# The impact of technology and connectivity on trade patterns

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# The impact of technology and connectivity on trade patterns *

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**Abstract**

In this paper, we investigate how new digital technologies and robotization foster trade in intermediate goods and services. Two sets of estimations are conducted. First, relying on Trade in Value-Added (TiVA) database for 27 EU countries and 63 origin countries for the period 1995-2018, we show that digitalization strengthens the backward Global Value Chain (GVC) participation. Second, we employ the International Federation of Robotics database along with the OECD Inter-Country Input-Output (ICIO) data set and investigate the effects of intensity in robot use on the forward GVC participation. We consider 61 exporting countries and 20 EU importing economies, over the period 2000-2018. We find that new technologies enhance GVCs participation, with the installation and the stock of robots being the relevant components that cause this enhancement. Our results differ for EU and non-EU exporting countries confirming the new organisation of production in Europe stated by Baldwin (2017).

Keywords: trade in value-added, robotization, digitalization, offshoring

JEL codes: F14, J24, L80, O33

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## Contents

# 1 Introduction

In 2017, Adidas decided to reshore part of its production of trainees from Asia towards Ansbach (Germany) and in Atlanta (USA). It aims to use robots and additive manufacturing techniques to produce more timely models and adapt to the fast-changing preferences of the clients through a digital design process, for instance (Economist, 2017). Unfortunately, on November 13, 2019, Adidas decided to close its German and U.S. Robot factories. The reason for this change in international strategy was linked to the lack of value-added available components: the shoes had to be simplified and they lost their consumer appeal (The Economist, 2020).

The example illustrates that technology 4.0 has clear impacts on globalization involving both trade and the location of firms; however, the links are complex. We first need to understand better what these new digital technologies include (Evenett and Baldwin, 2020). They can be gathered into three categories (Chen and Volpe Martincus, 2022). The first group comprises technologies that lower communications and transaction costs, and expand market access such as online trade platforms, and some applications of AI (artificial intelligence) and blockchain. The second category is made of technologies including innovations that decrease production costs: the introduction of robots and automation, 3D printing, and cloud computing. The third set contains financial innovations allowing to manage business and personal financial operations more efficiently. They include fintech innovations (mobile banking and mobile money), or some blockchain applications facilitating lending and insurance.

The productivity gains from these innovations are unquestionable. However, they raise concerns about how they might reshape the patterns of global production networks and thus trade. In this context, one needs to answer an important question, which is also our research question of interest: How does these new technologies affect the location of production (offshoring, reshoring)?

Our work relates to two strands of literature: the work on Input/Output tables assessing the participation of countries in sectoral global value chains, the analysis of the macroeconomic impact of the new digital revolution.

Our contribution to the literature is to analyse the impact of technology 4.0 on disaggregated sectoral bilateral trade, whereas most papers analyse either sectoral unilateral trade or bilateral trade without sectoral breakdown (see Bachmann et al. (2022) and Lewandowski et al. (2022).

First, relying on the TiVA database we analyse foreign value added in gross exports by country of origin to assess the role of digitalization on the importance of backward GVC (Global Value Chain) participation. Second, based on inter-country input-output tables (ICIO data) we investigate the impact of sectoral use of robots (drawn from the International Federation of Robotics - IFR) on imported intermediate products to capture the effects on the forward GVC participation. In each case, we make comparisons between the EU countries and all countries in the sample and we also single out services trade. Based on gravity equations, controlling for traditional determinants like population and GDP per capita and its potential endogeneity, we show that internet use and fixed broadband subscriptions per 100 inhabitants, in both origin and destination countries, tend to increase backward GVC participation. Hence, we highlight the positive impact of digitalization on trade, as value added. Further, we investigate the impact of robotization on forward GVC participation.

Based on gravity equations, controlling for traditional determinants like population and GDP per capita and its potential endogeneity, we show that internet use and fixed broadband subscriptions per 100 inhabitants, in both origin and destination countries, tend to increase backward GVC participation. To solve the endogeneity bias of simultaneity between technical progress and rising trade (through the channel of increased growth), we implement a control function following Wooldridge (2015) and show that endogeneity does not pose a concern for our model of interest.

Further, we investigate the impact of robotization on forward GVC participation. Here, results are mixed, suggesting an exponential impact in some cases, which may be explained (under specific circumstances) by the presence of possible reshoring.

Hence, we highlight the positive impact of digitalization on trade as value added.

The remainder of this paper is divided as follows. First, in Section 2, we propose a literature review of the impact of new digital technologies on trade, on the one hand, and offshoring/reshoring, on the other hand. We discuss some stylised facts in Section 3. We present an overview of the proposed methodology and the data used in the analyses in Section 4, followed by the results in Section 5. Some conclusions are drawn at the end of the paper in

Section 6.

## 2 Survey of the Literature

### 2.1 Digital technology and trade

Since the Great Financial Recession, globalization has slowed down significantly. This movement should be put in perspective with the sharp acceleration of trade flows from the late 1980s until 2007, with a rate of growth of world trade flows nearly twice bigger than that of world GDP (from 1986 to 2007, trade increase by a factor 1.72). During that period, economies witnessed an important disintegration of production process across borders[1].

First, the information and communication technology (ICT) revolution allowed by improvement in ICT (Information and Communication Technologies) helped to facilitate the design and implementation of supply chains by easing communications. At the same time, trade costs have significantly fallen by a reduction of trade barriers, and faster shipping of goods. Finally, political changes have led to a greater involvement in market economies and trade of more countries, in particular the integration of Eastern European countries and of China into the world economy. After this "hyper-globalisation", a period of "slowbalisation", to use the concept proposed by The Economist (2019), was inevitable (Antràs, 2020).

In a recent work Lewandowski et al. (2022) underline differences between the impact of technology and globalization on the breakdown of tasks. From micro-data surveys on job tasks collected in 47 countries and 19 industries,

[1] On that subject see also S. Jean (2017a) and (2017b).

they show that computer use and robotization (for middle-skilled workers only) are associated with low routine task intensity (RTI), whereas globalisation, measured by the foreign share of value-added (backward linkage) in an economy-industry, involves a rise in RTI in low- and middle-income countries. In high-skilled occupations, the differences in RTI are mainly explained by differences in technology and skills' supply; this finding is in line with the complementarity between technology and non-routine cognitive tasks. Among low-skilled occupations, globalization contributes the most insofar as offshoring enables nations to specialise, within industries, in the activities relatively intensive in their abundant factors.

When it comes to the relation between digital technology and globalization or trade, in one of the forerunner papers on the topic, Freund and Weinhold (2004) show that a 10% rise in internet penetration was associate with a 1.7 percent point increase in export growth and a 1.1 percent point increase in import growth. They found that the internet has allowed to around one percentage point rise in annual export growth from 1997 to 1999.

Later, keeping the gravity equation framework and controlling for individual country-sector-year supply and demand conditions, González and Ferencz (2018) found that a 10% increase in the bilateral digital connectivity (share of population using the internet) raises goods trade by nearly 2%. In developed countries a 10% increase in bilateral digital connectivity is associated with a 5% increase in exports. For developing countries, the rise in exports from an equivalent increase in digital connectivity is 0.12%. The impact varies also among sectors. In post and telecommunications, a 10% increase in minimum internet use between countries is associated with a 3.2% rise in exports. In contrast, in construction or wholesale and retail trade, the impact is negative.

In a follow up of Freund and Weinhold (2004), Visser (2019) looks at the impact of internet penetration, measured by broadband subscriptions on the extensive and intensive margins of exports in differentiated goods. He relies on a gravity panel model for 162 exporting countries and 175 destinations over the period 1998-2014. He finds a positive relation between the rise in internet penetration and both the extensive and the intensive margins of differentiated exports. Internet penetration may foster the extensive margin of exports between low- and high-income countries, but not within these groups. The linguistic distance on both the extensive and intensive margins of differentiated exports is reduced by rising internet penetration.

Andrenelli and González (2021) study the impact of 3D printing technologies on international trade disruptions. They show that 3D printing is unlikely to have important macroeconomic impact on international trade in the short and medium terms because the number of products that can be 3D printed is still limited. For a large scope of products, the advantages of traditional manufacturing (cost, speed, quality and economies of scale) remain. Using proxies for 3D printable goods, they find few evidence of a replacement of trade in goods by the adoption of 3D printing. Empirically, in a system Generalised Method of Moments (GMM), a dynamic panel estimation reveals a positive and significant impact of imports of 3D printers on exports of 3D printable goods, for the decade 2010-2018 but not for the previous decade 2002-2009, for OECD countries. As they stated: "a 1% increase in the value of imports of 3D printers corresponds to a +0.02% increase in the value of exports of 3D printable items.” The more complex are the products, the higher the impact. The effect also shows up for developing countries. This indicates trade complementarities between 3D printing adoption and trade in goods. Thus, it is premature to state that technology will replace international trade.

Alternatively, Abeliansky et al. (2020) show that the trade effect of 3D printing can also be negative, relying on a gravity equation in cross-section for the year 2013 and in panel during the period 1997 to 2013. They show that (i) 3D printers are set in areas facing high transport costs; (ii) with technical progress in 3D printing, FDI dependent on traditional techniques is gradually replaced by FDI based on 3D-printing; (iii) with wider implementation of 3D printing, further technological progress leads to a gradual replacement of international trade. Focusing on the industries with the highest rates of 3D printing adoption, empirical evidence supports the second and third hypotheses. Thus, the traditional export-led-industrialisation strategy of developing countries could be threatened by the wide adoption of 3D printing that replace international trade. Based on this, one can conclude that 3D printing has mixed effects on trade.

As for more novel digital technologies, Chen and Volpe Martincus (2022) highlighted several stinking stylised facts. First, firms export more products to more destinations online than offline; the extensive margin, more precisely, the numbers of buyers and markets, contribute the most to the growth of online exporters. Second, online exports are highly concentrated among superstar exporters. However, online superstars do not necessarily exhibit quality advantage. Third, distance deters online trade, but to a lesser extent than for offline trade. Fourth, when it comes to online trade platforms, they observe a rise in total exports, the extensive margin, for small and medium-sized businesses, especially at the product and buyer margins.

### 2.2 Digital technology and reshoring

Technologies might however have a deglobalization effect. Automation offers an alternative to offshoring for European firms which set up manufacturing processes intensive in automation in their domestic countries, while designing their production processes, when seeking to reduce their labour costs. Thus, insofar as automation and offshoring appear to be substitutes, future automation spread could lead to increased reshoring on the one hand, while on the other hand, these technologies require intermediary consumption that can only be produced abroad and thus offshored. Hence whether automation and offshoring are substitutes or complements remains a pending question.

As an alternative view about the widespread belief of 3D printing disruption effect on world trade, using difference-in-difference and synthetic control methods, Freund et al. (2022) find an 80% rise in exports of hearing aids after the introduction of 3D printing technology, paying attention to variation in the timing adoption of the new technology by producers. No localisation effect shows up, insofar as the overall trade in hearing aids increases by a similar amount. For 35 other products partially 3D printed, a positive and significant effect on trade was also highlighted. These impacts are stronger for more complex and lighter goods. Their result is in line with previous findings on the trade boosting impact of technological progress, when production costs decrease, and quality improves. With a similar mechanism as for automation, 3D printing has a direct effect on trade reduction with increased productivity and input demand which may need to be imported (Antràs, 2020). Thus, 3D printing impact on trade is at this point mixed.

Consider now some cutting-edge technologies which are likely to foster trade. Digital technologies reduce barriers to GVC participation. For example, digital platforms ease the matching of buyers and sellers and facilitate GVC participation of small firms, in particular in the provision of services. Monitoring and verification are improved by rating systems in digital platforms and open distributed ledger (eg. Blockchain) which ease GVC participation of countries with weak institutions. AI, big data and machine learning levy language barriers and facilitate trade, in particular in services. Thus, the advances in digital technologies might ensure the continuous growth in GVCs (Antràs, 2020). Most of the fixed cost linked to the organisation of international production networks are sunk: neither relationship specific physical assets can be easily sold, nor relational capital and search cost are kept when location choice changes. Then, as stated by Antràs (2020): *"domestic manufacturing (re-shoring) will require a much higher erosion of foreign competitiveness ex-post than ex-ante"* (p. 23). Therefore, firm localisation's decisions are relatively sticky. There is an asymmetry in the choices of where to organise production: re-shoring operations appear more costly than off-shoring ones. The geography of worldwide production will only change when large shocks in the world economy are forecasted to be persistent. Even with moderate costs shocks (rising wages or trade costs) that may make production unprofitable, European firms might be reluctant to relocate production. European firms may abandon their locations only if the trend costs are viewed as secular, (Antràs, 2020).

What do stylised facts found in the literature tell us? Do they confirm the general theoretical views or the results of empirical analyses? The effect of reshoring is small and less convincing than anecdotal cases. According to a study from the OECD, about 2% of all German manufacturing companies have made back-shoring between 2010 to mid-2012: four times less than their offshoring activities. Meanwhile, around 4% of European manufacturing firms have moved production activities back home; much lower than the 17% of firms which have off-shored in the decade before. For the UK, surveys report that about 15% of British manufacturing firms are engaged in back-shoring (Foster, 2017).

Ancarani et al. (2019) surveyed 500 European firms and find that only 14% of back-shoring initiatives cite advanced robotics and/or additive manufacturing as the reason of their change in international strategy. The complexity of these technologies is a major impediment to their adoption; so only firms possessing the necessary capabilities can acquire them. These firms adopt mainly technologies responding to challenges tied to production and prototyping. Back-shoring firms opt for new technologies when technology intensity and complexity of supply chains are high and when there are high risks of loss of control over offshored manufacturing process or intellectual property rights. They found that re-shoring mainly occurred without resorting to labour saving technologies.

Using a cross-country firm-level panel dataset from Orbis over the period 2001 to 2007, Alfaro and Chen (2015) analyse the variation of location patterns of multinational firms depending on their levels of ICT adoption, measured by internet access, fixed broadband subscription, telephone subscriptions, business use of ICTs. They found that the level of ICT adoption has a positive impact on multinational entry. The effect of business computer and internet use happened to be larger for less routine and more communication-intensive industries.

Relying on a firm-level dataset on Spanish manufacturing firms from 1990 to 2016, Stapleton and Webb (2020) highlight that the use of robots had a positive effect on their imports from, and number of subsidiaries in lower-cost countries. Robot adoption permits firms to expand production, increase labour and total factor productivity. When firms had not already offshored towards lower-wage economies, robot adoption gives them incentives to delocalize, in line with the rising production and income effects. In opposite, when the firms had previously offshored their production to low-wage economies, robot adoption has no impact on the value of their imports from lower-wage economies, and decreases their shares of imports sourced from those countries.

Nievas Offidani (2019) find that rise in the robot intensity tends to reduce the degree of offshoring. They build a panel data set of 71 countries and seven manufacturing activities for 1993-2015 from data on robot stocks and trade in intermediary goods. They estimate that when a manufacturing industry moves from the bottom to the top of the ranking of changes in robotization, offshoring decreases by 16%. This change comes from the fact that automation lowers domestic production costs in advanced economies and their incentives to offshore operations to lower-wage countries.

