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2024-4 Document de Travail/ Working Paper

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Global Value Chains and Productivity: Causal Evidence for Firms Worldwide

Iván Ledezma * Antonia López-Villavicencio†

December 20, 2023

Abstract

We study how global value chain participation causally affects productivity at the firm level. We utilize an extensive dataset encompassing firms from countries of different income levels over the period 2006-2021, together with matching approaches to control for endogeneity. Our primary finding underscores that the simultaneous coordination of importing and exporting activities within a single firm leads to an increase in labor productivity. Positive effects on TFP are significant only within the subgroup of firms in the less developed countries and those operating in low-tech industries. Increased capital intensity appears as a plausible explanation of labor productivity gains. We also find higher innovation propensity, quality enhancements, and labor-cost reductions for two-way traders as channels through which GVC participation influences firms' technical change. The lower responsiveness of TFP in advanced countries can be explained by the different nature of technical change for firms operating closer to the world technology frontier

Keywords: Global value chains, productivity, firm, development, endogeneity.
JEL Classification: C31, D24, F14, F15, O5.

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1 Introduction

Economic globalization has brought about profound changes in international trade. Among all of them, perhaps the most prominent one is the surging volume of trade in intermediates, which once integrated into final products are dispatched to consumers all over the world. This international fragmentation of production along global value chains (GVCs), which are now a key feature of the world economy, has renewed the debate on the costs and benefits of globalisation, particularly, but not exclusively, for developing economies (Baldwin, 2014; World Bank, 2020).

Although not without debate and empirical challenges, the economic literature has long identified positive effects of trade on productivity. In particular, participating in GVCs is usually seen as a favorable strategy for fostering industrialization and productivity growth in developing and emerging economies.[1] As we document in more detail below, firms participating in GVC from developing countries are expected to simultaneously benefit from several channels related to trade within GVCs and the international organization of production. Outsourcing specific production components from international suppliers enables firms to access inputs of higher quality and in wider variety. Exporting to foreign customers in the chain increases the opportunities of learning and of increasing the scale and the value of production. The related higher profitability also provides incentives to invest and innovate, thereby raising productivity. Additionally, the integration of foreign firms and local suppliers within the same supply chain requires collaboration and coordination to ensure the seamless functioning of the chain. This collaborative dynamic facilitates the transfer of tacit knowledge, potentially bolstering domestic innovative capabilities. Consequently, the emergence of GVCs is supposed to alleviate traditional constraints faced by firms, particularly in emerging countries, allowing them to move beyond traditional production processes, probably of higher value added.

Despite the potential benefits, only a limited number of developing economies have deeply immersed themselves in GVCs, with China standing out as a prime example. However, it is important to consider this as an evolving process. As China experiences a rise in income and undergoes a transformation in the tradable sector of its economy, moving away from labor-intensive process manufacturing and assembly, one might anticipate that these tasks would shift towards lower-income countries, generating opportunities for industrialization (World Bank, 2017). For instance, low- and middle-income countries in Asia, such as Cambodia and Vietnam, absorb labor-intensive manufacturing inputs from China for their production

[1] See Criscuolo and Timmis (2017) for a policy-oriented overview and section 2 for closely-related references to our analysis.

and export.[2] Upper-middle-income countries in the same region, such as Malaysia and Thailand, and larger economies, such as India, tend to import medium-low or medium-high technology inputs from China since they have already upgraded in the chain and have the industrial capacity to produce and export high-technology products. A similar integration process could be anticipated in other regions, such as Africa and Latin America, which on average have lower GVC participation and remain important suppliers of raw materials.

The rapid ascent of the GVC phenomenon and its potential to enhance technical change provides thus a rationale for countries to actively pursue a prominent role in these production chains from a policy standpoint. The description of historical trends and macro-level evidence exploiting trade in value-added statistics had given support to this rationale (e.g. Gereffi, 1999; Baldwin, 2016; Constantinescu et al., 2019; Pahl and Timmer, 2020). However, countries themselves do not engage in trade. Instead, 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. This paper aims at contributing to the micro-level literature on firm internationalization and productivity, which provides a crucial complementary view to the macro-level evidence.

Although some lessons can be drawn from empirical micro-level studies on trade and FDI, the intricate nature of trade and production within GVC call for further exploration, namely on the heterogeneity of the domestic context of production (e.g. institutions, national capacities, market failures, etc.) and the specific mechanisms through which GVC participation shapes firm's technical change. On the one hand, most existing studies tend to restrict the analysis to a singular component of the trading inherent in a global value chain, namely 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 activities (Amiti and Wei, 2009; Schwörer, 2013). On the other, when explicitly dealing with GVC, micro-level studies had mostly relied on country-specific cases (e.g., Yan and Baldwin, 2014 for the case of Canadian firms, Prete et al., 2017 for North African firms, and Benkovskis et al., 2020 for firms in Latvia), which tends to limit the scope of conclusions to the singularity of the country under analysis.

In this paper, we take first steps towards documenting how firms participation in GVCs relates to productivity in a large sample of firms from 144 countries with

[2]Cambodia, partnered with China in the textile industry, mainly by importing low-technology fabrics for manufacturing final goods for EU and U.S. consumer markets.

varying income levels, covering the period from 2006 to 2021. One important point of departure from previous studies is our aim to identify the channels through which productivity gains take place for different country groups. Given the characteristics of the sample and the methodology we use, we are able to examine innovation, average costs, quality certifications, and capital intensity. Productivity is alternatively measured through total factor productivity (TFP) and the more direct single-factor index of labor productivity.

We use data from the World Bank's Enterprise Surveys (WBES), which is a representative survey, comparable among countries, and encompassing a wide array of variables, allowing to get information on firm's characteristics, financial aspects, performance indicators, infrastructure, sales, supplies, and trade. Through all the analysis, we aim at shedding light on the causal relationship between GVC integration and firm-level productivity. In particular, the data allows us assessing the productivity differences between firms engaged in GVCs relative to firms that do not participate in such trade but are otherwise similar in relevant attributes. In order to ensure capturing GVC related channels (and not just trade), in our robustness tests we further compare GVC participant firms to those engaged in pure exporting or pure importing activities.

It is important to acknowledge that endogeneity, due to reverse causality and selection bias, complicate the understanding of the subject. Indeed, certain initial firm attributes can influence both the decisions to enter into a sequential supply chain and the subsequent productivity outcomes. For example, it can be argued that due to the entry costs associated with exporting and re-importing across various production stages, only the most productive firms in a particular industry can successfully enter and thrive within these global production chains. Heterogeneous firms models of international trade (i.e. the so-called "new new" trade theory) posit the existence of fixed sunk costs and show that firms will engage in exporting, FDI or outsourcing and vertical integration activities abroad only if the expected profits derived from such participation outweigh the entry costs (Melitz, 2003; Helpman et al., 2004; Antràs and Helpman, 2004). Consequently, it is more likely that the most productive firms, often larger ones, are the ones engaging in offshoring and exporting activities within GVCs (Yan and Baldwin, 2014). Similarly, firms that modify their patterns of engagement in foreign trade often possess specific characteristics and respond to changes in variables influenced by GVCs.

The interplay between firm-level attributes and GVC participation, along with the potential bidirectional causation and selection bias, underscores the need for careful empirical analyses. There is no simple solution to tackle these complexities but several partial approaches that can help addressing these challenges. In this study, we employ two prominent methods, namely Propensity Score Matching (PSM) and Entropy Balancing (EB), to identify the causal effect of GVC participation on firm productivity. PSM techniques explicitly handle the issue of self-selection bias by matching firms engaged in GVC (identified as those performing two-way trading) with similar firms that do not engage in this type of trade but share all other relevant characteristics —what we call, for the sake of simplicity, the "control" group. This matching approach enables us to isolate the effect of GVC integration on firm productivity, thereby providing more reliable and robust results. As an alternative matching technique we use entropy balance methods, which have the advantage of avoiding strong assumptions about the distribution of characteristics among matched units while addressing the issue of non-random sample selection. It accomplishes this by placing more weight on firms that are similar across a rich range of observable characteristics, thus ensuring a more balanced comparison between GVC participants and non-participants.

Our results suggest that the opportunities for leveraging productivity gains via GVC participation depend on country-development levels and the technology intensity of sectors. GVC participants from low- and lower-middle income countries, or operating in low-tech industries, exhibit higher labor productivity and also higher total factor productivity than their respective control groups. For the rest of income categories and technology intensities, firms participating in GVCs do present higher labor productivity but no significant differences show up on TFP. This finding, based on cross-section analysis, is robust to a difference-in-difference implementation exploiting the implicit panel structure of the data (at the cost of heavily reducing our sample size).

Conceptually, firms may increase their labor productivity even in the absence of TFP variation, whenever they become more capital intensive. This is exactly what we observe when looking at the impact of GVC participation on capital intensity, which reveals prominent effects for firms in high income countries.

GVCs participants, here again relative to their matched control groups, also present higher propensity to innovate and lower average labor costs. On the other hand, they use inputs with larger unit costs and have a higher propensity to engage in quality certifications, which is consistent with the idea of quality upgrading through more suitable imported inputs. These results are robust to restricting the sample of control groups to pure exporters or pure importers, and thus comparing GVC participation to pure one-way trading.

