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Technical Change Through Global Value Chains: Evidence From Firms Worldwide

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ABSTRACT

We study the impact of global value chain (GVC) participation on firms' innovation, productivity, and other indicators of technical change. Our dataset encompasses heterogeneous firms from 144 countries at different income levels over the period 2006–2025. Using difference-in-differences and matching strategies, we find that GVC participation leads to increased innovation and other technological improvements, with gains driven primarily at the extensive margin and by importing rather than exporting activities. Among innovation types, product innovation responds more strongly than process innovation. Importantly, the nature of innovation differs systematically across development levels: GVC participants in lower-income countries benefit from access to foreign technology, while those operating in more advanced economies engage more in formal, R&D-intensive innovation.

JEL Classification: C31, F14, F15, O31, O33

1 | Introduction

The increased complexity of economic globalization has significantly transformed international trade. One of the most notable changes is the increase in the trade of intermediate goods, which are parts or components sent around the world to be further transformed and assembled into final products for consumers. This process, known as the international fragmentation of production along global value chains (GVCs), has become a central part of the world economy, renewing the debate on the costs and benefits of globalization (R. Baldwin 2014).

Participation in GVCs is often seen as a key strategy for innovating or catching up with frontier technologies and achieving higher productivity growth. The literature identifies several channels supporting this strategy.[1] By outsourcing specific tasks to international suppliers, companies gain access to higher-quality and more diverse intermediate goods. At the same time, selling to foreign buyers within these chains offers learning opportunities, larger production scales, and higher profits. Greater profitability then encourages firms to invest and innovate, boosting productivity. In addition, collaboration between foreign and domestic suppliers within a value chain facilitates knowledge transfer and technological spillovers through relational transactions and backward linkages (Antràs 2020; Ambos et al. 2021). Clearly, understanding these mechanisms requires paying attention to the specific internationalization activities at play and to the heterogeneity of the domestic production contexts of firms.

Historical trends and macro-level data on GVCs, such as trade in value-added statistics, help to characterize the global macroeconomic picture (e.g., Gereffi 1999; R. E. Baldwin 2016; Constantinescu et al. 2019; Pahl and Timmer 2020). However, countries themselves do not engage in trade. In practice, GVCs are driven by individual firms' decisions of importing foreign inputs to produce the goods and services they export and/or by exporting domestically produced inputs to partners in charge of downstream production stages. The study of firm-level determinants and consequences of this international organization

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of production belongs to a renewed research agenda that seek to document firms' international ties (Antràs 2020). This paper aims at contributing to this micro-level literature by proposing a focus on innovation outcomes from firms operating in different domestic contexts around the world.

While valuable insights emerge from empirical micro-level studies on trade and foreign direct investment (FDI), the complexity of trade and production within GVCs calls for deeper investigation. Most existing research examines only one trade-related dimension of GVC participation—such as exporting (e.g., Benkovskis et al. 2020), importing (e.g., Amiti and Konings 2007; Goldberg et al. 2010; Bas and Strauss-Kahn 2014; Halpern et al. 2015), or offshoring (e.g., Amiti and Wei 2009; Schwörer 2013)—with each dimension examined in isolation. Moreover, micro-level analyses often focus on country-specific cases (e.g., Yan and Baldwin 2014; Prete et al. 2017; Benkovskis et al. 2020; Brancati et al. 2017; Reddy et al. 2021), which constrains the generalization of their findings and the possibility of identifying different reactions of GVC participants according to their location. Yet, understanding how the impact of GVC participation on firms' technological progress varies with the local level of development and institutional framework requires comparative data across diverse production contexts and an emphasis on the overall coordination of trade flows within firms.

In this paper, we document the relationship between firms' participation in GVCs and innovation in a large sample of heterogeneous firms from 144 countries with different income levels, covering the period 2006–2025. We assimilate firms' GVC participation to their simultaneous coordination of importing and exporting activities. Our sample and methodology allow us to examine different types of innovation—namely product, process, and market innovation—which are our main outcomes of interest. We further characterize this innovation activity by analysing the engagement in R&D activities, the use of foreign technology, and skill intensity. In addition, we examine whether GVC participation ultimately translates into technological changes such as higher productivity or lower unit cost, changes in capital intensity, and quality upgrades. These exercises provide a better understanding of the implications of GVC participation on overall firms' technical change.

We use data from the World Bank Enterprise Surveys (WBES), a representative cross-country survey providing comprehensive information on firm characteristics (Reddy et al. 2021; Prete et al. 2017). This dataset allows us to compare innovation activities between GVC-participating firms and non-participating ones, while controlling for comparable firm-level attributes. To ensure that our results capture GVC-specific effects rather than arm's-length trade more broadly, we further contrast GVC-participating firms with those engaged exclusively in conventional exporting or importing activities. Following Antràs (2020), we interpret two-way trade activity as an indication of the "extensive" margin of GVC participation. We also seek to obtain further insights on the "intensive" margin by comparing GVCs firms of different levels of import and export activity.

From an empirical point of view, understanding the relationship between GVC participation and innovation is complicated by endogeneity issues due to reverse causality and selection bias. Certain initial characteristics of firms—including innovation itself (Reddy et al. 2021)—can influence both their decision to enter GVCs and their future technical progress. This complex relationship highlights the importance of rigorous empirical approaches. While no single method can fully address these challenges, various strategies can help.

In this study, we apply different methods inspired by design-based identification. First, exploiting a panel data structure available for a subset of firms, we use a dynamic difference-in-differences (DiD) approach that allows staggered treatment, meaning that firms may enter GVCs at different times within a panel dataset. Second, using a larger dataset with a cross-section structure, we apply propensity score matching (PSM) to address self-selection bias. By matching firms involved in two-way trade (our definition of GVC participants) with similar firms that are not engaged in such trade (our "control" group), we consistently isolate the effects of GVC integration on innovation and related outcomes. Alternatively, within this cross-section analysis, we also employ entropy balancing (EB) and coarsened exact matching (CEM) methods to address non-random sample selection. Complementing the dynamic panel identification with this cross-section evidence provides further characterization of the implications of GVCs on technical change.

Our results consistently show that participation in GVCs fosters innovation and increases labor productivity relative to firms that do not engage in two-way trade. However, a closer look at the mechanisms suggests that these gains are driven mainly by importing rather than exporting activities. Specifically, while two-way traders exhibit a higher innovation probability than pure exporters, the performance gap between two-way traders and pure importers is statistically insignificant (in panel estimates) or smaller in magnitude (in cross section). These results suggest that GVC participation enhances firm-level innovation mainly through learning-by-importing rather than learning-by-exporting. This is consistent with previous evidence on productivity documented by Muûls and Pisu (2009) for Belgian firms, which is extended here to innovation outcomes in a globally representative sample and using design-based estimation techniques.

We also document that, among innovation types, product innovation responds more strongly to GVC participation than process innovation across all specifications. Consistently, GVC firms are more likely to pursue quality certifications, exhibit lower average labour costs, but use higher-cost inputs – reflecting an emphasis on quality upgrading through specialized imported inputs. Within the group of GVC participants, we find that higher intensity of two-way trade flows does not deliver further innovation, a result that qualifies the broadly positive narrative on GVC participation on its "intensive" margin.

Beyond the average effects, our cross-country design allows us to uncover an important dimension of heterogeneity that has received limited attention in the existing literature: the type of innovation associated with GVC participation differs systematically across development levels. In lower-income countries, GVC participation is primarily associated with the adoption of foreign

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technologies—closer to imitation than to technology-frontier innovation. Firms in these economies benefit mainly from exposure to foreign inputs and knowledge spillovers that enable them to upgrade their products and processes without necessarily engaging in formal R&D. By contrast, firms in upper-middle and high-income economies leverage GVC participation to pursue more R&D-intensive innovation with increased skill intensity. They also become more capital-intensive. This distinction between technology adoption from abroad and knowledge creation represents a substantive contribution of our analysis that could not be identified in single-country studies.

The remainder of the paper is organized as follows. Section 2 reviews the related literature, discusses the mechanisms linking GVC participation and firm innovation, and presents the main research hypotheses. Section 3 outlines the empirical identification strategy. Section 4 describes the data and sample. Section 5 presents the empirical results on innovation and explores the underlying channels. Section 6 briefly concludes.

2 | GVC Participation and Firm Innovation: Mechanisms and Hypotheses

Participation in GVCs can influence firm-level innovation through multiple, interconnected channels. GVC participants simultaneously import intermediate inputs and export outputs across internationally fragmented production networks, creating opportunities for technology diffusion, knowledge transfer, and stronger R&D incentives. This section reviews the main theoretical and empirical literature underpinning these channels, moving from importing or exporting to the combined role of two-way trade within GVCs. We close each subsection by deriving testable research questions that guide our empirical analysis.

2.1 | Importing: Quality, Variety, and Learning-By-Importing

Importing intermediate goods can improve firm performance through several interconnected mechanisms. First, access to a broader variety of foreign inputs increases complementarity between domestic and imported technologies, enabling firms to produce goods they could not have manufactured otherwise (Grossman and Helpman 1991; Markusen 1989). Second, imported inputs often incorporate superior foreign technologies, directly raising the quality of domestic production and enabling firms to respond to more sophisticated demand (Halpern et al. 2015; Bas and Strauss-Kahn 2014). Third, exposure to foreign suppliers generates knowledge spillovers—a mechanism closely related to "learning-by-importing"—through which firms absorb technological and organizational knowledge embodied in imported goods and supplier relationships (Coe and Helpman 1995; Keller and Yeaple 2013; Loof and Andersson 2010).

These channels have direct implications for innovation. By broadening the set of available technologies, expanding knowledge and raising the quality of intermediate inputs, importing lowers the cost of innovation and increases its expected returns. Firms gain access to process innovations embodied in imported machinery and components, and product innovations become feasible through the combination of domestic and foreign knowledge. This logic is formalized in models of endogenous innovation with heterogeneous inputs (Grossman and Helpman 1991; Rivera-Batiz and Romer 1991), where a greater variety of intermediate goods raises the productivity of the innovation sector.

Empirical evidence supports these channels across both emerging and developed economies. Productivity and innovation gains linked to imported inputs have been documented for Brazil (Schor 2004), Chile (Kasahara and Rodrigue 2008), India (Goldberg et al. 2010; Topalova and Khandelwal 2011), Hungary (Halpern et al. 2015), France (Bas and Strauss-Kahn 2014), and Sweden (Loof and Andersson 2010). Using Indonesian data, Amiti and Konings (2007) show that trade liberalization in intermediate inputs raises firm-level productivity substantially, primarily through access to higher-quality imported inputs. Halpern et al. (2015) provide direct evidence for Hungary, showing that importing raises firm productivity through both the variety and quality of imported inputs, with foreign-owned firms benefiting most. Importantly, these productivity gains are closely associated with innovation: firms that import more diverse and higher-quality inputs are more likely to introduce new products and processes, as access to superior intermediates reduces the technological distance to the technology frontier.

2.2 | Exporting: Learning-By-Exporting and Demand Incentives

Exporting exposes firms to international standards and practices, stimulating innovation through mechanisms commonly described as "learning-by-exporting". Selling in foreign markets encourages firms to upgrade their products, adopt new technologies, and improve production processes in order to meet international demand and remain competitive. Beyond learning effects, the anticipation of higher demand and export profits can itself act as a powerful incentive for firms to invest in R&D and innovation, a mechanism typically present in models featuring heterogeneous firms and endogenous technological change (Costantini and Melitz 2007; Bustos 2011; Bas and Ledezma 2015; Kugler and Verhoogen 2012). In appraising export profits, forward-looking firms invest in R&D and accelerate innovation in order to ensure a profitable entry into export markets. When innovation is driven by current R&D expenditure—instead of sunk investments—the level of R&D spending and the probability of successful innovation are also higher for exporters, with new exporters making significant jumps (Akcigit and Melitz 2022).

