The impact of technology and connectivity on trade patterns *

Isabelle Rabaud† Camelia Turcu ‡ Marcel Voia §

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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. This suggests an increase in the offshoring of intermediary inputs. 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 52 exporting countries and 20 EU importing economies, over the period 2000-2018. The results are mixed, suggesting non-linearities in some cases. Several explanations can be put forward, among which, under specific circumstances, the presence of possible reshoring.

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

JEL codes: F14, J24, L80, O33

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†University of Orléans, LEO, corresponding author, Email: isabelle.rabaud@univ-orleans.fr

‡University of Orléans, LEO, Email:camelia.turcu@univ-orleans.fr

§University of Orléans, LEO, Email:marcel.voia@univ-orleans.fr

Contents

1 Introduction

In 2017, Adidas decided to re-yshore part of its production of trainees from Asia towards Ansbach (Germany) and 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 and in general lives 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. How does these new technologies affect the location of production (offshoring, reshoring)? This is our research question.

The impacts of technology on the level and the quality of employment and growth have been largely explored (Acemoglu and Restrepo (2020); Autor et al. (2016); Bachmann et al. (2022); Dauth et al. (2021); and Lewandowski et al. (2022)). The role of the development of the internet on trade expansion has also been considered. However the impact of the new technological revolution, with both increased digitalisation of production and higher intensity of robot on the participation in Global Value Chains (GVCs) has focused less attention, in particular in the service sector. This paper fills this gap by investigating the impact of both digitalisation and robotisation on both backward and forward GVCs participations in manufacturing and services activities.

First, relying on the TiVA database we analyze 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, 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 in value added. Further, we investigate the impact of robotization on forward GVC participation. Here, results are mixed, suggesting non-linearities in some cases. Several explanations can be put forward, among which, under specific circumstances, is the presence of possible reshoring.

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

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/re—shoring, on the other hand. We propose some stylised facts in Section 3. We present an overview of the data and methodology in Section 4, followed by the results presented in Section 5. Some conclusions are drawn at the end of the paper in Section 7.

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 lead to a greater involvement in market economies and trade of more countries, in particular the integration of Eastern European countries and the integration 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 globalisation on the breakdown of tasks. From micro-data surveys on job tasks collected in 47 countries and 19 industries, they show that computer use and robotisation (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.

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

Among low-skilled occupations, globalization contributes the most insofar as offshoring enables nations to specialise in the activities relatively intensive in their abundant factors, within industries.

When it comes to the relation between digital technology and globalisation 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.

In opposite, 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 re-shoring, on the one hand. On the other hand, these technologies require intermediary consumption that can only be produced abroad and thus off-shored. Hence whether automation and offshoring are substitute or complementary remain a pending question.

In opposite to 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 not clear-cut.

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 offshoring has been. The geography of worldwide production will only change when large shocks in the world economy are forecasted to be persistent. Even if relative costs shocks (rising wages or trade costs) make production unprofitable, European firms might be reluctant to relocate production. Only if that trend costs are viewed as secular, will they choose to abandon locations (Antràs, 2020).

What do stylised facts in the literature tell us? Do they confirm the general view 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 off-shored 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 off-shored 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 off-shored 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 that 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 re-shoring measure laborg 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 re-shoring, 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 the speeds of information transmission over fiber optic cable increased less; 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 might have gone down. Meanwhile, the amount of R&D spending needed to respect Moore's 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. On the opposite, the number of mobile phones has reached a ceiling since 2012 in the EU.

Regarding broadband access, we observe a progression of the equipment between 2010 and 2020. The rise is the most important for Central and Eastern European Countries (CEECs), see figure 5.

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 6). Figure 7 shows the four big countries remain the leaders in the robot intensity of manufacturing industries in 2020. Germany strengthens its leadership. However, we note the emergence of Central countries of the EU15 such as Poland, the Czech Republic or Slovakia. Medium size European countries also catch up the biggest followers in this technology rice, like the Netherlands and Austria (see figure 7).

When it comes to the sectoral distributions of robots, on figure 8, we also observe a strong concentration. 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 reinforce the existence of a high concentration of robot in the extractive sector (see figure 9).

4 Methodology and data

4.1 Methodology

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 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 (PPML, thereafter) estimator in order to consider zero flows and to take into account the issue of heteroscedasticity in bilateral trade data. Second, we introduce 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 (country j) of gross exports (X_{ijt}^k) from sector k 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:

$$
\begin{aligned}
X_{ijt}^k = exp[&\beta_0 + \beta_1 ln(\text{pop}_{it}) + \beta_2 ln(\text{pop}_{jt}) + \beta_3 ln(\text{GDPC}_{it}) + \beta_4 ln(\text{GDPC}_{jt}) \\
&+ \beta_5 ln(\text{GFCF}_{it}) + \beta_6 ln(\text{GFCF}_{jt}) + \beta_7 ln(Techno_{it}) + \beta_8 ln(Techno_{jt}) \\
&+ \beta_9 ln(dist_{ij}) + \beta_{10} Gravity_{ij} + \lambda_i + \lambda_j + \lambda_k + \lambda_t]\xi_{ijt}^k, (1)
\end{aligned}
$$

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 takes the values of:

- $internet_use$: 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, participation in common Regional Trade Agreements (RTA) for both country i and the country j,

a set of fixed effects, exporter λ_i, origin country of VA λ_j, sectoral λ_k, and temporal λ_t, and

ϵ_{ijt}^{k}, an error term.

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 of productivity insofar as Adarov et al. (2022) have shown that tangible and intangible ICT capital enhances productivity both at aggregate and sectoral level, 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 Robot_{rit} (Robot_{sjt}), is either the installations or the operational stock of robot in industry r (s) of country i (i) 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 calculate it under the assumption of an average service life of 12 years, after which the robot is totally depreciated and its value drops to zero.

As previously, we use the Pseudo Poisson Maximum Likelihood (PPML)[2] for our reported specifications.

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 intermediary consumption of product that is coming from 63 origin countries (of which 36 non-EU) to 27 EU destination countries over the period 2000 until 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. 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

[2]As a robustness check we are employing the transformed LSDV specification.

which can be 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.[3]

We have 36 non-EU origin countries.[4]

Table 2 presents the Eurostat classification of economic activities by NACE 2 sectors[5]

Summary statistics by origin and destination countries of the variables used in Model 1 are presented in Table 3.

Model 2 analyses 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 loose Bulgaria, Croatia, Cyprus, Luxembourg, Roumania, Slovenia and the United Kingdom. As for the origin countries, they include the 20 EU

[3]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 Kingdom.

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

[5]The considered economic activities by NACE 2 sectors are: Agriculture, forestry and fishing, Mining and quarrying, Food products, beverages and tobacco, Textiles, wearing apparel, leather and related products, Wood and paper products, printing and reproduction of recorded media, Coke and refined petroleum products, Chemicals and chemical products, Rubber and plastics products, and other non-metallic mineral products, Other non-metallic mineral products, Basic metals and fabricated metal products, except machinery and equipment, Electrical and optical equipment, Machinery and equipment n.e.c., Transport equipment , Other manufacturing; repair and installation of machinery and equipment, Electricity, gas and water supply, Construction, Wholesale and retail trade; repair of motor vehicle, Land transport and transport via pipelines, Water transport, Air transport, Warehousing and support activities for transportation, Postal and courier activities, Accommodation and food service activities, Information and communication, Financial and insurance activities, Real estate activities, Professional, scientific, technical, administrative and support service activities, Community social and personal services, total industries.

exporting countries plus 2 other EU countries (Romania, and the United Kingdom) and 30 remaining non-EU countries are the same as for Model 1 and table 1, with the exception of Brunei, Chile, Iceland, Kazakstan, Laos, and Myanmar. We conduct the analysis using 18 used destination industries coming from 18 origin sectors (see table 4). 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, re-programmable, 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 "installation" 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 10 industries.

Summary statistics by origin and destination countries of the variables used in Model 2 are presented in Table 5.

5 Results interpretation

5.1 Baseline specifications

In Model 1, we test the impact of the internet use and fixed broadband subscriptions as proxies for digitalisation in both partner countries focusing on the backward GVC participation. We apply Pseudo Poisson Maximum Likelihood (PPML) to control for the missing observations and for heteroscedascitiy we relate to the literature (see Silva and Tenreyro (2006), Silva and Tenreyro (2011), Yotov et al. (2016) and Borchert et al. (2021)). The results from the baseline scenario specification are summarized in Table

In Model 1, we test the impact of the internet use and fixed broadband subscriptions in both partner countries on backward GVC participation. We apply Pseudo Poisson Maximum Likelihood (PPML) to control for the missing observations and for heteroscedascitiy, in line with the literature (see Silva and Tenreyro (2006), Silva and Tenreyro (2011), Yotov et al. (2016) and Borchert et al. (2021)). The baseline scenario results are summarized in table 6 for the sectoral breakdown of the exporting country (i) and table 7 for the sectoral detail of the country of origin of VA (j).

When looking at sectoral detail of the exporting country, in table 6, we find a non-significant impact of the population of both countries. Nation size does not affect the backward participation. 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 impact trade (columns (1) and (2)). These results hold with both country individual and dyadic fixed effects. In the second case, the stock of fixed capital of the country of origin of value added increases trade, while the one of the exporting country remains non significant. This outcome highlights the differences in endowments of countries depending on the level at which they participate in GVCs (see columns (3) and (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 legal system behave as usual: distance deters trade, whereas similar legal institutions boosts it. However, shared borders and language 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 GVCs participation. Finally, using all sample data, we find no significant impact of technologies on trade, with the exception of the positive and significant effect of internet use of the exporting country, when we control for the dyadic specificity of countries (see column (3)).

