beyond scale expansion. We estimate TFP using the Levinsohn and Petrin (2003) semiparametric approach[16]. In the LP method, we use the energy input of firms as a proxy for the unobserved productivity shocks. Output is measured as sales deflated by industry-specific Wholesale Price Indices (WPI)[17] sourced from the Office of the Economic Adviser, Government of India. To construct the capital stock variable, we use the firm-level gross fixed assets (GFA)[18]. We consider capital stock as the accumulation of past investment flows, adjusted for a depreciation rate of 6%. Energy input is measured as expenditure on power and fuel deflated by the energy component of the WPI. Since PROWESS database lacks reliable information on the number of employees data, we construct labour input by dividing the firm's total wage bill by the industry-average wage rate derived from the Annual Survey of Industries (ASI)[19]. We also winsorize the input variables to limit the influence of extreme outliers. TFP is estimated separately for each 2-digit NIC industry to allow production function parameters to vary across sectors. (Appendix B provides detailed information on variables construction and TFP estimation following the methodology of Levinsohn and Petrin (2003).

2.3.2 Firm-level GVC Upstreamness

GVC positioning reflects a firm's location along the sequential value-added stages of a GVC, extending from material extraction to downstream production, distribution and final consumption. We use the upstreamness index[20] developed by Antràs et al. (2012) and Fally (2012) to measure this positioning. This index quantifies the average number of production stages a firm's output undergoes

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[15] Labour productivity, capital intensity, sales growth and operating profit

[16] We estimate this production function using LP specification within the PRODEST command in STATA.

[17] Industry-level deflators are used since aggregate deflators mask sectoral price movements.

[18] Capital stock is constructed using the perpetual inventory method with a rolling base year.

[19] To calculate the emoluments per employee for a specific year, we divide the total emoluments by the total number of persons employed at the 2- digit industry level. To obtain the firm-level measure of employment, we use the firm's year wage bill divided by the average emoluments per employee (average wage rate).

[20] $U_v^k = 1 + 2\sum_{w=1}^{W}\sum_{l=1}^{L}\alpha_{vw}^{kl}\frac{F_w^l}{Y_v^k} + 3\sum_{w=1}^{W}\sum_{l=1}^{L}\sum_{x=1}^{W}\sum_{m=1}^{l}\alpha_{vw}^{kl}\alpha_{wx}^{lm}\frac{F_x^m}{Y_v^k} + \ldots.$ Upstreamness index shows an industry's position in the GVC network using the share of intermediary inputs brought and sold compared to the production final goods.

before reaching the final demand. A higher upstreamness value indicates proximity to initial production stages, while a lower value indicates proximity to final consumers.

We construct firm-specific upstreamness indices using a two-stage approach following Herkenhoff et al. (2024) This method exploits the complementary strength of industry-level production linkage with firm-level product portfolio to arrive at firm-level upstreamness. In the first stage, we obtain industry-level upstreamness measure based on multi-regional input-output tables provided by the OECD TiVA database (Mancini et al., 2024). The TiVA database covers 45 industries (ISIC Rev. 4) across 66 countries over the period 1995-2023[21].

In the second stage, we map this industry-level upstreamness to firm-specific production activities using product sales information obtained from the PROWESS database. For each firm, a weighted average of the firm's upstreamness is computed using the following formula:

$$U_{it} = \sum_{v=1}^{V} \frac{sales_{i,vt}}{sales_{it}} U^{vt} \quad (1)$$

In equation (1), U_{it} denotes the upstreamness index of firm i at time t, which is the weighted average of product level sales information multiplied by industry level upstreamness U^{vt}. $sales_{it}$ is the sum of sales value of all products of firm i at time t and $sales_{i,vt}$ is the sum of sales of individual products. Our firm-level upstreamness index is constructed from the sample of 216,081 product-firm-year observations from 2000 to 2015. We have 13,201 unique firms producing 2490 distinct products at the most disaggregated level. Multi-product firms constitute 78.17% of observations, while single-product firms account for 21.83%[22].

The firm upstreamness index has three sources of variation: changes in a firm's product portfolio, changes in the sales weight of its products, and finally changes in industry level GVC upstreamness (Herkenhoff et al., 2024). Here, the first two variations reflect the firm-level strategic choices on which products to emphasize, while the third variation captures the exogenous shift in industry-level GVC. Therefore, our firm-level upstreamness captures both firm and industry-specific changes in GVC.

We used the concordance mapping of products in PROWESS to its corresponding ISIC Rev.4 industry as listed in TiVA industry classification. This process ensured consistency across

[21] This global coverage is essential because Indian firms may supply inputs to industries abroad, making purely domestic input-output tables inadequate for measuring true GVC upstreamness.
[22] For firms with missing product-level information, we use industry-level upstreamness as substitutes.

industries while maintaining maximum granularity (see Appendix Table A.2 for the complete NIC 2008 to OECD TiVA concordance).

Table 1: Summary Statistics of Firm-Level Upstreamness by OECD TiVA Sector

OECD TiVA Sectors	Mean	Std.Dev.	Min	Max
Basic Metals	1.743	0.271	1.193	3.463
Chemicals	2.805	0.221	1.193	3.599
Coke & Petroleum	2.636	0.352	1.500	2.991
Computer & Electronics	1.702	0.312	1.330	3.199
Electrical Equipment	2.115	0.292	1.193	3.073
Fabricated Metals	1.580	0.344	1.193	3.064
Food & Beverages	2.972	0.298	1.250	3.493
Machinery n.e.c.	2.567	0.366	1.193	3.435
Motor Vehicles	2.735	0.368	1.193	3.585
Non-Metallic Minerals	1.945	0.261	1.333	3.585
Other Transport Equipment	2.576	0.296	1.442	3.599
Paper & Printing	2.399	0.267	1.330	3.497
Pharmaceuticals	2.987	0.496	1.333	3.493
Rubber & Plastics	2.865	0.335	1.333	3.599
Textiles & Leather	3.130	0.355	1.333	3.493
Wood & Cork	3.314	0.237	2.143	3.599
Total	2.504	0.317	1.193	3.599

Source: Authors' calculation based on OECD TiVA data

Table 1 shows the summary statistics of our upstreamness index for the sample firms based on the OECD TiVA classification over 2000-2015 period. Across the study period, the average firm upstreamness in Indian industries ranged from 1.58 (Fabricated metals) to 3.31 (Wood and cork). The average firm upstreamness across all industries is 2.50. The most upstream firms belong to the Wood & cork (3.31), Textiles & leather (3.13) and Pharmaceuticals (2.98). These industries operate at the early stages of GVC and are characterized by output that pass through on average of three or more production stages before reaching final demand. Accordingly, these industries occupy relatively high upstream positions in the Indian GVC context. Wood products primarily serve as input for construction and furniture manufacturing, while textile fibers are woven, dyed and assembled into garments. Upstream activities are characterized by being more intricate and technology intensive which yield higher value-added benefits compared to downstream activities (Bian & Fan, 2024). Pharmaceutical industry, which is one of the key pillars of India's exports sector represents successful upgrading through its upstream position[23]. On the other hand, prominent downstream industries that exhibit downstream position are Fabricated metals (1.58)

[23] India serves as the world's third-largest producer of pharmaceuticals by volume, meeting approximately 20% of the total global demand for generic medicines and exporting to over 190 countries (PIB, 2026). https://www.pib.gov.in/PressReleasePage.aspx?PRID=2221080&reg=3&lang=2

and Computer & electronics (1.7). Indian firms in these industries are concentrated towards the final stages of production primarily engaged in assembly, finishing, or customization activities on near-complete products. The global upstream stages of these industries are often technology heavy and highly lucrative. Countries like Taiwan and the Netherlands hold a near-monopoly over semi-conductor industries while, Germany and Japan are the world leaders in high end machinery and fabricated metal products[24] (Stöllinger et al., 2018). Fig. 2 illustrates this industry-wise variation in mean firm upstreamness graphically.