Krenz et al. (2021) propose a theoretical framework that highlights how an increased productivity in automation leads to a relocation of previously off-shored production back to the home advanced economy. However, neither improvement of wages, nor the creation of jobs occur for low-skilled workers, whereas high-skilled wages increase. Thus, automation-induced re-shoring leads to increasing inequality. They develop a reshoring measure showing by how much domestic inputs increased relative to foreign inputs compared to the previous year. Combining data from the World Input-Output Database (WIOD) table and statistics on the stock of robots from the International Federation of Robotics (IFR), they provide evidence for automation-driven reshoring, for 43 countries, including all EU economies, for the period 2000 to 2014. On average, within manufacturing sectors, an increase by one robot per 1,000 workers is associated with a 3.5% increase in reshoring activity. They also find that reshoring improves wages and employment for workers in professional occupations, but not for workers in elementary routine occupations. A rise in tariffs leads to an increased intensity of reshoring: the share of offshored firms diminishes in favor of firms producing with industrial robots at home. Then, as raised by Chen and Volpe Martincus (2022), the adoption of robots and automation in advanced countries can have mixed effects on trade and offshoring to less developed countries.

In the following, we will investigate the use of different new digital technologies and applications on backward and forward GVC participation.

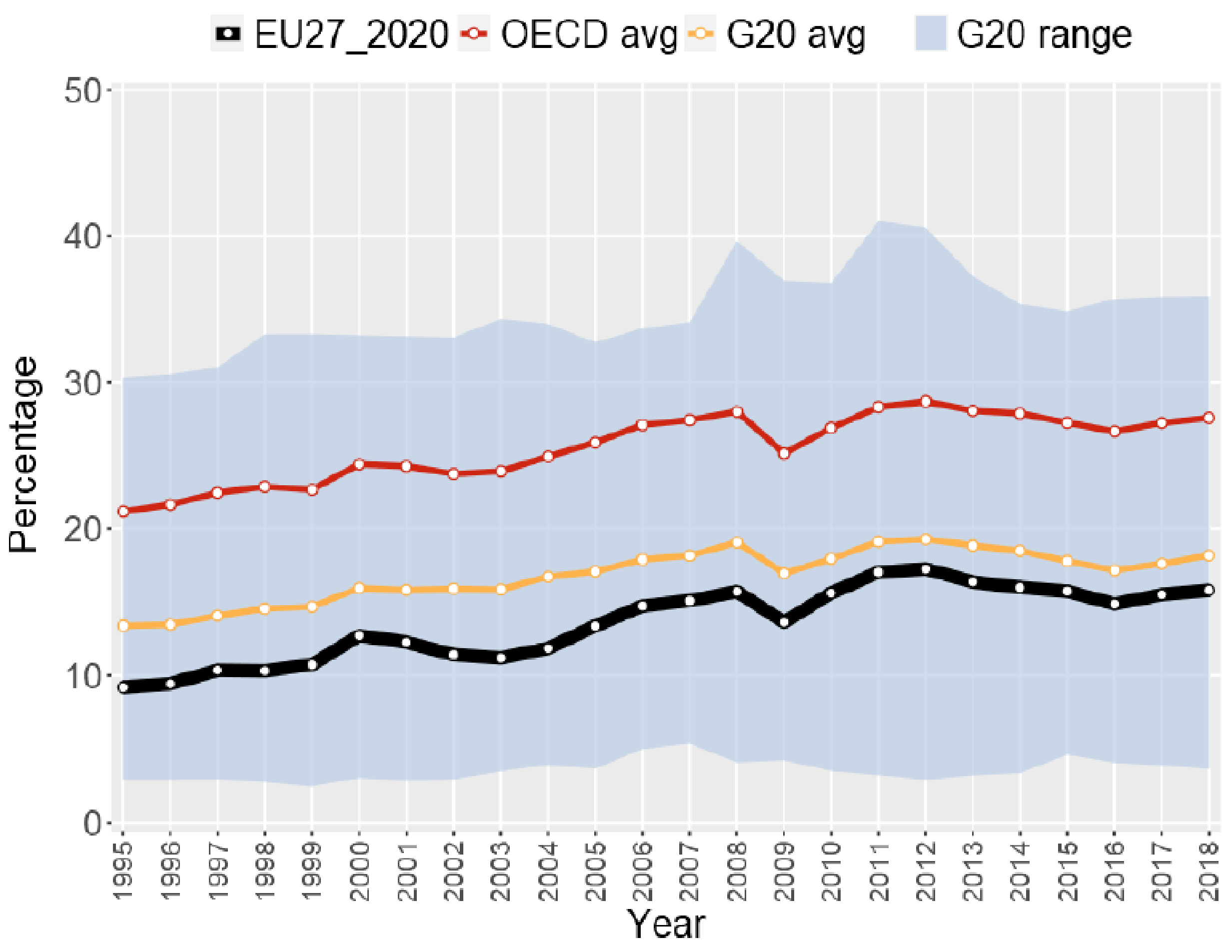
## 3 Stylized facts

TiVA database confirms the slowdown of GVC integration since the Great Financial Crisis of 2008-2009. Foreign value added increase between 2016 and 2018. The Foreign content of exports stays steady at 15.7% between 2008 and 2018 (see figure 1).

Of the total value of EU imports of intermediate goods and services in 2018, 30.6% was subsequently embodied in exports, below the OECD average of 47.4%, and above the share in 2008 (25.4%). The originating industries with the highest shares of intermediate imports used in EU exports were Other transport equipment (45.7%), Basic metals (38%), and Motor vehicles (36.8%, see figure 2).

This slowdown in trade flows is not associated with a slowing down of the rate of technological change for certain key digital industries, such as microprocessors. In figure 3, we show that the number of transistors integrated into a microprocessor still double every two years until 2018, following Moore's law. We also observe that ever-raising speeds of information transmission over fiber optic cable had the smallest increase, Antràs (2020) assess that the marginal benefits of those innovations have reached diminishing returns. Once the internet can support smooth communication for international production teams, the returns to further advances in technology might have gone down. Meanwhile, the amount of R&D spending needed to respect Moore's

Figure 1: Foreign value-added content of gross exports (*as a percent of total gross exports, 1995 to 2018)*



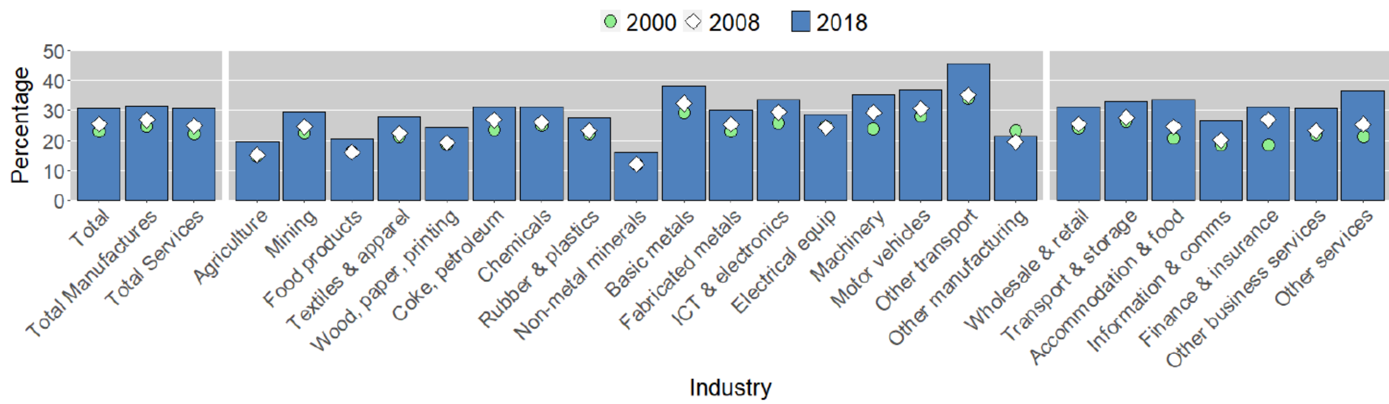

Source: OECD (2022)

Law today is much higher than it was in the 1970s and 1980s. That point of view is somehow refuted by the evidence shown on graph 2 indicating that the rate of growth of internet adoption has slowed down in the 2000s and 2010s, but it accelerated again since 2020.

The rise in new digital technologies can also be assessed in graph 4, illustrating the rise in fixed broadband subscriptions. The equipment in fixed broadband accelerates sharply in the EU since 2015.

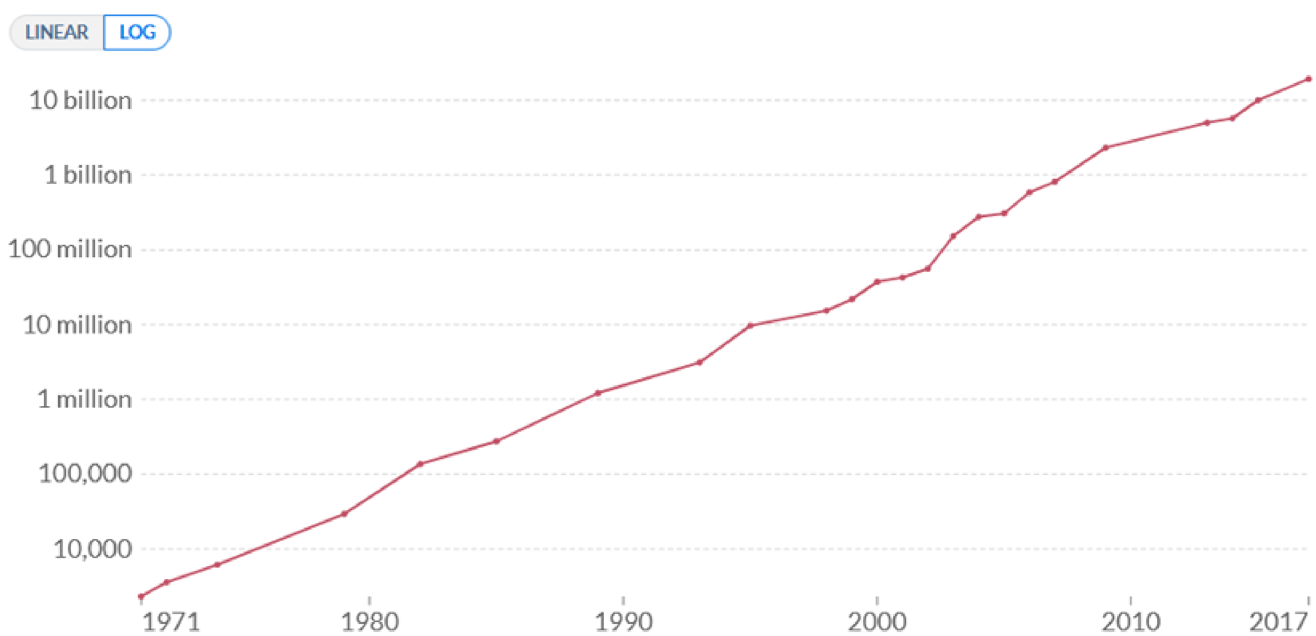
Regarding broadband access, we observe a progression of the equipment

Figure 2: European Union - industry share of domestic and foreign value-added content of gross exports *As a percent of total gross exports, 2018*



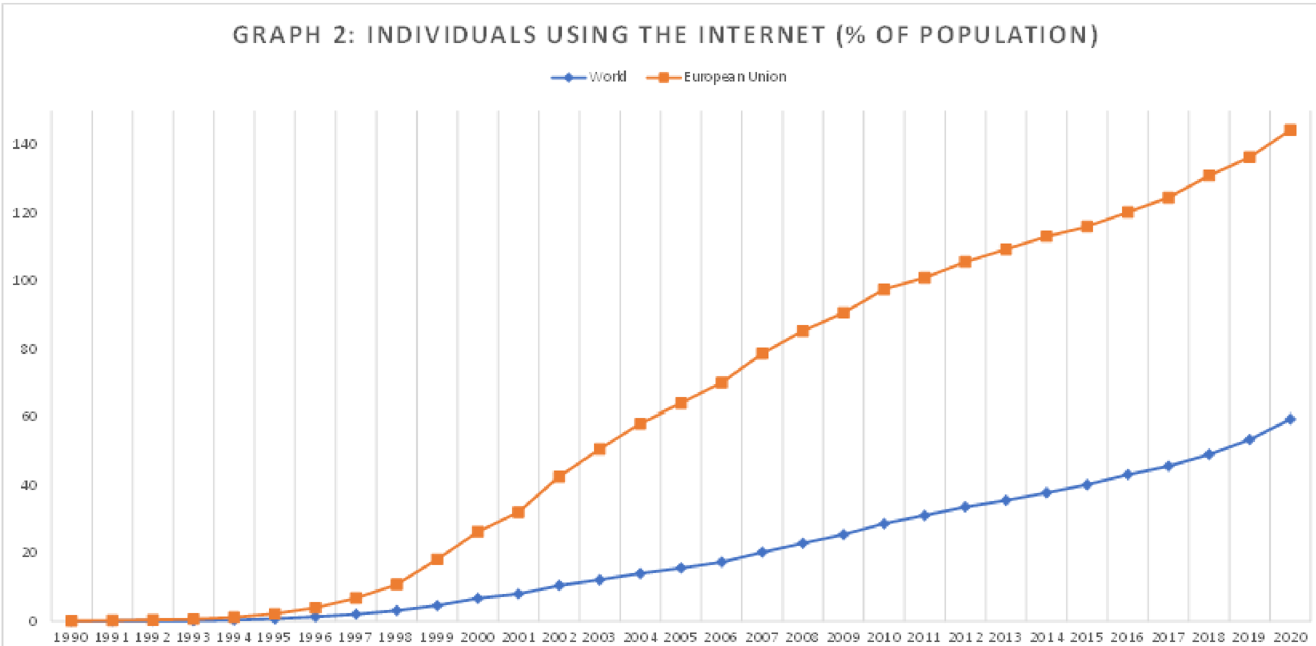

Source: OECD (2022)

Figure 3: Moore's law: The number of transistors (log scale) per microprocessor (1971-2018)



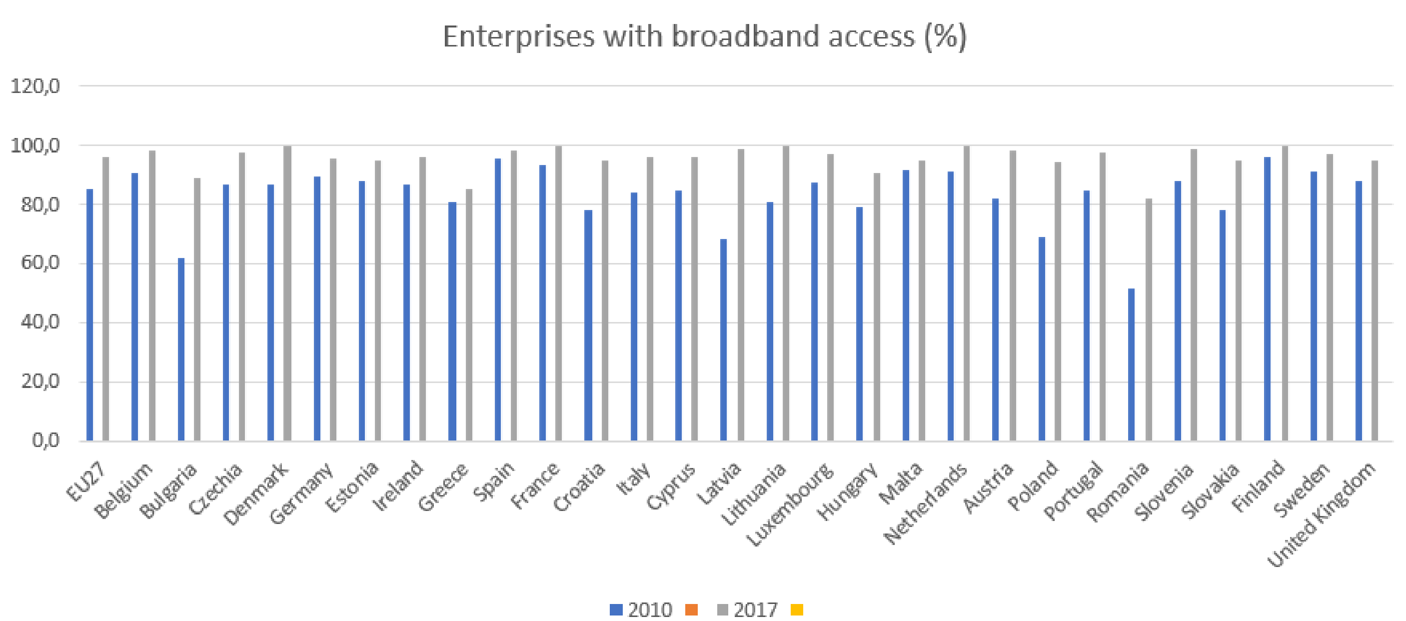

Source: Karl Rupp. 40 Years of Microprocessor Trend Data. Retrieved from Our World in Data
Note: Number of transistors which fit into a microprocessor. The observation that the number of transistors on an integrated circuit doubles approximately every two years is called 'Moore's Law'.

between 2010 and 2020. The rise is the most important for Central and Eastern European Countries (CEECs), see figure 4.




