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Global Value Chains and Productivity: Micro Evidence from Estonia

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Global Value Chains and Productivity: Micro Evidence from Estonia[*]

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Abstract

The COVID-19 pandemic has led to an unprecedented collapse in global economic activity and trade. The crisis has also highlighted the role played by global value chains (GVC), with countries facing shortages of components vital to everything from health systems to everyday household goods. Despite the vulnerabilities associated with increased interconnectedness, GVCs have also contributed to increasing productivity and long-term growth. We explore empirically the impact of GVC participation on productivity in Estonia using firm-level data from 2000 to 2016. We find that higher GVC participation at the industry level significantly boosts productivity at both the industry and the firm level. Frontier firms, large firms, and exporting firms also benefit more from GVC participation than non-frontier firms, small firms, and non-exporting firms. We also find that GVC participation of downstream industries has a negative correlation with productivity. Frontier firms and large firms benefit more from GVC participation of upstream industries, while non-frontier firms and small firms benefit more from GVC participation of downstream industries. Our results suggest that policies designed to promote participation in GVCs are important to raise aggregate productivity and potential growth in Estonia.

JEL Classification Numbers: F14, F15, L25, O47

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I. Introduction

The COVID-19 pandemic has led to an unprecedented collapse in global economic activity and trade. Like other European economies, Estonia is also expected to see a sharp drop in GDP growth and trade. The crisis has also highlighted the role played by global value chains (GVC), with countries facing shortages of components vital to everything from health systems to everyday household goods. While long-term outcomes of the crisis are yet to be seen, economies may face further uncertainty from global supply chain reconfigurations as companies try to enhance their resilience to supply disruptions. These dynamics could that affect exports and market access.

Despite the vulnerabilities associated with increased interconnectedness, GVCs have also contributed to increasing productivity and long-term growth. Estonian firms have successfully engaged in Global Value Chains (GVCs). According to Statistics Estonia, Estonia's exported goods were worth around 80 percent of GDP, while imports to Estonia amounted to above 75 percent in 2016. In value added terms, exports contributed 44 percent of total GDP, while imports accounted for 43 percent of total GDP in 2014 (OECD, 2017a). Finland, Sweden, Latvia and Germany are the country's main trading partners. Intermediates represents 69 percent of Estonia's total exports and 67 percent of the country's total imports. Finland is the most important direct destination of Estonia's intermediate exports (accounting for around 18 percent of total exports), followed by Sweden and Russia. The Estonian economy is well integrated into global trade and export performance has been resilient.

Studies have shown that engaging in GVCs provides opportunities for technology transfer or knowledge spillovers. These advantages are particularly favorable to local firms through pooling knowledge with foreign suppliers and using more differentiated variety of inputs and higher-quality foreign services and inputs. Bas and Strauss-Kahn (2014) find that an increase in the share of imported inputs used in production raises firm-level productivity and exports in France. Another mechanism through which GVCs might raise incentives to innovate and adopt foreign technologies of local firms is increasing pressure to match international standards (Pietrobelli and Rabellotti, 2011). By making increasing use of available foreign knowledge and technology, local firms are expected to boost their own innovation activity and lift productivity.

Although Estonia's response to the Covid-19 crisis has been remarkably successful, its exports and imports of goods and services have been sharply affected. Consensus forecasts across the board predicts that the Estonian economy is likely to shrink by around 7 percent this year compared to last year. At the same time, most firms in Estonia are micro and small firms (only about 4% are firms with more than 50 employees in 2016 in the ORBIS database) who are most vulnerable to the pandemic. Estonian government has introduced economic stimulus package to overcome the crisis and help companies. However, policies to push productivity to raise competitiveness in the long term are also important. Therefore, understanding how GVC participation could affect productivity would have meaningful policy implications in Estonia.

Estonia thus represents an interesting country case to study the impact of GVC participation on productivity. Despite rapid convergence since joining the EU in 2004, continued strong productivity growth is needed to ensure that the convergence process continues. Yet, the Estonian economy has been growing more slowly in recent years as unused production resources are becoming scarcer while new resources are added slowly (Eesti Pank, 2018). Going forward, potential growth over the medium term is expected to decline due to ageing population and slow productivity growth (IMF Country Report, 2018). Moreover, in the context of a small-open economy, access to foreign market under the GVC participation is essential. Estonian firms could take advantage of economy of scales and enhance know-how through technology transfer and improved worker skills. Therefore, understanding how GVC participation could affect productivity would have meaningful policy implications in Estonia.

The empirical literature on GVC participation is ample for advanced and emerging countries, but rather sparse on Estonia. Benkovskis et al. (2018) investigate the effect of export status on productivity, employment and wages of Latvian and Estonian firms. However, GVC participation is not measured directly, but rather proxied by export status. Criscuolo and Timmis (2018) study the effect of the changing structure of GVC on firm productivity for firms operating in OECD countries including Estonia. Yet, they focus on GVC centrality but not directly on GVC participation and do not separately investigate the effect for Estonian firms.

Using Estonian firm-level data and data on GVC at industry level, we estimate the effects of GVC participation on productivity at both the industry level and the firm level. We construct measure of GVC participation and measure of upstreamness following Koopman et al. (2010) and estimate firm-level productivity using the method proposed by Ackerberg et al. (2015). To deal with endogeneity concerns, we instrument GVC participation in Estonia with average GVC participation by industry measured at world level. We find that GVC participation has a positive impact on productivity. In terms of firm heterogeneity, we find that frontier firms, large firms (both by size and by sales), and exporting firms benefit more from GVC participation than non-frontier firms, small firms, and non-exporting firms. We also explore the impact of the upstream and downstream spillover effects of GVC participation and find a positive correlation between productivity and GVC participation of upstream industries.

Against this background, our study contributes to the ongoing debate on the benefits and drawbacks of GVC. We first show that GVC participation improves productivity and the effect is larger for large firms and exporting firms. We also explore the upstream and downstream spillover effects of GVC participation. Highly productive firms and large firms are benefited more from GVC participation of upstream industries and less from GVC participation of downstream industries. Since productivity is the key for Estonia to converge to the income level of other rich OECD countries (OECD 2017, IMF 2018), the paper provides new policy insights for Estonia to raise aggregate productivity and thus economic growth.

We utilize the most recent method proposed by Ackerberg et al. (2015) to estimate firm-level productivity. Past studies have typically used total factor productivity estimated at an aggregated level (e.g. Chiacchio et al., 2018) or simple measures of productivity such as the ratio of sales to the number of employees or real value added per worker. However, sales- or gross output- based labor productivity measures do not take into account intermediate input usage. Value added-based labor productivity controls for intermediate inputs, but this measure still cannot distinguish differences in capital intensity across firms. The productivity estimation approach in our paper controls for potential endogeneity problems as well as relaxes the assumption of constant returns to scale which is needed when measuring productivity using index number measures (e.g. relating output to a weighted sum of inputs).

The rest of the paper will proceed as follows. In Section II, we present the literature review. In Section III, we describe the data and the methodology, in particular the measurement of GVC and the estimation of productivity. Section IV summarizes the stylized facts. Section V discusses the econometric results. Section VI provides main conclusions.

II. LITERATURE REVIEW

The concept of GVC did not follow a linear development path and emerged in recent decades as a worldwide phenomenon. When the movement of goods, people, and ideas was not as frictionless as it is today, economic activities were organized mostly within the boundaries of a small-scale community. International trade began to develop at the beginning of the 19th century when steam engines rapidly improved land and water transportation, triggering unprecedented expansion of trade activities. The point of consumption was unbundled from the point of production. Paradoxically, during the unbundling phase, production was clustered locally in factories and industrial districts.

The information technology revolution in the 1980s completely changed this picture. With telexes, facsimiles, and the Internet – along with high speed international communication networks – it became cheaper and easier to coordinate complexity at a distance, which brought the second unbundling (FGI, NTU, and WTO, 2013). With falling trade barriers and communication costs in the 21st century, production has become "longer" and has often involved different stages in different countries. The rise and changes of GVCs has been facilitated by technological progress, trade costs, transport and communication costs, access to resources and markets, and trade policy reforms (De Backer and Miroudot, 2014).

The main characteristic of the GVC paradigm is the variety of its intellectual origins. GVCs have been described in the literature using different terms, such as fragmented production blocks and service links (Jones and Kierzkowski, 1990), global commodity chain (Gereffi, 1994), offshore sourcing (Arndt, 1997), disintegration of production (Feenstra, 1998), global production sharing (Yeats, 2001), vertical specialization (Hummels et al., 2001), outsourcing (Grossman and Helpman, 2002), vertical production networks (Hanson et al., 2005), trade in tasks (Grossman and Rossi-Hansberg, 2008) and the second unbundling (Baldwin, 2013). Humphrey and Schmitz (2002) and Gereffi, Humphrey, Sturgeon (2005) developed a comprehensive analytical framework on the structure and mechanism of value distribution among countries, using the term "global value chain".

The GVC literature draws a wedge between "producer-driven" and "buyer-driven" chains. In producer-driven GVCs, lead firms are placed upstream and control the design of products and most of the assembly. By contrast, retailers and branded marketers control the production which can be totally outsourced in buyer-driven chains. Recent research puts the emphasis on the concept of "network" rather than “chain” (Coe and Hess, 2007). In this paper, by measuring the position and participation of countries in global production, we focus on “global value chains” instead of network analysis.

Studies have found that countries could reap great benefits from GVC participation. In general, GVCs increase efficiency in the globalized system of production (Baldwin, 2012; Grossman and Rossi-Hansberg, 2008). GVCs also provide opportunities for developing countries to increase their participation in global trade and to diversify their exports. Without GVCs, firms in a developing country would have to be able to build a whole course of production capacity in order to expand a new product and participate in the global economy (Kowalski et al., 2015). Moreover, more employment opportunities are created when countries participate in GVCs (UNCTAD, 2013). As we mentioned, GVCs also provide opportunities for technology transfer and knowledge spillover (Pietrobelli and Rabellotti, 2011; Kawakami et al., 2012). However, gains from GVC participation would vary depending on the position in the chains.

Empirical studies on GVCs combining firm-level data and sectoral level data are still relatively scarce but are expanding rapidly. Attempts have been made to investigate how firms shape the organization of GVCs using firm-level data. Alfaro et al. (2018) link firm level data with information from standard Input-Output tables to study integration choices along value chains. They find that firms’ elasticities of demand for a final product crucially determines the direction of integration on the GVCs. Using firm-level data in 150 countries, Del Prete and Rungi (2017) find similar empirical evidence. A different strand of research merges firm-level data and measures of position in GVCs at industry level to study the impact of GVCs on firms’ response to exchange rate movements (Ahmed et al., 2015; Berthou and Dhyne, 2018).

Our paper is also directly related to the literature studying the link between GVC participation and productivity gains. Using data at the industry-country level, Constantinescu et al. (2017) investigate the impact of GVC participation on labor productivity and find that an increase of 10 percent in the level of global value chain participation increased average productivity by close to 1.7 percent. An increase in GVC participation is also found to have a positive effect on firm patenting. Increased GVC participation also leads to higher employment growth for the average firm and faster employment growth for patenting firms (IMF World Economic Outlook, 2018). Benkovskis et al. (2018) investigate the effect of export status on productivity, employment and wages of Latvian and Estonian firms. They find that exporting firms in Latvia and Estonia are more productive, larger and pay higher wages, and are more capital intensive than non-exporting firms. Del Prete et al. (2017) study the effect for North African firms and find that firms participating in GVCs both perform better ex ante and obtain productivity gains ex post. These papers estimated total factor productivity using the method of Levinsohn and Petrin (2003) and Ackerberg et al. (2015). However, GVC participation is not observed directly, but rather proxied either by export status (Benkovskis et al., 2018) or indicators for internationally recognized quality certification (Del Prete et al., 2017).