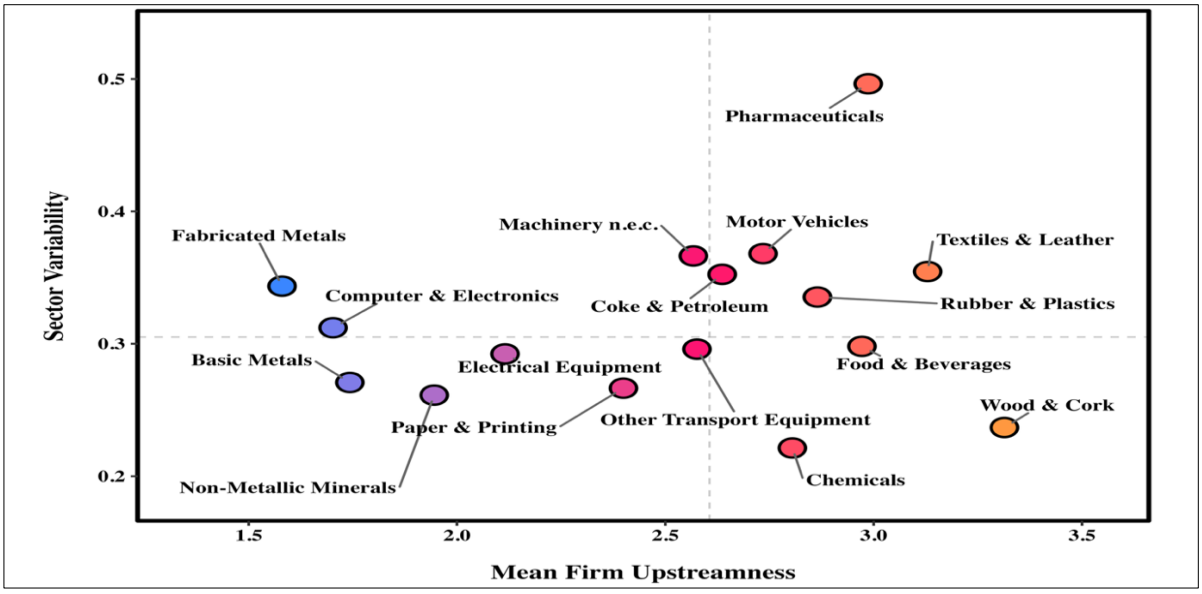


Fig. 2: Industry-wise mean firm upstreamness in India

2.3.3 Control variables

In our empirical analysis, we account for several firm level controls that may influence productivity. First, we controlled for firm size (Size), by measuring the natural logarithm of annual sales of a firm normalized by the industry (NIC 5-digit)-year median. This measure captures the firm's size relative to its industry peers, effectively controlling for industry-specific trends in firm scale. The impact of firm size on productivity is theoretically ambiguous. While large firms may benefit from resource abundance and market share (De & Nagaraj, 2014), they can be also very vulnerable to bureaucratic bottlenecks and diseconomies of scale that dampens productivity

[24]Taiwan's TSMC and the Netherlands' ASML maintain near-monopoly in the semi-conductor chain, controlling 86% of revenue, while Japan and Germany anchor the upstream machinery sector alongside Germany's continued dominance in high-precision industrial exports.

(Braguinsky et al., 2011). Second, we controlled for firm age (Age) as a control variable to control for experience-based productivity gains. We calculate Age as the number of years since the incorporation year of a firm. Older firms tend to show lower levels of innovation while new firms are more open to innovation (Huergo & Jaumandreu, 2004). Table 2 provide description of all the variables used in the analysis along with their sources.

Table 2: Variable Description

Variables	Description	Source
TFP	Total Factor Productivity is estimated using the Levinsohn and Petrin (2003) method.	PROWESS IQ
Firm- Upstreamness	Firm-level product weighted average of Industry upstreamness index	PROWESS IQ + OECD TiVA
GVC Intensity	Categorical index (0–3) representing the depth of GVC integration	PROWESS IQ
Controls		
Size	Natural log of real sales, normalized by the industry-year median	PROWESS IQ
Age	Natural logarithm of firm age (years since incorporation)	PROWESS IQ
Mediation		
R&D Expenditure	Natural logarithm if investment for in house research and development.	PROWESS IQ
Royalty	Natural log of expenditure on the imported technology	PROWESS IQ

2.4 Empirical specification

To empirically examine the relationship between firm upstreamness and TFP, we estimate panel fixed effect regression models. Equation (2) presents our baseline specification.

$$lnTFP_{it} = \alpha_0 + \beta_1 FU_{i,t-1} + \beta_2 X_{i,t-1} + \gamma_{jt} + \delta_s + \varepsilon_{it} \quad (2)$$

l$nTFP_{it}$ denotes the Total Factor Productivity of firm *i* at time *t* in logarithm format.c$FU_{i,t-1}$ denotes our measure of upstreamness, while $X_{i,t-1}$ is vector of firm level controls, including firm Size and Age. The model also incorporates industry*year (γ_{it}) and (δ_s) state fixed effects to account for unobserved heterogeneity across industry, time, and states. ε_{it} denotes the idiosyncratic error term. To account for serial correlation, standard errors are clustered separately at the industry and firm level. Furthermore, all explanatory variables are lagged one period to mitigate concerns of reverse causality and to allow time required for changes in upstreamness to translate into productivity gains. Subsequently using equation (3), we examine whether productivity gains associated upstreamness vary with the depth of GVC integration.

$$\ln TFP_{it} = \alpha_0 + \beta_1 FU_{i,t-1} + \sum_{k=1}^{K-1} \beta_{2k}\, GVC_Intensity_{k,it} + \sum_{k=1}^{K-1} \beta_{3k} \left(FU_{i,t-1} \times GVC_Intensity_{k,it}\right) + \beta_4 X_{i,t-1} + \gamma_{jt} + \delta_s + \varepsilon_{it} \quad (3)$$

Here $GVC_Intensity_{k,it}$ is the categorical variable[25] that measures the intensity of GVC participation as discussed in section 2.2. The interaction term ($FU_{i,t-1} \times GVC_Intensity_{k,it}$) ensures that the effect of firm upstreamness varies across different GVC intensities. Due to the limited number of firms in the High GVC category[26] in our sample, we combine High and Intermediate GVC groups for estimation. The coefficient of primary interest is the interaction term β_{3k}, which captures the marginal effect of GVC integration intensity on the relationship between upstreamness and firm performance.

Table 3: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Log TFP (Levinsohn-Petrin)	32644	2.006	.987	-5.100	6.491
Firm Upstreamness Index	32644	2.501	.600	1.193	3.599
Log Age	32644	3.104	.651	0	4.600
Log Size	32644	-.002	1.356	-8.82	5.530
GVC Intensity	32644	-	-	0	3
Log R&D Expenditure	32644	.646	1.335	0	9.526
Log Royalties	32644	.498	1.301	0	10.188

Note: The sample consists of firm-year observations.

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Table 3 presents the summary statistics of all the variables used in our estimations. On average, TFP of our sample firms are 2.006. The mean firm upstreamness indicates that the average firm operates approximately 2.5 production stages away from final demand. GVC intensity is the categorical variable[27], representing various GVC classification discussed in section 2.2.

3 Empirical results

In this section, we present empirical evidence on the relationship between upstreamness and TFP. We begin the analysis by using high dimensional fixed-effects regression to identify the linear relationship between our key variables. Subsequently, we conduct marginal analysis to

[25] High, Intermediate, Limited, Marginal (two-way) and Marginal(one-way).
[26] There are no high GVC category in Wood & Cork and Paper & Printing sector.
[27] We use Marginal (one-way) firms as the base category across all specifications

examine how this relationship varies across levels of GVC intensity. Finally, to address potential endogeneity concerns, we use 2SLS estimation with shift-share IV.

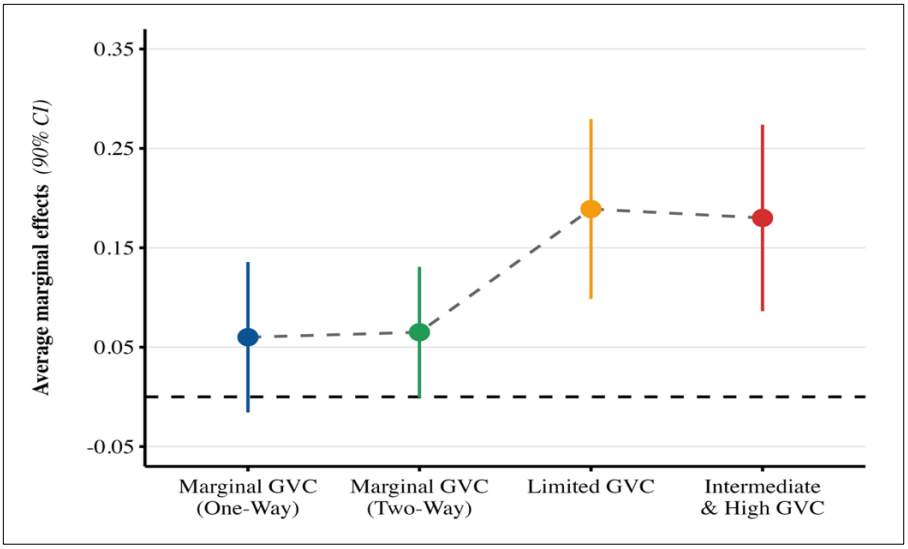
3.1 Baseline results

Table 4: Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm upstreamness	0.095**	0.102**	0.100**	0.103**	0.095**	0.102***	0.100***	0.103***
	(0.044)	(0.046)	(0.043)	(0.044)	(0.038)	(0.038)	(0.037)	(0.038)
Age			-0.208***	-0.205***			-0.208***	-0.205***
			(0.023)	(0.022)			(0.020)	(0.020)
Size			0.092***	0.089***			0.092***	0.089***
			(0.014)	(0.014)			(0.010)	(0.010)
Constant	1.771***	1.751***	2.398***	2.382***	1.771***	1.751***	2.398***	2.382***
	(0.112)	(0.115)	(0.132)	(0.133)	(0.097)	(0.097)	(0.112)	(0.112)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes	No	No	Yes	Yes
Number of Clusters	368	368	368	368	4162	4156	4162	4156
Adj. R^2	0.395	0.403	0.421	0.427	0.395	0.403	0.421	0.427
Observations	25,363	25,306	25,363	25,306	25,363	25,306	25,363	25,306