Empirical evidence on learning-by-exporting is mainly concentrated in developing and newly industrialized economies. Studies have documented learning effects in African countries (Van Biesebroeck 2005), and in emerging or transition economies such as Slovenia (De Loecker 2007, 2013), and Estonia and Latvia in the context of GVC participation (Benkovskis et al. 2020). Evidence from developed countries is more limited but points in a similar direction, particularly when tracking knowledge flows related to foreign sales (Crespi et al. 2008). Using Taiwanese data, Aw et al. (2011) show that export decisions and

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R&D investments are closely intertwined. Similarly, Lileeva and Trefler (2010) find that Canadian plants that expanded exports following the Canada–U.S. Free Trade Agreement achieved productivity gains, higher innovation rates, and greater technology adoption—benefits that were amplified by improved access to U.S. intermediate inputs, illustrating a complementarity between importing and exporting (Feng et al. 2016; Bas and Strauss-Kahn 2014; Chor et al. 2021; Muûls and Pisu 2009). Using Belgian firm-level data, Muûls and Pisu (2009) show that firms engaging in both imports and exports are the most productive, followed in descending order by importers only, exporters only, and non-traders—a productivity hierarchy that parallels our findings for innovation outcomes.

Importantly, the literature also provides guidance for distinguishing between differentiated incentives for introducing new product or new processes. Klepper (1996) shows that product innovation dominates at the beginning of the product life cycle, when firms focus on introducing and differentiating new offerings, while process innovation becomes more relevant in later stages as firms seek efficiency gains at scale. Similar strategies are plausible when entering international markets. A closely related insight is that the scope for product differentiation in a market provides additional returns to product innovation, whereas with homogeneous goods, process innovation is the optimal strategy (Flach and Irlacher 2018). We expect these differentiated incentives to be particularly present in GVCs as the output required within an international production process is likely to be customized and requires continuous adaptation.

2.3 | Global Networks: Interactions Between Different Innovation Forms From Different Development Levels

Beyond individual trade flows, firms participating in GVCs operate within globally coordinated production networks in which tasks are allocated according to comparative advantage, inducing efficiency in global factor allocation (Grossman and Rossi-Hansberg 2008). Crucially, GVC participation combines both importing and exporting activities simultaneously, mostly through relational transaction, which creates synergies that go beyond what either activity generates in isolation. Participation in such networks of specialized tasks facilitates knowledge transfer and interactions through multiple channels, including training by lead firms, the diffusion of quality standards, managerial exchanges, and collaboration (Keller and Yeaple 2013; Pietrobelli and Rabellotti 2011). Through these mechanisms, GVC participation can generate distinctive and probably complementary innovation processes both through the adoption of existing technologies—that is, imitation—and through the creation of new knowledge—that is, technology-frontier innovation.

This distinction has important implications for how firms benefit from GVC participation across different stages of economic development, according to their position relative to the technology frontier as emphasized by the endogenous growth literature on innovation and catching-up Acemoglu et al. (2006). Firms in lower-income countries often lack the internal research capabilities necessary to generate technological breakthroughs. As a result, their innovation activity tends to rely primarily on the adoption and adaptation of foreign technologies and learning gained through international production networks. By contrast, firms in upper- middle- and high-income countries typically operate closer to the technology frontier with formally trained staff, enabling them to leverage GVC integration to pursue formal, research-intensive innovations. We can expect GVCs to connect different innovation processes to each other, as learning is expected to be interactive, which means that technology-frontier innovating firms also benefit from international knowledge flows.

This network-based view of innovation can be related to the recent evolution of "innovation models" (i.e., a paradigm conceptualizing innovation) described by Cohendet and Simon (2017) within an interdisciplinary literature at the frontier of economics, management, geography, and sociology. Early models of innovation—the linear & closed model (from world war I to the mid-1980s) and the interactive & closed model (from the mid-1980s to early 21st century)—treat innovation as largely confined within firm boundaries. In these frameworks, knowledge generation may either be centralized in a home-country R&D laboratory or distributed across internal subsidiaries, but it remains internal to the firm. A third model, the interactive & open innovation framework, emerges in the early 2000s and extends this perspective by emphasizing the role of external collaborations and geographically dispersed knowledge sources (Chesbrough 2003). In this setting, firms increasingly rely on external actors (suppliers, consumers, users, etc.) and global knowledge networks for technological development. As noted by Ambos et al. (2021), key international business phenomena associated with this model—including R&D offshoring, outsourcing, and global knowledge networks—correspond closely to the defining characteristics of GVC participation.

Empirical evidence supports the idea that firms embedded in global production networks benefit from such knowledge linkages. Using firm-level data for Italy, Brancati et al. (2017) show that relational GVC participation—involving hardly codifiable production processes and skill-intensive firms with an active role in value-chain governance—is associated with a significantly higher propensity to engage in innovative activities and R&D investment. In contrast, other forms of GVC participation offer no clear innovation premium relative to purely domestic firms.

2.4 | Research Hypotheses

Taken together, the literature suggests that participation in GVCs can foster innovation through access to new technologies, profit incentives, and different forms of learning and network effects, but that the magnitude and nature of these effects depend both on the type of innovation considered and on the development level of the participating economy. These considerations motivate a stepwise investigation of the impact of GVC participation on firm innovation. We begin with a broad comparison and progressively refine our hypotheses to account for the type

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of innovation and the role of development level. Our testable hypotheses can be summarized as follows:

Hypothesis 1. *Participation in GVCs indices a higher probability of innovation than having no trade or traditional trade activity. As discussed previously, GVC participation simultaneously exposes firms to new technologies and foreign inputs (through importing) and to international quality standards, higher demand, and competitive pressures (through exporting), while embedding them in global knowledge networks that provide both the resources and the incentives to innovate.*

Hypothesis 2. *Among innovation outcomes, product innovation responds more strongly to GVC participation than process innovation. Joining GVCs implies entering a global production network where, before gaining scale effects, product customization and quality improvement are dominant strategies.*

Hypothesis 3. *The type of innovation differs across levels of development: technology adoption and imitation dominate in GVC participants in lower-income countries, whereas R&D-intensive and high-skill innovation activities dominate in more advanced economies. This hypothesis follows from the insights provided by the endogenous-growth literature emphasizing different innovation strategies according to firms' distance to the world technology frontier. The prediction is also complemented by the view that innovation paradigms have shifted toward an interactive and open innovation model, with GVCs putting these innovation modes into direct interaction.*

3 | Empirical Strategy

The most straightforward way to evaluate the effects of GVC participation would be to assume that participation is randomly distributed among firms. In that case, the effects could be assessed through a simple comparison of innovation outcomes between firms engaged in GVCs and those that are not. However, firms involved in two-way trade are likely to differ systematically from other firms (e.g., size or experience), and these differences may also influence their propensity to innovate. If so, GVC participation is not randomly assigned and simple comparisons would yield biased estimates. Therefore, in order to identify causality, a key challenge is to control for potential confounders and, if possible, to exploit individual-level variations. To address these issues, we implement two complementary approaches using panel and cross-section information.

3.1 | Panel-Data Identification

We first exploit the panel structure of the data for firms observed in more than one survey wave. For this subsample we implement a Difference-in-Differences (DiD) approach to estimate the causal effect of GVC participation by comparing firms that switch into GVC participation with comparable firms that do not change participation status. The DiD framework controls for unobserved time-invariant factors affecting both treatment and outcomes and relies on the parallel trends assumption.

Our analysis follows a staggered treatment design, as proposed by de Chaisemartin and D'Haultfoeuille (2024), allowing firms to enter treatment at different points in time. Using the authors' notation, let $Y_{g,t}$ denote the actual outcome of group (firm) g at time t, and $Y_{g,t}(d_1, \ldots, d_t)$ the potential outcome if the treatment history from period 1 to t were $(d_1, \ldots, d_t)$. Suppose that the first period of treatment of group g is $F_g \geq 2$. The parameter of interest is the expected difference between the observed outcome after ℓ periods of treatment and the counterfactual outcome that would have been obtained if the initial treatment status had remained unchanged (from $t = 1$ to $t = F_{g-1+\ell}$):

$$\delta_{g,\ell} = E\left(Y_{g,F_g-1+\ell} - Y_{g,F_g-1+\ell}(D_{g,1}, \ldots, D_{g,1})\right) \quad (1)$$

The unobserved counterfactual in Equation (1) is the main identification challenge. In our case, the treatment is binary (two-way trade) and firms can potentially enter and leave treatment within the sample.[2] The treatment assignment can be written as follows:

$$\forall (g,t), D_{g,t} = 1\{E_g \geq t \geq F_g\}, \text{with } 2 \leq F_g \leq E_g \quad (2)$$

where $D_{g,t}$ denotes the treatment status of group g at period t, F_g the first treatment period and E_g the last. Since treatment can last several periods ($T > 2$) and firms may enter or exit treatment at different times, the expected effect becomes:

$$\delta_{g,\ell} = E\left(Y_{g,F_g-1+\ell}\left(\mathbf{0}_{F_g-1}, \mathbf{1}_{E_g-F_g}, \mathbf{0}_{F_g-1+\ell-E_g}\right) - Y_{g,F_g-1+\ell}\left(\mathbf{0}_{F_g-1+\ell}\right) | \mathbf{D}\right) \quad (3)$$

where $\mathbf{D}$ is the vector containing the treatment status of all groups across periods. When $F_g - 1 + \ell > E_g$, the outcome is measured after treatment has ended and is compared to the counterfactual of remaining untreated.

To estimate $\delta_{g,\ell}$, de Chaisemartin and D'Haultfoeuille (2024) propose an event-study estimator, DID_ℓ, which is conditionally unbiased under the assumptions of non-anticipation and parallel trends. The estimator compares the outcome evolution of firms that switch into treatment with that of firms sharing the same initial treatment status but that have not yet switched. The parallel trends assumption can be assessed conditional on observable characteristics. We therefore control for firm-level characteristics such as size, age, foreign ownership, and access to credit (discussed in Section 4.4), as well as firm and time fixed effects to account for unobserved firm heterogeneity and common time shocks.

3.2 | Matching and Weighting Techniques in Cross-Section

Our second approach exploits the full sample using cross-sectional matching and reweighting techniques—propensity score matching (PSM), entropy balancing (EB), and coarsened exact matching (CEM). These methods address selection bias by comparing treated firms with observationally similar control firms based on observable characteristics.

Let D be a binary indicator of treatment status, equal to one if a firm is a two-way trader and zero otherwise. Let Y_i^1 denote the

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innovation outcome for firm i if the firm is engaged in two-way trade and Y_i^0 otherwise, all other characteristics being equal. The treatment effect for firm i can be written as $Y_i^1 - Y_i^0$, where one outcome is observed and the other represents the counterfactual. We are interested in estimating the average treatment effect on the treated firms (ATT), that is:

$$\begin{aligned} ATT &= E\left[Y_i^1 \mid D=1\right] - E\left[Y_i^0 \mid D=1\right] \\ &= E\left[Y_i^1 \mid D=1\right] - E\left[Y_i^0 \mid D=0\right] - \left(E\left[Y_i^0 \mid D=1\right] - E[Y_i^0 \mid D=0]\right) \end{aligned} \tag{4}$$

where $E\left[Y_i^1 \mid D=1\right]$ and $E\left[Y_i^0 \mid D=0\right]$ are observed and $E\left[Y_i^0 \mid D=1\right] - E\left[Y_i^0 \mid D=0\right]$ represents the selection bias. Hence, Equation (4) can only be identified if this bias disappears, that is, if $E\left[Y_i^0 \mid D=1\right] = E\left[Y_i^0 \mid D=0\right]$.