III. DATA AND METHODOLOGY

A. Data

The firm-level data used in this paper is taken from the ORBIS database, which is a commercial database containing information on companies or business records from around the world. The dataset covers information on sales, material costs, number of employees, and capital stock, which allows us to estimate firm productivity according to the methodology described in the next section. For the purpose of this project, we use Estonian firm-level data. There are more than 103,000 firms in 19 NACE (General Industrial Classification of Economic Activities within the European Community) sectors, from 1999 to 2016. We drop firms whose accounting period is not 12 months. Observations with missing or negative values of sales, employees, capital and material costs are also removed from our sample. After comparing summary statistics on output, value added, and number of employees between Orbis data and published data from Statistics Estonia, we restrict sample to the years from 2002 to 2016 to have a good representative sample for all Estonian firms. We end up with a sample of 27,451 firms with more than 216,000 observations. Material costs and capital stock are deflated using industrial producer price index (PPI) from Eurostat, and sales are deflated using domestic output price indexes from Eurostat. For two-digit NACE industries with missing values on domestic output price index from Eurostat[2], we replace domestic output price by Harmonized Indices of Consumer Prices (HICP). We construct deflators by matching HICP goods/ services with two-digit NACE sectors in firm-level data. Table 1 provides descriptive statistics for the sample, including information on the number of firms, total value-added, sales, and productivity.

Table 1: Summary statistics

Variables	Observations	Mean	Standard deviation
ln(Sales)	216,020	7.35	1.80
ln(Materials)	216,020	6.37	2.25
ln(Capital)	216,020	5.22	2.20
ln(Employees)	216,020	1.29	1.21
ln(TFP)	215,979	1.27	0.21

Source: ORBIS data and author's calculation. Values are in real terms, the base year for the price index: 2015.

We also provide a comparison of total output, value added, employment and exports between data from Orbis and aggregate data from Statistic Estonia in Tables B1, B2, B3, B4 in the appendix. After cleaning the data, our estimation sample covers more than 60% of total output, above 30% of total employees, over 30% of total value added and about 60% of total exports in Estonia.

The data used to construct measures of GVC participation and position in the GVCs is the Eora Multi-Region Input-Output (MRIO) database (Lenzen et al., 2012 and Lenzen et al., 2013). This dataset provides a set of both national and global input-output tables, covering 26 industries in 189 countries

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[2] Most of these industries belong to services sector.

from 1990 to 2015. This database contains detailed information on final demand matrices, intermediate input matrices, and value-added matrices. Thus, the MRIO table allows us to measure value added embodied in gross trade flows. This data set has been used in several papers such as Del Prete et al. (2017) and Aslam et al. (2017).

B. Measures of Global Value Chains

Measure of GVC Participation

A measure of GVC participation based on Input-Output (IO) tables was first proposed by Hummels et al. (2001). They provide measures of both direct value-added trade and indirect value-added trade that passes through third countries. However, their measures face the problem of "double counting" when intermediates cross borders more than once (Koopman et al. (2010)). Therefore, we apply the GVC participation measure proposed by Koopman et al. (2010) which captures all sources of value added in gross exports and eliminates the "double counting" problem.[3] The GVC participation index is defined as:

$$GVCp_{cs} = \frac{FVA_{cs}+DVX_{cs}}{Gross\ Exports_c} \tag{3.2.1}$$

where FVA_{cs} denotes foreign value added of sector s in country c, DVX_{cs} indicates the indirect value added of sector s in country c and $Gross\ Exports_c$ refers to the total exports of country c. FVA_{cs} measures imported intermediate input content of exports and is referred to as a measure of "backward participation". DVX_{cs} counts the portion of exports that are used as inputs by another country in the production of its export goods. DVX, thus, could be considered as a measure of "forward participation". The larger the ratio, the greater the intensity of involvement of a sector in a country in GVCs.

Measure of position in GVCs

Position of a sector in the GVCs is defined as the log ratio of a country-sector's supply of intermediates used in other countries' exports to the use of imported intermediates in its own exports (Koopman et al. (2010)).

$$Upstream_{cs} = \ln\left(1 + \frac{DVX_{cs}}{Gross\ Exports_c}\right) - \ln\left(1 + \frac{FVA_{cs}}{Gross\ Exports_c}\right) \tag{3.2.2}$$

An upstream sector participates in the global value chain by producing inputs for others. This implies that its indirect value-added exports (DVX) share in gross exports will be higher than its foreign value added (FVA) share; thus, the numerator in (3.2.2) will be larger than the denominator. On the other hand, a downstream sector in the global value chain will use a large portion of intermediates from other

[3] The Matlab codes used to calculate the measure of GVC participation are taken from Aslam et al. (2017).

countries to produce its final goods, meaning its FVA share will be higher than its DVX share. In this case, if a country-sector lies downstream, the denominator in (3.2.2) will be larger than the numerator.

C. Productivity Estimation Method

Estimates of the production function are obtained by applying the method proposed by Ackerberg et al. (2015). Consider the following general production function with a scalar Hicks-neutral productivity term and with technology parameters that are common across firms within a sector:

$$Q_{it} = F(L_{it}, M_{it}, K_{it}; \beta) \tag{3.3.1}$$

where L_{it} and M_{it} are labor and intermediate inputs which are assumed to be flexible; K_{it} denotes capital input which is assumed to be fixed; Q_{it} refers to output quantity and β is a set of common technology parameters to be estimated. All variables are indicated in quantity. The log version of equation (3.3.1) is

$$y_{it} = h(l_{it}, m_{it}, k_{it}; \beta) + \omega_{it} + \varepsilon_{it} \tag{3.3.2}$$

where all lower-case variables indicate the natural log transform, ω_{it} is the firm's productivity that is observed by the firm but not by the econometrician, and ε_{it} captures unobservables that affect output and are unobservable to both the firm and the econometrician.

We use the translog production function, since this function allows for returns to scale, thus ω_{it} is not affected by increasing or decreasing returns, as follows:

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + C + \omega_{it} + \varepsilon_{it} \tag{3.3.3}$$

where C is a set of other control variables including firm fixed effects, industry fixed effects, and year fixed effects. We include firm fixed effects to control for differences in productivity that may arise from differences in the number of products that firms produce (Amiti and Konings, 2007) and differences in firms' characteristics. Note that estimates of the production function can be biased due to the use of aggregate price indices for capital and material. When inputs are deflated based on aggregate price indices, there is no differences between firms using inputs of different quality and prices and those using different quantity of inputs.

The inclusion of the export dummy in the production function helps to control for quality and to allow exporters to produce under a different technology. However, we do not have information on export status for years before 2009. Therefore, we could not control for export status in our specifications. Another source of bias might derive from the differences in input allocation across products in multi-product firms (De Loecker et al., 2016). We therefore rely on single-product firms to estimate the production function in (3.3.3). The parameter vector β includes the coefficients on labor, capital, material, their squares, and their interaction terms.

We assume inputs l_{it}, m_{it}, k_{it} are chosen by firms after observing (or partially observing) their productivity level. As a result, one cannot estimate equation (3.3.2) using simple OLS regression because l_{it}, m_{it}, k_{it} are correlated with the unobserved ω_{it}. One could use input and output prices to instrument for inputs. However, this would require that firms operating in perfectly competitive input or output markets (This is more realistic for input markets than for output markets). Unfortunately, data on these input and output prices are usually not available. Input prices also often vary little across firms. Moreover, if the variation in wages is actually due to the variation in unobserved labor quality, wages are not a valid instrument for labor input. Therefore, we follow the method proposed by Ackerberg et al. (2015), relying on material to proxy for productivity to take into account this endogeneity problem. In other words, endogeneity problem in (3.3.2) is due to the unobserved ω_{it}. By using the material equation to make ω_{it} "observable", the endogeneity problem will be eliminated.

Assuming that material is decided after labor and capital are chosen, we can write:

$$m_{it} = f_t(k_{it}, \omega_{it}, l_{it}) \tag{3.3.4}$$

Assuming strict monotonicity, this conditional intermediate input demand function can be inverted to get the productivity:

$$\omega_{it} = f_t^{-1}(k_{it}, m_{it}, l_{it}) \tag{3.3.5}$$

Substituting into the production function to get

$$y_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + C + f_t^{-1}(k_{it}, m_{it}, l_{it}) + \varepsilon_{it} \tag{3.3.6}$$

$$\text{or } y_{it} = \Phi_{\mathrm{it}}(k_{it}, m_{it}, l_{it}, \boldsymbol{C}) + \varepsilon_{it} \tag{3.3.7}$$

Since we do not know the form of the function f_t^{-1}, we treat f_t^{-1} non-parametrically, i.e. we set it to the third-order polynomial where all logged inputs, logged inputs squared, logged inputs cubed and interaction terms between all logged inputs and logged inputs squared are included. We have therefore eliminated the unobservable variation causing the endogeneity problem. However, now, because of the collinearity problem, we cannot separately identify coefficients of the production function from the polynomial. But we can still identify the composite term $\widehat{\Phi}_{it}$. Thus, we regress equation (3.3.7) to purge the error term (ε_{it}) from expected output and to get estimated values of y_{it} (i.e. $\widehat{\Phi}_{it}$). Given estimates of coefficients of the production function, implied $\widehat{\omega}_{it}(\beta)$ is computed from (3.3.5) and (3.3.6).

In order to obtain estimates of all production function coefficients, we rely on the law of motion for productivity:

$$\omega_{it} = g_t(\omega_{it-1}) + \gamma_{it} \quad \text{where } E[\gamma_{it}|I_{it-1}] = 0 \text{ (i.e. } E[\gamma_{it}|\omega_{it-1}] = 0) \tag{3.3.8}$$

with ω_{it-1} denoting lagged productivity and I_{it-1} indicating the information set at time *t-1*. γ_{it} is the productivity innovation, which is assumed to be realized after capital and labor are chosen and at the same time as material is decided. The function g is approximated by a fourth-order polynomial. Based on (3.3.8), we regress $\widehat{\omega}_{it}(\beta)$ on $\widehat{\omega}_{it-1}(\beta)$ to obtain the innovation to productivity which is recovered as the residual term ($\hat{\gamma}_{it}(\beta)$).

As suggested by Ackerberg et al. (2015), we use the generalized method of moments to obtain the estimates of the production function, where we rely on the following moment conditions:

$$E(\hat{\gamma}_{it}(\beta)\boldsymbol{B}) = 0 \tag{3.3.9}$$

where the vector **B** contains lags of all the variables in the translog production function and vector $\boldsymbol{C} = (l_{it}, k_{it}, l_{it}^2, k_{it}^2, l_{it}k_{it}, l_{it}m_{it-1}, k_{it}m_{it-1}, l_{it}k_{it-1}, l_{it-1}k_{it}, l_{it}k_{it}m_{it-1}, l_{it}k_{it-1}m_{it-1}, l_{it-1}k_{it}m_{it-1})$. This condition states that the productivity innovation in the current period is assumed to be uncorrelated with inputs (material, labor and capital) in the previous period and also uncorrelated with labor and capital in the current period. These variables are valid instruments since we assume that capital is chosen before labor and both are chosen before the full realization of shock to productivity, while material is chosen when the firm learns its productivity. In other words, we have $m_{it-1}, l_{it}, k_{it} \in I_{it-1}$, while m_{it} *and* $\gamma_{it} \in I_{it}$, where I_{it-1} and I_{it} are information sets at time *t-1* and *t*, respectively. Therefore $E(\gamma_{it}m_{it-1}) = 0, E(\gamma_{it}l_{it}) = 0, E(\gamma_{it}k_{it}) = 0$.

Once the coefficients are estimated, productivity is computed as:

$$\widehat{\omega}_{it} = \widehat{\Phi}_{it} - \hat{h}(l_{it}, m_{it}, k_{it}; \beta) \tag{3.3.10}$$

where $\hat{h}$ represents the estimated contribution of the production factors to total output.

Following De Loecker et al. (2016), we estimate the model on a sample of firms that manufacture a single product for at least three consecutive years for two reasons. First, the moment conditions require at least two years of data to have lagged values. And second, adding a third year of data allows for potential measurement error in the precise timing of a new product introduction (De Loecker et al., 2016).

