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Impact of firms' global value chain participation on total factor productivity: Evidence from the Indian manufacturing

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TITLE: IMPACT OF FIRMS' GLOBAL VALUE CHAIN PARTICIPATION ON TOTAL FACTOR PRODUCTIVITY: EVIDENCE FROM THE INDIAN MANUFACTURING INDUSTRY.

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Abstract

This Chapter focuses on firm productivity arising from firms' participation in Global Value Chain (GVC). Empirical results indicate a positive and statistically significant impact of firms' GVC participation on productivity. In addition, firms involved in forward GVCs bring more productivity gains than those engaging in backward GVCs though both participation increases productivity. Applying quantile estimation technique and estimating the GVC participation throughout the entire productivity distribution, we find that forward GVC's impact is positive at all productivity distributions but highest at the lowest quantiles. Besides firms participating in forward and backward GVCs, non-GVC firms like two-way traders and final demand goods¹ exporters also increase productivity compared to other firms importing raw materials without export.

Keywords: Productivity, GVC, BEC, forward, backward, export & import.

¹ Capital and consumption goods are the final demand goods.

1. Introduction

Total factor productivity (TFP) measures firms' production efficiency and is important in improving firm competitiveness (Linh, 2021). In recent decades, technology advancements and cost reductions in transportation and communication have changed the goods production technique with increased specialisation and division of labour among firms in different countries. Therefore, Global Value Chains (GVCs) are the key to understanding recent international trade patterns (Giovannetti and Marvasi, 2016). Moreover, GVCs have intensified and transformed international trade (Antràs, 2020). Following various theoretical approaches, the literature has recognised global value chains (GVCs) as a vital driver of manufacturing productivity enhancement (Banga, 2022; Urata and Baek, 2022). GVCs have a beneficial effect on manufacturing firms as GVCs facilitate firms to produce efficiently and, in that way, improve productivity or competitiveness and increase their profits. Participation in GVCs enables firms to access high-quality foreign intermediate goods and engage in export activities (Urata and Baek, 2021).

GVCs can improve firm productivity through a range of different channels such as diffusion effects, training effects, availability and quality effects and others, allowing firm specialisation in particular tasks, offering more accessible access to international markets; especially firms in developing countries benefit from this framework (Giovannetti and Vannelli). The assistance of final goods-producing firms to input suppliers leads to knowledge and technology diffusion in the suppliers. Firms participating in GVCs are more likely to receive training from their international buyers. GVC participation increases the availability of better-quality inputs for buyer firms (Taglioni and Winkler, 2016). In contrast, buyers support their input suppliers for capacity building to overcome skill constraints (WDR, 2020). Though existing literature on GVCs has successfully analysed whether it matters for firm productivity, there are still different essential angles to see the role of GVCs as the driver of productivity.

Firms can participate in GVCs by using imported inputs in their exports or supplying intermediate inputs to third-country exports (Report, 2020). Importing intermediate goods and using those to produce export goods becomes a vital feature of modern globalisation (Zhu, 2022). GVC participation is backward when a firm adds additional

value to imported raw materials or intermediate goods for producing its exported items. Therefore, backward GVC participation is defined as "Importing inputs to produce goods or services that are exported" (WDR, 2020, p.265). It mainly involves importing intermediate or semi-finished goods and adding value to them to export finished goods. For example, suppose a manufacturing firm in China uses imported intermediates to export smartphones. This type of GVC participation is considered backward since the intermediate goods used in exports come from the preceding stage (Report, 2020).

Generally, manufacturing firms in developing countries participate in backward GVCs by importing foreign intermediate goods and using them as raw materials for exporting products (Urata and Baek, 2021). Low-skilled workers stimulate backward GVC participation, the entry point to backward involvement. Therefore, in some manufacturing firms in advanced countries, low-skilled workers have lost their job opportunities because of the increased import of competing raw materials from developing countries (Report, 2020).

Endogenous growth theory argues that promoting technological progress is the fundamental way to enhance TFP in the long term. Developed countries control the higher value-added segment of GVC since these countries are important sources of new technologies. Therefore, GVC participating firms in developing countries achieve technological progress through the "learning effects" from the firms of developed countries, thus promoting the TFP. High-quality product demand of importers in developed countries and the fierce competition in the international market force GVC firms in developing countries to do their best to increase their productivity. On the other hand, GVC firms import technology-intensive intermediate and capital goods from developed countries. Therefore, firms' integration into GVC is beneficial for developing countries to exert comparative advantages, thereby significantly improving their technology level (Ge et al., 2018).

The empirical evidence suggests that many studies find a positive association between firms' GVC participation and productivity (Urata and Baek, 2021; Del Prete et al., 2017; Urata and Baek, 2022). Some researchers found the effectiveness of the selection effect since GVC participating firms had high productivity before participating in it. In addition, firms enjoy additional productivity improvement after joining GVCs through the learning effect (Urata and Baek, 2021; Del Prete et al., 2017). On the other hand,

a few studies ended with insignificant findings to support the learning effects of GVC participation (Van Biesebroeck, 2008; Vogel and Wagner, 2010).

This GVC participation which is well recognised and established in GVC literature, is backward. Therefore, we are dealing with one part of the value chain and ignoring another part, called the forward GVC participation. We aim to give insight into this forward GVC participation besides the backward participation. Forward GVC participation is defined as "Exporting domestically produced inputs to partners for the production of goods or services that they export" (WDR, 2020, p.265). Firms² are engaged in forward GVC participation through exporting raw materials (Report, 2020).

GVC participation is forward when a firm's exports are not fully absorbed by the importing firm but embodied in the importing firm's exports to another firm in third countries. Thus, an exporter participates in forward GVC if its position is in the early production stage. In the smartphone example, if Indian manufacturing firms send copper or other metals to Chinese firms, where it is further used in producing the exported smartphone, then Indian firms' GVC participation is considered forward as the exporter is at the initial production stage of the smartphone. If exporting firms import raw materials and export semi-finished goods, they are engaged in both forward and backward participation in GVC. An exporting firm's imported goods are intermediate inputs, so it is easily understandable that this firm is using foreign value added in its exported products. Firm-level forward GVC participation is difficult to measure even if a firm is identified as an exporter of intermediate inputs (Report, 2020). In the Prowess database, each firm reports the product information they are producing, and there is no information on which goods are exported.

Forward GVC participation is an essential wing of GVC, driven by abundant natural resources since different downstream production processes use agricultural products and commodities that usually cross several national boundaries (Report, 2020). Previous researchers ignore firms' forward GVC participation and their impact on productivity.

This Chapter aims to investigate whether firms' participation in forward global value chains, besides backward participation, matters for firm productivity. Our contributions

² Firms in manufacturing industries.

to the previous GVC literature are as follows. Firstly, we focus on forward GVC participation, whereas the existing literature mainly examines backward GVC participation.

Secondly, we estimate GVC participation according to the Broad Economic Categories (BEC) and end-use of manufactured products. Most current research considers a firm involved in GVC if they export, import, or do both. If any of these three conditions are fulfilled, the firm participates in GVC; otherwise, it does not.

Interestingly, GVC requires importing raw materials or intermediate goods, not finished ones, and exporting either raw materials or final goods, depending on the nature of GVCs. Therefore, GVC firms must specify the nature of the product they are exporting, intermediates, or final consumption goods. A few researchers considered imports as raw materials purchased from foreign countries but did not differentiate between exporting goods (Goldar and Goldar, 2022).

Thirdly, we analysed firms' international trade engagement besides GVC participation. Previous researchers provide insight into GVC-productivity linkage. We focused on other firms not involved in GVC but participating in international trade doing one-way trading, such as importing raw materials and using these for domestic consumption or exporting final goods using domestic raw materials. Therefore, we can compare the strength of GVC and non-GVC international trading firms to boost productivity.

Fourthly, a vital contribution of this research is methodological, applying a quantile regression estimator for panel data models (QRPD). In contrast to previous research, the empirical analysis of this Chapter tests for heterogeneous effects of GVC participation among different quantiles of the productivity distribution. Using this technique, we estimate how GVC firms impact their productivity at different quantiles instead of evaluating only the average effects. Quantile regression analysis allows us to investigate the impact of explanatory variables on separate quantiles of the dependent variable's distribution; thus, we get a complete illustration of the relationship between TFP and GVC variables. Previous researchers primarily focused on the effects of firms' GVC participation on productivity, on average.

Moreover, the quantile regression analysis is helpful in this context where GVC participation or the variables of interest may have differing effects throughout the TFP or outcome distribution (Powell and Wagner, 2014). Therefore, Quantile regression is

essential to get an accurate GVC impact on TFP, as firms' productivity responds differently at different quantiles. This QRPD estimator accounts for firm-level fixed effects. It is appropriate for our analysis since unobserved firm factors may exist outside the model or in the composite error term those impact productivity and correlate with GVC status.

The empirical analysis is based on a panel dataset of Indian manufacturing firms. The panel dataset is unbalanced and consists of 12,341 firms in India's manufacturing industry from 1992 to 2019. The manufacturing industry in India is selected for various justifications, especially to investigate how firms' forward GVC participation affects productivity. First, India is the world's third raw material exporter, including cotton and other fabrics, synthetic rubber, filaments, chemicals, plastics, tanning and dyes, etc. In addition, it is the largest cotton exporter and the second-largest exporter of leather garments (Kukreja, 2022). Second, Indian firms are the prime source of raw materials for several global manufacturing companies. For example, Biesse group purchase 64% of their raw materials from Indian firms and, thus, develops their businesses (Ahmed, 2022). Finally, time-series financial data of many publicly listed and unlisted companies of India are available in the Prowess database.

Indian trade liberalisation in 1991 and data availability dictated our focus from 1992 to 2019. India's trade, industrial policies, and technology reforms were intensified in 1991 (Kathuria, 2002). Thus, the trade liberalisation of the 1990s provided enough scope to investigate the effects of liberalised international trade on firm performance (Topalova and Khandelwal, 2011). The sample covers 23 manufacturing industries at the two-digit level, broadly classified by National Industrial Classification, 2008 (NIC-2008) and Broad Economic Category (BEC).