Notes: Robust standard error are clustered at 5-digit industry level in columns (1) to (4) and firm level in columns (5) to (8)
Dependent variable is TFP in logarithmic format
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 4 presents baseline estimates of the relationship between firm upstreamness and TFP using equation (2). Across all columns, upstreamness exhibits a positive and statistically significant association with TFP. In column (8) with all specifications, including industry*year, and state fixed effects, a one-unit increase in upstreamness raised firm productivity by 10.3 percent. As we progressively tighten the specifications, the estimated coefficient remains stable across the columns (0.095 - 0.103), indicating robustness to regional and industry-year characteristics. These empirical results are consistent with the existing literature on upstreamness and firm performance (Ju & Yu, 2015; Mahy et al., 2022). Building on these baseline findings, next we examine how this positive relationship varies with the degree of GVC integration.



Notes: Standard errors are clustered at the firm level.
Industry*firm and state fixed effects. All firm controls are included

Fig. 3: Average marginal effects of firm upstreamness on TFP by GVC integration (90% confidence intervals)

Fig. 3 presents the average marginal effects of firm upstreamness on TFP across different levels of GVC integration estimated using equation (3). For firms in the Marginal GVC category (one-way and two-way traders), the confidence intervals overlap with zero, indicating that upstream positioning does not provide a statistically significant productivity advantage for these groups. However, we observe a clear shift once firms reach the limited GVC integration tier. Beyond this threshold, the marginal effect remains largely stable for firms in the Intermediate and High GVC categories. This step-like pattern suggests that the productivity benefits associated with moving upstream strengthens once firms attain a minimum level of GVC integration.

These results indicate that crossing into meaningful GVC participation is what drives the upstreamness-productivity premium. Initial integration brings large productivity gains (technology transfer, knowledge spillovers, quality upgrading pressure from buyers), but very deep integration introduces rising coordination costs, monitoring costs, and dependency/lock-in effects that partially offset those gains. This would predict exactly what we observe, a rise then a mild fall possibly because of "coordination costs," "hold-up problem," "GVC complexity costs". Full marginal effects estimates underlying this figure are reported in Appendix Table A.5.

As discussed in Section 2.2 , a firm is considered a Limited GVC category firm if it satisfies one of these three core criteria: (i) intensive export, (ii) intensive import or (iii) major business group. Most of our sample firms operate below this threshold. Specifically, the shares of marginal one-way

traders (25.47%) and two-way traders (39.03%) each exceed the share of Limited GVC firms (19.58%). This pattern implies that mere participation in GVC is insufficient; firms must attain sufficient GVC intensity to realize upstreamness-productivity premium.

3.2 Endogeneity

While our baseline regressions show evidence of upstream-productivity nexus, potential endogeneity is a concern which may bias our results. As discussed in Section 2.3.2, changes in firm upstreamness index can arise from two distinct sources. The first reflects GVC restructuring at the global-industry level, which is plausibly exogenous to individual firms. The second arises from firm level adjustments in product portfolio, which is an internal decision that may itself respond to firm-specific shocks. When a firm experiences productivity shocks they may strategically adjust their product portfolio, moving into more upstream or downstream activities (Herkenhoff et al., 2024). Since these changes in product portfolio is endogenous, a firm specific shock can simultaneously affect firm upstreamness as well as TFP.

We address this concern using a Two-Stage Least Squares (2SLS) estimation using Bartik style shift-share IV strategy (Autor et al., 2013; Borusyak et al., 2025). The construction of this shift-share instrument involves combining two components. First is the firm specific 'share' which is the upstreamness value of the firm as it first appears in our panel. This share component captures the initial and predetermined exposure to GVCs based on early product mix of these firms. We used weighted sales ratio to construct the firm level upstreamness which ensures that the index captures actual firm level variation rather merely reflecting changes in industry level upstreamness.

The second is the 'shift' component defined as the leave-one-state- out (LOSO) average upstreamness of all firms operating in the same 5-digit NIC as firm *i,* excluding firms located in the same state as firm *i*. We construct the 'shift' component using the following formula:

$$\overline{U}_{v,-s,t} = \frac{\sum_{i\in\Omega_{vt}} F\,U_{it} - \sum_{i\in\Omega_{vst}} F\,U_{it}}{N_{vt} - N_{vst}} \tag{4}$$

In equation (4),c$\bar{U}_{v,-st}$ represents the out-of-state peer average upstreamness of firms' industry v at time t (shift-component). Ω_{vt} denotes the set of all manufacturing firms operating within the 5-digit industry (v) at time (t), while Ω_{vst} denotes the subset of firms in the same industry that are located within the focal firm's state 's' at time 't'. FU_{it} denotes our firm level upstreamness index for firm i. Finally, N_{vt} and N_{vst} denote the total number of firms in industry 'v' at time 't'

nationwide and state-specific number of firms within industry '*v*' and time '*t*' respectively. Here we subtract the state-level aggregate from the national aggregate to ensure that the shift component ($\bar{U}_{v,-st}$) is orthogonal to any shocks or state-level policy shifts that might directly influence the productivity of firm '*i*'.

As the final step, we interact the share component with the shift to construct our Bartik-style instrument using equation (5).

$$Z_{it} = U_{i,0} \times \bar{U}_{v,-s,t} \tag{5}$$

Here, Z_{it} is our shift-share instrument for firm '*i*' at time '*t*'. $U_{i,0}$ denotes the share and $\bar{U}_{v,-st}$ is the shift components. Here follow the exogenous shift approach and assume that the firms operating in the same industry tends to move together in response to a common sectoral shock which satisfies the relevancy condition for an IV. Additionally, the exclusion restriction underlying the shift share requires that the changes in average upstreamness of out-of-state industry peers affect firm *i*'s productivity only through their impact on firm *i*'s own upstreamness and not through any other direct channel. We argue that this assumption is plausible since firms located in different states are insulated from common local demand shocks, regional input market conditions and state specific government policy interventions that could drive both upstreamness and productivity within that specific state. In this model, we restrict the reference group to firms in the same industry but different state which ensures that the instrument captures exogenous industry-level shifts in GVC positioning while removing the state specific variation that would otherwise affect the identification.

3.2.1 2SLS baseline linear model

Firms might strategically adjust their product portfolio in response to the unobserved productivity shocks. Therefore, we re-estimate our baseline model using a 2SLS Shift-Share instrument variable method. We estimate the following first and second stage equations:

First stage:

$$FU_{i,t-1} = \pi_0 + \pi_1 Z_{i,t-1} + \pi_2 \mathrm{X}_{\mathrm{i,t-1}} + \gamma_{jt} + \delta_s + \nu_{it} \tag{6}$$

Second stage:

$$\ln TFP_{it} = \alpha_0 + \beta_1 \widehat{FU}_{i,t-1} + \beta_2 \mathrm{X}_{\mathrm{i,t-1}} + \gamma_{jt} + \delta_s + \varepsilon_{it} \tag{7}$$

In these equations, $Z_{i,t-1}$ is the lagged Bartik style shift-share instrument and $\widehat{FU}_{i,t-1}$ is the predicted value of lagged firm level upstreamness obtained from the first stage. $X_{i,t-1}$ represents the lagged control variables. The terms 'γ_{it}' and 'δ_s' represent industry*year and state fixed effects, respectively, while v_{it} and ε_{it} are the idiosyncratic error terms.

