DIGITAL INTENSITY, TRADE COSTS AND EXPORTS' QUALITY UPGRADING

Raphaël Chiappini

Cyrielle Gaglio

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CONTACT US

OFCE
10 place de Catalogne | 75014 Paris | France
Tél. +33 1 44 18 54 24
www.ofce.fr

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Raphaël Chiappini and Cyrielle Gaglio
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ABOUT THE AUTHORS

Raphaël Chiappini, University of Bordeaux, CNRS, BSE, Pessac, France,
Email Address: raphael.chiappini@u-bordeaux.fr
Cyrielle Gaglio, University of Helsinki, Finland, and Sciences Po, OFCE, France,
Email Address: cyrielle.gaglio@helsinki.fi

ABSTRACT

This paper studies the relationships between digitalization, trade costs, quality upgrading and trade flows using an extended version of a gravity model. Based on information from different sources of data, we estimate the relations sequentially for a sample of 40 countries, 18 manufacturing and 14 services industries over the period of 2000-2014. Using input-output tables from the WIOD, we define an original measure of digitalization at the country-sector level that reflects the use of digital inputs in the production function. Using trade databases from the CEPII and OECD, we estimate a series of gravity models of trade augmented with this measure of digitalization. Our results show that sectoral digital intensity positively affects sectoral exports. We prove that this result is not ruled out by other possible factors, such as internet adoption or global value chain participation. A heterogeneous analysis also reveals that the effect of digital intensity is greater for manufacturing trade and for trade between emerging economies. We find that digital intensity facilitates trade between countries by reducing communication and transportation costs. Finally, digital intensity improves the quality of exported products. Our results are robust to alternative specifications and to identification by instrumental variables.

KEYWORDS

Digital intensity, Trade flows, Trade costs, Export upgrading, Gravity model.

JEL

F10, O30.

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Raphaël Chiappini*and Cyrielle Gaglio†

Abstract

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Keywords: Digital intensity – Trade flows – Trade costs – Export upgrading – Gravity model
JEL classification: F10 – O30

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*Univ. Bordeaux, CNRS, BSE, UMR 6060, Pessac F-33600, France. Email:raphael.chiappini@u-bordeaux.fr

†University of Helsinki, Department of Economics and Management, Finland, and Sciences Po, OFCE, France. Email: cyrielle.gaglio@helsinki.fi.

1 Introduction

The waves of recent globalization resulted from the fragmentation of production processes along global value chains (GVCs) combined with fast-paced technological change. The fragmentation of production processes in itself is far from being a new phenomenon (Gereffi and Lee, 2012), and it has shaped globalization: it has grown since the 1980s and, in the 1990s and early 2000s, contributed to the unprecedented development of GVCs and thus to the growth of world trade (Gaulier et al., 2020). However, rapid technological advances (cheaper telecommunications, more powerful personal computers, etc.) have reduced the communication, coordination and transaction costs of the complex activities associated with GVCs (Forman et al., 2005; OECD, 2013; Gooris and Peeters, 2016). Thus, in addition to trade and financial liberalization or the expansion of markets at the international level, technological changes also contribute to the evolution of GVCs.

Many studies from the OECD have shown how the intensification of GVCs is linked to the widespread adoption and diffusion of information and communication technologies (ICTs): *"advances in technology, particularly in ICTs, also lie behind the international fragmentation of production and the offshoring of activities within GVCs"*, (OECD, 2013, p.36). In this report, the authors explain how rapid advances in ICTs have facilitated both the spread of GVCs (by decreasing transaction and coordination costs) and the tradability of service activities (old and new kinds of services). Cusolito et al. (2016) discuss the role of ICT tools and networks in the integration and participation of small and medium-sized firms in GVCs. For example, access to broadband networks allows these firms to engage more easily and quickly in e-commerce, to reach foreign markets more easily and to reduce existing barriers to digital trade.

More recent studies have focused on the role of digital technologies in the insertion of countries along GVCs. An OECD report (2018) sees digital technologies as driving the next revolution in production with implications for productivity, employment, skills, income distribution, trade, welfare and the environment. This observation applies to both developing and developed countries. For developing countries, adequate absorption of digital technologies would contribute to the structural transformation of their economies. For developed countries, because digital technologies require substantial investments, the role of public authorities would be to effectively support investments in these technologies. On the trade side, these digital technology improvements enhance trade opportunities, including by reducing trade costs such as cultural and language barriers (Baldwin, 2019) and the cost of organisation for multinational firms. At the same time, they will accelerate the pace of trade between locations. A European Commission report (2018) identified nine key digital technologies (social media, mobile services, cloud technologies, the internet of things, cybersecurity solutions, robotics and automated machinery, big data and data analytics, 3D printing, and artificial intelligence) and highlighted the disruptive nature of these technologies for production, supply and value chains. For instance, De Backer et al. (2018) specifically study the impact of robotics at the location of production and the organisation of production within GVCs, i.e., future changes in the international fragmentation of production.

Even if the foregoing relationships between GVCs and either the adoption and diffusion of ICTs or the uses of digital technologies converge on a reduction of trade barriers (particularly trade costs, which is intended to increase trade)[1], they have two shortcomings. On the one hand, one limitation of traditional metrics (those that reflect the penetration of digital technologies) is that they do not mirror the fast pace at which digital transformation is occurring (Calvino et al., 2018). On the other hand, a complementary approach should focus on the determinants of product quality improvements in parallel with digital technology improvements. While the literature has demonstrated the link between the quality of imported inputs and export upgrading (Manova and Zhang, 2012; Fan et al., 2015), previous studies have remained rather silent on the relationship between digital technologies and product quality. Among the few studies that have looked at this relationship, it is once again the uses (ICT adoption in particular) that are at the heart of the analyses. Huang and Song (2019) studied the impact of internet adoption on the export improvement of Chinese firms and showed that Chinese exporters (using the internet) offer a greater variety of products (cost-reduction effect) but that the average quality of their exports decreases after internet adoption (competition effect).