Overall, our results confirm the idea of cumulative opportunities of technical change (i.e. product or process upgrading) for the "happy few" GVC participants in developing countries. Firms engaged in GVCs in advanced countries are in fact investing, introducing new product and process, improving quality, and also obtaining the expected labor cost reduction. However, as they operate closer to the world technology frontier (i.e. with the most efficient available technologies), increasing their multifactor efficiency may require more costly cutting-edge innovation rather than imitating or adopting existing technologies. We consider this as an important divide to understand firms' opportunities offered by GVC participation in developing and advanced countries.

The remainder of the paper is structured as follows. Section 2 covers the related literature and discusses the underlying mechanisms of the effect of GVC participation on firm productivity. Section 3 introduces our empirical identification strategy. Section 4 provides a description of the data and the most salient sample characteristics. The empirical findings on productivity are presented and discussed in Section 5. Section 6 empirically explores the channels. Section 7 concludes.

2 GVC participation and firm efficiency

Although ex-ante self-selection into foreign markets has been strongly emphasized in "new new" trade models featuring heterogeneous firms, the literature analyzing trade and technical change also highlights that efficiency improvements can be obtained through different international activities. The crucial point we want to highlight is that most of these channels can be simultaneously operative in firms participating in GVC, especially in developing countries.

Most commonly acknowledged mechanisms are related to import activities. At the aggregate level, open-economy endogenous growth models provide theoretical grounds for the growth-enhancing role played by knowledge spillovers associated to R&D and traded inputs, which boost growth under expanding-variety innovation (e.g. Grossman and Helpman, 1991; Rivera-Batiz and Romer, 1991a,b). At the firm level, the common theoretical proposition is that trading in intermediate goods can boost productivity. This occurs through increased complementarity between foreign and domestic input usage (Markusen, 1989) price-adjusted quality advantages, and a greater variety of goods (Halpern et al., 2015).

The previosly mentioned channels have received wide empirical support, mainly from emerging economies —e.g. Brazil (Schor, 2004), Chile (Kasahara and Rodrigue, 2008), Indonesia (Amiti and Konings, 2007), India (Goldberg et al., 2010;

Topalova and Khandelwal, 2011), or Hungary (Halpern et al., 2015). Additionally, some evidence from advanced countries indicates that the impact is notably pronounced when imported inputs originate from other developed countries—e.g. in France (Bas and Strauss-Kahn, 2014) or Sweden (Loof and Andersson, 2010).

Engaging in GVCs also involves the exports of the domestic value added within the production chain. In particular, firms participating in GVCs are expected to gain from the learning-by-exporting opportunities. The act of selling products abroad involves a continuous process of improving both product and process to meet the standards of foreign customers and international competitors.

Despite the potential benefits, well-established surveys and comparative empirical analyses (e.g. Keller, 2010; Wagner, 2007) show mixed or non-significant results, which contrasts with the widely documented finding of self-selection into foreign markets. The extensive literature on this debate, however, highlights that the learning-by-exporting hypothesis is not limited to case studies on Asian "newly" industrialized countries. It may also apply to developing countries, such as African countries e.g., (Van Biesebroeck, 2005), or economies in an emerging or transition stage —e.g. Chile (Alvarez and Lopez, 2005), Slovenia (De Loecker, 2007, De Loecker, 2013), Estonia and Latvia in the context of GVC participation (Benkovskis et al., 2020). While evidence in developed countries is more limited, some empirical support exists, particularly when the data allows tracking knowledge sources associated to foreign sales —e.g.(Crespi et al., 2008) for the UK.

A closely related but conceptually different channel involves incentives to engage in productivity-enhancing investments, such as R&D or technology adoption, driven by the anticipation of higher profits from export activities. These "Schumpeterian" incentives, which manifest as ex-post innovation rents, are prominent in models featuring heterogeneous firms and endogenous productivity variations (Costantini and Melitz, 2007; Bustos, 2011; Bas and Ledezma, 2015) or quality improvements (Kugler and Verhoogen, 2012).

Using Taiwanese data, Aw et al. (2011) show that the decision on the previous activities are intertwined and represent key determinants of productivity. Lileeva and Trefler (2010) show that Canadian plants that began exporting or increased their exports following the Canada-US free trade agreement, improved their labor productivity, innovated more, and had higher technology adoption rates. The authors also document that these plants additionally benefited from the better access to US intermediate inputs, which shows the cumulative nature of import and export channels. Other studies have also documented this complementarity between import and export activities (e.g. Feng et al., 2016, Bas and Strauss-Kahn, 2014, Chor et al., 2021).

Firms integrated within GVC not only trade. More generally they are participating into an internationally coordinated production network, where production tasks are performed in different locations according to comparative advantages. Grossman and Rossi-Hansberg (2008) show that improvements in the cost of offshoring of low-skilled tasks, providing incentives to the international division of labor, ultimately induce a labor-augmenting technological progress in domestic firms. In addition, within GVC, knowledge is expected to circulate more fluidly. As an important part of international production remains organized within the boundaries of multinational firms, there are more incentives to engage in the transfer of knowledge to foreign affiliates or to long-term outsourcing counterparts. Stressing the relevance of these knowledge flows, Keller and Yeaple (2013) estimate a theoretically grounded gravity-like framework to show that the arbitrage between embodied and disembodied knowledge transfers in the context of trade costs and knowledge transfer costs (communication, codification, etc.) may well explain the pattern of foreign affiliates' sales. In a complementary way, some strands of the literature on innovation systems have detected different forms of interactive learning taking place in GVC, ranging from simple absorption of knowledge spillovers to pressures for conformity to quality standards, face-to-face interactions, training, manager turnover, and imitation —see (Pietrobelli and Rabellotti, 2011) for a synthetic overview.

All these mechanisms related to technical efficiency can be complemented with the opportunity to exploit scale economies, leading to reduced average costs through foreign sales. Observing this cost-efficiency channel in micro-level data can be challenging as several other determinants of average costs can be involved in GVC participation. While average costs may decline with increased output in non-convex technologies, as illustrated in various "new" trade theory models with fixed costs and variable markups, it is important to recognize that productivity and input prices also contribute to shaping the average cost function. The productivity-enhancing effects mentioned earlier should manifest in changes to average costs.

In the context of sourcing intermediate inputs abroad, it is conceivable that higher-quality inputs, available in a wider suitable variety, may come at an increased cost-a trade-off that could be justified to enhance product quality. Kugler and Verhoogen (2012) propose that importing firms often access a larger variety of inputs and purchase higher-quality items, albeit at higher input prices on international markets compared to domestic ones. Importantly, this observation aligns with the concept of better quality-adjusted input prices and, consequently, increased profitability.

Labor is another important input determining unit costs. While higher labor productivity and low-wage outsourcing typically result in fewer labor units and a decrease in the average wage bill, as depicted in conventional outsourcing models (e.g. Feenstra and Hanson, 1997), an improved quality of capital inputs may lead to skill-biased technology adoption, augmenting labor compensation. Numerous studies confirm that among developing countries, trade liberalization has increased the relative plant-level demand for skilled labor (Sanchez-Paramo and Schady, 2003; Goldberg and Pavcnik, 2007; Kasahara et al., 2016). Additionally, the labor-augmenting technological progress of low-skill workers, theoretically identified by Grossman and Rossi-Hansberg (2008) for firms offshoring low-skill tasks, will tend to increase their real wage (in the domestic firm's market). This effect is thus more likely to be observed in developed countries.

In summary, all these channels suggest that firms in developing countries that participate in GVCs stand to potentially benefit from various incentives and drivers of technical change. The constraints imposed from limited access to high-quality inputs, inadequate local knowledge spillovers and capabilities, and a small domestic market size are likely more constraining in developing countries. Joining a GVC can help alleviate these constraints, potentially accelerating technical change more significantly than in advanced countries. While advanced countries may still experience average cost reduction and incentives for technology investment, they rely more on innovation for long-term growth rather than imitation. This aligns with the broader idea that in the early stages of technology development, economies depend more on imitation, whereas those closer to the technology frontier emphasize innovation (Acemoglu et al. (2006)). For firms in advanced countries, offshoring production typically focuses on cost reduction, which, compared to developing countries upgrading their production processes, may be less conducive to generating new knowledge. While cost-minimizing strategies in advanced countries may enhance resource allocation to technological progress or skill-intensive tasks, their impact on productivity appears less immediate than for GVC participants in developing countries. The heterogeneous effects of GVCs will be further explored in our empirical analysis below.

However, there is a notable caveat to the optimistic narrative for developing countries. Producing manufacturing goods without having to build all industrial stages within the national market is an appealing strategy, but it also prevents learning. This includes general forms of learning-by-doing (Thompson, 2010) and learning what can be produced with comparative advantage. As pointed out by Hausmann and Rodrik (2003), when there are cost uncertainties regarding the use of production technologies, industrial development can be seen as a process of self-discovery. Such a process may inevitably generate path dependency and externalities. Based on these insights, it is reasonable to speculate that, in the short run, most productivity gains in developing nations will likely be evident in mature and presumably low-tech industries. This is particularly true where international standardization minimizes uncertainty regarding the technology of production.