Table 5: 2SLS Baseline Linear Effect of Upstreamness on TFP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm upstreamness	0.165**	0.163**	0.181***	0.175**	0.165***	0.163***	0.181***	0.175***
	(0.068)	(0.070)	(0.065)	(0.068)	(0.055)	(0.056)	(0.053)	(0.054)
Age			-0.212***	-0.209***			-0.212***	-0.209***
			(0.023)	(0.022)			(0.020)	(0.020)
Size			0.092***	0.089***			0.092***	0.089***
			(0.014)	(0.014)			(0.010)	(0.010)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes	No	No	Yes	Yes
F-statistics	685	694	683	691	1075	1093	1066	1084
K-P LM (P-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of Clusters	275	275	275	275	3997	3991	3997	3991
Observations	23,899	23,843	23,899	23,843	23,899	23,843	23,899	23,843

Notes: Robust standard error are clustered at 5-digit industry level in columns (1) to (4) and firm level in columns (5) to (8)
Dependent variable is TFP in logarithmic format
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 5 presents the 2SLS estimates for our baseline specification estimated using equation (7). The results indicate that the effect of firm upstreamness on TFP remains positive and statistically significant ($p<0.01$) even after endogeneity correction. In column (8) with complete specifications, firm upstreamness increase productivity by 17.5 percentage which is an improvement compared to the 10.3 percent from fixed effects estimates in Table 4. Kleibergen-Paap Wald F-statistics exceeds well above the conventional threshold of 10 across the specifications, indicating that weak instrument concerns are unlikely. Furthermore, the statistically significant Kleibergen-Paap LM test rejects the null hypothesis of under identification, confirming the relevance of the instruments. Across all the specifications, the coefficients remain stable ranging from 0.163 - 0.181. This endogeneity corrected results provide robust evidence of a positive effect of firm upstreamness on firm performance. First-stage regression results are reported in Appendix Table A.6.

3.2.2 2SLS interaction model

In this section, we model how the returns to upstreamness varies across different GVC integration intensities. To overcome the multiple endogeneity issues of the interaction term, we

treat both the firm upstreamness and GVC intensity interactions as endogenous regressors. $GVC_Intensity_{k,it}$ is the categorical variable comprising four distinct GVC groups. We interact the shift share instrument ($Z_{i,t-1}$) with each of the GVC intensity dummies to generate a complete vector of excluded instruments ($Z_{i,t-1} \times$ GVC$_Intensity_{k,it}$).

We create a system of simultaneous first-stage equations for both the standalone endogenous regressor ($FU_{i,t-1}$) and interaction variable ($FU_{i,t-1} \times$ GVC$_Intensity_{k,it}$).

First stages:

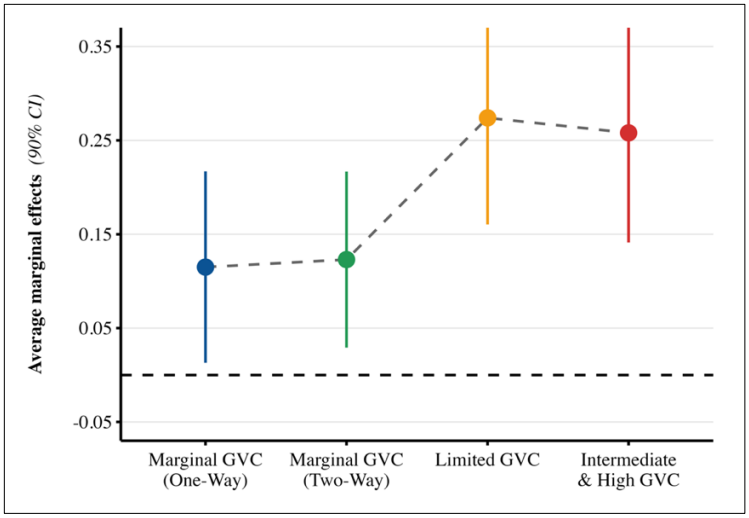
$$FU_{i,t-1} = \pi_0 + \pi_1 Z_{i,t-1} + \sum_{k=1}^{K-1} \pi_{2k} \left(Z_{i,t-1} \times GVC_Intensity_{k,it}\right) + \sum_{k=1}^{K-1} \pi_{3k}\, GVC_Intensity_{k,it} + \pi_4 X_{i,t-1} + \gamma_{jt} + \delta_s + \mu_{it} \quad (8)$$

$$\left(FU_{i,t-1} \times GVC_Intensity_{k,it}\right) = \phi_0 + \phi_1 Z_{i,t-1} + \sum_{k=1}^{K-1} \phi_{2k} \left(Z_{i,t-1} \times GVC_Intensity_{k,it}\right) + \sum_{k=1}^{K-1} \phi_{3k}\, GVC_Intensity_{k,it} + \phi_4 X_{i,t-1} + \gamma_{jt} + \delta_s + \eta_{it} \quad (9)$$

Second stage:

$$\ln TFP_{it} = \alpha_0 + \beta_1 \widehat{FU}_{i,t-1} + \sum_{k=1}^{K-1} \beta_{2k}\, GVC_Intensity_{k,it} + \sum_{k=1}^{K-1} \beta_{3k} \left(\widehat{FU}_{i,t-1} \times GVC_Intensity_{k,it}\right) + \beta_4 X_{i,t-1} + \gamma_{jt} + \delta_s + \varepsilon_{it} \quad (10)$$

In Equation (10), $lnTFP_{it}$ denotes the natural logarithm of Total Factor Productivity for firm '*i*' at time '*t*'. The term GVC$_Intensity_{k,it}$ represents the categorical indicator defining the specific GVC integration tier *k* of firm '*i*' at time '*t*'. Crucially, the coefficients on the instrumented interaction terms (β_{3k}), measure the differential productivity returns to upstreamness for firms in tier '*k*' relative to the baseline group.



Notes: Standard errors are clustered at the firm level.
Industry*year and state fixed effects. All firm controls included

Fig. 4: 2SLS Average Marginal Effects of Firm Upstreamness on TFP by GVC Integration With 90% Confidence Intervals

Figure 4 reports the 2SLS marginal effects across heterogenous levels of GVC intensity with a horizontal dotted line showing 90% confidence interval estimated using equation (10)[28]. None of the average marginal effects intersects with the confidence interval line at zero showing a significance across GVC intensities. These positive coefficients show a step-like pattern where the effect progressively increases from Marginal to High GVCs. Moreover, a sharp discontinuity is visible while moving from Marginal to Limited GVC indicating a critical threshold point in the upstreamness-productivity linkage. Beyond this threshold, the effect does not increase further as confirmed by Wald Chi-squared tests (Table A.10). Taken together, these results provide support to our core arguments: (i) positive relationship between firm upstreamness and performance; (ii) existence of a threshold effect based on GVC intensity; (iii) the marginal returns is non-monotonic beyond the threshold point. Full marginal effects estimates underlying this figure are reported in Appendix Table A.7.

4 Robustness

4.1 Alternative TFP Estimations

To assess the robustness of our results, we re-estimate the main specification using three

[28] With this interaction model, we are instrumenting for four separate endogenous regressors (FU and its three tier-interactions) with four instruments (Z and its tier-interactions). Therefore, to test for weak instruments with a model containing multiple endogenous variables, we use Sanderson-Windmeijer (SW) conditional F-statistic (Sanderson & Windmeijer, 2016). Refer Appendix A.8 for SW test statistics.

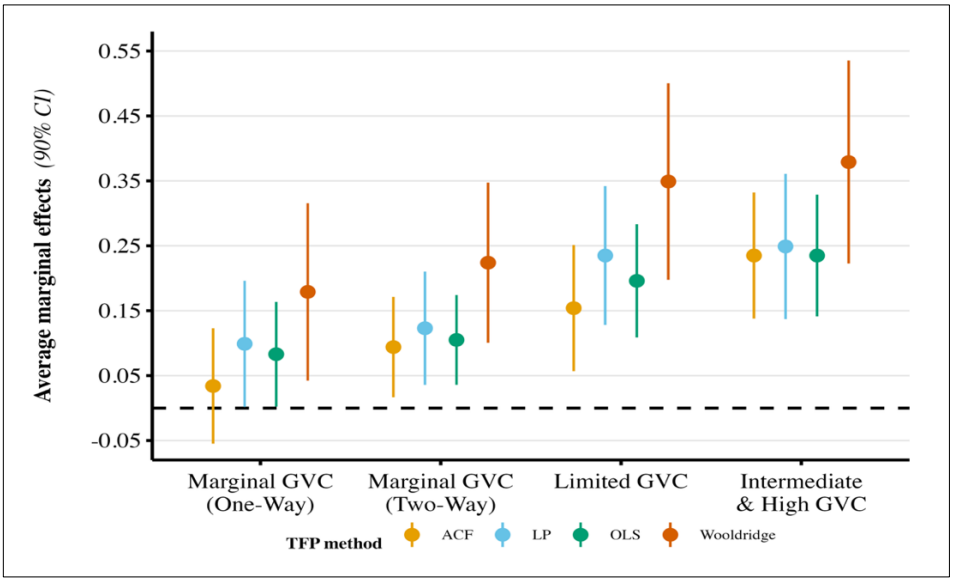
alternative TFP measures. In addition to LP method, we estimate TFP using ordinary least squares (OLS), the semiparametric control-function estimator proposed by Ackerberg, Caves, and Frazer (2015), and the two-step system generalized method of moments (GMM) approach developed by Wooldridge (2009).