IV. STYLIZED FACTS

A. Global Value Chain Participation of Estonia

Estonia's participation in GVCs was the most intense among the three Baltic countries (Figure 1). The share of Estonia's total value-added export and import in gross export (GVC participation measure) was always higher than 70% during the period from 1995 to 2015. The intensity of GVC participation in Estonia increased slightly from 2000 until 2008, following by a modest decline following the global economic crisis. It subsequently recovered to its highest level in 2011 (at around 80%) but started falling again afterwards. However, in general, Figure 1 shows a general trend for deeper GVC participation in Estonia from 1996 to 2015.

Figure 1. GVC Participation of Baltic countries

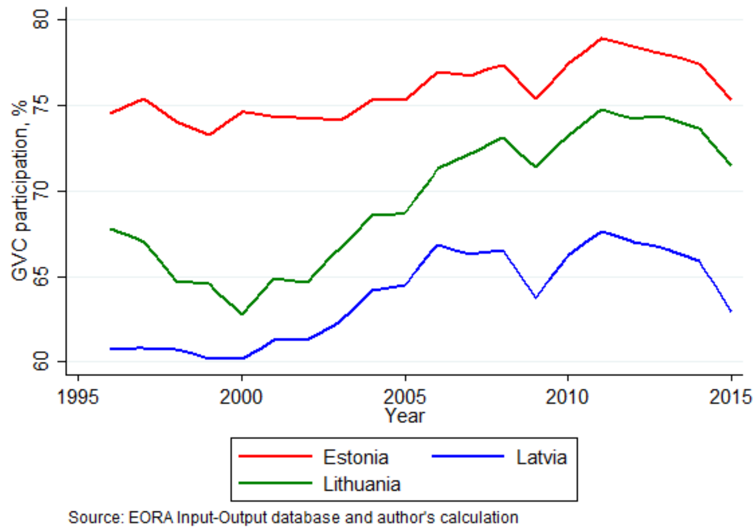


Figure 2: Top 10 destination and source countries of Estonian value-added exports in 2015

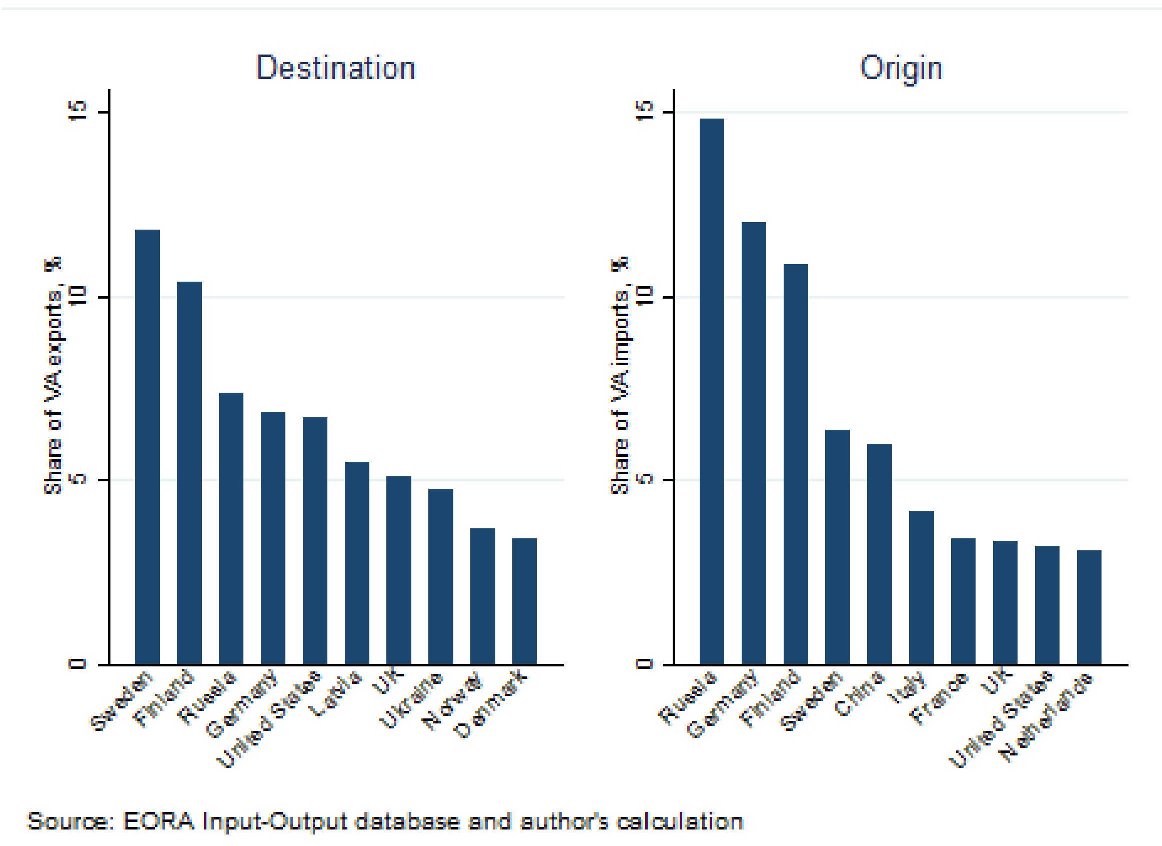
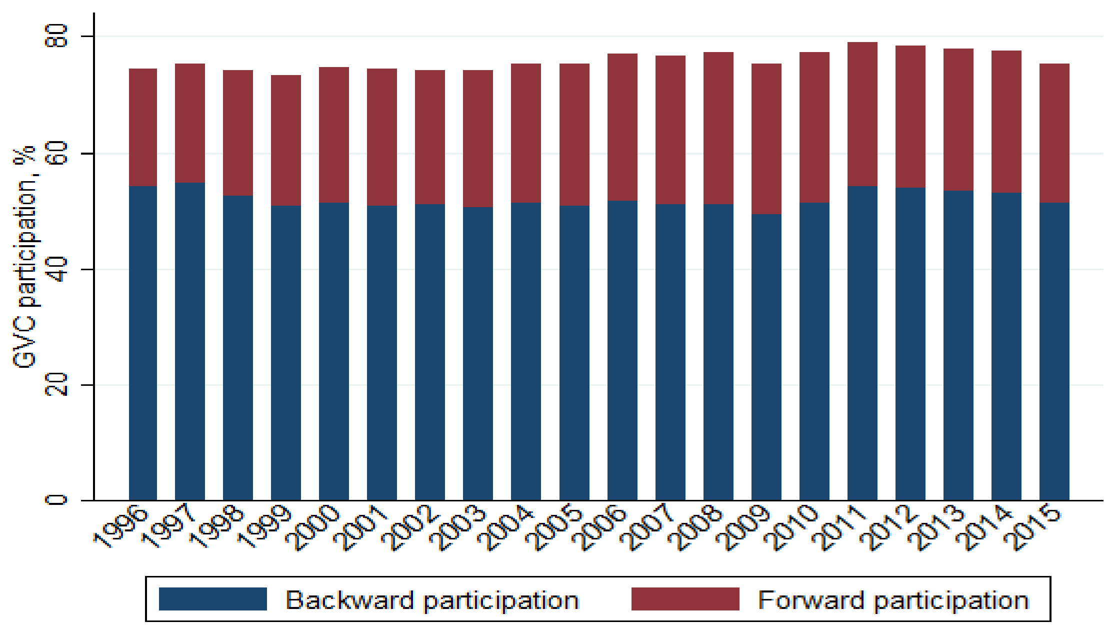


Figure 2 shows that Estonia is more involved in regional rather than global value chains. Top destinations and origin countries of Estonian value-added exports and imports are mostly European countries except for the US and China. Sweden and Finland are the two most important direct destinations of Estonia's value-added exports with each country accounting for more than 10% of Estonia's value-added exports. The top 10 destination countries account for more than three-quarters of Estonia's total value-added exports. On the other hand, around 15 percent of Estonia's value-added imports originate in Russia. Germany, Finland and Sweden are other important source countries of Estonia's value-added imports. While most of the Asian countries account for a small share of Estonian total value-added imports, China is one of the significant providers of value-added to Estonia.

Figure 3: Estonia GVC participation over time



Source: EORA Input-Output database and author's calculation

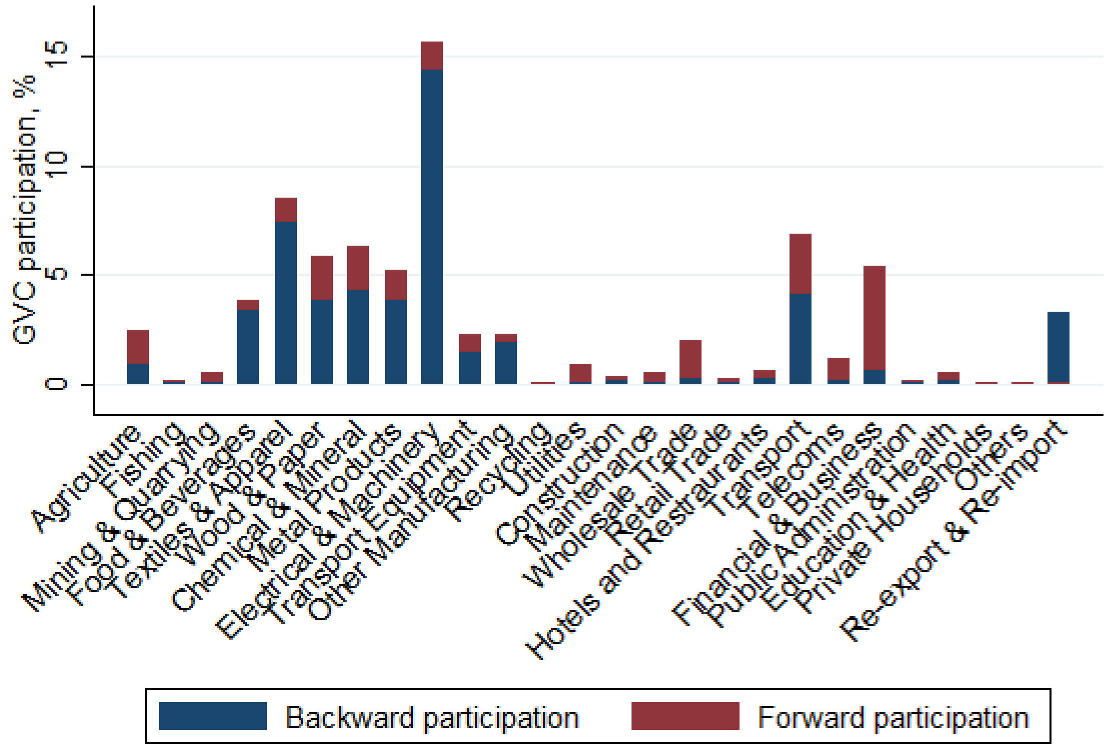
Estonia's participation in the GVCs is mainly driven by the use of foreign intermediates in Estonia's exports (backward participation) (Figure 3). The intensity of GVC participation is considerably different between service and manufacturing sectors with services exhibiting more forward cross-border linkages. Table 6 reports GVC participation and position indices of major manufacturing and service sectors in Estonia in 2015. Manufacturing sectors participate more intensively in GVCs than service sectors. Higher backward linkages are also observed in these manufacturing industries reflecting that the production in these sectors uses considerable foreign inputs, which is consistent with high shares of intermediate imports in Estonia. Similarly, these manufacturing sectors have lower values in upstream indexes (e.g. shorter distance to final consumer). In the service sectors, Estonia participates most intensively in transport and financial services value chains. While transport services show a higher backward participation, all other services industries tend to have higher forward linkages (e.g. use limited foreign inputs) and higher upstreamness values (e.g. longer distance to final consumer). Other sectors such as recycling, mining and quarrying, and construction tend to participate least intensively in the GVCs.