PSM, EB, and CEM address this selection problem by constructing comparable treatment and control groups based on observable characteristics, **X**. This requires that the treatment satisfies some form of exogeneity, namely the conditional independence assumption. This assumption states that, conditional on a vector of observable characteristics, the outcome of interest (innovation) is independent of treatment status. Conditional on **X**, expected innovation in the absence of GVC participation would therefore be the same for paired firms, that is, $E\left[Y_i^0 \mid D=1, \mathbf{X}\right] = E\left[Y_i^0 \mid D=0, \mathbf{X}\right]$.

Imbens (2004) shows that if the conditional independence assumption holds, biases due to observable factors can be removed by conditioning on the propensity score. The ATT under PSM becomes:

$$ATT = E\left[Y_i^1 \mid D=1, p(\mathbf{X})\right] - \mathrm{E}\left[\mathrm{Y}_\mathrm{i}^0 \mid \mathrm{D}=0, \mathrm{p}(\mathbf{X})\right] \tag{5}$$

where $p(\mathbf{X})$ denotes the probability of treatment conditional on observable characteristics.

We proceed in two steps to obtain the ATT under PSM. First, we estimate the propensity score using a benchmark probit model explaining the likelihood that a firm is a two-way trader. The dependent variable takes the value of one if the firm is a two-way trader and zero otherwise. We include the determinants of GVC participation described in Section 4.1 as well as country, industry, and year fixed effects. Second, firms are matched based on their estimated propensity scores using a nearest neighbour algorithm.[3]

Entropy balancing, in turn, reweights observations so that the distribution of observable characteristics is balanced between the treatment and control groups. In our implementation, weights are chosen to satisfy balancing constraints on the first and second moments of the covariates $\boldsymbol{X}$. Compared with conventional matching approaches where control units may be discarded, entropy balancing retains all observations by reweighting them to achieve covariate balance.

CEM differs from PSM and EB in that it temporarily coarsens continuous variables into substantively meaningful intervals and performs exact matching within the resulting strata. Units that do not share common support within these coarsened groups are excluded from the analysis. Compared to PSM, which relies on an estimated propensity score, and EB, which directly reweights observations to satisfy balance constraints, CEM emphasizes ex ante covariate stratification and may lead to some sample reduction due to the coarsening structure.

4 | Data and Descriptive Statistics

4.1 | Data Sources

We use firm-level data obtained from the World Bank's Enterprise Surveys (WBES) spanning 144 countries from 2006 to 2025. These datasets are based on stratified random samples of firms, drawn from the eligible population using stratification by size, location, and sector.[4] While the WBES is not designed to provide national representativeness, the stratification across three dimensions facilitates coverage of a significant portion of total trade.

4.2 | GVC Participation

At a firm level, GVC participation can be constructed with information from surveys asking specific questions about a firm's GVC participation. Unfortunately, this type of data is restricted to a few countries and few years. We therefore build on the approaches adopted by Benkovskis et al. (2020) and Rigo (2021) and assume that a firm participates in GVCs if it imports inputs and exports its output—a measure of the extensive margin of GVC participation according to (Antràs 2020). To discern the patterns of engagement in GVCs among firms in our sample, we extract relevant information from the survey using the following questions: (1) "What proportion of the establishment's material inputs or supplies, purchased during the year, originated from foreign sources?"; (2) "What percentage of the establishment's sales constituted direct exports?"

We construct our benchmark GVC participation measure as a binary indicator variable, equal to one for firms engaged in two-way trade, that is, simultaneously involved in both exporting and importing activities, and zero otherwise. Exporters are defined as firms directly exporting a portion of their sales, while importers are those firms procuring a fraction of their material inputs or supplies from foreign countries.[5] We also identify firms that are exclusively engaged in importing (pure importers) or exclusively engaged in exporting activities (pure exporters).

Examining the pattern of international trade implication of firms, Table 1 reveals that among our 196,515 observations having non-missing information in our main variables, nearly 52% pertain to firms that do not participate in foreign trade, a proportion notably higher among firms in low and low-middle income countries. Among the observations indicating trade activity, the majority, especially in developing economies (which represent the bulk of our sample), are firms engaged solely in imports. Considering the full sample, two-way traders represent

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TABLE 1 | Export–import status for firms in the sample.

	Income level				
Trade status	**Low**	**Low-middle**	**Upper-middle**	**High**	**All**
Non-traders (%)	59.25	58.65	47.74	41.00	51.93
Traders (%) *of which*	40.75	41.35	52.26	59.00	48.07
Pure exporters	4.65	5.13	6.96	7.03	5.94
Pure importers	28.70	26.46	29.84	29.78	28.40
Two-way traders	7.40	9.76	15.45	22.20	13.73
Obs.	30,215	72,629	46,512	47,159	196,515

Note: The table reports the percentage of observations according to trade status for the 2006–2025 period. The sample is restricted to non-missing information for trade status and the baseline cross-section model (column (2) in Table A4).

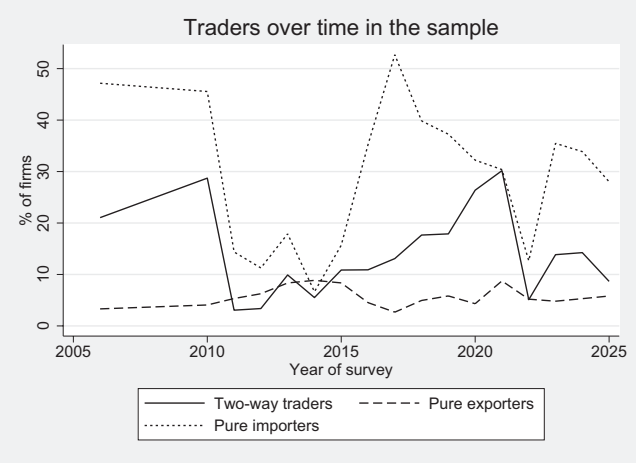

FIGURE 1 | Evolution of two ways traders, importers, and exporters over time. *Source:* Own calculation based on the WBES data.

approximately 14% of observations showing trade, a share that is notably higher in high-income countries.

Figure 1 provides basic facts about the evolution of trading firms in our sample over time. As seen, the fraction of firms that are engaged in trade is relatively small but has increased over time. Note that two-way traders became increasingly important after 2010: before the COVID-19 crisis, they constituted about only 30% of the sample. The figure also shows that the pandemics primarily affected GVC operations in 2021 and 2022. By examining the previous distribution of firms engaged in international trade, it appears, albeit not conclusively, that importing often precedes exporting (and so two-way trade). This pattern may reflect the fact that importing generally involves lower entry barriers: it is typically less costly and subject to less market uncertainty than exporting.

4.3 | Innovation and Related Outcomes

Our main outcome variable is firm innovation. Following the Schumpeterian perspective, innovation refers to the introduction of new combinations in production and markets, including new products, new production methods, and new organizational forms. Empirical practice typically distinguishes between product and process innovation, which capture different dimensions of technological change. Product innovations refer to the introduction of new or significantly improved goods or services. They relate to what firms produce, including both tangible goods and intangible services. Process innovations, in contrast, refer to how goods and services are produced, encompassing new or improved production methods, technologies, or organizational processes that enhance efficiency.

We consider two main indicators of innovation. First, product innovation is measured using a binary variable, *Firm Product Innovation*, which takes the value of one if the firm introduced a new or significantly improved product or service during the previous 3 years and zero otherwise. To capture the scope of product innovation, we construct the variable *Market Product Innovation*, which equals one if the firm reports that at least one of its new or improved products was also new to the firm's main market.

Second, we measure process innovation through the binary variable *Process Innovation*, which takes the value of one if the firm introduced a new or significantly improved production process during the same period (the previous 3 years). According to the WBES questionnaire, process innovations may involve "new methods of manufacturing products or offering services; logistics, delivery, or distribution methods for inputs, products, or services; or supporting activities for processes".

In addition to these specific indicators, we construct two additional measures of innovation. The first is a broader indicator, *Any Innovation*, which takes the value of one if the firm reports having undertaken any form of innovation activity, and zero otherwise. The second is a more stringent indicator, *Product and Process Innovation*, which equals one if the firm introduced both a product innovation and a process innovation during the period. With this latter indicator we seek to capture changes in firms' business model as they generally need the introduction of both new product and new process. Since all innovation measures are binary indicators, the estimated coefficients in the empirical analysis are interpreted as changes in the probability of introducing an innovation.

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TABLE 2 | Two-sample *t*-test for innovation outcomes.

Innovation form	Two-way trade	Obs.	Mean	SE	$\Delta<0$ *p*	$\Delta\neq0$ *p*	$\Delta>0$ *p*
Any	Yes	26,981	0.602	0.003			
Innovation	No	169,534	0.373	0.001			
	All	196,515	0.405	0.001			
	Δ		0.229	0.003	1.000	0.000	0.000
Product & Process	Yes	26,981	0.299	0.003			
	No	168,557	0.163	0.001			
Innovation	All	195,538	0.182	0.001			
	Δ		0.136	0.003	1.000	0.000	0.000
Firm-product Innovation	Yes	26,981	0.502	0.003			
	No	169,533	0.285	0.001			
	All	196,514	0.315	0.001			
	Δ		0.217	0.003	1.000	0.000	0.000
Market-product	Yes	25,821	0.323	0.003			
	No	165,419	0.171	0.001			
Innovation	All	191,240	0.192	0.001			
	Δ		0.151	0.003	1.000	0.000	0.000
Process innovation	Yes	26,981	0.400	0.003			
	No	168,558	0.252	0.001			
	All	195,538	0.272	0.001			
	Δ		0.148	0.003	1.000	0.000	0.000

Note: The table reports mean differences tests (Δ) for innovation engagement dummies between two-way traders and the rest of firms during 2006–2025 period. Unequal variances are considered. The sample is restricted to non-missing information in innovation outcomes and the baseline cross-section model (column (2) in Table A4).
Abbreviation: SE, standard error.

A preliminary analysis of the relationship between innovation and GVC participation can be obtained by comparing the mean differences between the treated and control groups (see Table 2). The results show a significantly higher propensity to innovate among two-way traders relative to other firms. This pattern holds across all four innovation indicators considered. As expected, these primary statistics also document a larger propensity for firm-product innovation over process innovation for two-way traders. A smaller fraction of these GVC participants engage in both types of innovation. In order to formally test for Hypothesis 2, positing product innovation as a dominant strategy over process innovation along GVC, we construct a specific outcome variable, *Product* versus *Process*, as the difference between the Firm-Product Innovation and Process Innovation, which seeks to measure at the firm level the increased incidence of product innovation.

In order to further explore the nature of innovation at different development stages, we move beyond measuring innovation outcomes to distinguish whether innovations are more likely to stem from formal knowledge creation or from the adoption and adaptation of existing technologies. This distinction is in line with research Hypothesis 3 and is particularly relevant in lower-income economies, where firms are often expected to rely more on imitation and adoption of existing innovations rather than on the generation of entirely new inventions, and where formal R&D activities may be less prevalent.