We estimate TFP using microdata of Indian manufacturing firms from 1992 to 2019, employing a standard TFP estimation technique of Levinsohn and Petrin (2003) with Akerberg-Caves-Frazer (ACF) correction. This method's prime advantage is overcoming productivity shocks and endogeneity issues arising from traditional methods such as SFA (Stochastic Frontier Analysis), which generates new methods (Singh and Sharma, 2020). Applying the quantile regression and Smoothed Instrumental Variable Regression models, we find positive and significant impacts of forward GVCs on firm productivity at different quantiles. However, forward GVC

participating firms bring productivity gains more than firms engaged in backward GVCs, though both participation experiences an increase in productivity. On the other hand, firms exporting final goods and two-way traders also enjoy increased productivity.

The remainder of Chapter 2 is structured as follows. Section 2 reviews the relevant literature. Section 3 provides the theoretical justification of firm productivity improvement through participating in GVC. Section 4 delivers the methods, data, variables, and descriptive statistics. We report the results of the empirical analysis in Section 5. In addition, this Section brings a few robustness checks of our empirical findings. Finally, Section 6 concludes.

2. Literature review

The GVCs is a concept that involves the product design to distribute the final product; all activities are essential in bringing a good or service to the final consumer. GVCs require a vertical fragmentation of the production process. Inputs of production, like parts and components, are produced by various firms in different countries; these may be integrated or not within a firm's commercial boundary. After that, they assembled consecutively along the chain or in a final location (Del Prete et al., 2017). Therefore, regional trade agreements are sufficient to further welfare enhancements if value chains are divided within regions, while value chains beyond the region require multiregional agreements (Dedrick et al., 2010).

The empirical productivity literature has investigated firms' learning effects after participating in GVC, and most of them found that firms' productivity improves using imported intermediate inputs in production activities. The theoretical justifications for this productivity enhancement are the availability of better-quality imports, advanced technology, and knowledge by participating global value chains. GVC participation enables a firm to produce specialised items with a comparative advantage; thus, firms can efficiently use its resources like labour, raw materials, energy and capital. Otherwise, a firm may obtain advanced technology information and learns its operation process from overseas suppliers and buyers through importing and exporting (Urata and Baek, 2021).

Additionally, better-quality foreign inputs are available to importing firms, and they can extract technology embodied in imported intermediates and capital goods. Firms face fierce competition in overseas markets while exporting, pushing them to improve competitiveness to survive in international markets. These types of mechanisms are likely to enhance the productivity of GVC participating firms (Urata and Baek, 2022). Likewise, GVC participation leads to a smaller productivity gap between foreign and domestic firms. Usually, domestic firms' productivity gains come from intermediate goods production using high-content foreign raw materials; since increased foreign content on exported items (intermediate and final goods) generates additional productivity gains (Hagemejer, 2015).

Sometimes firms' GVC participation reflects the selection effect indicating high productivity before participating in GVCs and high productivity growth after joining GVCs through the learning effect (Urata and Baek, 2021). On the other hand, the impact of manufacturing firms' GVC participation brings a weak result on productivity though it is still positive. This weakness depends on the time and experience of GVC participating firms to assimilate new technology acquired through GVC participation (Urata and Baek, 2022). A few researchers (Urata and Baek, 2021) found an endogenous relationship between firm productivity and GVC participation and established the theoretical justification of the selection and learning effects of GVC participation.

Different studies define GVC participation differently. To investigate the impact of firms' participation in global value chains (GVCs) on their productivity, Urata and Baek (2021) categorise three types of GVC participation; a firm imports intermediate goods and exports directly, imports intermediate goods but does not export directly and exports directly but does not import intermediate goods. Indirect import means a firm purchases intermediate goods from local suppliers, who produce them using foreign materials. Similarly, indirect export implies a firm produces products used in the goods exported by other firms. Besides, Del Prete et al. (2017) considered firms' GVC participation as international traders (importers or exporters) receiving an internationally recognised quality certification to analyse North African firms' GVC participation and its effects on productivity.

Therefore, to be a GVC firm, it must simultaneously do export and import activities. Importing or exporting firms are international trading firms, not GVC ones. Additionally, to participate in GVC, a firm must import raw materials and export either intermediate or final-demand goods. As we are considering WDR's (2020) GVC definition and products according to their end-use, product-level information is required to verify that the goods imported by an exporting firm are intermediate inputs (rather than final goods) and that this firm uses foreign value-added in its products designed for exports.

Moreover, selection and learning effects are also found for firms that import intermediate goods and export output, not for those that either export or import (Urata and Baek, 2021). Likewise, international trade literature indicates that high-quality imported inputs have a greater effect on firm performance (Bas and Strauss-Kahn, 2014; Feng et al., 2016).

Many researchers use International input-output tables (IIOTs) to specify firms' GVC positions (Wang et al., 2021). Others (Vrh, 2019; Lu et al., 2019; Lu et al., 2018) calculate the Foreign value-added ratio (FVAR) and Domestic value-added ratio (DVAR) in exports to identify a firm's GVC participation. Some studies (Hagemejer, 2015) considered both World Input-Output Database (WIOD) & foreign value added (FVA) to construct GVC measures. An increasing share of FVA in final goods export indicates firms' participation on the low end of a global value chain.

Still, it is unclear which kind of products firms are exporting, raw materials or only final demand goods, since the nature of the exported products is essential to specify a firm's GVC position, backward or forward. However, the existing literature above investigates firms' backward participation and its impact on productivity. Previous studies (Hagemejer, 2015) ignore the downstream or forward GVCs since firms may export raw materials or intermediate inputs using domestic resources without foreign elements.

Manufacturing firms that export final goods using domestically produced raw materials contribute largely to productivity. For example, high-quality demand by global value chains improved horticulture processes in South Africa, Kenya and Uganda, allowing variation and higher yields from fruit and vegetable exports. In addition, by adopting the quality standards demanded by international buyers, firms income increased in Kenya (Barrientos et al., 2016).

India's manufacturing exports have grown between 5% and 10% in pre-Covid-19 years. After the pandemic, global supply chain diversification positively impacted India's export growth. It is expected that India's textile and apparel exports to grow to \$95 billion–\$110 billion by 2028. The presence of a complete value chain, from raw materials to finished goods, favoured market access and the competitive cost of manufacturing will drive this expansion of textile exports (Jain et al., 2022).

Hence, the existing gvc-productivity link and probable improvement in TFP from the forward GVC wing motivated us to investigate this research. It is worth investigating this part of GVC, especially for developing countries with abundant resources like India, since India is the world's third raw material exporter, including cotton and other fabrics, synthetic rubber, filaments, chemicals, plastics, tanning and dyes, etc. India is the largest cotton exporter and the second largest exporter of leather garments (Kukreja, 2022).

Furthermore, abundant resources do not always bring sustainable growth; sometimes, it has adverse effects, called a "resource curse", arising from weaker institutions, more corruption and less educated people. In such cases, exporting excess raw materials may be used by expert producers abroad to add more value; in turn, export earnings improve firm productivity in developing countries. Notably, firms in OECD countries import 4% of their raw materials from India and also highly depend on India for critical raw materials like iron, steel, copper and aluminium (Kowalski and Legendre, 2023).

To do our analysis, we used Broad Economic Categories (BEC) classification to classify the intermediate and final demand (capital and consumption) goods. We followed a few studies that have used Broad Economic Categories (BEC) product classification (Bems and Kikkawa, 2021; Mazzi et al., 2021; Wang et al., 2021; McCleery and DePaolis, 2014). Among these analyses, Mazzi et al. (2021) investigated the effect of firms' GVC participation on firm productivity in Brazil. The researchers found that the fragmentation of exported goods increases firm productivity in Brazil.

Based on the above-explained motivations, the following research question has been raised: Does global value chain involvement affect manufacturing firm productivity? To investigate the research question, we explore two aspects of GVC, backward and forward. First, the impact of firms involved in importing intermediates and exporting

final consumption goods on productivity. Second, exporting firms impact productivity by exporting intermediate goods instead of final consumption goods.

This Chapter aims to assess the presence and relative strength of Indian manufacturing firms' GVC participation in their productivity. We contribute to the existing literature by establishing an innovative link between the international trade literature and the GVC approach by differentiating the product types a firm exports and combining these exports with importing intermediate goods. The reason is that there is no global value addition from exporting final consumption goods without importing raw materials. Additionally, importing intermediates does not create extra value in the global supply chain if the importing firm does not use them in their goods exported to a third country or if imported goods are consumed domestically.

In addition, GVC participation occurs in two ways, backward and forward. Existing studies (Hagemejer, 2015) either ignore the imports of intermediate inputs or specify GVC firms by; importing intermediate goods or exporting output or exporting and importing simultaneously. However, according to the World Development Report 2020 of the World Bank, export and import activities simultaneously represent backward GVC when firms import raw materials and export finished goods for consumption. Only exporting activities may also define GVC participation, but in this case, it depends on the type of products that are exported. If exported items are raw materials, firms can be classified as forward GVC participating firms.

Conversely, Mazzi et al. (2021) nicely represented the fragmentation of exported items and their impact on firm productivity. However, GVC participation requires importing raw materials besides exporting raw materials or final demand goods (WDR, 2020). Also, exporting final goods is not included in GVC participation without importing raw materials or semi-finished goods. Therefore, this research ignores firms' upstreamness or the use of imported intermediates in exported goods.

Moreover, a few researchers (Del Prete et al., 2017) just identified which firms participate in GVCs without any specification of GVC (backward or forward) position or the type of goods (intermediates or capital or final consumption goods) that are exported.

Our research has filled the gap by introducing firms' forward GVC participation and its relationship with productivity. We specify firms with imported raw materials, exported

raw materials, or final-demand goods. This type of product identification determines whether a firm's position in GVCs contributes to a backward or forward global value chain.