Table 2: GVC Participation and Position by Sector in Estonia in 2015

Sector	GVC Participation index: Total	GVC Participation index: Backward linkage	GVC Participation index: Forward linkage	Position index: Upstream
Manufacturing				
Food & Beverages	3.80	3.36	0.44	-0.029
Textiles and Wearing Apparel	8.49	7.42	1.07	-0.061
Wood and Paper	5.87	3.89	1.98	-0.019
Petroleum, Chemical Products	6.32	4.35	1.97	-0.023
Metal Products	5.18	3.85	1.33	-0.025
Electrical and Machinery	15.65	14.40	1.25	-0.122
Transport Equipment	2.30	1.51	0.79	-0.007
Other Manufacturing	2.28	1.94	0.34	-0.016
Services				
Wholesale Trade	1.98	0.29	1.69	0.014
Retail Trade	0.30	0.06	0.23	0.002
Hotels and Restaurants	0.62	0.30	0.32	0.000
Transport	6.90	4.09	2.81	-0.012
Post and Telecommunications	1.20	0.23	0.98	0.007
Financial Intermediation and Business Activities	5.44	0.68	4.76	0.040
Public Administration	0.13	0.07	0.06	0.000
Education, Health and Other Services	0.56	0.19	0.37	0.002
Others				
Agriculture	2.45	0.91	1.55	0.006
Fishing	0.08	0.06	0.03	0.000
Mining and Quarrying	0.58	0.09	0.48	0.004
Recycling	0.04	0.05	-0.01	-0.001
Electricity, Gas and Water	0.91	0.08	0.83	0.008
Construction	0.40	0.15	0.25	0.001
Maintenance and Repair	0.52	0.08	0.44	0.004
Average				
Manufacturing	6.24	5.09	1.15	-0.038
Services	2.14	0.74	1.40	0.007
Others	0.71	0.20	0.51	0.003
Total	3.13	2.09	1.04	-0.010

Source: EORA Input-Output table and author's calculation

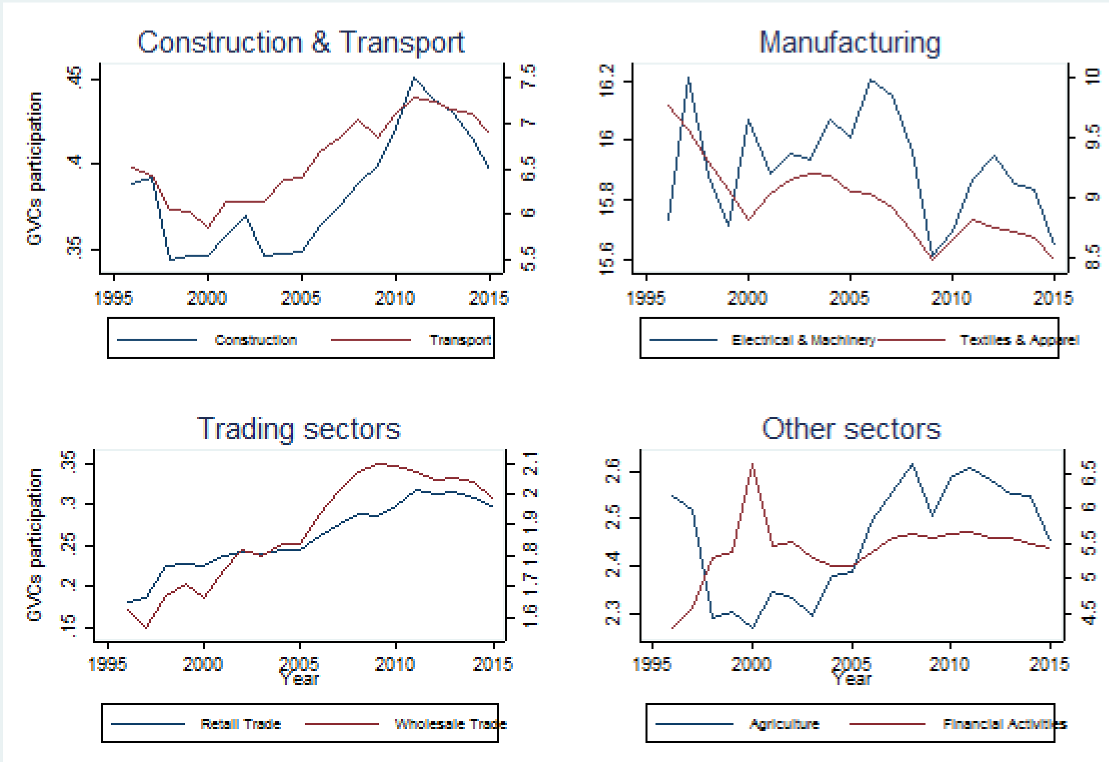
Figure 4: GVC participation by industry in 2015



Source: EORA Input-Output database and author's calculation

The changes in GVC participation also differs across industries (Figure 5). Most sectors such as construction, transport, agriculture and trading sectors experience an increasing trend, whereas manufacturing sectors saw a sharp decline after 2008 as a result of the financial crisis.

Figure 5: GVC participation over time



Source: EORA Input-Output database and author's calculation

B. Productivity of Estonian firms

Average productivity in Estonia has fluctuated over the sample period but has broadly followed an overall increasing trend. The largest productivity gains are observed in the manufacturing industries (Figure 6). During the 2002-2016 period, average productivity in some manufacturing industries increased by close to 20 percent. In contrast, services experienced little increases or even declines in average productivity. Average productivity also increased in all firm-size categories, but variability is small (Figure 7). Figure 7 also shows no superior performance of large firms on average.

Figure 6. Productivity over time

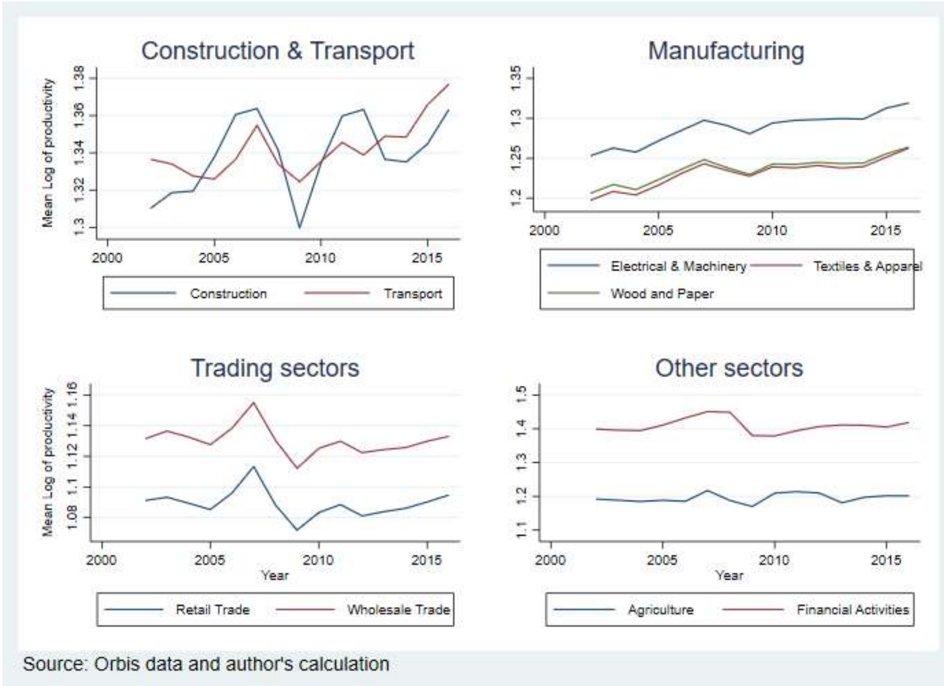
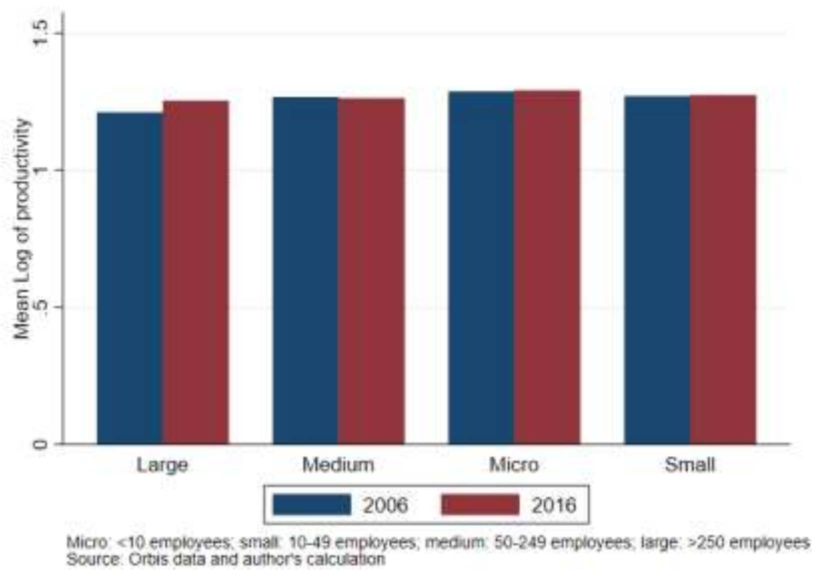


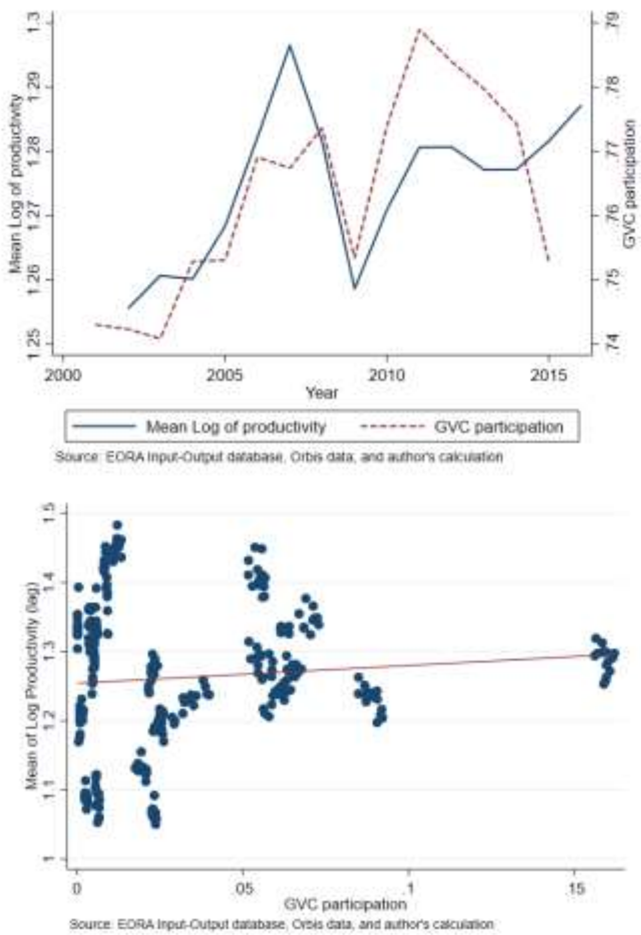
Figure 7: Productivity trends by firm size



C. GVC participation and Productivity

Figure 8 provides a first visual evidence for a positive correlation between GVC participation and productivity, which is the motivation of our empirical study. In Figure 8, panel 1, GVC participation and productivity tends to fluctuate in the same direction. Moreover, it seems that it takes time for GVC participation to have impact on productivity. The bottom panel of Figure 8 plots (lagged) mean of log productivity (at year level) against GVC participation measures and its fitted line. The figure shows a positive relationship between GVC participation and productivity. Although instructive, these simple correlations do not take into account other factors that affect both productivity and GVC participation as well as do not detect channels through which participation in GVC can impact firms' productivity.

Figure 8. GVC participation and Productivity



V. Econometric results

A. Impact of Global Value Chains participation on productivity at industry level

In this section we outline our approach to examining the relationship between GVC participation and productivity. An emerging literature shows that engaging in GVCs facilitate the transmission of knowledge and technology. The evidence reported in the previous section also suggests that GVC participation has been positively related to productivity for Estonian firms. In the subsequent empirical analysis, we investigate the impact of GVC participation on productivity both at the industry level and the firm level. Unlike other studies identifying GVC participation at firm level as a dummy indicator, we measure GVC participation as a continuous variable. Thus, we can study the effect of the intensity of GVC participation on productivity. However, we could only calculate the measure of GVC participation at the industry level, but this is probably an issue of any study on this topic as tracking the flow of inputs and outputs across firms is not feasible given data limitations.