When analysing the sectoral detail of the country of origin of VA in table 7, we still find a positive impact of GDP per capita, while population and gross fixed capital formation (GFCF) remain non significant. The sign of the gravity variables remains also the same with a decreased participation in backward GVC with distance and increased participation with similarity to legal systems. However, with dyadic fixed effect, which controls for omitted shocks affecting simultaneously both countries, we found a negative impact of the population of the VA origin country and a positive effect of its GFCF. This outcome confirms the highest openness to trade, and participation in GVSx of small countries, on the one hand. On the other hand, it highlights the differences in endowments of countries depending on the level at which they participate in GVCs. As for technology, we still find a positive and significant effect of internet use of the exporting country, when we control for the dyadic specificity of countries (see column (3)).

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 raises also this participation. The GDPC in country i acts in the same direction while the size of country has a negative effect. All the other variables related to population or gross fixed captial formation (GFCF) are non significant (see table 8).

5.2 Results for subsamples

We enrich the previous analysis along several directions. First, we re-run Model 1 for the case of specific sectors (i.e. service-related sectors only). Second, in Model 1, we put a focus on the case of EU countries. Third, we apply the Model 1 both to the case of services and the EU countries. Fourth, we reconsider Model 2 allowing for non-linearities, in order to check the presence of possible thresholds. First, in the case of services, 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 9, the results are slightly changed when we consider only services.

First, the population of the exporting country now has a positive impact on its backward participation to GVCs, as well as that of the country of origin of value added. When we control for shocks common to both countries, the population of the VA origin country has a negative impact on trade (see columns (4) and (5)). The GDP per capita of both partners still increases their implication in backward GVCs. The stock of fixed capital remains non-significant for both countries, in line with the idea that physical capital is not a major factor in most services production. Distance keep its negative impact on trade as is the case for shared language, border and colonial history, whereas common legal system continues to positively impact trade. As for the whole sample, only the internet use of the country of origin of VA has a positive and significant impact on GVCs participation, when we control for dyadic country shocks (see columns (4) and (5)).

Second, we have also restricted the sample to EU exporting countries only. Table 10 underlines results similar to the overall sample. Population is not significant while GDPC in both destination and origin countries stimulate the participation in the backward GVC. GFCF is still non significant. However, the digitalization has a higher impact. The internet use of the exporting country and the broadband subscription of the country of origin of VA now foster participation if backward GVCs, which highlights the different levels of development and wealth of participants on each size (see columns (1) and (2)). When we control for shocks commons to both countries, the internet use of the EU exporting countries and the broadband subscription of the VA origin country become slightly negative, which reinforces the differences of digital infrastructure effect on each size of the GVC (see columns (3) and (4)).

Third, we re-run Model 1 by considering the EU countries and activities in the services sectors only. We found similar results for macroeconomic and gravity variables as for the estimations of services (see Table 11); the internet use or the VA origin country has a positive impact, when we control for common country shocks.

When we consider the sectoral breakdown of the VA origin country, we find the same outcome for the subsamples of services (see table 12. As for the EU subsample in table 13, the macroeconomic and gravity variables have the same effect.

We found similar results for macroeconomic and gravity variables as in the estimations of services (see table 11); the internet use and broadband subscription of the exporting EU country boosts backward GVC participation, while internet use of VA origin country deters such trade. When common shocks of countries are controlled for, we also find a negative impact of broadband subscription of VA origin country. Finally, in table 14, besides services sectors and EU exporting countries, we found similar results as for the whole sample, except for a positive impact of the population of the exporting country, see columns (columns (3) and (4)). This confirms the role of the size of the market on the settlement of backward activity.

5.3 Taking non-linearities into account

Finally, non-linearities in terms of robot installations and stocks are added to the Model 2 in order to test possible threshold effects (that could eventually suggest re-shoring). The equation that is tested is the following:

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

$$+ \beta_5 ln(\mathrm{GFCF}_{it}) + \beta_6 ln(\mathrm{GFCF}_{jt}) + \beta_7 ln(dist_{ij}) + \beta_8 Robot_{rit}$$
$$+ \beta_9 Robot_{rit}^2 + \beta_{10} Robot_{sjt} + \beta_{10} Robots_{sjt}^2$$
$$+ \lambda_i + \lambda_j + \lambda_k + \lambda_t]\xi_{ijt}^{k}, (3)$$

where $Robot_{rit}$ ($Robot_{sjt}$) can take the values:

- $InstallationRobot_{rit}^2$ ($InstallationRobot_{sjt}^2$), the intensity of robot installation in sector r (s) in country i (j) in year t,
- $StockRobots_{rit}^2$ ($StockRobots_{sjt}^2$), the intensity of the stock of robot in sector r (s) in country i (j) in year t,

$InstallationRobot_{rit}^2$ ($InstallationRobot_{sjt}^2$) and $StockRobots_{rit}^2$ $StockRobots_{sjt}^2$ are quadratics of $InstallationRobot_{rit}$ ($InstallationRobot_{rit}$) and $StockRobots_{rit}$ ($StockRobots_{sjt}$) variables.

Both variables related to robots installation and stocks are introduced separately in the regression to avoid multi-collinearity,. The results suggest an exponential effect of robot installations and stocks on the forward GVC participation (see table 15. As for the stocks, a linear effect seems to dominate.

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, exponentially. Further investigations are needed to confirm these findings.

References

Abeliansky, A. L., I. Martínez-Zarzoso, and K. Prettner (2020). 3d printing, international trade, and fdi. *Economic Modelling 85*, 288–306.

Acemoglu, D. and P. Restrepo (2020). Robots and jobs: Evidence from us labor markets. *Journal of political economy 128*(6), 2188–2244.

Adarov, A., D. Klenert, R. Marschinski, and R. Stehrer (2022). Productivity drivers: empirical evidence on the role of digital and intangible capital, fdi and integration. *Applied Economics*, 1–17.

Adarov, A. and R. Stehrer (2021). Implications of foreign direct investment, capital formation and its structure for global value chains. *The World Economy 44*(11), 3246–3299.

Alfaro, L. and M. X. Chen (2015). Multinational activity and information and communication technology. *World Development Report*.

Ancarani, A., C. Di Mauro, and F. Mascali (2019). Backshoring strategy and the adoption of industry 4.0: Evidence from europe. *Journal of World Business 54*(4), 360–371.

Andrenelli, A. and J. L. González (2021). 3d printing and international trade: What is the evidence to date?

Antràs, P. (2020). De-globalisation? global value chains in the post-covid-19 age. Technical report, National Bureau of Economic Research.

Autor, D. H., D. Dorn, and G. H. Hanson (2016). The china shock: Learning from labor-market adjustment to large changes in trade. *Annual review of economics 8*, 205–240.

Bachmann, R., M. Gonschor, P. Lewandowski, and K. Madoń (2022). The impact of robots on labour market transitions in europe.

Borchert, I., M. Larch, S. Shikher, and Y. V. Yotov (2021). The international trade and production database for estimation (itpd-e). *International Economics 166*, 140–166.

Chen, M. and C. Volpe Martincus (2022). Digital technologies and globalization: A survey of research and policy applications.

Dauth, W., S. Findeisen, J. Suedekum, and N. Woessner (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association 19*(6), 3104–3153.

Economist (2017). "adidas's high-tech factory brings production back to germany. *The Economist*.

Evenett, S. J. and R. E. Baldwin (2020). *Revitalising Multilateralism: Pragmatic Ideas for the New WTO Director-General.* CEPR Press.

Foster, C. (2017). Digitalisation and trade: what hope for lower income countries. *Background paper for the UNCTAD Information Economy Report*.

Freund, C., A. Mulabdic, and M. Ruta (2022). Is 3d printing a threat to global trade? the trade effects you didn't hear about. *Journal of International Economics 138*, 103646.

Freund, C. L. and D. Weinhold (2004). The effect of the internet on international trade. *Journal of international economics 62*(1), 171–189.

González, J. L. and J. Ferencz (2018). Digital trade and market openness.

Krenz, A., K. Prettner, and H. Strulik (2021). Robots, reshoring, and the lot of low-skilled workers. *European Economic Review 136*, 103744.

Lewandowski, P., A. Park, W. Hardy, Y. Du, and S. Wu (2022). Technology, skills, and globalization: Explaining international differences in routine and nonroutine work using survey data. *The World Bank Economic Review 36*(3), 687–708.

Nievas Offidani, G. (2019). Robots and offshoring.

