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Southern Africa – Towards Inclusive Economic Development

Exporters and global value chain participation

Firm-level evidence from South Africa

Caio Torres Mazzi, Gideon Ndubuisi, and Elvis Avenyo

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Southern Africa –Towards Inclusive Economic Development (SA-TIED)

SA-TIED is a unique collaboration between local and international research institutes and the government of South Africa. Its primary goal is to improve the interface between research and policy by producing cutting-edge research for inclusive growth and economic transformation in the southern African region. It is hoped that the SA-TIED programme will lead to greater institutional and individual capacities, improve database management and data analysis, and provide research outputs that assist in the formulation of evidence-based economic policy.

The collaboration is between the United Nations University World Institute for Development Economics Research (UNU-WIDER), the National Treasury of South Africa, the International Food Policy Research Institute (IFPRI), the Department of Monitoring, Planning, and Evaluation, the Department of Trade and Industry, South African Revenue Services, Trade and Industrial Policy Strategies, and other universities and institutes. It is funded by the National Treasury of South Africa, the Department of Trade and Industry of South Africa, the Delegation of the European Union to South Africa, IFPRI, and UNU-WIDER through the Institute's contributions from Finland, Sweden, and the United Kingdom to its research programme.

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Abstract: Using the South African Revenue Service and National Treasury firm-level panel data for 2009–17, this paper investigates how global value chain-related trade affects the export performance of manufacturing firms in South Africa. In particular, the paper uses extant classifications of internationally traded products to identify different categories of global value chain-related products and compares the productivity premium of international traders for these different categories. Also, the paper investigates possible differences in learning-by-exporting effects across the identified categories of global value chain-related products by estimating the effect of exporting before and after entry into foreign markets. The results confirm that global value chain-related trade is associated with a higher productivity premium compared with traditional trade. However, within the categories of exporters, only the firms that trade in global value chain-related products and simultaneously engage in research and development in the post-entry periods appear to learn from exporting.

Key words: global value chain, learning-by-exporting, productivity premium, South Africa

JEL classification: F12, F14, O3, O33

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1 Introduction

Following Yeats (1999), empirical studies that use trade data to compute cross-border flows of 'parts and components' or intermediary products have proliferated (e.g., Jones et al. 2005; Lall et al. 2004; Ng and Yeats 2001; Sturgeon and Memedovic 2010). Evidence from this literature points to important changes in the nature of cross-border flows of goods and services. In particular, trade in 'parts and components', a subset of intermediates mainly associated with machinery products, are found to represent a growing share of international trade (Athukorala 2010; Jones et al. 2005; Schmidt and Ferrantino 2018; Yeats 1999), with electronics being responsible for most of this growth.[1]

More recently, emerging firm-level literature has indicated that exporters of intermediate products benefit relatively more from participating in international markets when compared to firms that sell final products, although the latter still tend to maintain an overall superior performance (Accetturo and Giunta 2018; Agostino et al. 2015; Veugelers 2013). Underlying this empirical regularity is the idea that intermediate products, especially 'customized intermediates', are traded via global value chains (GVCs), requiring outright knowledge transfer and exchange between upstream and downstream firms. This differs from the conventional learning-by-exporting hypothesis, wherein the exporter premia are explained by automatic knowledge spillovers in the international market (Wagner 2016).

The available evidence suggests that developing countries have been quickly gaining participation in overall trade, and this process has been even more intense in 'parts and components' and 'customized' intermediary products—a group of more complex intermediates that characterizes supplier–buyer relationships in GVCs (Foster-McGregor et al. 2015; Ndubuisi and Owusu 2020; Sturgeon and Memedovic 2010). Nevertheless, available studies that examine the differential premia for exporters of intermediate products remain nascent and largely focused on developed economies, for which a richer set of firm-level surveys is available. Against this backdrop, this paper examines the effects of these recent trends in international trade on the performance of exporters in South Africa.

More specifically, we follow the firm-level international trade literature and analyse both the productivity premia and the learning-by-exporting hypotheses associated with trading in the context of fragmented trade. However, rather than analysing whether international traders outperform firms that are restricted to local markets, we look deeper into heterogeneities between exporters and the factors explaining these differences among firms in South Africa. In particular, we follow the GVC literature and concentrate on 'customized' intermediates as the product types that are most closely associated with fragmented trade. This allows us to compare the productivity of firms that trade these products with those that trade other types of products, and with those that do not trade at all. Since the gains from GVC participation are not automatic—as it may have a disproportionate impact on firms at different stages of advancement, capabilities, and different regions (Morrison et al. 2008), we also analyse the role of firm capabilities. For this, we focus on research and development (R&D) investment.

[1] Since 2008, and especially from 2011, there has been a strong de-acceleration of international trade and some receding in GVC trade. There is evidence that GVCs peaked around 2008, and slowly started to fall afterward, especially after 2011, until at least 2016. This pattern is observed, for instance, for the foreign value-added (FVA) share of gross exports of the three world GVC centres, i.e. Europe, North America, and South and East Asia, the last of which has observed a fall of almost a third as measured by the OECD's TiVA (OECD 2018). Nonetheless, GVC trade remains highly relevant, accounting for around 50 per cent of world exports (World Bank 2020).

To preview our results, our empirical analyses show that exporters have a higher productivity premium compared with non-exporters. Comparing the productivity premium of firms trading GVC-related products and those that do not, we find that firms that trade GVC-related products have higher premia compared with those that are engaged only in traditional trade. Results on the learning effect for the full population of firms in South Africa show evidence for learning, while, when we consider the different subcategories, we do not find any such evidence that is specific to exporting only GVC-related products. Once we consider firms that export GVC-related products and simultaneously engage in R&D in the post-entry period, we find evidence for learning.

Our paper adds to the literature in several ways. We contribute to the international firm-level trade literature by characterizing performance and learning in the context of fragmented trade. In the case of GVC studies, we advance the literature by characterizing performance differences before and after entry into foreign markets, thereby assessing learning effects related to GVC participation. As noted earlier, we attain this feat by identifying heterogeneous effects of trade on the performance of firms according to specific product characteristics associated with production fragmentation. Hence, our paper extends the analysis in Edwards et al. (2018) by estimating separate regressions for categories of traders according to the products traded by these firms and by testing the hypothesis of learning-by-exporting. Finally, we contribute to the firm-level trade and GVC literature by examining the role of firm capability in mediating the benefits of GVC participation and trade in general. Our study contributes further to this literature by identifying the heterogeneous effects of trade on firms' performance according to specific product characteristics associated with production fragmentation.

The remainder of the paper is as follows: Sections 2 and 3 discuss the related literature and the product classification, respectively. Section 4 presents the data sources and empirical strategy. Section 5 concludes the paper. We present the next steps for the paper in section 6.

2 Related literature

The firm-level international trade literature has expanded dramatically since the pioneering work of Bernard and Jensen (1999). The primary evidence from this literature is that exporters perform better than non-exporters, particularly in terms of productivity (as well as other performance indicators) (Wagner 2016). Recently, however, a related micro-level research agenda in the context of the GVC approach has emerged (see, among others, Gereffi et al. 2005; Giovannetti and Marvasi 2016; Giuliani et al. 2005; Humphrey and Schmitz 2002). While this literature is still in its infancy, the available evidence supports a positive association between supplying in GVCs and firms' performance. For instance, Giovannetti and Marvasi (2016) show that firms in Tuscany that participate in hierarchical global (as opposed to local) value chains, especially midstream producers (buyers and suppliers of intermediates), are the best performing group. This result is confirmed by evidence indicating positive and significant premia for exporters of intermediate products (Accetturo and Giunta 2018; Veugelers 2013), while Agostino et al. (2015) present evidence that the export premia of suppliers that innovate are as high as those of exporters of final goods. Brancati et al. (2017) show that participation in specific types of GVCs has a positive impact on innovation, R&D, and Italian firms' productivity.

While extant studies have offered important insights on the nexus between GVC participation and firm performance, there has been little success in disentangling learning and self-selection as done in the international trade literature. In general, there is more emphasis on learning and upgrading, and the empirical evidence at the firm level is mostly correlational. Only the studies of Brancati et al. (2017) and Agostino et al. (2015) offer evidence of GVC participation with ex-post performance gains by suppliers. This literature tends to consider that GVC participation favoors learning because the firms that lead value chains may promote—explicitly or tacitly—knowledge transfers and upgrading opportunities for their suppliers, especially in value chains where coordination is stronger and engagement by leaders is higher (Giuliani et al. 2005). A similar idea in the international trade literature, since Blalock and Gertler (2004) advocated for the existence of learning-by-exporting in the case of firms in developing countries, involves supply relationships with higher degrees of customization or 'extended coordination'.

Nevertheless, learning is not the only relevant factor in the context of fragmented trade. First, trade in GVCs is characterized by higher transactional complexity, which entails higher relationship-specific investments, for example, in the development and adaptation of products and plants to the specific needs of buyers (Antràs and Chor 2013). Second, because these relationships involve higher-quality standards and specification requirements, international buyers will tend to 'cherry pick' the most capable suppliers to avoid production line delays and quality debasements caused by problems in the supply base. Third, some studies indicate that transactional frictions such as transportation and communication costs, and language and cultural differences, which are also directly linked to fixed and variable costs of exporting, can be more intense for trade in intermediates, parts, and components (Jones et al. 2005; Kimura et al. 2007; Kowalski et al. 2015; UNIDO 2018).