First, we investigate the impact of GVC participation on productivity at the industry level:

$$\ln(\omega)_{st} = \alpha_1 GVCp_{st-1} + \beta_2 \ln(Output)_{st} + \gamma_t + \varepsilon_{st} \tag{5.1}$$

where $GVCp_{st-1}$ denotes GVC participation measured according to (3.2.1) and $\ln(\omega)_{st}$ denotes median log productivity of all firms in sector s as a proxy for aggregate productivity at the sectoral level. We include year fixed effects and sectoral gross output to control for macro shocks at the country and sector levels that may also affect productivity.

Causal interpretation of the relationship between the degree of GVC participation and productivity at the industry level can be problematic given endogeneity concerns and potential for reverse causality. It is unclear from correlations whether GVC participation improves firms' performance and drives industry productivity growth or higher productivity growth makes it easier for firms and industries to participate in GVCs. Therefore, following Constantinescu et al. (2017), we lag the GVC participation variable by one year as the effects of GVC participation on productivity at both industry level and firm level are unlikely to be instantaneous (which is what we observe in Figure 8). This may alleviate to some extent concerns of reverse causality. However, since GVC participation is likely serially correlated, we also instrument for the measure of industry-level GVC participation using average GVC participation measures in all countries in the world for the same industry. Specifically, we instrument the measured GVC participation variable for Estonia $GVCp_{cs}$ with average GVC measure at world level $GVCp\_IV_s$:

$$GVCp\_IV_s = \frac{1}{C}\sum_c (GVCp_{cs}) \tag{5.2}$$

This approach requires that the driving forces of the increases in GVC participation intensity of a particular sector in Estonia and on the world are similar, which is likely to be the case. It also requires that these forces affect productivity developments in Estonia only through their impact on GVC participation. One potential threat to this assumption is that spillovers from GVC participation at the global level could affect other industries in Estonia. To account for these potential spillover channels, we include sectoral gross output and year fixed effects, which should largely control for more diffuse spillovers from the global GVC participation to other industries.[4]

Table 3 below reports results of both OLS and IV regressions at the industry level. The dependent variable in all columns is the sectoral median of log productivity. The coefficient on lagged GVC participation in column (2) is positive and statistically significant. This result suggests that GVC participation positively affects productivity at the industry level. An increase of 1 percentage point in the intensity of GVC participation of an industry raises median productivity of that industry by around 0.48 percent. This number is consistent with what is shown in Figure 8. This impact is also similar to the effect of less than 1 percent of a reduction in tariffs on productivity in Amiti and Konings (2007).

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[4] It was not possible to include more endogenous variables and instruments for example by adding GVC participation of upstream and downstream industries due to high correlation between GVC participation across industries at the global level. Test for weak instruments in the presence of multiple endogenous regressors are very demanding in terms of statistical power and we do not have enough variation in our data to reject the null with more than one endogenous variable. See Angrist and Piscke (2008).

Table 3 shows that GVC participation has a positive effect on productivity when instrumented. If the reverse effect is also positive (i.e. higher productivity growth leads to higher GVC participation), OLS estimate should be overestimated. However, the OLS estimate in Table 3 is close to zero and not statistically significant. While this result is puzzling, one potential explanation is that the OLS estimate suffers from attenuation bias due to measurement error in the GVC participation variable.

The last two rows of Table 3 report the Kleibergen-Paap (KP) LM test statistic for under identification test and the KP Wald F statistic for weak identification test of the instrumental variable. These test statistics confirm the validity of the instrument.

Table 3: GVC participation and productivity at industry level

	Direct effect	
	(1)	(2)
VARIABLES	OLS	IV
Lagged GVC	-0.012	0.478*
	(0.120)	(0.256)
Log industry output	0.019***	0.012*
	(0.006)	(0.007)
Year FE	Y	Y
Observations	301	301
KP LM stat		64.90
KP Wald F stat		109.8

Note: All regressions are run for 26 sectors from 2002 to 2016. The dependent variable is the log of median productivity of all firms in each sector-year. In the IV regression, GVC participation is instrumented with average GVC participation measure at world level. Bottom rows of the table report statistics for under identification and weak identification tests of the instrumental variable. Robust standard errors are shown in parentheses. *, **, and *** indicate coefficients significantly different from zero at the 10, 5, and 1% level, respectively.

B. Impact of Global Value Chains participation on productivity at firm level

Direct effect

Then we study the direct impacts and spillover effects at firm level. By using firm-level data, we can control for firm-level characteristics that may also determine productivity to improve identification of the effect of GVC participation. Specifically, we estimate the following model

$$ln\ (\omega)_{ist} = \alpha_1 GVCp_{st-1} + \beta_1 Firm\ Control_{ist-1} + \beta_2 Sector\ Controls_{st} + \gamma_s + \gamma_r + \gamma_t\ + \varepsilon_{ist} \tag{5.3}$$

where $ln\ (\omega)_{ist}$ refers to log Total Factor Productivity (TFP) of firm i in sector s at time t. Firm-level controls include capital intensity ($\ln \left(\frac{K}{L}\right)_{ist-1}$), sector controls include sector gross output ($\ln(Output)_{st}$) and Herfindahl-Hirschman index at four-digit NACE industry level (HHI_{ht}). γ_s is sector fixed effects, and γ_r is region fixed effects, and γ_t is year fixed effects. Robust standard errors are clustered at the industry-year level, where industry reflects the 25 EORA industries.

The inclusion of sector fixed effects and year fixed effects means we are comparing across firm changes in productivity within an industry due to industry-level changes in GVC participation. We do not include firm fixed effects because our variable of interest, GVC participation, is measured at the industry level, thus we focus on the changes across firms within an industry, but not the changes within firms. The sector fixed effects control for any time-invariant sector (and thus also and/or country) characteristics, region fixed effects control for any time-invariant region characteristics (such as distance to the market), and year fixed effects control for any time-variant factors common across firms (such as macro shocks at the country, region, and sector levels as well as controlling for confounding factors associated with our instrument as discussed above). Controlling for firms' capital intensity and sector gross output takes into account time-varying characteristics at the firm and sector levels that may affect productivity.

One concern might be that GVC participation may affect firm productivity through competition but not through knowledge diffusion. We address this concern by controlling for the Herfindahl-Hirschman index (HHI) at the four-digit NACE industry level. The HHI measures industry concentration and is calculated as the sum of the squares of firm shares in total industry production: $HHI_h = \sum_i (share_i^h)^2$. The index ranges between 1/N (equal shares) and 1 (maximum concentration), where N is the number of firms in industry h. High concentration industry (at four-digit NACE level) is an indicator equal 1 if the HHI of the industry is in the last quarter of HHI distribution, and 0 otherwise.

Another potential concern is that firms may self-select into GVC participation, i.e. some initial attributes of firms in GVCs may affect both participation decisions and outcomes. The use of firm-level data and sector-level GVC participation measures reduces the scale of this endogeneity concern, as it is unlikely that many firms are able to influence the intensity of GVC participation of their entire industry. GVC participation is thus likely to be exogeneous from a firm perspective, especially for small and medium sized firms. However, a group of highly productive firms might account for the bulk of input flows across borders. To mitigate this concern, we use lagged GVC participation as a predictor and use weighted average of GVC participation measures in all countries of the same industry as an instrumental variable as what we did above.

Column (1) of Table 4 reports the result on the effect of GVC participation on firm productivity. We still find positive effect of GVC participation on productivity at the firm level. If an industry moves from the 10th percentile to the 90th percentile of the GVC participation, productivity of a firm in that industry would increase by approximately 23 percent. For example, if a firm is at the 10th percentile of the productivity distribution, that firm will move to the 50th percentile if the industry moves from the 10th percentile to the 90th percentile of the GVC participation. The coefficient on lagged GVC measure is still significantly positive, but a much higher than the estimate at industry level. The difference in magnitude of the effect between the industry level and the firm level could come from the use of median productivity as an aggregate productivity at the industry level.

Table 4: GVC participation and productivity at firm level

VARIABLES	(1)	(2)	(3)	(4)	(5)
Lagged GVC	3.405**	3.309*	3.403**	3.337*	-4.550
	(1.717)	(1.710)	(1.715)	(1.707)	(5.667)
GVC*Initial Frontier		1.351***			
		(0.120)			
GVC*Large firm (size)			0.029		
			(0.018)		
GVC*Large firm (sales)				0.233***	
				(0.043)	
GVC*Initial export status					0.257***
					(0.040)
Observations	165,055	165,055	165,055	165,055	107,771
INDUSTRY FE	Y	Y	Y	Y	Y
REGION FE	Y	Y	Y	Y	Y
YEAR FE	Y	Y	Y	Y	Y
FIRM CONTROLS	Y	Y	Y	Y	Y
INDUSTRY CONTROLS	Y	Y	Y	Y	Y
KP LM stat	8.154	8.153	8.201	8.165	11.92
KP Wald F stat	25.88	12.94	13.06	12.97	11.17
First stage F-stat 1	25.88	15.02	24.87	22.87	12.03
First stage F-stat 2		403.5	368.5	412.3	219.9

Note: All regressions are run for firm-level data from 2002 to 2016. The dependent variable is the log of firms' productivity. GVC participation is instrumented with average GVC participation measure at world level, the interaction terms are instrumented with the interaction between the average GVC participation at world level and the other variable in the interaction terms. Bottom rows of the table report statistics from the first stage regressions and statistics for under identification and weak identification tests of the instrumental variables. Standard errors clustered at industry-year level are shown in parentheses. *, **, and *** indicate coefficients significantly different from zero at the 10, 5, and 1% level, respectively.

Heterogeneity in the direct effect

Column (1) of Table 4 examines productivity effect for the "average" firm, however, this effect is not necessarily homogenous across firms. According to a Neo-Schumpeterian model, a country's productivity growth depends on its distance to the frontier. Intuitively, expanding this model to the firm level could imply that more productive firms could benefit relatively more from GVC participation. These frontier firms are more likely to be able to overcome the sunk costs to benefit from exposure to new technologies.

Therefore, in columns (2), (3), and (4) of Table 4 we examine whether there are heterogenous impacts by firm productivity and firm size. We define frontier firms as those in the top quartile of most productive firms in our sample (column (2)) and large firms as those in the top quartile of largest firms in size (column (3)) or largest firms in sales (column (4)). We measure these firm characteristics at the start of the period (i.e. 2002), since these characteristics may be influenced by changes in the GVC participation over time. We use an indicator for frontier firms/ large firms and interact this indicator with the GVC participation measure. The non-interacted term therefore captures the effect for non-frontier firms/ small firms, while the interaction captures additional impact for frontier firms/ large firms.

Columns (2), (3), and (4) shows that there is substantial heterogeneity in the impact across firm types with stronger evidence using productivity or sales rather than employment. Firms closest to the frontier are those with fastest productivity increase caused by GVC participation. On the other hand, firms furthest from the frontier are less likely to benefit from GVC participation. Largest firms by sales also experience higher effect on productivity than smaller firms.

Exporting activities are expected to provide firms' exposure to new ideas and incentives to upgrade. Thus, exporting firms in industries that participate more intensively in the GVCs should reap more benefits from GVCs than non-exporting firms. In column (5), we interact GVC participation variable with firm's initial export status to test this hypothesis. We run this regression for a subsample from 2009 to 2016 since we do not have information on firms' export status before 2009. The coefficient on GVC participation now becomes negative and insignificant, which suggests that the productivity benefits of GVCs are concentrated among exporters in a given industry. The coefficient on the interaction term is significantly positive, which confirms that exporting firms reap more benefits from GVCs than non-exporting firms.