One strand of the literature focuses on the narrower relationship between internet adoption, trade costs, and exports. Freund and Weinhold (2004) show that internet adoption contributed to an increase of approximately one percentage point in annual export growth over the period of 1997-1999. The authors explain that internet adoption has reduced market-specific trade costs. However, they find no evidence of a decrease in the impact of geographical distance on trade due to the diffusion of the internet. This positive link is confirmed by Lin (2015) for a sample of nearly 200 countries for the period of 1990-2006, with an estimated impact of 0.2%-0.4% of a 10% increase in internet users on trade flows. The benefits of internet adoption are also found to be important for trade in services (Freund and Weinhold, 2002; Choi, 2010). While these previous studies justify the impact of internet adoption on trade by showing that its diffusion reduces the costs of trade, they do not test this hypothesis empirically. Visser (2019), using an analysis of 162 countries' exports to 175 destinations for the period of 1998-2014, finds that increasing the number of broadband subscriptions decreases the impact of language distance on trade. This result holds for both trade margins (i.e., intensive and extensive). The impact of internet penetration on the extensive margin of trade has been confirmed for Chinese firms even before the emergence of broadband and Alibaba (Fernandes et al., 2019) and for SMEs (Sun, 2021). Kitenge and Lahiri (2021) complement the analysis of Visser (2019) by constructing a bilateral measure of internet adoption for a large sample of countries for the

[1]Trade costs are still very important in explaining bilateral trade flows. For instance, Hummels and Schaur (2013) show that delays in transit are equivalent to an ad-valorem tariff of 0.6 to 2.3 percent, while the analysis of Volpe Martincus et al. (2015) reveals that exports decline by 3.8% in response to a 10% increase in customs delays. ICTs, such as GPS or electronic systems for customs, can lower these important trade costs.

period of 1954-2014 and show that language elasticity on trade is lower when trading partners have internet access. However, the authors find no evidence of a mitigating effect of internet penetration on the negative effect of geographical distance on trade. In contrast, Akerman et al. (2022), using Norwegian firm-level data, show that broadband internet adoption makes trading patterns more sensitive to geographical distance. ICT adoption can be very important for developing and emerging economies. For instance, Clarke and Wallsten (2006) and Clarke (2008) show that the increase in the number of internet users mainly stimulates exports from developing economies to developed markets, while Aker and Mbiti (2010) indicate that the adoption of mobile telephony can have a significant effect on the export behaviour of African farmers by reducing search costs. Therefore, this strand of the literature focuses only on the adoption and diffusion of ICTs and not on digitalization per se.

In such a context, the intensification of the fragmentation of international production processes has offered a variety of intermediate inputs that are of better quality and/or less expensive. Some of these inputs are purely digital, while others have become digitized. Even if the digitalization of economies is a modern marker of changes in our modes of production, consumption, and communication and paves the way to new forms of sharing, creation, collaboration and innovation (Gaglio and Guillou, 2018a), the effect of digitalization on international trade (whether on trade costs, trade flows or trade quality) remains little discussed in the economic literature. As mentioned above, the studies carried out in this respect have mainly focused on either ICTs or on the uses of digital technologies.

Given the importance of digitalization in trade and countries' competitiveness, this paper aims to assess the relationships between digitalization at the country-sector level, trade costs, quality upgrading and trade flows. Digitalization can be a driver in simultaneously reducing trade costs and improving product quality. We develop an original measure of the digitalization of economies that, unlike existing ones, does not reflect the uses of digital technologies. Our digital intensity measure reflects the use of digital inputs in the production function of a country. We define this measure as the consumption of a sector in digital inputs (i.e., digital goods and services) over the total input consumption of the same sector (i.e., market goods and services). A firm can use these digital inputs to expand its scope of production but also of differentiation. Therefore, our measure allows us to draw conclusions on both trade costs and quality upgrading. Using WIOD, CEPII and OECD data, we estimate an augmented gravity model of trade, including our digital intensity measure, and use the Poisson Pseudo Maximum Likelihood (PPML) estimator to evaluate the impact of digital intensity on bilateral trade flows for a sample of 40 countries, 18 manufacturing and 14 services industries for the period of 2000-2014. While there is evidence of the clear digitalization of economies, few quantitative studies have focused on the introduction of digital inputs into production processes and their impacts on trade.

This paper contributes to filling this gap in our knowledge by making four contributions. First, it provides an analysis of the relationship between digitalization and bilateral trade flows at the country-sector level. Our main findings point (i) to a positive relation between sectoral digital intensity and exports, (ii) a stronger effect for the manufacturing sector than for services and a stronger effect of digital intensity on exports from emerging economies, and (iii) a mitigating effect of sectoral digital intensity on the negative impact of geographical distance on exports, where sectors with the highest levels of digital intensity appear to defy gravity. Second, we show that increasing sectoral digital intensity improves the quality of exported products. We provide strong evidence between digital inputs and improved exports, which may explain the greater effect of digital intensity in the manufacturing sector. Our approach is similar to that adopted by Huang and Song (2019) but provides different results. Indeed, these authors find an average decrease in product quality after internet adoption. This difference is explained by our measure of digital intensity, which is based on digital inputs and is thus more related to Manova and Zhang (2012)'s finding of a link between the quality of inputs and the quality of exported products. Third, we offer a broad analysis as we disentangle the effects by sector and income level of exporting and importing countries. However, we find no evidence of a significant effect of the sectoral digital intensity of the importing country on trade flows. Fourth, from a purely methodological point of view and contrary to previous studies, our paper directly tackles the issue of endogeneity, which could bias the results, by relying on an identification strategy using instrumental variables (IVs) following the approach developed by Acemoglu et al. (2019).

The remainder of the paper is structured as follows. Section 2 presents our measures of digital intensity and offers associated descriptive statistics. Section 3 explains the gravity model we adopt and describes the data. Section 4 discusses the results. Section 5 provides robustness checks. Section 6 concludes.

2 An approach to measuring digitalization

2.1 The measures of digital intensity

In the context of increasing the penetration of (new) digital technologies into production processes, we assume that digitalization means that the production function of a sector in a country uses more digital inputs than in the past. Digitalization entails either the inclusion of more technicians or computer scientists in the workforce or the use of new tools regardless of digital goods or services such as computers or communication devices in the portfolio of inputs. Digitalization can also be the result of an increase in new firms entering the market, whose production functions are much more digitized than those of incumbents. Two effects are to be separated. (i) At the global level, we expect to observe a rise in digital inputs as a result of the increase in intangible assets, which is currently a primary cause of value added (VA) (Haskel and Westlake, 2017). (ii) At the sectoral level, we expect the pace of technological change to create between-sector differences.