3. Theoretical justification

GVCs can cover a full range of interrelated activities performed by firms in different geographic locations to bring out a product from conception to complete production and delivery to final consumers. Typically, a GVC is structured around a central firm, frequently located in a developed country and a network of suppliers in developing countries. The suppliers can be foreign affiliates of the prominent firm or subcontractors (Report, 2020). For example, manufacturing firms in India are the suppliers of foreign firms. Therefore, these GVC firms' productivity gain comes from task specialisation since growth in global value chains increases specialisation in specific activities through trade cost reduction and ICT innovation (Criscuolo et al., 2016).

Final goods production requires many stages that need to function in a planned way. At different stages, suppliers provide inputs that engage in relationship-specific investments to make their parts compatible with other suppliers along the value chain (Alfaro et al., 2019).

Interdependence between international firms may share technology with suppliers because this type of sharing improves the input quality and subsequently boosts the productivity of both firms. In this way, the backward GVC participating firm provides technical support to forward GVC participating firms, and both will benefit. In traditional international trade, firms in different countries compete, but GVCs are firms' networks having common goals, including production cost minimisation or profit maximisation of the whole production chain. Conversely, downstream or backward GVC participating firms benefit when their suppliers or forward GVC participating firms become more productive. GVC firms find sharing their production process and product innovations with their GVC coparticipants beneficial. Furthermore, the relational GVCs benefit firms from learning-by-importing and learning-by-exporting through repeated interactions with highly productive global firms (WRD, 2020).

Besides, the resource-Based View (RBV) theory focuses on external learning in the context of manufacturing firms. It may happen as inter-organisational learning through problem-solving with suppliers and customers (Schroeder et al., 2002). GVCs usually build long-term firm-to-firm relationships, and this relational nature makes GVCs a powerful mechanism for technology transfer along the value chain. GVC firms are interested in technology exchange, specialising in specific tasks and learning from each other (WDR, 2020). The relationships between high-performance importers and their overseas suppliers are characterised by more relational factors, such as trust, interdependency or relation-based investment, compared to less successful importers (Skarmeas and Katsikeas, 2001).

'Learning by exporting' leads to significant performance improvements like firm productivity. This type of improvement comes from exporters being exposed to technology transfers, technical assistance, knowledge flows and spillover and more intense competition in international markets (Montalbano et al., 2018). This learning-by-exporting hypothesis is supported by many empirical studies (Bernard et al., 2003; Verhoogen, 2008; Fafchamps et al., 2008).

Moreover, firms' GVC participation improves their performance in various ways, such as increased opportunities to access managerial expertise, innovation channels, technical knowledge and new markets, as well as allowing a more efficient transfer of resources, thus enhancing their productivity (Agostino et al., 2015; Giovannetti et al., 2015; Theyel, 2013; Woldeesenbet et al., 2012). For example, in the cashew value chain, Mozambique reconstructed its processing industry by partly replacing traditional labour-intensive technology with advanced semi-automatic types of equipment and increasing the installed capacity. This procedure boosted capacity, lowered production costs, and enhanced productivity (Costa and Delgado, 2019).

In contrast, firms' productivity also plays the most prominent role in GVC participation. According to the theoretical studies of heterogeneous firm models, only the more productive firms can afford fixed export costs, such as; transportation costs, distribution or marketing costs and, in turn, become exporters (Melitz, 2003; Bernard et al., 2003). A wide range of empirical analyses has supported this productivity selection theory, and researchers found that more productive firms can become exporters (Mallick and Yang, 2013; Amiti and Konings, 2007).

Regarding the GVC position, firms in developing countries are attracted to backward GVC involvement since it may bring benefits, like improved productivity (Urata and Baek, 2021). Backward GVC participation improves firm productivity through access to high-quality imported inputs (Bas and Strauss-Kahn, 2014; Feng et al., 2016) and knowledge spillovers (Agostino et al., 2016). Firms participating in backward GVC have unrestricted access to high-quality & low-cost imported intermediate inputs, improving export performance using those intermediate inputs (Torres Mazzi and Foster-McGregor 2021).

GVC participation favours learning because the lead firms in developed countries explicitly transfer knowledge and upgrade their suppliers' opportunities, particularly in 'relational' value chains where the coordination is stronger, like leaders' engagement and suppliers' capability to absorb new knowledge both are higher (Brancati et al., 2017). Low-priced imported inputs enhance firm productivity through the direct channel since the expected earnings from exports containing those inputs increase. Imported inputs boost productivity through the indirect channel by overcoming fixed export costs. In addition, importing intermediate inputs reduce export fixed costs by providing the required technology demanded in export markets. Thus, the technology channel boosts firm productivity again (Bas and Strauss-Kahn, 2014).

Conversely, if the domestic market is large, local firms dominate as input suppliers, lowering backward GVC participation. But it increases firms' forward GVC participation. Because of enough industrial capacity in India, manufacturing firms can reduce the use of imported inputs compared to locally sourced inputs in their exports, that lower backward GVC integration. Also, more forward GVC participation and smaller backward GVC participation highlight the importance of domestic suppliers for GVC participation (WDR, 2020). Therefore, Indian manufacturing firms participate more in forward GVC than backward GVC for abundant raw materials.

4. Empirical Framework

4.1 Econometric strategy

As stated in Section 1, this Section intends to find the effects of GVC participation on Indian manufacturing firm productivity. To this end, we specify the following model:

$$tfp_{ijt} = \alpha + \mu_i + \theta_t + \beta_1 for_gvc_{ijt} + \beta_2 back_gvc_{ijt} + \beta_3 two_way_{ijt} + \beta_4 export_final_{ijt} + \gamma' X_{it} + \epsilon_{ijt} \quad (1)$$

Where, tfp_{ijt} indicates the total factor productivity (TFP)³ for firm i operating in industry j observed in year t . for_gvc_{ijt} is a dummy variable equal to 1 if firm i , export raw materials. At the macrolevel, we can easily calculate a country's or an industry's GVC participation level using value-added trade data. However, at the firm level for India, value-added data does not exist. Therefore, following Mazzi et al. (2021), we apply the end-use category of exported goods. According to the GVC definition of WDR (2020), we identify GVC firms based on the import of raw materials and what is the end use of exported goods. Still, the Prowess database provides only information on products firms produce or trade. We do not have the exact information on which firms trade which goods. So, we consider a firm as a forward GVC participant if it is an exporting firm and its associated product is identified as a raw material according to the End-Use category.

Similarly, $back_gvc_{ijt}$ is another dummy variable that takes the value 1 when firm i imports raw materials and adds value to produce exported items. Again, we specify a firm as a backward GVC participant if it is an importing and exporting firm and its associated product is identified as a final good according to the End-Use category. Since we consider raw materials the only imported goods, our main focus is the type of exported goods.

International trade variables like $export_final$ is a dummy variable equal to 1 if the firm i , does not import raw materials but export only final demand goods and two_way_{ijt} represents a dummy variable taking value 1 if firm i , is not a GVC firm but doing exports and imports, a two-way trader.

Additionally, X_{ijt} represents the set of control variables such as size, age, R&D, leverage, and ownership for firm i operating in industry j and observed in year t . Control

³ The detailed TFP calculation is shown in the appendix part.

variables affect a firm's production and later systematically impact firm productivity. μ_i is the firm-specific effect, such as heterogeneity in firms' resources and organisational or managerial structure, θ_t is the time-specific effect or time dummy and ϵ_{ijt} is the random disturbance. Time dummies allow us to control for macroeconomic variables' effect on TFP.

Table 1 represents the definition of the dependent, explanatory and control variables. We winsorised all the continuous explanatory variables at the 1st and 99th percentiles to reduce the impact of outliers. Total factor productivity (tfp) is the dependent variable; GVC and international trade variables are the explanatory variables; age, size, R&D, leverage, and ownership variables are the control variables in our analysis.

Table 1: Variable definition

Variable	Definition and construction	Source
Dependent variable		
TFP	Predicted residual of the production function.	Prowess database
Explanatory variables		
Forward GVC	=1 if a firm exports raw material and 0 otherwise	HS to ISIC to End-use concordance & Prowess database
Backward GVC	=1 if a firm imports raw materials and exports final goods; and 0 otherwise	HS to ISIC to End-use concordance & Prowess database
Two-way traders	=1 if a firm imports and exports but does not participate in GVCs; and 0 otherwise	HS to ISIC to End-use concordance & Prowess database
Final good exporting firms	=1 if a firm exports final goods without importing raw materials and 0 otherwise	Prowess database
Only importing firms	=1 if a firm imports raw material and sells final goods in the domestic market but does not export; and 0 otherwise	Prowess database
Control variables		
Age	Difference between the considered year and establishment year = (year – incorporation year + 1)	Prowess database
Size	Natural logarithm of firm's total assets	Prowess database
R&D intensity	R&D expenditure as a share in sales	Prowess database
Leverage	Natural logarithm of firm's total debt and shareholder's equity ratio	Prowess database
Indian ownership	Proportion of equity shares held by the Indian promoters.	Prowess database
Foreign ownership	Proportion of equity shares held by the foreign promoters.	Prowess database
Institution ownership	Proportion of equity shares held by institutions as non-promoters.	Prowess database

TFP is defined as the predicted residual of the production function. We estimate TFP using the ACF-corrected Levinson-Petrin method.

In productivity estimation, aggregation bias is a common feature of most empirical studies on productivity in developing countries (Kathuria et al., 2010). Aggregating the Translog production function generates biases in total factor productivity (Biørn and Skjerpen, 2004). For instance, domestic firms are less productive than foreign-invested firms; thus, using aggregate data that include foreign firms may exaggerate the positive effects of foreign technology or capital on domestic firms' productivity, generating upward aggregation bias (Hale and Long, 2011). In our analysis, one industry's technologies might affect firms' productivity in other industries, creating upward or downward bias. To avoid this bias, we estimate the production function for several industries, employing 23 Indian manufacturing industries and thus estimated TFP at a disaggregated level rather than an aggregate level.

Firm-level TFP is estimated using the firm-level variables from the Prowess database, such as industrial sales, compensation to employees, gross fixed assets, power and fuel expenses, and raw material expenses. Using ACF correct LP estimator, we predict the residuals after estimating the translog production function. The predicted residuals are total factor productivity. Since we used a natural log of labour, capital, power & fuel and raw materials, the predicted residuals are also in the natural log form. Thus, we estimate the natural logarithm of total factor productivity.