Accordingly, we consider three indicators. First, we use a binary variable capturing whether the firm conducts research and development activities (*Doing R&D*). Engagement in R&D is interpreted as a proxy for innovation driven by formal devices of knowledge creation through trained staff aiming at the development of new technologies or products.[6] Second, we use a binary variable indicating whether the firm makes use of technology licensed from a foreign-owned company, excluding office software (*Foreign Technology*). This variable is interpreted as capturing innovation through the adoption or adaptation of externally developed technologies, which is closely associated with imitation-based or technology-transfer processes. Third, we include the *Skill share*, defined as the proportion of workers with upper (tertiary) education relative to the total number of employees in the firm. This variable captures the firm's human capital intensity and its capacity to absorb, adapt, and generate new knowledge.

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TABLE 3 | Descriptive statistics of control covariates, by income group (raw sample).

Income level	Statistics	Size category	Firm's age	Foreign ownership	Access to credit
Low	Mean	1.578	16.206	0.123	0.230
	SD	0.719	13.759	0.329	0.421
	Obs.	30,215	30,215	30,215	30,215
Low-middle	Mean	1.782	20.307	0.070	0.303
	SD	0.777	15.242	0.254	0.460
	Obs.	72,629	72,629	72,629	72,629
Upper-middle	Mean	1.799	20.624	0.087	0.401
	SD	0.784	16.570	0.282	0.490
	Obs.	46,512	46,512	46,512	46,512
High	Mean	1.725	26.482	0.094	0.455
	SD	0.757	23.423	0.291	0.498
	Obs.	47,159	47,159	47,159	47,159
All	Mean	1.741	21.233	0.088	0.351
	SD	0.769	17.959	0.283	0.477
	Obs.	196,515	196,515	196,515	196,515

Note: The table provides descriptive statistics for main control variables (excluding country, industry, and year dummies). The sample is restricted to non-missing information for the baseline cross-section model (column (2) in Table A4).
Abbreviation: SD, standard deviation.

In order to further characterize the innovative process of firms, we use broader technical change indicators that allow us to grasp insights on the ensuing consequences of innovation. First, we measure *Labor Productivity* as the value added per worker (in constant terms). The World Bank also provides estimates of total factor productivity (*TFP*), based on gross output using a translog production function and taking into account heterogeneity across countries and industries. This information exists, however, for a reduced sample of firms in the WBES. We match this information with our panel and cross-section datasets.

Secondly, *Capital Intensity*, defined as capital stock over permanent full-time workers, allows for understanding whether labour productivity improvements are related to capital-labour substitution rather than to improvements in total factor productivity or in labour-augmenting technical change. Finally, several indicators on average costs and a binary variable indicating if the firm has an internationally-recognized *Quality Certification* will help to analyse how GVC participation induces cost-saving and/or quality upgrading. Among the measures of average costs we consider: the *Average costs of Intermediates* measured as the cost of intermediate inputs per unit of sales, the *Average Cost of Labour*, computed as labour costs per unit of sales, and *Variable Average Costs*, defined here as the sum of the previous components. Descriptive statistics of innovation-related outcomes by country income category are presented in Table A3 in Appendix.

4.4 | Control Variables

We complement our data set with the following variables that have been identified as systematic determinants of GVC participation at the firm level: (1) Size, which is a categorical variable for small, medium, and large firms according to the number of employees; (2) The firm's age in years; (3) Foreign ownership, which is a dummy variable indicating if the firm has at least 10% share of equity held by foreign companies, zero otherwise; (4) Access to credit, which is a dummy variable that takes the value of one if the establishment has a line of credit or loan from a financial institution, zero otherwise.[7]

The first variables, related to firm's size and age, allow us to control whether larger and older firms can more easily afford the sunk costs of a vertical integration decision (Blomström and Lipsey (1991)). Moreover, smaller firms are also supposed to be in a less advantageous situation vis-à-vis production and sales due to their small-scale production and sales, which makes it difficult for them to take advantage of the benefits arising from scale economies. At the same time, old firms might be more competitive as they have survived competition and have accumulated capital and experiences, which help them participate in GVC networks (Urata and Baek (2020)). Accordingly, we expect firm size and age to have a positive impact on GVC participation. Next, poor access to credit makes it difficult for firms to enter exports if they have to finance entry costs upfront (Chaney (2016)). In addition to the sunk cost, exporters need trade finance to pay for variable costs, including costs of intermediate goods and labour because the receipt from the export sales tends to lag for a relatively long period compared to domestic sales. Credit constraints have indeed been shown to severely impede firms' export activity (Minetti and Zhu (2011)). Foreign ownership of a firm is likely to be positively correlated with GVC participation, as one of the main objectives of multinational corporations establishing

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a foreign affiliate, especially under vertical integration, is to construct GVCs. These firm characteristics are also typically considered as influencing innovation propensity as innovation requires sunk investments under uncertainty (see Mairesse et al. (2025) for a recent survey). They are thus crucial for addressing potential endogeneity bias.

Table 3 presents descriptive statistics for covariates across both the treatment and control groups. Marked differences are evident between the two groups. Specifically, firms involved in GVCs tend to be larger in terms of workforce size and older. They also possess a larger propensity to have foreign-owned equity shares and enjoy greater access to credit. These characteristics align with the anticipated relationship between two-way trade engagement and the various control variables previously discussed.[8]

5 | Results

The WBES predominantly follows a cross-sectional approach, with each wave capturing a distinct set of firms at a specific point in time. However, given the enhanced time span provided by recent updates, we can identify firms surveyed in at least two waves, enabling us to implement a panel DiD analysis within this subset of heterogeneous firms. To complement this initial panel data analysis, we also conduct PSM, EB, and CEM estimations based on a cross-sectional approach, which allows us to increase the number of observations and to test the impact of GVC participation on a variety of related channels and identify potential heterogeneity across countries and specific trade activities.

5.1 | A Panel Data DiD Approach

The DiD approach requires panel data in which treated and untreated cohorts share the same initial status, followed by some firms switching their treatment status while others remain untreated throughout—allowing for a comparison of pretreatment innovation indicators. Therefore, we identify firms that have been surveyed in at least two country-specific waves. This selection, however, results in a reduction in the overall number of observations. Nevertheless, the panel component is not negligible: approximately 20,541 firms (24.5% of the available sample) are observed in at least two waves, including nearly 3000 observed three times. Table A1 reports the distribution of observations across waves and innovation types, confirming that innovation incidence is meaningful in every wave, which ensures that identification does not rely on marginal subsamples.[9]

5.1.1 | Baseline DiD Estimates

The DiD graphs display the placebo estimators for the wave preceding the first treatment onset, as well as the dynamic effects with the confidence intervals. In both cases, the evolution of the outcome variable (i.e., the various forms of innovation) is measured relative to the last period before the treatment changes, $t = 0$. Contrary to the regular difference-in-differences, that takes advantage of all the data in the entire "after" period to estimate the effect, each period's effect estimate in the dynamic treatment effects approach relies on data exclusively from that one period and from the reference period.

The dynamic DiD results should be interpreted as follows. With cohorts beginning treatment at varying times, the dynamic effects aggregate these groups by aligning them according to the number of years post-treatment initiation. Given that we have data from at most four waves, with few countries having a fourth one, we estimate only the first two dynamic effects, which capture the evolution in process or product innovation after one or two periods (waves) of exposure to GVC. Estimations control for individual and time fixed effects, and for some relevant firm characteristics that may vary over time—namely size, age, access to credit, and foreign ownership. The parallel trend assumption has thus been taken conditionally on these covariates.

Figure 2 presents the benchmark results, where the treatment group consists of two-way traders and the control group includes all other firms—that is, only importers, only exporters, and nontraders. Placebo estimates are close to zero and statistically insignificant (shown to the left of $t=0$). These placebo tests suggest that, in the years preceding GVC participation, the differences in outcome variables between treated and control firms were, on average, not statistically different from zero. This absence of pretreatment trends implies that selection bias is unlikely to drive the results.[10]

The immediate effect at $t=1$, which captures the impact at the onset of treatment, reveals a significant increase in the probability of innovating. The average DiD for all three types of innovation activities, including the simultaneous introduction of new products and processes—which can capture deeper innovations at the core of business models—is statistically significant and approximately 0.1, that is, a 10% increase in innovation propensity. The results also support the hypothesis that the treatment effect evolves as a function of the time elapsed since participation began. We observe a decline in the magnitude and statistical significance of the innovation impulse after two periods of exposition, although the cumulative effect (not reported) remains significant.

5.1.2 | GVC Vs. Traditional Trade

We now aim to gain a better understanding of how two-way traders compare to firms with alternative trade statuses. The rationale is that firms engaged in both importing and exporting activities tend to be more deeply integrated into international production networks. If such increased internationalization drives technical change, two-way traders are expected to achieve innovative advantages over firms that do not trade at all, but do they have advantages relative to firms engaged in traditional trade, without being involved in global production networks?—that is, relative to firms that buy foreign inputs but sell all their output domestically or relative to firms that sell abroad but use only domestic inputs?

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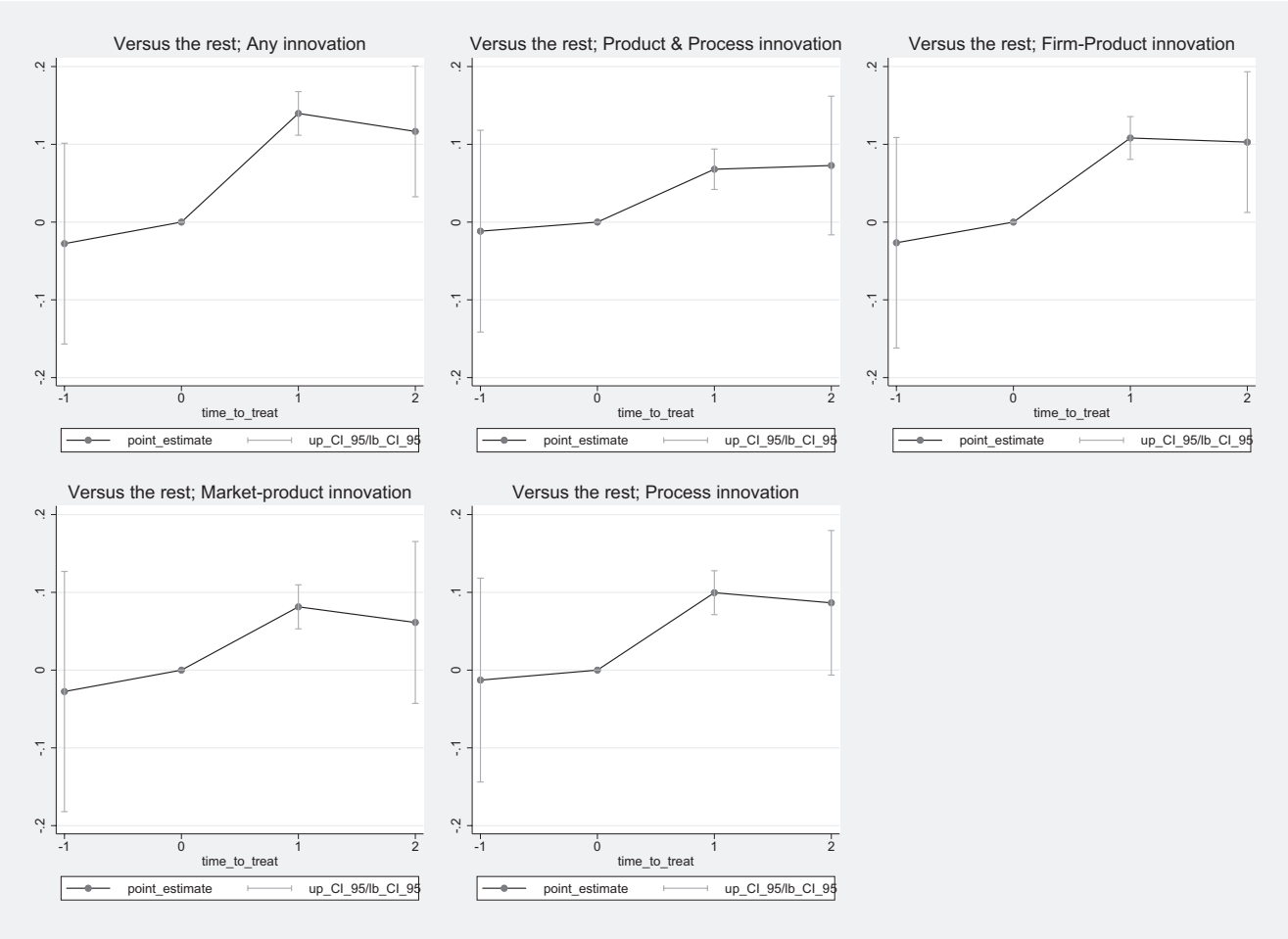

FIGURE 2 | Impact of two-way trading on innovation, relative no-trade or one-way trade (DiD estimates). The figures show the average effect of two-way trading on firm's innovation. It measures the average difference between the outcome evolution of firms that both import and export at the same time and the outcome evolution of those that did not. In the *x*-axis values before zero represent the placebo (parallel trend assumption). The zero value represents the reference pre-treatment date and values above are dynamic effects after exposition to treatment.