Given the importance of digitalization in trade and countries' competitiveness, many attempts to quantify this phenomenon are found in the institutional literature. For example, the European Commission (2017) defines a micro-based digital intensity index that measures the share of firms using digital technologies (out of 12) in a specific country[2]. Values of this index are ranked between 0 and 12. Then, it is split into four levels: between 0 and 3, the digital intensity index is considered *"very low"*; between 4 and 6, it is considered *"low"*; between 7 and 9, it is considered *"high"*; and between 10 and 12, it is considered *"very high"*. For each of these four levels, the EU digital intensity index estimates (for a country) the share of firms using monitored digital technologies. In 2016, only three European countries (Denmark, Finland and Sweden) had a very high digital intensity index. The same index is then implemented across sectors, and it seems that firms in services are more intensive users of digital technologies than manufacturing firms.

The European Commission measures the use of digital technologies while we seek to measure the use of digital inputs. Our digital intensity measure reflects the use of digital inputs in the production function of a country. We define this measure as the consumption of a sector in digital inputs (i.e., digital goods and services) over the total input consumption of the same sector (i.e., market goods and services). Our measure is thus in line with the indicator developed by Calvino et al. (2018), called purchases of ICT intermediates, which relies on the composition of intermediate material consumption to assess the digital intensity of sectors. We define digital goods and services according to the OECD definition as follows: digital goods refer to the manufacture of computer, electronic and optical products (division 26 of sector C from ISIC[3], revision 4), while digital services include software publishing (division 582 of sector J), telecommunications (division 61 of sector J), computer programming, consultancy and related activities, and information service activities (divisions 62-63 of sector J). When digital intensity increases, the economy uses more computers, more software and/or more IT services relative to other inputs than it used to. This may also mean that digital inputs are becoming increasingly expensive relative to non-digital inputs. When digital intensity decreases, the opposite changes will prevail (Gaglio and Guillou, 2018b).

We define four measures of digital intensity (DI; see Table 1). The first measure (DI_{it}) represents the total digital intensity of a country i for a specific year t. The second measure (DI_{it}^{d}) is the same as the first but focuses on the domestic component d, which means that a country only consumes digital inputs that it has produced itself. The third measure (DI_{ikt})

[2]These digital technologies are defined as follows: *"internet for at least 50% of employed persons, recourse to ICT specialists, fast broadband (30 Mbps or above), mobile internet devices for at least 20% of employed persons, a website, a website with sophisticated functions, social media, paying for advertising on the internet, the purchase of advanced cloud computing services, sending e-invoices, e-commerce turnover accounting for over 1% of total turnover and business-to-consumer web sales of over 10% of total web sales"*, (European Commission, 2017). For more information, see `https://ec.europa.eu/digital-single-market/en/news/europes-digital-progress-report-2017`.

[3]International Standard Industrial Classification (ISIC).

is finer than the previous ones and represents the sectoral digital intensity of a country-sector ik for a specific year. The fourth measure (DI^d_{ikt}) is the same as the third but focuses only on the domestic component. For each of these four measures, we study the manufacturing industry and each of its branches as well as the service industries (i.e., transportation and storage; accommodation and food service activities; information and communication; financial and insurance activities; real estate activities; and professional, scientific and technical activities). Note that for the first two measures, a country indifferently consumes digital inputs that are produced by itself and other countries.

Table 1: Measures of digital intensity

	Measure	**Definition**	**Level**
1	DI_{it}	Total consumption in digital inputs/ Total consumption in all inputs	By country and year
2	DI^d_{it}	Total domestic consumption in domestic digital inputs/ Total domestic consumption in all domestic inputs	
3	DI_{ikt}	Sectoral consumption in digital inputs/ Total consumption in all inputs	By country, sector and year
4	DI^d_{ikt}	Sectoral domestic consumption in domestic digital inputs/ Sectoral domestic consumption in all domestic inputs	

Source: Authors' definition.

2.2 Patterns of digitalization

Differences by country. In Figure 1, we present the total digital intensity measure (manufacturing + service industries) and rank countries according to their level in 2014: less than 8%, between 8 (included) and 12%, between 12 (included) and 16%, and equal to or greater than 16%. Among the 43 countries in our sample, 17 have a digital intensity of greater than 12%. Only 4 out of 17 have a digital intensity of higher than 16% in 2014: Hungary (16.2%), Japan (17.2%), Ireland (20.2%), and Malta (21.4%)[4]. These 17 countries form a heterogeneous mix, but idiosyncratic policy can explain their common high digital intensities. Ireland has promoted a tax policy in favour of intangible assets. Japan and Korea are technology-oriented countries. An increasing share of the global production of electronic and computer components is located in Asia along GVCs, and Asian countries increased their digital VA (producer side) in 2014 relative to 2000 levels. Finland, following Nokia's failure in smartphones, has placed itself at the forefront of the digital revolution by improving the quality of its transmission networks,

[4]In the appendix, we present the domestic digital intensity in 2014 (see Figure A1). A salient fact emerges. Among the 17 countries with a digital intensity level greater than 12%, 10 remain at the top of the ranking, which means that they produce some of the digital inputs they consume. Ireland's domestic digital intensity (31.4%) is even higher than its total digital intensity.

focusing on open access to public data, and developing digital technology in the education system. Romania has simultaneously benefited from a technological leap thanks to the direct deployment of very high-speed infrastructures (i.e., cable and optical fibre) by operators and the rise of online commerce. Denmark has been pursuing a very proactive policy in the area of e-government for almost twenty years. Brazil followed the digitalization of Danish public services to support the digital transformation of its economy.

Figure 1: Digital intensity by country in 2014 (in %)