3 Empirical Strategy

The most straightforward approach to evaluate the effects of global value chain participation is when participation is distributed randomly among firms. This means that there is no selection process. The effects of participation would be easily assessed by a simple comparison of productivity indicators of countries participating in GVCs with those of countries not participating.

However, it might be the case that two-way traders of goods or services are significantly more likely to engage in highly productive activities. If that is the case, GVC participation is not allocated randomly and there exists some form of selection process. This means that some factors might influence the likelihood of participation, and thus the simple comparison of indicators of productivity cannot be used, because it would be biased. Moreover, since two-way traders may also have higher productivity for other reasons than participating in value chains, a challenge in evaluating the benefits of participating is to disentangle the direction of causality.

In order to examine whether firm's that engaged on global value chains present higher productivity than firms that do not, we must properly control for endogeneity and self-selection bias. Fortunately, there are a number of ways to account for these issues. The first and more obvious approach is to use an instrument for becoming two-way trader. This standard approach to rely on an instrumental variable that affects the participation but does not directly affect productivity is criticized mainly because it the difficulty of finding good instruments. Another, less standard approach, is to employ impact assess methods such as propensity score matching (PSM) and entropy balancing (EB). These matching techniques were developed precisely for the bias associated with this type of estimation problems. Using matching techniques represents a valid strategy to isolate the economic indicators of two-way traders and may lead to more robust and reliable results than more standard techniques. These are precisely the approaches that we follow in this paper.[3]

[3]Note that no methodological approach is perfect, and we always need to bear in mind the

The idea behind both PSM and EB is to determine whether a treatment (in our case participation in GVCs) leads to different outcomes relative to an absence of the treatment by matching treated observations with control observations that share similar characteristics other than the presence of the treatment. Following the matching of observations, we assess the "treatment effect" by measuring the difference in the productivity between the two groups. That is, we see global value chain participation as a "natural experiment," so we seek to reestablish the conditions of a randomized experiment where the participation mimics a treatment.

More in detail, let D be a binary indicator that equals one if a firm is a two-way trader, zero otherwise. Also, let Y_i^1 denote productivity for firm i if the firm is engaged in a two-way trade (i.e. if the firm is in the treated group) and Y_i^0 if not, all other characteristics of the firm 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 one is the counterfactual. We are interested in estimating the average treatment effect on the treated (ATT) firms, that is:

$$ATT = E[Y_i^1|D = 1] - E[Y_i^0|D = 1] \tag{1}$$

Introducing the control group, we can write the average treatment as:

$$ATT = E[Y_i^1|D = 1] - E[Y_i^0|D = 0] - E[Y_i^0|D = 1] + E[Y_i^0|D = 0] \tag{2}$$

where $E[Y_i^1|D = 1]$ and $E[Y_i^0|D = 0]$ are observed and $E[Y_i^0|D = 0] - E[Y_i^0|D = 1]$ is the selection bias. Hence, Eq.(2) can only be identified if this selection bias disappears, i.e. if $E[Y_i^0|D = 1] = E[Y_i^0|D = 0]$.

The PSM and EB deal with this selection problem by pairing each treated observation with control observations that are otherwise similar based on a set of observable characteristics, $\mathbf{X}$. This requires that the treatment satisfies some form of exogeneity, namely the so-called conditional independence assumption. This assumption states that, conditional on a vector of observable characteristics, the variable of interest (productivity) is independent of the treatment status. Conditional on this vector $\mathbf{X}$, expected productivity in the absence of GVC participation would then be the same for paired firms, that is $E[Y_i^0|D = 1, \mathbf{X}] = E[Y_i^0|D = 0, \mathbf{X}]$, and the bias would disappear. Under this assumption then the ATT effect is written as:

$$ATT = E[Y_i^1|D = 1, \mathbf{X}] - E[Y_i^0|D = 0, \mathbf{X}] \tag{3}$$

limitations of each approach.

In Eq. (3) $E[Y_i^1|D=1,\mathbf{X}]$ controls for the relevant set of characteristics, $\mathbf{X}$. This set should include variables that are co-determinants of both participation (the treatment) and productivity (the outcome), and conditioning on all relevant variables may be a challenge. Rosenbaum and Rubin (1983) and Imbens (2004) show that if the hypothesis of conditional independence holds then all biases due to observable components can be removed by conditioning on the propensity score. Therefore, the ATT in the PSM becomes:

$$ATT = E[Y_i^1|D=1,p(\mathbf{X})] - E(Y_i^0|D=0,p(\mathbf{X})] \quad (4)$$

where $E[Y_i^1|D=1,p(\mathbf{X})]$ denotes the fact that we control for the probability of observing the treatment conditional on the set $\mathbf{X}$ of variables. $p(\mathbf{X})$, the propensity score, should reflect a compromise between the potential influence of a variable on the outcome and its ability to improve the matching.

To obtain the ATT, we proceed in two steps. We first estimate the propensity score by a benchmark probit equation explaining the likelihood of a firm receiving the treatment. To this end, the dependent variable takes the value of one if the firm is a two-way trader, zero otherwise. We consider a number of potential determinants of GVC participation: size, a dummy variable indicating if the firm is engaged in research and development, the interaction variable between the previous two variables, the firm's age in years, a dummy variable indicating if the firm has a share of equity held by foreign companies, a dummy variable indicating if the firm has access to credit, the share of skilled labor, income and GVC participation both at the country level, and industry dummy variables[4]. Then, we match firms within each group by their propensity scores obtained from the probit specifications. We employ the nearest neighbor algorithm, pairing each observation in the treatment group with the closest observation and the three closest observations (in term of propensity score) from the control group.[5]

Entropy balancing, in turn, aims to balance the distribution of observable characteristics between the treatment and control groups. It assigns weights to each individual in the groups to make them more comparable based on their observable characteristics. The idea is to create balance so that the treatment and control groups are similar in terms of those characteristics.

More in detail, estimating the ATT by entropy balancing involves two steps. The first is to compute weights for the control group. These weights may satisfy pre-specified balanced constraints involving sample moments of observable charac-

[4]See next Section for the motivation to consider these variables.

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

teristics (which are the covariates X). We choose balanced constraints that impose equal covariate means and variances between the treatment and control groups. In doing so, we want to ensure that the control group, on average, has non-treatment units that are as similar as possible to the treated units. The second step uses the weights from the first step in a regression analysis where productivity is the dependent variable. In this step, we control for the covariates employed in the first step. This is equivalent to including control variables in a randomized experiment and increases estimation efficiency. Importantly, compared to conventional matching where the control units are either discarded or matched, entropy balancing uses more flexible re-weighting schemes. It re-weights units with the goal of achieving balance between treated and untreated units while keeping the weights as close as possible to the base weights to avoid a loss of information.

4 Data Selection and Descriptive statistics

4.1 Data

We use firm-level data obtained from the World Bank's Enterprise Surveys (WBES) and covering 144 countries over the period from 2006 to 2021. These data-sets are derived from stratified random samples of firms, wherein efforts are made to draw samples from the eligible firm population, employing stratification techniques based on size, location, and sector.[6] While the primary objective of WBES is not to achieve national representativeness, the three dimensions of stratification facilitate coverage of a substantial portion of total trade. The surveys encompass a wide array of variables pertaining to firm characteristics, regulatory framework, taxation, corruption, crime, financial aspects, performance indicators, informality, infrastructure, labor aspects, sales, supplies, and trade. An important feature of these data lies in the consistent administration of identical questions across different countries. A further advantage is that special emphasis is placed on the quality of the information.[7]

At a firm level, GVC participation can be constructed with information from surveys asking specific questions about a firm's GVC participation —see Harvie et al. (2010) or Wignaraja (2013). Unfortunately, this type of data is restricted to a few countries and few years. In this paper, we build upon the approaches adopted

[6]The universe of firms can be described as the non-agricultural formal, private economy and it includes manufacturing, retail, other services, IT, construction, and transport. All firms with 5 employees or more are included. For our purposes, we retain only manufacturing firms for which we have data on productivity.

[7]Experience shows that this is highly correlated to the length of the questionnaire which also affects the response rate. Consequently, the questionnaire is designed to not take longer than 1 hour to complete. A unique global questionnaire is used across all regions.

Table 1: Export-import status for firms in the sample (in percentage)

Indicator	Low and low middle income	Upper middle income	High income	**Total**
No traders	51.33	35.1	20.8	41.6
Traders	48.8	64.9	79.2	58.4
of which pure exporters	8.1	10.40	8.1	8.9
of which pure importers	64.5	52.63	33.4	53.9
of which two-ways traders	27.3	37.0	58.6	37.2

Notes: (a) This table reports the average percentage of firms according to trade status for the 2006-2021 period.

by Benkovskis et al. (2020) and Rigo (2021) and assume that a firm participates in GVCs if it imports inputs and exports output. To discern the patterns of engagement in GVCs among the 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 thus our benchmark GVC participation measure as a binary indicator variable, equal to one for firms engaged in two-way trade, i.e., 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.[8] We also identify firms engaging exclusively in import or exclusively in export activities.