OECD (February 2022). *Trade in Value Added: European Union.*

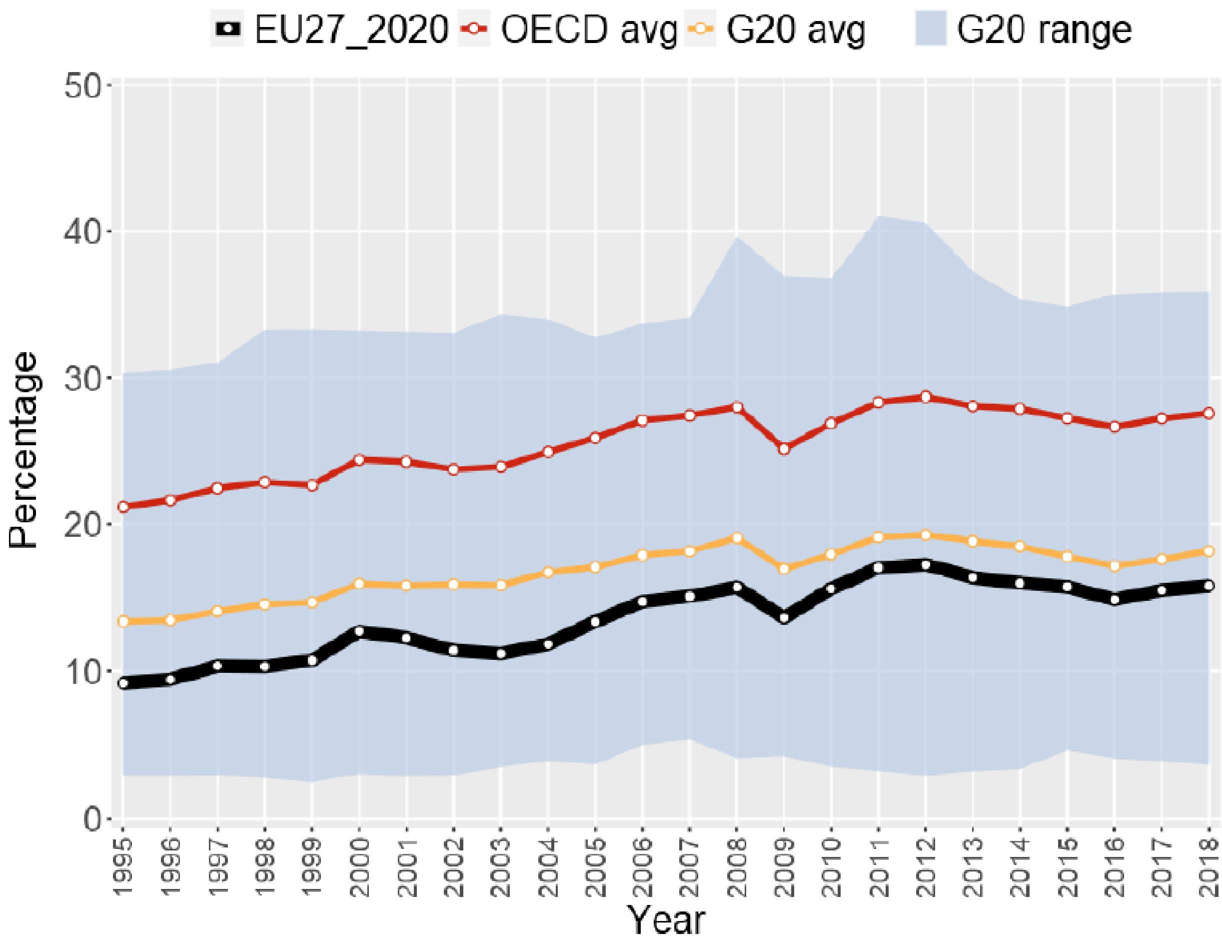
Silva, J. S. and S. Tenreyro (2006). The log of gravity. *The Review of Economics and statistics 88*(4), 641–658.

Silva, J. S. and S. Tenreyro (2011). Further simulation evidence on the performance of the poisson pseudo-maximum likelihood estimator. *Economics Letters 112*(2), 220–222.

Visser, R. (2019). The effect of the internet on the margins of trade. *Information Economics and Policy 46*, 41–54.

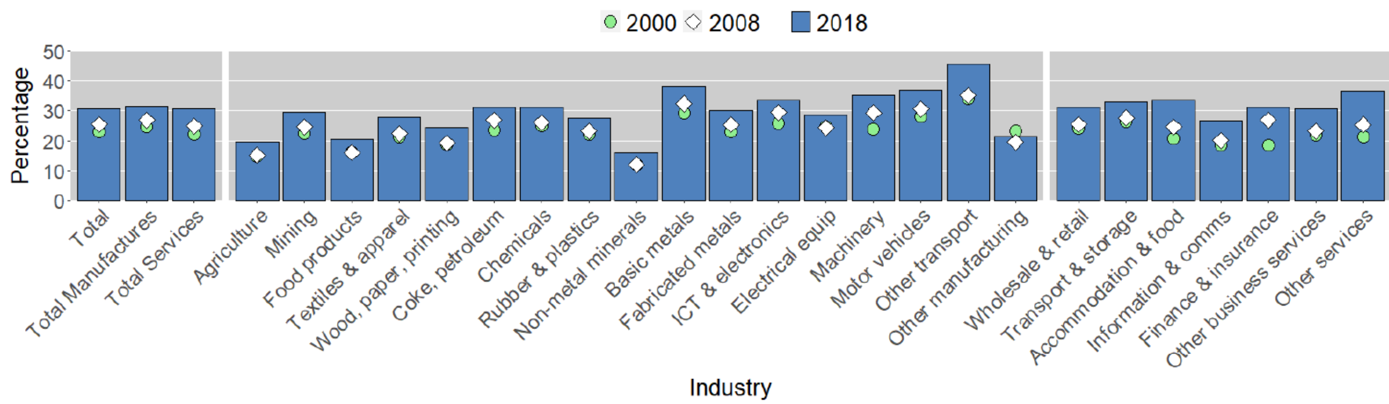
Yotov, Y. V., R. Piermartini, J.-A. Monteiro, and M. Larch (2016). *An advanced guide to trade policy analysis: The structural gravity model*. World Trade Organization Geneva.

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



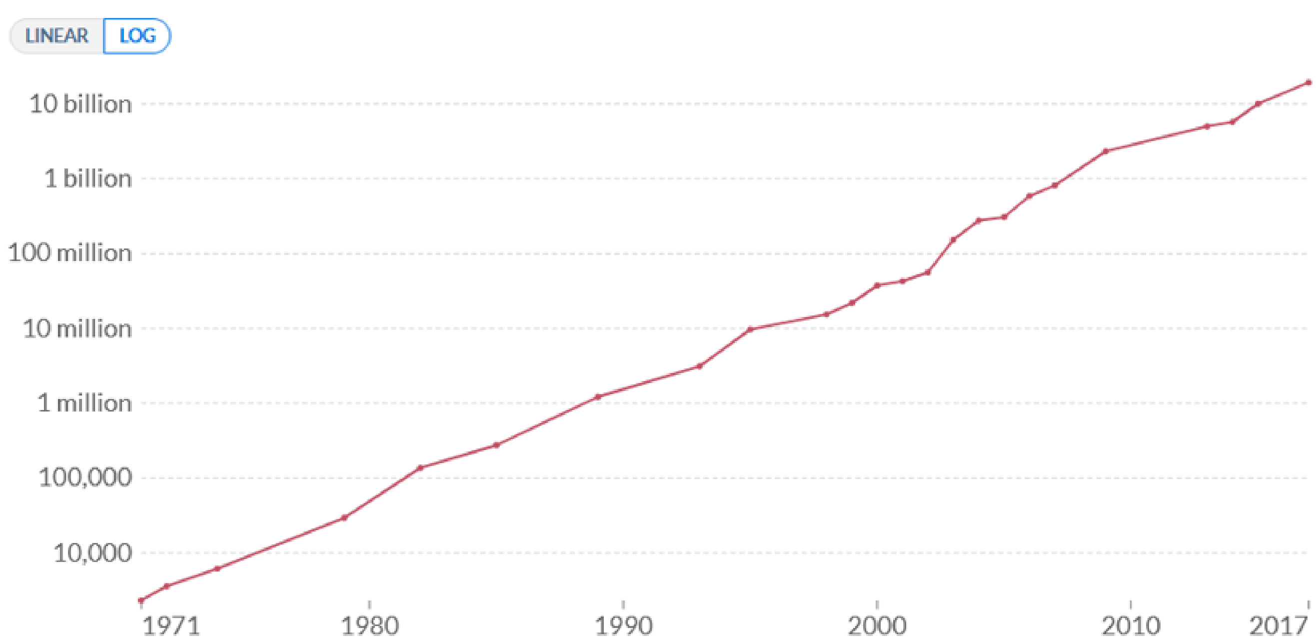
Source: OECD (2022)

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



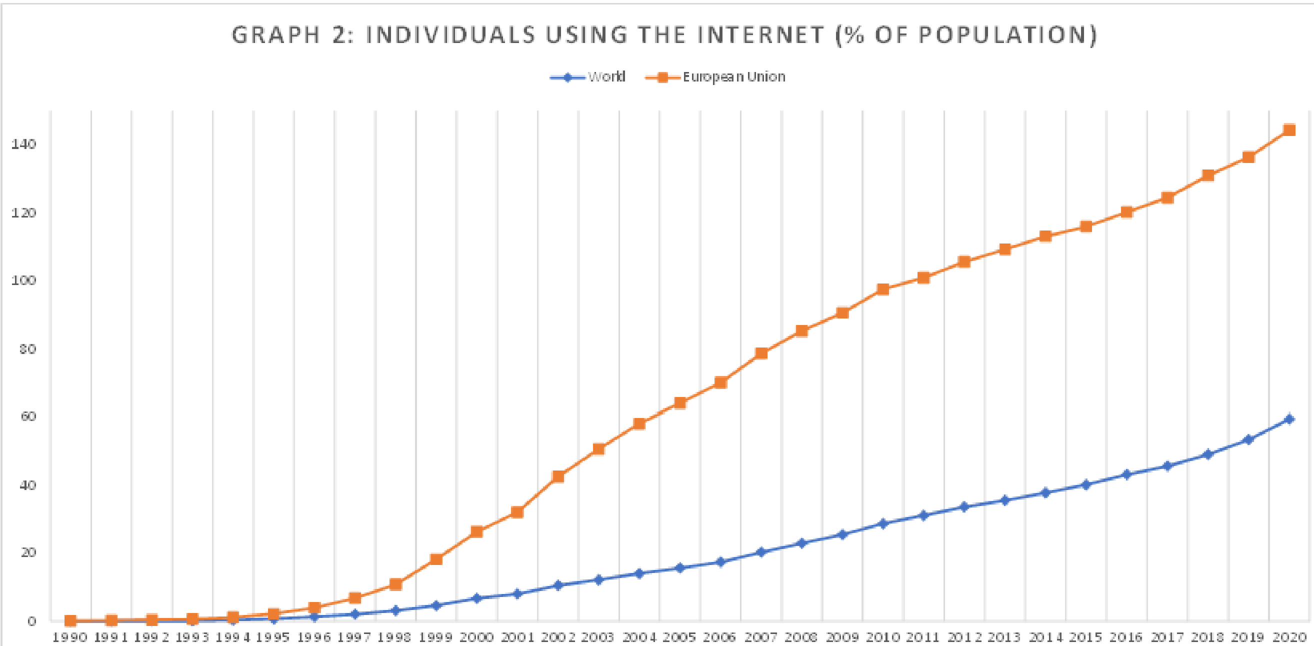
Source: OECD (2022)