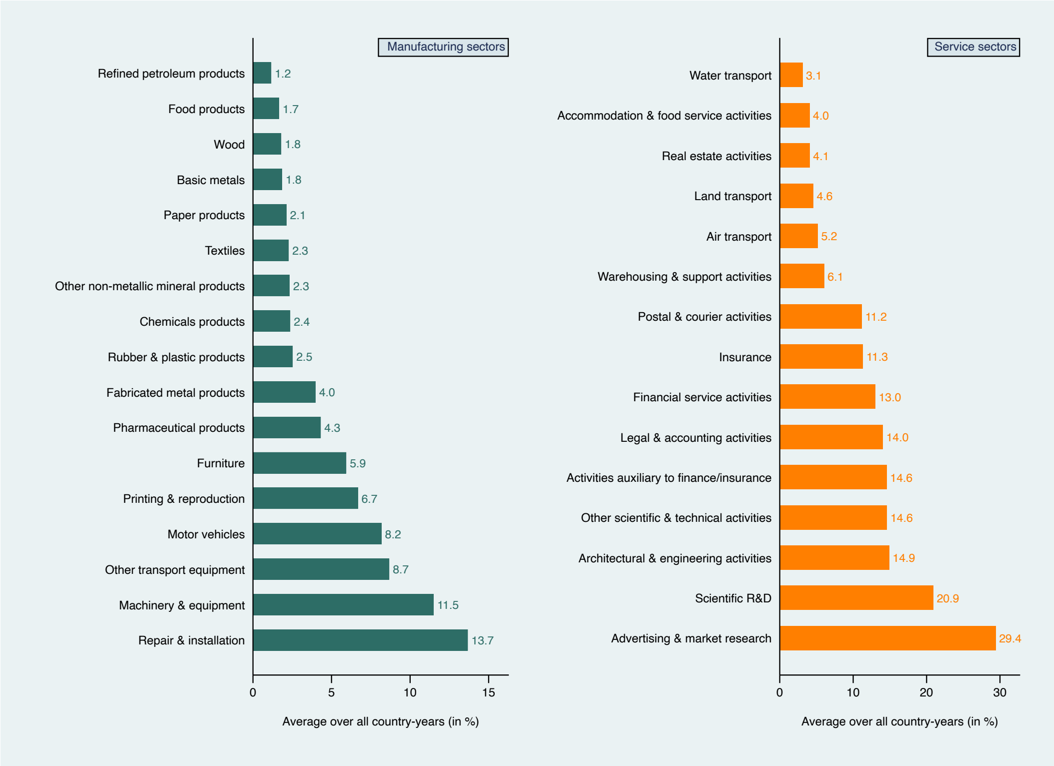
Source: WIOD - Authors' calculations.

The other countries have a digital intensity of less than 12% or less than 8%. Examples include India (7.8%), Russia (6.8%), Lithuania (6.2%), and Turkey (4.3%). European countries fall somewhere in between, particularly because of the national digital programs they have individually initiated[5]: the Netherlands (13.2%), Germany (12.4%), France (12.2%), Italy (9.8%), Spain (8.8%) and Belgium (8.1%). So, countries have experienced different trends over time.

Differences by sector. A few salient characteristics emerge from these measures of digital intensity. First, except for Luxembourg, Ireland, and Malta, digital inputs are used more in service industries than in manufacturing (see Figure 1). This is partly due to the dual decline faced by most European countries (which constitute a large part of our sample) and the

[5] At the European level, several initiatives have been launched to support citizens and firms in the *"digital decade"*. The more recent digital program aims to stimulate high-performance computing, artificial intelligence, cybersecurity, advanced digital skills and the widespread use of digital technologies throughout society.

Figure 2: Average of digital intensity by sector (in %)



Source: WIOD - Authors' calculations.

United States, which have experienced manufacturing decline in the electronics sectors along with a decline in ICT prices. In addition, partly due to the expansion of platform activities, new players in the digital economy have replaced traditional industrial activities in sectors as varied as transport, retail, music trade, and the hotel industry. Among manufacturing sectors, the sectoral digital intensity varies between 1.2% for the manufacture of coke and refined petroleum products and 13.7% for the repair and installation of machinery and equipment (see Figure 2). The range of variation in digital intensity is wider for the service sectors, varying from 3.1% for water transport to 29.4% for advertising and market research. Therefore, services are more intensive in digital inputs. Note that this first characteristic is in line with the previously mentioned conclusions made by European Commission (2017). Second, digital inputs are heavily consumed by the digital sectors themselves. On the manufacturing side, on average over all countries and years, the manufacture of electrical equipment consumes 28.4% of digital inputs, while the manufacture of computer, electronic and optical products consumes 48.5%. On the services side, the levels are 19.1% for publishing activities, 42.7% for information services activities, 50.4% for motion picture and television programme production, and 53.1% for telecommunications. The measures of digital intensity are thus calculated excluding these digital sectors. Third, most digital service inputs are domestic; hence, a highly digitized economy is likely to have a thriving sector of digital services. The relation is less true for digital goods for which imports may be important.

3 Empirical approach and data sources

3.1 Gravity model

Model specification. We rely on a theory-consistent estimation of the gravity model of trade to quantify the effect of digitalization on international trade flows. Since the pioneering work of Anderson (1979), the equation has become the workhorse model to explore the relationship between international trade flows and policy variables of interest (Head and Mayer, 2014). In their seminal paper, Anderson and Wincoop (2003) derive a gravity model from a model with a constant elasticity of substitution demand function and Armington (1969) hypothesis of product differentiation. The authors provide evidence of the importance of controlling the model for relative trade costs because trade flows between two countries are determined not only by trade barriers separating the two countries but also relative to the average trade barrier of each country with all its partners (i.e., "multilateral resistance"). Omitting these multilateral price terms is described by Baldwin and Taglioni (2006) as the *"gold medal mistake"*, especially for longer panels for which multilateral resistance can change over time. Note that Arkolakis et al. (2012) explicitly show that the standard empirical gravity model is very general and can be derived from other structural models such as Ricardian models (Eaton and Kortum, 2002) or models with heterogeneous firms (Melitz, 2003; Chaney, 2008).

Following Anderson and Yotov (2010), who indicate that this practice reduces aggregation bias, we estimate a structural gravity model at the sectoral level as specified in equation (1):

$$X_{ij}^k = \frac{E_j^k Y_i^k}{Y^k} \left(\frac{t_{ij}^k}{P_j^k \Pi_i^k} \right)^{(1-\sigma^k)} \tag{1}$$

where X_{ij}^k is the value of exports from origin i to destination j in sector k, E_j^k is the expenditure at destination j on goods from sector k from all origins, Y_i^k refers to the sales of goods from i in sector k to all destinations, t_{ij}^k are trade costs on the shipment of goods from i to j in sector k, P_j^k is inward multilateral resistance, Π_i^k is outward multilateral resistance, and σ^k represents the elasticity of the substitution parameter for goods of sector k.

As in Anderson and Yotov (2010), unobservable costs are assumed to be related to observable characteristics, as specified in equation (2):

$$(t_{ij}^k)^{(1-\sigma^k)} = e^{(-\theta_1 ln(D_{ij}) + \theta_2 contig_{ij} + \theta_3 colony_{ij} + \theta_4 COL_{ij} + \theta_5 FTA_{ij})} \tag{2}$$

where D_{ij} is the distance in kilometres between country of origin i and destination country j, $contig_{ij}$ is a dummy variable that captures whether the two countries share a common border, $colony_{ij}$ is a dummy variable equal to 1 if the two countries have ever had a colonial relationship, COL_{ij} is a dummy variable that captures whether the two countries use the same official languages, and FTA_{ij} is a dummy variable equal to 1 if the two countries have ratified a free trade agreement (FTA).