To this end, two-way traders are designated as the treatment group, while the original control group is decomposed into three categories: (i) non-traders, (ii) pure exporters, and (iii) pure importers, which are used as separate control groups in distinct DiD estimations. Non-traders are firms that have neither exports nor imports at a given wave. Pure exporters are defined as firms with direct exports but no imports, while pure importers conduct imports only.

Figure 3 presents the DiD results for the previously described decomposition of control groups. As expected, when comparing two-way traders with non-traders, we observe significant positive effects, consistent with theoretical mechanisms discussed in Section 2. Importantly, while two-way traders exhibit a higher probability of engaging in product innovation than pure exporters—with estimated impact ranging from 8% to 10% in the first period of treatment—no significant differences emerge when the control group consists of pure importers, even at the onset of treatment.

Our finding suggests that the primary source of innovative advantage stems from importing activities rather than exporting ones. In other words, learning-by-importing—through the technology and knowledge embodied in intermediate inputs, machinery, and supplier relationships—accounts for most of the observed gains, whereas learning-by-exporting in our sample fails to substitute those learning channels for imports.

5.2 | A Cross-Section Approach

We turn now to a cross-section perspective and use matching and reweighting techniques to exploit the full sample of firms with available innovation data. Given the largely cross-sectional nature of the WBES data, our primary focus is on firm-level observations across countries and industries rather than firm-level evolutions. The value of this exercise lies in its ability to provide additional insights on country-level heterogeneity and on the intensity of GVC participation, which could not be captured with the panel approach due to its relatively small sample size. As suggested by our previous results, the causal impact of GVC participation on innovation tends to materialize in the short run, so we can expect significant differences between treated and untreated firms within cross-section comparisons.

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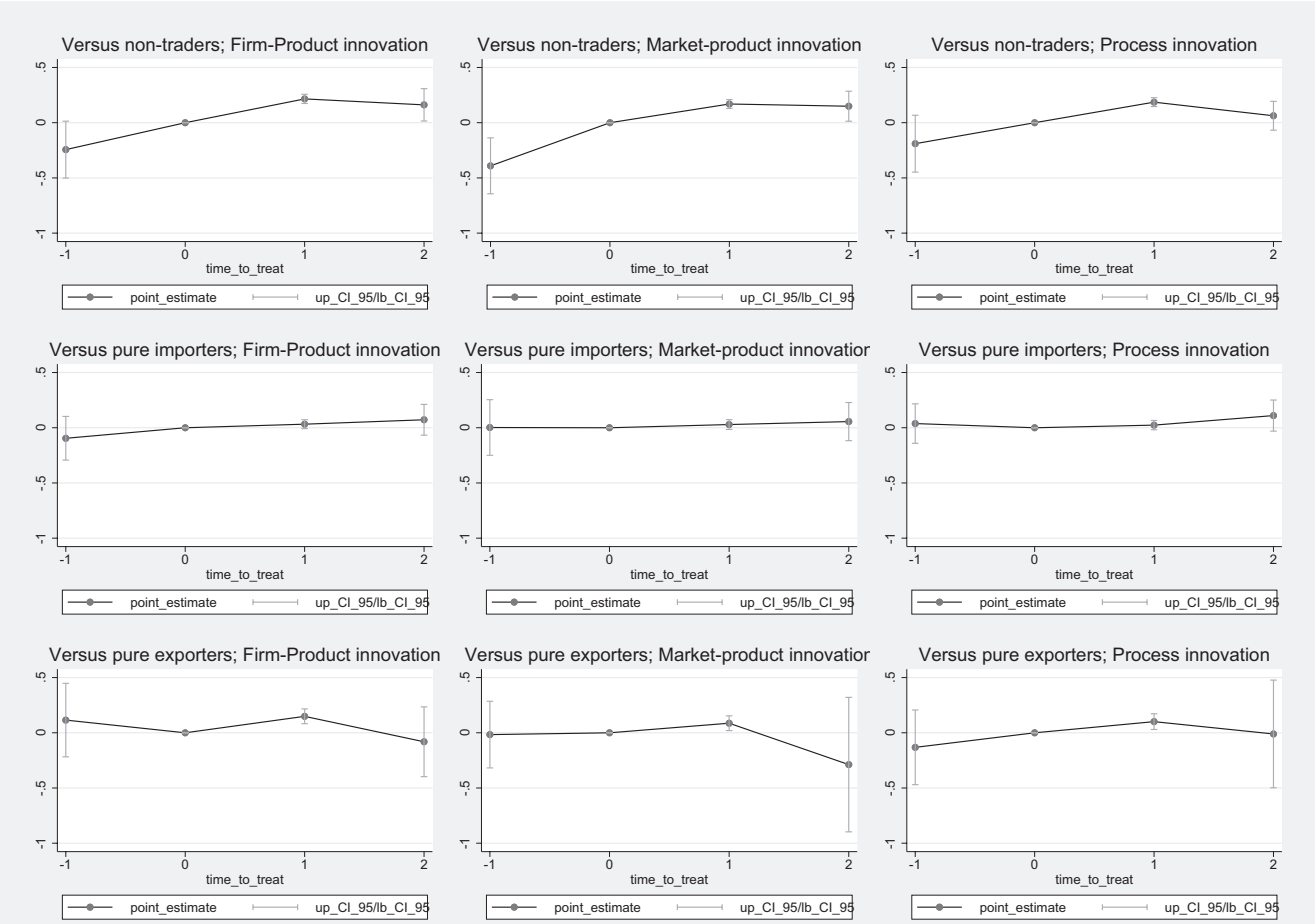

FIGURE 3 | Impact of two-way trading on innovation relative to different control groups (DiD estimates). The figures show the average effect of two-way trading on firms' innovation. It measures the average difference between the outcome evolution of firms that both import and export at the same time and the outcome evolution of those that did not but kept either import or export activities. In the *x*-axis, values before zero represent the placebo (parallel trend assumption). The zero value represents the reference pre-treatment date and values above are dynamic effects after exposition to treatment.

5.2.1 | First-Stage Balancing and Full Sample Results

Identification relies on covariates conditioning and cross firm variation within country, sector and year cells, with all estimations controlling for country, industry and year fixed effects throughout. Hence, although the number of observations varies considerably across countries—ranging from 103 to 18,657—identification comes from within-country firm heterogeneity rather than cross-country differences, which mitigates concerns about unequal country representation.

Table A4 in the Appendix presents the probit estimates for the entire sample, along with segmented analyses based on country-level income classifications. The estimations indicate that the likelihood of engagement in a GVC is notably higher for large, older firms (regarding the number of years in activity), maintaining foreign-owned equity shares exceeding 10% and having access to credit. In PSM estimates for the full sample, we use the probit model of the second column in Table A4 and match firms in the treatment group (i.e., two-way traders) to firms in the control group (i.e., importers, exporters, or non-trading firms) based on their propensity scores.[11] Figure A2 in the Appendix shows the distribution of propensity scores across the different treatment status before and after the matching, allowing for a visual inspection of their alignment after the PSM adjustment.

The effectiveness of the matching can also be assessed in Table A5 in the Appendix, which presents the balance achieved in the PSM method, summarizing the standardized mean differences (SMD) and variance ratios. The table also shows the mean and variance after weighting by entropy balancing, which uses a similar conceptual model for selection. As seen, after weighting, there remain no disparities between the groups regarding their first and second moments. In all cases, most of the discrepancies between the groups have been minimized. This first-stage adjustment ensures a robust assessment of the causal effect of GVC participation on innovation activities in the following cross-section analyses.

Estimates of the ATT using PSM, EB, and CEM over the full sample are presented in Table 4. While the estimates indicate a statistically significant and positive average treatment effect of GVC participation on all types of innovation (Hypothesis 1), magnitudes also give support to Hypothesis 2, which posits that

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TABLE 4 | ATT of GVC participation on innovation (whole sample).

	Innovation form					
ATT method	**Any innovation**	**Product & process**	**Firm-product**	**Market-product**	**Process**	**Product vs. process**
PSM	0.089*** (0.005)	0.060*** (0.005)	0.095*** (0.005)	0.066*** (0.005)	0.060*** (0.005)	0.027*** (0.006)
EB	0.101*** (0.005)	0.070*** (0.004)	0.101*** (0.005)	0.076*** (0.005)	0.069*** (0.005)	0.033*** (0.005)
CEM	0.154*** (0.003)	0.091*** (0.003)	0.154*** (0.004)	0.107*** (0.003)	0.090*** (0.002)	0.064*** (0.003)
Treated Obs.	26,981	26,981	26,981	25,821	26,981	26,981
Total Obs.	195,538	195,539	196,514	191,240	196,515	196,515

Note: Coefficients are the estimated average treatment effect on the treated. When the probability of innovating is higher for the treated observations than the non-treated after controlling for selection, the ATT shows a positive and significant value. Estimations stem from propensity score matching (PSM), entropy balancing (EB), and coarsened exact matching (CEM). All models include the full set of covariates in Table 3 and country, industry, and year dummies. Standard errors are presented in parentheses, with *, **, *** denoting significance at the 10%, 5%, and 1%.

product innovation responds more strongly to GVC participation than process innovation. This is formally captured by the firm-level difference in product versus process innovation propensity Tables A6 and A7.

5.2.2 | Heterogeneity Across Country Income Level, Firms' Trade Status, and GVC Intensity

While the full-sample estimates presented above account for country characteristics, our approach required that both the first-stage selection estimates and ATTs remain consistent across all country categories of development. This uniform specification may, however, hide underlying heterogeneity associated with country- and trade-specific factors. This section explores different dimensions of heterogeneity within our sample, focusing on the country income level, firms' trade status, and the intensity of their participation in GVCs.

We first split the sample into income-level categories as defined by the World Bank: low, lower-middle, upper-middle, and high-income countries. These categories often reflect varying levels of access to external resources that influence technical change, including institutional frameworks, provision of public goods, and domestic absorptive capacity. As before, all estimations include year, as well as country and industry fixed effects to account for additional heterogeneity within each sub-sample. For the sake of brevity, henceforth we only present entropy balancing estimates, which are close and qualitatively similar to those offered by PSM and CEM techniques—as Table 4 illustrates.