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



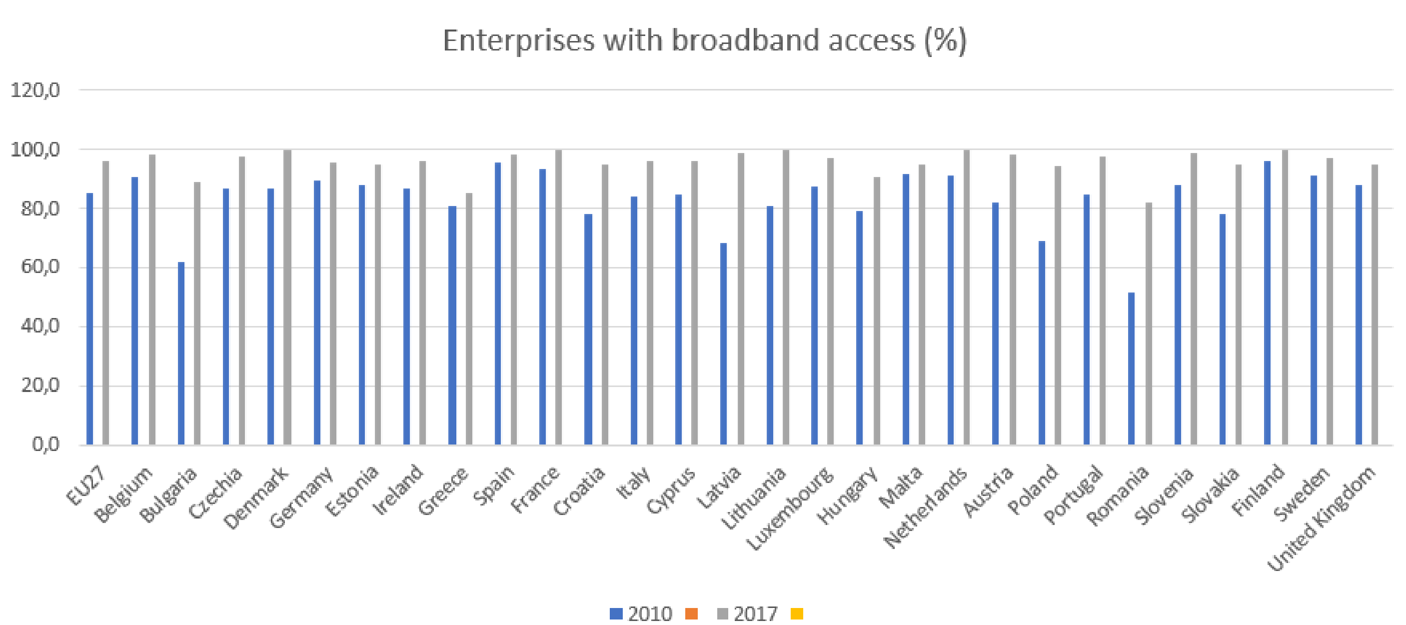
Source: Karl Rupp. 40 Years of Microprocessor Trend Data. Retrieved from Our World in Data
Note: Number of transistors which fit into a microprocessor. The observation that the number of transistors on an integrated circuit doubles approximately every two years is called 'Moore's Law'.

Figure 4: Individuals using the internet (% of the population)



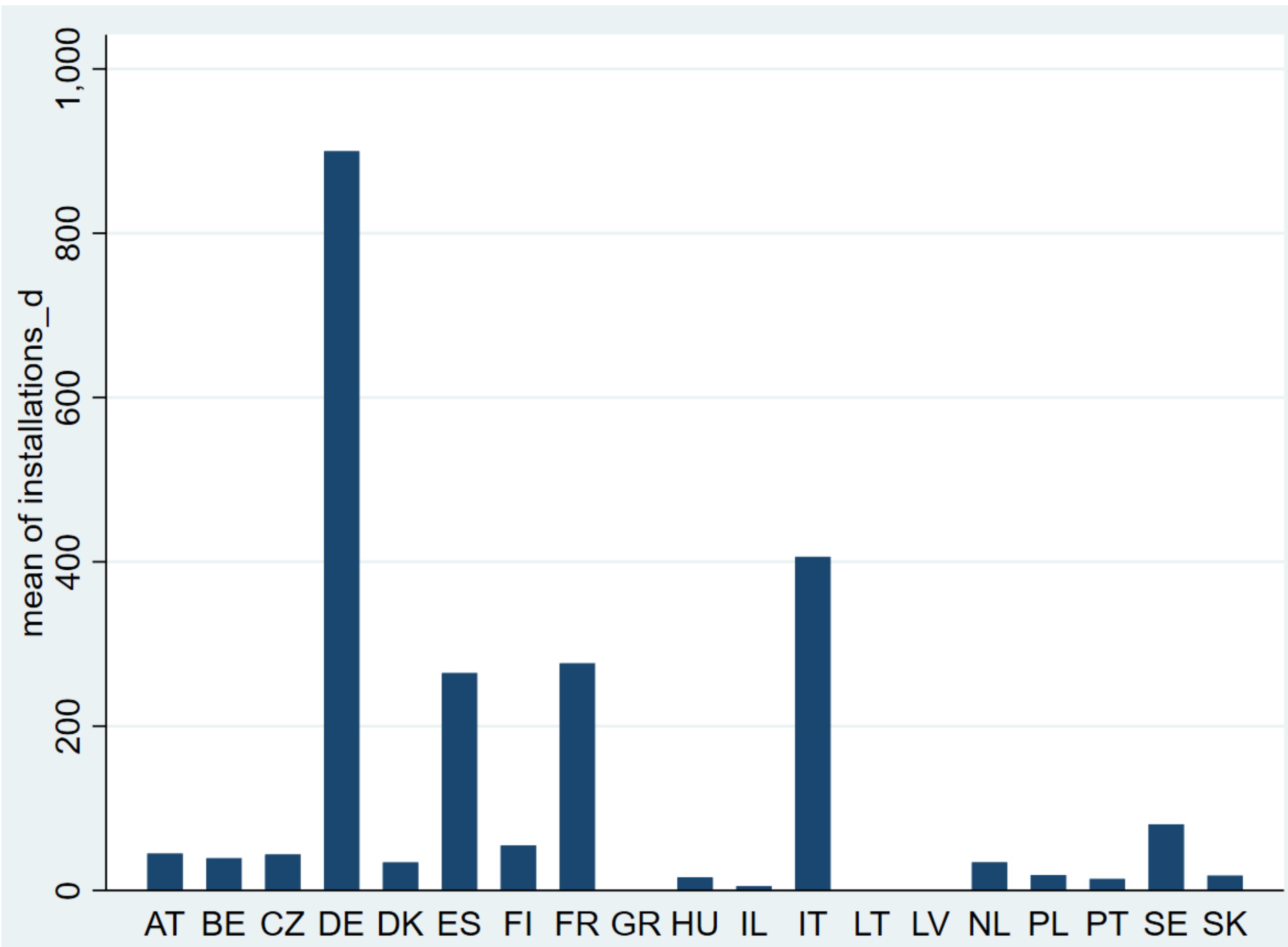
Source: World Bank's World Development indicators