In this paper, we take a step forward to characterize performance and learning in the context of fragmented trade, differentiating the productivity premium between exporting firms trading GVC-related products and those that do not. By distinguishing between the types of products that a firm exports when estimating the export premia and learning-by-exporting effects, we establish a fruitful connection between the international trade literature and the GVC approach. In that way, we demonstrate the existence of heterogeneous performance and learning trajectories for international traders related to their participation and position in GVC-related trade in South Africa.

3 Data and empirical model

3.1 Product classification

Products traded within GVCs are often complex intermediates that are either part of intra-firm trade or exchanged in networks that involve higher degrees of customization and coordination between firms. Hence, to identify GVC-related products, we utilize the United Nations Broad Economic Categories classification (BEC5) which divides products into four categories according to their end use (intermediates versus finals) and 'specification' type ('generic' versus 'specific'): 'specific' intermediates, 'generic' intermediates, final goods, and a residual group containing other exporters, especially exporters of unprocessed (primary) goods. We take a conservative approach by including in the residual category exports of products that have ambiguous classifications in terms of the 'specification' dimension and end use. These are a small group, comprising about 9 per cent of total Harmonised System (HS) Classification codes. However, we do not have a consistent criterion to reassign them and therefore choose to focus the analysis on products that can be classified without ambiguity.

As a robustness check, we also depict results using a classification based on the complexity or 'contract intensity' of products, as identified by the conservative version of Rauch's (1999) list of differentiated products, a taxonomy that has become popular in the economic literature (Andersson and Weiss 2012; Antràs and Chor 2013; Del Prete and Rungi 2015). This method consists of dividing products into three categories: traded in organized exchanges, reference priced in trade publications, and all others. The first two categories indicate homogeneous products traded in dense markets, while the residual identifies differentiated products more likely to be traded based on networks. We use the end-use classification to divide products into 'generic' intermediates (intermediates traded in organized exchanges or reference priced), 'specific' intermediates (intermediates classified in Rauch's 'others' group), finals, and the residual group.

In both classifications, Rauch and BEC5, exports of specific intermediates indicate GVC-related trade, and generic intermediates indicate non-GVC trade, which are the main comparison groups of interest in our study. Exports of final goods do not necessarily relate to specific or generic products but indicate downstream trade in value chains and, therefore, are related to firms' positions. The residual group is not the focus of our analysis, but we maintain controls for exports of these products in all regressions as they are correlated with both performance and the other three export categories.

3.2 Data and descriptive statistics

The data used for our analysis are sourced from the South African Revenue Service and National Treasury (SARS-NT) (National Treasury and UNU-WIDER 2019). The SARS-NT database is an unbalanced firm-level panel data compiled from four main sources: company income tax data, employee data, value-added tax data, and customs records. The data have an extensive timeframe covering the period 2009–17. The company income tax data is the parent dataset in the SARS-NT, and it covers tax returns of companies in a given financial year. The customs data contain detailed transaction-level information on the export and import activities of firms. The VAT data comprise indirect tax data on the consumption of goods and services charged either at the production and/or distribution stage of the product, while the employee tax data mainly cover individual employee tax information. However, the SARS-NT panel does not cover groups such as informal enterprises, young, and small firms (see Kreuser and Newman 2016; Pieterse et al. 2018; Edwards et al. 2018, for a detailed description of the database).

To make the panel compatible across all four data sources, we restrict our sample to observations for which deflators, the value of sales, labour costs, employment, and fixed capital are available, resulting in the loss of a significant number of observations. Our final sample size comprises 120,635 firms. Due to cross-missing observations, we observe drops in the number of firms when we use additional co-variables such as fixed capital and R&D. We deflate the fixed capital variables using a gross capital formation deflator, wages using the Consumer Price Index (CPI) and firms' remaining nominal variables using the Producer Price Index (PPI), all economy-wide deflators provided by Statistics South Africa. The average wage is calculated as total labour costs divided by the average number of employees. Capital is proxied by total assets or fixed assets (measured as plants, equipment and other fixed assets), whereas R&D investments are self-declared values obtained from firms' tax returns. Finally, we measure labour productivity and capital per worker as value added (sales minus the cost of intermediates) and capital divided by the average number of employees, respectively.

Table 1: Descriptive statistics of gross variables for all firms, exporters, and non-exporters.

	Total sample			Exporters			Non-exporters		
Variable	Obs.	Mean	SD	Obs.	mean	SD	Obs.	Mean	SD
ITR14 total assets (thousands)	90,652	70,030	1,027,000	29,181	174,900	1,684,000	61,471	20,260	448,100
k input (fixed assets, in thousands)	120,635	14,160	280,700	38,558	37,680	491,300	82,077	3,112	45,550
g sales (total sales, in thousands)	120,635	86,140	1,593,000	38,558	228,500	2,805,000	82,077	19,260	140,500
VA (total VA, in thousands)	120,635	23,120	407,800	38,558	59,030	717,300	82,077	6,245	42,350
g cos2 (prod. costs, in thousands)	120,635	63,030	1,388,000	38,558	169,500	2,448,000	82,077	13,010	105,400
x wages (wages paid, in thousands)	58,775	12,070	93,310	26,637	21,520	135,800	32,138	4,233	22,270
x labcost (labour costs, in thousands)	120,635	7,662	75,800	38,558	18,150	131,400	82,077	2,735	16,160
x rd (r&d expenditures)	52,753	100,332	3,167,318	24,599	197,543.35	4,600,646	28,154	15,395	537,298
x royalties (royalties expenditures)	52,914	726,147	15,540,000	24,659	1,478,289	22,690,000	28,255	69,731	1,535,792
# employees	120,635	43.52	301.8	38,558	85.75	450.1	82,077	23.69	193.5
ITR14_x_training	29,559	291,069	3,617	17,360	414,913.45	3,723,200	12,199	114,830	3,453,068
value exports (in thousands)	120,635	3,735	100,400	38,558	9,396	71,830	82,077	0	0
value imports (in thousands)	120,635	6,774	239,500	38,558	17,430	350,200	82,077	1,767	163,100

Note: the variable ‘k_input’ is built by adding plants, equipment, and other fixed assets (variables k_ppe and k_faother, respectively, in the original dataset). Variable ‘VA’ equals total sales (g_sales) minus production costs (g_cos2). Variable ‘# employees’ is chosen from the original dataset as the total number of people with employment income supplied by firms weighted by the effective period of employment (irp5_empl_weight).

Source: authors’ calculations based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

Table 2: Description of main variables across exporters and non-exporters.

	Total sample			Exporters			Non-exporters		
Variable	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD
VAE (labour productivity)	120,334	598,001	26,630,000	38,523	995,109	46,750,000	81,811	411,011	3,724,670
KE (K Intensity)	120,334	243,962	9,055,764	38,523	373,023	15,660,000	81,811	183,190	2,268,086
wage (average wage)	120,334	238,151	7,591,037	38,523	360,191	13,190,000	81,811	180,685	1,666,773
assets per employee	90,416	1,365,437	30,260,000	29,155	2,068,353	49,738,747	61,261	1,030,909	13,180,000
red (r&d/sales)	52,180	0.0007	0.042	24,599	0.00089	0.03	27,581	0.000640	0.050
p red (R&D binary)	52,180	0.049	0.220	24,599	0.078	0.27	27,581	0.024	0.15
train (training/sales)	29,244	0.0008	0.005	17,360	0.00084	0.0028	11,884	0.00076	0.0075
p train (training binary)	29,244	0.430	0.49	17,360	0.47	0.50	11,884	0.36	0.48
roy (royalties/sales)	52,342	0.0014	0.027	24,659	0.0018	0.026	27,683	0.0011	0.028
p roy (roylaty dummy)	52,342	0.088	0.28	24,659	0.12	0.320	27,683	0.062	0.24
p exp (exporter dummy)	120,635	0.32	0.47	38,558	1	0	82,077	0	0
p imp (importer dummy)	120,635	0.32	0.47	38,558	0.72	0.45	82,077	0.12	0.33

Note: labour productivity equals value added/employees, capital intensity (KE) equals fixed assets/employees, assets per employee equals total assets/employees, and wage equals labour costs/employees.

Source*:* authors' calculations based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

The basic descriptive statistics of all the variables we use from the SARS-NT panel data in our model are presented in Tables 1 to 3. We present summary statistics for the entire sample and disaggregate by exporters and non-exporters.[2] More details about variable construction are presented in the notes to these tables. In Table 1, the data show that exporters have higher values across all variables of interest compared with their non-exporting counterparts, in line with the literature (Edwards et al. 2018; Kreuser and Newman 2016). The data also suggest that exporters, on average, have more assets and employees, sell more, are more capital intensive, pay higher wages, import more, are more innovative (higher investments in R&D and royalties), and invest more in training. Table 2 shows interesting insights related to the percentage of firms that undertake R&D, training and pay royalties. For instance, 4.9 per cent of all firms perform R&D, 8.8 per cent pay royalties, and 43 per cent invest in training, on average. These values differ between exporting and non-exporting firms, with exporters having higher values on average compared with non-exporters. This confirms a hierarchy in knowledge-generating activities, where R&D seems to be the noblest and rarest knowledge-generation activity, followed by technology licensing and training. Table 3 reveals that firms in South Africa specialize mostly in the production and export of non-customized intermediates and primary (unprocessed) products. This reflects its pattern of comparative advantage and trade participation, based on commodity exports and natural resource insensitive manufacturing. However, we do observe significant participation in customized intermediate exports in absolute numbers. This is in line with similar developing countries with a similar pattern of comparative advantage and size, such as Brazil.