Examining the pattern of engagement in international trade, Table 1 reveals that among 53,503 firms for which we have data on productivity, about 42% do not engaged in foreign trade, the proportion being considerably higher for firms in low and low-middle income. Of the trading firms, a predominant majority, especially among those in developing economies —comprising the majority in our sample—are engaged exclusively in importing. On average, around 37% of trading firms are categorized as two-way traders, a proportion significantly elevated in high-income countries.

Our outcome variables are labor productivity and total factor productivity. The first variable corresponds to value added per worker (in constant terms). TFP, in turn, is based on a Cobb-Douglas production function were the capital stock is prox-

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

ied by the replacement value of machinery, vehicles, and equipment, labor by total employment and value added by the difference between total annual sales of the establishment and annual cost of inputs. Firms' (logged) TFP is estimated as a sum of the constant and the residual of the estimated Cobb-Douglas equation.[9]

As it is usually the case with this type of estimations, productivity, particularly TFP, suffers from several caveats, some of them unsolved. First, there are issues associated with the fact that often only monetary (as opposed to physical) output and input expenditure are observed in typical firm-level data. A second caveat relates to the importance of the functional form of the production function which assumes a constant elasticity of output regardless of other output choices. The WBES address this point by estimating TFP separately for each two-digit ISIC industry. Moreover, in order to control for potential differences in production technology between countries, wherever possible, the production coefficients are allowed to vary by the income-level grouping of the corresponding economy by adding interaction terms between income group and factor inputs. The estimated equation also follows a translog-type specification.

We complement our data set with the following variables that have been identified as systematic determinants of global value chain participation at the firm level: 1) *size*, which is a categorical variable for small, medium and large firms according to the number of employees; employment, which is the number of permanent, full-time workers of the company; 2) *RD*, which is a binary indicator variable equal to one for firms that spend on research and development (excluding market research) and zero otherwise; 3) *sizexrd* corresponding to the interaction variable between the previous two variables; 4) *age* for the firm's age in years; 5) $foreign$, which is a dummy variable indicating if the firm has a share of equity held by foreign companies, zero otherwise; 6) *credit*, which is a dummy variable that takes the value of one if the establishment have a line of credit or loan from a financial institution, zero otherwise; 7) *skill_share* is the proportion of skilled labor in total labor; 8) *income*, which is a categorical variable for low and low-middle income, upper-middle income and high income; 9) the interaction between the two previous variables and 10) GVC participation at the country level to give account of a favorable country environment for participating in GVC (source: EORA database).

Finally, to identify the possible channels of transmission, we rely on specifications that include: 1) capital intensity, defined as capital stock over permanent full-time workers; 2) a binary variable for innovation. This dummy variable takes on the value of one if the firm has introduced a new product or service over the last three

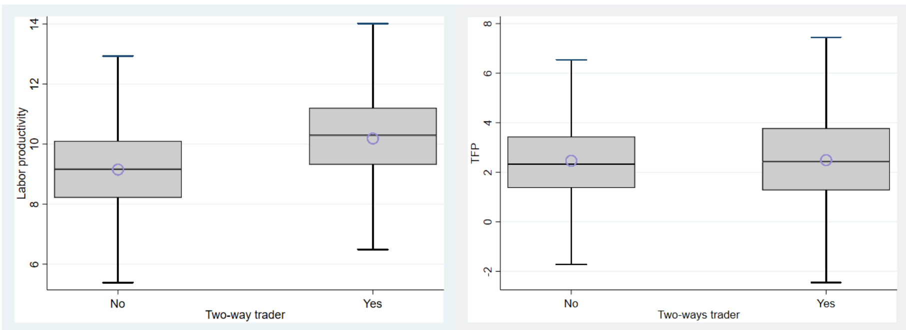
[9]See Francis et al. (2020) for more details.

years, or if the firm has introduced a new or improved process —i.e. we aggregate process and product innovation into a single binary variable to ensure a relatively larger proportion of innovative firms is captured; 3) the average cost of intermediate inputs, the average cost of labor, and total average costs. We consider here the cost of inputs per unit of sales, the cost of labour per unit of sales, and the sum of both; and 4) a binary variable if the establishment has an internationally-recognized quality certification.[10]

4.2 Descriptive statistics

An initial examination of the association between productivity and participation in GVCs can be attained by contrasting the productivity levels of the treated and control groups. The utilization of box-plots, as illustrated in Fig. 1, allows for a visual comparison of labor productivity disparities between firms engaged in two-way trade and those not engaged in such trade. As seen in the figure, firms involved in two-way trade display higher median labor productivity levels, as indicated by the central line within the box, as well as higher 25th and 75th percentiles, representing the lower and upper hinges of the box, respectively, when compared to control firms. However, it is noteworthy that no substantial disparities exist between the two groups in terms of Total Factor Productivity (TFP).

Figure 1: Labour productivity and TFP according to GVC participation



Notes: In the box plots, Yes represents participation in GVCs. The lower and upper hinges of each box show the 25th and 75th percentiles of the samples, the line in the box indicates the respective medians,and the end-points of whiskers mark next adjacent values.

To gain an initial perspective on the differences in productivity between treated and control firms, we employ statistical tests to compare their mean productivity levels. The outcomes of these tests are presented in Figure 1 and Table 2. They

[10]In all the cases, responses indicating “do not know/spontaneous” were treated as missing data.

Table 2: Labor productivity and TFP by type of GVC-trade: mean-comparison tests

	Mean				
Indicator	Non two-way traders	Two-ways traders	Diff.	T-test	P-value
Labor productivity	9.150	10.183	-1.033	-75.409	0.000
TFP	2.464	2.490	-0.026	-1.523	0.127

Notes: (a) This table reports descriptive statistics for all the firms in the sample for the 2006-2021 period.

reveal that firms involved in global value chains exhibit significantly higher levels of labor productivity. It is important to note that while this observation underscores a correlation between GVC participation and labor productivity at the firm level, it does not, by itself, establish a causal link. Nevertheless, this finding provides a preliminary insight into the treatment effect. At the same time, it is worth noting that we do not observe similar statistically significant differences in TFP.

Table 3 present some descriptive statistics for the covariates for both the treatment and control groups, before implementing the matching. The objective is to assess discrepancies, beyond participation status, between these two categories of firms. It is evident that substantial differences exist between these two groups. Specifically, treated firms, i.e., firms engaged in global value chains, exhibit larger size in terms of the number of employees and are well-established enterprises. They also display a higher propensity to invest in research and development, possess a higher share of equity held by foreign companies, and have easier access to credit. These firms align with the expected relationship between two-way trading and the various control variables discussed earlier. Notable differences also emerge among firms in different countries. As seen in Table A.2, firms in low and low-middle income countries are generally smaller in size, allocate fewer resources to research and development, attract less foreign capital investment, and have limited access to credit compared to their counterparts in more advanced economies.

The aforementioned differences between treated and control firms and firms in lower income economies underscore the critical importance of carefully selecting an appropriate control group to ensure the accurate estimation of the treatment effect of GVC participation in the context of your study.

5 Results

We start by presenting the propensity scores for participation in GVCs and their impact on productivity. We are particularly interested in the effect of receiving the treatment and therefore focus the discussion on the ATT estimates (see Eq. 3). We

Table 3: Descriptive statistics of covariates **(before matching adjustment)**

	No two-way traders		**Two-way traders**		**Whole sample**	
Variable	Mean	SD	Mean	SD	Mean	SD
Size	1.69	0.73	2.31	0.73	1.83	0.77
R&D	0.20	0.40	0.45	0.50	0.26	0.44
Firm's age	19.96	16.74	29.01	24.12	21.98	19.02
Foreign ownership	0.06	0.24	0.24	0.43	0.10	0.30
Access to credit	0.36	0.48	0.58	0.49	0.41	0.49
Skill share	0.71	0.31	0.70	0.32	0.71	0.31
Country's GVC	40.21	8.80	45.13	11.00	41.30	9.56

Notes: (a) This table reports descriptive statistics for the 2006-2021 period.

then assess possible heterogeneity across countries, sectors and firms.

5.1 The propensity score for GVC participation and full-sample average treatment effects

The first stage of the estimations for the average treatment effect is interesting in its own, as it elucidates the primary determinants of GVC participation within the sample. Table 4 presents the probit estimates for the entire sample, along with segmented analyses based on country-level income classifications. In sum, the estimations indicate that the likelihood of engagement in a GVC is notably higher for large, well-established firms (regarding the number of years in activity) that engage in R&D, maintain foreign ownership shares exceeding 10%, have access to credit, and operate within a country actively participating in GVCs.

As seen in the table, in high-income countries, the skill intensity is associated with lower probability of participation. Note that low-skill-intensive firms in these high-income regions may actually display a heightened propensity to engage in offshoring activities, particularly within the framework of cost-reduction strategies. Furthermore, the somewhat perplexing negative coefficient associated with the interaction term between the size variable and the R&D dummy variable does not diminish the overall positive marginal effect of these variables, which remain largely positive.[11] This negative interaction primarily manifests within the low and lower-middle income sub-sample, suggesting a strategic trade-off between investments in R&D and the scale of production when pursuing internationalization strategies in the context of developing economies.

Using the results from the previous probit models, we match firms in the treat-

[11]The marginal effects are not shown but they are available upon request from the authors.