The first rows of Table 5 report the ATT of GVC participation on innovation across income groups. The results indicate that GVC participation significantly increases the probability of all types of innovation (product, process, market, and combined) across all income categories. Hence, Hypothesis 1—stating that firms increase their innovation output through participation in GVCs–, is consistent across all domestic contexts of development stage. Importantly, from the firm-level comparison of product versus process innovation, a similar conclusion can be drawn for Hypothesis 2, which postulates that product innovation responds more strongly to GVC participation than process innovation.

The cross-section sample also allows us to grasp insights on the "intensive" margin of GVC participation. To this end, we classified firms as high- or low-intensity participants in GVCs. High-intensity firms are defined as those that export more than 50% of their total sales and source more than 50% of their material inputs or supplies from foreign origins. In order to verify a potentially different impact driven by firms engaged in pure outward processing or export-platform—as defined in the classification of networking FDI supply chain proposed by Baldwin and Okubo (2014)—we then exclude from the high-intensity group "platform firms", classified as those firms that import most of their inputs and export most of their sales (more than 90% in each case). Table 5 presents the results following this classification. Interestingly, comparisons of high versus low GVC intensity reveal negative coefficients for innovation, some of which are statistically significant. This pattern may reflect some form of diminishing returns to GVC integration for firms that already

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TABLE 5 | ATT of GVC participation on innovation by income level, firms' trade status, and intensity of GVC participation.

	Innovation form				
	Firm-product	**Market-product**	**Process**	**Product & process**	**Product vs. process**
Income level					
Low	0.091*** (0.013)	0.076*** (0.012)	0.059*** (0.013)	0.063*** (0.012)	0.032** (0.014)
Treated Obs.	2237	2237	2237	2237	2237
Total Obs.	30,215	30,215	30,215	30,215	30,215
Low-Middle	0.087*** (0.008)	0.059*** (0.007)	0.061*** (0.008)	0.056*** (0.007)	0.026*** (0.008)
Treated Obs.	7087	6530	7087	7087	7087
Total Obs.	72,629	70,277	72,629	72,629	72,629
Upper-Middle	0.111*** (0.009)	0.085*** (0.008)	0.085*** (0.008)	0.080*** (0.008)	0.026*** (0.009)
Treated Obs.	7188	6585	7188	7188	7188
Total Obs.	46,511	43,589	45,536	45,535	45,535
High	0.102*** (0.008)	0.079*** (0.008)	0.061*** (0.008)	0.070*** (0.008)	0.041*** (0.009)
Treated Obs.	10,469	10,469	10,469	10,469	10,469
Total Obs.	47,159	47,159	47,159	47,159	47,159
The intensive margin: GVC intensity of two-way traders (Full sample)					
High vs. Low	−0.064*** (0.015)	−0.037*** (0.014)	−0.020 (0.014)	−0.031** (0.014)	−0.044*** (0.014)
Treated Obs.	6745	6579	6745	6745	6745
Total Obs.	14,876	14,282	14,876	14,876	14,876
High vs. Low (no platform)	−0.035*** (0.013)	−0.012 (0.012)	−0.007 (0.012)	−0.011 (0.012)	−0.028** (0.013)
Treated Obs.	4693	4561	4693	4693	4693
Total Obs.	12,824	12,264	12,824	12,824	12,824
Trade status: Two-way Traders vs One-way traders (full sample)					
Vs Pure Exporters	0.107*** (0.008)	0.080*** (0.008)	0.057*** (0.008)	0.074*** (0 0.007)	0.049*** (0.009)
Treated Obs.	26,981	25,821	26,981	26,981	26,981
Total Obs.	38,660	37,210	38,608	38,608	38,608
Vs Pure Importers	0.055*** (0.005)	0.050*** (0.005)	0.039*** (0.005)	0.042*** (0.005)	0.016*** (0.006)
Treated Obs.	26,981	25,821	26,981	26,981	26,981
Total Obs.	82,794	79,499	82,794	82,793	82,793

Note: The table reports entropy balancing estimates. Coefficients are treatment effects (the difference between the treated and control groups). Standard errors are presented in parenthesis. All estimations include country and industry dummies. *, **, *** denotes significance at the 10%, 5% and 1%.

participate extensively. For example, managing highly complex supply chains can increase coordination costs and reduce the marginal benefits of additional imported inputs. These negative estimates lose magnitude and significance when excluding platform firms. We may thus conjecture that the negative result is partly driven by firms more interested in re-exporting rather than absorbing foreign knowledge in order to improve local production processes or to introduce new products.

Finally, mirroring our DiD estimations in Figure 3 the last rows show the ATT according to trade status. As seen, two-way traders show positive and significant innovation gains compared to pure exporters, especially for product and process innovation. Compared to pure importers, the gains are smaller but still statistically significant. These results broadly align with what we found in our panel data approach and suggest that while exporting provides exposure to foreign

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TABLE 6 | Differences in ATT of GVC participation on innovative sources according to broad income categories.

	Doing R&D	Foreing technology	Skill share
GVC	0.109*** (0.006)	0.093*** (0.006)	−0.025*** (0.006)
UM&H	0.048*** (0.006)	0.017*** (0.006)	0.004 (0.007)
GVC × UM&H	0.041*** (0.009)	−0.049*** (0.008)	0.041*** (0.010)
ATT of GVC in UM&H Income firms	0.151*** (0.006)	0.044*** (0.005)	0.016** (0.007)
Obs.	195,540	185,285	115,685

Note: The table reports entropy balancing estimates of a differentiated ATT of GVC according to broad country income categories of firms—upper-middle and high (UM&H) income versus Low and Low-middle income. The bottom line provides the magnitude and significance of the overall ATT of GVC participation for firms in the UM&H income group, captured by the linear combination $\widehat{\beta}_{GVC} + \widehat{\beta}_{GVC\times UM\&H}$, where $\widehat{\beta}_X$ is the estimated coefficient on X. Standard errors are presented in parenthesis. All Estimations include in the first stage the full set of covariates as well as country, industry, and year dummies. *, **, *** denotes significance at the 10%, 5% and 1%.

markets and learning-by-exporting, the primary driver of innovation gains is importing intermediate inputs. Two-way traders combine both effects but benefit most from backward linkages (importing), consistent with the empirical literature discussed in Section 2.1.

5.2.3 | Different Innovation Modes Across Income Groups

In Table 6 we test whether the mechanisms linking participation and GVC innovation differ between levels of economic development by focusing on three indicators that characterize innovative activity: adoption of foreign technologies, participation in R&D activities, and the share of skilled workers. To facilitate the interpretation, we consider two broad categories of country-income groups: (i) upper-middle and high-income countries, and (ii) low and lower-middle income countries. We assimilate the former to emerging and advanced economies, and the latter to low-income developing economies.

Identification relies on the same first-stage entropy balancing weighting scheme—including as before the full set of covariates as well as country, industry, and year dummies—and using in the second stage an interaction term between our treatment variable and a dummy indicating if the firm belongs to the upper-middle and high income group (UM&H). For each outcome, the coefficient on the interaction term between this dummy and our GVC indicator (two-way trading) thus gives an estimate of the differentiated impact of GVC participation for firms in emerging and advanced economies relative to those operating in low income developing countries. The bottom line of the table gives the magnitude and significance of the overall effect of GVC participation in the UM&H income category.

Results reveal systematic differences across development levels in the type of innovation fostered by GVCs. In particular, the effects of GVC participation in emerging and advanced economies on the propensity to engage in R&D and on skill intensity are stronger than in low-income developing economies, indicating a shift toward more knowledge-intensive forms of innovation. On the other hand, in low-income developing economies GVC participation is strongly associated with the adoption of foreign technologies, which is in line with a mechanism of technology upgrade taking place relatively far from the technology frontier.

Taken together, these results support our research Hypothesis 3. They suggest that the nature of innovation associated with GVC participation evolves with the level of development: firms in less developed economies mainly engage in technology adoption and absorb foreign-created knowledge, whereas firms in more advanced economies rely more on formal R&D-based innovation activities. Such differences align with the view that technical change relies more on imitation far from the technology frontier, whereas R&D- and skill-intensive innovation is necessary when firms already operate with leading-edge technologies.

5.2.4 | A Broader Impact of GVC Participation on Technological Change

In the previous sections we showed that participation in GVCs is associated with a higher likelihood of innovation. We now turn to the related question of whether this participation also drives observable technological improvements. Specifically, we examine whether GVC participation leads to higher labour and total factor productivity, improved product quality, and potential reductions in average variable cost of production. In order to better understand the effects on labour productivity we also pay attention to capital intensity. By testing for treatment effects on these outcomes we want to further explore the implications of our research Hypothesis 2—whereby GVC participation is relatively more oriented toward product (rather than process) innovation—and analyse whether GVC participation is inducing production efficiency and cost saving, product quality upgrading, or both.

We proceed in a similar way as previously and present ATT for two-way traders with respect to all the rest of the firms in Table 7. Firms are grouped by the country's income level. The bottom line shows estimates for the full sample. The overall pattern reveals that GVC-integrated firms tend to exhibit higher labour productivity, capital intensity, and product quality (measured by quality certifications), though the magnitude and direction of effects vary by income level. In detail, across all income levels, labour productivity increases significantly for two-way traders, with the largest effects observed in low- and low-middle-income countries. This finding is consistent with previous literature, where beyond the self-selection

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TABLE 7 | ATT of GVC on related outcomes of technological change.

	TFP	Labour productivity	Capital intensity	Av. cost of intermediates	Av. cost of labour	Av. variable costs	Quality certification
Low	0.052 (0.058)	0.298*** (0.054)	−0.120 (0.103)	−0.051 (0.039)	−0.094*** (0.032)	−0.065*** (0.023)	0.084*** (0.011)
Treated Obs.	1285	1562	1636	1607	2310	1572	2811
Total Obs.	11,547	13,796	14,225	13,894	31,067	13,713	38,578
Low-Middle	0.005 (0.036)	0.285*** (0.025)	0.029 (0.069)	0.019 (0.025)	0.004 (0.018)	0.007 (0.012)	0.139*** (0.007)
Treated Obs.	3942	5061	4873	5147	6423	5047	7933
Total Obs.	27,840	37,216	32,865	37,399	70,293	37,005	84,734
Upper-Middle	−0.010 (0.041)	0.174*** (0.024)	0.135** (0.060)	0.066*** (0.022)	−0.045*** (0.016)	0.019 (0.012)	0.140*** (0.008)
Treated Obs.	4311	5583	5243	5632	7012	5565	8452
Total Obs.	18,497	23,214	22,452	23,334	48,167	23,085	59,051
High	0.002 (0.041)	0.177*** (0.020)	0.339*** (0.059)	0.121*** (0.017)	−0.095*** (0.013)	0.015* (0.009)	0.108*** (0.008)
Treated Obs.	5735	6829	6509	6850	9718	6801	10,881
Total Obs.	13,704	16,829	15,940	16,863	41,775	16,709	50,597
All	0.010 (0.022)	0.257*** (0.017)	0.107*** (0.037)	0.064*** (0.011)	−0.050*** (0.009)	0.012* (0.006)	0.123*** (0.004)
Treated Obs.	15,273	19,035	18,261	19,236	25,463	18,985	30,077
Total Obs.	71,588	91,055	85,482	91,490	191,302	90,512	232,960

Note: The table reports entropy balancing estimates. Coefficients are treatment effects (the difference between the treated and control groups). Standard errors are presented in parenthesis. All Estimations include country and industry dummies. *, **, *** denotes significance at the 10%, 5% and 1%.

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of the most productive firms into international markets, the exposure to foreign customers and inputs fosters efficiency. Combining these results with our previous estimates on importing channels, we conjecture that for developing economies, productivity gains mainly reflect learning-by-importing effects—access to higher-quality intermediates and knowledge spillovers that improve efficiency.