Spillover effects

Endogeneity concerns of spillover specification at the firm level will be alleviated since spillover GVC participation variables are calculated at the industry level, while productivity is estimated at the firm level. We thus consider the spillover effects at the firm level:

$$ln\,(\omega)_{ist} = \alpha_1 GVCp_{st-1} + \alpha_2 GVCp\_buyers_{st-1} + \alpha_3 GVCp\_suppliers_{st-1} + \beta_1 Firm\ Control_{ist-1} + \beta_2 Sector\ Controls_{st} + \gamma_s + \gamma_r + \gamma_t + \varepsilon_{ist} \quad (5.4)$$

where $GVCp\_buyers_{st-1}$ refers to the weighted average GVC participation intensity of all buyer (downstream) industries of sector s and $GVCp\_suppliers_{st-1}$ is the weighted average GVC participation intensity of all supplier industries (upstream) of sector s.

$GVCp\_buyers_{st}$ captures the average effect of GVC participation of all buyers of sector s on the productivity of sector s, while the effect of GVC participation of all suppliers is captured by $GVCp\_suppliers_{st}$. They are calculated as:

$$GVCp\_buyers_{st} = \sum_b share_{bs0} * GVCp_{bt} \quad (5.5)$$

$$GVCp\_suppliers_{st} = \sum_p share_{ps0} * GVCp_{pt} \quad (5.6)$$

$share_{bs0}$ denotes the share of inputs from sector s that is used in sector b in total inputs from sector s that is used by all sectors in 2001. $share_{ps0}$ refers to the share of inputs from sector p that is used in sector s in total inputs used by sector s in 2001. $GVCp_{bt}$ and $GVCp_{pt}$ measures GVC participation of sector b and p at time t, respectively. Input shares ($share_{bs}$ and $share_{ps}$) might be endogenous as variation in the shares might reflect industries' response to changes in GVC participation of industries. Therefore, we use constant shares in the initial year in our sample, 2001, to mitigate any endogeneity concerns.

We also interact our main variables of interest (GVC, GVC_buyers, GVC_suppliers) with indicators for frontier firms, large firms (by size and sales), and export status to consider the heterogeneity of the effect. We do not use IV for the spillover specifications[5].

Results of spillover effects are reported in Table 5. All coefficients on GVC participation are economically and statistically significant except for the coefficient in column (5) where we restrict the sample to the period after 2008. Both coefficients on GVC from buyers and GVC from suppliers are negative and have high standard errors. However, GVC from buyers is significant at 10% level, while GVC from suppliers is insignificant. Coefficients on the interaction between GVC participation and indicators are positive, which is consistent with results in Table 4.

Table 5 shows a negative relationship between GVC participation of forward linkages and productivity. Moreover, all interaction terms between GVC participation of buyer industries and frontier and export status indicators are significantly negative. Highly productive firms, large firms, and export firms have benefited less from more intensive GVC participation of downstream industries than less productive firms and small firms. One possible reason for this is because frontier firms/large firms/export firms have market power toward their buyers, thus they are not placed under pressure to match international standards, while this is not the case for small firms/non-export firms. Therefore, small firms/non-export firms have higher incentives to innovate and adopt foreign technologies to match international standard.

On the other hand, all interaction terms between GVC participation of upstream industries and frontier/export status indicators are significantly positive. Highly productive firms and large firms are more benefited from greater GVC participation of upstream industries. In the previous stylized fact section, we showed that the use of foreign intermediates in Estonia's exports is the main driver of Estonia's participation in the GVCs. If supplier sectors participate more intensively in GVCs (i.e. use more foreign intermediates), productivity of firms in these sectors is likely to be improved through technology transfer, knowledge spillover, higher-quality inputs, or economies of scale. These firms, thus, can provide higher-quality inputs to their buyers, and boost productivity of these sectors. This result is consistent with a large literature on the productivity effects of imported inputs where they find

[5] As discussed in footnote 4, we could in theory instrument $GVCp_{bt}$ and $GVCp_{pt}$ in equations (5.4) and (5.5) with weighted average of GVC participation measures in all countries in the world of the same buyer/ supplier industry. However, because of high correlation between GVC, and components of GVC of Suppliers and GVC of Buyers as well as components of the IVs, the IVs for GVC, GVC of Suppliers and GVC of Buyers will be even more correlated. Therefore, we do not use IV for the spillover specifications. The results cannot be interpreted as causal effects in this case.

that cheaper imported inputs can raise productivity via learning, variety, and quality effects (Amiti and Konings, 2007).

Table 5: Spillover effects at firm level

VARIABLES	(1)	(2)	(3)	(4)	(5)
Lagged GVC	3.605**	4.484***	3.644**	3.602**	-4.563
	(1.566)	(1.576)	(1.568)	(1.572)	(4.218)
From BUYERS (Lag)	-5.619*	-7.062**	-5.733*	-5.757*	4.034
	(3.061)	(3.054)	(3.060)	(3.061)	(7.091)
From SUPPLIERS (Lag)	-0.585	-0.143	-0.529	-0.653	-10.948**
	(1.777)	(1.771)	(1.776)	(1.778)	(4.768)
GVC*Initial Fontier		0.613***			
		(0.116)			
GVC Buyer*Initial Fontier		-0.437**			
		(0.213)			
GVC Supplier*Initial Fontier		1.321***			
		(0.115)			
GVC*Large firm (size)			0.087**		
			(0.035)		
GVC Buyer*Large firm (size)			-0.179***		
			(0.056)		
GVC Supplier*Large firm (size)			0.071***		
			(0.016)		
GVC*Large firm (sale)				0.490***	
				(0.099)	
GVC Buyer*Large firm (sale)				-0.683***	
				(0.136)	
GVC Supplier*Large firm (sale)				0.219***	
				(0.023)	
GVC*Initial export status					0.305***
					(0.076)
GVC Buyer*Initial export status					-0.276**
					(0.115)
GVC Supplier*Initial export status					0.161***
					(0.037)
Observations	165,055	165,055	165,055	165,055	107,771
INDUSTRY FE	Y	Y	Y	Y	Y
REGION FE	Y	Y	Y	Y	Y
YEAR FE	Y	Y	Y	Y	Y
FIRM CONTROLS	Y	Y	Y	Y	Y
INDUSTRY CONTROLS	Y	Y	Y	Y	Y

Note: All regressions are run for firm-level data from 2002 to 2016. The dependent variable is the log of firms' productivity. Standard errors clustered at industry-year level are shown in parentheses. *, **, and *** indicate coefficients significantly different from zero at the 10, 5, and 1% level, respectively.

C. Robustness checks

In this section, we perform a series of robustness checks to our main empirical results. These include alternative measures of outcomes and the interaction variables. For instance, using mean log productivity as an alternative measure of aggregate productivity at industry level, using continuous variables of initial log productivity, initial firm size, initial firm sale, and initial export share as alternative measures of indicators for frontier firms, large firms, and export status, and using labor productivity as an alternative measure of TFP. In addition, we restrict the sample to exclude multinationals.

Table 6: GVC participation and productivity at industry level – mean productivity

	Direct effect	
	(1)	(2)
VARIABLES	OLS	IV
Lagged GVC	0.003	0.506**
	(0.119)	(0.258)
Log industry output	0.019***	0.012
	(0.006)	(0.007)
Year FE	Y	Y
Observations	301	301
KP LM stat		64.90
KP Wald F stat		109.8

Note: All regressions are run for 26 sectors from 2002 to 2016. The dependent variable is the log of mean productivity of all firms in each sector-year. In the IV regression, GVC participation is instrumented with average GVC participation measure at world level. Robust standard errors are shown in parentheses. *, **, and *** indicate coefficients significantly different from zero at the 10, 5, and 1% level, respectively.

One concern might be that median productivity is not a good proxy for aggregate productivity at the industry level. We use mean log productivity as an alternative measure of aggregate productivity at the industry level (Table 6) and use labor productivity defined as the ratio of value-added to total number of employees in each firm as an alternative measure of productivity at the firm level (Table 7). We find our results are unchanged to the new measure aggregate of productivity in Table 6. However, the results in Table 7 where we use log of labor productivity as the dependent variable are much higher than our main results despite the same signs, and standard errors of the lagged GVC variable are much higher. But the size of the effect doesn't change. For example, if a firm is at the 10^{th} percentile of the labor productivity distribution, that firm will move to the 50^{th} percentile if the industry moves from the 10^{th} percentile to the 90^{th} percentile of the GVC participation. Higher magnitudes of the coefficients in Table 7 come from the difference in the magnitudes and the distribution of the two measures of productivity – TFP and labor productivity.

Table 7: GVC participation and productivity at firm level – labor productivity

VARIABLES	(1)	(2)	(3)	(4)	(5)
Lagged GVC	14.042	14.068	13.834	11.833	20.938
	(9.773)	(9.478)	(8.745)	(8.544)	(31.180)
GVC*Initial Frontier		6.215***			
		(0.686)			
GVC*Large firm (size)			5.309***		
			(0.355)		
GVC*Large firm (sales)				10.823***	
				(0.553)	
GVC*Initial export status					7.767***
					(0.691)
Observations	151,221	151,221	151,221	151,221	97,699
INDUSTRY FE	Y	Y	Y	Y	Y
REGION FE	Y	Y	Y	Y	Y
YEAR FE	Y	Y	Y	Y	Y
FIRM CONTROLS	Y	Y	Y	Y	Y
INDUSTRY CONTROLS	Y	Y	Y	Y	Y
First stage F-stat 1	26.21	15.14	25.37	22.43	11.93
First stage F-stat 2		406	367.6	409.6	217.5
KP LM stat	8.099	8.100	8.145	8.111	12.21
KP Wald F stat	26.21	13.10	13.22	13.13	11.14

Note: All regressions are run for firm-level data from 2002 to 2016. The dependent variable is the log of firms' labor productivity. GVC participation is instrumented with average GVC participation measure at world level, the interaction terms are instrumented with the interaction between the average GVC participation at world level and the other variable in the interaction terms. Bottom rows of the table reports statistics from the first stage regressions and statistics for under identification and weak identification tests of the instrumental variables. Standard errors clustered at industry-year level are shown in parentheses. *, **, and *** indicate coefficients significantly different from zero at the 10, 5, and 1% level, respectively.

In analyses thus far we have employed indicators to study the heterogeneity in the effects, which might capture too much variation in the sample. We examine the robustness of our results using the continuous variables of these indicators (Tables 8, 9). Our results are largely robust to these new measures except for the results in the interaction between GVC participation and firm size in column (2) of Table 8. The coefficients and standard errors of column (1) in both Tables 8 and 9 are much higher than our main results. One possible reason for this is the correlation between the initial log productivity and the dependent variable (log productivity).

Table 8: GVC participation and productivity at firm level

VARIABLES	(1)	(2)	(3)	(4)
Lagged GVC	-48.690***	3.406**	2.782	-4.442
	(7.724)	(1.718)	(1.702)	(5.664)
GVC*Initial Productivity	40.210***			
	(5.803)			
GVC*Initial firm size		-0.007		
		(0.010)		
GVC*Initial firm sales			0.080***	
			(0.015)	
GVC*Initial export share				0.359***
				(0.044)
Observations	165,029	165,055	165,055	107,771
INDUSTRY FE	Y	Y	Y	Y
REGION FE	Y	Y	Y	Y
YEAR FE	Y	Y	Y	Y
FIRM CONTROLS	Y	Y	Y	Y
INDUSTRY CONTROLS	Y	Y	Y	Y
Marginal effect	1.972	3.397	3.364	-4.397
S.E.	2.332	1.721	1.697	5.665
First stage F-stat 1	13.17	22.07	21.96	12.62
First stage F-stat 2	497	309.2	380.6	208.5
KP LM stat	8.155	8.225	8.177	11.92
KP Wald F stat	12.94	13.06	13.02	11.17

Note: All regressions are run for firm-level data from 2002 to 2016. The dependent variable is the log of firms' productivity. GVC participation is instrumented with average GVC participation measure at world level, the interaction terms are instrumented with the interaction between the average GVC participation at world level and the other variable in the interaction terms. Bottom rows of the table reports statistics from the first stage regressions and statistics for under identification and weak identification tests of the instrumental variables. Standard errors clustered at industry-year level are shown in parentheses. *, **, and *** indicate coefficients significantly different from zero at the 10, 5, and 1% level, respectively.