Figure 5: Broadband access in various European countries, 2010 and 2022



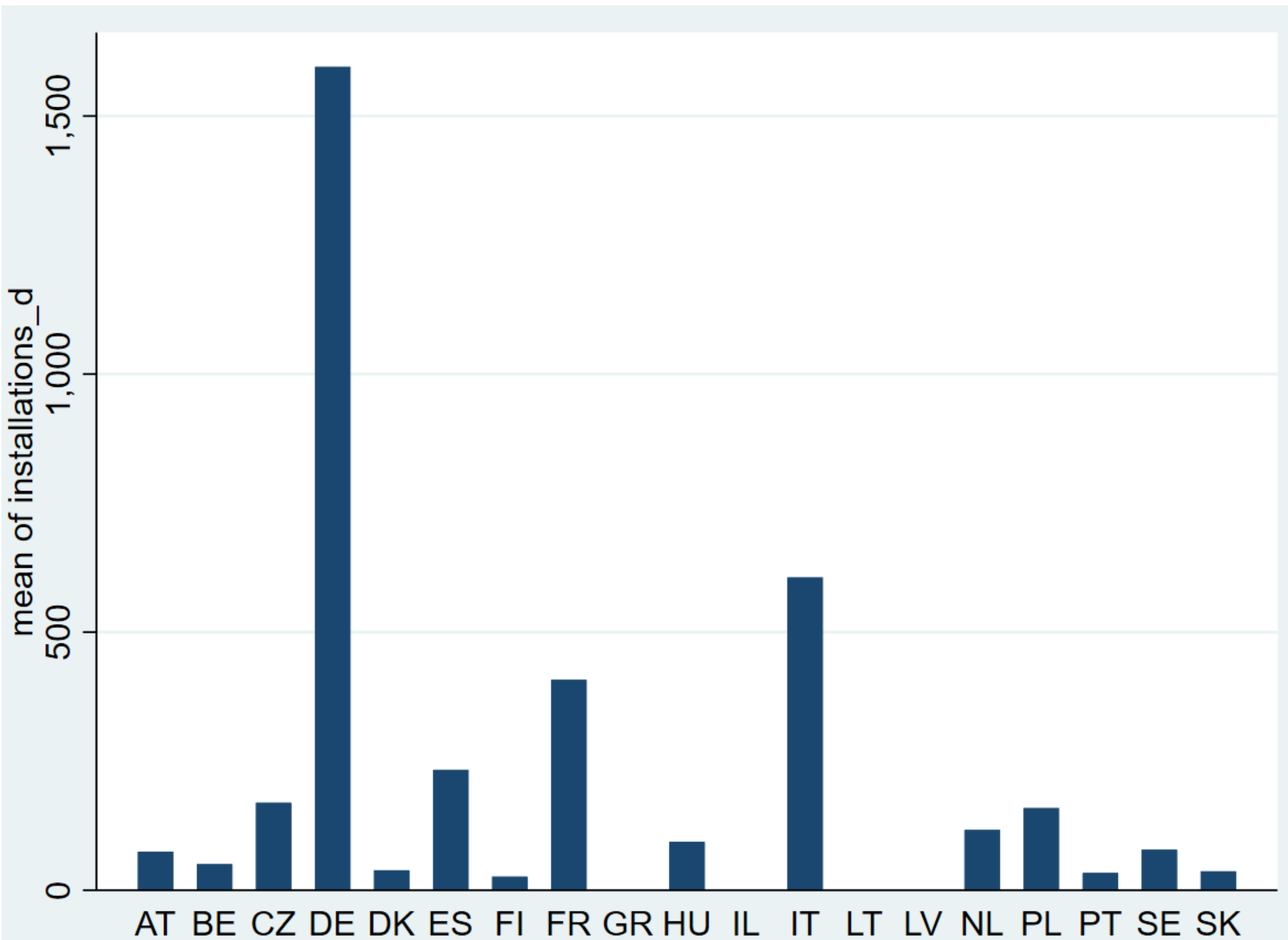
Source: Eurostat

Figure 6: Robot installation, in European countries in 2005



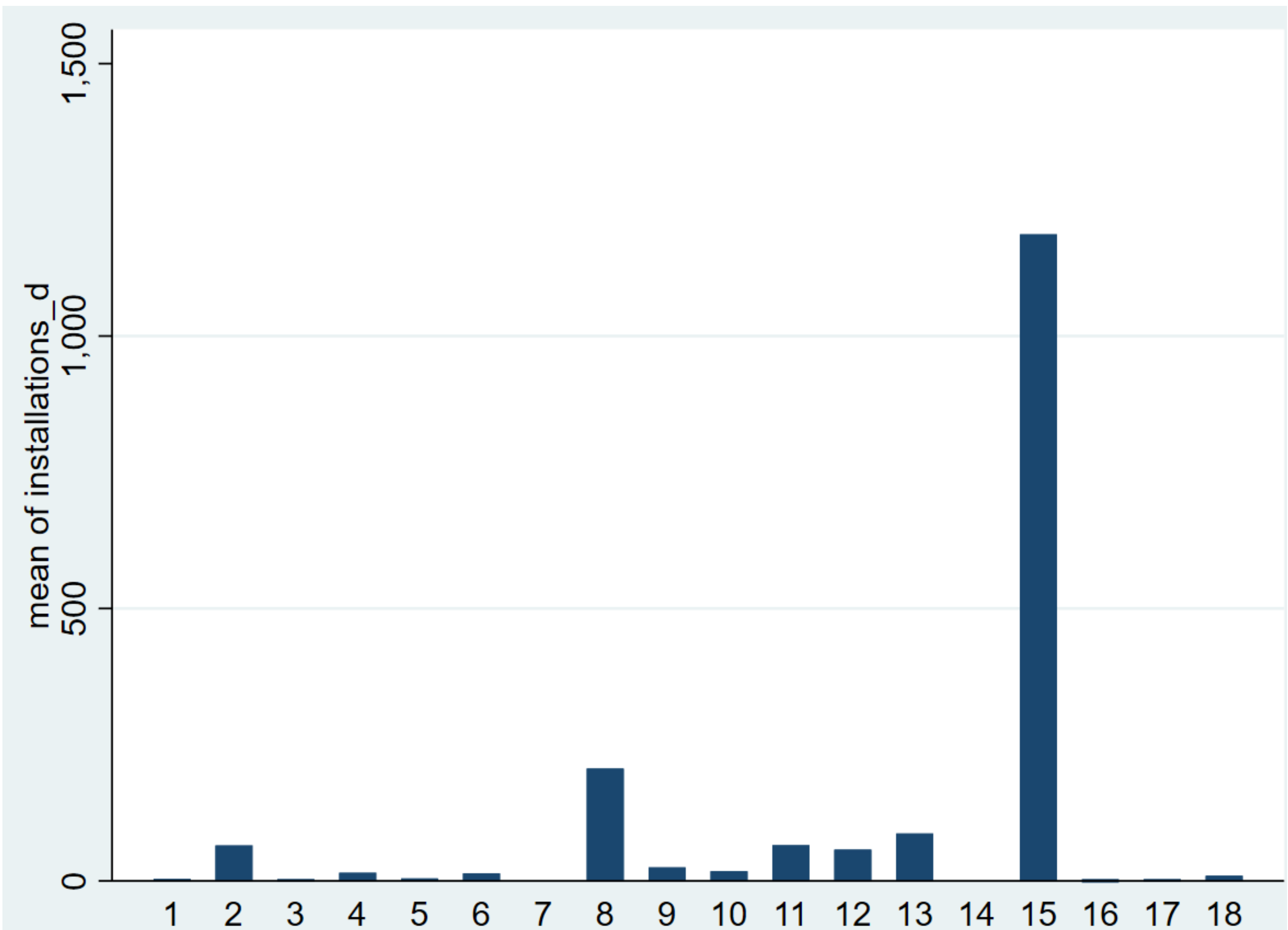
Source: International Federation of Robots

Figure 7: Robot installation, in European countries in 2020



Source: International Federation of Robots

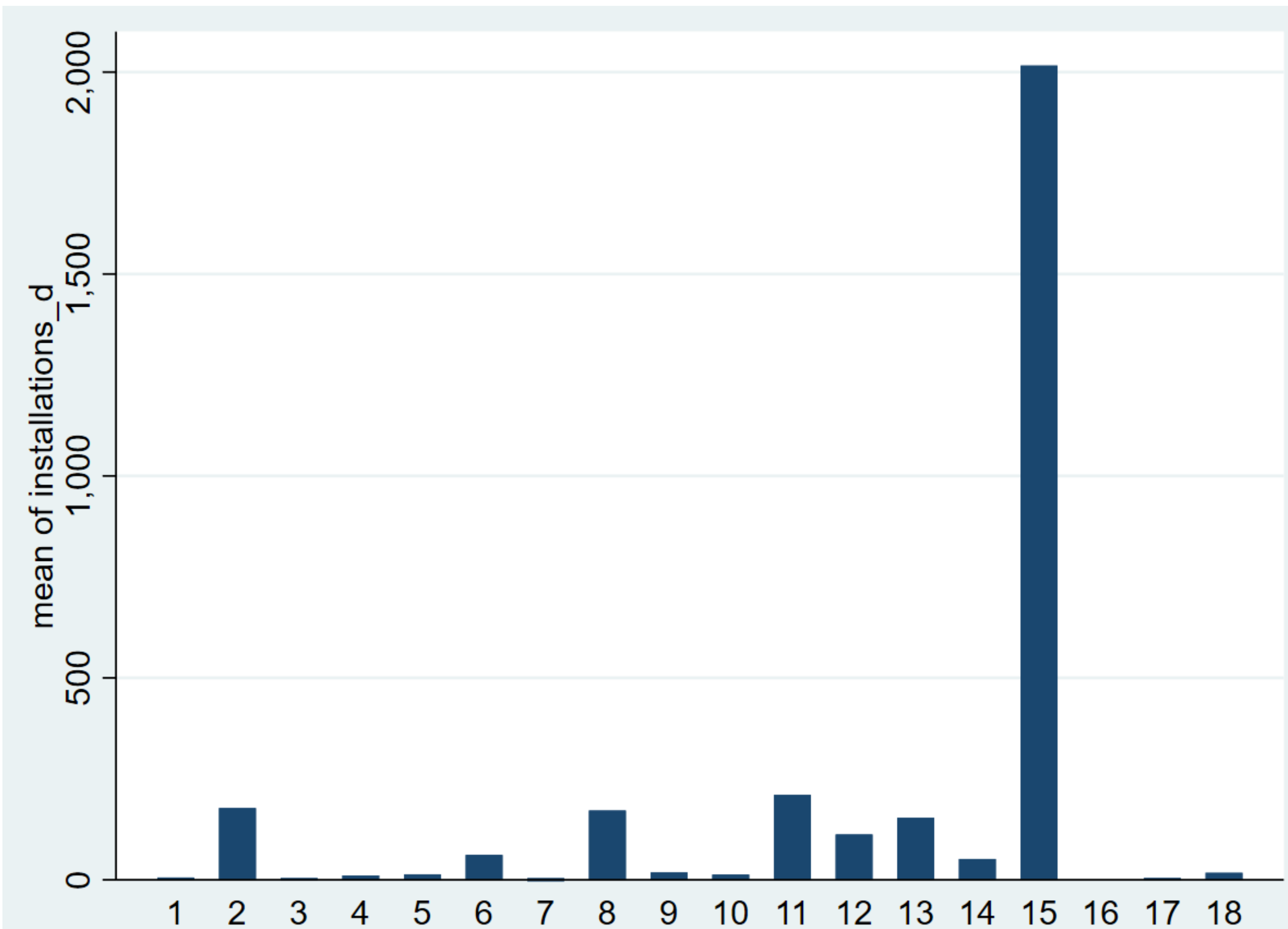
Figure 8: Robot installation in the European Union, by industry, in 2005