Source: World Bank's World Development indicators

Figure 4: Broadband access in various European countries, 2010 and 2022




Source: Eurostat

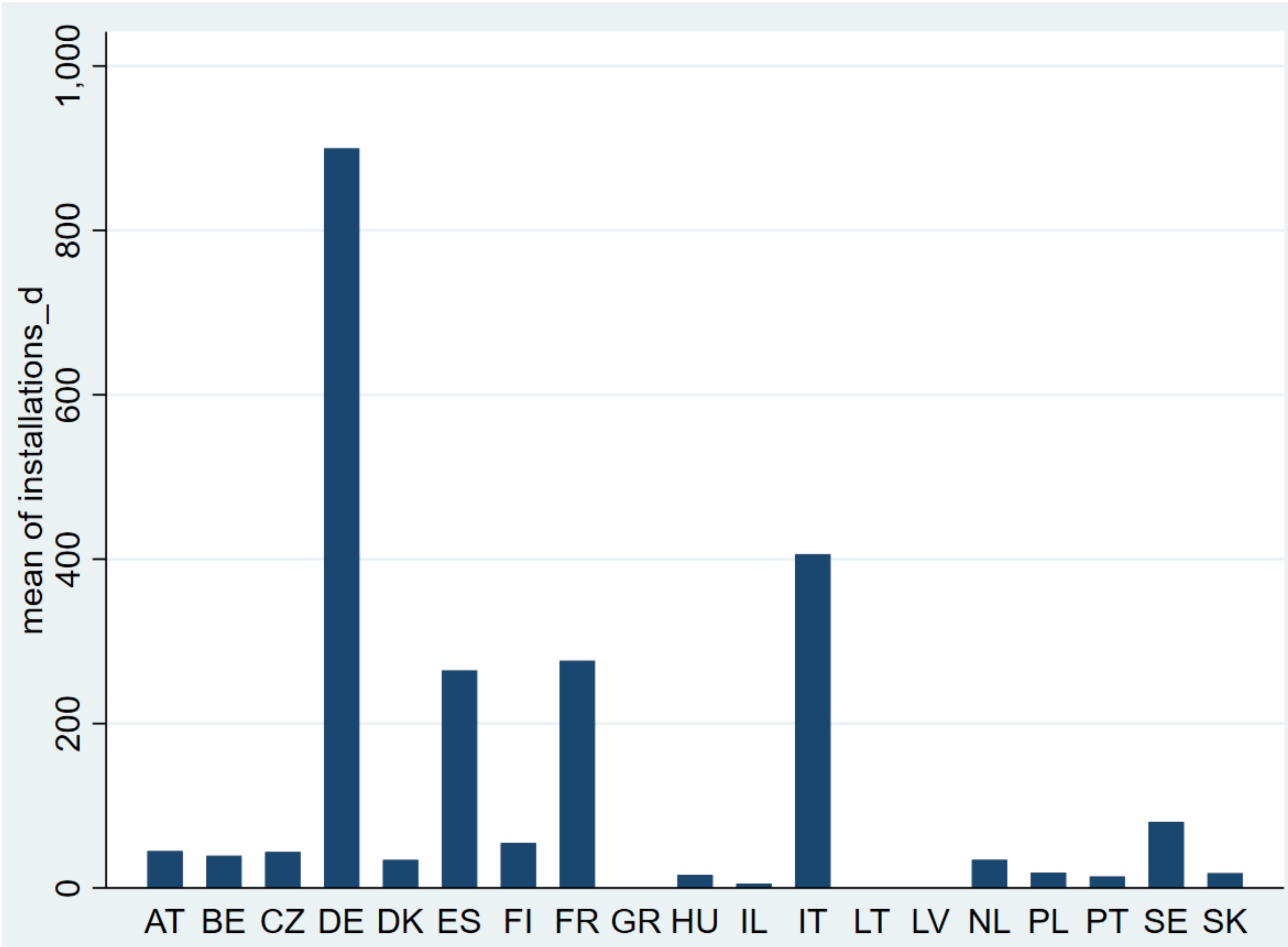
When it comes to the installation of robots, we compare the numbers for 2000 and 2020 for European countries and observe a clear rise. We also look at the installations of robot for all 20 European countries of our sample by industries and observe important differences between activities.

In 2005, the EU country that was the best equipped in robots was Germany, followed by Italy, France and Spain. In addition to the size effect, this ranking attests of the modernism and dynamism in the adoption of the new technologies of the industries of the biggest European countries (see figure 5). Figure 6 shows that the four big countries remain the leaders in the robot intensity of manufacturing industries in 2020, with Germany strengthening its leadership. However, we note the emergence in these industries of Central European countries of the EU15 such as Poland, the Czech Republic or Slovakia. Medium size European countries such as Netherlands and Austria also catch up the biggest followers in this technology race (see figure 6).

Looking at the sectoral distributions of robots (see figure 7), we also observe strong concentrations. The sector of energy (15: Electricity, gas and air conditioning supply) appears as the main user of robots in 2005. It is followed by the production of rubber and plastics (sector 8). To a lesser extent, the production of transport equipment (sector 13), metal products (sector 11), electricity and optical equipment (sector 12) and food (sector 2) are also important users of robots.

The robot intensity of the different activities in 2020, confirm the tendencies observed in 2005. The emergence of coke (sector 6) also reinforces the existence of a high concentration of robot in the extractive sector (see figure 8).

Figure 5: Robot installation, in European countries in 2005




Source: International Federation of Robots

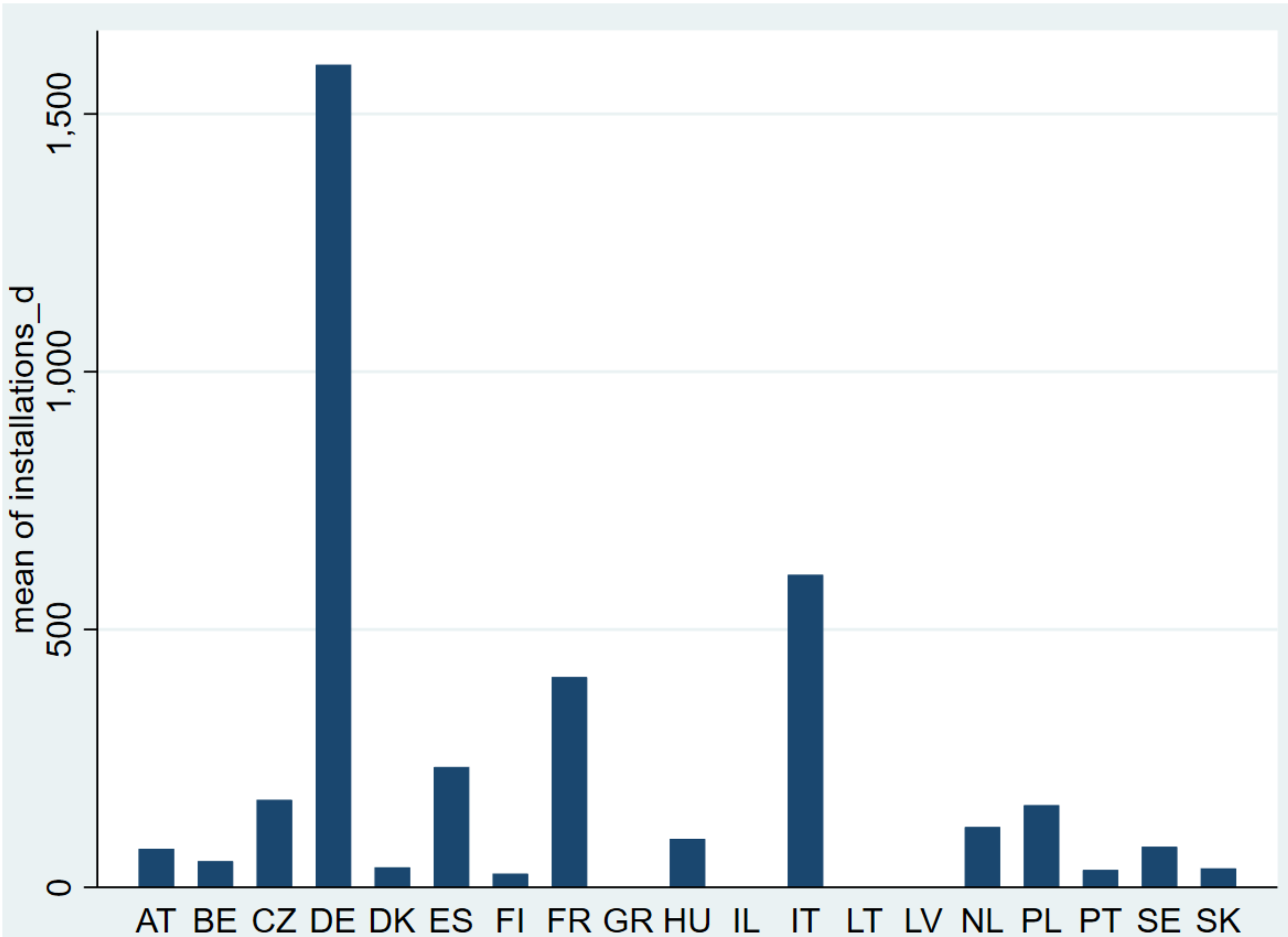
# 4 Methodology and data

## 4.1 Methodology

### 4.1.1 Basic model

To assess the impact of new technologies on trade, we use a gravity equation, the workhorse of empirical international economics. Two models of interest are used in our analysis. The first model (Model 1 hereafter) assesses the impact of digitalisation, captured into a broad sense (ICTs) on backward GVC participation. We expect a higher degree of diffusion of ICTs to raise

Figure 6: Robot installation, in European countries in 2020

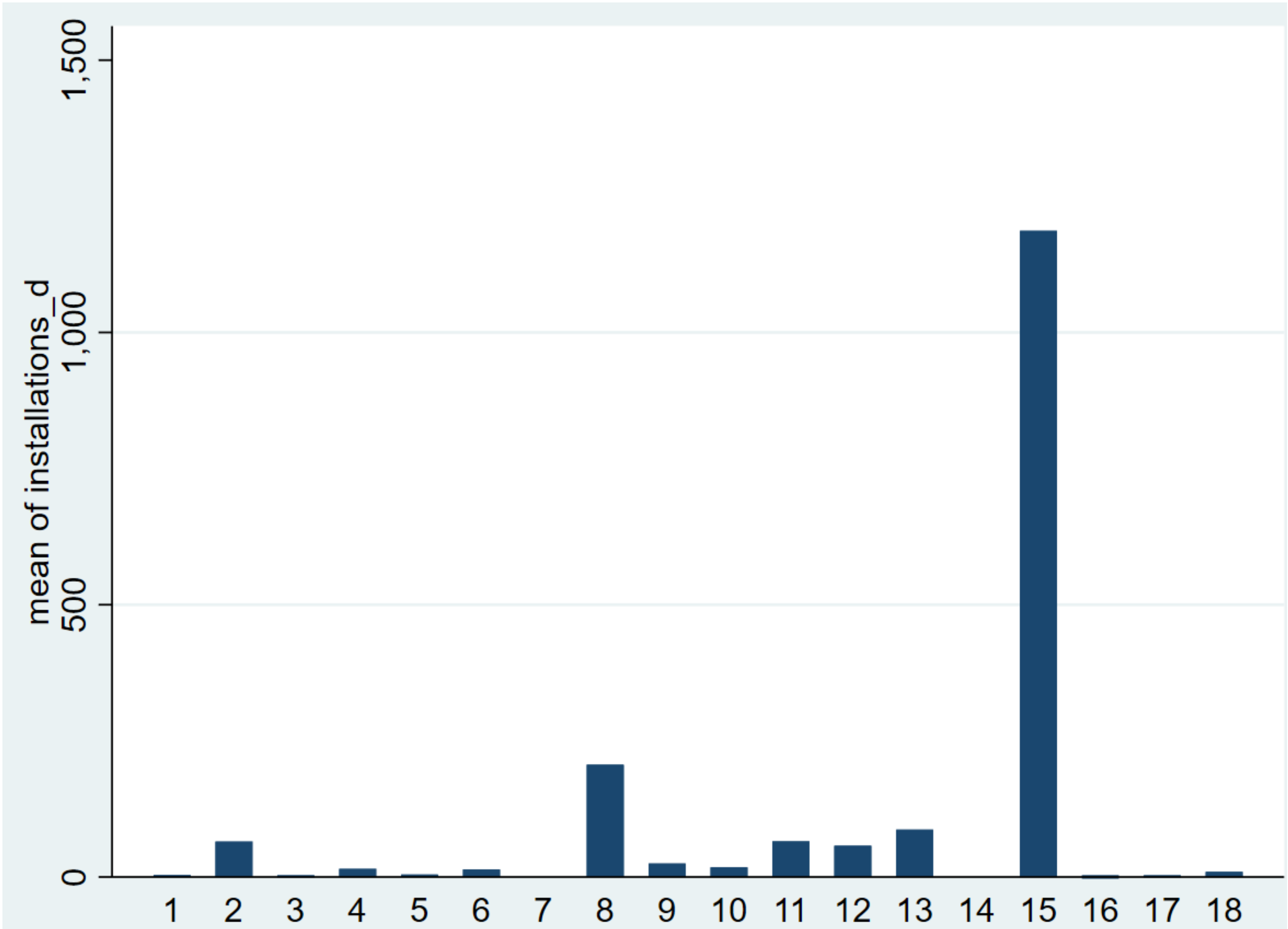



Source: International Federation of Robots

backward linkages in line with easier communication and lower costs of coordination. The second model (Model 2 hereafter) takes a step further and investigates how introducing new technologies into a more profound way in the production process, through robotisation, increases imports of intermediary products by industry and country.