We need value-added, labour, capital, and intermediate input variables to estimate the production function. We consider the cost of raw materials and energy consumption as the intermediate inputs (Choudhry, 2021; Bos and Vannoorenberghe, 2018). The value-added variable is calculated by subtracting the cost of intermediate inputs from total sales. Here, sales mean industrial sales since industrial sales are the company's income from manufacturing goods and related products. Following Bos and Vannoorenberghe (2018), we consider employee compensation as the proxy measure of labour since the database only contains information on monetary terms. Gross fixed assets are the proxy of capital as industrial sales are in gross value. TFP is estimated using the ACF corrected LP approach dividing all manufacturing firms into groups of 23 industries to avoid aggregation bias.

We define imports as the import of raw materials and purchase by the total cost of indigenous and imported raw materials, following Blalock and Veloso (2007). Exports and sales are defined by the export of goods and the total revenue from industrial sales. Then we generate export, import and trade dummies to create GVC and other international trade variables. Trading firms are either exporting or importing or doing both.

Using the Broad Economic Categories (BEC) and the Bilateral Trade in Goods by Industry and End-use Category (BTDIxE) databases, we identified forward, backward, and both types of GVC firms. We find the impact of GVC participation on Indian manufacturing firm productivity.

We define GVC firms according to the World Development Report (2020) definition. Hence, our GVC measures are the dummy variables taking the value 1 if a firm participates in GVC and 0 otherwise. We consider a firm involved in GVC if it imports raw materials or exports raw materials or intermediate goods identified from the end-use categories.

A firm participates in forward GVC if it exports raw materials. Similarly, backward GVC participation indicates firms' involvement with importing raw materials and exporting final or semi-finished goods. If any firm does both actions, it participates in backward and forward GVCs. In the Prowess dataset, there is no information about the exported product. Since we have the information on the firm's main product group from which it gets more than half its revenue, we assume it is exporting that product.

Besides these GVC firms, some participate in international trade by exporting or importing. We classify firms as final goods exporting firms if they export only final goods without importing raw materials. Other firms may import raw materials but not export their finished products or supply them to domestic markets. We mention these firms as only importing firms.

We estimate model (1) using panel data methodology for the following advantages. First, it controls for firm-specific effects or unobserved heterogeneity. For example, firms' organisational or managerial structure differs from firm to firm, which is unobservable and affects their level of productivity. Second, this methodology helps to alleviate the endogeneity problem. Endogeneity arises when a correlation exists between the error term and any of the explanatory variables. It arises in any of the

following three ways: Omitted variables, Measurement error and Simultaneity or reverse causality (Wooldridge, 2010). For example, GVC participation affects firm productivity; simultaneously, productivity may also impact GVC participation through the self-selection effect. Higher productive firms tend to participate more in GVCs. The endogeneity problem can be solved by Applying dynamic regression models where lagged dependent variables are used as instruments. Also, panel data methodology allows us to remove the aggregation bias which arises if time-series models are used to characterise the behaviour of firms.

After the FE (mean-effect) estimation, we consider the following equation shows the quantile fixed effects approach:

$$Q_{tfp_{ijt}}(\tau_j | gvc_{ijt}, Z_{ijt}) = \alpha_1(\tau_j) \times for_gvc_{ijt} + \alpha_2(\tau_j) \times back_gvc_{ijt} + Z'_{ijt}\beta(\tau_j) + \mu_i(\tau_j) + \theta_t(\tau_j), \tau_j \in (0, 1) \quad (2)$$

Here, Z' indicates the vector of covariates such as the final good-exporting dummy, two-way traders dummy, only importing firms and other control variables. μ_i and θ_t are unobserved firm and year-fixed effects. τ_j is the quantile at the j th percentile.

One of the most interesting characteristics of quantile regression is that it can estimate quantile-specific effects, describing the impact of GVC variables not only on the centre but also on the tails of the TFP distribution. Conditional mean regression provides the central or mean effects with interesting summary statistics of the impact of an explanatory variable. Still, they cannot describe the full distributional impact unless the variable affects both the central and the tail quantiles similarly (Chernozhukov and Hansen, 2008). The quantile regression analysis enables us to identify whether the impact of GVC variables is consistent at higher or lower quantiles of TFP distribution (Das and Dutta, 2020).

4.2 Data and model specification

4.2.1 Data

We use the Prowess database provided by the Centre for Monitoring the Indian Economy (CMIE). The Prowess database contains time-series financial data of many publicly listed and unlisted companies in India. The database consists of 16,479 manufacturing firms over the period 1988 to 2019. This database has several

advantages, such as the Prowess data are a panel of firms that enables researchers to track firm performance over time (Goldberg, P.K. et al., 2010).

Firms having missing information on key variables like sales, exports, total assets and the year of establishment are deleted from the sample. A few observations need to be dropped because of economically infeasible values, such as negative values of firm age & power and fuel expenditure, export and intermediate inputs greater than sales. Moreover, the upper and lower 1 per cent quantile of all monetary variables is deleted from the sample to eliminate extraordinary firm shocks from the sample. In addition, we drop firms having only one year's observation to validate the time-fixed effects. By doing several data cleaning processes, we obtained an unbalanced firm-level panel dataset of 23 manufacturing industries classified by NIC-2008 of 5,961 firms and 53,226 firm-year observations in India's manufacturing industry from 1992 to 2019. Focusing on the period of Indian trade liberalisation in 1991, we start our GVC-productivity analysis from 1992 instead of 1988 and consider the investigation period from 1992 to 2019.

Then, we construct the GVC dataset. To do so, we use Broad Economic Categories (BEC revision 4) classification provided by the United Nations Statistics Division (UNSD) to classify the products' nature and firms' GVC participation. At first, we matched the UNSD's 6 digits H.S. (Harmonised System) product codes with the Broad Economic Categories. Then again, we matched the BEC product codes with the International Standard Industrial Classification (ISIC Rev.4) codes. ISIC product classification codes match the Bilateral Trade in Goods by Industry and End-use Category (BTDIxE). H.S. is a standardised numerical method to categorise traded products. We use the UNSD's H.S. to BEC to EUC concordances for product matching. Following the methodology of Carrico et al. (2020), we have selected the HS-2012 version to BEC revision 4 to EUC concordances. ISIC product codes are similar to the National Industrial Classification (NIC-2008) codes. The NIC is a system of classification of all economic activities. We have NIC-2008 codes in the Prowess dataset. Therefore, we merge the Prowess and GVC datasets using the industrial classification codes. After that, we deflate all the monetary variables by the industry average wholesale price indices (WPI) with the base year of 2011-12.

Table 2: Prevalence of GVC, international trading and non-trading firms.

Type of firm	N	N (firm-type)	Share of firms	Average TFP
Forward GVC	109447	12,563	0.115	1.982
Backward GVC	109447	14,761	0.135	1.170
Two-way traders	109447	18,680	0.171	1.165
Final good exporting firms	109447	10,546	0.096	1.900
Only importing firms	109447	11,102	0.101	0.977
Non-trading firms	109447	41,795	0.382	1.608

Source: Authors' calculations from Prowess database.

Table 2 reports the number and observations of each type of firm and their share in the total firms. The table illustrates 109,447 firm-year observations in the sample, of which about 11% are classified as forward GVC firms and 14% participate in backward GVCs. GVC participating firms are mutually exclusive. Regarding international trading firms, 18% are involved with non-GVC two-way trade, 10% participate in exporting final goods and 10% import raw materials. Finally, 38% of firms are fully non-trading, doing business only in domestic markets. Figure 1 nicely represents the proportion of each firm type.

Among all firms, TFP is the highest for those that are participating in forward GVC and lowest for firms that are only involved in importing without any value addition in exports. Therefore, importing raw materials is not good for a firm unless those imported goods are used to produce exported final or semi-finished goods. For comparison with others, we consider this group as the base group.

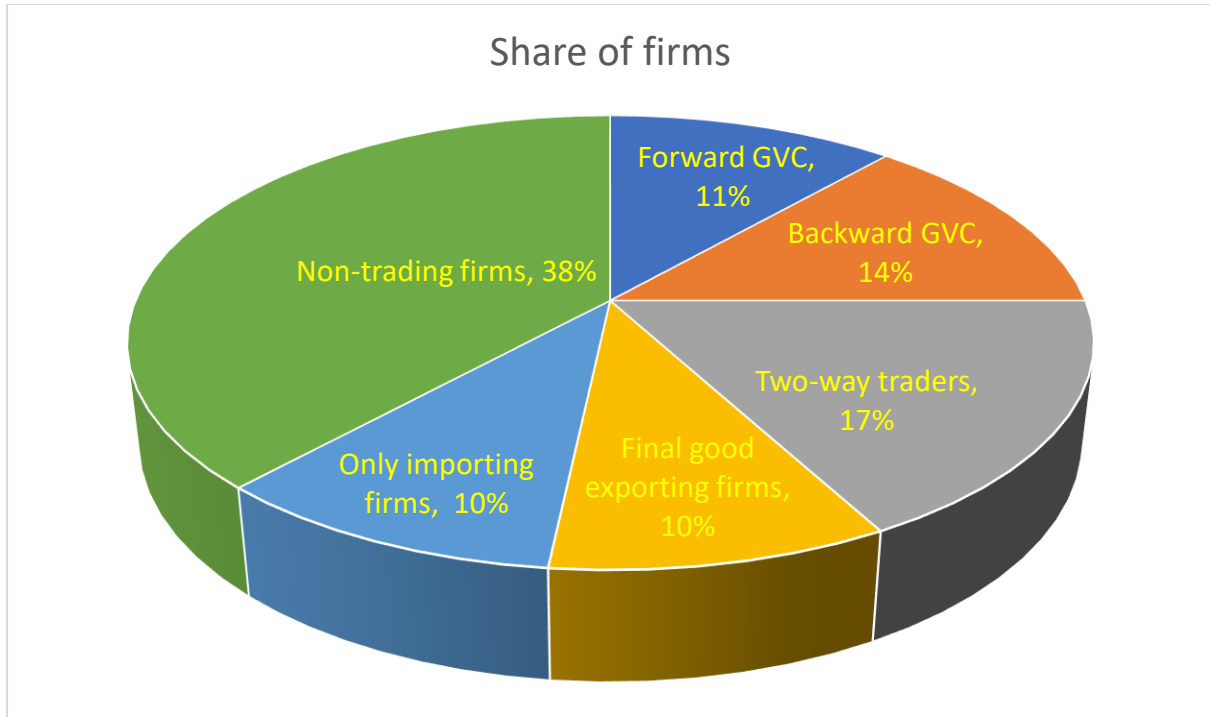


Figure 1: Share of firms based on the type of trading.