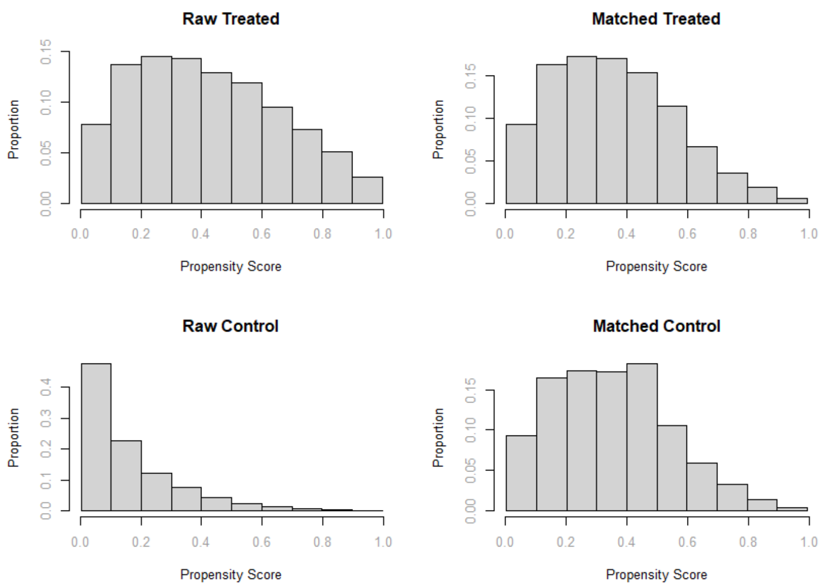
Table 4: Probability of participation in GVC. Whole sample and by income groups. Probit estimates

	Whole sample	Low and lower middle income	Upper middle income	High income
Size	0.621***	0.737***	0.600***	0.440***
	(0.013)	(0.021)	(0.023)	(0.026)
Size x R&D	-0.077***	-0.084**	-0.047	-0.044
	(0.021)	(0.037)	(0.036)	(0.043)
R&D	0.591***	0.561***	0.480***	0.639***
	(0.049)	(0.090)	(0.085)	(0.090)
Firm age	0.003***	0.003***	0.003***	0.003***
	(0.000)	(0.001)	(0.001)	(0.001)
Foreign	0.702***	0.679***	0.759***	0.639***
	(0.023)	(0.036)	(0.039)	(0.051)
Credit	0.203***	0.229***	0.197***	0.164***
	(0.016)	(0.026)	(0.028)	(0.032)
Country GVC participation	0.030***	0.008	0.037***	0.005
	(0.004)	(0.010)	(0.007)	(0.007)
Skill share	-0.072	-0.060	-0.055	-0.181***
	(0.057)	(0.042)	(0.041)	(0.052)
Income x Skill share	-0.001			
	(0.020)			
Income	0.012			
	(0.026)			
Constant	-7.755	-7.375	-4.295***	-2.233***
	(98.814)	(81.206)	(0.327)	(0.285)
Isic dummies	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes
Observations	51071	25914	15701	9456

Notes: (i) *,**,*** denotes significance at the 10, 5 and 1%. (ii) Estimations include country and industry dummies.

ment group (i.e. two-way traders) to firms in the control group (i.e. one-way traders or non-trading firms) based on their propensity score. For each firm, the propensity score can be intuitively considered as the probability of receiving the treatment, calculated from the range of covariates (and potential confounders) in Table 2. Two firms, one from the treatment group and one from control group, are considered to be a match if the difference between their propensity score is small. Figure 2 shows the distribution of propensity score across the different treatment status before and after the matching, so that one can visualize their imbrication. A PSM will not be appropriate if there is not a satisfactory overlap in the propensity score distribution between the matched treated group and the matched control group.[12] The large number of matched firms is reassuring about the quality of the PSM modeling.

Figure 2: Distribution of the probability of participating in a global value chain for treated and untreated firms.



Notes: The figure shows the distribution of propensity scores for matched and unmatched observations within both treated and untreated groups.

The effectiveness of the matching can also be visualized in Table 5. The table presents the mean values after weighting by entropy balance, for the treatment and synthetic groups. As seen, after weighting, there remain no disparities between groups. Furthermore, Figure 3 illustrates the balance achieved in the PSM method,

[12]From all the firms in the sample, unmatched participants are discarded.

Table 5: Descriptive statistics of covariates after entropy balance matching

	Treated		Control	
Variable	Mean	Variance	Mean	Variance
$size$	2.327	0.526	1.744	0.554
rd	0.434	0.245	0.200	0.160
$size \times rd$	1.046	1.636	0.402	0.7603
age	29.740	590.900	21.030	291.700
$foreign$	0.242	0.183	0.0558	0.0527
$credit$	0.5594	0.246	0.345	0.226
$skillshare$	0.688	0.106	0.705	0.104
$income$	2.725	1.514	2.032	1.416
$skill \times income$	1.899	1.792	1.432	1.346
GVC	44.430	126.200	40.050	85.670

Notes: (a) This table reports descriptive statistics for all the firms in the sample for the 2006-2021 period.

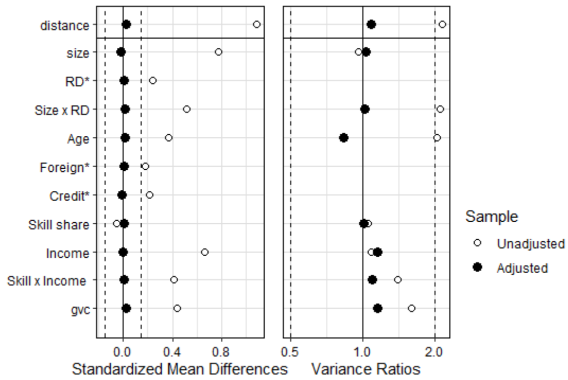
visually summarizing the standardized mean differences (SMD) and variance ratios. These love plots capture the hierarchical patterns observed with respect to several characteristics.[13] The plots show that, following the balancing procedure, most of the discrepancies between the groups have been minimized.

In sum, the observed reduction in differences between the treatment and control groups, suggests the successful alignment of these groups. Consequently, our proposed methodologies enable the construction of a reliable control group that closely resembles two-way trader firms, i.e. a counterfactual. This ensures a robust assessment of the causal effect of GVC participation on productivity.

Estimates of the ATT using both PSM and entropy balancing are presented in Table 6. We retain labor productivity and total factor productivity as our main measures of firm efficiency, with estimations being performed over the full sample. In the case of propensity score matching, we consider alternatively 1 and 3 "neighbors" in pairing the observations (NN1 and NN3 respectively in the table). Both estimation techniques suggest a statistically significant positive average treatment effect of GVC participation on labor productivity but not on TFP. Such a contrast between the estimated TFP and labor productivity outcomes are in line with the

[13]The SMD represents the standardized difference in means for each covariate between the treatment groups, with standardization performed to ensure the same scale for all covariates. The standardization factor typically corresponds to the standard deviation of the covariate in the treated group, and it should remain consistent before and after matching to avoid confounding effects due to changes in the covariate's standard deviation. SMDs closer to zero indicate a favorable balance. Additionally, the variance ratio denotes the ratio of the variance of a covariate in one group to that in the other. A variance ratio close to 1 indicates a satisfactory balance, implying similar variances between the samples.

Figure 3: Covariate balance



Notes: The love plots display vertical lines at 0.15 standardized mean difference units and 0.5 variance ratios. * indicates (dummy) variables for which the displayed value is the raw (unstandardized) difference in means. Distance is total distances between treatment and control groups.

previous descriptive unadjusted mean comparisons (see Figure 1).

These estimates for the entire sample naturally raise the possibility of heterogeneity across countries and sectors. The different results on TFP and labor productivity could also stem from the distinctive nature of the two efficiency proxies being utilized. Whereas TFP represents a measure of multifactor efficiency, labor productivity is intricately linked to TFP and capital intensity. The latter variable, capital intensity, might exhibit more rapid responsiveness to internationalization within GVCs than the complete causation chain responsible for TFP alterations. This typical chain initiates with R&D efforts, which eventually lead to innovations. Subsequently, once these innovations are adopted, they can increase firm productivity. To address these questions, the subsequent sections delve into a comprehensive exploration of potential sources of heterogeneity and various mechanisms of technical change.

5.2 Heterogeneity across countries, sectors and firms

While the full-sample estimates presented above where obtained after controlling for various country and industry characteristics, our approach constrained the first-stage scoring coefficients and the ATT to be the same across all countries and sectors. As a result, these estimated ATT for GVC participation may conceal some underlying heterogeneity stemming from distinct country and production characteristics. Like-

Table 6: **Average Treatment Effect (ATT) of GVC participation on labor productivity and TFP. Whole sample.**

	Labour productivity			**TFP**		
Matching	**PSM**		**Entropy**	**PSM**		**Entropy**
algorithm	**NN1**	**NN3**	**balancing**	**NN1**	**NN3**	**balancing**
Whole sample	0.203***	0.200***	0.198***	0.034	0.010	0.021
	(0.028)	(0.024)	(0.016)	(0.044)	(0.038)	(0.020)
N. Treated	11328	11328	11328	9489	9489	9489
N. Obs.	51071	51071	51118	39755	39755	39815

Notes: (i) Observed coefficient is treatment effect (the difference between the treated and controls). When productivity is higher for the treated observations than the non-treated, the ATT shows a positive and significant value; (ii) Standard errors are presented in parenthesis; (iii) *,**,*** denotes significance at the 10, 5 and 1%; (iv) Estimations include country and industry dummies; (v) NN1 and NN3 stand for PSM algorithm matching each treated observation with at least 1 and at least 3 control group observations, respectively.

wise, at the firm level, we also controlled for numerous individual characteristics. However, it is important to acknowledge that unobservable firm heterogeneity may still persist. Given that the WBES data are primarily cross-sectional in nature, our primary focus remains on the observation level rather than the firm level. Nonetheless, there are a few firms that appear in two or more survey waves so that we can exploit this reduced panel structure in order to further analyze the robustness of our findings. We deal in this section with these different aspects of heterogeneity within our sample.