Table 6: 2SLS Baseline Regression (Alternative TFP Measures)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LP	OLS	ACF	WRDG	LP	OLS	ACF	WRDG
Firm upstreamness	0.175**	0.138***	0.114*	0.260***	0.175***	0.138***	0.114**	0.260***
	(0.068)	(0.049)	(0.060)	(0.093)	(0.054)	(0.040)	(0.046)	(0.073)
Age	-0.209***	-0.230***	-0.182***	-0.339***	-0.209***	-0.230***	-0.182***	-0.339***
	(0.022)	(0.018)	(0.017)	(0.030)	(0.020)	(0.016)	(0.016)	(0.028)
Size	0.089***	0.180***	0.242***	-0.354***	0.089***	0.180***	0.242***	-0.354***
	(0.014)	(0.013)	(0.014)	(0.020)	(0.010)	(0.008)	(0.008)	(0.013)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	23,843	23,843	23,843	23,843	23,843	23,843	23,843	23,843

Notes: Robust standard error are clustered at 5-digit industry level in columns (1) to (4) and firm level in columns (5) to (8) Dependent variable is the log of TFP. ACF denote Ackerberg, Caves, and Frazer (2015), while WRDG denote Wooldridge (2009)
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 6 presents the upstreamness-productivity linkage across alternative TFP estimation methods. The coefficient on firm upstreamness remains positive and significant, confirming the robustness of our baseline results. The estimated coefficient ranges from 0.114 (ACF) to 0.260 (WRDG). This consistency of these estimates indicates that the positive relationship between upstreamness-productivity is not driven by the choice of the TFP estimator used, thereby reinforcing the robustness of our main findings.



Notes: Standard errors are clustered at the firm level.
Industry*year and state fixed effects. All firm controls included

Fig. 5: Robustness of 2SLS Marginal Effects to Alternative TFP Measures

Figure 5 reports the marginal results with different TFP estimates are consistent with our baseline results and follow the same step-like pattern. This strengthens our argument that upstreamness-productivity premium is conditional on firm's GVC intensity.

4.2 Dynamic gestation periods

To check whether the results are persistent in the long run, we use different lags of the firm-level upstreamness and re-estimated the model.

Table 7: 2SLS Regression with Lagged Upstreamness (Marginal Results)

	(1)	(2)
	t-2	t-3
Intermediate + High GVC	0.265***	0.273***
	(0.077)	(0.080)
Limited GVC	0.310***	0.318***
	(0.076)	(0.077)
Marginal GVC - Two Way Traders	0.139**	0.131**
	(0.062)	(0.063)
Marginal GVC - One Way Traders	0.124*	0.090
	(0.067)	(0.071)
Controls	✓	✓
Number of Clusters	3101	2821
Observations	19,849	17,381

Notes: Robust standard error are clustered at firm level
Dependent variable is TFP in logarithmic format
All columns report marginal effects
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 7 reports that the conditional effect of gvc intensity is remarkably robust. The coefficients follow the step-like pattern across GVC intensities and is significant even at lag of five years (t-3).

4.3 Sensitivity analysis

As a sensitivity analysis, we relax thresholds use to construct GVC intensity categories. Specifically, we reduced threshold values of intensive exporters from 66 percent to 50 percent and 33 percent to 25 percent for intensive importers. This analysis is carried out to assess whether our results are sensitive to the choice of classification of GVC intensity thresholds.

Table 8: Sensitivity Analysis with Alternate GVC Intensity Thresholds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intermediate + High GVC	0.214**	0.215**	0.252***	0.248***	0.214***	0.215***	0.252***	0.248***
	(0.087)	(0.086)	(0.085)	(0.085)	(0.068)	(0.068)	(0.066)	(0.066)
Limited GVC	0.252***	0.247***	0.256***	0.246***	0.252***	0.247***	0.256***	0.246***

	(0.080)	(0.082)	(0.080)	(0.082)	(0.069)	(0.070)	(0.068)	(0.068)
Marginal GVC - Two Way Traders	0.129*	0.131*	0.146**	0.144**	0.129**	0.131**	0.146**	0.144**
	(0.070)	(0.071)	(0.067)	(0.069)	(0.059)	(0.060)	(0.057)	(0.058)
Marginal GVC - One Way Traders	0.106	0.100	0.130*	0.122	0.106	0.100	0.130**	0.122*
	(0.081)	(0.081)	(0.076)	(0.078)	(0.064)	(0.064)	(0.062)	(0.062)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes	No	No	Yes	Yes
Number of Clusters	275	275	275	275	3997	3991	3997	3991
Observations	23,899	23,843	23,899	23,843	23,899	23,843	23,899	23,843

Notes: Robust standard error are clustered at 5-digit industry level in columns (1) to (4) and firm level in columns (5) to (8)
Dependent variable is TFP in logarithmic format
All columns report marginal effects
* p < 0.10, ** p < 0.05, *** p < 0.01

Sensitivity results in Table 8 show that the main results remain robust to the alternative GVC intensity thresholds. The estimated coefficients remain stable and significant across all specifications.

5 Mechanism analysis

In this section, we empirically examine the underlying mechanisms through which upstreamness causes firm performance. We hypothesize that high upstream firms upgrade their production capabilities using two primary pathways: (i) innovation (R&D) and (ii) external technology acquisitions (royalty payments).

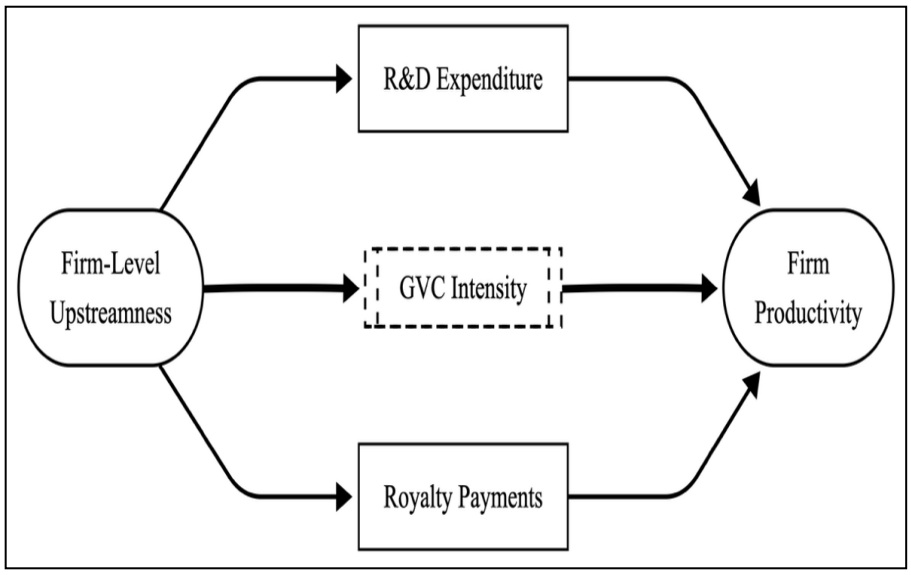


Fig. 6: Mechanism channel

Fig. 6 provides the conceptual framework of mechanism analysis. As discussed previously, the central pathway shows GVC intensity as the primary mechanism. Additionally, we identify two complementary mechanisms (R&D expenditure and royalty payments) that converts upstream position into better firm performance. We rely on 2SLS approach to mitigate the endogeneity concerns.

Table 9: Mechanism Analysis (2SLS)

	(1) TFP	(2) R&D	(3) Royalty
Firm upstreamness	0.175***	0.239**	0.202*
	(0.054)	(0.114)	(0.120)
Age	-0.209***	0.259***	-0.084**
	(0.020)	(0.031)	(0.034)
Size	0.089***	0.419***	0.271***
	(0.010)	(0.021)	(0.024)
Controls	✓	✓	✓
Observations	23,843	23,658	23,658

Notes: Standard errors in parentheses are clustered at the firm level.
All models instrument lagged firm upstreamness with the lagged shift-share IV via 2SLS.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.1 Internal innovation: The R&D channel

Column (2) of Table 9 report the impact of upstreamness on R&D expenditure. The results shows that one unit increase in upstreamness is associated with a 23.9 percent increase in R&D expenditure. As discussed in Section1, positioning further exposes firms to more demanding buyer (Xu et al., 2024), creating pressure to invest in innovation simply to remain a qualified supplier. We test whether this pressure operates through a distinct innovation channel. Further, constant buyer-supplier interactions and exposure to global production technologies of upstream firms give them the knowledge base required to meet this innovation efficiency (Ambos et al., 2021).