Table 3 reports the descriptive statistics of major variables used in the econometrics analysis. The mean value of the natural log of TFP is 1.48, indicating that, on average, firms in this sample have 1.48% total factor productivity. Regarding firm ownership, approximately 43% of ownership goes to Indian promoters, 4.4% ownership holds by foreign promoters, and institutions hold 5.5% ownership as non-promoters, on average.

Table 3: Descriptive statistics

Variables	All firms		GVC firms		Non-GVC firms	
	Mean	SD	Mean	SD	Mean	SD
TFP	1.480	1.056	1.543	0.888	1.459	1.106
Age	25.135	18.497	26.555	18.196	24.663	18.573
Size	2.679	1.756	3.261	1.554	2.485	1.776
R&D	0.268	1.207	0.368	1.258	0.234	1.188
Leverage	-0.176	1.341	-0.266	1.365	-0.146	1.332
Indian ownership	43.092	23.876	42.803	24.119	43.189	23.794
Foreign ownership	4.395	14.393	4.628	14.958	4.317	14.2
Institution ownership	5.536	10.003	5.606	10.13	5.512	9.961

Source: Authors' calculations from Prowess database.

Among different groups, GVC participating firms have 1.54%, and non-GVC firms experience 1.46% productivity, on average. Additionally, Table 3 compares and

indicates whether Indian manufacturing firms participating in GVCs differ from those not. It compares GVC firms and non-GVC firms on key characteristics. It finds that firms engaged in GVCs have statistically significantly higher R&D intensity, total factor productivity and foreign ownership than non-GVC firms.

Table 4: Firms' GVC participation at different quantiles of TFP.

Type of firms	p10		p25		p50		p75		p90	
	N	Percentage	N	Percentage	N	Percentage	N	Percentage	N	Percentage
Forward GVC	233	6.39%	591	9.06%	1,289	14.05%	2,490	22.81%	3,214	27.25
Backward GVC	521	14.29%	1,393	21.37%	2,288	24.93%	2,581	23.65%	2,653	22.50
Total firms	3,646		6,520		9,176		10,914		11,793	
Observations	10,944		27,361		54,723		82,085		98,502	

Source: Authors' calculations from Prowess database.

Table 4 illustrates that firms participate in GVCs differently at different quantiles. In the 10th percentile of TFP, there are 3,646 firms, among which 233 firms participate in forward GVC, meaning that 6.39% of the lower productive firms (10% quantile) involve in forward GVC. In the 25th percentile or 25% quantile, 6,520 firms exist, and 1,393 firms participate in backward GVC, implying that 21.37% of firms are involved in backward GVC at the 1st quartile. Similarly, at the 2nd quartile or 50% quantile, among 9,176 firms, 2,288 firms participate in backward GVCs, indicating that 24.93% of firms are involved in forward GVCs at the 50th percentile.

Overall, higher productive firms are more engaged in forward GVC than backward GVC. In contrast, lower-productive firms tend to participate in backward GVCs. These findings indicate that firms' GVC participation increases with productivity but up to a certain point (50th percentile), then decreases those joining backward GVCs. Instead, with the increase in productivity, firms forward GVC participation raises to the last decile of TFP distribution. With productivity improvement, firms become more capable of installing their own technology and less dependent on foreign raw materials, thus increasing the export of raw materials or intermediate goods.

GVC and non-GVC firms are highly heterogeneous concerning productivity. Using a t-test of mean difference, we found that productivity differences between GVC and non-GVC firms at the mean are statistically highly significant for each quantile.

Table 5: Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	
TFP	1.000													
Forward GVC	0.171	1.000												
Backward GVC	-0.116	-0.142	1.000											
Two-way traders	-0.135	-0.163	-0.179	1.000										
Final good exporting firms	0.130	-0.118	-0.129	-0.148	1.000									
Only importing firms	-0.160	-0.121	-0.133	-0.152	-0.110	1.000								
Non-trading firms	0.095	-0.283	-0.310	-0.357	-0.257	-0.264	1.000							
Age	-0.154	-0.007	0.063	0.101	-0.001	-0.024	-0.102	1.000						
Size	0.209	0.087	0.161	0.229	0.049	-0.043	-0.351	0.208	1.000					
R&D	0.050	-0.021	-0.061	-0.057	-0.039	-0.003	0.127	-0.070	-0.013	1.000				
Leverage	-0.002	0.039	-0.086	-0.011	-0.017	0.009	0.048	-0.107	-0.019	0.004	1.000			
Indian ownership	0.002	-0.010	0.001	-0.018	0.006	0.020	0.004	-0.009	-0.002	0.009	-0.006	1.000		
Foreign ownership	-0.002	0.002	0.010	0.002	-0.002	-0.010	-0.003	0.009	-0.002	-0.004	-0.008	-0.393	1.000	
Institution ownership	0.011	0.004	0.002	-0.009	0.004	-0.009	0.006	0.012	-0.005	-0.008	0.004	-0.135	0.095	1.000

Source: Prowess database - Author's own calculation.

Table 5 reports the pairwise correlation matrix. The correlation matrix shows that the firm's total factor productivity is positively correlated with forward GVC participation (0.171) and export of final goods (0.130). This table also shows that the forward GVC participation negatively correlates with final consumption goods export (-0.118). This correlation suggests that forward GVC participation and export participation (final goods) are substituted in Indian manufacturing. Additionally, the matrix indicates that a GVC firm should mainly focus on exporting; exporting raw materials or final consumption goods improves firm productivity. Table 5 additionally illustrates the collinearity among explanatory and control variables. Our model is free from multicollinearity problems since independent and control variables correlate poorly (less than 40%).

4.2.2 Empirical specification

The prowess dataset provides no information on foreign value added (FVA) or domestic value added (DVA). Therefore, we move to product end-use to identify whether the exported goods entail imported raw materials. Still, we cannot measure the exact domestic value addition to foreign imported inputs. A similar measure is

frequently used to analyse the impact of GVC participation on firm productivity (Mazzi et al., 2021).

Alternative estimation measures are considered to check the empirical findings' robustness. We use alternate product-based TFP estimation instead of an industry-based estimation technique. In our dataset, we consider 13 different types of manufacturing products and calculate TFP. In addition, we utilise different subsets of control variables to authenticate the robustness of our empirical findings.

Besides GVC and international trade variables, several control variables may affect firm productivity. Theoretically, firm size represents a source of heterogeneity because large firms are significantly more productive than small firms (Montalbano et al., 2018). According to the theoretical models of industrial dynamics with heterogeneous firms, larger firms are more productive (Jovanovic, 1982). Therefore, firm size plays an essential role in explaining the differences in productivity among firms. Following Ren et al. (2023), we specify the size of a firm with the natural logarithm of total assets of firm i , in year t .

According to the enterprise or firm life cycle theory, TFP differs depending on the stage the firm is in. In the development stage, TFP is higher due to learning by doing and R&D innovation. In the advanced stage, enterprise TFP is lower as they only follow the same routine. Moreover, age is a vital control variable in our analysis since firm age affects productivity (Tang et al., 2020). In addition, the inverted U-shaped life-cycle pattern indicates that firms start at low TFP; they learn by doing, participating in international markets, undertaking new investments, or realising economies of scale as they age, which increases TFP. After a certain age, their technology, modes of production, and operations likely become obsolete, and TFP advantage wears away (Fernandes, 2008).

The learning and selection effects mainly drive the relationship between firm age and productivity. New firms usually enter the market with a below-average productivity level. Still, they either learn to adapt to the industry's rules to survive or exit it in the next few years. Learning occurs differently by doing, experiencing, and copying others. In addition, firms learn from other firms' investment decisions in research and development, leading to product innovation that improves productivity. Through the

selection process, new firms that find insufficient productivity to generate profits exit the industry within a few years (De Kok et al., 2006).

Research and development expenditure (R&D) also directly impacts firm productivity (Bournakis et al., 2019). Following Banga (2022), we calculate R&D expenditure as a share of sales. Moreover, firm leverage or debt-equity ratio highly impacts firm productivity (Ren et al., 2023). Specifically, when debt rises relative to net worth or a high level of leverage increases the probability of bankruptcy (Nucci et al., 2005). A high ratio implies the firm has excess financial leverage to raise capital and will take on greater risks (Czarnitzki and Hottenrott, 2011). Following Banga (2022), firm leverage is calculated using the natural logarithm of firms' total debt and shareholder's equity ratio. The ratio indicates the ratio of borrowed funds to own funds.

Ownership is a control variable in productivity literature since firm ownership is vital to producing and improving firm productivity (Alvarez and López, 2008; Békés and Harasztosi, 2020; Harris, 2021). Researchers found that Indian ownership in the form of family-controlled firms or business group affiliation of family firms has a direct positive effect on innovation productivity (Lodh et al., 2014). Thus, innovation productivity, in turn, increases total factor productivity. Also, foreign ownership impacts TFP positively since foreign capital inflows increase the total factor productivity by bringing new technologies and their spillover effects to other firms (Batoool et al., 2009). Besides, empirical evidence suggests that institutional ownership positively affects firm performance (Boyd and Solarino, 2016). We consider all types of ownership; Indian, foreign and institutional ownership.