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

Figure 9: 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

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 by Origin and Destination Countries - Model 1**

	Destination				Original			
Variable	Obs	Mean	Min	Max	Obs	Mean	Min	Max
value_FV	937,251	210.0	0	1193876	1,249,668	244.2	0	2043726
GDPC	937,251	23659.4	128	123679	1,249,668	19266.2	128	102914
pop	937,251	79100000	281205	1400000000	1,249,668	125000000	281205	1400000000
broadband	937,251	14.7	0	46	1,249,668	11.6	0	46
internet_u	937,251	51.1	0	99	1,249,668	45.6	0	99
mobiler	937,251	95.3	0	266	1,249,668	86.9	0	266
server	443,961	5193.2	0	123154	591,948	4114.9	0	100582
contig	937,251	0.0	0	1	1,249,668	0.0	0	1
dist	937,251	5018.3	19	19586	1,249,668	8485.3	10	19772
comlang_off	937,251	0.0	0	1	1,249,668	0.1	0	1
comcol	937,251	0.0	0	1	1,249,668	0.0	0	1
comrelig	888,212	0.2	0	1	1,229,832	0.1	0	1
legal_old	922,374	2.3	1	5	1,249,668	2.4	1	5
legal_new	937,251	2.0	1	4	1,249,668	1.8	1	4
comleg_pre~	936,700	0.2	0	1	1,249,668	0.3	0	1
comleg_pos~	937,251	0.3	0	1	1,249,668	0.3	0	1
sever_year	13,775	1921.7	1867	1960	73,283	1869.1	1763	1984
sib_conflict	13,775	0.6	0	1	73,283	0.3	0	1
gatt	937,251	0.8	0	1	1,249,668	0.8	0	1
wto	937,251	1.0	0	1	1,249,668	0.9	0	1
eu	937,251	0.4	0	1	1,249,668	0.0	0	0
rta	937,251	0.6	0	1	1,249,668	0.3	0	1
rta_coverage	937,251	1.4	0	3	1,249,668	0.6	0	3
rta_type	937,251	4.3	1	7	1,249,668	5.7	1	8
isoVAo	937,251	32.0	1	63	1,249,668	32.0	1	63
indusex	937,251	15.0	1	29	1,249,668	15.0	1	29
isoo	937,251	29.1	3	57	1,249,668	34.2	1	63

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

Table 4: **Classification of sectors in Model 2 (ICIO)**

NACE 2 codes	Sector description (base on NACE 2)	Label
01-09	Agriculture, forestry and fishing	1-AGMI
	Mining and quarrying	
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	14-TRAN
	Other manufacturing; repair and installation of machinery and equipment	
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 5: **Summary Statistics - Model 2**

Variable	Obs	Mean	Min	Max
$intermediate\_conso_{ijt}^{rs}$	6,149,520	11.09962	0	166966.3
pop_{it}	6,149,520	9.39E+07	1314545	1.40E+09
pop_{jt}	6,149,520	2.10E+07	1317384	8.29E+07
$GDPC_{it}$	6,149,520	23692.82	390.0933	102913.5
$GDPC_{jt}$	6,149,520	30284.77	3293.23	79107.6
$GFCF_{it}$	6,031,260	6.28E+15	1.52E+09	4.28E+17
$GFCF_{jt}$	6,149,520	2.26E+14	1.99E+09	6.57E+16
$installations_{rit}$	6,149,520	217.5644	0	125754
$linstallations_{rit}$	6,149,520	1.521206	0	10.12379
$dist_{ij}$	6,149,520	5044.766	59.617	19586.18
$comlang\_off_{ij}$	6,149,520	0.0408851	0	1
$contig_{ij}$	6,149,520	0.0605901	0	1
$comleg\_posttrans_{ij}$	6,149,520	0.2898841	0	1

Note: The table shows the summary statistics for Model 2

Table 6: **Model 1 - PPML on the whole sample for exporter's sectors, with various fixed effects**

VARIABLES	(1) PPML	(2) PPML	(3) PPML	(4) PPML
$lpop_{it}$	-0.2028	-0.2060	0.0094	0.0228
	(0.180)	(0.179)	(0.114)	(0.112)
$lpop_{jt}$	0.2275	0.2814	0.1400	0.1578
	(0.176)	(0.175)	(0.109)	(0.107)
$lGDPC_{it}$	0.2727***	0.2943***	0.2043***	0.2164***
	(0.041)	(0.038)	(0.021)	(0.020)
$lGDPC_{jt}$	0.4845***	0.4832***	0.5139***	0.5166***
	(0.041)	(0.038)	(0.019)	(0.018)
$lGFCF_{it}$	-0.0027	-0.0030	-0.0056	-0.0057
	(0.006)	(0.006)	(0.005)	(0.005)
$lGFCF_{jt}$	0.0036	0.0035	0.0060**	0.0058*
	(0.005)	(0.005)	(0.003)	(0.003)
$ldist_{ij}$	-1.6664***	-1.6665***		
	(0.007)	(0.007)		
$comlang\_off_{ij}$	-0.8294***	-0.8291***		
	(0.040)	(0.040)		
$contig_{ij}$	-1.8512***	-1.8512***		
	(0.029)	(0.029)		
$comcol_{ij}$	-0.0747	-0.0752		
	(0.059)	(0.059)		
$comleg\_posttrans_{ij}$	1.0516***	1.0515***		
	(0.015)	(0.015)		
$linternet\_use_{it}$	0.0318		0.0201*	
	(0.023)		(0.011)	
$linternet\_use_{jt}$	0.0091		0.0094	
	(0.022)		(0.009)	
$lbroadband_{it}$		-0.0035		-0.0006
		(0.022)		(0.010)
$lbroadband_{jt}$		0.0107		0.0083
		(0.020)		(0.008)
Constant	11.5930***	10.6242***	0.3731	-0.2368
	(4.007)	(3.873)	(3.481)	(3.400)
VA origin country FE	X	X		
Exporter FE	X	X		
Country pair FE			X	X
Time FE	X	X	X	X
Sectoral FE	X	X	X	X
Pseudo_R^2	0.9227	0.9226	0.9604	0.9604
Observations	2,186,919	2,186,919	2,186,919	2,186,919

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

Table 7: **Model 1 - PPML for sector and country of VA origin, various fixed effects**

VARIABLES	(1) PPML	(2) PPML	(3) PPML	(4) PPML
$lpop_{it}$	-0.2049	-0.2082	0.0092	0.0225
	(0.177)	(0.176)	(0.110)	(0.109)
$lpop_{jt}$	-0.2516	-0.1966	-0.3689***	-0.3542***
	(0.176)	(0.173)	(0.109)	(0.108)
$lGDPC_{it}$	0.2734***	0.2949***	0.2056***	0.2175***
	(0.040)	(0.036)	(0.017)	(0.015)
$lGDPC_{jt}$	0.4837***	0.4824***	0.5125***	0.5154***
	(0.040)	(0.036)	(0.015)	(0.014)
$lGFCF_{it}$	-0.0027	-0.0030	-0.0056	-0.0058
	(0.006)	(0.006)	(0.005)	(0.005)
$lGFCF_{jt}$	0.0036	0.0035	0.0060*	0.0059*
	(0.005)	(0.005)	(0.003)	(0.003)
$ldist_{ij}$	-1.6664***	-1.6665***		
	(0.006)	(0.006)		
$comlang\_off_{ij}$	-0.8294***	-0.8291***		
	(0.039)	(0.039)		
$contig_{ij}$	-1.8512***	-1.8512***		
	(0.028)	(0.027)		
$comcol_{ij}$	-0.0747	-0.0752		
	(0.058)	(0.058)		
$comleg\_posttrans_{ij}$	1.0516***	1.0515***		
	(0.015)	(0.015)		
$linternet\_use_{it}$	0.0318		0.0199**	
	(0.023)		(0.009)	
$linternet\_use_{jt}$	0.0089		0.0094	
	(0.022)		(0.008)	
$lbroadband_{it}$		-0.0034		-0.0006
		(0.021)		(0.009)
$lbroadband_{jt}$		0.0104		0.0081
		(0.020)		(0.007)
Constant	11.5432***	10.5799***	0.3098	-0.2940
	(3.878)	(3.747)	(3.322)	(3.242)
VA origin country FE	X	X		
Exporter FE	X	X		
Country pair FE			X	X
Time FE	X	X	X	X
Sectoral FE	X	X	X	X
Pseudo_R^2	0.9324	0.9324	0.9706	0.9706
Observations	2,186,919	2,186,919	2,186,495	2,186,495

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

Table 8: **Model 2 - PPML with robot installation and stock, with EU intermediate product importing countries, various fixed effects**