For estimation, we follow Yotov et al. (2016). First, we estimate the gravity equation (1) in panel data with Poisson Pseudo Maximum Likelihood estimator (PPML, thereafter) in order to consider zero flows and to take into account the issue of heteroscedasticity in bilateral trade data. Second, we in-

Figure 7: Robot installation in the European Union, by industry, in 2005

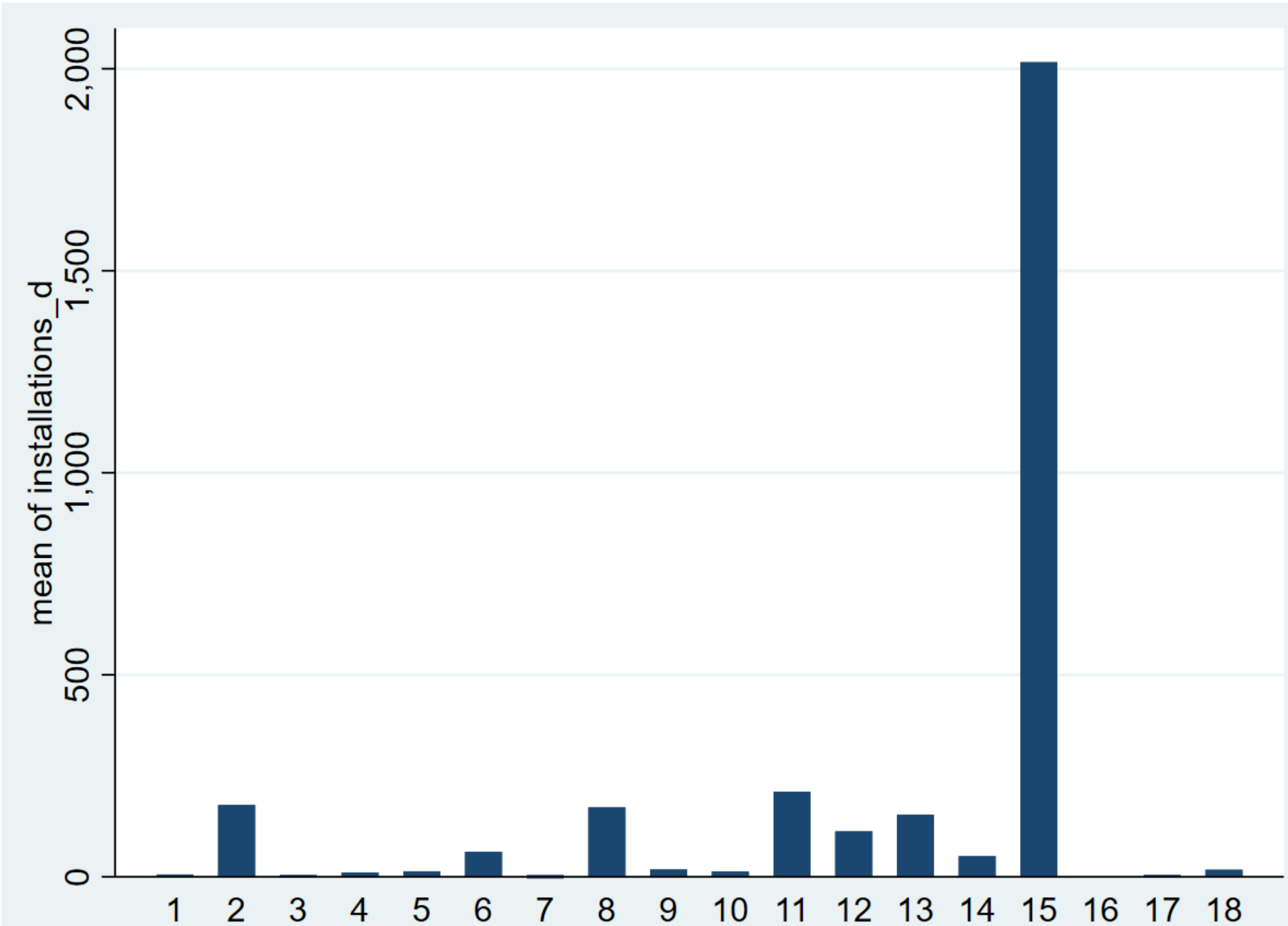



Source: International Federation of Robots
Note: 1-AGMI, 2-FOOD, 3-TXTL, 4-WOOD, 5-PAPE, 6-COKE, 7-CHEM, 8-RUB1, 9-RUB2, 10-MET1, 11-MET2, 12-ELEC, 13-MACH, 14-TRAN, 15-GASA, 16-GASW, 17-CONS, 18-EDUC

troduce four sets of fixed effects to control for unobservable country-specific, sector- specific, and time-specific characteristics (see Baier et al. (2019)).

In Model 1 we analyse the value-added origin sector $s$ and country $j$ of gross exports ($X_{ijt}^{rs}$) from sector $r$ of country $i$ in year $t$. This is our dependent variable extracted from the OECD TiVA database for 63 countries over the period 1998 to 2018. Model 1 is estimated in a multiplicative form. The baseline scenario for our analysis is the following:

Figure 8: Robot installation in the European Union, by industry, in 2020




Source: International Federation of Robots.
Note: 1-AGMI, 2-FOOD, 3-TXTL, 4-WOOD, 5-PAPE, 6-COKE, 7-CHEM, 8-RUB1, 9-RUB2, 10-MET1, 11-MET2, 12-ELEC, 13-MACH, 14-TRAN, 15-GASA, 16-GASW, 17-CONS, 18-EDUC

$$X_{ijt}^{rs} = exp[\beta_0 + \beta_1 ln(\text{pop}_{it}) + \beta_2 ln(\text{pop}_{jt}) + \beta_3 ln(\text{GDPC}_{it}) + \beta_4 ln(\text{GDPC}_{jt})$$

$$+ \beta_5 ln(\text{GFCF}_{it}) + \beta_6 ln(\text{GFCF}_{jt}) + \beta_7 ln(Techno_{it}) + \beta_8 ln(Techno_{jt})$$

$$+ \beta_9 ln(dist_{ij}) + \beta_{10} Gravity_{ij} + \lambda_i + \lambda_j + \lambda_r + \lambda_s + \lambda_t]\xi_{ijt}^{rs}, (1)$$

with, $pop_{it}$, the population of the exporting country $i$ in year $t$, $pop_{jt}$, the population of the value-added (VA) origin country $j$ in year $t$, $GDPC_{it}(GDPC_{jt})$, the gross domestic product per capita of the exporting (origin of VA) country $i$ *(j)* in year $t$, $GFCF_{it}(GFCF_{jt})$, the gross fixed capital formation of the exporting (origin of VA) country $i$ *(j)* in year $t$, $Techno_{it}(Techno_{jt})$, the technological variable of exporting (origin of VA) country $i$ *(j)* in year $t$, which are defined and measured as follows:

- $internet\_use$: percentage of individual using the internet per 100 people,
- broadband: percentage of fixed broadband subscriptions per 100 people,

$dist_{ij}$ the geographical distance between country $i$ and country $j$,
$Gravity_{ij}$, a set of dyadic dummy variables including common border, legal system, language, joint participation in a Regional Trade Agreement (RTA),for both country $i$ and country $j$,
a set of fixed effects for the exporters $\lambda_i$, origin country of VA $\lambda_j$, sectors $\lambda_r$ and $\lambda_s$, and temporal dimension $\lambda_t$, and a random error $\epsilon_{ijt}^{rs}$.

We include factor endowments with the variable GFCF (gross fixed capital formation) to test whether the factorial model of trade holds: countries tends to specialise on exports products in which they are relatively abundant. Moreover, GFCF, can also be interpreted as a proxy for productivity, In particular, Adarov et al. (2022) have shown that tangible and intangible ICT capital, enhances productivity both at aggregate and sectoral levels for 20 EU countries over the period 2000 to 2017.

Model 2 aims at explaining the exports of intermediate product $Y_{ijt}^{rs}$, of sector $s$ from country $j$ and year $t$ that are used as inputs for the production of sector $r$ in exporting country $i$ in year $t$. It is written as follows:

$$Y_{ijt}^{rs} = exp[\beta_0 + \beta_1 ln(\text{pop}_{it}) + \beta_2 ln(\text{pop}_{jt}) + \beta_3 ln(\text{GDPC}_{it}) + \beta_4 ln(\text{GDPC}_{jt})$$

$$+ \beta_5 ln(\text{GFCF}_{it}) + \beta_6 ln(\text{GFCF}_{jt}) + \beta_7 ln(dist_{ij}) + \beta_8 \text{Gravity}_{ij} + \beta_9 \text{Robot}_{rit}$$
$$+ \beta_{10} \text{Robot}_{sjt} + \lambda_i + \lambda_j + \lambda_r + \lambda_s + \lambda_t] + \epsilon_{ijt}^{rs}, (2)$$

where $\text{Robot}_{rit}$ ($\text{Robot}_{sjt}$), is either the installations or the operational stock of robots from industry $r$ ($s$) of country $i$ ($j$) in year $t$; all other variables are the ones already employed in Model 1 and defined above. The IFR (International Federation of Robots) surveys on annual installations of robots either by counting the actual installation of the robot at the customers' site or referring to the shipment of the robot.

The operational stock of robots measures the number of robots currently deployed. The IFR calculates this number under the assumption of an average service life of 12 years, after which the robot is totally depreciated and its value drops to zero.

For this model we again use the Pseudo Poisson Maximum Likelihood (PPML) for our reported specifications.

#### 4.1.2 Endogeneity issues

The development and usage of ICT fosters the economic growth and increase the standards of living (proxied by GDP per capita). However, the converse is also true: higher GDP per capita allows for an increased use of ICT. As purchasing power also boosts trade, we might have an endogeneity bias in our estimation. However, as we use highly disaggregated trade data at the sector level for both partner countries, the risk of endogeneity is low.

We were testing this assumption about endogeneity using in our gravity models a correction term based on a control function methodology following Bachmann et al. (2022) and Acemoglu and Restrepo (2019). In the case endogeneity is present, the proposed correction term is significant and there are observed significant changes in the parameter estimates of the endogenous variable (and potential other control variables).

To address (and test) the potential endogeneity between the GDPC and our outcome, defined as the value added of gross exports (for Model 1), we are proposing a two stage methodology based on a control function. In this case, the control function is proposed by Wooldridge (2015) to address endogeneity in nonlinear models. As our estimation method is nonlinear, and is based on Poisson pseudo-likelihood regression with multiple levels of fixed effects, we consider the control function approach also as a contribution to the application of this model.

In particular, in the first stage, we model the GDP per capita (GDPC) as a function of components of GDPC, here we consider: exports of goods and services, imports of goods and services, consumption of fixed capital, gross fixed capital formation, general government final consumption and gross fixed capital formation in the private sector in levels.

Some of the components of the GDPC are considered as exclusion restrictions, in particular, they are used to explain the GDPC but are not relevant at explaining trade in value added model.

The first stage is modeled using a linear specification as follows:

1. First stage - Model of GDPC

$$Y_{jt} = \delta C_{jt} + \gamma Z_{jt} + u_{jt}$$

$Y_{jt}$ is the gross domestic product per capita (GDPC) for country $j$ at time $t$, $C_{it}$ are country level observables (exports and imports of goods and services, consumption of fixed capital); $Z_{it}$ is the exclusion restriction that includes country level observables such as: gross fixed capital formation, general government final consumption.

Post estimation, the residuals from the first stage will be retained and they will be used as a correction term (control function - $\widehat{CF}_{jt}$) introduced in the second stage, which is the estimation of our benchmark specification of Model 1, equation (1).

2. Second Stage - Model of value added (backward linkages):

$$X_{ijt}^{rs} = exp[\beta_0 + \beta_1 ln(\text{pop}_{it}) + \beta_2 ln(\text{pop}_{jt}) + \beta_3 ln(\text{GDPC}_{it}) + \beta_4 ln(\text{GDPC}_{jt})$$

$$+ \beta_5 \widehat{CF}_{jt} + \beta_6 ln(\text{GFCF}_{it}) + \beta_7 ln(\text{GFCF}_{jt}) + \beta_8 ln(Techno_{it})$$

$$+ \beta_9 ln(Techno_{jt}) + \beta_{10} ln(dist_{ij}) + \beta_{11} Gravity_{ij} + \lambda_i + \lambda_j + \lambda_r + \lambda_s + \lambda_t]\xi_{ijt}^{k},$$

where the variables in the second stage have been previously defined.

If endogneity is present in the baseline model, in the second stage model with control function correction, the significance of the correction term in the second stage and of the exclusion restrictions in the first stage will provide evidence that the endogeneity was corrected. Alternatively, if the first stage exclusion restrictions are significant, and the second stage correction term is not significant, it shows evidence that endogeneity may not be present in the baseline model.

### 4.2 Data

Three sources of data are used to do our Model 1 analysis. First, we use the OECD Trade in Value Added (TiVA) database, which provides information about the global production networks and supply chains, to extract the information about our outcome of interest, the foreign value added that is coming from 63 origin countries (of which 36 non-EU) and present in the exports of 27 EU destination countries in sub-sample 1 and 36 non-EU countries is sub-sample 2, over the period 2000 to 2018. Second, we use the World Development Indicator (WDI) of the World Bank to extract the information at the country level about the technological variables and other control variables used in the analysis both for the baseline and the control function estimations. Lastly, we use the CEPII's distances measures from the Gravity geographical data to account for our dyadic variables, which include a set of different distance measures and dummy variables used to identify particular links between countries such as common legal system, shared languages, contiguity.

Table 1 presents all the countries used in the Model 1[2]. We have 36 non-

[2]The 27 European Union destination countries used in the analysis are: Austria, Belgium, Bulgaria, Croatia, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and United

EU origin countries[3]. We study 28 sectors[4] (see table 2).

Summary statistics by origin and destination countries of the variable used in Model 1 are presented in Tables 3 to 6, respectively for all sectors and EU and non-EU exporting countries, then services for EU and non-EU exporting countries.

In Model 2, we analyse the impact of the intensity in robot use of the imported products on the receiving industry in the destination country. Due to the different geographical coverage of the Robot Industrial Use database of the International Federation of Robotics and the ICIO data set, we kept only 61 countries among the exporting ones and we focus on 20 EU importing countries. As for the 20 EU countries, among the 27 of our first database we lose Bulgaria, Croatia, Cyprus, Luxembourg, Romania, Slovenia and the United Kingdom. As for the origin countries, they include the 20 EU exporting countries plus 2 other EU countries (Romania, and the United Kingdom) and the 30 remaining non-EU countries are the same as for Model 1 and table 1, with the exception of Brunei, Chile, Iceland, Kazakhstan, Laos, and Myanmar. We conduct the analysis using 18 destination industries coming

Kingdom.

[3]Argentina, Australia, Brazil, Brunei Darussalam, Canada, Chile, China, Colombia, Costa Rica, Hong Kong, Iceland, Indonesia, India, Israel, Japan, Kazakhstan, Korea, Lao, Malaysia, Mexico, Morocco, Myanmar, New Zealand, Norway, Peru, Philippines, Russia, Saudi Arabia, Singapore, South Africa, Switzerland, Thailand, Tunisia, Turkey, United States, Vietnam.

[4]Following the NACE Rev. 2 classification, the 28 industries are: 01-03: Agriculture, forestry and fishing; 05-09: Mining and quarrying; 10-12: Food products, beverages and tobacco; 13-15: Textiles, wearing apparel, leather and related products; 16-18: Wood and paper products, printing and reproduction of recorded media; 19: Coke and refined petroleum products; 20-21: Chemicals and chemical products; 22: Rubber and plastic products; 23: Other non-metallic mineral products; 24-25: Basic metals and fabricated metal products; 26-27: Electrical and optical equipment; 28: Machinery and equipment n.e.c.; 29-30: Transport equipment; 31-33: Other manufacturing: repair and installation of machinery and equipment; 35-39: Electricity, gas and water supply; 41-43: Construction; 45-47: Wholesale and retail trade, repair of motor vehicle; 49: Land transport and transport via pipelines; 50: Water transport; 51: Air transport; 52: Warehousing and support activities for transportation; 53: Postal and courier activities; 55-56: Accommodation and food service activities; 58-63: Information and communication; 64-66: Financial and Insurance activities; 68: Real estate activities; 69-82: Professional, scientific, technical, administrative, and support service activities; 84-98: Community social and personal services.

from 18 origin sectors; 17 manufacturing ones, with a breakdown similar to Model 1, plus education[5] (see table 7). The considered time span is 2000-2018.