Therefore, firm ownership plays an important role in running a business and changes in firm productivity. The Prowess database has several categories of firm ownership: Indian, foreign, and institutional ownership. Indian ownership indicates the proportion of equity shares that are held by the Indian promoters of the company among total equity. Owners are Indian individuals, Hindu Undivided Families, Central and State governments, corporate bodies, financial institutions, banks, and other promoters. Foreign ownership indicates the percentage of equity shares held by the company's foreign promoters among total equity. Foreign individuals, corporate bodies, institutions, and other foreign promoters are owners. Similarly, institution ownership

indicates the proportion of equity shares that institutions hold as non-promoters of the company among total equity. These are financial institutions and governments.

5. Empirical analysis

In this Section, we explain the main findings of empirical analysis. Section 5.1 estimates manufacturing firms' productivity effects from GVC participation using static (Fixed effects & Quantile regression) models. Section 5.2 provides a robustness check of the empirical findings. We make our analysis different by measuring GVC firms' impact on productivity for different quantiles. We also estimate productivity effects through the forward wing besides the previously investigated backward wing of GVC. The previous researchers overlooked the forward participation of GVC firms. A rigorous investigation between forward GVC and firm productivity link is required because of the increasing demand for Indian raw materials and significant export earnings from those raw materials.

5.1 GVC and firm productivity

Table 4 shows how firm productivity responds to GVC participation or international trading activities. It indicates a positive and statistically significant impact of firms' GVC participation on their productivity. In addition, firms involved in forward GVCs bring more productivity gains than those engaging in backward GVCs though both participation increases productivity. Additionally, two-way traders and final goods exporting firms significantly and positively impact their productivity.

Existing studies on firm-level GVC-productivity analysis estimated the GVC participation coefficients at the mean of the conditional distribution of firm TFP. Although, coefficients are not only estimated at the mean of TFP distribution as the previous studies undertake but also in other quantiles (first quantile, median, third quantile, etc.). Our study will cover this gap using a quantile regression model to investigate Indian manufacturing firms' GVC-productivity analysis at different quantiles.

Table 6: Effect of global value chain participation on firm productivity.

Dep.variable: TFP	(1) Mean effect	(2) p10	(3) p25	(4) p50	(5) p75	(6) p90
Forward GVC	0.912*** (0.011)	1.017*** (0.054)	0.970*** (0.038)	0.906*** (0.037)	0.853*** (0.055)	0.818*** (0.071)
Backward GVC	0.098*** (0.010)	0.206*** (0.049)	0.157*** (0.034)	0.091*** (0.033)	0.036 (0.049)	-0.000 (0.064)
Two-way traders	0.124*** (0.010)	0.248*** (0.047)	0.192*** (0.032)	0.116*** (0.032)	0.054 (0.048)	0.012 (0.061)
Final good exporting firms	0.875*** (0.012)	0.963*** (0.056)	0.923*** (0.039)	0.869*** (0.038)	0.825*** (0.057)	0.796*** (0.073)
Age	-0.021*** (0.001)	-0.021*** (0.003)	-0.021*** (0.002)	-0.021*** (0.002)	-0.021*** (0.003)	-0.021*** (0.004)
Size	0.216*** (0.004)	0.304*** (0.021)	0.264*** (0.015)	0.211*** (0.014)	0.166*** (0.022)	0.137*** (0.028)
R&D	-0.051*** (0.002)	-0.071*** (0.013)	-0.062*** (0.009)	-0.050*** (0.009)	-0.040*** (0.014)	-0.034* (0.017)
Leverage	-0.035*** (0.002)	-0.041*** (0.009)	-0.038*** (0.006)	-0.035*** (0.006)	-0.032*** (0.009)	-0.030** (0.012)
Indian ownership	-0.000 (0.000)	-0.000 (0.001)	-0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Foreign ownership	0.001*** (0.000)	0.001 (0.002)	0.001 (0.001)	0.001 (0.001)	0.001 (0.002)	0.001 (0.002)
Institution ownership	0.001** (0.000)	0.001 (0.002)	0.001 (0.002)	0.001 (0.001)	0.001 (0.002)	0.000 (0.003)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	12,341	12,341	12,341	12,341	12,341	12,341
R-squared	0.741					
Observations	109,447	109,447	109,447	109,447	109,447	109,447

Notes: (i) Robust standard errors are reported in the parentheses; (ii) ***, **, and * respectively represent significance at 1%, 5%, and 10%; (iii) FE estimates are reported in column (1), columns (2) to (6) report quantile estimates.

To avoid the estimation bias resulting from the extreme values, columns 2 to 6 of Table 6 report the regression estimates for five different quantiles, 10%, 25%, 50%, 75% and 90% of the total factor productivity distribution. We can see that the mean coefficients

(FE model) for all explanatory variables are not exactly but approximately similar to the median value of quantile distribution. However, there is a significant difference between the impact on lower (10th) and higher (90th) quantiles. The results showed that at a lower level of productivity, the manufacturing firms' forward GVC participation brings more productivity enhancement. This effect is significantly positive throughout the entire distribution of TFP.

At each quantile, including the mean, forward GVC firms' impact is statistically significant at a 1% significance level. Interestingly, the strength of this impact reduces with the increase in quantiles. Participating in forward GVC, firms' productivity increases by 1.02% more than only importing firms in the 10th quantile. But at the 90th quantile, the impact reduces to 0.82%.

Therefore, if a firm starts exporting raw materials can improve its productivity. Still, the higher productive firms gain less improvement than lower productive firms since lower productive firms have more space to absorb the advantages from forward GVC participation. Also, on average, participating forward GVC increases firm productivity by 0.91% more than one-way importing firms. Likewise, those firms are participating in exporting final goods, enjoying 0.17% more productivity gain than other firms. Firms' GVC participation creates enough scope for learning since the lead firms in developed countries explicitly transfer knowledge and upgrade their suppliers' opportunities in developing countries, particularly if suppliers can absorb new knowledge (Brancati et al., 2017; Report, 2020).

The backward GVC participation also positively and significantly (at a 1% significance level) affects the productivity distribution up to the 50th percentile; their impact becomes insignificant afterwards. Fixed effects estimate indicates that by participating in backward GVC, firms' productivity reduces by 0.10% compared to base group firms. These GVC firms increase productivity increases by 0.21% more than only importing firms at the 10th quantile, and this impact becomes 0.09% at the 50th quantile. Since better-quality foreign inputs improve the quality of exported products, these mechanisms will likely enhance the productivity of backward GVC participating firms (Urata and Baek, 2022; Hagemejer, 2015).

Export enhances productivity; thus, on average, final goods exporting firms increase their productivity by 0.88% more than only importing firms. This impact is positive and

statistically significant at a 1% significance level at each quantile. Exports facilitate knowledge transfer from technologically advanced foreign buyers through learning by exporting (Bigsten and Gebreeyesus, 2009; Benkovskis et al., 2020).

Similarly, non-GVC firms engaged in two-way trade experience a 0.12% productivity improvement compared to only importing firms. Two-way trading (importing and exporting) firms improve total factor productivity through the selection and learning effects (Urata and Baek, 2021; Del Prete et al., 2017).

Our estimated coefficients are positive and statistically significant, indicating a positive relationship between forward GVC and firm productivity, and this finding is consistent with the GVC theory (Montalbano et al., 2018).

Regarding the control variables, firm age has a statistically significant negative impact on the firm's productivity at each quantile and mean level. Our finding indicates that for firms operating in the Indian manufacturing industry, productivity deteriorates as time goes by. Our estimated age coefficients are broadly consistent with the findings of other researchers (Pervan et al., 2017).

Besides, a positive and statistically significant size coefficient is supported by the findings of Ren et al. (2023). As firm size increases, TFP also improves. Conversely, the significantly negative effect of leverage is consistent with Ren et al. (2023) and Banga's (2022) findings. As debt increases compared to firm equity, productivity tends to decrease. Size and leverage are highly significant variables at each quantile.

In addition, the negative coefficient of R&D is supported by the findings of Fernandes (2008). Our findings suggest that engaging in R&D activities firms are getting no TFP advantage. It may happen for lower overall R&D expenditures in Indian manufacturing firms. The adaptation of technology and production processes have not translated into TFP improvements for firms in our sample. Also, a few firms invest in research and development a small amount. Others are not interested in expenses for this purpose. The results suggest that firms engaged in R&D activities do not benefit enough from using advanced technology.

A negative correlation between advanced technology and firm TFP indicates that firms using newer machinery are undergoing a learning process. The firms' absorptive capacity has not developed sufficiently to benefit from the potential efficiency

improvements related to more advanced technologies. However, these technologies will likely be productivity-enhancing once optimal use is reached (Fernandes, 2008). R&D significantly impacts TFP at each quantile.

Moreover, another study found that new technology adoption is associated with reducing the productivity of US manufacturing plants (Syverson, 2004).

Finally, ownership plays a positive role in firm productivity. Though Indian ownership is statistically insignificant, foreign and institutional ownership significantly and positively affect firm productivity. Our findings are similar to the analysis of Batool et al. (2009) & Boyd and Solarino (2016). However, foreign ownership impacts TFP positively since foreign capital inflows increase the total factor productivity by bringing new technologies and their spillover effects to other firms (Batool et al., 2009). Besides, empirical evidence suggests that institutional ownership positively affects firm performance (Boyd and Solarino, 2016).

5.2 Robustness checks

In this Section, we perform robustness checks to validate our earlier findings. We start using alternate product-based TFP estimation instead of an industry-based estimation technique. One commodity group's technology might affect other groups' productivity in the same or different industries, creating upward or downward bias. To avoid this bias, we estimate the production function for 13 different types of manufacturing product groups and calculate TFP. Therefore, we estimated TFP at a disaggregated level rather than an aggregate level.

Table 7 illustrates that the findings of our empirical analysis are robust through checking with different TFP estimation methods. Industry-based and product-based methods bring coefficients' similar sign and significance of GVC and international trade variables.

Table 7: Impact of global value chain participation on firm productivity (product-based).