VARIABLES	(1) PPML	(2) PPML	(3) PPML	(4) PPML
$lpop_{it}$	0.1771	-0.2885	0.1771	-0.2885
	(0.215)	(0.224)	(0.215)	(0.224)
$lpop_{jt}$	0.1362	-0.3261	0.1362	-0.3261
	(0.390)	(0.401)	(0.390)	(0.401)
$lGDPC_{it}$	0.6553***	0.5919***	0.6553***	0.5919***
	(0.049)	(0.048)	(0.049)	(0.048)
$lGDPC_{jt}$	0.6816***	0.4350***	0.6816***	0.4350***
	(0.108)	(0.109)	(0.108)	(0.109)
$lGFCF_{it}$	0.0038	0.0050	0.0038	0.0050
	(0.006)	(0.006)	(0.006)	(0.006)
$lGFCF_{jt}$	0.0020	-0.0001	0.0020	-0.0001
	(0.006)	(0.006)	(0.006)	(0.006)
$linstallations_{ri}$	0.1208***		0.1208***	
	(0.007)		(0.007)	
$linstallations_{sj}$	0.0607***		0.0607***	
	(0.007)		(0.007)	
$ldist_{ij}$	-1.8098***		-1.8098***	
	(0.010)		(0.010)	
$comlang\_off_{ij}$	0.1267***		0.1267***	
	(0.028)		(0.028)	
$contig_{ij}$	-1.1780***		-1.1780***	
	(0.017)		(0.017)	
$comleg\_posttrans_{ij}$	0.7903***		0.7903***	
	(0.012)		(0.012)	
$loperationalstock_{ri}$		0.1255***		0.1255***
		(0.007)		(0.007)
$loperationalstock_{sj}$		0.0701***		0.0701***
		(0.007)		(0.007)
Constant	-4.3154	4.8774	-4.3154	4.8774
	(9.132)	(9.235)	(9.132)	(9.235)
Exporter FE	X		X	
Importer FE	X		X	
Country pair FE		X		X
Time FE	X	X	X	X
Sectoral FE	X	X	X	X
Pseudo_R^2	0.7026	0.7244	0.7026	0.7244
Observations	5,794,740	5,794,740	5,794,740	5,794,740

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

Table 9: **Model 1 - PPML on the Services sample for exporter's sectors, with various fixed effects**

VARIABLES	(1) PPML	(2) PPML	(3) PPML	(4) PPML
$lpop_{it}$	0.8788***	0.9126***	1.2951***	1.3144***
	(0.205)	(0.204)	(0.172)	(0.175)
$lpop_{jt}$	-0.2717	-0.2301	-0.5816***	-0.5414***
	(0.213)	(0.214)	(0.182)	(0.185)
$lGDPC_{it}$	0.2518***	0.2540***	0.1395***	0.1206***
	(0.044)	(0.041)	(0.032)	(0.031)
$lGDPC_{jt}$	0.4113***	0.4264***	0.4895***	0.5235***
	(0.040)	(0.037)	(0.026)	(0.024)
$lGFCF_{it}$	-0.0015	-0.0016	-0.0034	-0.0032
	(0.005)	(0.005)	(0.004)	(0.004)
$lGFCF_{jt}$	0.0031	0.0027	0.0047	0.0042
	(0.005)	(0.005)	(0.003)	(0.003)
$ldist_{ij}$	-1.9093***	-1.9094***		
	(0.009)	(0.009)		
$comlang\_off_{ij}$	-0.5549***	-0.5548***		
	(0.036)	(0.036)		
$contig_{ij}$	-2.7170***	-2.7169***		
	(0.037)	(0.037)		
$comcol_{ij}$	-0.2460***	-0.2463***		
	(0.068)	(0.068)		
$comleg\_posttrans_{ij}$	1.3701***	1.3700***		
	(0.021)	(0.021)		
$linternet\_use_{it}$	0.0149		-0.0161	
	(0.025)		(0.017)	
$linternet\_use_{jt}$	0.0304		0.0546***	
	(0.024)		(0.015)	
$lbroadband_{it}$		0.0090		0.0203
		(0.023)		(0.017)
$lbroadband_{jt}$		0.0022		-0.0068
		(0.021)		(0.015)
Constant	1.3728	0.0037	-10.1008***	-11.1955***
	(4.044)	(4.053)	(3.660)	(3.712)
VA origin country FE	X	X		
Exporter FE	X	X		
Country pair FE			X	X
Time FE	X	X	X	X
Sectoral FE	X	X	X	X
$\text{Pseudo}_R\hat{2}$	0.9228	0.9228	0.9406	0.9406
Observations	904,932	904,932	904,932	904,932

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

Table 10: **Model 1 - PPML on the EU sample for exporter's sectors, with various fixed effects**

VARIABLES	(1) PPML	(2) PPML	(3) PPML	(4) PPML
$lpop_{it}$	0.1265	0.1446	0.1697	0.1513
	(0.190)	(0.190)	(0.130)	(0.130)
$lpop_{jt}$	-0.1578	-0.1138	-0.1000	-0.0195
	(0.160)	(0.159)	(0.097)	(0.096)
$lGDPC_{it}$	0.6074***	0.5577***	0.5536***	0.5160***
	(0.063)	(0.061)	(0.045)	(0.044)
$lGDPC_{jt}$	0.5647***	0.6270***	0.5748***	0.6282***
	(0.033)	(0.030)	(0.017)	(0.015)
$lGFCF_{it}$	-0.0057	-0.0053	-0.0058**	-0.0057**
	(0.005)	(0.005)	(0.002)	(0.002)
$lGFCF_{jt}$	0.0035	0.0029	0.0035	0.0031
	(0.005)	(0.005)	(0.002)	(0.002)
$ldist_{ij}$	-2.0025***	-2.0025***		
	(0.008)	(0.008)		
$comlang\_off_{ij}$	-0.1611***	-0.1614***		
	(0.028)	(0.028)		
$contig_{ij}$	-1.4394***	-1.4391***		
	(0.023)	(0.023)		
$contig_{ij}$	-0.3903***	-0.3898***		
	(0.079)	(0.079)		
$comleg\_posttrans_{ij}$	1.1365***	1.1365***		
	(0.020)	(0.020)		
$linternet\_use_{it}$	-0.0437		-0.0307*	
	(0.032)		(0.018)	
$linternet\_use_{jt}$	0.0860***		0.0717***	
	(0.020)		(0.010)	
$lbroadband_{it}$		0.0572***		0.0688***
		(0.020)		(0.013)
$lbroadband_{jt}$		-0.0027		-0.0152*
		(0.016)		(0.008)
Constant	8.6368**	7.4451**	-3.0534	-4.2894
	(3.612)	(3.572)	(3.178)	(3.165)
VA origin country FE	X	X		
Exporter FE	X	X		
Country pair FE			X	X
Time FE	X	X	X	X
Sectoral FE	X	X	X	X
Pseudo_R^2	0.9493	0.9493	0.9718	0.9718
Observations	937,251	937,251	937,251	937,251

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

Table 11: **Model 1 - PPML on the EU Services sample for exporter's sectors, with various fixed effects**

VARIABLES	(1) PPML	(2) PPML	(3) PPML	(4) PPML
$lpop_{it}$	0.8788***	0.9126***	1.2951***	1.3144***
	(0.205)	(0.204)	(0.172)	(0.175)
$lpop_{jt}$	-0.2717	-0.2301	-0.5816***	-0.5414***
	(0.213)	(0.214)	(0.182)	(0.185)
$lGDPC_{it}$	0.2518***	0.2540***	0.1395***	0.1206***
	(0.044)	(0.041)	(0.032)	(0.031)
$lGDPC_{jt}$	0.4113***	0.4264***	0.4895***	0.5235***
	(0.040)	(0.037)	(0.026)	(0.024)
$lGFCF_{it}$	-0.0015	-0.0016	-0.0034	-0.0032
	(0.005)	(0.005)	(0.004)	(0.004)
$lGFCF_{jt}$	0.0031	0.0027	0.0047	0.0042
	(0.005)	(0.005)	(0.003)	(0.003)
$ldist_{ij}$	-1.9093***	-1.9094***		
	(0.009)	(0.009)		
$comlang\_off_{ij}$	-0.5549***	-0.5548***		
	(0.036)	(0.036)		
$contig_{ij}$	-2.7170***	-2.7169***		
	(0.037)	(0.037)		
$comcol_{ij}$	-0.2460***	-0.2463***		
	(0.068)	(0.068)		
$comleg\_posttrans_{ij}$	1.3701***	1.3700***		
	(0.021)	(0.021)		
$linternet\_use_{it}$	0.0149		-0.0161	
	(0.025)		(0.017)	
$linternet\_use_{jt}$	0.0304		0.0546***	
	(0.024)		(0.015)	
$lbroadband_{it}$		0.0090		0.0203
		(0.023)		(0.017)
$lbroadband_{jt}$		0.0022		-0.0068
		(0.021)		(0.015)
Constant	1.3728	0.0037	-10.1008***	-11.1955***
	(4.044)	(4.053)	(3.660)	(3.712)
VA origin country FE	X	X		
Exporter FE	X	X		
Country pair FE			X	X
Time FE	X	X	X	X
Sectoral FE	X	X	X	X
Pseudo_R^2	0.9228	0.9228	0.9406	0.9406
Observations	904,932	904,932	904,932	904,932

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

Table 12: **Model 1 - PPML for service sector and country of VA origin, various fixed effects**