5.2 External technology acquisition: The royalty channel

Column (3) shows whether upstreamness facilitates firms' foreign technology acquisition. The positive and significant coefficient indicates that one unit increase in firm upstreamness is associated with 20.2 percent increase in royalty payments. This result is consistent with the mechanism outlined earlier: sustained contact with international buyers and multinational suppliers' function as a conduit for technology transfer that firms further downstream do not have equal access to (Gereffi et al., 2005). Upstream position of firms signals credible production capabilities to foreign licensors that strengthens the buyer supplier relationship which makes it easier to acquire foreign technology.

5.3 Heterogeneity across different GVC intensity

We further examine these transmission channels by interacting upstreamness with varying levels of GVC intensities.

Table 10: Mechanism Analysis across GVC Intensities (Marginal Effects)

	(1) TFP	(2) R&D	(3) Royalty
Intermediate + High GVC	0.270***	0.355**	0.249*
	(0.082)	(0.163)	(0.151)
Limited GVC	0.280***	0.153	0.279*
	(0.080)	(0.129)	(0.156)
Marginal GVC - Two Way Traders	0.135**	0.276**	0.142
	(0.067)	(0.115)	(0.123)
Marginal GVC - One Way Traders	0.116*	0.104	0.202*
	(0.070)	(0.112)	(0.123)
Controls	✓	✓	✓
Observations	23,658	23,658	23,658

Notes: Standard errors in parentheses are clustered at the firm level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10 reports the heterogenous effects of mechanism variables across different levels of GVC intensity. For firms in the high/intermediary category, one unit increase in upstreamness is associated with a substantial 35.5 percent increase in R&D investment. Surprisingly this effect is not significant for firms in the limited GVC category. This pattern indicate that R&D is an important mechanism through which upstreamness affects firms which are more deeply integrated into GVCs. By contrast, the royalty channel is significant for firms with limited GVC participation and those in the highly integrated GVC category, indicating that technology acquisition through royalty payments operates across different levels of GVC integration.

6 Conclusion

This paper uses product-firm level data to analyze the impact of firm level upstreamness on TFP among Indian manufacturing firms over the period 2000-2015. We classify firms along a five tier GVC intensity spectrum to understand how this upstreamness-productivity relationship varies conditional on firm's GVC integration. After correcting for endogeneity using Bartik-style shift share instruments, the result indicates a significant positive effect of upstreamness on firm performance. The findings suggest that a one-unit increase in firm upstreamness is associated with a 25.8% increase in TFP for high/intermediate-GVC firms, but only an 11.5% increase for marginal one-way traders. The highest productivity premium (27.4%) is observed among firms with limited GVC integration, thereby confirming our threshold hypothesis. The majority of the

sample firms, however, fall under Marginal GVC category which limit their potential for improved productivity through moving to upstream stages of production. The mechanism analysis reveal that upstreamness-productivity relationship operates through two complementary pathways of within firm innovation and external technology acquisition which is also conditional on a certain level of GVC intensity. Our results are robust to alternative measures of TFP and dynamic specifications. These findings shed light into a broader debate on GVC upgrading in emerging economies. Our result suggests that increase in GVC intensity along with upstream positioning is vital to break out of the low value added GVC trap faced by firms in developing countries.

Our findings have important implications for the policy debate on whether India is 'stuck in assembly'. The results suggest that promoting upstream movement alone is unlikely to generate productivity gains unless we look into how deep these firms are integrated into GVC networks. This finding points to three complementary policy directions. First, there should be greater emphasis on intermediate-input and component production rather than final assembly alone. Second, since ownership linkages constitute an important dimension of deeper GVC integration in our framework, facilitating FDI and joint ventures in upstream-intensive industries may be more effective than broad-based investment liberalization in enabling firms to realize the productivity benefits of upstream positioning. Third, our finding that productivity premium observed for two-way traders when compared to one-way traders suggest that policies should target firms to increase their import linkages for intermediate inputs, which will enhance deeper participation in GVCs than just export promoting exports in isolation.

Our analysis is restricted to 2000–2015. This reflects significant changes in the coverage of the PROWESS database after 2015 as well as our intention to avoid confounding effects of major macroeconomic shocks, including India's 2016 demonetization and the COVID-19 pandemic. Additionally, we study the micro perspective of a single emerging economy locked into low level GVC stages and this can very well be extended for a large set of developing countries. Therefore, future research could revisit the upstreamness-productivity relationship using more recent data and extend the analysis to a broader set of emerging economies.

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Appendix A

Table A.1: Construction of the Estimation Sample

	Dropped observations	**Total observations**
Prowess CMIE (2000–2015), manufacturing firms	-	501,432
Exclude observations with missing sales or gross fixed assets	419,516	81,916
Exclude observations with missing labor or fuel inputs	1,134	80,782
Exclude outliers	8,936	71,846
Exclude firms with no international trade activity	23,872	47,974
Merge with product-level trade data (retain matched observations)	15,330	32,644
Final sample	-	32,644

Table A.2: Concordance between NIC 2008 and OECD TiVA Sector Classifications

TiVA ID	**OECD TiVA Sector**	**NIC 2008 Code**	**NIC 2008 Description**
9	Food, Beverages & Tobacco	10, 11, 12	Manufacture of food products; beverages; tobacco
10	Textiles, Apparel & Leather	13, 14, 15	Manufacture of textiles; wearing apparel; leather
11	Wood & Cork Products	16	Manufacture of wood and products of wood and cork
12	Paper & Printing	17, 18	Manufacture of paper products; printing and reproduction
13	Coke & Refined Petroleum	19	Manufacture of coke and refined petroleum products
14	Chemicals	20	Manufacture of chemicals and chemical products
15	Pharmaceuticals	21	Manufacture of basic pharmaceutical products and preparations
16	Rubber & Plastics	22	Manufacture of rubber and plastic products
17	Non-Metallic Minerals	23	Manufacture of other non-metallic mineral products
18	Basic Metals	24	Manufacture of basic metals (iron, steel, and non-ferrous)
20	Fabricated Metal Products	25	Manufacture of fabricated metal products, except machinery
21	Computer & Electronics	26	Manufacture of computer, electronic and optical products
22	Electrical Equipment	27	Manufacture of electrical equipment
23	Machinery, n.e.c.	28	Manufacture of machinery and equipment n.e.c.
24	Motor Vehicles & Trailers	29	Manufacture of motor vehicles, trailers and semi-trailers
26	Other Transport Equipment	30	Manufacture of other transport equipment

Table A.3: Distribution of GVC Intensity across Manufacturing Sectors in India

	GVC Intensity				
OECD TiVA Sector	Marginal GVC (One-way traders)	Marginal GVC (Two-way traders)	Limited GVC	Intermediate GVC	High GVC
Food & Beverages	34.92	33.13	21.91	9.65	0.39
Textiles & Leather	22.32	42.58	18.58	14.35	2.16
Wood & Cork	34.11	30.62	19.77	15.50	0.00
Paper & Printing	39.65	33.50	20.29	6.56	0.00
Coke & Petroleum	23.64	9.30	43.41	23.26	0.39
Chemicals	21.43	37.53	17.44	22.40	1.20
Pharmaceuticals	20.88	39.95	20.53	14.84	3.80
Rubber & Plastics	26.79	41.42	19.23	10.79	1.76
Non-Metallic Minerals	24.87	35.79	17.90	18.50	2.95
Basic Metals	32.70	35.87	19.36	11.50	0.57
Fabricated Metals	32.15	43.63	14.34	8.94	0.93
Computer & Electronics	17.86	24.45	33.03	22.18	2.48
Electrical Equipment	23.65	40.19	16.92	17.20	2.04
Machinery n.e.c.	17.56	46.06	20.57	15.06	0.75
Motor Vehicles	21.17	47.41	18.22	13.01	0.18
Other Transport Equipment	27.91	46.34	15.72	8.13	1.90
Total	25.47	39.03	19.58	14.65	1.27

Source: Own calculation based on Prowess IQ data (2000 - 2015)

Table A.4: Distribution of Firms by GVC Intensity, 2000–2015

Year	Marginal GVC (One-way Traders)	Marginal GVC - Two Way Traders	Limited GVC	Intermediate GVC	High GVC
2000	26.87	37.56	18.72	15.80	1.06
2001	25.62	37.48	19.05	16.91	0.95
2002	25.03	37.42	19.59	16.90	1.06
2003	25.48	37.23	20.44	15.85	1.01
2004	26.13	36.21	21.07	15.57	1.01
2005	26.70	36.65	19.37	16.15	1.13
2006	24.95	38.72	19.55	15.77	1.00
2007	24.98	40.24	19.38	14.38	1.02
2008	24.98	40.50	19.25	13.88	1.39
2009	25.66	39.38	18.91	14.73	1.31
2010	25.39	39.08	19.50	14.67	1.36
2011	24.73	41.73	18.36	13.91	1.27
2012	23.27	43.30	18.71	13.20	1.52
2013	24.40	41.93	18.39	13.71	1.58
2014	25.56	39.20	20.67	12.93	1.64
2015	27.38	36.58	21.41	13.05	1.58
Total	25.47	39.03	19.58	14.65	1.27

Notes: Entries are row percentages. GVC intensity categories are constructed following the Meyer framework.