Conversely, estimations show no significant differences between treated and control firms regarding total factor productivity (TFP). This result—already suggested by raw sample distributions in Figure A1—may reflect the time lag necessary for translating the introduction of new or improved processes and inputs into productivity gains. However, within a multifactor production function, even in the absence of TFP gains, labour productivity may still increase if firms become more capital intensive. Indeed, two-way traders exhibit higher capital intensity, particularly in upper-middle and high-income countries, reflecting a capital-labour substitution strategy. In low-income developing economies, we conjecture a labour-augmenting technical change, given the reduction in average labour costs. While input costs tend to rise (positive coefficients), labour costs mostly decline. The first may reflect access to better quality inputs. Probably more expensive, these inputs may still represent better quality-adjusted prices. The second may indicate efficiency improvements from process innovation or capital-labour substitution. As the effects on these two components of variable costs are contradictory to each other, the impact on overall average variable cost is ambiguous and mostly without statistical significance.

On the other hand, higher quality certification increases strongly and consistently across all income levels, which we interpret as improvements in product quality. We see this result combined with those revealing higher quality intermediates, a non-significant TFP change, and a labour productivity that seems to be mainly shifted by capital-labour substitution, as the consequence of a relative predominance of product innovation along GVCs. The table's final row puts forth this insight for the full sample.

6 | Final Discussion

This paper examines the effect of firms' simultaneous combination of importing and exporting activities on their likelihood of introducing product, process, and market innovations. We also explore whether this GVC participation affects the ensuing technological change, including productivity, capital intensity, quality, and average production costs.

We use a diverse and substantial sample of firms from 144 countries and rely on panel and cross-country firm-level data over the period 2006–2025. We employ difference-in-differences, propensity score matching, entropy balancing, and coarsened exact matching methods to reduce selection bias, isolating the effect of two-way trading—which we assimilate to GVC participation—on innovation and related outcomes.

Our results consistently show that firms adopting a two-way trade strategy innovate more than firms that do not follow such an internationalization pattern, a finding that is robust across estimators and samples. Two-way traders also exhibit higher labour productivity, higher capital intensity, engage more with international quality standards, and incur relatively higher input costs, only partially offset by reductions in labour costs.

A closer examination reveals that innovation gains are primarily driven by importing rather than exporting. Compared to pure importers, firms that switch to two-way trade do not achieve significant additional innovation gains, suggesting that learning-by-importing is the dominant channel. Among innovation types, product innovation responds more strongly to GVC participation than process innovation, consistent with the higher robustness of results regarding quality improvements relative to cost efficiency.

Beyond average effects, we document systematic differences in the nature of innovation across development levels. In lower-income countries, GVC participation is primarily associated with foreign technology adoption, suggesting a mechanism of technology diffusion through international production networks. In upper-middle and high-income economies, GVC participation is instead associated with R&D-intensive and skill-intensive innovation, reflecting the evolving nature of technical progress as economies become closer to the world technology frontier. This distinction between technology adoption and knowledge creation across different participants represents a contribution of our analysis that could not be identified in single-country studies.

All these findings relate to the fact of joining a GVC –that is, the extensive margin of GVC participation. Once we explore the intensity of participation within the group of two-way traders –that is, the intensive margin–, our estimations show diminishing returns to GVC integration for firms that already participate, a result that qualifies the broadly positive narrative on GVC participation and suggests that the marginal benefits of deeper integration decline as supply chain complexity increases.

Our study is not free from limitations. First, the data lack the granularity to trace the origins and destinations of trade flows, limiting our ability to identify direct linkages between firms at different stages of the GVC. This is particularly relevant for developing countries, where proximity to wealthier buyers within the value chain is associated with productivity gains and quality upgrades. This type of data may also help to better identify the positioning of firms within GVCs. Further research should investigate the magnitude and diffusion of these gains across the broader economy.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available in WBES at https://www.enterprisesurveys.org/en/data?utm_source=chatgpt.

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com. These data were derived from the following resources available in the public domain: –World Bank, https://www.enterprisesurveys.org/en/data?utm_source=chatgpt.com.

Endnotes

[1] See Section 2 for a review where we focus on channels related to technical change.

[2] See Appendix Table A1 for our panel-sample structure.

[3] See Heckman et al. (1998) for more details on matching algorithms.

[4] The firm universe is defined as the non-agricultural, formal, private economy, covering sectors like manufacturing, retail, other services, IT, construction, and transport. Firms with five or more employees are included, though our analysis is restricted to firms with available information for innovation.

[5] Inputs, as per the WBES definition, encompass materials undergoing mechanical, physical, or chemical transformations that eventually contribute to the production of a final good.

[6] The WBES questionnaire explicitly excludes broader interpretations of R&D, such as market research surveys.

[7] A potentially pertinent variable is the proportion of skilled labor in total labor. However, this information is missing for more than half of observations. We decided then not to include it in order to maximize sample size. Results remain qualitatively similar.

[8] Further differences are also apparent across firms from different countries, as seen in Table 3. Firms from low income countries are typically smaller, attract less foreign capital, and have more limited credit access compared to firms in higher-income economies. Such disparities underscore the need to carefully select an appropriate control group.

[9] The table is based on the available panel sample, composed of firms having a panel identifier and non-missing information on innovation.

[10] Prior to implementing the staggered DiD estimator, we estimate a standard Two-Way Fixed Effects (TWFE) specification as a benchmark. Results, reported in Table A2, confirm a positive and significant effect of two-way trading on all innovation outcomes, consistent with our preferred estimator.

[11] Two firms, one from the treatment group and one from the control group, are considered a match if the difference between their propensity scores is minimal. We consider one nearest neighbour when pairing observations.

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Appendix A

List of countries: Afghanistan, Georgia, Niger, Albania, Germany, Nigeria, Angola, Ghana, North Macedonia, Antigua and Barbuda, Greece, Pakistan, Argentina, Grenada, Panama, Armenia, Guatemala, Papua New Guinea, Austria, Guinea, Paraguay, Azerbaijan, Guinea-Bissau, Peru, Bahamas, The, Guyana, Philippines, Bangladesh, Honduras, Poland, Barbados, Hungary, Portugal, Belarus, India, Romania, Belgium, Indonesia, Russian Federation, Belize, Iraq, Rwanda, Benin, Ireland, Senegal, Bhutan, Israel, Serbia, Bolivia, Italy, Sierra Leone, Bosnia and Herzegovina, Jamaica, Slovak Republic, Botswana, Jordan, Slovenia, Brazil, Kazakhstan, Solomon Islands, Bulgaria, Kenya, South Africa, Burkina Faso, Kosovo, South Sudan, Burundi, Kyrgyz Republic, Spain, Cambodia, Lao PDR, Sri Lanka, Cameroon, Latvia, St. Kitts and Nevis, Chad, Lebanon, St. Lucia, Chile, Lesotho, St. Vincent and the Grenadines, China, Liberia, Sudan, Colombia, Lithuania, Suriname, Congo, Dem. Rep., Luxembourg, Sweden, Costa Rica, Madagascar, Tajikistan, Croatia, Malawi, Tanzania, Cyprus, Malaysia, Thailand, Czech Republic, Mali, Timor-Leste, Cote d'Ivoire, Malta, Togo, Denmark, Mauritania, Trinidad and Tobago, Djibouti, Mauritius, Tunisia, Dominica, Mexico, Turkey, Dominican Republic, Moldova, Uganda, Ecuador, Mongolia, Ukraine, Egypt, Montenegro, Uruguay, El Salvador, Morocco, Uzbekistan, Estonia, Mozambique, Venezuela, RB, Eswatini, Myanmar, Vietnam, Ethiopia, Namibia, West Bank and Gaza, Finland, Nepal, Yemen, Rep., France, Netherlands, Zambia, Gambia, Nicaragua, Zimbabwe.

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TABLE A1 | Number of observations by wave and innovation type (panel database).

	Product innovation			Process innovation			Market innovation		
Participation	**Total**	**Yes**	**No**	**Total**	**Yes**	**No**	**Total**	**Yes**	**No**
Wave 1	83,816	27,413	56,403	83,816	24,735	59,081	80,716	15,852	64,864
Wave 2	20,541	5681	14,860	20,541	4365	16,176	20,541	3615	16,926
Wave 3	2825	1064	1761	2825	754	2071	2825	754	2071
Wave 4	107	35	72	107	28	79	107	21	86

Note: The table reports the number of observations by survey wave and innovation type. Wave 1 refers to the first survey in which a firm appears; subsequent waves correspond to follow-up surveys. Firms surveyed in Wave 4 have thus also been surveyed in the previous three waves. Yes/No indicates whether the firm reported the corresponding innovation activity during the previous 3 years.

TABLE A2 | Impact of two-way trading on innovation. Two-way fixed effects (TWFE) estimates.

	Process innovation	Firm product innovation	Market innovation
Two-way trader s.e	0.094*** (0.011)	0.058*** (0.011)	0.067*** (0.011)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: Standard errors in parentheses. Controls include firm size, age, foreign ownership, and access to credit. The dependent variables are binary indicators equal to one if the firm introduced a new process, product, or market innovation during the previous 3 years.
***$p < 0.01$.

TABLE A3 | Descriptive statistics of innovation-related outcomes, by income group. Raw sample.

Income level	Statistics	TFP	Doing R&D	Foreign tech.	Labour productivity	Quality certif.	Av. cost of labour	Av. cost of intermed.	Capital intensity
Low	Mean	2.150	0.128	0.141	8.177	0.127	−2.068	−1.308	13.235
	SD	1.624	0.334	0.348	1.692	0.333	1.441	1.102	3.414
	Obs.	11,547	30,215	25,526	13,796	38,578	31,067	13,894	14,225
Low-middle	Mean	2.208	0.164	0.133	9.008	0.218	−1.987	−1.176	12.587
	SD	1.712	0.370	0.339	1.300	0.413	1.153	1.063	3.250
	Obs.	27,840	72,629	63,705	37,216	84,734	70,293	37,399	32,865
Upper-middle	Mean	2.378	0.185	0.165	9.761	0.295	−1.844	−1.272	11.444
	SD	1.763	0.388	0.371	1.236	0.456	1.038	1.037	2.893
	Obs.	18,497	45,537	48,744	23,214	59,051	48,167	23,334	22,452
High	Mean	2.164	0.208	0.156	10.876	0.338	−1.586	−1.222	11.686
	SD	1.778	0.406	0.363	1.062	0.473	0.903	0.900	2.638
	Obs.	13,704	47,159	47,310	16,829	50,597	41,775	16,863	15,940
All	Mean	2.234	0.174	0.148	9.419	0.249	−1.877	−1.229	12.227
	SD	1.727	0.379	0.355	1.564	0.432	1.142	1.035	3.152
	Obs.	71,588	195,540	185,285	91,055	232,960	191,302	91,490	85,482

Note: The table reports descriptive statistics for innovation-related outcomes. The sample is restricted to non-missing information in the outcome variable and the set of controls used in the first-stage (i.e., two-way trade status, size, age, foreign ownership, access to credit, industry affiliation, country, and year). Doing R&D, Foreign technology, and Quality certifications are binary variables. The remaining continuous variables are expressed in natural logs.
Abbreviation: SD, standard deviation.

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Details on matching and weighting.