VARIABLES	(1) PPML	(2) PPML	(3) PPML	(4) PPML
$lpop_{it}$	0.0186	0.0435	0.3514***	0.3619***
	(0.165)	(0.166)	(0.115)	(0.115)
$lpop_{jt}$	-0.1002	-0.0432	-0.3197**	-0.2807**
	(0.181)	(0.181)	(0.134)	(0.137)
$lGDPC_{it}$	0.3120***	0.3197***	0.2355***	0.2309***
	(0.037)	(0.034)	(0.023)	(0.021)
$lGDPC_{jt}$	0.4920***	0.4993***	0.5212***	0.5362***
	(0.036)	(0.034)	(0.022)	(0.021)
$lGFCF_{it}$	-0.0026	-0.0028	-0.0043	-0.0043
	(0.005)	(0.005)	(0.003)	(0.003)
$lGFCF_{jt}$	0.0010	0.0007	0.0025	0.0022
	(0.004)	(0.004)	(0.003)	(0.003)
$ldist_{ij}$	-1.6266***	-1.6267***		
	(0.006)	(0.006)		
$comlang\_off_{ij}$	-0.6925***	-0.6924***		
	(0.034)	(0.034)		
$contig_{ij}$	-1.9522***	-1.9522***		
	(0.028)	(0.028)		
$comcol_{ij}$	1.1756***	1.1755***		
	(0.015)	(0.015)		
$comleg\_posttrans_{ij}$	0.0178	-0.0026		
	(0.021)	(0.014)		
$linternet\_use_{it}$	0.0261		0.0354***	
	(0.019)		(0.011)	
$linternet\_use_{jt}$	0.0740	0.0736		
	(0.062)	(0.062)		
$lbroadband_{it}$		0.0015		0.0064
		(0.020)		(0.012)
$lbroadband_{jt}$		0.0176		0.0138
		(0.018)		(0.010)
Constant	2.3947	0.7709	-8.4782***	-9.6624***
	(3.704)	(3.687)	(3.151)	(3.218)
VA origin country FE	X	X		
Exporter FE	X	X		
Country pair FE			X	X
Time FE	X	X	X	X
Sectoral FE	X	X	X	X
Pseudo_R^2	0.9279	0.9279	0.9604	0.9604
Observations	904,571	904,571	904,571	904,571

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

Table 13: **Model 1 - PPML for sector and country of VA origin, EU exporting countries, various fixed effects**

VARIABLES	(1) PPML	(2) PPML	(3) PPML	(4) PPML
$lpop_{it}$	0.1249	0.1430	0.1680	0.1499
	(0.180)	(0.181)	(0.113)	(0.113)
$lpop_{jt}$	-0.7191***	-0.7377***	-0.6709***	-0.6445***
	(0.165)	(0.166)	(0.093)	(0.093)
$lGDPC_{it}$	0.6083***	0.5584***	0.5545***	0.5168***
	(0.059)	(0.057)	(0.038)	(0.036)
$lGDPC_{jt}$	0.5635***	0.6258***	0.5734***	0.6269***
	(0.033)	(0.030)	(0.016)	(0.014)
$lGFCF_{it}$	-0.0057	-0.0053	-0.0058**	-0.0057**
	(0.005)	(0.005)	(0.002)	(0.002)
$lGFCF_{jt}$	0.0035	0.0029	0.0035	0.0031
	(0.005)	(0.005)	(0.002)	(0.002)
$ldist_{ij}$	-2.0025***	-2.0025***		
	(0.008)	(0.008)		
$comlang\_off_{ij}$	-0.1611***	-0.1614***		
	(0.027)	(0.027)		
$contig_{ij}$	-1.4394***	-1.4391***		
	(0.022)	(0.022)		
$comcol_{ij}$	1.1365***	1.1365***		
	(0.020)	(0.020)		
$comleg\_posttrans_{ij}$	-0.0437		-0.0304*	
	(0.030)		(0.016)	
$linternet\_use_{it}$	0.0857***		0.0713***	
	(0.019)		(0.010)	
$linternet\_use_{jt}$	-0.3903***		-0.3898***	
	(0.079)		(0.079)	
$lbroadband_{it}$		0.0573***		0.0690***
		(0.020)		(0.011)
$lbroadband_{jt}$		-0.0030		-0.0156*
		(0.016)		(0.008)
Constant	8.6278***	7.4426**	-3.0687	-4.2988
	(3.326)	(3.310)	(2.812)	(2.826)
VA origin country FE	X	X		
Exporter FE	X	X		
Country pair FE			X	X
Time FE	X	X	X	X
Sectoral FE	X	X	X	X
Pseudo_R²	0.9547	0.9226	0.9718	0.9718
Observations	937,063	937,063	937,063	937,063

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

Table 14: **Model 1 - PPML for service sector and country of VA origin, EU exporting countries, various fixed effects**

VARIABLES	(1) PPML	(2) PPML	(3) PPML	(4) PPML
$lpop_{it}$	1.1492***	1.1787***	1.2121***	1.2104***
	(0.333)	(0.334)	(0.317)	(0.319)
$lpop_{jt}$	-0.4047	-0.3549	-0.4469	-0.3585
	(0.322)	(0.315)	(0.319)	(0.312)
$lGDPC_{it}$	0.5049***	0.4510***	0.4473***	0.4057***
	(0.115)	(0.111)	(0.112)	(0.109)
$lGDPC_{jt}$	0.4866***	0.5667***	0.5126***	0.5859***
	(0.056)	(0.050)	(0.048)	(0.042)
$lGFCF_{it}$	-0.0032	-0.0025	-0.0034	-0.0029
	(0.007)	(0.007)	(0.005)	(0.005)
$lGFCF_{jt}$	0.0044	0.0035	0.0045	0.0038
	(0.007)	(0.007)	(0.005)	(0.005)
$ldist_{ij}$	-2.3177***	-2.3176***		
	(0.011)	(0.011)		
$comlang\_off_{ij}$	-0.2811***	-0.2814***		
	(0.049)	(0.049)		
$contig_{ij}$	-1.8912***	-1.8909***		
	(0.031)	(0.031)		
$comcol_{ij}$	-1.6836***	-1.6841***		
	(0.112)	(0.112)		
$\_\ comleg\_posttrans_{ij}$	1.3475***	1.3478***		
	(0.027)	(0.027)		
$linternet\_use_{it}$	-0.0628		-0.0543	
	(0.050)		(0.044)	
$linternet\_use_{jt}$	0.1263***		0.1162***	
	(0.034)		(0.029)	
$lbroadband_{it}$		0.0507		0.0602*
		(0.033)		(0.031)
$lbroadband_{jt}$		0.0085		-0.0013
		(0.025)		(0.022)
Constant	-3.0223	-4.5720	-14.4542**	-16.2032**
	(6.826)	(6.752)	(6.735)	(6.645)
VA origin country FE	X	X		
Exporter FE	X	X		
Coutnry pair FE			X	X
Time FE	X	X	X	X
Setoral FE	X	X	X	X
Pseuso_R^2	0.9325	0.9325	0.9565	0.9565
Observations	387.928	387.928	387.928	387.928

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 EU intermediate product importing countries, nonliniarities and various fixed effects**

VARIABLES	(1) PPML	(2) PPML	(3) PPML	(4) PPML
$lpop_{it}$	0.1626	-0.2009	-0.0834	-0.2009
	(0.216)	(0.225)	(0.217)	(0.225)
$lpop_{jt}$	0.1629	-0.2570	-0.4976	-0.2570
	(0.394)	(0.407)	(0.403)	(0.407)
$lGDPC_{it}$	0.6937***	0.6870***	0.6774***	0.6870***
	(0.049)	(0.048)	(0.107)	(0.048)
$lGDPC_{jt}$	0.7308***	0.5704***	0.5704***	0.5704***
	(0.110)	(0.110)	(0.113)	(0.110)
$lGFCF_{it}$	0.0042	0.0046	0.0041	0.0046
	(0.006)	(0.006)	(0.006)	(0.006)
$lGFCF_{jt}$	0.0028	0.0007	0.0012	0.0007
	(0.006)	(0.006)	(0.006)	(0.006)
$linstallations_{ri}$	0.0227	0.0201		
	(0.015)	(0.015)		
$linstallations_{sj}$	0.0135	0.0131		
	(0.016)	(0.016)		
$linstallations^2_{ri}$	0.0081***	0.0080***		
	(0.002)	(0.002)		
$linstallations^2_{sj}$	0.0158***	0.0160***		
	(0.002)	(0.002)		
$ldist_{ij}$	-1.8099***		-1.8099***	
	(0.010)		(0.010)	
$comlang\_off_{ij}$	0.1257***		0.1257***	
	(0.028)		(0.028)	
$contig_{ij}$	-1.1781***		-1.1781***	
	(0.017)		(0.017)	
$comleg\_posttrans_{ij}$	0.7905***		0.7899***	
	(0.012)		(0.012)	
$loperationalstock_{ri}$			0.0107	0.0109
			(0.011)	(0.011)
$loperationalstock_{sj}$			0.0065	0.0069
			(0.011)	(0.011)
$loperationalstock^2_{ri}$			0.0142***	0.0141***
			(0.001)	(0.001)
$loperationalstock^2_{sj}$			0.0085***	0.0085***
			(0.001)	(0.001)
Constant	-5.4212	-0.1419	11.1054	0.1419
	(9.238)	(9.379)	(9.417)	(9.379)
Exporter FE	X		X	
Importer FE	X		X	
Country pair FE		X		X
Time FE	X	X	X	X
Sectoral FE	X	X	X	X
Pseudo_R²	0.7036	0.7248	0.7046	0.7260
Observations	5,794,740	5,794,740	5,794,740	5,794,740

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