The International Federation of Robotics provides data on robot installations at the customer's site by type, country, industry, and application, and on the operational stock of industrial robots. The latter concerns the number of robots currently deployed, at year-end. Data is collected from industrial robot suppliers and national robotics associations. An industrial robot is defined as an automatically controlled, reprogrammable, multipurpose, manipulator that is programmable in at least three axes, either fixed in place or mobile and intended for and used in industrial applications.

We use both variables related to "installations" and "operational stock" to assess the robot intensity in the various industries of intermediate goods and services, for origin countries, for each year. Insofar as the industry classification of the IFR data set and that of the TiVA database differ, we could only keep 17 manufacturing industries plus education (see the details in table 7).

Summary statistics by origin and destination countries of the variables used in Model 2 are presented in Tables 8 and 9, respectively for EU and non-EU exporting countries.

[5]Following the NACE Rev.2 classification, the 17 manufacturing sectors are: 01-09: Agriculture, forestry and fishing, mining and quarrying; 10-12: Food products, beverages and tobacco; 13-15: Textiles, wearing apparel, leather and related products; 16: Wood; 17-18: Paper products, printing and reproduction of recorded media;19: Coke and refined petroleum products; 20-21: Chemicals and chemical products; 22: Rubber and plastic products; 23: Other non-metallic mineral products; 24: Manufacture of basic metals; 25: Fabricated metal products; 26-27: Electrical and optical equipment; 28: Machinery and equipment n.e.c.; 29-33 : Transport equipment; 35: Electricity, gas and conditioning supply; 36-39: Water supply; 41-43: Construction. In addition, we also consider the service activity 85: Education.

# 5 Results interpretation

## 5.1 Model 1

### 5.1.1 Baseline specifications

In Model 1, we test the impact of the internet use and fixed broadband subscriptions in both partner countries focusing on the backward GVC participation. We apply Pseudo Poisson Maximum Likelihood (PPML) to control for heteroscedasticity and missing observations as suggested in the literature (see Silva and Tenreyro (2006), Silva and Tenreyro (2011), Yotov et al. (2016) and Borchert and Di Ubaldo (2021)).

For heterogeneity reasons and size and volume of data, we have separated our datasets in two sub-samples: one for the 27 EU exporting countries and the other for the 36 non-EU exporting countries, while keeping all countries for the origin value added exported. The EU exporting data set includes 25 million observations, whereas the non-EU ones has 19 million observations. For instance, in the first subsample we include the microprocessors produced by Korea (country of origin of VA) and incorporated in German exported cars.

We enrich the previous analysis with a study of the case of specific sectors (i.e. service-related sectors only). We keep sectors from NACE code 41 to 98, that is: construction, wholesale and retail trade, transports, postal activities, accommodation and food services, information and communications, insurance and financial services, real estate, professional, scientific, technical, administrative, and support service activities, and community social and personal services.

In table 10, looking at EU exporting countries, for all sectors, we find non-significant impact of the population of both countries. However, the backward participation in GVC raises with GDP per capita, that is with the level of development, and wealth of both partners. The stock of fixed capital of neither country impacts trade. These results hold with both country individual and dyadic fixed effects (columns (1) to (4)). All estimations include sector and time-fixed effects. In the estimation with the country fixed effects (columns (1) and (2)), we note that distance, and common language and legal system behave as usual: distance deters trade, whereas similar legal institutions and language boost it. Colonial links show an usual negative effect which comes from the ability to trade with more different countries provided by a high fragmentation of the components of products allowed by participation in GVCs. As for common membership in colony or a RTA, they present a significant negative sign with internet use and a positive and significant sign with broadband subscriptions (see columns (1) and (2)). Finally, we find no significant impact of technologies on trade for the exporting country i. In opposite, both internet use (columns (1) and (3)) and broadband subscription (columns (2) and (4)) of the country of origin of VA show a positive and significant sign. This outcome highlights the importance of digital technology to participate in GVCs for backward steps of production.

In table 11, analysing non-EU exporting countries, we still find a positive impact of GDP per capita, while population and gross fixed capital formation (GFCF) are never significant. As for gravity variables, distance remains negative and significant and common legal system positive and significant. The other dyadic variables always show a negative sign (see columns (1) and (2)). When it comes to technology variables, internet use show a positive and significant sign for the exporting country, while it slightly negative for the country of origin of VA with dyadic fixed effects (column (3)). The subscription of broadband is positive and significant for the exporting country and non significant for the country of origin of VA (columns (2) and (4)).

As far as services are concerned, only few changes are observed. In table 12, the role of GDP per capita on participation to GVCs is confirmed. In the meantime, population of exporting countries only has a positive and significant impact, while gross capital formation remains non significant. Distance still shows its negative impact and common legal its positive one. We find a negative impact for common borders, in line with the possibility to organise trade with more distant countries in GVCs. Other dyadic variables show ambiguous effect. As it was the case of all sectors, internet use and broadband subscriptions still have a positive effect for countries VA origin and no impact for exporting countries.

In table 13, we analyse the services for non-EU exporting countries. Population of the exporting countries becomes slightly significant and positive for internet use, while for broadband subscription, population of the country of origin of VA is positive and significant with country fixed effects (columns (1) and (3), respectively). GDP per capita remains positive and significant, while all dyadic variable show a negative and significant sign. However, for the technological variables, the results differ. The use of the internet is no longer significant (columns (1) and (3)), while broadband subscriptions is only slightly significant and positive for exporting countries (columns (2) and (4)).

#### 5.1.2 Correction of endogeneity bias: control function

The development of the use of the information and communication technologies (ICT) is concomitant with economic growth. If an increase in the employment of those technologies foster the growth of GDP and GDP per capita, the converse also holds: a higher level of living, assessed by a higher GDP per capita allows a more intensive use of ICT technology (internet and broadband, in our case). Insofar as GDP per capita is also one of the main determinants of trade, we might have an endogeneity bias in our baseline scenario. However, insofar as we are using highly disaggregated data at the sector level for both partner trading countries, the risk of endogeneity is lower than if we were only relying on macroeconomic data. Nevertheless, we have tested and corrected this likelihood of an endogeneity bias with a control function approach, as proposed by Wooldridge (2015) and implemented for ICT by Bachmann et al. (2022) and Acemoglu and Restrepo (2019).

The results of the assessment of endogeinity bias are shown in columns (5) to (8) of tables 10 to 13 for the four samples, where we include in our baseline estimation the residual of stage one estimation (the control function). For the EU, this correction term is always non-significant, which highlights the absence of endogeneity bias. Moreover, the sign, the significance and the value of the estimated coefficients remain the same whether we include the control function term or not (see tables 10 and 12). In the non-EU sample, the control function term is significant (at 1% for the whole sectors and 10% for services activities), however the sign, significance and value of the coefficients are still the same, signaling the absence of endogeneity bias (see tables 11 and 13 , respectively).

So, as endogeneity is not impacting our results, means that disaggregation of data on trade in value added mittigate this potential issue, which can be present at the agrregate level.

### 5.2 Model 2

In Model 2 we analyse the sectoral use of industrial robot by both the exporting country i and the importing country j. We consider 17 manufacturing sectors plus education. The number of observations is smaller than for Model 1: 2.7 millions for the EU exporting countries and 3 millions for the non-EU nations. Both variables related to robots installation and stocks are introduced separately in the regression to avoid multi-collinearity.

In Table 14, the results obtained for Model 2 suggest that the sectoral intensity in robots installation and stock do increase the forward GVC participation for both partners. GDP per capita of both countries has a significant and positive sign, while the population and the gross formation of fixed capital are non-significant. As for gravity variables, they show up with the expected sign: negative for distance and positive for common language and legal system. The only exception is the shared border which shows a negative sign (see columns (1) and (2)).

In table 15, considering only non-EU exporting countries, we still find a positive effect of installation and operational stocks of robots on forward trade for both partner countries. The results are similar to those for the EU, with two exceptions. While population remains most of the time non-significant, it shows up positive and significant for exporting countries when we include the stock of capital. Opposed to the case of EU exporting countries, common borders show a positive sign. So, in manufacturing activities, EU exporting countries tend to develop forward trading links with remote partners, while for the non-EU nations, they reinforce their relations with neighbouring countries. The latter outcome confirms the intuition of Baldwin (2019) of the development of three big hubs of production: factory Europe, factory Americas and factory Asia.

## 6 Conclusion

The use of ICTs - internet use, or fixed broadband subscriptions - in both partner countries tends to raise trade in value added intermediary products, in general. This can indicate an increase in offshoring activities as well. Our robustness checks confirm overall these results. The use of robots (measured through robots installations or stocks) stimulates in general the forward GVC participation.

Among the new challenges faced by our society, digitalisation and automation appear to be the less detriment to the current organisation of production networks. They tend to strengthen the existing backward and forward links existing between countries. Therefore, the current decrease in trade flows could only be the sign of the strengthening of the regional organisation of value chain in factory Europe, factory Asia and factory America, stated by Baldwin (2017).

Information on the Project UNTANGLED

UNTANGLED is a three-year interdisciplinary Horizon 2020 research project that seeks to examine the interconnected trends of globalization, demographic change and technological transformation, and their effects on labour markets in the European Union and beyond. By engaging a broad range of stakeholders, including companies and civil society organisations, we will develop practical policy proposals to help governments cushion the negative impacts of these trends and ensure their benefits are enjoyed fairly across regions and sectors.

Detailed information can be found on the website: $www.untangled-project.eu$

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Table 1: List of countries in our sample by destination (X) and origin

| Country | ISO3 code | EU | Country | ISO3 code | EU |
|---|---|---|---|---|---|
| Argentina | ARG | | Japan | JPN | |
| Australia | AUS | | Kazakstan | KAZ | |
| Austria | AUT | X | Korea | KOR | |
| Belgium | BEL | X | Laos | LAO | |
| Bulgaria | BGR | X | Lithuania | LTU | X |
| Brazil | BRA | | Luxembourg | LUX | X |
| Brunei | | | Latvia | LVA | X |
| Darassalam | BRN | | Morocco | MAR | |
| Canada | CAN | | Mexico | MEX | |
| Switzerland | CHE | | Myanmar | MMR | |
| Chile | CHL | | Malaysia | MYS | |
| China | CHN | | Netherlands | NLD | X |
| Colombia | COL | | Norway | NOR | |
| Costa Rica | CRI | | New Zealand | NZL | |
| Cyprus | CYO | X | Peru | PER | |
| Czeckia | CZE | X | Philippines | PHL | |
| Germany | DEU | X | Poland | POL | X |
| Denmark | DNK | X | Portugal | PRT | X |
| Spain | ESP | X | Roumania | ROU | X |
| Estonia | EST | X | Russia | RUS | |
| Finland | FIN | X | Saudi | | |
| France | FRA | X | Arabia | SAU | |
| United | | X | Singapore | SGP | |
| Kingdom | GBR | X | Slovakia | SVK | X |
| Greece | GRC | X | Slovenia | SVN | X |
| Hong Kong | HKG | | Sweden | SWE | X |
| Hungary | HUN | X | Thailand | THA | |
| Croatia | HRV | X | Tunisia | TUN | |
| Indonesia | IDN | | Turkey | TUR | |
| India | IND | | United | | |
| Ireland | IRL | X | states | USA | |
| Iceland | ISL | | Vietnam | VNM | |
| Israel | ISR | X | South Africa | ZAF | |
| Italy | ITA | X | | | |

**Source: Own elaboration**

Table 2: **Classification of sectors in Model 1 (TiVA)**

| NACE 2 codes | Sector description (base on NACE 2) | Label |
|---|---|---|
| 01-03 | Agriculture, forestry and fishing | 1-AGRI |
| 05-09 | Mining and quarrying | 2-MIN |
| 10-12 | Food products, beverages and tobacco | 3-FOOD |
| 13-15 | Textiles, wearing apparel, leather and related products | 4-TXTL |
| 16-18 | Wood and paper products, printing and reproduction of recorded media | 5-WOOD |
| 19 | Coke and refined petroleum products | 6-COKE |
| 20-21 | Chemicals and chemical products | 7-CHEM |
| 22 | Rubber and plastics products, and other non-metallic mineral products | 8-RUBB1 |
| 23 | Other non-metallic mineral products | 9-RUBB2 |
| 24-25 | Basic metals and fabricated metal products, except machinery and equipment | 10-METL |
| 26-27 | Electrical and optical equipment | 11-ELEC |
| 28 | Machinery and equipment n.e.c. | 12-MACH |
| 29-30 | Transport equipment | 13-TRAN |
| 31-33 | Other manufacturing; repair and installation of machinery and equipment | 14-OMAN |
| 35-39 | Electricity, gas and water supply | 15-GASW |
| 41-43 | Construction | 16-CONS |
| 45-47 | Wholesale and retail trade; repair of motor vehicle | 17-WHSA |
| D49 | Land transport and transport via pipelines | 18-TRA9 |
| D50 | Water transport | 19-TRA0 |
| D51 | Air transport | 20-TRA1 |
| D52 | Warehousing and support activities for transportation | 21-TRA2 |
| D53 | Postal and courier activities | 22-POST |
| 55-56 | Accommodation and food service activities | 23-ACCO |
| 58-63 | Information and communication | 24-INFO |
| 64-66 | Financial and insurance activities | 25-FINA |
| 68 | Real estate activities | 26-REAL |
| 69-82 | Professional, scientific, technical, administrative, and support service activities | 27-PROF |
| 84-98 | Community social and personal services | 28-SOCI |
| 100 | all industries | 00-TOTL |

(Source: Own elaboration from Adarov and Stehrer (2021)) Note: The table shows the classification of sectors used for the first estimation with all sectors with corresponding NACE Rev. 2 codes, sector full name (based on NACE Rev. 2), and short labels.