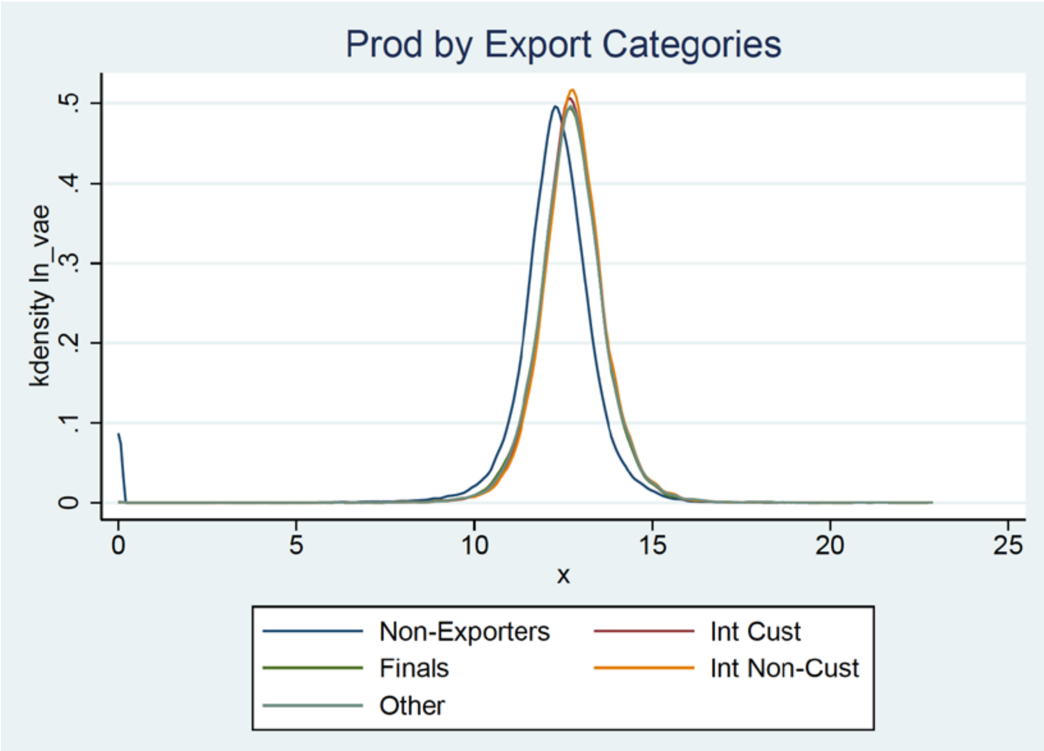
Table 3: Exports and Imports by product category across years (in 1,000)

Year	Customized intermediates (b5_spcf)	Finals (b5 finals)	Non-customized (b5 nspcs)	Primary and residual (b5 others)
Exports				
2009	611,416	515,668	462,701	299,766
2010	5,743,630	5,138,611	18,596,285	9,684,517
2011	3,541,288	3,767,819	3,953,806	3,667,013
2012	12,563,479	11,418,007	24,589,027	17,614,349
2013	14,268,567	12,359,209	31,531,125	21,336,659
2014	8,547,839	7,465,717	28,441,578	11,768,18
2015	16,801,805	14,742,870	19,802,807	17,647,488
2016	8,179,19	7,563,348	10,326,569	7,756,878
2017	17,154,478	14,581,521	34,023,008	24,210,282
Imports				
2009	817,539	515,668	292,369	263,974
2010	6,699,844	5,138,611	17,774,586	9,550,001
2011	3,867,995	3,767,819	3,840,254	3,453,858
2012	16,056,760	11,418,007	21,753,011	16,957,084
2013	17,166,748	12,359,209	29,396,224	20,573,380
2014	9,989,098	7,465,717	27,556,472	11,212,034
2015	19,884,959	14,742,870	17,755,833	16,611,309
2016	10,162,776	7,563,348	8,963,561	7,136,307
2017	21,333,138	14,581,521	30,823,402	23,231,229

Source: authors' calculations based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

[2] See Appendix B for the definition of all variables.

Figure 1: Kernel densities for the export categories and non-exporters



Source: authors' figure based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

Figure 1 shows the kernel density estimation for the four categories of exporters' labour productivity (log). Two observations stand out. First, as expected, exporters' distribution dominates that of non-exporters. Second, exporters of non-customized intermediates appear to be the most productive, followed by customized intermediates, although the difference is not large. It is important to highlight, however, that these are unconditional results and therefore they do not control for other factors that might affect this distribution, such as sectors and size.

3.3 Econometric model

To estimate the export premia for different categories of firms classified according to their export destinations, we follow the methodology developed by Bernard and Jensen (1999), although with relevant adaptations. Importantly, our formulation estimates separate productivity premia for firms that export different types of products, as opposed to the single exported premium studied in Bernard and Jensen (1999) and other pioneering studies of this literature. This approach connects our study to the later works of this literature that use trade data at the transaction level and allow for the presence of heterogeneity between exporters (see Wagner (2007, 2012, 2016) for a thorough review of these studies). Moreover, we include firm fixed effects to account for unobserved firm characteristics correlated with the firm's export status or the control variables, which has become a common concern in this literature. We also control for the effect of importing similar product categories, as most studies indicate that importing is frequently associated with higher productivity (Foster-McGregor et al. 2014a). Therefore, the productivity premia are defined as the difference in productivity between firms that export (import) a positive value of a given type of product and those that do not export (import) the same product type, conditional on firm-level controls that include other export and import behaviours. We assume that different trade behaviours are not mutually exclusive: firms can—and frequently do—export and/or import more than one product category. We adopt the following semi-logarithmic equation:

$$lnLP_{it} = \alpha_0 + \beta X_{it} + \Phi Z_{it} + \alpha_i + \alpha_t + \varepsilon_{it} \tag{1}$$

where LP_{it} indicates labour productivity, X_{it} designates the vector of dummies indicating if firm *i* exports one of the product categories at time *t*. Following the empirical literature (Foster-McGregor et al. 2014a; Edwards et al. 2018), Z_{it} is a vector of controls which also includes different import behaviours of firms, the number of employees, capital per labour, and wages. α_i and α_t are firms and year fixed effects.

We evaluate the learning-by-exporting hypothesis using a leads-and-lags approach. Inspired by Autor (2003), the method has also been explored elsewhere in the learning-by-exporting literature (e.g., Mazzi et al. 2021; Pisu 2008; Schwarzer 2017) as opposed to the conventional approach of using matching techniques. This method explores two main aspects of the panel. First, it allows us to estimate a long-term 'learning curve' for firms, tracking their productivity premium trajectory across years before and after entry into the export market, which provides a picture of longer trends. Second, it also maximizes the number of observations for export entries in each export category due to the fact we can keep starts from different years in the sample in the same regression. The estimated equation is formulated as follows:

$$LnLP_{it} = \alpha_0 + \sum_{s=-n}^{n} \beta_s X_{is} + \Phi Z_{it} + \alpha_i + \alpha_t + \varepsilon_{it} \tag{2}$$

where all variables and vectors have the same meaning as in (1), except for X_{is} which indicates if firm *i* is an exporter in time *t* and takes value one if, and only if, $s = t - K_i$, where K_i indicates the year firm i started exporting each product category and n is the range of the learning curve, which depends on the total periods of the panel. The SARS-NT panel ranges from 2009 to 2017, but the sample is better populated from 2013 onwards. Therefore, we use the complete panel to estimate equation (1) but focus on the firms present in the final five years of the sample for the estimation of equation (2) to observe export starters for longer periods either before or after entry. We also drop firms that start exporting in their first two years in the sample (2013, 2014) when estimating equation (2) to be as sure as possible that the remaining exporters are export starters and not permanent or intermittent exporters. As a result, we look at four cohorts of starters (2014, 2015, 2016, 2017) and the maximum range n of the learning curve will be 8, i.e. 4 periods before the last entry (2017) and 3 periods after the earliest (2014),[3] totalling with the year of entry 8 binary variables for each GVC export category $(s \in [-4, 3])$.

The learning curve provides an insightful visualization tool but also allows us to identify more formally the existence of learning-by-exporting. The learning hypothesis is tested by comparing productivity premia before and after entry into exporting, i.e. by checking if $\beta_{0-l} = \beta_{0+f}$, where *l* and *f* are, respectively, the periods chosen before and after entry for comparison. We call these tests 'Test 1', 'Test 2', and 'Test 3' in the empirical section, depending on the values we choose for *l*. Additionally, we check for differences in the *change* of the productivity premium before and after entry into exporting, in this case, if $\beta_{-1} - \beta_{-1-m} = \beta_{-1+m} - \beta_{-1}$. This is equivalent to testing if $\beta_{-1} = 0.5 * (\beta_{-1+m} + \beta_{-1-m})$, where *m* is the interval of periods before and after entry chosen to evaluate the change in the productivity premium. Intuitively, the test checks whether the mean of coefficients β_{-1+m} and β_{-1-m} is significantly different from β_{-1}. This holds only when the productivity premium increases by a higher (or lower) amount after entry. Implicitly, this

[3] We also drop intermittent exporters, since the pre- and post-effects of exporting are confounded for these firms. We initially classify intermittent exporters as firms that return to exporting after having stopped exporting for one period but also test with longer intervals of two and three periods.

last test checks whether the entry into export markets affects previously existing trends in the *growth* of firms' productivity premium. We choose m=2 in the empirical section and call this test 'Test 4'.