Table 9: Spillover effects at firm level

VARIABLES	(2)	(3)	(4)	(5)
Lagged GVC	11.105***	3.655**	2.782*	-4.605
	(4.182)	(1.565)	(1.536)	(4.230)
From BUYERS (Lag)	-37.473***	-5.764*	-4.791	4.189
	(8.700)	(3.055)	(3.005)	(7.116)
From SUPPLIERS (Lag)	-16.564***	-0.466	-1.277	-10.915**
	(2.115)	(1.774)	(1.770)	(4.778)
GVC*Initial TFP	-3.309			
	(2.527)			
GVC Buyer*Initial TFP	20.922***			
	(5.676)			
GVC Supplier*Initial TFP	20.964***			
	(1.195)			
GVC*Initial size		0.022		
		(0.016)		
GVC Buyer* Initial size		-0.072***		
		(0.024)		
GVC Supplier* Initial size		0.027**		
		(0.011)		
GVC*Initial sales			0.135***	
			(0.030)	
GVC Buyer* Initial sales			-0.187***	
			(0.041)	
GVC Supplier* Initial sales			0.087***	
			(0.011)	
GVC*Initial export share				0.422***
				(0.097)
GVC Buyer*Initial export share				-0.309**
				(0.143)
GVC Supplier*Initial export share				0.135**
				(0.060)
Observations	165,029	165,055	165,055	107,771
INDUSTRY FE	Y	Y	Y	Y
REGION FE	Y	Y	Y	Y
YEAR FE	Y	Y	Y	Y
FIRM CONTROLS	Y	Y	Y	Y
INDUSTRY CONTROLS	Y	Y	Y	Y

Note: All regressions are run for firm-level data from 2002 to 2016. The dependent variable is the log of firms' productivity. Standard errors clustered at industry-year level are shown in parentheses. *, **, and *** indicate coefficients significantly different from zero at the 10, 5, and 1% level, respectively.

Another concern might be that our results are driven by the presence of multinational firms since multinational firms usually are those with higher productivity and larger size and operating in several countries. Thus there may be reverse causality for multinationals, the performance of multinationals may determine GVC participation, rather than the other way around. We address this concern by restricting the sample of firms to exclude multinationals. We use information on immediate shareholder, global ultimate owner, and domestic ultimate owner. This leaves us with only more than 7000 observations in our sample. The signs of all coefficients are the same as before. However, some coefficients lost their significance. This is probably due to a large decrease in the number of observations. Our conclusions on the heterogeneity of the effect are unchanged.

Table 10: GVC participation and productivity at firm level – exclude multinationals

VARIABLES	(1)	(2)	(3)	(4)	(5)
Lagged GVC	5.538*	5.345	5.558*	5.621*	-6.899
	(3.177)	(3.427)	(3.152)	(3.122)	(10.404)
GVC*Initial Frontier		2.147***			
		(0.339)			
GVC*Large firm (size)			0.127		
			(0.086)		
GVC*Large firm (sales)				0.386***	
				(0.077)	
GVC*Initial export status					0.338***
					(0.065)
Observations	7,100	7,100	7,100	7,100	4,517
INDUSTRY FE	Y	Y	Y	Y	Y
REGION FE	Y	Y	Y	Y	Y
YEAR FE	Y	Y	Y	Y	Y
FIRM CONTROLS	Y	Y	Y	Y	Y
INDUSTRY CONTROLS	Y	Y	Y	Y	Y
First stage F-stat 1	23.38	14.61	20.24	20.58	10.77
First stage F-stat 2		355.8	416.5	403.8	226
KP LM stat	8.105	8.111	8.247	8.203	11.66
KP Wald F stat	23.38	11.70	11.98	11.87	9.950

Note: All regressions are run for firm-level data from 2002 to 2016. The dependent variable is the log of firms' productivity. GVC participation is instrumented with average GVC participation measure at world level, the interaction terms are instrumented with the interaction between the average GVC participation at world level and the other variable in the interaction terms. Bottom rows of the table reports statistics from the first stage regressions and statistics for under identification and weak identification tests of the instrumental variables. Standard errors clustered at industry-year level are shown in parentheses. *, **, and *** indicate coefficients significantly different from zero at the 10, 5, and 1% level, respectively.

VI. Conclusion and Policy Implications

With the current outbreak of COVID-19, various economies have faced shortages of components vital to everything from health systems to everyday household goods. These shortages prompt countries to bring manufacturing home, for governments to begin looking after their own citizens rather than signing up for a global agenda. However, since modern supply networks require high degrees of specialization, as well as modern manufacturing operations focus on maximizing utilization of plant and equipment, it is not easy for countries to bring industries back home. Estonia, with its deep involvement in regional rather than global value chains, is expected to more closely integrate into European trade and production or, especially trade and production within Baltic countries thanks to the Rail Baltica project.

In this paper, we showed GVC participation has a positive and significant impact on the productivity of Estonian firms. The impact is heterogeneous depending on firms' characteristics related to productivity, size, and export status. Initially frontier firms, large firms by sales, and exporting firms can reap more benefits from GVC participation than non-frontier firms, small firms, and non-exporting firms. We also find a positive correlation between the intensity of GVC participation of supplier industries and productivity of their client industries. Frontier firms and large firms benefit more from GVC participation of upstream industries, while non-frontier firms and small firms benefit more from GVC participation of downstream industries. Given that growth in the Estonian economy has shown signs of weakness recent years (Eesti Pank 2018), our findings have implications on policies to boost productivity growth in Estonia.

VII. REFERENCES

1. Ackerberg, A. Daniel, Caves, Kevin and Frazer, Garth. 2015. "Identification Properties of Recent Production Function Estimators." *Econometrica* 83(6): 2411-2451.
2. Ahmed, Swarnali, Appendino, Maximiliano and Ruta Michele. 2015. "Global Value Chains and the Exchange Rate Elasticity of Exports." *IMF Working Paper* No. 15/252.
3. Ali-Yrkko, Jyrki, Mattila, Juri and Seppala, Timo. 2017. "Estonia in Global Value Chains". *ETLA Reports* No. 69. https://pub.etla.fi/ETLA-Raportit-Reports-69.pdf
4. Amiti, Mary and Konings, Jozef. 2007. "Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia." American Economic Review Vol. 97, No.5.
5. Antras, Pol and Chor, Davin. 2013. "Organizing the Global Value Chain". *Econometrica* 81(6): 2127-2204.
6. Armando Rungi and Davide Del Prete. 2018. "The smile curve at the firm level: Where value is added along supply chains". *Economics Letters* 164(2018): 38-42.
7. Arndt, S. 1997. "Globalization and the Open Economy." *The North American Journal of Economics and Finance* 8(1): 71-79.
8. Aslam, A., Novta, N., and Rodrigues-Bastos, F. 2017. "Calculating Trade in Value Added." *IMF Working Paper* No. WP/17/178.
9. Baldwin, R. 2012. "Global Supply Chains: Why They Emerged, Why They Matter, and Where They are Going." *CEPR Discussion Papers* No. 9103.
10. Baldwin, R. 2013. "Trade in Industrialization after Globalization's Second Unbundling: How Building and Joining a Supply Chain Are Different and Why It Matteres." Chapter in NBER book *Globalization in an Age of Crisis: Multilateral Economic Cooperation in the Twenty-First Century* (2014), Robert C. Feenstra and Alan M. Taylor, editors (p. 165-212). University of Chicago Press.

11. Bas, M. and V. Strauss-Kahn. 2014. "Does Importing More Inputs Raise Exports? Firm-level Evidence from France." *Review of World Economics* 50 (2): 241–275.
12. Benkovskis K. et al. 2017. "Export and Productivity in Global Value Chains: Evidence from Latvian and Estonian firms." *OECD Economics Department Working Papers* No. 1448. OECD Publishing, Paris.
13. Berthuou, Antoine and Dhyne, Emmanuel. 2018. "Exchange Rate Movements, Firm-Level Exports and Heterogeneity." Banque De France Working Paper No. 660.
14. Chiacchio, Francesco, Gradeva, Katerina and Lopez-Garcia, Paloma. 2018. "The Post-crisis TFP Growth Slowdown in CEE Countries: Exploring the Role of Global Value Chains". *European Central Bank Working Paper No. 2143.*
15. Coe, N. M. and M. Hess. 2007. "Global production networks: debates and challenges." paper prepared for the GPERG workshop. University of Manchester.
16. Constantinescu, Cristina, Mattoo, Aaditya, and Ruta, Michele. 2017. "Does Vertical Specialization Increase Productivity?" *World Bank Policy Research Working Paper* No. 7978.
17. Criscuolo, Chiara and Timmis, Jonathan. 2018. "GVC Centrality and Productivity: Are Hubs Key to Firm Performance ?" OECD Productivity Working Papers No. 14.
18. Davide Del Prete and Armando Rungi. 2017. "Organizing the Global Value Chain: A Firm-level Test". *Journal of International Economics* 109(2017): 16-30.
19. De Backer, K. and Miroudot, S. 2014. "Mapping Global Value Chains" *European Central Bank Working Paper Series* No. 1677.
20. De Loecker, J., Goldberg, K. P., Khandelwal, A. K. and Pavcnik, N. (2016). "Prices, Markups, and Trade Reform." *Econometrica*, Vol. 84, No. 2, pp. 445-510.
21. De Loecker, J. and Warzynski, F. (2012). "Markups and Firm-Level Export Status". *American Economic Review*, Vol. 102, pp. 2437-2471.
22. De Prete, Davide, Giovannetti, Giorgia and Marvasi, Enrico. 2017. "Global Value Chains Participation and Productivity Gains for North African Firms." *Review of World Economics* 153: 675-701.
23. Del Prete, D., G. Giovannetti and E. Marvasi. 2017. "Global Value Chains Participation and Productivity Gains for North African Firms", *Review of World Economics*, ISSN: 1610-2878, doi:10.1007/s10290-017-0292-2
24. Del Prete, D., G. Giovannetti and E. Marvasi. 2017. "Global Value Chains: new evidence for North Africa", *International Economics*, ISSN: 2110-7017, doi: 10.1016/j.inteco.2017.03.002
25. Del Prete, Davide and Rungi, Armando. 2017. "Organizing the Global Value Chain: A Firm-level Test." *Journal of International Economics* 109(2017): 16-30.
26. Eesti Pank. 2018. "Estonian Economy and Monetary Policy."
27. European Commission. 2019. Country Report Estonia 2019. Brussels.
28. Feenstra, R. 1998. "Integration of Trade and Disintegration of Production in the Global Economy." *Journal of Economic Perspectives* 12(4): 31-50.
29. Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer. 2015. "The Next Generation of the Penn World Table." *American Economic Review*. 105(10), 3150-3182, available for download at www.ggdc.net/pwt
30. Fung Global Institute (FGI), Nanyang Technological University (NTU) and World Trade Organization (WTO). 2013. "Global Value Chains in a Changing World". Edited by Deborah K. Elms and Patrick Low. WTO Secretariat, Switzerland, 2013.