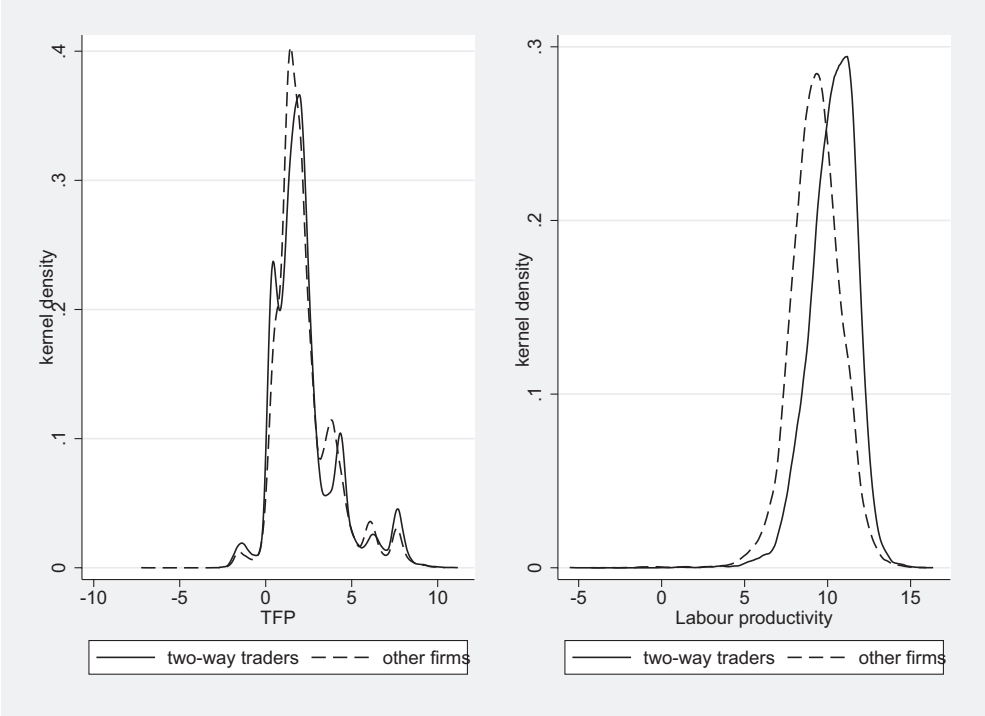

FIGURE A1 | Productivity distributions according to GVC participation (Raw sample). The graphs show density plots of productivity for two-way traders and ther est. of firms.

TABLE A4 | Probability of participation in GVC.

	Income level					
	All	**All**	**Low**	**Lower middle**	**Upper middle**	**High**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Size	0.411*** (0.006)	0.460*** (0.006)	0.503*** (0.018)	0.569*** (0.011)	0.473*** (0.012)	0.338*** (0.011)
Firm's Age	0.004*** (0.000)	0.002*** (0.000)	0.001 (0.001)	0.003*** (0.000)	0.003*** (0.000)	0.002*** (0.000)
Foreign Ownership	0.722*** (0.012)	0.677*** (0.013)	0.613*** (0.032)	0.758*** (0.023)	0.749*** (0.025)	0.573*** (0.024)
Access to credit	0.305*** (0.008)	0.241*** (0.009)	0.243*** (0.028)	0.267*** (0.017)	0.244*** (0.017)	0.212*** (0.016)
Low-middle Income	−0.009 (0.015)					
Upper-middle Income	0.191*** (0.015)					
High Income	0.587*** (0.016)					
Constant	−1.990*** (0.026)	−2.068*** (0.201)	−2.550*** (0.234)	−2.277*** (0.168)	−2.744*** (0.214)	−1.955*** (0.087)
Isic dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Country dummies	No	Yes	Yes	Yes	Yes	Yes
Obs.	196,515	196,515	30,215	72,629	46,512	47,159

Note: The table reports first-stage (probit) estimates of propensity score matching for the whole sample and by income category.

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TABLE A5 | Covariate balance before and after matching.

	Entropy balancing						PSM			
	Treated		Control before		Control after		Standard difference		V. ratio	
Variable	Mean	Variance	Mean	Variance	Mean	Variance	Before	After	Before	After
Size	2.239	0.582	1.662	0.547	2.239	0.582	0.768	−0.005	1.064	1.001
Age	28.930	552.319	20.008	275.019	28.930	552.314	0.439	0.019	2.008	0.929
Foreign	0.239	0.182	0.064	0.060	0.239	0.182	0.505	0.004	3.051	0.995
Credit	0.545	0.248	0.321	0.218	0.545	0.248	0.465	−0.019	1.138	1.004

Note: The table reports diagnostic statistics for entropy balancing (first and second moments of covariates for treated and control groups) and propensity score matching (standardized differences and variance ratios for raw and matched samples). All estimations include country, industry, and year fixed effects.

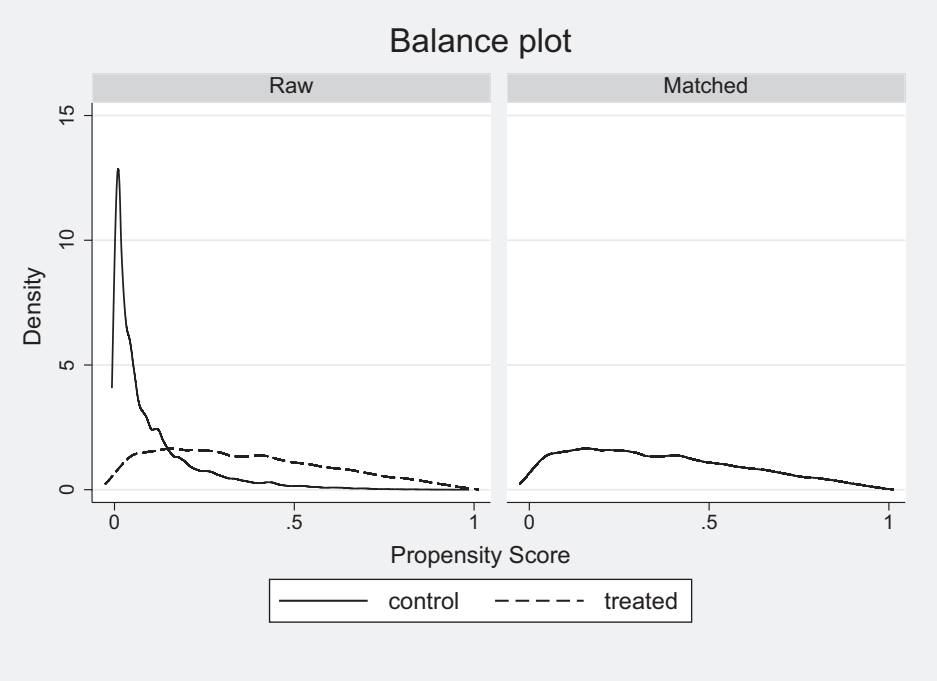

FIGURE A2 | Distribution of the probability of participating in a global value chain for treated and untreated firms. The figure shows the distribution of propensity scores for matched and unmatched observations within both treated and untreated groups. The underlying model is the baseline cross-section estimation of the full sample (column (2) in Table A4).

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TABLE A6 | ATT of GVC participation on innovation. Robustness checks on alternative specifications and two-way trade definition.

	Innovation form				
	Any innovation	**Product & process**	**Firm-product**	**Market-product**	**Process**
Baseline model, excluding firms with missing trade information					
ATT	0.094*** (0.005)	0.065*** (0.004)	0.096*** (0.005)	0.074*** (0.005)	0.063*** (0.005)
Treated Obs.	26,981	26,981	26,981	25,821	26,981
Total Obs.	170,493	170,488	170,492	165,693	170,489
Alternative model 1					
ATT	0.095*** (0.005)	0.065*** (0.005)	0.096*** (0.005)	0.070*** (0.005)	0.064*** (0.005)
Treated Obs.	26,909	26,909	26,909	25,751	26,909
Total Obs.	195,466	194,489	195,465	190,205	194,490
Alternative model 1, excluding firms with missing trade information					
ATT	0.088*** (0.005)	0.060*** (0.005)	0.090*** (0.005)	0.069*** (0.005)	0.057*** (0.005)
Treated Obs.	26,909	26,909	26,909	25,751	26,909
Total Obs.	169,749	169,744	169,748	164,963	169,745
Alternative model 2					
	0.058*** (0.005)	0.033*** (0.005)	0.058*** (0.005)	0.043*** (0.005)	0.032*** (0.005)
Treated Obs.	26,981	26,981	26,981	25,821	26,981
Total Obs.	195,540	195,538	195,539	190,740	195,539
Alternative model 2, excluding firms with missing trade information					
ATT	0.056*** (0.005)	0.032*** (0.005)	0.058*** (0.005)	0.043*** (0.005)	0.030*** (0.005)
Treated Obs.	26,981	26,981	26,981	25,821	26,981
Total Obs.	170,490	170,488	170,489	165,691	170,489

Note: Coefficients are the estimated average treatment effect on the treated. When the probability of innovating is higher for the treated observations than the non-treated after controlling for selection, the ATT shows a positive and significant value. Estimations stem from entropy balancing applied to different alternative specifications, alternatively excluding missing trade information or considering it as no trade activity. All models start from the full sample baseline specification (Column (2) in Table A4). Alternative Model 1 considers continuous covariates (including FTE instead of size category) in logs. Alternative Model 2 considers R&D as an additional covariate to control for selection. Standard errors are presented in parentheses, with *, **, *** denoting significance at the 10%, 5% and 1%.

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TABLE A7 | ATT of GVC on related outcomes of technological change. Robustness checks on sample selection.

	TFP	Labour productivity	Capital intensity	Av. cost of intermediates	Av. cost of labour	Av. variable costs	Quality certification
Low	0.069 (0.072)	0.368*** (0.070)	−0.255* (0.135)	−0.073 (0.050)	−0.098*** (0.038)	−0.084*** (0.030)	0.085*** (0.012)
Treated Obs.	856	1097	1118	1130	1803	1102	2237
Total Obs.	6939	8854	8859	8924	23,814	8767	30,215
Low-Middle	0.043 (0.038)	0.297*** (0.026)	0.119 (0.073)	0.023 (0.027)	−0.025 (0.019)	0.003 (0.013)	0.147*** (0.008)
Treated Obs.	3492	4450	4313	4522	5739	4436	7087
Total Obs.	24,877	33,233	29,110	33,378	60,702	33,076	72,629
Upper-Middle	−0.039 (0.047)	0.151*** (0.027)	0.144** (0.069)	0.071*** (0.024)	−0.038** (0.018)	0.024* (0.014)	0.148*** (0.009)
Treated Obs.	3492	4603	4273	4642	5948	4581	7188
Total Obs.	15,014	19,174	18,301	19,273	37,987	19,043	46,512
High	−0.012 (0.042)	0.191*** (0.020)	0.356*** (0.060)	0.121*** (0.017)	−0.103*** (0.013)	0.017* (0.009)	0.107*** (0.008)
Treated Obs.	5511	6524	6219	6543	9397	6495	10,469
Total Obs.	13,104	15,995	15,156	16,027	39,199	15,881	47,159
All	0.003 (0.024)	0.284*** (0.018)	0.156*** (0.040)	0.068*** (0.012)	−0.063*** (0.009)	0.013** (0.007)	0.127*** (0.005)
Treated Obs.	13,351	16,674	15,923	16,837	22,887	16,614	26,981
Total Obs.	59,934	77,256	71,426	77,602	161,702	76,767	196,515

Note: The table reports entropy balancing estimates. Coefficients are treatment effects (the difference between the treated and control groups). The sample has been restricted to non missing information on "any innovation" for comparability with estimations related to innovation outcomes. Standard errors are presented in parenthesis. All Estimations include country and industry dummies. *, **, *** denotes significance at the 10%, 5% and 1%.

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