Table 3: **Summary Statistics - Model 1 - (a) the EU**

| Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| value_FV$^{rs}_{ijt}$ | 25,335,199 | 3.88526 | 210.3494 | 0 | 125888.5 |
| pop$_{it}$ | 25,338,096 | 15.98197 | 1.299554 | 12.98608 | 18.23322 |
| pop$_{jt}$ | 25,338,096 | 16.67732 | 1.714288 | 12.54684 | 21.06171 |
| GDPC$_{it}$ | 25,338v096 | 10.01857 | 0.8000393 | 7.390948 | 11.72544 |
| resid_GDPC$_{it}$ | 25,338,096 | -8.14.E-10 | 0.6968459 | -2.908097 | 1.812278 |
| GDPC$_{jt}$ | 25,338,096 | 9.495106 | 1.264522 | 4.852809 | 11.72544 |
| lGFCF$_{it}$ | 25,338,096 | 24.51117 | 1.744671 | 21.14039 | 38.72428 |
| lGFCF$_{jt}$ | 24,703,056 | 24.97768 | 2.727621 | 19.26333 | 40.59829 |
| dist$_{ij}$ | 25,338,096 | 7.975413 | 1.184326 | 2.951101 | 9.88258 |
| comlang_$off_{jj}$ | 25,338,096 | 0.0393886 | 0.1945177 | 0 | 1 |
| concol$_{jj}$ | 25,338,096 | 0.0094062 | 0.0965285 | 0 | 1 |
| contig$_{jj}$ | 25,338,096 | 0.0499706 | 0.2178842 | 0 | 1 |
| comleg_posttrans$_{jj}$ | 25,338,096 | 0.2886537 | 0.4531366 | 0 | 1 |
| rta$_{jj}$ | 25,338,096 | 0.5580928 | 0.4966138 | 0 | 1 |
| lbroadband$^s_{it}$ | 24,251,472 | 2.412766 | 1.592516 | -5.977956 | 3.812693 |
| lbroadband$^s_{jt}$ | 24,004,512 | 1.783169 | 2.105365 | -8.262551 | 3.836059 |
| linternet$^s_{it}$ | 25,338,096 | 3.908982 | 0.6736459 | 0.6816968 | 4.586361 |
| linternet$^s_{jt}$ | 25,253,424 | 3.574376 | 1.229029 | -8.149084 | 4.595231 |

Note: The table shows the summary statistics by origin and destination country for Model 1 for the EU exporting countries

Table 4: **Summary Statistics - Model 1 - (b) the EU and services**

| Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| value_FV$^{rs}_{ijt}$ | 10,856,748 | 5.015239 | 235.0851 | 0 | 92557.88 |
| pop$_{it}$ | 10,859,184 | 15.98197 | 1.299554 | 12.98608 | 18.23322 |
| pop$_{jt}$ | 10,859,184 | 16.67732 | 1.714288 | 12.54684 | 21.06171 |
| GDPC$_{it}$ | 10,859,184 | 10.01857 | 0.8000393 | 7.390948 | 11.72544 |
| resid_GDPC$_{it}$ | 10,859,184 | -8.14.E-10 | 0.6968459 | -2.908097 | 1.812278 |
| GDPC$_{jt}$ | 10,859,184 | 9.495106 | 1.264522 | 4.852809 | 11.72544 |
| lGFCF$_{it}$ | 10,859,184 | 24.51117 | 1.744671 | 21.14039 | 38.72428 |
| lGFCF$_{jt}$ | 10,587,024 | 24.97768 | 2.727621 | 19.26333 | 40.59829 |
| dist$_{ij}$ | 10,859,184 | 7.975413 | 1.184326 | 2.951101 | 9.88258 |
| comlang_$off_{jj}$ | 10,859,184 | 0.0393886 | 0.1945177 | 0 | 1 |
| concol$_{jj}$ | 10,859,184 | 0.0094062 | 0.0965285 | 0 | 1 |
| contig$_{jj}$ | 10,859,184 | 0.0499706 | 0.2178843 | 0 | 1 |
| comleg_posttrans$_{jj}$ | 10,859,184 | 0.2886537 | 0.4531366 | 0 | 1 |
| rta$_{jj}$ | 10,859,184 | 0.5580928 | 0.4966138 | 0 | 1 |
| lbroadband$^s_{it}$ | $10_3 93_4 88$ | 2.412766 | 1.592516 | -5.977956 | 3.812693 |
| lbroadband$^s_{jt}$ | 10,287,648 | 1.783169 | 2.105365 | -8.262551 | 3.836059 |
| dist$_{ij}$ | 10,859,184 | 7.975413 | 1.184326 | 2.951101 | 9.88258 |
| linternet$^s_{it}$ | 10,859,184 | 3.908982 | 0.6736459 | 0.6816968 | 4.586361 |
| linternet$^s$_$jt$ | 10,822,896 | 3.574376 | 1.229029 | -8.149084 | 4.595231 |

Note: The table shows the summary statistics by origin and destination country for Model 1 for the EU exporting countries and service actitivites

Table 5: **Summary Statistics - Model 1 - (c) non-EU**

| Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| value_FV$^{rs}_{ijt}$ | 19,302,736 | 7.60684 | 452.8035 | 0 | 314279.5 |
| pop$_{it}$ | 19,305,216 | 17.19884 | 1.800451 | 12.54684 | 21.06171 |
| pop$_{jt}$ | 19,305,216 | 17.19884 | 1.800451 | 12.54684 | 21.06171 |
| GDPC$_{it}$ | 19,305,216 | 9.102505 | 1.399493 | 4.852809 | 11.54164 |
| resid_GDPC$_{it}$ | 18,430,272 | -1.46.E-10 | 0.580127 | -2.809004 | 2.834987 |
| GDPC$_{jt}$ | 19,305,216 | 9.102505 | 1.399493 | 4.852809 | 11.54164 |
| lGFCF$_{it}$ | 18,458,496 | 25.34362 | 3.25324 | 19.26333 | 40.59829 |
| lGFCF$_{jt}$ | 18,458,496 | 25.34362 | 3.25324 | 19.26333 | 40.59829 |
| lbroadband$^{s}_{it}$ | 18,148,032 | 1.302403 | 2.312333 | -8.262551 | 3.836059 |
| lbroadband$^{s}_{jt}$ | 18,148,032 | 1.302403 | 2.312333 | -8.262551 | 3.836059 |
| dist$_{ij}$ | 19,305,216 | 8.819942 | 0.9488124 | 2.257588 | 9.892039 |
| comlang_$off_{jj}$ | 19,305,216 | 0.1157407 | 0.3199138 | 0 | 1 |
| concol$_{jj}$ | 19,305,216 | 0.0416667 | 0.1998263 | 0 | 1 |
| contig$_{jj}$ | 19,305,216 | 0.0401235 | 0.1962487 | 0 | 1 |
| comleg_posttrans$_{jj}$ | 19,305,216 | 0.3641975 | 0.4812044 | 0 | 1 |
| rta$_{jj}$ | 19,305,216 | 0.2843567 | 0.4511075 | 0 | 1 |
| linternet$^{s}_{it}$ | 19,192,320 | 3.321945 | 1.469531 | -8.149084 | 4.595231 |
| linternet$^{s}_{jt}$ | 19,192,320 | 3.321945 | 1.469531 | -8.149084 | 4.595231 |

Note: The table shows the summary statistics by origin and destination country for Model 1 for non-EU exporting countries

Table 6: **Summary Statistics - Model 1 - (d) non-EU and services**

| Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| value_FV$^{rs}_{ijt}$ | 8,271,184 | 7.850621 | 403.8498 | 0 | 177768.6 |
| pop$_{it}$ | 8,273,664 | 17.19884 | 1.800451 | 12.54684 | 21.06171 |
| pop$_{jt}$ | 8,273,664 | 17.19884 | 1.800451 | 12.54684 | 21.06171 |
| GDPC$_{it}$ | 8,273,664 | 9.102505 | 1.399493 | 4.852809 | 11.54164 |
| resid_GDPC$_{it}$ | 7,898,688 | -1.46.E-10 | 0.580127 | -2.809004 | 2.834987 |
| GDPC$_{jt}$ | 8,273,664 | 9.102505 | 1.399493 | 4.852809 | 11.54164 |
| lGFCF$_{it}$ | 7,910,784 | 25.34362 | 3.25324 | 19.26333 | 40.59829 |
| lGFCF$_{jt}$ | 7,910,784 | 25.34362 | 3.25324 | 19.26333 | 40.59829 |
| lbroadband$^{s}_{it}$ | 7,777,728 | 1.302403 | 2.312333 | -8.262551 | 3.836059 |
| lbroadband$^{s}_{jt}$ | 7,777,728 | 1.302403 | 2.312333 | -8.262551 | 3.836059 |
| dist$_{ij}$ | 8,273,664 | 8.819942 | 0.9488124 | 2.257588 | 9.892039 |
| comlang_$off_{jj}$ | 8,273,664 | 0.1157407 | 0.3199138 | 0 | 1 |
| concol$_{jj}$ | 8,273,664 | 0.0416667 | 0.1998263 | 0 | 1 |
| contig$_{jj}$ | 8,273,664 | 0.0401235 | 0.1962487 | 0 | 1 |
| comleg_posttrans$_{jj}$ | 8,273,664 | 0.3641975 | 0.4812044 | 0 | 1 |
| rta$_{jj}$ | 8,273,664 | 0.2843567 | 0.4511075 | 0 | 1 |
| linternet$^{s}_{it}$ | 8,225,280 | 3.321945 | 1.469531 | -8.149084 | 4.595231 |
| linternet$^{s}_{jt}$ | 8,225,280 | 3.321945 | 1.469531 | -8.149084 | 4.595231 |

Note: The table shows the summary statistics by origin and destination country for Model 1 for non EU exporting countries and service actitivites

Table 7: **Classification of sectors in Model 2 (ICIO)**

| NACE 2 codes | Sector description (base on NACE 2) | Label |
|---|---|---|
| 01-09 | Agriculture, forestry and fishing<br>Mining and quarrying | 1-AGMI |
| 10-12 | Food products, beverages and tobacco | 2-FOOD |
| 13-15 | Textiles, wearing apparel, leather and related products | 3-TXTL |
| 16 | Wood and product of wood | 4-WOOD |
| 17-18 | Paper products, printing and reproduction of recorded media | 5-PAPE |
| 19 | Coke and refined petroleum products | 6-COKE |
| 20-21 | Chemicals and chemical products | 7-CHEM |
| 22 | Rubber and plastics products, and other non-metallic mineral products | 8-RUB1 |
| 23 | Other non-metallic mineral products | 9-RUB2 |
| 24 | Manufacture of basic metals | 10-MET1 |
| 25 | Fabricated metal products, except machinery and equipment | 11-MET2 |
| 26-27 | Electrical and optical equipment | 12-ELEC |
| 28 | Machinery and equipment n.e.c. | 13-MACH |
| 29-33 | Transport equipment<br>Other manufacturing; repair and installation of machinery and equipment | 14-TRAN |
| 35 | Electricity, gas and air conditionning supply | 15-GASA |
| 36-39 | Water supply | 16-GASW |
| 41-43 | Construction | 17-CONS |
| 85 | Education | 18-EDUC |

Source: Own elaboration

Note: The table shows the classification of sectors used for the second estimation with all sectors with corresponding NACE Rev. 2 codes, sector full name (based on NACE Rev. 2), and short labels.

Table 8: **Summary Statistics - Model 2 - the EU**

| Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| $IC^{rs}_{ijt}$ | 3,429,540 | 1.819512 | 45.0518 | 0 | 13,626.96 |
| GDPC$_{it}$ | 3,429,540 | 18,073.36 | 19,943.12 | 390.0933 | 102,913.5 |
| GDP$_{it}$ | 3,429,540 | 1.38E+12 | 3.09E+12 | 1.50E+10 | 2.05E+13 |
| GFCCF$_{it}$ | 3,311,280 | 1.13E+16 | 5.89E+16 | 2.96E+09 | 4.28E+17 |
| pop$_{it}$ | 3,429,540 | 1.51E+08 | 3.15E+08 | 3,857,700 | 1.40E+09 |
| lGDP$_{it}$ | 3,429,540 | 26.75838 | 1.464006 | 23.43222 | 30.65277 |
| lGDPC$_{it}$ | 3,429,540 | 9.129783 | 1.256141 | 5.966386 | 11.54164 |
| lGFCF$_{it}$ | 3,311,280 | 25.85749 | 3.305358 | 21.80714 | 40.59829 |
| pop$_{it}$ | 3,429,540 | 17.62796 | 1.515601 | 15.16558 | 21.06171 |
| GDPC$_{jt}$ | 3,429,540 | 30,284.77 | 16,421.83 | 3,293.23 | 79,107.6 |
| GDP$_{jt}$ | 3,429,540 | 6.64E+11 | 8.84E+11 | 7.96E+09 | 3.98E+12 |
| GFCC$_{jt}$ | 3,429,540 | 2.26E+14 | 3.54E+15 | 1.99E+09 | 6.57E+16 |
| pop$_{jt}$ | 3,429,540 | 2.10E+07 | 2.34E+07 | 1,317,384 | 8.29E+07 |
| lGDP$_{jit}$ | 3,429,540 | 26.43142 | 1.339072 | 22.79755 | 29.01162 |
| lGDPC$_{jt}$ | 3,429,540 | 10.12979 | 0.671418 | 8.099624 | 11.27856 |
| lGFCC$_{jt}$ | 3,429,540 | 24.97657 | 1.627158 | 21.41045 | 38.72428 |
| resid_GDPC$_{jt}$ | 3,311,886 | 0.0030016 | 0.6048944 | -2.249245 | 2.834987 |
| installatiions$^{s}_{jt}$ | 3,429,540 | 122.4577 | 859.5701 | 0 | 24,928 |
| operatioStock$^{s}_{jt}$ | 3,429,540 | 1,121.793 | 8,199.691 | 0 | 184,261 |
| installatiions$^{r}_{it}$ | 3,429,540 | 301.6514 | 3,130.341 | 0 | 125,754 |
| operatioStock$^{r}_{it}$ | 3,429,540 | 1,906.479 | 19,337.02 | 0 | 524,273 |
| loperatioStock$^{r}_{it}$ | 3,429,540 | 1.723737 | 2.62732 | 0 | 13.16977 |
| loperatioStock$^{s}_{jt}$ | 3,429,540 | 2.905406 | 2.864001 | 0 | 12.12411 |
| linstallatiions$^{r}_{it}$ | 3,429,540 | 0.9393569 | 2.008054 | 0 | 11.74209 |
| linstallatiions$^{s}_{jt}$ | 3,429,540 | 1.521206 | 2.13744 | 0 | 10.12379 |
| linstallatiions$^{2s}_{jt}$ | 3,429,540 | 6.882715 | 13.1398 | 0 | 102.4911 |
| linstallatiions$^{2r}_{it}$ | 3,429,540 | 4.91467 | 14.4102 | 0 | 137.8767 |
| loperatioStock$^{2s}_{jt}$ | 3,429,540 | 16.64388 | 23.02306 | 0 | 146.9941 |
| loperatioStock$^{2r}_{it}$ | 3,429,540 | 9.874077 | 21.91575 | 0 | 173.4428 |
| dist$_{ij}$ | 3,429,540 | 8,036.203 | 4,109.639 | 417.566 | 19,586.18 |
| ldist$_{ij}$ | 3,429,540 | 8.789192 | 0.7415824 | 6.034442 | 9.88258 |
| contig$_{jj}$ | 3,429,540 | 0.0127539 | 0.1122107 | 0 | 1 |
| comlang_$off_{jj}$ | 3,429,540 | 0.0400567 | 0.1960922 | 0 | 1 |
| concol$_{jj}$ | 3,429,540 | 0 | 0 | 0 | 0 |
| comleg_posttrans$_{jj}$ | 3,429,540 | 0.2543222 | 0.4354796 | 0 | 1 |
| rta$_{jj}$ | 3,429,540 | 0.2685876 | 0.443225 | 0 | 1 |