31. Gal, N. Peter. 2013. “Measuring Total Factor Productivity at the Firm Level using OECD-ORBIS.” OECD Economics Department Working Papers No. 1049.
32. Gereffi, Gary 1994, “The organization of buyer-driven global commodity chains: how US retailers shape overseas production networks”, in G. Gereffi and M. Korzeniewicz (eds). *Commodity Chains and Global Capitalism*. Westport. CT: Praeger. pages 95-122.
33. Gereffi, G., Humphrey, J. and Sturgeon, T. 2005. “The Governance of Global Value Chains.” *Review of International Political Economy*. 12, 78-104.
34. Grossman, G. and E. Helpman. 2002. “Integration versus Outsourcing in Industry Equilibrium.” *Quarterly Journal of Economics* 117: 85-120.
35. Grossman, G.M. and Rossi-Hansberg, E. 2008. “Trading Tasks: A Simple Theory of Offshoring.” *The American Economic Review* 98(5): 1978-1997.
36. Hanson, H. Gordon, Mataloni Jr., J. Raymond and Slaughter, J. Matthew. 2015. “Vertical Production Networks in Multinational Firms.” *Review of Economics and Statistics* 87(4): 664-678.
37. Hummels, D., Ishii, J. Yi, K. 2001. “The Nature and Growth of Vertical Specialization in World Trade.” *Journal of International Economics* 54:75–96.
38. Humphrey, J. and Schmitz, H. 2002. “How does insertion in global value chains affect upgrading in industrial clusters?” *Regional Studies* 36:9, 1017-1027.
39. International Monetary Fund. 2018. “IMF Country Report No. 18/125”.
40. International Monetary Fund. 2018. “World Economic Outlook: Cyclical Upswing, Structural Change.” Chapter 4. Is Productivity Growth Shared in a Globalized Economy? Washington, D.C.
41. James Gillies, Jaak Leimann and Rein Peterson. 2002. “Making a Successful Transition from a Command to a Market Economy: the lessons from Estonia”. *Corporate Governance* 10(3): 175-186.
42. Jones, R. and Kierzkowski, H. 1990. “The Role of Services in Production and International Trade: A Theoretical Framework.” in R. Jones and A. Krueger, eds., The Political Economy of International Trade, Basil Blackwell, Oxford.
43. Kawakami, M. and Sturgeon, T.J. 2012. “The Dynamics of Local Learning in Global Value Chains: Experiences from East Asia.” IDE-JETRO Series, Palgrave Macmillan.
44. Konstantins Benkovskis & Jaan Masso & Oleg Tkacevs & Priit Vahter & Naomitsu Yashiro, 2018. "Export And Productivity In Global Value Chains: Comparative Evidence From Latvia And Estonia," University of Tartu - Faculty of Economics and Business Administration Working Paper Series 107, Faculty of Economics and Business Administration, University of Tartu (Estonia).
45. Koopman, Robert, William Powers, Zhi Wang, and Shang-Jin Wei. 2010. “Give Credit Where Credit is Due: Tracing Value Added in Global Production Chains.” *NBER Working Paper* 16426..
46. Koopman, Robert, William Powers, Zhi Wang, and Shang-Jin Wei. 2011. “Give Credit Where Credit is Due: Tracing Value Added in Global Production Chains.” *Hong Kong Institute for Monetary Research Working Paper* No.31/2011.
47. Koopman, Robert, Zhi Wang, and Shang-Jin Wei. 2014. “Tracing Value-Added and Double Counting in Gross Exports.” *American Economic Review* 104(2): 459–494.
48. Kowalski, P. et al. 2015 “Participation of Developing Countries in Global Value Chains: Implications for Trade and Trade-Related Policies” *OECD Trade Policy Papers* No. 179
49. Krugman, P., 1995. “Growing World Trade: Causes and Consequences.” Brookings Papers on Economic Activity.

50. Laura Alfaro, Pol Antras, Davin Chor, and Paola Conconi. 2018. “Internalizing Global Value Chains: A Firm-Level Analysis.” *ULB Institutional Repository* 2013/264398. ULB – Universite Libre de Bruxelles.
51. Lenzen M, Kanemoto K; Moran D, and Geschke A (2012) Mapping the structure of the world economy, Environmental Science & Technology 46(15) pp 8374-8381. DOI: 10.1021/es300171x
52. Lenzen, M., Moran, D., Kanemoto, K., Geschke, A. (2013) Building Eora: A Global Multi-regional Input-Output Database at High Country and Sector Resolution. *Economic Systems Research*, 25:1, 20-49, DOI:10.1080/09535314.2013.769938
53. OECD Economic Outlook, Volume 2019 Issue 1.
54. OECD. 2017a. Estonia: Trade and Investment Statistical Note.
55. OECD. 2017b. OECD Economic Survey: Estonia. OECD Publishing. Paris.
56. Pietrobelli, Carlo and Rabellotti, Roberta. 2011. “Global Value Chains Meet Innovation Systems: Are There Learning Opportunities for Developing Countries?”. *World Development* 39(7): 1261-1269.
57. Rungi, Armando and Del Prete, Davide. 2018. “The Smile Curve at the Firm level: Where Value is Added Along Supply Chains.” *Economics Letters* 164(2018): 38-42.
58. UNCTAD. 2013. “World Investment Report 2013: Global Value Chains: Investment and Trade for Development” United Nations Conference on Trade and Development. United Nations Publication ISBN 978-92-1-112868-0.
59. Yeats, A. 2001. “Just How Big is Global Production Sharing?” in L. Cheng and H. Kierzkowski, eds., Globalization of Trade and Production in South-East Asia, New York: Kluwer Academic Press.

VIII. APPENDIX

A. Variables used in the productivity estimation

Table A1 contains information on the specific data used in the productivity estimation. Gross output, employment and intermediate inputs are taken directly from ORBIS variables.

Table A1: Variable definitions

Variable	ORBIS variable(s) involved (short name)
Gross output, Y	SALES (OPERATING_REVENUE_TURNOVER if SALES is missing or negative)
Value added, VA	VA=COSTS_OF_EMPLOYEES (wL)+ EBITDA (rK) (ADDED_VALUE if VA is missing)
Employment, L	NUMBER_OF_EMPLOYEES
Capital, K	TANGIBLE_FIXED_ASSETS, DEPRECIATION_AND_AMORTIZATION
Intermediate inputs, M	MATERIAL_COSTS (SALES-VA if MATERIAL_COSTS is missing)

Value added is imputed using other variables in ORBIS. We follow Gal (2013) to calculate value added (VA) as the sum of factor incomes going to employees (total wage bill, wL) and capital owners (profits, rK):

$$VA = wL + rK.$$

The counterparts to these variables in ORBIS are the COSTS_OF_EMPLOYEES and EBITDA (Earnings Before Interest Taxes Depreciation and Amortisation). If at least one of these two variables is missing, we replace by the ADDED_VALUE variable in ORBIS.

Following Gal (2013), capital stock is computed using the standard Perpetual Inventory Method (PIM). The level of real capital stock K_{it} in firm i in year t is calculated as:

$$K_{it} = K_{i,t-1}(1 - \delta_{it}) + I_{it},$$

where I_{it} refers to real investments and are calculated as:

$$I_{it} = (K_{it}^{BV} - K_{i,t-1}^{BV} + DEPR_{it}^{BV})/P_t,$$

with K^{BV} and $DEPR^{BV}$ denoting the book value of fixed tangible assets (TANGIBLE_FIXED_ASSETS in ORBIS) and depreciation (DEPRECIATION_AND_AMORTIZATION in ORBIS), respectively. P is the industrial producer price index (PPI) from Eurostat used as the investment price deflator. δ is the depreciation rate and is defined as $\delta_{it} = DEPR_{it}^{BV}/K_{it}^{BV}$. We trim the top 1% and the bottom 99% of the distribution of δ to mitigate measurement error concerns.

For the first observed year of the firm or for years where both real investment and depreciation rate are missing, we calculate the real capital stock as the book value of fixed tangible assets delated by the PPI:

$$K_{i0} = \frac{K_{i0}^{BV}}{P_0}.$$

B. Comparison between Orbis and Statistics Estonia

Table B1: Comparison between Orbis and Statistics Estonia, Output

(millions euro, nominal values)

		Orbis					
		After cleaning			Before cleaning		
Year	Statistics Estonia	Output	% over Statistics Estonia	Number of firms	Output	% over Statistics Estonia	Number of firms
1999	10870.5				5,670	52.2	10,693
2000	12787.7				7,600	59.4	13,405
2001	14626				8,920	61.0	15,394
2002	16211.1	6,950	42.9	8,113	12,400	76.5	18,246
2003	17804.5	9,700	54.5	8,897	16,800	94.4	20,914
2004	19973.7	13,000	65.1	9,809	22,300	111.6	23,788
2005	23055.8	13,400	58.1	10,565	23,500	101.9	26,819
2006	27187.9	18,600	68.4	11,576	33,100	121.7	30,913
2007	32089.7	24,700	77.0	13,033	44,500	138.7	35,862
2008	33123.2	24,700	74.6	14,207	44,500	134.3	40,529
2009	26499.5	18,300	69.1	13,122	36,200	136.6	44,629
2010	29361.8	17,800	60.6	15,973	38,600	131.5	50,411
2011	34377.3	20,800	60.5	17,379	47,700	138.8	56,835
2012	36954.2	23,500	63.6	19,290	53,400	144.5	65,450
2013	39024.5	27,000	69.2	20,937	59,200	151.7	74,399
2014	40218.4	25,000	62.2	22,684	55,700	138.5	84,020
2015	40860.1	20,900	51.2	23,077	48,900	119.7	86,298
2016	42086.8	21,200	50.4	19,547	47,400	112.6	81,483

Table B2: Comparison between Orbis and Statistics Estonia, Employees (thousands)

Year	Statistics Estonia	Orbis			
		After cleaning		Before cleaning	
			% over Statistics Estonia		% over Statistics Estonia
1999	530.4			150.8	28.4
2000	534.5			177.5	33.2
2001	541.1			189.2	35.0
2002	542.3	131.0	24.2	207.5	38.3
2003	548.1	142.2	25.9	221.3	40.4
2004	540.9	155.6	28.8	245.7	45.4
2005	564.1	167.1	29.6	258.3	45.8
2006	589.4	176.1	29.9	269.0	45.6
2007	583.5	178.6	30.6	272.9	46.8
2008	591	179.9	30.4	279.2	47.2
2009	527.9	153.1	29.0	237.0	44.9
2010	501	148.9	29.7	226.0	45.1
2011	532.7	156.2	29.3	244.3	45.9
2012	539.7	161.7	30.0	258.1	47.8
2013	544.6	173.4	31.8	279.2	51.3
2014	549.4	180.8	32.9	305.9	55.7
2015	564.6	175.4	31.1	301.6	53.4
2016	565.2	171.2	30.3	302.6	53.5

Table B3: Comparison between Orbis and Statistics Estonia, Value added

(millions euro, nominal values)

Year	Statistics Estonia	Orbis			
		After cleaning		Before cleaning	
			% over Statistics Estonia		% over Statistics Estonia
1999	4836.2			934	19.3
2000	5512.9			1,260	22.9
2001	6227.2			1,410	22.6
2002	6914.8	1,520	22.0	1,970	28.5
2003	7773	2,130	27.4	2,610	33.6
2004	8595.8	2,800	32.6	3,680	42.8
2005	9972.7	2,980	29.9	3,530	35.4
2006	11889	4,210	35.4	5,600	47.1
2007	14258.5	5,540	38.9	6,840	48.0
2008	14719.2	4,960	33.7	6,310	42.9
2009	12281	3,830	31.2	5,180	42.2
2010	12874.3	4,080	31.7	5,610	43.6
2011	14616.4	4,660	31.9	6,330	43.3
2012	15676	5,220	33.3	7,090	45.2
2013	16590.9	6,350	38.3	8,050	48.5
2014	17201.9	5,670	33.0	7,640	44.4
2015	17610.4	5,050	28.7	7,220	41.0
2016	18118.1	5,140	28.4	7,090	39.1

Table B4: Comparison between Orbis and Statistics Estonia, exports

(millions euro, nominal values)

		Orbis			
		After cleaning		Before cleaning	
Year	Statistics Estonia		% over Statistics Estonia		% over Statistics Estonia
2004	4768.7	0	0.0	0	0.0
2005	6201.9	0	0.0	0	0.0
2006	7719.0	0	0.0	0	0.0
2007	8033.5	0	0.0	0	0.0
2008	8470.1	0	0.0	0	0.0
2009	6486.9	4,060	62.6	6,390	98.5
2010	8743.0	4,920	56.3	9,280	106.1
2011	12003.4	6,090	50.7	11,700	97.5
2012	12521.1	7,000	55.9	13,900	111.0
2013	12288.2	7,780	63.3	15,600	127.0
2014	12006.0	7,140	59.5	14,900	124.1
2015	11575.3	6,130	53.0	12,800	110.6
2016	11904.8	5,660	47.5	12,300	103.3