3.4 Estimation

Our empirical analysis proceeds in two steps. First, we estimate equation (1) and evaluate the export premia for firms according to the three categories of products described above.[4] In this step, we are interested in comparing productivity differentials associated with different categories of products, focusing especially on customized intermediates. Next, we estimate equation (2) and evaluate export premia for starters in the same categories of products before, during, and after entry into international markets. In this case, we test whether productivity differentials were built after entry into international markets—which we consider to be supportive of learning-by-export.

4 Empirical results

4.1 Analysis of GVC-related export premia

Table 4 reports the initial results from the fixed-effect estimation of GVC-related trade on labour productivity. We sequentially introduce controls to test the robustness of our results. The estimation results are consistent across all specifications, with trade-related dummies having positive and significant labour productivity effects. This confirms that exporting is associated with higher labour productivity in firms. A further look at the results shows that the size of the estimated coefficient of customized intermediaries is larger, followed by final goods and non-customized intermediaries. This suggests that GVC-related trade is associated with higher productivity premia compared to non-GVC intermediates and downstream exporters of final goods. The result is robust to different covariates and classifications. The result is, therefore, consistent with extant results in the GVC firm-level literature (Accetturo and Giunta 2018; Agostino et al. 2015; Veugelers 2013) and indicates that GVC participation is associated with higher productivity premia. The result is also consistent with findings in the GVC literature which suggest that GVC participation reduces the performance gap between downstream and upstream, which in our case is captured by an inverted hierarchy between final goods and intermediate producers that are in GVCs (Agostino et al. 2015; Brancati et al. 2017; Giuliani et al. 2005). These results also corroborate recent findings by Mazzi et al. (2021) in the Brazilian manufacturing sector. In Appendix Table A1, we also report results for the Rauch (1999) classification for robustness, which remains compatible.

[4] We estimate all models including the residual category ('others') to control for other export behaviours.

Table 4: GVC-related trade and firm productivity premium

	(1)	(2)	(3)	(4)	(5)
Dependent variable			Ln Vae		
Customized intermediates	0.1938	0.1592	0.1541	0.0332	0.0620
	(0.0176)***	(0.0143)***	(0.0161)***	(0.0095)***	(0.0082)***
Finals	0.1332	0.1123	0.0951	0.0171	0.0442
	(0.0162)***	(0.0134)***	(0.0149)***	(0.0092)*	(0.0081)***
Non-customized intermediaries	0.1156	0.1039	0.0866	-0.0077	0.0226
	(0.0170)***	(0.0139)***	(0.0159)***	(0.0088)	(0.0075)***
Others	0.2000	0.1635	0.1696	0.0323	0.0568
	(0.0181)***	(0.0150)***	(0.0170)***	(0.0092)***	(0.0079)***
Ln Emp.		-0.3479			-0.6427
		(0.0217)***			(0.0106)***
Ln K Intensity		0.0807			0.0282
		(0.0035)***			(0.0014)***
Ln Wage		0.2863			0.0964
		(0.0107)***			(0.0039)***
p_b5_spcf_int_imports			0.2283		
			(0.0209)***		
p_b5_finals_int_imports			0.1518		
			(0.0162)***		
p_b5_nspcf_int_imports			0.1909		
			(0.0202)***		
p_b5_others_imports			0.1736		
			(0.0174)***		
r_b5_spcf_int_exports				-0.2227	-0.3673
				(0.1692)	(0.1573)**
r_b5_finals_int_exports				-0.1432	-0.0823
				(0.0988)	(0.0872)
r_b5_nspcf_int_exports				-0.3355	-0.3933
				(0.1536)**	(0.1475)***
r_b5_others_exports				-0.0664	-0.1892
				(0.2221)	(0.2123)
Observations	120,334	120,334	120,334	118,271	118,271
Number of clusters	28,504	28,504	28,504	28,077	28,077
R-squared	0.0357	0.219	0.0446	0.105	0.314
F	65.28	132.4	60.10	167.9	367.5

Note: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source*:* authors' calculations based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

Next, we consider export intensity as reported in columns 4, 5, and 8 of Table 4. The results suggest that productivity premia reduce as export intensity increases, especially when we control other covariates (column 5). However, it is important to note that the intensive margin effect is quite small for most firms. For example, for exporters of customized intermediates reported in column 5, the entry effect is [exp(0.0620) -1]*100 = 6.39 per cent. On the other hand, the median effect of export intensity is only [exp(-0.3673*0.0021)-1]*100 = -0.07 per cent, where p50 = 0.0021, which amounts to an overall premium of 6.32 per cent for the median intensity exporter of customized intermediates. This is in line with the firm heterogeneity trade models (e.g. Melitz 2003), suggesting that the fixed costs of exporting are strongly responsible for the performance premia of exporters.

Existing studies suggest that importing firms acquire technical knowledge and superior inputs that offer some performance gains compared to firms that do not import (e.g., Edwards et al. 2018; Foster-McGregor et al. 2014a). We tested this conjecture, and the results are reported in column 3. The results show that importing firms have higher productivity premia than non-importing firms, with the import of customized intermediaries having the highest productivity gains. Our import variables' coefficients are greater in size than those of our export variables, in line with the empirical literature which suggests that imports generate higher productivity premia than exports (Edwards et al. 2018; Foster-McGregor et al. 2014a). For instance, in their study of the relationship between imports of intermediate inputs and export performance in South African manufacturing firms, Edwards et al. (2018) find that access to imported intermediate inputs is critical for firms' productivity, in line with our results.

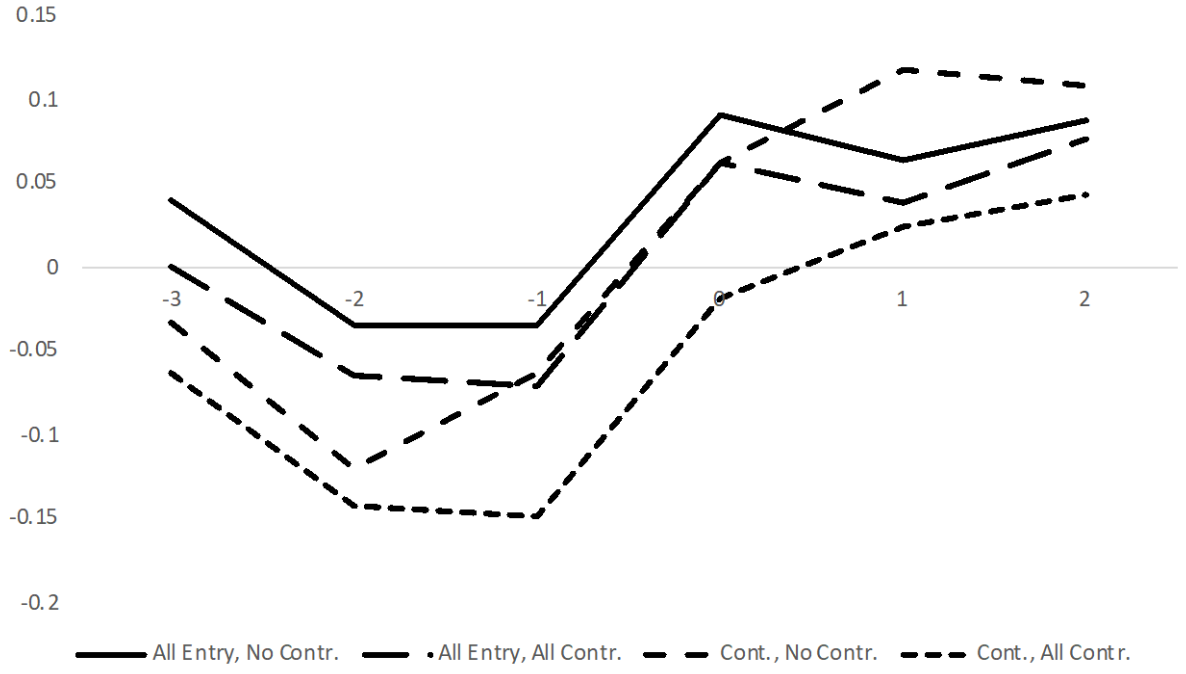
Other control variables in Table 4 include employment, capital per worker, and wages (columns 2, 5, 7, and 8). Our results are in line with the extant literature which shows that higher wages are positively correlated with labour productivity, indicating that higher wages are likely connected to increases in the quality of the firm's labour pool, while increases in capital intensity per worker tend to complement labour and lead to higher labour productivity. Regarding employment, we observe a negative point estimate, indicating that increases in the number of employees lead to less than proportional increases in total value added, reducing value added *per employee*, although the size of the coefficient still points to an overall positive effect on *total* value added.

4.2 Analysis of GVC-related learning-by-exporting

Figure 2 shows the productivity premia (per cent) for export starters based on equation (2). Period $t = 0$ indicates the first year of exporting, periods to the left of $t = 0$ represent estimates for periods before entry, while periods to the right of $t = 0$ indicate periods after entry. As the model is in log-linear form, we transform the estimated coefficients using the equation $e^{\beta} - 1$ to obtain export premia as percentages. Each curve represents a different regression with different samples or controls as reported in Table 5. The first curve (All Entry, No Contr.) shows the model with all export entrants and no time-varying controls, only firm and time fixed effects. The next curve (All Entry, Contr.) includes the full set of time-varying controls. The remaining curves follow the same logic, except now only continuous exporters (i.e. firms that continue to export for at least two consecutive years) are considered as export starters. Continuous exporters remain involved in foreign markets for a longer period and in theory, are more likely to experience learning effects.