Note: The table shows the summary statistics for Model 2, with EU exporters

Table 9: **Summary Statistics - Model 2 - non-EU**

| Variable | Obs | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| $IC_{ijt}^{rs}$ | 2,719,980 | 22.80062 | 472.5902 | 0 | 166,966.3 |
| $\text{GDPC}_{it}$ | 2,719,980 | 30778.23 | 18,658.31 | 1,659.908 | 91,254.03 |
| $\text{GDP}_{it}$ | 2,719,980 | 6.95E+11 | 9.20E+11 | 5.69E+09 | 3.98E+12 |
| $\text{GFCF}_{it}$ | 2,719,980 | 1.87E+14 | 3.22E+15 | 1.52E+09 | 6.57E+16 |
| $\text{pop}_{it}$ | 2,719,980 | 2.15E+07 | 2.35E+07 | 1,314,545 | 8.29E+07 |
| $\text{lGDP}_{it}$ | 2,719,980 | 26.39573 | 1.448789 | 22.46137 | 29.01162 |
| $\text{lGDPC}_{it}$ | 2,719,980 | 10.10271 | 0.7517358 | 7.414517 | 11.4214 |
| $\text{lGFCC}_{it}$ | 2,719,980 | 24.9404 | 1.647463 | 21.14039 | 38.72428 |
| $\text{pop}_{it}$ | 2,719,980 | 16.29302 | 1.108011 | 14.089 | 18.23322 |
| $\text{GDPC}_{jt}$ | 2,719,980 | 30,284.77 | 16,421.83 | 3,293.23 | 79,107.6 |
| $\text{GDP}_{jt}$ | 2,719,980 | 6,64E+11 | 8.84E+11 | 7.96E+09 | 3.98E+12 |
| $\text{GFCF}_{jt}$ | 2,719,980 | 2.26E+14 | 3.54E+15 | 1.99E+09 | 6.57E+16 |
| $\text{pop}_{jt}$ | 2,719,980 | 2.10E+07 | 2.34E+07 | 1,317,384 | 8.29E+07 |
| $\text{lGDP}_{jit}$ | 2,719,980 | 26.43142 | 1.339072 | 22.79755 | 29.01162 |
| $\text{lGDPC}_{jt}$ | 2,719,980 | 10.12979 | 0.6714181 | 8.099624 | 11.27856 |
| $\text{lGFCC}_{jt}$ | 2,719,980 | 24.97657 | 1.627158 | 21.41045 | 38.72428 |
| $\text{installatiions}_{jt}^{s}$ | 2,719,980 | 122.4577 | 859.5701 | 0 | 24,928 |
| $\text{operatioStock}_{jt}^{s}$ | 2,719,980 | 1,121.793 | 8,199.692 | 0 | 184,261 |
| $\text{installatiions}_{it}^{r}$ | 2,719,980 | 111.5418 | 795.6912 | 0 | 24,928 |
| $\text{operatioStock}_{it}^{r}$ | 2,719,980 | 1,008.226 | 7,559.898 | 0 | 184,261 |
| $\text{loperatioStock}_{it}^{r}$ | 2,719,980 | 2.866642 | 2.828028 | 0 | 12.12411 |
| $\text{loperatioStock}_{jt}^{s}$ | 2,719,980 | 2.905406 | 2.864001 | 0 | 12.12411 |
| $\text{linstallatiions}_{it}^{r}$ | 2,719,980 | 1.509965 | 2.111154 | 0 | 10.12379 |
| $\text{linstallatiions}_{jt}^{s}$ | 2,719,980 | 1.521206 | 2.13744 | 0 | 10.12379 |
| $\text{linstallatiions2}_{jt}^{s}$ | 2,719,980 | 6.882715 | 13.13981 | 0 | 102.4911 |
| $\text{linstallatiions2}_{it}^{r}$ | 2,719,980 | 6.736964 | 12.80388 | 0 | 102.4911 |
| $\text{loperatioStock2}_{jt}^{s}$ | 2,719,980 | 16.64388 | 23.02306 | 0 | 146.9941 |
| $\text{loperatioStock2}_{it}^{r}$ | 2,719,980 | 16.21538 | 22.46401 | 0 | 146.9941 |
| $\text{resid\_GDP}_{jt}$ | 2,719,980 | -0.0021179 | 0.6829899 | -2.908097 | 1.812278 |
| $\text{contig}_{jj}$ | 2,719,980 | 0.1209053 | 0.3260173 | 0 | 1 |
| $\text{dist}_{ij}$ | 2,719,980 | 1272.954 | 724.1518 | 59.617 | 3362.978 |
| $\text{comlang\_}off_{jj}$ | 2,719,980 | 0.0419297 | 0.2004286 | 0 | 1 |
| $\text{concol}_{jj}$ | 2,719;980 | 0.0095295 | 0.0971528 | 0 | 1 |
| $\text{comleg\_posttrans}_{jj}$ | 2,719,980 | 0.334723 | 0.4718936 | 0 | 1 |
| $\text{rta}_{jj}$ | 2,719,980 | 0.9432996 | 0.2312693 | 0 | 1 |
| $\text{ldist}_{ij}$ | 2,719,980 | 6.920584 | 0.7846199 | 4.087941 | 8.120583 |

Note: The table shows the summary statistics for Model 2 - non-EU exporters

Table 10: **Model 1 - PPML the EU exporters and all sectors, with various fixed effects**

| VARIABLES | No CF Model 1 PPML | No CF Model 2 PPML | No CF Model 3 PPML | No CF Model 4 PPML | With CF Model 1 PPML | With CF Model 2 PPML | With CF Model 3 PPML | With CF Model 4 PPML |
|---|---|---|---|---|---|---|---|---|
| $\text{pop}_{it}$ | -0.2748 | -0.3192 | 0.1761 | 0.0478 | -0.2530 | -0.2826 | 0.2112 | 0.0984 |
| | (0.263) | (0.286) | (0.255) | (0.281) | (0.263) | (0.287) | (0.255) | (0.281) |
| $\text{pop}_{jt}$ | 0.1361 | 0.1893 | -0.1076 | -0.0775 | 0.1406 | 0.1969 | -0.1049 | -0.0735 |
| | (0.213) | (0.231) | (0.215) | (0.230) | (0.212) | (0.230) | (0.215) | (0.229) |
| $\text{lGDPC}_{it}$ | 0.7679*** | 0.6800*** | 0.5514*** | 0.5018*** | 0.7380*** | 0.6502*** | 0.5057*** | 0.4620*** |
| | (0.094) | (0.096) | (0.098) | (0.100) | (0.093) | (0.095) | (0.096) | (0.099) |
| $\text{resid\_lGDPC}_{it}$ | | | | | -0.0186 | -0.0201 | -0.0270 | -0.0257 |
| | | | | | (0.018) | (0.019) | (0.018) | (0.019) |
| $\text{lGDPC}_{jt}$ | 0.6584*** | 0.6585*** | 0.5781*** | 0.5965*** | 0.6580*** | 0.6580*** | 0.5800*** | 0.5979*** |
| | (0.029) | (0.030) | (0.027) | (0.028) | (0.029) | (0.030) | (0.027) | (0.028) |
| $\text{lGFCF}_{it}$ | -0.0076 | -0.0071 | -0.0058 | -0.0057 | -0.0087 | -0.0083 | -0.0074 | -0.0072 |
| | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) | (0.006) |
| $\text{lGFCF}_{jt}$ | 0.0045 | 0.0042 | 0.0034 | 0.0033 | 0.0045 | 0.0042 | 0.0034 | 0.0033 |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| $\text{linternet\_use}_{it}$ | 0.0242 | | -0.0294 | | 0.0302 | | -0.0202 | |
| | (0.042) | | (0.042) | | (0.042) | | (0.043) | |
| $\text{linternet\_use}_{jt}$ | 0.0298** | | 0.0640*** | | 0.0289** | | 0.0627*** | |
| | (0.014) | | (0.014) | | (0.014) | | (0.014) | |
| $\text{lbroadband}_{it}$ | | 0.0142 | | -0.0105 | | 0.0155 | | -0.0089 |
| | | (0.012) | | (0.013) | | (0.012) | | (0.013) |
| $\text{lbroadband}_{jt}$ | | 0.0133** | | 0.0281*** | | 0.0129* | | 0.0276*** |
| | | (0.007) | | (0.007) | | (0.007) | | (0.007) |
| $\text{ldist}_{ij}$ | -0.9674*** | -0.9232*** | | | -0.9676*** | -0.9234*** | | |
| | (0.007) | (0.007) | | | (0.007) | (0.007) | | |
| $\text{comlang\_}off_{jj}$ | 0.2082*** | 0.2174*** | | | 0.2084*** | 0.2175*** | | |
| | (0.017) | (0.017) | | | (0.017) | (0.017) | | |
| $\text{contig}_{jj}$ | -0.1937*** | -0.1457*** | | | -0.1943*** | -0.1462*** | | |
| | (0.014) | (0.014) | | | (0.014) | (0.014) | | |
| $\text{comleg\_posttrans}_{jj}$ | 0.4309*** | 0.4143*** | | | 0.4310*** | 0.4144*** | | |
| | (0.008) | (0.008) | | | (0.008) | (0.008) | | |
| $\text{rta}_{ijt}$ | -2.5440*** | -2.6376*** | | | -2.5433*** | -2.6369*** | | |
| | (0.019) | (0.019) | | | (0.019) | (0.019) | | |
| Constant | -1.9915 | -1.3001 | -7.8380 | -5.7112 | -2.1193 | -1.7139 | -8.0211 | -6.2129 |
| | (7.834) | (8.450) | (7.770) | (8.391) | (7.823) | (8.431) | (7.754) | (8.369) |
| Observations | 24,636,655 | 22,806,015 | 24,636,655 | 22,806,015 | 24,636,655 | 22,806,015 | 24,636,655 | 22,806,015 |
| Pseudo R-squared | 0,66 | 0,66 | 0,67 | 0,67 | 0,66 | 0,66 | 0,67 | 0,67 |
| Country i FE | YES | YES | NO | NO | YES | YES | NO | NO |
| Country j FE | YES | YES | NO | NO | YES | YES | NO | NO |
| Country pair FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Sectoral FE (2 countries) | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES |

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: **Model 1 - PPML non-EU exporters and all sectors, with various fixed effects**

| VARIABLES | No CF<br>Model 1<br>PPML | No CF<br>Model 2<br>PPML | No CF<br>Model 3<br>PPML | No CF<br>Model 4<br>PPML | With CF<br>Model 1<br>PPML | With CF<br>Model 2<br>PPML | With CF<br>Model 3<br>PPML | With CF<br>Model 4<br>PPML |
|---|---|---|---|---|---|---|---|---|
| pop$_{it}$ | -0.0034 | 0.1046 | 0.0621 | 0.0005 | -0.0855 | 0.0323 | -0.0460 | -0;0883 |
| | (0.336) | (0.356) | (0.345) | (0.368) | (0.339) | (0.358) | (0.347) | (0.369) |
| pop$_{jt}$ | 0.4055 | 0.2409 | 0.3534 | 0.3645 | 0.4279 | 0.2652 | 0.4096 | 0.4088 |
| | (0.277) | (0.289) | (0.267) | (0.276) | (0.277) | (0.289) | (0.269) | (0.278) |
| lGDPC$_{it}$ | 0.2164*** | 0.2139*** | 0.1226** | 0.1174** | 0.2181*** | 0.2149*** | 0.1220** | 0.1176** |
| | (0.045) | (0.044) | (0.050) | (0.050) | (0.045) | (0.044) | (0.050) | (0.050) |
| resid_lGDPC$_{it}$ | | | | | 0.0688*** | 0.0661** | 0.0673** | 0.0680** |
| | | | | | (0.027) | (0.028) | (0.027) | (0.028) |
| lGDPC$_{jt}$ | 0.5087*** | 0.4918*** | 0.5554*** | 0.5462*** | 0.5046*** | 0.4897*** | 0.5536*** | 0.5448*** |
| | (0.034) | (0.036) | (0.034) | (0.035) | (0.034) | (0.036) | (0.034) | (0.035) |
| lGFCF$_{it}$ | 0.0005 | 0.0003 | -0.0050 | -0.0049 | -0.0005 | -0.0005 | -0.0061 | -0.0060 |
| | (0.023) | (0.023) | (0.029) | (0.030) | (0.023) | (0.023) | (0.029) | (0.030) |
| lGFCF$_{jt}$ | 0.0058 | 0.0043 | 0.0110 | 0.0107 | 0.0058 | 0.0041 | 0.0111 | 0.0108 |
| | (0.012) | (0.012) | (0.009) | (0.009) | (0.012) | (0.012) | (0.009) | (0.009) |
| linternet_use$_{it}$ | 0.0453** | | 0.0463** | | 0.0381* | | 0.0442** | |
| | (0.019) | | (0.020) | | (0.020) | | (0.020) | |
| linternet_use$_{jt}$ | -0.0231 | | -0.0297* | | -0.0140 | | -0.0271* | |
| | (0.016) | | (0.016) | | (0.016) | | (0.016) | |
| ldist$_{ij}$ | -1.6987*** | -1.6959*** | | | -1.6983*** | -1.6958*** | | |
| | (0.010) | (0.010) | | | (0.010) | (0.010) | | |
| comlang_off_{jj$ | -0.9254*** | -0.8935*** | | | -0.9251*** | -0.8926*** | | |
| | (0.032) | (0.032) | | | (0.033) | (0.033) | | |
| contig$_{jj}$ | -1.8855*** | -1.9103*** | | | -1.8848*** | -1.9094*** | | |
| | (0.036) | (0.038) | | | (0.036) | (0.038) | | |
| comleg_posttrans$_{jj}$ | 0.5120*** | 0.4803*** | | | 0.5124*** | 0.4802*** | | |
| | (0.015) | (0.015) | | | (0.015) | (0.015) | | |
| rta$_{ijt}$ | -0.6185*** | -0.6364*** | | | -0.6193*** | -0.6371*** | | |
| | (0.022) | (0.022) | | | (0.022) | (0.022) | | |
| lbroadband$_{it}$ | | 0.0320*** | | 0.0290*** | | 0.0281*** | | 0.0276*** |
| | | (0.010) | | (0.010) | | (0.010) | | (0.010) |
| lbroadband$_{jt}$ | | -0.0028 | | -0.0050 | | 0.0013 | | -0.0039 |
| | | (0.009) | | (0.009) | | (0.009) | | (0.009) |
| Constant | 1.8971 | 3.2160 | -8.5101 | -7.3978 | 3.0510 | 4.1486 | -7.4941 | -6.5299 |
| | (10.905) | (11.446) | (10.602) | (11.100) | (10.934) | (11.472) | (10.626) | (11.126) |
| Observations | 17,492,552 | 16,116,652 | 17,492,552 | 16,116,652 | 17,465,112 | 16,089,212 | 17,465,112 | 16,089,212 |
| Pseudo R-squared | 0,66 | 0,66 | 0,67 | 0,67 | 0,66 | 0,66 | 0,67 | 0,67 |
| Country i FE | YES | YES | NO | NO | YES | YES | NO | NO |
| Country j FE | YES | YES | NO | NO | YES | YES | NO | NO |
| Country pair FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Sectoral FE (2 countries) | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES |

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: **Model 1 - PPML the EU exporters and services, with various fixed effects**

| VARIABLES | No CF Model 1 PPML | No CF Model 2 PPML | No CF Model 3 PPML | No CF Model 4 PPML | With CF Model 1 PPML | With CF Model 2 PPML | With CF Model 3 PPML | With CF Model 4 PPML |
|---|---|---|---|---|---|---|---|---|
| $\text{pop}_{it}$ | 0.480* | 0.0715 | 0.540** | 0.418 | 0.5086* | 0.1028 | 0.5695** | 0.4587 |
| | (0.275) | (0.301) | (0.267) | (0.292) | (0.275) | (0.302) | (0.267) | (0.293) |
| $\text{pop}_{jt}$ | 0.0541 | 0.316 | 0.0623 | 0.110 | 0.0524 | 0.3247 | 0.0679 | 0.1157 |
| | (0.297) | (0.312) | (0.302) | (0.322) | (0.297) | (0.312) | (0.302) | (0.322) |
| $\text{lGDPC}_{it}$ | 0.579*** | 0.638*** | 0.526*** | 0.477*** | 0.5389*** | 0.6047*** | 0.4785*** | 0.4347*** |
| | (0.125) | (0.127) | (0.127) | (0.132) | (0.127) | (0.129) | (0.130) | (0.134) |
| $\text{resid\_lGDPC}_{it}$ | | | | | -0.0223 | -0.0204 | -0.0255 | -0.0243 |
| | | | | | (0.022) | (0.022) | (0.022) | (0.022) |
| $\text{lGDPC}_{jt}$ | 0.553*** | 0.665*** | 0.564*** | 0.591*** | 0.5542*** | 0.6641*** | 0.5669*** | 0.5936*** |
| | (0.0437) | (0.0468) | (0.0409) | (0.0433) | (0.044) | (0.047) | (0.041) | (0.043) |
| $\text{lGFCF}_{it}$ | -0.00396 | -0.00540 | -0.00412 | -0.00397 | -0.0051 | -0.0065 | -0.0056 | -0.0054 |
| | (0.00686) | (0.00671) | (0.00677) | (0.00676) | (0.007) | (0.007) | (0.007) | (0.007) |
| $\text{lGFCF}_{jt}$ | 0.00377 | 0.00441 | 0.00379 | 0.00366 | 0.0036 | 0.0044 | 0.0038 | 0.0037 |
| | (0.00744) | (0.00741) | (0.00737) | (0.00737) | (0.007) | (0.007) | (0.007) | (0.007) |
| $\text{linternet\_use}_{it}$ | -0.0634 | | -0.0535 | | -0.0556 | | -0.0452 | |
| | (0.0564) | | (0.0569) | | (0.057) | | (0.057) | |
| $\text{linternet\_use}_{jt}$ | 0.104*** | | 0.0955*** | | 0.1021*** | | 0.0936*** | |
| | (0.0194) | | (0.0188) | | (0.019) | | (0.019) | |
| $\text{ldist}_{ij}$ | -2.005*** | -0.874*** | | | -2.0049*** | -0.8739*** | | |
| | (0.00793) | (0.0102) | | | (0.008) | (0.010) | | |
| $\text{comlang\_}off_{jj}$ | -0.270*** | 0.223*** | | | -0.2704*** | 0.2232*** | | |
| | (0.0300) | (0.0230) | | | (0.030) | (0.023) | | |
| $\text{comcol}_{ij}$ | -0.709*** | 0.0998** | | | -0.7089*** | 0.1009** | | |
| | (0.0486) | (0.0451) | | | (0.049) | (0.045) | | |
| $\text{contig}_{jj}$ | -1.431*** | -0.132*** | | | -1.4308*** | -0.1321*** | | |
| | (0.0205) | (0.0202) | | | (0.020) | (0.020) | | |
| $\text{comleg\_posttrans}_{jj}$ | 1.212*** | 0.379*** | | | 1.2121*** | 0.3793*** | | |
| | (0.0197) | (0.0104) | | | (0.020) | (0.010) | | |
| $\text{lbroadband}_{it}$ | | 0.0127 | | -0.0156 | | 0.0139 | | -0.0142 |
| | | (0.0166) | | (0.0174) | | (0.017) | | (0.017) |
| $textlbroadband_{jt}$ | | 0.0284*** | | 0.0416*** | | 0.0278*** | | 0.0409*** |
| | | (0.00925) | | (0.00915) | | (0.009) | | (0.009) |
| $[rta]_{ijt}$ | | -2.797*** | | | | -2.7965*** | | |
| | | (0.0272) | | | | (0.027) | | |
| Constant | -5.341 | -9.837 | -16.31* | -14.68 | -5.3846 | -10.1439 | -16.4247* | -15.0354 |
| | (8.962) | (9.715) | (8.993) | (9.647) | (8.957) | (9.708) | (8.985) | (9.638) |
| Observations | 10,557,372 | 9,772,812 | 10,557,372 | 9,772,812 | 10,557,372 | 9,772,812 | 10,557,372 | 9,772,812 |
| Country i FE | YES | YES | NO | NO | YES | YES | NO | NO |
| Country j FE | YES | YES | NO | NO | YES | YES | NO | NO |
| Country pair FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Sectoral FE (2 countries) | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES |

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: **Model 1 - PPML the non-EU exporters and services, with various fixed effects**

| VARIABLES | No CF Model 1 PPML | No CF Model 2 PPML | No CF Model 3 PPML | No CF Model 4 PPML | With CF Model 1 PPML | With CF Model 2 PPML | With CF Model 3 PPML | With CF Model 4 PPML |
|---|---|---|---|---|---|---|---|---|
| $pop_{it}$ | 0.2795 | 0.4239 | 0.4892* | 0.3899 | 0.2040 | 0.3624 | 0.3666 | 0.2885 |
| | (0.255) | (0.266) | (0.260) | (0.275) | (0.258) | (0.268) | (0.268) | (0.279) |
| $pop_{jt}$ | 0.5808** | 0.3222 | 0.3669 | 0.3717 | 0.5775** | 0.3253 | 0.4304* | 0.4271 |
| | (0.256) | (0.269) | (0.257) | (0.269) | (0.255) | (0.269) | (0.259) | (0.271) |
| $lGDPC_{it}$ | 0.2600*** | 0.2511*** | 0.1314*** | 0.1150** | 0.2629*** | 0.2534*** | 0.1316*** | 0.1160** |
| | (0.046) | (0.045) | (0.048) | (0.047) | (0.046) | (0.045) | (0.048) | (0.047) |
| $resid\_lGDPC_{it}$ | | | | | 0.0571* | 0.0530 | 0.0550* | 0.0551* |
| | | | | | (0.031) | (0.033) | (0.031) | (0.032) |
| $lGDPC_{jt}$ | 0.5214*** | 0.5150*** | 0.5884*** | 0.5933*** | 0.5193*** | 0.5143*** | 0.5887*** | 0.5939*** |
| | (0.038) | (0.039) | (0.039) | (0.041) | (0.038) | (0.039) | (0.039) | (0.041) |
| $lGFCF_{it}$ | -0.0019 | -0.0034 | 0.0010 | 0.0019 | -0.0034 | -0.0047 | -0.0002 | 0.0006 |
| | (0.007) | (0.007) | (0.006) | (0.006) | (0.007) | (0.007) | (0.006) | (0.006) |
| $lGFCF_{jt}$ | -0.0050 | -0.0069 | -0.0063 | -0.0076 | -0.0049 | -0.0069 | -0.0064 | -0.0076 |
| | (0.007) | (0.007) | (0.006) | (0.006) | (0.007) | (0.007) | (0.006) | (0.006) |
| $linternet\_use_{it}$ | 0.0406 | | 0.0387 | | 0.0345 | | 0.0372 | |
| | (0.027) | | (0.029) | | (0.027) | | (0.029) | |
| $linternet\_use_{jt}$ | -0.0111 | | -0.0145 | | -0.0033 | | -0.0126 | |
| | (0.019) | | (0.018) | | (0.019) | | (0.018) | |
| $ldist_{ij}$ | -1.6220*** | -1.6194*** | | | -1.6217*** | -1.6193*** | | |
| | (0.008) | (0.008) | | | (0.008) | (0.008) | | |
| $comlang\_off_{jj}$ | -0.7325*** | -0.7058*** | | | -0.7319*** | -0.7048*** | | |
| | (0.040) | (0.040) | | | (0.040) | (0.040) | | |
| $comcol_{ij}$ | -2.1211*** | -2.1476*** | | | -2.1206*** | -2.1468*** | | |
| | (0.051) | (0.053) | | | (0.051) | (0.053) | | |
| $contig_{jj}$ | 0.6731*** | 0.6446*** | | | 0.6733*** | 0.6444*** | | |
| | (0.016) | (0.016) | | | (0.016) | (0.016) | | |
| $comleg\_posttrans_{jj}$ | -0.6458*** | -0.6637*** | | | -0.6470*** | -0.6647*** | | |
| | (0.020) | (0.020) | | | (0.020) | (0.020) | | |
| $lbroadband_{it}$ | | 0.0309** | | 0.0271* | | 0.0278** | | 0.0263* |
| | | (0.014) | | (0.015) | | (0.014) | | (0.015) |
| $lbroadband_{jt}$ | | -0.0029 | | -0.0034 | | 0.0007 | | -0.0026 |
| | | (0.011) | | (0.010) | | (0.011) | | (0.010) |
| $rta_{ijt}$ | -7.4617 | -5.0233 | -16.6244** | -14.6903* | -5.9681 | -3.9168 | -15.4944* | -13.8136 |
| | (8.543) | (8.948) | (8.395) | (8.717) | (8.594) | (8.979) | (8.425) | (8.738) |
| Constant | -7.4617 | -5.0233 | -16.6244** | -14.6903* | -5.9681 | -3.9168 | -15.4944* | -13.8136 |
| | (8.543) | (8.948) | (8.395) | (8.717) | (8.594) | (8.979) | (8.425) | (8.738) |
| Observations | 7,495,432 | 6,905,772 | 7,495,432 | 6,905,772 | 7,483,672 | 6,894,012 | 7,483,672 | 6,894,012 |
| Country i FE | YES | YES | NO | NO | YES | YES | NO | NO |
| Country j FE | YES | YES | NO | NO | YES | YES | NO | NO |
| Country pair FE | NO | NO | YES | YES | NO | NO | YES | YES |
| Sectoral FE (2 countries) | YES | YES | YES | YES | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES | YES | YES | YES | YES |

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: **Model 2 - PPML with robot installation and stock, with EU intermediate product importing countries, various fixed effects**

| VARIABLES | (1)<br>Eq.1<br>PPML | (2)<br>Eq.2<br>PPML | (3)<br>Eq.3<br>PPML | (4)<br>Eq.4<br>PPML |
|---|---|---|---|---|
| $\text{pop}_{it}$ | 0.2186 | -0.3067 | 0.1603 | -0.3673 |
| | (0.306) | (0.309) | (0.317) | (0.320) |
| $\text{pop}_{jt}$ | 0.1264 | -0.4021 | 0.2320 | -0.2558 |
| | (0.335) | (0.339) | (0.336) | (0.340) |
| $\text{lGDPC}_{it}$ | 0.6356*** | 0.5100*** | 0.7222*** | 0.6011*** |
| | (0.079) | (0.077) | (0.080) | (0.078) |
| $\text{lGDPC}_{jt}$ | 0.6497*** | 0.5345*** | 0.5506*** | 0.4414*** |
| | (0.092) | (0.090) | (0.092) | (0.091) |
| $\text{lGFCF}_{it}$ | 0.0010 | 0.0004 | 0.0017 | 0.0014 |
| | (0.006) | (0.006) | (0.005) | (0.005) |
| $\text{lGFCF}_{jt}$ | 0.0048 | 0.0042 | 0.0041 | 0.0033 |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $\text{lGFCF}_{it}$ | 0.0010 | 0.0004 | 0.0017 | 0.0014 |
| | (0.006) | (0.006) | (0.005) | (0.005) |
| $\text{lGFCF}_{jt}$ | 0.0048 | 0.0042 | 0.0041 | 0.0033 |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| $\text{installations}^{r}_{it}$ | 0.0881*** | | 0.0862*** | |
| | (0.008) | | (0.008) | |
| $\text{installations}^{s}_{jt}$ | 0.0638*** | | 0.0635*** | |
| | (0.008) | | (0.008) | |
| $\text{loperatioStock}^{r}_{it}$ | | 0.0928*** | | 0.0916*** |
| | | (0.008) | | (0.008) |
| $\text{loperatioStock}^{s}_{jt}$ | | 0.0719*** | | 0.0716*** |
| | (0.013) | | (0.013) | |
| $\text{ldist}_{ij}$ | -1.8004*** | -1.8000*** | | |
| | (0.010) | (0.010) | | |
| comlang_$off_{jj}$ | 0.1080*** | 0.1086*** | | |
| | (0.031) | (0.031) | | |
| $\text{contig}_{jj}$ | -1.1396*** | -1.1392*** | | |
| | (0.017) | (0.017) | | |
| comleg_posttrans$_{jj}$ | 0.9147*** | 0.9144*** | | |
| | (0.007) | (0.007) | | |
| Constant | -4.5610 | 15.9291 | -14.4114 | 5.3041 |
| | (10.361) | (10.530) | (10.327) | (10.498) |
| Observations | 2,719,980 | 2,719,980 | 2,719,980 | 2,719,980 |
| Pseudo R-squared | 0.7083 | 0.7086 | 0.7278 | 0.7281 |
| Country i FE | YES | YES | NO | NO |
| Country j FE | YES | YES | NO | NO |
| Country pair FE | NO | NO | YES | YES |
| Sectoral FE (2 countries) | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES |

Note: Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: **Model 2 - PPML with robot installation and stock, with non-EU intermediate product importing countries, various fixed effects**

| VARIABLES | (1) Eq. 1 PPML | (2) Eq. 2 PPML | (3) Eq. 3 PPML | (4) Eq. 4 PPML |
|---|---|---|---|---|
| $\text{pop}_{it}$ | 0.3093 | 0.8943*** | 0.3673 | 0.9327*** |
| | (0.309) | (0.313) | (0.300) | (0.307) |
| $\text{pop}_{jt}$ | -0.5854 | -0.7243 | -0.5206 | -0.6140 |
| | (0.471) | (0.467) | (0.486) | (0.489) |
| $\text{lGDPC}_{it}$ | 0.8104*** | 0.7030*** | 0.7984*** | 0.6939*** |
| | (0.052) | (0.052) | (0.051) | (0.051) |
| $\text{lGDPC}_{jt}$ | 0.9158*** | 0.8654*** | 0.7855*** | 0.7089*** |
| | (0.128) | (0.127) | (0.127) | (0.126) |
| $\text{lGFCF}_{it}$ | 0.0041 | 0.0098 | 0.0045 | 0.0101 |
| | (0.012) | (0.012) | (0.011) | (0.012) |
| $\text{lGFCF}_{jt}$ | -0.0063 | -0.0071 | -0.0061 | -0.0065 |
| | (0.008) | (0.008) | (0.008) | (0.008) |
| $\text{ldist}_{ij}$ | -1.6291*** | -1.6305*** | | |
| | (0.055) | (0.055) | | |
| $\text{comlang\_off}_{jj}$ | 0.8129*** | 0.8121*** | | |
| | (0.045) | (0.045) | | |
| $\text{contig}_{jj}$ | 0.2048** | 0.1991** | | |
| | (0.082) | (0.081) | | |
| $\text{comleg\_posttrans}_{jj}$ | 0.1235*** | 0.1248*** | | |
| | (0.027) | (0.027) | | |
| $\text{installatiions}^{r}_{it}$ | 0.2064*** | | 0.2050*** | |
| | (0.007) | | (0.007) | |
| $\text{installatiions}^{s}_{jt}$ | 0.0402*** | | 0.0407*** | |
| | (0.008) | | (0.008) | |
| $\text{loperatioStock}^{r}_{it}$ | | 0.1972*** | | 0.1964*** |
| | | (0.007) | | (0.007) |
| $\text{loperatioStock}^{s}_{jt}$ | | 0.0624*** | | 0.0634*** |
| | | (0.008) | | (0.008) |
| Constant | 3.2731 | -3.8117 | -10.6055 | -17.8963* |
| | (10.553) | (10.582) | (10.247) | (10.386) |
| Observations | 3,074,760 | 3,074,760 | 3,074,760 | 3,074,760 |
| Pseudo R-squared | 0.5888 | 0.5890 | 0.6128 | 0.6130 |
| Country i FE | YES | YES | NO | NO |
| Country j FE | YES | YES | NO | NO |
| Country pair FE | NO | NO | YES | YES |
| Sectoral FE (2 countries) | YES | YES | YES | YES |
| Time FE | YES | YES | YES | YES |

Note: Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$