Therefore, we split the sample based on income level categories, which encompass low- and lower-middle income, upper-middle income, and high income brackets.[14] These categories are often associated with varying degrees of external resources related to firms' technical change, including institutions, the provision of public goods, and absorptive capacity. All estimations incorporate country and industry dummies to account for potential internal sub-sample variations.[15]

Results, as presented in Table 7, once more illustrate a positive average treatment effect of GVC participation on labor productivity across all income categories. Notably, the magnitude of the ATT estimated through entropy balancing and PSM techniques is quite similar, with the effect being particularly pronounced for firms operating in low and lower-middle income countries. It is worth noting that it is specifically in this low and lower-middle income category where the ATT considering TFP as the outcome also exhibits a significantly positive impact. In contrast,

[14]The definition of income categories follows the World Bank.

[15]In order to save space we omit PSM estimations using a matching algorithm of 3 neighbors, which are all qualitatively similar to the standard of 1 neighbor.

Table 7: **Average treatment effect of GVC participation on labor productivity and TFP. Income group sample.**

	Labor productivity		TFP	
Matching algorithm	**PSM**	**Entropy balancing**	**PSM**	**Entropy balancing**
Low and lower middle income	0.382***	0.296***	0.159***	0.152***
	(0.048)	(0.030)	(0.056)	(0.030)
N. Treated	3292	3292	2530	2530
N. Obs.	25941	25941	18617	18665
Upper middle income	0.187***	0.183***	-0.033	-0.018
	(0.040)	(0.030)	(0.060)	(0.032)
N. Treated	3742	3742	3092	3092
N. Obs.	15701	15721	13039	13051
High income	0.099***	0.116***	0.088	-0.018
	(0.036)	(0.021)	(0.103)	(0.035)
N. Treated	4294	4294	3867	3867
N. Obs.	9456	9456	8099	8099

Notes: (1) Observed coefficient is treatment effect (the difference between the treated and controls). When productivity is higher for the treated observations than the non-treated, observed coefficient shows a positive and significant value, (2) Standard errors are presented in parenthesis, (3) *,**,*** denotes significance at the 10, 5 and 1%. (4) Estimations include country and industry dummies. PSM considers a pairing of at least 1 neighbor.

within the remaining sub samples, the average TFP of firms participating in GVCs does not exhibit a significant difference from that of the matched control group.

Note also that firms operating within distinct sectors may encounter diverse technology and market dynamics that influence their motivations to enhance productivity. It is widely acknowledged that high-tech industries place greater emphasis on market-share incentives and technological advancements. However, it is important to note that the investments required to boost productivity in such industries tend to be substantial and may lead to more pronounced internal creative destruction. In contrast, low-tech industries might see more incremental improvements in productivity. This is often accompanied by relatively lower costs of innovation, especially if firms can rely on imitation and catching up with existing technologies, rather than pioneering cutting-edge innovations.

To gain further insights into this matter, we adopt the categorization of industries into three groups based on their technological intensity, following the approach of Hatzichronoglou (1997) and Yan and Baldwin (2014). These groups are classi-

Table 8: **Average treatment effect of GVC participation on productivity for low, medium and high-tech industries**

	Labour productivity		**TFP**	
Matching algorithm	**PSM**	**Entropy balance**	**PSM**	**Entropy balance**
Low-tech industries	0.096***	0.135***	0.167***	0.185***
	(0.037)	(0.022)	(0.041)	(0.030)
N. Treated	4912	4912	4131	4131
N. Obs.	25734	25796	20593	20657
Low-medium-tech industries	0.180***	0.157***	-0.106	-0.137**
	(0.052)	(0.031)	(0.084)	(0.058)
N. Treated	2778	2778	2383	2383
N. Obs.	13703	13767	10396	105713
Medium-high- and high-tech industries	0.111**	0.172***	0.120	-0.019
	(0.051)	(0.031)	(0.114)	(0.095)
N. Treated	3635	3637	2970	2975
N. Obs.	11486	11553	8604	8645

Notes: (1) Observed coefficient is treatment effect (the difference between the treated and controls). When productivity is higher for the treated observations than the non-treated, observed coefficient shows a positive and significant value. (2) Standard errors are presented in parenthesis. (3) *,**,*** denotes significance at the 10, 5 and 1%.

fied as low, low-medium, and medium-high and high technology industries. The high technology category encompasses sectors such as aerospace, computers/office machinery, electronics/communications, and pharmaceuticals. Low technology sectors include paper printing, textiles, textile products, leather and footwear, food-beverages-tobacco, and wood-furniture products. The remaining industries fall under the medium technology category.[16]

The results according to each group of industries are presented in Table 8. Once again, the results reveal a consistent, positive, and statistically significant average treatment effect of GVC participation on labor productivity across all industry categories, irrespective of the chosen matching algorithm. However, clear-cut differences in TFP are less evident. The results show a clear positive and significant ATT only within the context of low-tech industries.

Within the low-tech industry group, it is noteworthy that 55.4% of observations are derived from low-income and lower-income countries, and 57.4% of observations within this country-income category belong to low-tech industries. This overlap underscores the resemblance of the positive ATT of GVC participation when consider-

[16]For a more comprehensive description, refer to Hatzichronoglou (1997).

ing TFP as an efficiency proxy to that found in Table 7. Firms operating in low-tech industries in developing countries seem to benefit not only from heightened labor productivity but also from an improvement in their multifactor efficiency. This improvement is likely driven by a technology catch-up facilitated by exposure to GVCs.

Conversely, the negative sign observed in middle-tech industries and the statistically non-significant ATT in high-tech industries concerning TFP as an outcome are consistent with the notion of a more intricate causal link between GVC participation and TFP. As mentioned previously, TFP, as a measure of firm efficiency, delves into factors that extend beyond mere inputs and is intricately tied to channels related to innovation. These innovation-related channels may be more challenging to capture within short-term cross-sectional analyses, particularly in more intricate industries that heavily rely on formal R&D activities and significant innovation processes.

Table 9: **Average treatment effect of GVC participation on productivity growth considering the panel dimension. Whole sample**

	Labour productivity		**TFP**	
Matching algorithm	**PSM**	**Entropy balance**	**PSM**	**Entropy balance**
New GVC participants	0.372*	0.258***	0.016	-0.024
	(0.191)	(0.100)	(0.258)	(0.127)
N. Treated	129	129	101	101
N. Obs.	1385	1385	1018	1018

Notes: (i) Observed coefficient is treatment effect (the difference between the treated and controls). When productivity is higher for the treated observations (new two-way traders) than the non-treated, observed coefficient shows a positive and significant value, (ii) Standard errors are presented in parenthesis, (iii) *,**,*** denotes significance at the 10, 5 and 1%. (iv) Estimations include country-income category and industry dummies.

Our further empirical step considers the panel dimension of our data set to conduct a thorough analysis of productivity changes attributed to GVC participation.[17] Thus, we identify firms that have been surveyed in at least two country-specific waves. Within this subset, we compare firms that transitioned into GVC participation between the two waves with those that were consistently present but never engaged in GVC activities.[18] The latter group is chosen based on their closest propensity score, ensuring a common support region. Hence, the treatment criterion in this scenario pertains to firms that begin their engagement in global value

[17]It should be noted that the WBES does not conform strictly to a panel data design, wherein the same firms are tracked across multiple waves. Rather, the survey predominantly follows a cross-sectional approach, wherein each wave captures a distinct set of firms at a specific point in time.

[18]It is important to note that there are at least two years between waves in the sample.

chains by participating in the two-way exchange of goods and services. The control group is composed of firms that never participate in GVCs. Firms that ceased their two-way trading activities and those that consistently engaged in two-way trading in the pre-treatment period are not included in this analysis.

Within this exercise, the propensity of a firm becoming a GVC participant is estimated by considering country-specific attributes and firm characteristics from the pre-treatment period as explanatory variables. In addition to the previous controls, we have also integrated the pre-treatment productivity level into our analysis, recognizing its pivotal role as a predictor of GVC engagement. Furthermore, the panel framework is also exploited for the outcome variable: our estimations now encompass the productivity changes experienced by firms between the pre- and post-treatment waves, enabling us to undertake a difference-in-difference assessment.