Based on equations (1) and (2), we extend the gravity framework by including our measure of digital intensity as specified in equation (3):

$$
\begin{aligned}
X_{ijkt} = exp[&\beta_0 + \beta_1 DI_{ikt} + \beta_2 DI_{jkt} + \beta_3 GVCB_{ikt} + \beta_4 GVCB_{jkt} + \beta_5 GVCF_{ikt} + \beta_6 GVCF_{jkt} \\
&+ \beta_7 INT_{ijt} + \theta_1 ln(D_{ij}) + \theta_2 contig_{ij} + \theta_3 colony_{ij} + \theta_4 COL_{ij} + \theta_5 FTA_{ijt} \\
&+ \lambda_{it} + \lambda_{jt} + \lambda_k + \epsilon_{ijkt}]
\end{aligned}
\tag{3}
$$

where X_{ijkt} refers to exports from country i to country j in sector k for specific year t, β_0 is the constant term, DI_{ikt} and DI_{jkt} represent the digital intensity measures of the two countries in sector k, $GVCB_{ikt}$ and $GVCB_{jkt}$ are the backward GVC participation of the two countries in sector k, and $GVCF_{ikt}$ and $GVCF_{jkt}$ are the forward GVC participation of the two countries in sector k. Following the analysis of Wang et al. (2017), we compute these two measures of GVC participation at the country-sector level. The first measure – backward participation – evaluates the domestic VA generated from a country sector's GVC activities through downstream firms as the share of the total VA of this country sector. The second measure – forward participation – describes the share of a country-sector's total production of final goods and services that is involved in GVC activities through upstream firms[6]. The main purpose of these two measures is to assess the linkages between countries within a trade value chain in which each country specialises in particular stages of the production process.

INT_{ijt} represents the internet network based on individuals who have access to the internet in country i and country j. We control for different types of fixed effects. As suggested by Baldwin and Taglioni (2006) and Yotov et al. (2017), λ_{it} refers to exporter-time fixed effects and accounts for the outward multilateral resistance term, while λ_{jt} refers to importer-time fixed effects and accounts for the inward multilateral resistance term. λ_k refers to sector dummies and reflects the long-term characteristics of each sector. β_1 to β_7 and θ_1 to θ_5 are the coefficients associated with the previous variables, and ϵ_{ijkt} is the error term.

Collinearity issues. The aim of this paper is to show that digital intensity affects exports. However, there is concern that our measures of digital intensity are too collinear with measures of GVC participation, especially since our measures are also based on input-output tables. In fact, the overall correlation rate between our sector-level digital intensity measure and the backward GVC participation measure is negative and equals -0.1156, while the correlation rate between our sector-level digital intensity measure and the forward GVC participation index is also negative and equals -0.0736[7]. Therefore, there is no systematic association between digital intensity and GVC participation.

[6]For more details on these two measures, see Wang et al. (2017).

[7]See the correlation matrix in the appendix, Table A3.

Estimation method. Following standard practice in the international trade literature, we estimate the model using the Poisson Pseudo Maximum Likelihood (PPML) estimator developed by Santos Silva and Tenreyro (2006). There are three reasons for this approach. First, disaggregated data entail a large number of zero-value observations (29% in our study)[8] and if these zeros are not randomly distributed, a selection bias occurs if zeros are dropped from the sample using a log-linearization method. Second, Santos Silva and Tenreyro (2006) provide evidence that this estimator out-performs OLS in the presence of heteroscedasticity, while Head and Mayer (2014) show that the PPML estimator remains consistent in the case of overdispersion in the data. As a consequence, Anderson and Yotov (2010) argue that the use of the PPML estimator to estimate the fixed effects and gravity coefficients is now standard in the empirical literature. Third, Fally (2015) indicates that the PPML estimator has another important advantage, as it leads to a perfect fit between the fixed effects and the multilateral resistance terms (Head and Mayer, 2014).

3.2 Data sources and sample

We combine information from four different sources to build an original dataset for the period of 2000-2014. Our sample covers 40 countries of origin and 40 destination countries in 18 manufacturing and 14 services industries[9]. The full description of the different variables and associated descriptive statistics are reported in Tables A4 and A5.

Input-output tables. Our main source of data is the World Input-Output Database (WIOD) provided by the European Commission[10]. The WIOD is an annual time series of world input-output tables and harmonizes a set of national use-resource tables that are connected to each other by bilateral international trade flows. The WIOD covers 56 sectors (ISIC, revision 4) and 44 countries (28 European countries, 15 other major economies such as China, Japan and the USA and a model for the rest of the world) for between 2000 and 2014. We use the 2016 version. Values are given in millions of US dollars. As mentioned by Timmer et al. (2015), the main advantage of the WIOD is that *"the combination of national and international flows of products provides a powerful tool for analysis of global production networks"*, (p.577-578).

Export data. We use two trade databases in our study. The first trade database is the Base pour l'Analyse du Commerce International (BACI) provided by the CEPII research center[11].

[8] Zero-value observations are especially important in service trade data. In our dataset, 89% of zero-value observations are recorded in the service sector.

[9] The complete list of countries is displayed in Table A1, while the complete list of manufacturing and services sectors is available in Table A2.

[10] Access date: November 2021. See Timmer et al. (2015; 2016). For more information, see `http://www.wiod.org/database/wiots16`.

[11] Access date: November 2021. See Gaulier and Zignago (2010). For more information, see `http://www.cepii.fr/CEPII/fr/bdd_modele/presentation.asp?id=37`.

The BACI covers bilateral values (in thousands of US dollars) and quantities (in tons) of world trade flows at HS[12] 6-digit product disaggregation for more than 200 countries and 5,000 products from 1995. Updated every year, these data are available with different revisions. We use the 1996 version. We aggregate trade flows at the 2-digit industry classification level and obtain bilateral trade flows for 18 manufacturing industries. The second trade database used is the International Trade in Services Statistics (ITSS) database provided by the OECD[13]. The ITSS database provides information on balance of payments data on international trade in services at a disaggregated level. We obtain bilateral trade flows for 14 services.

Trade costs. We use the Gravity database also provided by the CEPII, which gathers data required to estimate gravity equations for any country pair for between 1948 and 2019[14]. We obtain information on standard gravity variables such as geographical distance, colonial ties, contiguity and FTAs. We also rely on the common official languages (COL) variable constructed by Melitz and Toubal (2014) to evaluate language proximity. In their definition, an official language implies that all messages in the language are understood by everyone in the country at no marginal cost, regardless of the language they speak.