Table A.5: Marginal Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intermediate + High GVC	0.154**	0.168**	0.171**	0.180**	0.154***	0.168***	0.171***	0.180***
	(0.076)	(0.073)	(0.073)	(0.072)	(0.058)	(0.058)	(0.057)	(0.057)
Limited GVC	0.196***	0.202***	0.189***	0.189***	0.196***	0.202***	0.189***	0.189***
	(0.060)	(0.061)	(0.061)	(0.061)	(0.056)	(0.056)	(0.055)	(0.055)

Marginal GVC - Two Way Traders	0.052	0.061	0.061	0.065	0.052	0.061	0.061	0.065
	(0.046)	(0.048)	(0.045)	(0.047)	(0.040)	(0.041)	(0.040)	(0.040)
Marginal GVC - One Way Traders	0.050	0.054	0.060	0.060	0.050	0.054	0.060	0.060
	(0.057)	(0.057)	(0.055)	(0.055)	(0.048)	(0.047)	(0.047)	(0.046)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes	No	No	Yes	Yes
Number of Clusters	368	368	368	368	4162	4156	4162	4156
Adj. R^2	0.396	0.405	0.422	0.429	0.396	0.405	0.422	0.429
Observations	25,363	25,306	25,363	25,306	25,363	25,306	25,363	25,306

Notes: Robust standard error are clustered at 5-digit industry level in columns (1) to (4) and firm level in columns (5) to (8)
Dependent variable is TFP in logarithmic format
All columns report marginal effects
* p < 0.10, ** p < 0.05, *** p < 0.01

Table A.6: First-Stage Results – Baseline 2SLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shift-share IV	0.250***	0.251***	0.251***	0.251***	0.250***	0.251***	0.251***	0.251***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)
Age			-0.006	-0.008			-0.006	-0.008*
			(0.005)	(0.005)			(0.004)	(0.004)
Size			-0.000	0.000			-0.000	0.000
			(0.003)	(0.003)			(0.002)	(0.002)
Constant	0.817***	0.816***	0.834***	0.839***	0.817***	0.816***	0.834***	0.839***
	(0.065)	(0.065)	(0.066)	(0.065)	(0.053)	(0.052)	(0.053)	(0.052)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes	No	No	Yes	Yes
F-stat (Excluded IV)	685.574	694.358	683.777	691.897	1075.022	1093.937	1066.817	1084.825
Number of Clusters	275	275	275	275	3997	3991	3997	3991
Observations	23,899	23,843	23,899	23,843	23,899	23,843	23,899	23,843

Notes: Dependent variable is lagged firm upstreamness.
Robust standard error are clustered at 5-digit industry level in columns (1) to (4) and firm level in columns (5) to (8)
F-stat reports the joint significance of the excluded instrument.
* p < 0.10, ** p < 0.05, *** p < 0.01

Table A.7: 2SLS Estimation Results (Marginal Effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intermediate + High GVC	0.219**	0.224**	0.259***	0.258***	0.219***	0.224***	0.259***	0.258***
	(0.095)	(0.092)	(0.091)	(0.090)	(0.073)	(0.073)	(0.071)	(0.071)
Limited GVC	0.274***	0.273***	0.280***	0.274***	0.274***	0.273***	0.280***	0.274***
	(0.078)	(0.080)	(0.078)	(0.080)	(0.070)	(0.071)	(0.069)	(0.069)
Marginal GVC - Two Way Traders	0.108	0.110	0.125*	0.123*	0.108*	0.110*	0.125**	0.123**
	(0.069)	(0.071)	(0.066)	(0.069)	(0.058)	(0.059)	(0.056)	(0.057)
Marginal GVC - One Way Traders	0.100	0.094	0.124*	0.115	0.100	0.094	0.124**	0.115*
	(0.079)	(0.080)	(0.074)	(0.077)	(0.064)	(0.064)	(0.061)	(0.062)

Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes	No	No	Yes	Yes
Number of Clusters	275	275	275	275	3997	3991	3997	3991
Observations	23,899	23,843	23,899	23,843	23,899	23,843	23,899	23,843

Notes: Robust standard error are clustered at 5-digit industry level in columns (1) to (4) and firm level in columns (5) to (8)
Dependent variable is TFP in logarithmic format
All columns report marginal effects
* p < 0.10, ** p < 0.05, *** p < 0.01

Table A.8: Sanderson-Windmeijer Conditional F-Statistics by GVC Intensity

GVC Intensity	F Statistics
High/Intermediate GVC	6310
Limited GVC	6861
Marginal GVC - Two Way Traders	7789
Marginal GVC - One Way Traders	3098

Notes: (Sanderson & Windmeijer, 2016).

Table A.9: First-Stage Results – Interacted 2SLS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Shift-share IV	0.253***	0.253***	0.253***	0.253***	0.253***	0.253***	0.253***	0.253***
	(0.010)	(0.009)	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
(Intermediate+High GVC) # Shift-share IV	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Limited GVC # Shift-share IV	-0.000	-0.000	-0.000	-0.001	-0.000	-0.000	-0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Marginal GVC (Two-Way) # Shift-share IV	-0.004**	-0.004***	-0.004***	-0.004***	-0.004**	-0.004***	-0.004**	-0.004***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Age			-0.006	-0.007			-0.006	-0.007*
			(0.005)	(0.005)			(0.004)	(0.004)
Size			0.000	0.001			0.000	0.001
			(0.003)	(0.003)			(0.002)	(0.002)
Constant	0.808***	0.806***	0.824***	0.828***	0.808***	0.806***	0.824***	0.828***
	(0.064)	(0.064)	(0.065)	(0.065)	(0.052)	(0.052)	(0.052)	(0.052)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes
Firm Controls	No	No	Yes	Yes	No	No	Yes	Yes
F-stat (Excluded IVs)	182	187	183	188	294	302	293	301
Number of Clusters	275	275	275	275	3997	3991	3997	3991
Observations	23,899	23,843	23,899	23,843	23,899	23,843	23,899	23,843

Notes: Dependent variable is lagged firm upstreamness.
Robust standard error are clustered at 5-digit industry level in columns (1) to (4) and firm level in columns (5) to (8)
F-stat reports the joint significance of the main instrument and its GVC tier interactions.
* p < 0.10, ** p < 0.05, *** p < 0.01

Table A.10: Wald Test Results

	P values (Fixed effects)	P values (2SLS)
Marginal GVC (One-way) vs Marginal GVC (two-way)	0.896	0.670
Marginal GVC (One-way) vs Limited GVC	0.008	0.003
Marginal GVC (One-way) vs Intermediate/High GVC	0.019	0.021

Marginal GVC (two-way) vs Limited GVC	0.005	0.003
Marginal GVC (two-way) vs Intermediate/High GVC	0.012	0.025
Limited GVC vs Intermediate/High GVC	0.844	0.620

Notes: P-values from post-estimation Wald tests.
H0: Marginal effects of upstreamness are equal across the specified GVC tiers.
Standard errors are clustered at the firm level

Table A.11: Comparison of Fixed Effects and 2SLS Estimates

GVC Intensity	Fixed effects	2SLS	Change
Intermediate/High GVC	18.0%***	25.8 %***	+43.3%
Limited GVC	18.9%***	27.4%***	+45.0%
Marginal GVC (Two-way)	6.5% (n.s.)	12.3% **	+89.2%
Marginal GVC (One-way)	6.0% (n.s.)	11.5% *	+91.7%

Note :Standard errors are clustered at the firm level. All the results are with industry, year and state fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.12: Alternative TFP Measures (Marginal Effects)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	LP	OLS	ACF	WRDG	LP	OLS	ACF	WRDG
Intermediate + High GVC	0.258***	0.234***	0.239***	0.388***	0.258***	0.234***	0.239***	0.388***
	(0.090)	(0.068)	(0.076)	(0.126)	(0.071)	(0.054)	(0.060)	(0.095)
Limited GVC	0.274***	0.208***	0.183***	0.372***	0.274***	0.208***	0.183***	0.372***
	(0.080)	(0.059)	(0.066)	(0.108)	(0.069)	(0.053)	(0.061)	(0.095)
Marginal GVC - Two Way Traders	0.123*	0.101*	0.102	0.219**	0.123**	0.101**	0.102**	0.219***
	(0.069)	(0.052)	(0.067)	(0.097)	(0.057)	(0.042)	(0.049)	(0.076)
Marginal GVC - One Way Traders	0.115	0.074	0.029	0.168	0.115*	0.074	0.029	0.168**
	(0.077)	(0.062)	(0.075)	(0.107)	(0.062)	(0.048)	(0.054)	(0.084)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,843	23,843	23,843	23,843	23,843	23,843	23,843	23,843