This meticulous examination, however, comes at the expense of a reduction in the number of observations, as evidenced in Table 9.[19] The results remain consistent with our earlier cross-sectional estimates. Firms that start their participation in global value chains through importing and exporting experience an increase in labor productivity. However, this new GVC experience does not yield a significant change in TFP relative to the control group.[20]

In summary, our most robust finding thus far is the positive and significant difference in labor productivity between firms engaged in GVCs and their matched counterparts. This result holds true for the entire sample, all sub-samples based on country-income categories, as well as all sub-samples categorized by the technological intensity of industries. When we leverage the implicit panel structure of the data within a difference-in-difference framework, we also find that becoming a GVC participant fosters labor productivity growth. While this latter result should be interpreted with caution due to the substantial sample reduction, it aligns with the cross-sectional estimates. However, when considering TFP as the outcome variable, we generally observe non-significant productivity differences associated with GVC participation. Interestingly, there are notable exceptions in the sub-samples of developing countries and low-technology industries, where GVC participants exhibit a productivity advantage in terms of both labor productivity and TFP. The catching

[19]To mitigate potential incidental parameter issues in the first stage, we have limited our consideration to country-income categories (interacted with the skill share, as previously discussed) and excluded the complete set of country dummies. The ISIC industry categories continue to serve as predictors in our treatment analysis.

[20]Interestingly, the first-stage probit estimates reveal that, unlike labor productivity, TFP observed in the pre-treatment period is not a significant predictor of GVC participation (see Table A.3 in the Appendix).

up and learning channels are thus active for this group of firms.

6 Operating Mechanisms

The results discussed in the preceding sections call for further investigation into the potential drivers of productivity enhancement and the associated firm performance that might be further augmented by GVC participation. In the following, we explore the channels through which participation in global value chains can impact productivity at the firm level. We also look at particularities of two way traders versus one way traders.

6.1 Capital intensity, innovation, quality and costs

A first important aspect to explore is the role of capital intensity. As previously mentioned, capital intensity, in conjunction with TFP, plays a pivotal role in determining labor productivity within a multi-factor production framework. A second channel deserving attention is innovation. Indeed, while GVC participation may not immediately result in TFP growth, it could potentially stimulate a greater propensity to innovate, which, with some time lag, may ultimately lead to enhanced efficiency. Third, as discussed in our overview of mechanisms, the literature also highlights possible enhancements in quality, leveraged by the access to more suitable inputs. Finally, we investigate the impact of GVC participation on input, labor, and average costs.

Table 10 summarizes the results on all these outcomes. Positive and statistically significant differences in capital intensity associated with GVC participation are observed in the entire sample and, with varying degrees of significance, in most country-income categories. Notably, the results suggest a more pronounced impact in high-income countries. This finding, combined with those of the previous section, point to a North/South disparity in the opportunities for technical progress facilitated by GVCs. Indeed, in developing countries, we observe advantages in both TFP and labor productivity for firms participating in GVCs. In contrast, in high-income countries, the predominant channel (at least in the short-run) appears to be a robust capital-labor substitution mechanism that enhances labor productivity. The estimations also indicate that GVC participation leads to a higher propensity for innovation and adherence to higher quality standards. Even though this trend is consistent across all sub-samples, the innovation performed in developing countries seems to be more conductive in the short run to TFP enhancement. A possible explanation is that these innovations stem from imitation and learning of existing technologies and practices, which may rapidly fuel their catching-up process.

Regarding total average costs, no significant differences between GVC participants and their control-group counterparts are evident in PSM estimations. However, with entropy balancing matching, the results indicate higher total average costs in the entire sample and in high-income countries. As previously discussed in our review of mechanism, there are conflicting forces at play behind these findings. While average labor costs are generally lower (with the exception of upper middle-income countries), the average cost of inputs is larger across all samples. The higher average costs of inputs, some of which are outsourced from foreign markets, can be related to the wider use of inputs of increased. This in turn is consistent with the higher propensity to engage in quality upgrades and to introduce new process and products.

Average labor costs are the result of composition effects related to wages and the use of labor. On the one hand, labor productivity gains, scale economies, and increased capital-labor substitution collectively serve to decrease the use of labor per unit of output. On the other hand, standard theories of outsourcing suggest that trade in tasks tend to save low-skilled labor costs in high-income countries but to increase the skill share of labor in developing countries affiliates and suppliers. These contradicting forces may explain the non-significant results in emerging (upper-middle income) countries, which have experienced "functional" upgrading —i.e. the have integrated higher value-added tasks with increased skill-labor content. In the case of GVC participants from low and low-middle income countries, tasks are less skill intensive and the efficiency in the use of labor seems to be the predominant effect.

6.2 The gains of two-way traders versus one-way traders

Our final step consists on gaining a better understanding on the particularities of two-way traders compared to one-way traders. Our underlying idea is that firms simultaneously coordinating import and export activities have a deeper involvement in international production networks. If this increased internationalization matters in terms of technical change, two-way traders should present some advantages in efficiency relative to those firms performing only imports or exports.

To this end, in a first exercise we keep two way traders as the treatment group but pure exporters or pure importers, as control groups. Pure exporting firms are defined as those exhibiting positive (direct) exports while having no involvement in imports. Likewise, pure importing firms are identified as those with positive import activities but no exports. In order to provide a clearer understanding of each trading activity, in a second exercise we use alternatively pure exporters and pure importer as treatment units and compare them to no traders as a control group. This analysis offers more detailed insights into the performance of each subset of firms, which are part of the control group in the previous section.

In order to ease the presentation, we only show results using entropy balancing procedures to match treatment units with control firms. The first two rows in Table 6.2 present the ATT for productivity and the related channels for two-way traders compared to importers or exporters. As seen, firms engaged in global value chains performwith higher labor productivity than one-way traders, the difference being specially important when compared to pure importers. They are also more intensive in capital, innovate more, and have a higher propensity for quality certifications. Compared to pure exporting firms, two-way traders present higher input costs, suggesting strategies of a seek of higher quality inputs. Importantly, when compared to pure importers, two-way traders have lower labor costs. Participating in global value chains, where different stages of production occur in different countries, might allow firms to optimize costs by locating specific production processes in countries where the cost of labor is lower. This modular production system can contribute to labor cost reduction.

The last rows in the table show results that are standard in the literature: notable gains in productivity attributable to trade, especially evident among exporting firms. Differences in innovation propensity, concerning the relevant control group, are also more pronounced for firms engaged in importing or exporting activities. This heightened innovation activity is accompanied by increased unit costs in procuring inputs, presumably of superior quality, thereby facilitating the introduction of new products. Indeed, as proposed by (Verhoogen, 2023), access to high-quality inputs emerges as a robust catalyst for upgrading, particularly for firms in developing countries. It is important to note, however, that the greater average input costs is partially counterbalanced by corresponding reductions in labor costs. Lastly, in the pursuit of expanding foreign market sales, quality certification appears to be an integral market positioning strategy.

In summary, these results contribute to a deeper comprehension of our earlier findings regarding two-way traders, who effectively utilize various channels of technical change. In comparison to firms solely engaged in some form of trade activity, such as one-way exporters, two-way traders consistently engage more deeply in several aspects of technical change, particularly within the context of developing countries. These results underscore the advantage of simultaneously coordinating both the importing and exporting operations within a single firm, granting firms a distinctive and advantageous position within the dynamics of global trade.

Table 10: **Average treatment effect of GVC participation on drivers of productivity. Whole sample and by income group.**

	Cap.	**Innovation**	**Quality**	**Average Costs**		
	int.		**cert.**	**Inputs**	**Labour**	**Total**
			Propensity Score Matching			
All	0.211***	0.065***	0.109***	0.157***	-0.068***	0.020
	(0.065)	(0.008)	(0.008)	(0.023)	(0.019)	(0.013)
N. Treated	10889	14774	14610	11438	12099	11287
N. Obs.	46040	68282	67474	51301	54481	50739
Low and low-middle	0.283**	0.059***	0.129***	0.143***	-0.117***	0.022
income	(0.116)	(0.013)	(0.013)	(0.045)	(0.034)	(0.024)
N. Treated	3074	4589	4511	3362	3575	3287
N. Obs.	21614	34200	33785	26053	27579	25777
Upper-middle	0.139	0.051***	0.126***	0.072**	-0.027	0.016
income	(0.106)	(0.013)	(0.014)	(0.033)	(0.029)	(0.020)
N. Treated	3610	5061	5004	3771	4054	3722
N. Obs.	15279	21518	21227	15768	16861	15580
High	0.417***	0.046***	0.090***	0.187***	-0.094***	0.023
income	(0.097)	(0.016)	(0.017)	(0.037)	(0.029)	(0.019)
N. Treated	4205	5124	5095	4305	4470	4278
N. Obs.	9147	12564	12462	9480	10041	9382
			Entropy Balance			
All	0.184***	0.054***	0.113***	0.111***	-0.084***	0.020**
	(0.034)	(0.005)	(0.006)	(0.019)	(0.013)	(0.009)
N. Treated	10889	14774	14610	11438	12099	11287
N. Obs.	46117	68282	67474	51350	54525	50785
Low	0.116*	0.060***	0.136***	0.070**	-0.097***	0.006
income	(0.066)	(0.008)	(0.009)	(0.032)	(0.024)	(0.018)
N. Treated	3074	4589	4511	3362	3575	3287
N. Obs.	21691	34200	33785	26081	27623	25804
Middle	0.100*	0.052***	0.127***	0.052*	-0.032	0.012
income	(0.057)	(0.009)	(0.009)	(0.028)	(0.023)	(0.016)
N. Treated	3610	5061	5004	3771	4054	3722
N. Obs.	15279	21518	21227	15789	16861	15599
High	0.286***	0.047***	0.075***	0.201***	-0.106***	0.041***
income	(0.053)	(0.010)	(0.011)	(0.031)	(0.021)	(0.013)
N. Treated	4205	5124	5095	4305	4470	4278
N. Obs.	9147	12564	12462	9480	10041	9382

Notes: (1) Observed coefficient is treatment effect (the difference between the treated and controls). When productivity is higher for the treated observations than the non-treated, observed coefficient shows a positive and significant value, (2) Standard errors are presented in parenthesis, (3) *,**,*** denotes significance at the 10, 5 and 1%. Estimations include time and country dummies.