Internet variable. In the empirical literature, internet access is often treated as a proxy of connectivity between economic agents, which facilitates bilateral trade (Freund and Weinhold, 2004; Kitenge and Lahiri, 2021). Most empirical studies rely on the variable capturing the number of individuals with internet access in country i at time t provided in the World Development Indicators by the World Bank. However, in our specification, this variable would be absorbed by importer-time and exporter-time varying fixed effects. Therefore, we rely on the two-sided time-varying index developed by Kitenge and Lahiri (2021) to measure the value of the internet network. The variable is based on individuals who have access to the internet in both exporting and importing countries and defines the value of the complete network.

4 Results

4.1 The role of digitalization in trade flows

In Table 2, we provide the results of estimating equation (3) for various specifications of the gravity model. The determinants of trade are introduced in a stepwise way. The regression in column (1) includes our digital intensity measures and only the five trade characteristics.

[12] Harmonized System (HS).

[13] Access date: February 2022. For more information, see `https://stats.oecd.org/Index.aspx?DataSetCode=TISP_EBOPS2010`.

[14] Access date: February 2022. See Head et al. (2010); Head and Mayer (2014). For more information, see `http://www.cepii.fr/CEPII/fr/bdd_modele/presentation.asp?id=8`.

Columns (2) and (3) add the variables associated with the measures of GVC participation. Column (4) presents the complete specification, including the internet variable.

Table 2: PPML estimation – Baseline results

	(1)	(2)	(3)	(4)
DI_{ikt}	0.0315***	0.0297***	0.0294***	0.0294***
	(0.00403)	(0.00392)	(0.00376)	(0.00378)
DI_{jkt}	0.00323	0.00161	0.00110	0.00118
	(0.00309)	(0.00302)	(0.00290)	(0.00291)
FTA_{ijt}	0.381***	0.383***	0.382***	0.385***
	(0.0986)	(0.0987)	(0.0985)	(0.0966)
D_{ij}	-0.704***	-0.704***	-0.704***	-0.699***
	(0.0437)	(0.0436)	(0.0436)	(0.0432)
$contig_{ij}$	0.456***	0.457***	0.457***	0.482***
	(0.0797)	(0.0795)	(0.0795)	(0.0757)
$colony_{ij}$	0.115	0.116	0.115	0.126
	(0.0912)	(0.0912)	(0.0912)	(0.0915)
COL_{ij}	0.202**	0.200**	0.200**	0.194**
	(0.0979)	(0.0979)	(0.0978)	(0.0972)
$GVCB_{ikt}$		0.564	0.608	0.611
		(0.445)	(0.431)	(0.432)
$GVCB_{jkt}$		0.508	0.482	0.486
		(0.371)	(0.371)	(0.372)
$GVCF_{ikt}$			0.881**	0.876**
			(0.355)	(0.355)
$GVCF_{jkt}$			0.131***	0.131***
			(0.0379)	(0.0379)
INT_{ijt}				0.692***
				(0.222)
Constant	19.42***	19.14***	18.82***	-6.631
	(0.391)	(0.440)	(0.462)	(8.170)
Observations	582,330	582,330	582,330	576,273
Exporter-year FE	YES	YES	YES	YES
Importer-year FE	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES

Note: Standard errors, clustered at the exporter-importer level, are given in parentheses.
Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Of the two digital intensity measures, our results provide evidence that only the digital intensity of the exporting sector in the exporting country has a significant and positive impact on trade flows. This result is robust to adding the different controls and other covariates. Contrary to our expectations, the coefficient on digital intensity of the importing sector in the importing country is not significantly different from zero. This result contradicts previous analyses that focus exclusively on the internet, such as those of Clarke and Wallsten (2006) and Lin (2015), and is more in line with the results of Osgnago and Tan (2016), who found a weaker effect of internet adoption by importers on trade flows. Nevertheless, as mentioned above, digital intensity is a different concept from internet adoption. It involves the import of digital goods and services that can facilitate trade but also improve the quality of the exported product. Therefore, these initial results suggest that digital intensity plays a role independent of internet access in trade flows, perhaps linked to the improvement of the quality of exported products.

Except for the variable associated with colonial relationships, we find that traditional gravity variables are significant and have the expected sign. Geographical distance has a significant and large deterring effect on bilateral trade flows, while sharing a common border, using similar official languages and having ratified an FTA significantly increase bilateral trade. As expected, the forward GVC participation of both exporting and importing countries has a positive and significant coefficient, while the bilateral internet network significantly improves bilateral trade flows. The inclusion of the backward GVC participation measures in column (2), the forward GVC participation measures in column (3) and the internet variable in column (4) does not fundamentally affect the interpretation and magnitude of the coefficient on digital intensity.

4.2 Country and industry heterogeneity

Country heterogeneity. It is important to investigate whether the impact of digital intensity on trade flows depends on the income levels of trading partners. In Table 3, we provide the estimation results of equation (3) for categories of trade flows based on income level. We build four different categories of trade flows: in column (1), exports from high-income countries to other high-income countries; in column (2), exports from high-income countries to emerging countries; in column (3), exports from emerging countries to high-income countries; and in column (4), exports from emerging countries to other emerging countries. We use the World Bank income classification to determine the nature of the bilateral trade flows[15]. A country is considered a high-income economy if its GDP per capita is equal to or greater than \$12,696, while a country is considered as an emerging economy if its GDP per capita is between \$1,046 and \$12,695.

The results reveal that digital intensity has a stronger impact on exports from emerging economies (0.0568 and 0.0560) than on exports from high-income countries (0.0109 and 0.0344). This is particularly true when trade costs – reflected by the coefficient of geographical distance – are high, as in bilateral trade flows between emerging economies. As a result, one potential mechanism by which sectoral digital intensity affects export flows could be related to the reduction of communication and transportation costs.

[15] In the appendix, we present the classification of countries by income level (see Table A1).