Figure 2 shows that the productivity premia of export starters increase sharply on the year of entry relative to pre-entry levels. For instance, the productivity premium of continuous exporters jumps from around -5 per cent to 5 per cent between $t = -1$ to $t = 0$ in the model without time-varying controls. While the subsequent two periods do not show a clear trend, they, however, remain above those in the pre-entry period. The two curves for continuous exporters, in particular, appear to continue on a slow-growth trend.

Figure 2: Learning curves for export starters across different samples (all starters, and continuers).



Source: authors' figure based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

Turning to Table 5, we observe that the estimated productivity premia are small, and most are not statistically different from zero. These results are due to the fact that the average effect of being an export starter is captured by the firm fixed effects and does not mean the effect of exporting is zero.[5] We saw in the previous section that the export premia we estimate are positive and significant, and this is confirmed by estimations of equation (2) without firm fixed effects (not depicted, but available from the authors upon request). The firm fixed effects also make it necessary to omit one of the terms of the learning curve, for which we chose the last coefficient (X_{i3}).[6] Despite these disadvantages, we chose to keep the firm fixed effects to control for unobserved firm characteristics, which is highly important.

However, productivity premia before and after entry, which is our main concern in this section, tend to be statistically different from each other. In the bottom part of Table 5, we report the p-value for three different Wald tests for simple and composite linear hypotheses. Test 1 checks whether$\beta_{-3} = \beta_2$, i.e. whether the productivity premium the three years before entry equals the productivity premium two years after the year of entry. Test 2 checks whether$\beta_{-2} = \beta_2$, while Test 3 checks whether$\beta_{-1} = \beta_2$, therefore covering all periods before entry and comparing them with the last estimated period after entry. Although for Test 1 differences are not significant at 5

[5] One can note that for overall exporters $\sum_{s=-n}^{n} X_{is} = Starter_i$, where $Starter_i$ is a binary taking value 1 if the firm is an export starter and zero otherwise. It follows that $\sum_{s=-n}^{n} \beta_s X_{is} = \beta_{-n} Starter_i + \sum_{s=-n+1}^{n} \gamma_s X_{is}$, where $\gamma_s = (\beta_s - \beta_{-n})$. The estimates we observe in Table 5 are actually equivalent to γ_s and therefore can be seen as expressing time-related *deviations* of the export premium from an average for export starters given by β_{-n}. This coefficient (β_{-n}), however, is subsumed by the firm fixed effects and cannot be identified in equation (2) and, therefore, we are unable to recover the *real* premia given by β_s in model (2).

[6] This can also be observed in footnote 8, where one of the coefficients of the learning curve (X_{in}, in the example) has to be omitted for the estimation of $Starter_i$ (or firm fixed effects).

per cent, we can observe that in all but one case the null hypothesis is rejected at 5 per cent[7] for Tests 2 and 3, and more strongly for continuous exporters, indicating statistically different productivity premia after entry in export markets.

Table 5: Productivity premia for export starters divided by different samples (all starters, continuers)

	(1)	(2)	(3)	(4)
Dep variable	Ln Vae	Ln Vae	Ln Vae	Ln Vae
Sample	All entry	All entry	Continuers	Continuers
Export t-4	0.0254	-0.1086		
	(0.0976)	(0.0833)		
Export t-3	0.0152	-0.0324	-0.0339	-0.0654
	(0.0835)	(0.0754)	(0.1191)	(0.1082)
Export t-2	-0.0801	-0.0896	-0.1281	-0.1543
	(0.0854)	(0.0746)	(0.1306)	(0.1119)
Export t-1	-0.0678	-0.1406	-0.0660	-0.1613
	(0.0838)	(0.0718)*	(0.1284)	(0.1092)
Export t	0.0656	-0.0059	0.0597	-0.0193
	(0.0688)	(0.0576)	(0.0995)	(0.0824)
Export t+1	0.0500	-0.0115	0.1115	0.0238
	(0.0663)	(0.0562)	(0.0966)	(0.0802)
Export t+2	0.0624	0.0120	0.1020	0.0414
	(0.0643)	(0.0541)	(0.0957)	(0.0795)
Ln Emp.		-0.5899		-0.5865
		(0.0348)***		(0.0374)***
Ln K Intensity		0.0439		0.0442
		(0.0056)***		(0.0058)***
Ln Wage		0.1959		0.2031
		(0.0241)***		(0.0256)***
Importer		0.2291		0.2428
		(0.0441)***		(0.0511)***
Observations	26,631	26,631	24,477	24,477
R-squared	0.0411	0.1741	0.0406	0.1742
Year FE	YES	YES	YES	YES
Test 1	43%	44%	8%	15%
Test 2	3.1%	8.6%	1.9%	2.0%
Test 3	2.4%	0.3%	4.5%	0.4%
Test 4	0.8%	0.0%	9.1%	1.1%
F	18.24	47.11	17.82	43.75

Note: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

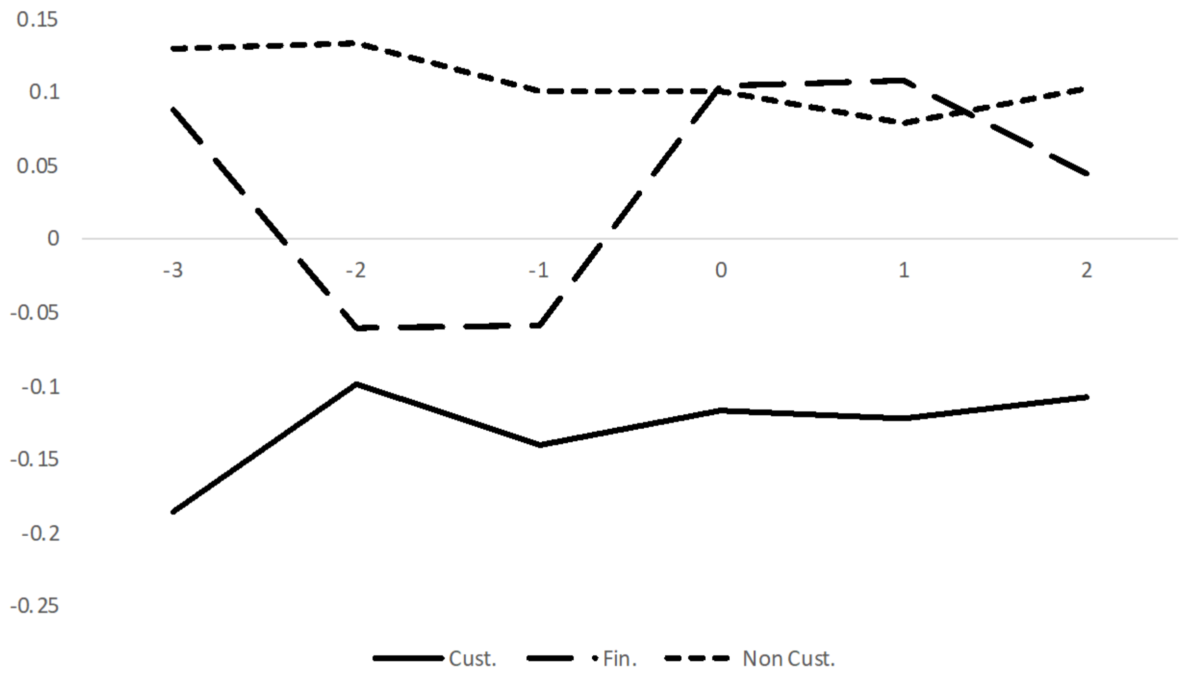
Source: authors' calculations based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

[7] In column (2), Test 2 depicts a p-value of 8.6 per cent.

Differences between these coefficients might result from the continuation of productivity trajectories that were already present before entry into export markets. Test 4, therefore, checks whether $\beta_{-1} - \beta_{-3} = \beta_1 - \beta_{-1}$, i.e. whether the change in productivity premia is equal before and after firms enter export markets. We find supportive evidence for this in all the models at a conventional statistical significance level. This result is consistent with Figure 2, where we observed that export premia are mostly stable or reducing before entry (between $t = -3$ and $t = -1$), and start increasing from the period of the entry ($t = 0$).

The above findings provide suggestive evidence of learning-by-exporting for the population of South African firms in our sample, corroborating findings in the context of other developing countries. For instance, Foster-McGregor et al. (2014b) found similar learning-by-exporting evidence for manufacturing firms in 19 sub-Saharan African countries. One of our paper's objectives is to check whether this learning-by-exporting is related to a firm's participation in GVCs. Hence, Figure 3 shows the curves for export starters based on our categorization of exported products i.e. customized, non-customized, and final products. We show results only for the model that includes the complete set of time-varying controls and for all starters, although results are similar for continuous exporters.

Figure 3: Learning curves for export starters divided by different product types, sample of all starters and complete set of controls



Source: authors' figure based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

As can be seen in Figure 3, for the different categories, we do not observe any growth trends. Exporters of customized and non-customized intermediates, in particular, appear quite stable, while exporters of final goods show more variation but no clear trend. Table 6 reports the regression results for the learning-by-exporting effects. It is important to observe that all columns of Table 6 reproduce results of the same regression, therefore the results for the control variables and regression statistics are equal in all columns. What we depict in separate columns are the estimates for each type of export behaviour obtained from the same regression. It is important to estimate all coefficients in the same model because firms export more than one product category and, therefore, we need to control for the effect of each product type separately. The dearth of empirical evidence on the learning-by-exporting effects across the product subgroups we observed in Figure 3 is confirmed further by the Wald tests we report at the bottom of Table 6. This suggests that exporting GVC-related intermediates separately is not related to the learning effects we observed for overall exporters or any other separate product categories.