Treatment/Control	**Labor**	**TFP**	**Cap. int.**	**Innovation**	**Quality cert.**	**Average Costs**		
						Inputs	**Labour**	**Total**
Two-way/Pure exporters	0.071**	-0.048	0.184***	0.042***	0.037***	0.191***	-0.003	0.070***
	(0.029)	(0.038)	(0.061)	(0.009)	(0.011)	(0.038)	(0.026)	(0.018)
N. Treated	11328	9489	10889	14774	14610	11438	12099	11287
N. Obs.	14716	11947	13783	19467	19216	14861	15729	14675
Two-way/Pure importers	0.169***	0.017	0.103***	0.022***	0.097***	0.050**	-0.049***	0.005
	(0.019)	(0.023)	(0.038)	(0.006)	(0.007)	(0.019)	(0.015)	(0.010)
N. Treated	11328	9489	10889	14774	14610	11438	12099	11287
N. Obs.	27117	22305	25859	36410	35985	27283	28934	26938
Pure exporters/No traders	0.288***	0.174***	0.346***	0.071***	0.133***	0.080***	-0.182***	-0.016
	(0.026)	(0.030)	(0.051)	(0.008)	(0.009)	(0.024)	(0.021)	(0.015)
N. Treated	2662	2095	2463	3675	3611	2683	2860	2659
N. Obs.	24681	17846	20631	32743	32343	24761	26310	24533
Pure importers/No traders	0.188***	0.040*	0.298***	0.101***	0.038***	0.164***	-0.114***	0.041***
	(0.016)	(0.020)	(0.035)	(0.005)	(0.005)	(0.015)	(0.013)	(0.009)
N. Treated	15063	12453	14539	20618	20380	15105	16065	14922
N. Obs.	36448	27895	32392	48962	48399	36535	38847	36153

Notes: (i) Observed coefficient is treatment effect (the difference between the treated and controls). When productivity or its drivers are higher for the treated observations than the non-treated, observed coefficient shows a positive and significant value; (ii) Standard errors are presented in parenthesis, (iii) *,**,*** denotes significance at the 10, 5 and 1%. Estimations include time and country dummies.

7 Final discussion

This paper aimed at investigating the potential impact of participating in GVCs on firm-level productivity across a substantial sample of economies. To achieve this objective, we used a comprehensive cross-country firm-level data spanning several years and employed propensity score matching and entropy balance techniques. These methods serve to effectively mitigate selection bias, which is a common concern in firm-level regressions that seek to explore the connection between trade outcomes and firm productivity. By adopting these empirical approaches, we meticulously control for crucial firm characteristics that could plausibly generate differences in productivity between firms in the control and treatment groups, with the sole distinguishing factor between these groups being their status as two-way traders in the context of international trade.

Across different estimators, we find robust evidence that firms engaged in two-way trade exhibit significantly higher levels of labor productivity. Exploiting the implicit panel structure of the data, we also observed that firms entering GVCs experience, after a few years, higher labor productivity growth than the rest of the firms. Furthermore, two-way trading firms tend to have a higher propensity to introduce new products and process. They also engage more in attaining international quality standards and exhibit relatively higher costs associated with intermediate inputs, in comparison to firms not engaged in global value chains. This phenomenon signifies a noteworthy trend of quality upgrading within these firms. Interestingly, such increase in the average cost of inputs is counter-weighted by the reductions on the average cost of labor. These outcomes still show up if one restricts the control group to firms exclusively having import or export activities.

Motivated by the different channels that can be at play in firms belonging to countries of different level of development, we paid particular attention to firms engaged in GVCs from low-income economies. In this sense, we see our results using TFP as the outcome measure, which yield to a more mitigated picture, as an illustration of the higher likelihood of observing learning and catching-up dynamics in developing countries, as compared with more advanced economies. Indeed, TFP is significantly higher for firms participating in GVCs, specifically within low and low-middle income countries. When splitting the sample by industry type, TFP is higher only within low-tech industries. This is perhaps not surprising as a substantial proportion of firms from low and low-middle income countries tend to be labor-intensive and operate in low-tech industries. These industries, as opposed to more capital- and technology-intensive industries more represented in high income countries (see table A.4 in the appendix), produce goods less complex and having more standardized technologies. In such a context, learning and adopting improved existing technologies is less uncertain and may provide a first impulsion of industrialisation and productivity growth.

Thus, our results suggest that the strategies for firms engaged in GVCs from low and low-middle income countries may significantly differ from those in more developed economies. Although the underlying economic rationale of mechanisms by which participation in GVCs enhances productivity are similar, the specific mix of active channels leveraging technical change in lower income countries diverge from that in advanced economies. High-income GVC participants mainly rely on strong capital labor substitution to increase their labor productivity whereas low- and lower-income countries are more directly taking advantage, in terms of multifactor efficiency, from their several upgrading efforts stemming from capital investment, innovation, and quality.

Our study is not free from limitations. First of all, our data lacks the granularity required to trace the origins and destinations of trade activities. Consequently, we are unable to establish direct connections between firms located in different countries and operating at various stages of the production process. This is particularly important for developing countries since selling directly to richer buyers, or supplying inputs in value chains selling eventually to richer buyers, appears to be robustly associated with upgrading (see Verhoogen (2023)). Furthermore, our analysis focuses exclusively on manufacturing firms, even though services have assumed a substantial role in emerging economies. Services now account for over 60 percent of GDP and constitute more than half of the total employment in these economies. While historically, the service sector has not been a dominant contributor to productivity growth, this landscape is evolving, partly driven by technological advancements. Are the related productive gains large enough? Can they be disseminated sufficiently quickly throughout the rest of the economy? What are the effect on labor markets? Further studies should progress in this front.

Competing interests:

We declare that we have no competing interests associated with this manuscript.

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A Appendix

Table A.1: **List of countries**

Country	**Country**	**Country**
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
CÃ´te 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

Table A.2: Descriptive statistics of covariates by income group

	Low income		**Middle income**		**High income**	
Variable	Mean	SD	Mean	SD	Mean	SD
Size	1.76	0.76	1.93	0.78	1.85	0.76
R&D	0.20	0.40	0.30	0.46	0.33	0.47
Firm's age	18.91	15.03	22.01	18.27	31.59	26.91
Foreign ownership	0.09	0.29	0.10	0.3	0.13	0.34
Acces to credit	0.30	0.46	0.50	0.5	0.56	0.50
Skill share	0.71	0.31	0.68	0.32	0.77	0.30
Country's GVC	37.54	6.98	41.56	8.8	52.41	9.16

Notes: (a) This table reports descriptive statistics for the 2006-2021 period.

Table A.3: Probability of starting two-way trading.

Outcome model	Labor Productivity	TFP
Labor productivity (t-1)	0.154***	
	(0.049)	
TFP (t-1)		0.004
		(0.043)
Size (t-1)	0.441***	0.520***
	(0.085)	(0.096)
Size x R&D (t-1)	-0.050	-0.044
	(0.155)	(0.188)
R&D (t-1)	0.610*	0.634
	(0.334)	(0.417)
Firm age (t-1)	0.005*	0.006*
	(0.003)	(0.003)
Foreign (t-1)	0.240	0.460**
	(0.199)	(0.212)
Credit (t-1)	-0.038	-0.041
	(0.114)	(0.133)
Skill share (t-1)	0.107	0.167
	(0.396)	(0.447)
Income x Skill share (t-1)	0.094	0.040
	(0.165)	(0.191)
Income (t-1)	-0.089	0.031
	(0.131)	(0.148)
Country-level GVC	0.013*	0.009
particpation (t-1)	(0.007)	(0.009)
Constant	-4.921***	-3.855***
	(0.639)	(0.549)
Isic dummies	Yes	Yes
N	1385	1018

Notes: (i) *,**,*** denotes significance at the 10, 5 and 1%. (ii) Estimations include industry dummies.

Table A.4: **Technology intensity. Percentage of firms for each income-country level**

Income	**Low and low middle**	**Upper middle**	**High**	**Total**
Low tech	67.34	60.88	42.65	60.95
Medium tech	18.88	16.07	30.13	19.94
High tech	13.77	23.05	27.22	19.11