Table 3: PPML estimation – Country heterogeneity

	(1) High-High	(2) High-Emerging	(3) Emerging-High	(4) Emerging-Emerging
DI_{ikt}	0.0109***	0.0344***	0.0568***	0.0560***
	(0.00367)	(0.00698)	(0.00646)	(0.0104)
DI_{jkt}	0.000519	0.0193***	-0.00385	0.00705
	(0.00314)	(0.00602)	(0.00592)	(0.00854)
FTA_{ijt}	0.418***	0.270	0.889***	0.537
	(0.134)	(0.169)	(0.189)	(0.365)
D_{ij}	-0.735***	-0.795***	-0.640***	-1.161***
	(0.0419)	(0.0639)	(0.106)	(0.243)
$contig_{ij}$	0.514***	0.748***	0.825***	-0.0665
	(0.0774)	(0.166)	(0.262)	(0.262)
$colony_{ij}$	-0.0808	0.855***	0.655***	0.219
	(0.0996)	(0.196)	(0.249)	(0.469)
COL_{ij}	0.418***	-0.550**	-0.612***	-0.139
	(0.0894)	(0.222)	(0.191)	(0.699)
$GVCB_{ikt}$	1.544***	0.520	0.0679	1.052
	(0.358)	(0.783)	(1.220)	(1.662)
$GVCB_{jkt}$	0.486	0.0489	1.337	2.176***
	(0.364)	(0.838)	(0.862)	(0.743)
$GVCF_{ikt}$	0.345***	1.214*	3.820***	4.860***
	(0.0793)	(0.661)	(0.689)	(0.945)
$GVCF_{jkt}$	0.147***	-1.274***	0.294**	0.178
	(0.0368)	(0.389)	(0.138)	(0.671)
INT_{ijt}	-3.387***	0.829	-0.298	0.0866
	(0.525)	(0.525)	(0.773)	(1.216)
Constant	138.9***	-10.52	29.85	17.84
	(18.63)	(19.63)	(30.05)	(47.47)
Observations	359,716	102,604	87,655	24,405
Exporter-year FE	YES	YES	YES	YES
Importer-year FE	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES

Note: Standard errors, clustered at the exporter-importer level, are given in parentheses.

Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Industry heterogeneity. While the literature has shown that internet adoption influences both manufacturing (Freund and Weinhold, 2004; Clarke and Wallsten, 2006; Lin, 2015) and services (Freund and Weinhold, 2002; Choi, 2010) trade, the magnitude of its impact seems to differ depending on the type of sector examined. Therefore, we also address the issue of sectoral heterogeneity by estimating the gravity models of the manufacturing and services sectors separately. In Table 4, we present the results of this estimation.

Table 4: PPML estimation – Industry heterogeneity

	(1) Manuf.	(2) Services
DI_{ikt}	0.0355***	0.0104***
	(0.00416)	(0.00285)
DI_{jkt}	0.000671	-0.00189
	(0.00319)	(0.00361)
FTA_{ijt}	0.427***	-0.0120
	(0.0973)	(0.163)
D_{ij}	-0.701***	-0.706***
	(0.0431)	(0.0837)
$contig_{ij}$	0.513***	0.168
	(0.0758)	(0.154)
$colony_{ij}$	0.119	0.213*
	(0.0940)	(0.115)
COL_{ij}	0.151	0.303**
	(0.102)	(0.150)
$GVCB_{ikt}$	0.277	2.374***
	(0.438)	(0.533)
$GVCB_{jkt}$	0.505	0.228
	(0.395)	(0.614)
$GVCF_{ikt}$	1.067***	2.379***
	(0.360)	(0.368)
$GVCF_{jkt}$	0.144***	-0.0488
	(0.0399)	(0.419)
INT_{ijt}	0.748***	4.654**
	(0.222)	(2.184)
Constant	-8.604	-151.3*
Observations	409,644	166,629
Exporter-year FE	YES	YES
Importer-year FE	YES	YES
Sector FE	YES	YES

Note: Standard errors, clustered at the exporter-importer level, are given in parentheses.
Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

First, we find that sectoral digital intensity significantly increases both manufacturing and service exports. Second, consistent with our previous results, we find no significant effect of the digital intensity of the importing sector in the importing country on either manufacturing or services trade. Third, we find that the effect of sectoral digital intensity is significantly greater in the manufacturing industry than in the service industry. This is in line with what is found for internet adoption by Osgnago and Tan (2016). In contrast, we find that the variables capturing common official languages and the internet network have a stronger impact on trade in services. As suggested by Mayer (2021), digital technologies affect trade costs in manufacturing and services differently. Indeed, according to the WTO analysis (2018), trade in services involves a higher share of information and transaction costs that could be reduced by internet adoption. However, sectoral digital intensity not only lowers trade costs but can also improve the quality of exported products through the use of digital inputs and, therefore, can have an additional effect on manufacturing exports.

4.3 Digitalization and trade costs

One transmission mechanism explaining the positive impact of sectoral digital intensity on export flows could be related to trade costs. Indeed, the use of digital inputs (in particular digital services) can help firms reduce the fixed costs of exporting by facilitating communication between buyers and suppliers and thus enhance trade. To study this hypothesis, we compute four different tests and provide the results in Table 5. In column (1), we interact the variable associated with geographical distance with dummy variables that capture each quartile of the distribution of the sectoral digital intensity of the exporting country. In column (2), we interact the variable associated with common official languages with the sectoral digital intensity of the exporting country. In column (3), we interact the variables associated with geographical distance and common official languages with the sectoral digital intensity of the exporting country. In column (4), we add two other interaction terms. Thus, we interact our measure of digital intensity at the sectoral level in the exporting country with all the variables that reflect trade costs (geographical distance, a common colonial history, common official languages and a common border). Note that all estimations include the GVC participation measures, bilateral internet variable and constant, but they are not reported in Table 5 to save space.

Digital intensity and geographical distance. An almost monotonic pattern appears in column (1). The sectors with the lowest digital intensity (first quartile) are more sensitive to geographical distance, while upper quartiles are less sensitive. The difference is highly significant between the extreme quartiles[16]. Coefficient equality across all quartiles is rejected at standard levels for geographical distance. This reveals that the use of digital inputs allows the exporting country's sectors to defy gravity. This pattern is confirmed in the estimations made in columns (3) and (4). Thus, we find that the interaction between variable DI_{ikt} and variable D_{ij} is significant and positive. Moreover, this confirms the decreasing impact of geographical distance on export flows when the digital intensity of the exporting sector increases in the exporting country.

Digital intensity and language. In column (2), the interaction between DI_{ikt} and COL_{ij} is negative and significant. This implies that the impact of digital intensity is greater when countries do not use the same official languages (0.0301) than when they do (0.011). Further-

[16]The test statistic is 33.49***.