Table 6: Productivity premia for export starters divided by different product types, sample of all starters, and complete set of controls.

	(1)	(2)	(3)	(4)
Dep. variable	Ln Vae	Ln Vae	Ln Vae	Ln Vae
Type of exporter	Cust.	Finals	Non cust.	Others
Sample	All Entry	All Entry	All Entry	All Entry
Export t-4	-0.2693	0.0829	0.1663	-0.0686
	(0.1541)*	(0.1317)	(0.1863)	(0.1233)
Export t-3	-0.2056	0.0851	0.1217	-0.0734
	(0.1212)*	(0.1189)	(0.1739)	(0.1140)
Export t-2	-0.1037	-0.0615	0.1254	-0.1246
	(0.1044)	(0.1220)	(0.1658)	(0.1166)
Export t-1	-0.1511	-0.0604	0.0965	-0.1559
	(0.0961)	(0.1108)	(0.1636)	(0.1135)
Export t	-0.1231	0.1000	0.0965	-0.0378
	(0.0836)	(0.0888)	(0.1471)	(0.0955)
Export t+1	-0.1291	0.1031	0.0760	-0.0165
	(0.0760)*	(0.0847)	(0.1388)	(0.0946)
Export t+2	-0.1139	0.0441	0.0985	0.0127
	(0.0857)	(0.1032)	(0.1390)	(0.0963)
Ln Emp.	-0.5945	-0.5945	-0.5945	-0.5945
	(0.0347)***	(0.0347)***	(0.0347)***	(0.0347)***
Ln K Intensity	0.0437	0.0437	0.0437	0.0437
	(0.0056)***	(0.0056)***	(0.0056)***	(0.0056)***
Ln Wage	0.1960	0.1960	0.1960	0.1960
	(0.0240)***	(0.0240)***	(0.0240)***	(0.0240)***
Importer Cust.	0.1179	0.1179	0.1179	0.1179
	(0.0382)***	(0.0382)***	(0.0382)***	(0.0382)***
Importer Fin.	0.1012	0.1012	0.1012	0.1012
	(0.0296)***	(0.0296)***	(0.0296)***	(0.0296)***
Importer Non Cust.	0.1139	0.1139	0.1139	0.1139
	(0.0347)***	(0.0347)***	(0.0347)***	(0.0347)***
Importer Others	0.1073	0.1073	0.1073	0.1073
	(0.0350)***	(0.0350)***	(0.0350)***	(0.0350)***

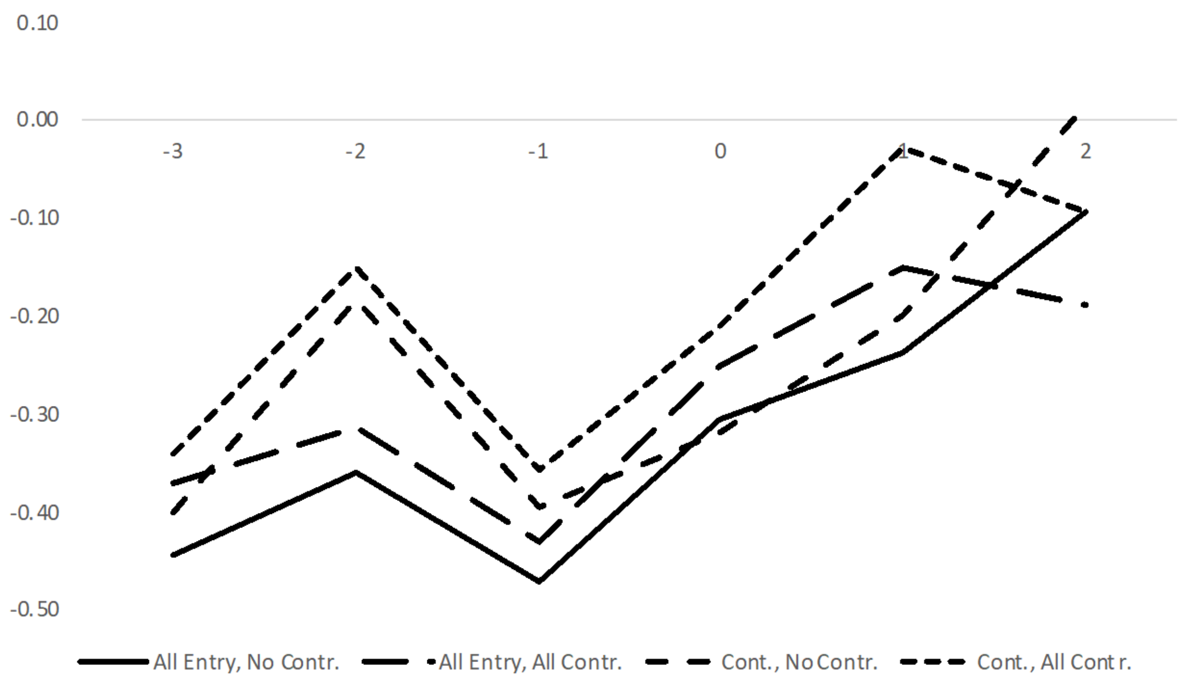
Observations	26,631	26,631	26,631	26,631
R-squared	0.1762	0.1762	0.1762	0.1762
Year FE	YES	YES	YES	YES
Test 1	39.2%	73.8%	81.7%	29.3%
Test 2	91.2%	42.3%	77.2%	12.8%
Test 3	63.6%	34.2%	97.9%	3.4%
Test 4	77.6%	0.2%	95.6%	2.4%
F	31.20	31.20	31.20	31.20

Note: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' calculations based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

One of the potential reasons for this is that successful exporters tend to diversify their exports in more than one product category, thereby accumulating the learning effects from different product categories, which cannot be captured by the model reproduced in Table 6. However, important insights from the broader GVC-related literature suggest that learning will frequently depend on firms' own internal innovation efforts. Firms need to 'invest in learning and building technological capabilities to innovate effectively' in value chains (Morrison et al. 2008: 51), among other reasons, because lead firms will rarely sustain the development of core capabilities by local firms. Hence, the productivity trajectories of exporters that invest in capabilities and innovation may be different from those that do not, especially for those involved in GVCs, where the learning potential, in theory, is higher.

Figure 4: Learning curves for export starters that invest in capabilities (R&D) after entry divided by different samples (all starters, continuers) and different sets of controls (no time-varying controls, complete set of controls)



Source: authors' figure based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

Against this backdrop, Figure 4 shows the learning curves for exporters that perform R&D after entering export markets for at least one period, i.e. in $t = 0$, $t = 1$or $t = 2$. Formally, the empirical model that leads to this figure is expressed in the following way:

$$LnLP_{it} = \alpha_0 + \sum_{s=-n}^{n} \beta_s X_{is} + \sum_{s=-n}^{n} \gamma_s X_{is} * R\&D\_entry_i + R\&D_{it} + \Phi Z_{it} + \alpha_i + \alpha_t + \varepsilon_{it} \quad (3)$$

where $R\&D\_entry_i$ is a dummy variable taking value 1 if the firm performed R&D after entering into the exports of products, therefore separating these firms' entire learning curves from those of exporters that do not perform R&D investments after entry. We use this variable to signal firms that perform internal investments in capabilities and innovation after entry, and not to capture the effect of R&D itself. The latter is captured by the variable $R\&D_{it}$, which is a dummy taking value one if the firm performs R&D in period *t* and complements the vector of controls $\boldsymbol{Z}$.

Figure 4 shows the same learning curves shown in Figure 2, but this time only for firms that invest in R&D after entry. As the figure indicates, these firms appear to experience sharp learning trajectories after entry. In Table 7, we report the associated regression results and observe the Wald tests that indicate significant differences in coefficients immediately before (β_{-1}) and two years after entry (β_2), called 'Test R&D 3' for these firms in the regressions without time-varying controls at the 5 per cent significance levels, therefore partially confirming the impressions observed on the graph. Despite the apparent growth trend observed after entry in Figure 4, the tests for changes in the productivity premia (Test_R&D 4) do not depict significant values in any of the columns. Table 7 also confirms that the learning trajectories for firms that do not perform R&D after entry indicate no signs of learning.