Notes: Robust standard error are clustered at 5-digit industry level in columns (1) to (4) and firm level in columns (5) to (8)
Dependent variable is TFP in logarithmic format
All columns report marginal effects
Total unique firms analyzed: 5,116.
* p < 0.10, ** p < 0.05, *** p < 0.01

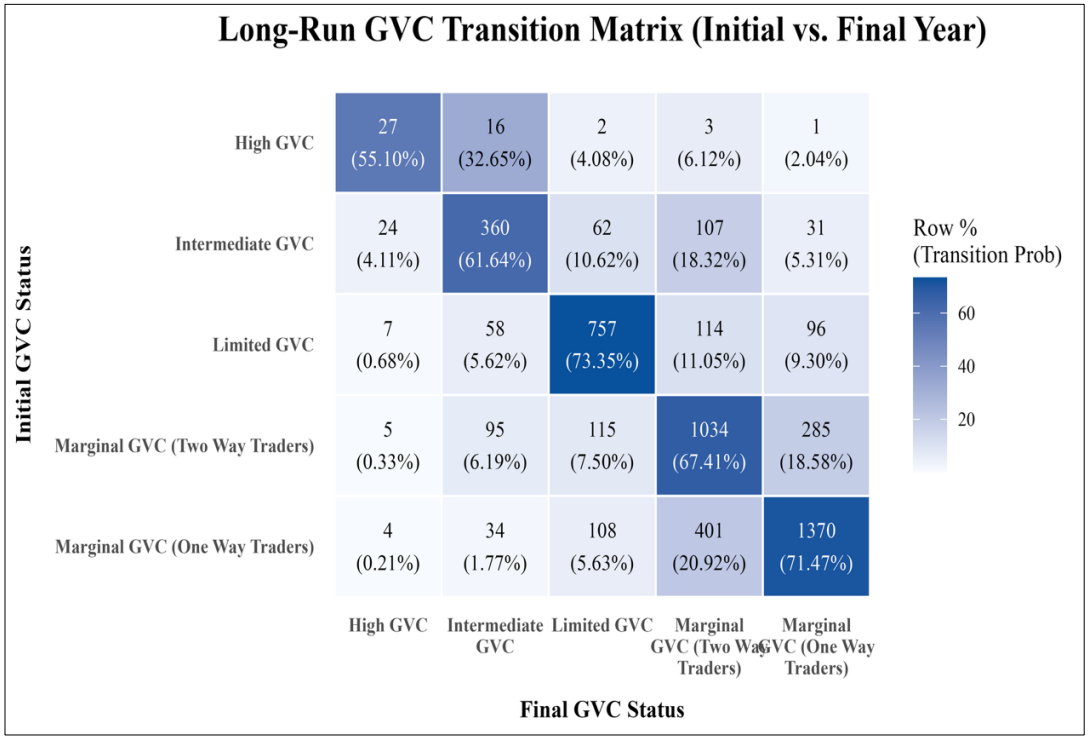


Fig.A.1: Long Run GVC Transition Matrix

Appendix B

B.1 Firm level production function estimation

Estimation of production function using Ordinary Least Square (OLS) presents a well-known simultaneity problem. Firms can identify certain productivity shocks before making any input decisions, which are unobservable to the econometrician. This creates a correlation between input variables and the error term making the OLS estimates biased and inconsistent.

To address this, TFP is estimated following the semiparametric estimator originally developed by Olley and Pakes (1996) and subsequently refined by Levinsohn and Petrin (2003), referred to as LP hereafter. This method uses intermediary inputs as a proxy for unobserved productivity shock.

First Stage

We assume production function in Cobb-Douglas (C-D) logarithmic form:

$$y_{it} = \beta_0 + \beta_1 l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it} \qquad (A.1)$$

Where Y_{it}, K_{it}, L_{it}, are the output, capital stock, and labour input of the firm respectively. ω_{it} and ε_{it} are the econometric unobservables. ε_{it} represents the idiosyncratic error terms, which captures the

elements of productivity shocks that are not predictable. ω_{it} is the productivity shocks which are potentially predictable based on the input decision made by the firms. ω_{it} assumed to follow exogenous first order-Markov process:

$$\omega_{it} = E(\omega_{it}|\omega_{it-1}) + \mu_{it} = \delta(\omega_{it-1}) + \mu_{it} \quad (A.2)$$

Here μ_{it} is the idiosyncratic error term which is uncorrelated all the input variables. LP method uses material inputs (f_{it}) (Energy and fuel) as a proxy variable, to invert and recover ω_{it}. These intermediary expenses are not included as a direct input in the production function (A.1) and it enters solely through proxy inversion. Using the control function method suggested by Levinsohn and Petrin (2003) the demand function for the proxy variable (f_{it}) as:

$$f_{it} = f_t(\omega_{it,} k_{it}) \quad (A.3)$$

Equation (A.3) assumes strict monotonicity and scalar unobservability of ω_{it} which makes it invertible i.e., $\omega_{it} = f_t^{-1}(f_{it}, k_{it})$. Substituting the proxy variable demand function (A.3) into C-D production function (A.1) we obtain:

$$Y_{it} = \beta_l l_{it} + \Phi_t(f_{it}, k_{it}) + \varepsilon_{it} \quad (A.4)$$

Where $\Phi_t(f_{it}, k_{it}) \equiv \beta_0 + \beta_k k_{it} + \omega_t(f_{it}, k_{it})$ is an unknown function approximated by a third-order polynomial in f_{it} and k_{it}. This solves the endogeneity problem since unobserved ω_{it} can now be observed. Therefore, estimating equation (A.4) gives consistent labour elasticity β_1 and composite function, ϕ_{it}.

Second stage

In the second stage, we identify capital elasticity (β_k) using the moment condition that, capital is orthogonal to the productivity innovation (ξ_{it}). For any β_k , this condition recovers the estimate of productivity shock as:

$$\hat{\omega_{it}}(\beta_k) = \hat{\Phi_{it}} - \beta_{it} k_{it} \quad (A.5)$$

the innovation (ξ_{it}) is the residual from a non-parametric regression on $\hat{\omega_{it}}$ on $\hat{\omega_{i,t-1}}$. We estimate the parameter β_k by satisfying the following moment condition:

$$E[\xi_{it} * Z_{it}] = 0, \quad Z_{it} \in \{k_{it}, f_{i,t-1}\} \quad (A.6)$$

After obtaining the consistent estimates of β_l and β_k, the model recovers firm level TFP as the residual:

$$TFP_{it} = y_{it} - \hat{\beta_1} l_{it} - \hat{\beta_k} k_{it} \qquad (A.7)$$

B.2 Productivity estimation variables

For estimating TFP of the Indian manufacturing firms (2000-2015), we apply Levinsohn and Petrin (2003) methodology to our firm-level panel. This approach assumes a two-input Cobb-Douglas production function with capital (i) and labour (l) as inputs and real value added (y) as output. We use fuel and energy expenses (f) as proxy variable to account for unobserved productivity shocks. The output variable is constructed as the sum of sales of goods and the change in stock of finished goods. We deflate this output variable with industry-specific wholesale price indices (WPI) from the Office of the Economic Advisor by the Government of India. We obtain these output deflators for Indian manufacturing industries and then mapped them to NIC 2008 industry classification. These deflators are then applied to firms belonging to these industries to obtain our real output variable.

To construct labor input, we divided compensation to employees from PROWESS by average industry wage rate from ASI data. We follow this approach due to the lack of number of employees data reported in PROWESS database. The average industry wage rate is derived from ASI data at the 3-digit NIC level by dividing total emoluments by the total number of persons engaged. This method converts financial expenditure into physical labor headcount.

We use power and fuel expenses, deflated using the corresponding WPI, as the intermediate inputs to proxy for unobserved productivity shocks in the estimation.

Capital stock is constructed using Perpetual Inventory Method. First, we apply a revaluation factor to the earliest observed Gross Fixed Assets (GFA) to account for capital inflation and investment growth since the firm's incorporation. We deflate this adjusted amount to base-year prices to establish the initial real capital stock. Then, we calculate annual real investment as the change in GFA, deflated by the capital goods Wholesale Price Index. Finally, we construct the ongoing capital series adding current real investment to the previous year's capital stock net of a 6 percent depreciation rate.