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.variable: TFP	Mean effect	p10	p25	p50	p75	p90
Forward GVC	0.954*** (0.013)	1.074*** (0.042)	1.019*** (0.029)	0.946*** (0.023)	0.888*** (0.031)	0.849*** (0.040)
Backward GVC	0.151*** (0.013)	0.329*** (0.040)	0.247*** (0.028)	0.138*** (0.022)	0.052* (0.029)	-0.008 (0.038)
Two-way traders	0.164*** (0.012)	0.294*** (0.036)	0.234*** (0.025)	0.155*** (0.019)	0.092*** (0.026)	0.048 (0.034)
Final good exporting firms	0.929*** (0.014)	1.027*** (0.046)	0.982*** (0.032)	0.922*** (0.025)	0.875*** (0.034)	0.842*** (0.044)
Age	-0.018*** (0.001)	-0.020*** (0.003)	-0.019*** (0.002)	-0.018*** (0.001)	-0.017*** (0.002)	-0.017*** (0.003)
Size	0.291*** (0.004)	0.405*** (0.018)	0.353*** (0.013)	0.283*** (0.010)	0.228*** (0.014)	0.190*** (0.018)
R&D	-0.068*** (0.003)	-0.102*** (0.011)	-0.086*** (0.008)	-0.065*** (0.006)	-0.049*** (0.008)	-0.038*** (0.011)
Leverage	-0.045*** (0.002)	-0.051*** (0.007)	-0.048*** (0.005)	-0.045*** (0.004)	-0.042*** (0.005)	-0.040*** (0.007)
Indian ownership	-0.000 (0.000)	-0.000 (0.001)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.001)	-0.000 (0.001)
Foreign ownership	0.001** (0.000)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Institution ownership	0.001 (0.001)	0.002 (0.002)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	-0.000 (0.002)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	12,341	12,341	12,341	12,341	12,341	12,341
R-squared	0.729					
Observations	109,447	109,447	109,447	109,447	109,447	109,447

Notes: (i) Robust standard errors are reported in the parentheses; (ii) ***, **, and * respectively represent significance at 1%, 5%, and 10%; (iii) FE estimates are reported in column (1), columns (2) to (6) report quantile estimates.

Additionally, in Table 8, we utilise different subgroups of control variables to authenticate the robustness of our empirical findings. All subgroups of control variables provide similar signs and significance of coefficients of GVC and international trade variables. Forward GVC and export final dummy variables coefficients are positive and statistically significant. Similarly, backward GVC and two-way traders' variables

significantly and positively impact firm productivity. These findings exactly reflect the outcome of previous empirical analysis. Therefore, our empirical analysis is firmly robust.

Table 8: Impact of global value chain participation on firm productivity (sub-group of control variables).

Dep.variable:	(1)	(2)	(3)	(4)	(5)	(6)
TFP						
Forward GVC	0.912*** (0.011)	0.912*** (0.011)	0.945*** (0.011)	0.942*** (0.011)	0.913*** (0.011)	0.912*** (0.011)
Backward GVC	0.098*** (0.010)	0.099*** (0.010)	0.155*** (0.011)	0.154*** (0.011)	0.098*** (0.010)	0.099*** (0.010)
Two-way traders	0.124*** (0.010)	0.123*** (0.010)	0.184*** (0.010)	0.181*** (0.010)	0.124*** (0.010)	0.123*** (0.010)
Final good exporting firms	0.875*** (0.012)	0.873*** (0.012)	0.901*** (0.012)	0.898*** (0.012)	0.875*** (0.012)	0.873*** (0.012)
Age	-0.021*** (0.001)	-0.020*** (0.001)			-0.021*** (0.001)	-0.020*** (0.001)
Size	0.216*** (0.004)	0.205*** (0.004)			0.216*** (0.004)	0.206*** (0.004)
R&D	-0.051*** (0.002)		-0.040*** (0.002)		-0.051*** (0.002)	
Leverage	-0.035*** (0.002)		-0.027*** (0.002)		-0.035*** (0.002)	
Indian ownership	-0.000 (0.000)			0.000 (0.000)		0.000 (0.000)
Foreign ownership	0.001*** (0.000)			0.001*** (0.000)		0.001*** (0.000)
Institution ownership	0.001** (0.000)			0.001** (0.000)		0.001** (0.000)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	12341	12341	12341	12341	12341	12341
R-squared	0.741	0.739	0.731	0.730	0.741	0.739
Observations	109,447	109,447	109,447	109,447	109,447	109,447

Notes: (i) Robust standard errors are reported in the parentheses; (ii) ***, **, and * respectively represent significance at 1%, 5%, and 10%; (iii) FE estimates are reported in column (1) to (6) with different subsets of control variables.

Regarding the key parameters of our analysis, our findings are consistent with the view that forward GVC firms, on average, show higher productivity improvement compared to backward GVCs.

6. Conclusion

In this Chapter, we examine whether firms' GVC participation acts as a driver for productivity enhancement. Our empirical analysis determines a positive and significant impact of forward and backward GVC participation on firm productivity. To conduct this analysis, we collect firm-level data from the Prowess database. Our empirical findings strengthen the concept that a manufacturing firm's GVC participation changes firm behaviour and productivity.

In most cases, more productive firms decide to participate in the GVC, and hence GVC participation, in turn, increases productivity. Furthermore, we prove that our finding of GVC participation as a driver of firm productivity is robust using alternate proxies for firm productivity and different sets of control variables. The empirical findings also report that participation in GVCs and position within GVCs affect firm productivity.

Our findings have strong policy implications and may help policymakers select the best policies to strengthen the relationship between GVC participation and firms' productivity. Henceforth, policymakers in India may reduce barriers to GVC participation to enhance manufacturing firms' productivity since firms that wish to export raw materials must go through the approval process, in the form of a license or permit, before the shipment. These processes increase uncertainty and costs (license fees) to obtain an export license, and at least some supplier firms become discouraged from exporting and foreign importers are also unwilling to purchase (Fliess et al., 2017). Import tariffs or quotas play a similar role in reducing firms' import of raw materials that may be used to produce better-quality exported products.

Our research has limitations like other studies, which open scopes for future researchers. Though we investigate the impact of the forward and backward GVC on firm productivity, there is still room to enhance this analysis. For future research, it might be interesting to identify the traded semi-finished goods. Since World Development Report 2020 defines a firm involved in forward and backward GVC simultaneously if it imports raw materials and exports semi-finished goods. On one side, the firm is involved in backward GVC by importing raw materials, adding value, and producing an exported product. Another side, the exported product is considered a raw material for the exported item of the imported country's firms. Therefore, the firm in the first country equally plays a role as a forward GVC participant besides a

backward one. Further researchers may investigate whether the impact of trading semi-finished goods differs for firms already existing in Global Value Chains.

References

- Ahmed, S. Manufacturing exports gaining from India's localisation push. *The Times Of India*. [Online]. 1 May, 2022. [Accessed 13 May 2023]. Available from: [Manufacturing exports gaining from India's localisation push \(indiatimes.com\)](https://indiatimes.com/manufacturing-exports-gaining-from-indias-localisation-push)
- Agostino, M., Giunta, A., Nugent, J.B., Scalera, D. and Trivieri, F. 2015. The importance of being a capable supplier: Italian industrial firms in global value chains. *International Small Business Journal*. **33**(7), pp.708-730.
- Agostino, M., Giunta, A., Scalera, D. and Trivieri, F. 2016. Italian firms in global value chains: Updating our knowledge. *Rivista di politica economica*. **7**, pp.155-186.
- Alfaro, L., Chor, D., Antras, P. and Conconi, P. 2019. Internalising global value chains: A firm-level analysis. *Journal of Political Economy*. **127**(2), pp.508-559.
- Amiti, M. and Konings, J. 2007. Trade liberalisation, intermediate inputs, and productivity: Evidence from Indonesia. *American Economic Review*. **97**(5), pp.1611-1638.
- Antràs, P. 2020. Conceptual aspects of global value chains. *The World Bank Economic Review*. **34**(3), pp.551-574.
- Banga, K. 2022. Impact of global value chains on total factor productivity: The case of Indian manufacturing. *Review of Development Economics*. **26**(2), pp.704-735.
- Barrientos, S., Knorringa, P., Evers, B., Visser, M. and Opondo, M. 2016. Shifting regional dynamics of global value chains: Implications for economic and social upgrading in African horticulture. *Environment and Planning A: Economy and Space*. **48**(7), pp.1266-1283.
- Bas, M. and Strauss-Kahn, V. 2014. Does importing more inputs raise exports? Firm-level evidence from France. *Review of World Economics*. **150**, pp.241-275.
- Batool, H., Sadia, H. and Ahmad, E. 2009. Impact of Foreign Ownership on Total Factor Productivity: Evidence from Food, Tobacco and Financial Business Sectors of Pakistan. *Journal of Economic Cooperation & Development*. **30**(2).
- Bems, R. and Kikkawa, A.K. 2021. Measuring trade in value added with Firm-Level Data. *Journal of International Economics*. **129**, p103434.
- Benkovskis, K., Masso, J., Tkacevs, O., Vahter, P. and Yashiro, N. 2020. Export and productivity in global value chains: Comparative evidence from Latvia and Estonia. *Review of World Economics*. **156**, pp.557-577.
- Bernard, A.B., Eaton, J., Jensen, J.B. and Kortum, S. 2003. Plants and productivity in international trade. *American economic review*. **93**(4), pp.1268-1290.
- Bigsten, A. and Gebreeyesus, M. 2009. Firm productivity and exports: Evidence from Ethiopian manufacturing. *The Journal of Development Studies*. **45**(10), pp.1594-1614.
- Biørn, E. and Skjerpen, T. 2004. Aggregation biases in production functions: a panel data analysis of Translog models. *Research in Economics*. **58**(1), pp.31-57.