Table 7: Productivity premia for export starters that invest in capabilities (R&D) after entry divided by different samples (all starters, continuous exporters) and different sets of controls (no time-varying controls, complete set of controls)

	(1)	(2)	(3)	(4)
Dep. variable	Ln Vae	Ln Vae	Ln Vae	Ln Vae
Sample	All entry	All entry	Continuers	Continuers
Export t-4	0.0484	-0.1172		
	(0.1134)	(0.0908)		
Export t-3	0.0769	-0.0085	-0.0183	-0.0778
	(0.0862)	(0.0766)	(0.1062)	(0.0922)
Export t-2	0.0389	0.0185	0.0252	-0.0429
	(0.0756)	(0.0648)	(0.0863)	(0.0742)
Export t-1	0.0666	0.0105	0.0800	-0.0151
	(0.0699)	(0.0586)	(0.0774)	(0.0677)
Export t	0.0835	0.0537	0.0464	-0.0134
	(0.0644)	(0.0562)	(0.0714)	(0.0644)
Export t+1	0.1080	0.0691	0.1006	0.0297
	(0.0587)*	(0.0482)	(0.0679)	(0.0557)
Export t+2	0.0156	0.0111	-0.0147	-0.0249
	(0.0474)	(0.0428)	(0.0574)	(0.0529)
Export t-4 * R&D_entry	-0.6572	-0.3612		
	(0.2210)***	(0.2748)		
Export t-3 * R&D_entry	-0.5879	-0.4648	-0.5095	-0.4174
	(0.1686)***	(0.2333)**	(0.1507)***	(0.2470)*
Export t-2 * R&D_entry	-0.4438	-0.3761	-0.2017	-0.1637
	(0.1753)**	(0.2215)*	(0.1645)	(0.2094)
Export t-1 * R&D_entry	-0.6368	-0.5603	-0.5019	-0.4410
	(0.2443)***	(0.3408)	(0.2096)**	(0.3697)

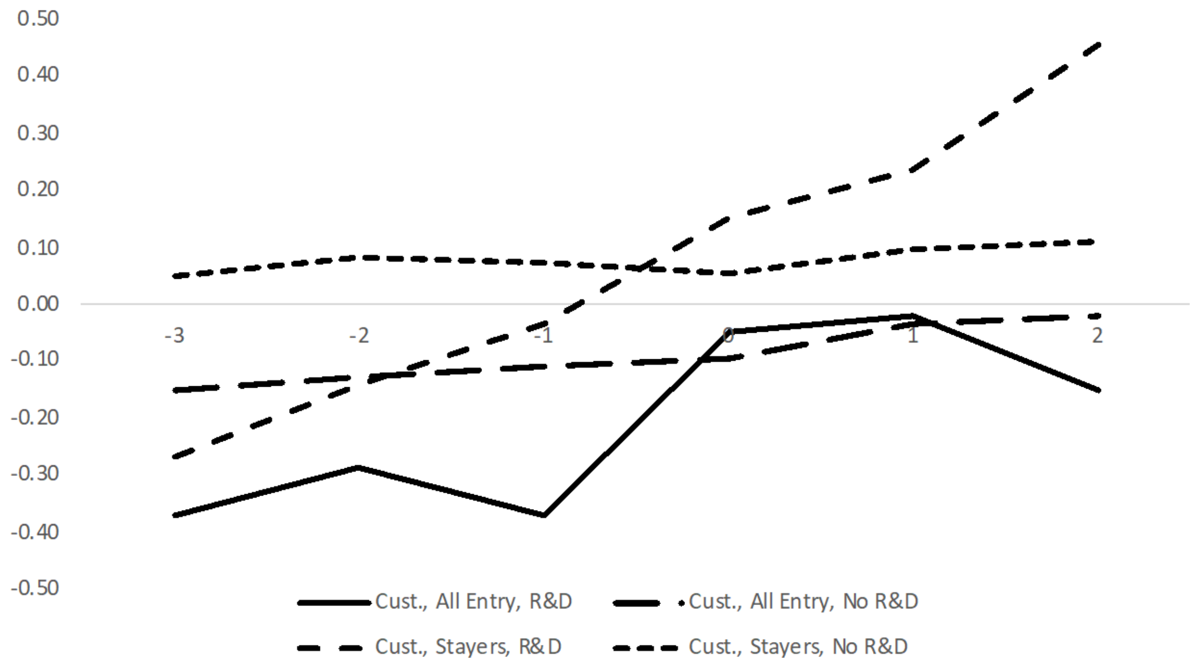
Export t * R&D_entry	-0.3661	-0.2875	-0.3839	-0.2355
	(0.1538)**	(0.1753)	(0.1887)**	(0.1908)
Export t+1 * R&D_entry	-0.2714	-0.1626	-0.2210	-0.0279
	(0.1293)**	(0.1686)	(0.1386)	(0.1562)
Export t+2 * R&D_entry	-0.0990	-0.2081	0.0161	-0.0965
	(0.1866)	(0.1652)	(0.2133)	(0.1722)
R&D	-0.0765	-0.0881	-0.0642	-0.0646
	(0.0828)	(0.0796)	(0.0847)	(0.0837)
Ln Emp.		-0.7123		-0.7028
		(0.0418)***		(0.0470)***
Ln K Intensity		0.0292		0.0282
		(0.0067)***		(0.0073)***
Ln Wage		0.0492		0.0472
		(0.0176)***		(0.0193)**
Importer		0.1236		0.1262
		(0.0360)***		(0.0390)***
Observations	6,050	6,050	5,339	5,339
R-squared	0.0952	0.2997	0.0973	0.2876
Year FE	YES	YES	YES	YES
Test 1	42%	77%	97%	53%
Test 2	72%	89%	60%	78%
Test 3	38%	99%	17%	86%
Test 4	62%	65%	51%	84%
Test 1_R&D	1%	16%	0%	12%
Test 2_R&D	7%	33%	24%	70%
Test 3_R&D	1%	15%	1%	21%
Test 4_R&D	28%	24%	49%	38%
F	94.28	42.05	91.13	36.54

Note: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' calculations based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

Could these results be connected to GVC-related intermediates? Figure 5 shows an affirmative answer to this conjecture. In particular, Figure 5 shows that the learning curves of firms exporting GVC-related products and performing R&D after entry present a clear increase after period $t = 0$ for all starters and a stable growth trend from period $t = -3$ for export continuers, suggesting that this growth trend was already present before exporting for these firms. Similar growth trends are not observed for firms which export GVC-related products but which do not perform R&D after entry. Table 8 shows that the coefficients have high standard errors. However, we see that the Test_R&D 1 presents a p-value of 6.8 per cent in the case of export continuers in column (2), which is therefore significant at the 10 per cent level.

Figure 5: Learning curves for export starters of customized intermediates according to investment in R&D after entry and by different samples (all starters, continuers).



Source: authors' figure based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

Table 8: Productivity premia for export starters of customized intermediates according to investment in R&D after entry and by different samples (all starters, continuers)

	(1)	(2)
Dep. variable	Ln Vae	Ln Vae
Type of exporter	Cust.	Cust.
Sample	All entry	Continuers
Export t-4	-0.2294	
	(0.1348)*	
Export t-3	-0.1644	0.0457
	(0.1132)	(0.1433)
Export t-2	-0.1389	0.0763
	(0.1035)	(0.1130)
Export t-1	-0.1160	0.0698
	(0.0983)	(0.1166)
Export t	-0.1013	0.0517
	(0.0866)	(0.1028)
Export t+1	-0.0347	0.0914
	(0.0740)	(0.0854)
Export t+2	-0.0221	0.1037
	(0.0637)	(0.0852)
Export t-4 * R&D_entry	-1.3458	
	(1.1624)	

Export t-3 * R&D_entry	-0.4641	-0.3151
	(0.9208)	(0.4508)
Export t-2 * R&D_entry	-0.3379	-0.1536
	(0.8547)	(0.4469)
Export t-1 * R&D_entry	-0.4617	-0.0383
	(0.7850)	(0.5637)
Export t * R&D_entry	-0.0507	0.1394
	(0.6318)	(0.3587)
Export t+1 * R&D_entry	-0.0219	0.2105
	(0.4469)	(0.3009)
Export t+2 * R&D_entry	-0.1669	0.3734
	(0.4336)	(0.2505)
R&D	-0.0785	-0.0645
	(0.0825)	(0.0858)
Observations	6,050	5,339
R-squared	0.3044	0.2915
Year FE	YES	YES
Test 1	13%	63%
Test 2	16%	74%
Test 3	23%	70%
Test 4	78%	99%
Test 1_R&D	63%	6.8%
Test 2_R&D	77%	17%
Test 3_R&D	56%	36%
Test 4_R&D	25%	98%
F	21.29	19.33

Note: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' calculations based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

The results above partially explain the learning effects observed for the overall population of exporters. The evidence for learning-by-exporting for the overall population of South African firms is strong, and this appears to be connected to firms that invest in capabilities after entry into foreign markets. Although this effect is also likely related to a process of diversification of export products to more than one of the export categories we classify, exporters of GVC-related intermediates that invest in the development of their internal technological capabilities are also partially responsible for these trends; although in the case of export continuers these trends appear to precede entry into foreign markets.

It is interesting to observe that we do not find similar trends for other export categories, i.e. the learning curves do not show any indication of learning for exporters of non-customized and final goods (Appendix Table A2). A related paper by Mazzi et al. (2021) also did not find evidence of a learning effect in trade in customized intermediates in Brazil. Conversely, the authors found evidence of learning in trade in final products, contrary to our evidence of no learning effect in South Africa. While South Africa and Brazil have apparently similar economic structures, largely built around the exploration, processing, and exports of natural resources, there are also important differences in the structure of the manufacturing sector of the two countries, which may be driving some of the differences in the results. Moreover, we do not find any evidence of learning-by-exporting for other firm expenditures connected to capability development, such as investments in training and payments of royalties (available from the authors upon request). Only R&D investments appear to influence firms' capacity to learn through export relationships.

5 Conclusion

Global value chains have changed the way international production is organized in line with the increasing importance of trade in specific groups of products whose transactions are characterized by higher levels of customization. Based on the emerging evidence that trade in 'parts and components' or intermediary products generate superior productivity premia, this paper examines the extent to which these trends have influenced the performance of exporting firms in South Africa. In particular, our paper examines the existence of export premia differentials between firms participating in fragmented trade and those firms that do not, as well as the presence of learning-by-exporting for these different product groups using panel data sourced from the South African Revenue Service and National Treasury (SARS-NT) covering the period 2009–17.