- Bournakis, I., Papanastassiou, M. and Pitelis, C. 2019. The impact of multinational and domestic enterprises on regional productivity: evidence from the UK. *Regional Studies*. **53**(2), pp.159-170.
- Boyd, B.K. and Solarino, A.M. 2016. Ownership of corporations: A review, synthesis, and research agenda. *Journal of Management*. **42**(5), pp.1282-1314.
- Brancati, E., Brancati, R. and Maresca, A. 2017. Global value chains, innovation and performance: firm-level evidence from the Great Recession. *Journal of Economic Geography*. **17**(5), pp.1039-1073.
- Butt, M.N., Baig, A.S. and Seyyed, F.J. 2021. Tobin's Q approximation as a metric of firm performance: an empirical evaluation. *Journal of Strategic Marketing*. pp.1-17.
- Chernozhukov, V. and Hansen, C. 2008. Instrumental variable quantile regression: A robust inference approach. *Journal of Econometrics*. **142**(1), pp.379-398.
- Costa, C. and Delgado, C. 2019. The Cashew Value Chain in Mozambique.
- Czarnitzki, D. and Hottenrott, H. 2011. R&D investment and financing constraints of small and medium-sized firms. *Small business economics*. **36**, pp.65-83.
- Das, D. and Dutta, A. 2020. Bitcoin's energy consumption: Is it the Achilles heel to miner's revenue? *Economics Letters*. **186**, p108530.
- De Kok, J., Fris, P. and Brouwer, P. 2006. On the relationship between firm age and productivity growth. *Scales Research Reports H*. **200617**, p4.
- DE L'OCDE, B.D.D. and LES ÉCHANGES, S. 2015. OECD BILATERAL TRADE DATABASE BY INDUSTRY AND END-USE CATEGORY.
- Dedrick, J., Kraemer, K.L. and Linden, G. 2010. Who profits from innovation in global value chains?: a study of the iPod and notebook PCs. *Industrial and corporate change*. **19**(1), pp.81-116.
- Del Prete, D., Giovannetti, G. and Marvasi, E. 2017. Global value chains participation and productivity gains for North African firms. *Review of World Economics*. **153**(4), pp.675-701.
- Fafchamps, M., El Hamine, S. and Zeufack, A. 2008. Learning to export: Evidence from Moroccan manufacturing. *Journal of African Economies*. **17**(2), pp.305-355.
- Feng, L., Li, Z. and Swenson, D.L. 2016. The connection between imported intermediate inputs and exports: Evidence from Chinese firms. *Journal of International Economics*. **101**, pp.86-101.
- Fernandes, A.M. 2008. Firm productivity in Bangladesh manufacturing industries. *World Development*. **36**(10), pp.1725-1744.
- Fliess, B., Idsardi, E. and Rossouw, R. 2017. Export controls and competitiveness in African mining and minerals processing industries.
- Galvao Jr, A.F. 2011. Quantile regression for dynamic panel data with fixed effects. *Journal of Econometrics*. **164**(1), pp.142-157.

- Ge, J., Fu, Y., Xie, R., Liu, Y. and Mo, W. 2018. The effect of GVC embeddedness on productivity improvement: From the perspective of R&D and government subsidy. *Technological Forecasting and Social Change*. **135**, pp.22-31.
- Giovannetti, G. and Marvasi, E. 2016. Food exporters in global value chains: Evidence from Italy. *Food Policy*. **59**, pp.110-125.
- Giovannetti, G., Marvasi, E. and Sanfilippo, M. 2015. Supply chains and the internationalisation of small firms. *Small Business Economics*. **44**, pp.845-865.
- Giovannetti, G. and Vannelli, G. Global Value Chains-Participation and Firm Productivity: Evidence from Egypt.
- Goldar, B. and Goldar, A. 2022. Impact of Participation in Global Value Chains on Productivity of Industrial Firms: Evidence from Indian Manufacturing. *Available at SSRN 4255082*.
- Hagemejer, J. 2015. Productivity spillovers in the GVC. *The case of Poland and the new EU member states*.
- Hale, G. and Long, C. 2011. Are there productivity spillovers from foreign direct investment in China? *Pacific Economic Review*. **16**(2), pp.135-153.
- Jovanovic, B. 1982. Selection and the Evolution of Industry. *Econometrica: Journal of the econometric society*. pp.649-670.
- Kaplan, D.M. 2022. Smoothed instrumental variables quantile regression. *The Stata Journal*. **22**(2), pp.379-403.
- Kathuria, V., Raj, R. and Sen, K. 2010. State business relations and manufacturing productivity growth in India. *Available at SSRN 1544290*.
- Kowalski, P. and Legendre, C. 2023. Raw materials critical for the green transition.
- Linh, D.T.T. 2021. Literature Review on Determinants of Total Factor Productivity (TFP) at the Firm-Level. *Cross Current Int J Econ Manag Media Stud*. **3**(4), pp.47-55.
- Lodh, S., Nandy, M. and Chen, J. 2014. Innovation and family ownership: Empirical evidence from India. *Corporate governance: An international review*. **22**(1), pp.4-23.
- Lu, Y., Lu, Y., Xie, R. and Yu, X. 2019. Does global value chain engagement improve firms' wages: Evidence from China. *The World Economy*. **42**(10), pp.3065-3085.
- Lu, Y., Shi, H., Luo, W. and Liu, B. 2018. Productivity, financial constraints, and firms' global value chain participation: Evidence from China. *Economic Modelling*. **73**, pp.184-194.
- Mallick, S. and Yang, Y. 2013. Productivity Performance of Export Market Entry and Exit: Evidence from Indian Firms. *Review of International Economics*. **21**(4), pp.809-824.
- Mazzi, C.T., Foster-McGregor, N. and de Sousa Ferreira, G.E. 2021. Production fragmentation and upgrading opportunities for exporters: An empirical assessment of the case of Brazil. *World Development*. **138**, p105151.

- McCleery, R. and DePaolis, F. 2014. So you want to build a trade model? Available resources and critical choices. *Economic Modelling*. **40**, pp.199-207.
- Melitz, M.J. 2003. The impact of trade on intra-industry reallocations and aggregate industry productivity. *econometrica*. **71**(6), pp.1695-1725.
- Montalbano, P., Nenci, S. and Pietrobelli, C. 2018. Opening and linking up: firms, GVCs, and productivity in Latin America. *Small Business Economics*. **50**(4), pp.917-935.
- Nucci, F., Pozzolo, A. and Schivardi, F. 2005. Is firm's productivity related to its financial structure? Evidence from microeconomic data. *Rivista di politica economica*. **95**(1), pp.269-290.
- Pervan, M., Pervan, I. and Ćurak, M. 2017. The influence of age on firm performance: Evidence from the Croatian food industry. *Journal of Eastern Europe Research in Business and Economics*. **2017**(1), pp.1-10.
- Powell, D. and Wagner, J. 2014. The exporter productivity premium along the productivity distribution: evidence from quantile regression with nonadditive firm fixed effects. *Review of World Economics*. **150**, pp.763-785.
- Ren, X., Jin, C. and Lin, R. 2023. Oil price uncertainty and enterprise total factor productivity: Evidence from China. *International Review of Economics & Finance*. **83**, pp.201-218.
- Ren, X., Zhang, X., Yan, C. and Gozgor, G. 2022. Climate policy uncertainty and firm-level total factor productivity: Evidence from China. *Energy Economics*. **113**, p106209.
- Report, W.D. 2020. *Trading for Development in the Age of Global Value Chains*. The World Bank Washington, DC, USA.
- Schroeder, R.G., Bates, K.A. and Junttila, M.A. 2002. A resource-based view of manufacturing strategy and the relationship to manufacturing performance. *Strategic management journal*. **23**(2), pp.105-117.
- Singh, A.P. and Sharma, C. 2020. Does selection of productivity estimation techniques matter? Comparative analysis of advanced productivity estimation techniques. *Indian Growth and Development Review*. **13**(1), pp.125-154.
- Skarmetas, D.A. and Katsikeas, C.S. 2001. Drivers of superior importer performance in cross-cultural supplier–reseller relationships. *Industrial Marketing Management*. **30**(2), pp.227-241.
- Syverson, C. 2004. Market structure and productivity: A concrete example. *Journal of political Economy*. **112**(6), pp.1181-1222.
- Taglioni, D. and Winkler, D. 2016. *Making global value chains work for development*. World Bank Publications.
- Tang, H.-l., Liu, J.-m. and Wu, J.-g. 2020. The impact of command-and-control environmental regulation on enterprise total factor productivity: A quasi-natural experiment based on China's "Two Control Zone" policy. *Journal of Cleaner Production*. **254**, p120011.

- Theyel, N. 2013. Extending open innovation throughout the value chain by small and medium-sized manufacturers. *International Small Business Journal*. **31**(3), pp.256-274.
- Urata, S. and Baek, Y. 2021. Does GVC participation improve firm productivity? A study of three developing Asian countries.
- Urata, S. and Baek, Y. 2022. Impacts of firm's GVC participation on productivity: A case of Japanese firms. *Journal of the Japanese and International Economies*. **66**, p101232.
- Van Biesebroeck, J. 2008. The sensitivity of productivity estimates: Revisiting three important debates. *Journal of Business & Economic Statistics*. **26**(3), pp.311-328.
- Verhoogen, E.A. 2008. Trade, quality upgrading, and wage inequality in the Mexican manufacturing sector. *The Quarterly Journal of Economics*. **123**(2), pp.489-530.
- Vogel, A. and Wagner, J. 2010. Higher productivity in importing German manufacturing firms: self-selection, learning from importing, or both? *Review of World Economics*. **145**(4), pp.641-665.
- Vrh, N. 2019. The DNA of the domestic value added (DVA) in exports: Firm-level analysis of DVA in exports. *The World Economy*. **42**(9), pp.2566-2601.
- Wang, W., Thangavelu, S. and Lin, F. 2021. Global value chains, firms, and wage inequality: Evidence from China. *China Economic Review*. **66**, p101585.
- Woldesenbet, K., Ram, M. and Jones, T. 2012. Supplying large firms: The role of entrepreneurial and dynamic capabilities in small businesses. *International Small Business Journal*. **30**(5), pp.493-512.
- Wooldridge, J.M. 2010. *Econometric analysis of cross section and panel data*. MIT press.
- Zhu, H. 2022. Global value chains, trade liberalisation, and productivity: a stochastic frontier analysis of Chinese manufacturing firms. *Applied Economics*. pp.1-14.