Evaluating the export premia for firms in an econometric model, our findings are consistent with the wider empirical literature which suggests that exporters have a higher productivity premium compared with non-exporters. However, firms that trade GVC-related products tend to have a higher premium compared with traditional trade, suggesting the positive benefits of GVC participation that have been underscored in the broader GVC literature. For the learning effect, while we find evidence of a learning effect in the full population of firms in South Africa, this is not the case when we consider firms that trade GVC-related products. However, we find evidence of a learning effect for firms that trade in GVC-related products and engage in R&D investment after entry, especially export continuers. This last result is consistent with the broader idea in the literature that successful learning and capability building in the GVC frequently depend on firms' own internal innovation efforts (Morrison et al. 2008: 51), partly due to the hierarchical constraints and skill intensity of advanced tasks in international value chains.

While several aspects of this paper can be extended, the policy relevance of our results in helping to fine-tune industrial policy towards increasing the quantity and the quality of South African intermediate manufacturing exports, aspects of trade that are often relegated and overlooked in the policy space, cannot be overemphasized. Future empirical research could consider and provide insights into specific manufacturing industries engaged in fragmented trade, and how these trade activities affect trade and industrial policy designs in South Africa and developing countries as a whole.

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Appendix A: additional regressions

Table A1: GVC-related trade and firm productivity premium for the Rauch classification

	(1)	(2)	(3)
	p_rch_*exports		p_rch_*exportsr_rch_*exports
p_rch_spcf_int_exports	0.2216	0.1880	0.0689
	(0.0190)***	(0.0152)***	(0.0082)***
p_rch_finals_int_exports	0.1358	0.1146	0.0445
	(0.0164)***	(0.0135)***	(0.0081)***
p_rch_nspcf_int_exports	0.1230	0.1071	0.0293
	(0.0186)***	(0.0152)***	(0.0078)***
p_rch_others_exports	0.1934	0.1556	0.0526
	(0.0178)***	(0.0146)***	(0.0076)***
r_rch_spcf_int_exports			-0.3559
			(0.1197)***
r_rch_finals_int_exports			-0.0804
			(0.0872)
r_rch_nspcf_int_exports			-0.4033
			(0.2090)*
r_rch_others_exports			-0.1902
			(0.2350)
Log #employees		-0.3484	-0.6429
		(0.0217)***	(0.0106)***
log Capital per labour		0.0807	0.0282
		(0.0035)***	(0.0014)***
Log Wage		0.2863	0.0965
		(0.0106)***	(0.0039)***
Observations	120,334	120,334	118,271
Number of clusters	28,504	28,504	28,077
R-squared	0.0359	0.219	0.314
F	65.63	132.5	368.5

Note: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' calculations based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

Table A2: Productivity premia for export starters of different export categories

	(1)	(2)	(3)	(4)
Dep. variable	Ln Vae	Ln Vae	Ln Vae	Ln Vae
Type of exporter	Cust.	Finals	Non cust.	Others
Sample	All entry	All entry	All entry	All entry
Export t-4	-0.2294	-0.0499	0.0482	0.1037
	(0.1348)*	(0.1587)	(0.1234)	(0.1362)
Export t-3	-0.1644	0.0215	0.0430	0.0977
	(0.1132)	(0.1420)	(0.1156)	(0.1224)
Export t-2	-0.1389	-0.0446	0.1250	0.0527
	(0.1035)	(0.1200)	(0.0973)	(0.1099)
Export t-1	-0.1160	0.0418	0.0782	-0.0342
	(0.0983)	(0.1076)	(0.0895)	(0.1052)
Export t	-0.1013	0.0808	0.0886	-0.0089
	(0.0866)	(0.1072)	(0.0866)	(0.0993)
Export t+1	-0.0347	0.0849	0.0187	-0.0255
	(0.0740)	(0.0901)	(0.0778)	(0.0904)
Export t+2	-0.0221	0.0100	0.0688	-0.0613
	(0.0637)	(0.0904)	(0.0727)	(0.0744)
Export t-4 * R&D_entry	-1.3458	1.1877	0.9887	-1.7260
	(1.1624)	(1.0191)	(0.6502)	(0.6791)**
Export t-3 * R&D_entry	-0.4641	0.6520	0.2319	-0.7854
	(0.9208)	(0.8925)	(0.5368)	(0.4529)*
Export t-2 * R&D_entry	-0.3379	0.6695	0.3433	-1.1919
	(0.8547)	(0.9426)	(0.4926)	(0.5538)**
Export t-1 * R&D_entry	-0.4617	0.5982	0.0934	-0.7971
	(0.7850)	(0.8614)	(0.5584)	(0.3709)**
Export t * R&D_entry	-0.0507	0.2819	-0.0627	-0.5072
	(0.6318)	(0.6327)	(0.4656)	(0.3195)
Export t+1 * R&D_entry	-0.0219	0.0820	0.4157	-0.4861
	(0.4469)	(0.5025)	(0.3609)	(0.3031)
Export t+2 * R&D_entry	-0.1669	0.1593	0.2148	-0.2714
	(0.4336)	(0.4651)	(0.3084)	(0.3058)
R&D	-0.0785	-0.0785	-0.0785	-0.0785
	(0.0825)	(0.0825)	(0.0825)	(0.0825)
Observations	6,050	6,050	6,050	6,050
R-squared	0.3044	0.3044	0.3044	0.3044
Year FE	YES	YES	YES	YES
Test 1	13%	92%	79%	10%
Test 2	16%	53%	46%	15%
Test 3	23%	68%	88%	71%
Test 4	78%	83%	34%	19%
Test 1_R&D	63%	34%	81%	25%
Test 2_R&D	77%	34%	17%	32%
Test 3_R&D	56%	96%	2%	39%
Test 4_R&D	33%	71%	4%	42%
F	21.29	21.29	21.29	21.29

Note: robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Source: authors' calculations based on SARS-NT panel (National Treasury and UNU-WIDER 2019).

Appendix B: data appendix

(In accordance with the guidelines to authors for compiling their data appendix)

Place of Access: National Treasury – Secure Data Facility, Pretoria
Name of the dataset used: SARS-NT, version 3.5
Software used: Stata 15/16
Period of use of the data: 12-19 March 2020 in loco, 21 July – 9 September 2020 remotely

The output of this work was checked so that no firm or individual information would be compromised. Our results do not represent any official statistics. The views expressed herein are the authors' only and do not necessarily reflect the views of the NT or SARS.

Summary of cleaning procedures

As noted, we restrict our sample to key variables in order to make the panel compatible across all four data sources employed in this paper. Our final sample size comprises 120,635 firms. Due to cross-missing observations, we observe drops in the number of firms when we use additional co-variables such as fixed capital and R&D. In the learning-by-exporting regressions additional observations are lost as we focus on the final five years of the sample for the estimation of equation (2) in order to observe export starters for longer periods either before or after entry. We also drop firms that start exporting in their first two years in the sample (2013, 2014) when estimating equation (2) to be as sure as possible that the remaining exporters are export starters and not permanent or intermittent exporters.

We deflate the capital variables using a gross capital formation deflator, wages using the Consumer Price Index (CPI), and firms' remaining nominal variables using the Producer Price Index (PPI), all economy-wide deflators provided by Statistics South Africa. Average wages are calculated as total labour costs divided by the average number of employees. Capital is proxied by total assets or fixed assets (measured as plants, equipment, and other fixed assets), whereas R&D investments are self-declared values obtained from firms' tax returns. Finally, we measure labour productivity and capital per worker as value added (sales minus the cost of intermediates) and capital divided by the average number of employees, respectively.

Table B1: Definitions of variables

Created variables	Definition
Customized intermediates	binary BEC5 or Rauch specific products exports
Finals	binary BEC5 or Rauch final products exports
Non-customized intermediaries	binary BEC5 or Rauch non-specific products exports
Others	binary BEC5 or Rauch primary and non-specified products exports
Ln Emp	log 1+employees
Ln_Cap. Intensity	log 1+capital/employees
Ln Wages	log 1+wages
value_imports	imported value
Importers	binary importers
p_b5_spcf_int_imports	binary BEC5 specific products imports
p_b5_finals_int_imports	binary BEC5 final products imports
p_b5_nspcf_int_imports	binary BEC5 non-specific products imports
p_b5_others_imports	binary BEC5 primary and non-specified products imports
r_b5_spcf_int_imports	imported value/sales ratio BEC5 specific products
r_b5_finals_int_imports	imported value/sales BEC5 final products
r_b5_nspcf_int_imports	imported value/sales BEC5 non-specific products
r_b5_others_imports	imported value/sales BEC5 primary and non-specified products
r_b5_spcf_int_exports	exported value/sales ratio BEC5 specific products
r_b5_finals_int_exports	exported value/sales BEC5 final products
r_b5_nspcf_int_exports	exported value/sales BEC5 non-specific products
r_b5_others_exports	exported value/sales BEC5 primary and non-specified products
value_exports	exported value
r_rch_spcf_int_exports	ratio Rauch specific products exports
r_rch_finals_int_exports	ratio Rauch final products exports
r_rch_nspcf_int_exports	ratio Rauch non-specific products exports
r_rch_others_exports	ratio Rauch other non-specified products exports
Ln Vae	Ln of value added per employee
VA	Total value added
assets per employee	Total assets/employees
VAE	VA/employees
CIT-IRP5 panel variables	Description
ITR14_k_total assets	Total assets
k_input	Total capital
g_sales	total sales
g_cos2	total cost of sales
x_wages	total wage costs
x_labcost	total labour costs
x_rd	total r&D costs
x_royalt	Total roylaties costs
employees	Total employment (irp5_empl_weight)
ITR14_x_training	Total training costs

Source: authors' illustration.