Table 5: PPML estimation – Digital intensity and trade costs

	(1)	(2)	(3)	(4)
DI_{ikt}	0.0310***	0.0301***	-0.0150	-0.0111
	(0.00373)	(0.00353)	(0.00911)	(0.00966)
DI_{jkt}	0.00171	0.00127	0.00214	0.00205
	(0.00298)	(0.00267)	(0.00284)	(0.00277)
FTA_{ijt}	0.395***	0.381***	0.369***	0.371***
	(0.0945)	(0.0969)	(0.0912)	(0.0914)
$contig_{ij}$	0.478***	0.485***	0.471***	0.496***
	(0.0763)	(0.0754)	(0.0757)	(0.0912)
$colony_{ij}$	0.131	0.125	0.135	0.195**
	(0.0899)	(0.0910)	(0.0896)	(0.0849)
COL_{ij}	0.189*	0.416***	0.366***	0.347***
	(0.0969)	(0.0972)	(0.0981)	(0.102)
$Q_1 * D_{ij}$	-0.852***			
	(0.0487)			
$Q_2 * D_{ij}$	-0.716***			
	(0.0505)			
$Q_3 * D_{ij}$	-0.687***			
	(0.0541)			
$Q_4 * D_{ij}$	-0.531***			
	(0.0561)			
D_{ij}		-0.700***	-0.786***	-0.781***
		(0.0433)	(0.0417)	(0.0425)
$DI_{ikt} * COL_{ij}$		-0.0191***	-0.0145***	-0.0131***
		(0.00368)	(0.00312)	(0.00400)
$DI_{ikt} * D_{ij}$			0.00532***	0.00489***
			(0.00103)	(0.00113)
$DI_{ikt} * contig_{ij}$				-0.00206
				(0.00437)
$DI_{ikt} * colony_{ij}$				-0.00511*
				(0.00305)
Observations	576,273	576,273	576,273	576,273
GVC indexes	YES	YES	YES	YES
Internet variable	YES	YES	YES	YES
Exporter-year FE	YES	YES	YES	YES
Importer-year FE	YES	YES	YES	YES
Sector FE	YES	YES	YES	YES

Note: Standard errors, clustered at the exporter-importer level, are given in parentheses.
Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

more, the benefits of using the same official languages decrease with higher digital intensity. This result is confirmed in column (4). For the other gravity variables, the interaction with the digital intensity measure is not significant at the 5% level.

Interpretation. Contrary to what is observed for internet networks (Kitenge and Lahiri, 2021), the use of digital inputs reduces both the negative impact of geographical distance on exports and the benefits of using similar official languages. Again, several transmission mechanisms can be put forward to explain these results. On the one hand, the stronger impact of digital intensity on exports between countries that do not use the same official languages could reflect the fact that the use of digital services (such as telecommunication or information service activities) facilitates the ability of firms to conduct business transactions or develop a network abroad. This argument is very similar to the one developed to explain the impact of internet access on trade (Freund and Weinhold, 2004; Lin, 2015; Visser, 2019; Kitenge and Lahiri, 2021). On the other hand, the channel at stake could also be quality. The use of digital inputs can increase the quality of exported products that are less sensitive to trade costs. Indeed, the trade literature on quality sorting and trade patterns has demonstrated that high-end products are less sensitive to geographical distance (Martin and Mayneris, 2015; Fontagné and Hatte, 2013; Bargain et al., 2020).

4.4 Digitalization and export quality upgrading

Another transmission mechanism could be related to product quality. The trade literature has shown that the use of imported inputs can improve export quality through two different channels. The first channel is called the variety effect. Trade liberalization allows firms access to a wider variety of inputs to produce their final product. This greater variety increases a firm's productivity (Ethier, 1982; Halpern et al., 2015). Several empirical studies have confirmed a positive link between imports of intermediate inputs and firm productivity, especially in the case of French firms (Bas and Strauss-Kahn, 2015). The second channel is called the innovation effect. The idea is that imported intermediate inputs incorporate foreign technology that could be absorbed by firms to produce new varieties of final products (Kugler and Verhoogen, 2009). Other empirical studies have shown a positive link between imports of intermediate inputs and export upgrading. For instance, Manova and Zhang (2012) demonstrate that most successful exporters are those that use higher quality inputs to produce higher quality goods, while Fan et al. (2015) show that lower import tariffs lead to higher quality and higher export prices for firms in industries where the scope of differentiation is broad. Using Chinese firm-level data, Zhu and Tomasi (2020) confirm that foreign sourcing improves the quality of exports. Consequently, the use of digital inputs (domestic or/and imported) should enhance the quality of exports.

To test this hypothesis, we follow the approach developed by Khandelwal et al. (2013) to infer the quality of exported products. The method is based on the estimation of an empirical demand function and infers the quality of product h exported by country i to country j at time t as specified in equation (4):

$$Q_{ijht} = (q_{ijht})^{\sigma-1} (p_{ijht})^{-\sigma} (P_{jt})^{\sigma-1} (Y_{jt}) \tag{4}$$

where Q_{ijht} is the quantity of product h exported by country i to destination country j at time t, q_{ijht} is the quality of the exported product, p_{ijht} is the price of the exported product, P_{jt} is the price index of destination country j, and Y_{jt} is the income level of destination country j. σ represents the elasticity of substitution, with $\sigma > 1$. Using the log transformation, the quality of each exporter-product-destination-year can be estimated as the residual of the following OLS regression as specified in equation (5):

$$ln\ Q_{ijht} + \sigma\ ln\ p_{ijht} = \alpha_h + \alpha_{jt} + \epsilon_{ijht} \tag{5}$$

where α_h represents product fixed effects that capture price and quantity differences between product categories, α_{jt} represents time-varying destination country fixed effects that capture both the price index and the income level of the destination country and ϵ_{ijht} is the error term. Thus, the inferred quality of exported products is $\hat{\phi_{ijht}} = \frac{\hat{\epsilon_{ijht}}}{\sigma-1}$. Following previous empirical studies such as Manova and Yu (2017) and Ndubuisi and Owusu (2021), we set the value of σ to 5. To estimate equation (5), we use the BACI database described in Section 3.2 and therefore focus only on manufacturing sectors. Each 6-digit HS code is considered a particular product, and we proxy the price of each product by its unit value (i.e., value divided by quantity). As a result, we obtain an exporter-importer-product-year specific quality measure. However, to match our previous analysis, we use a weighted average[17] across sectors of the measure. In a final step, we estimate equation (3) using our measure of export quality as the dependent variable. Note that since equation (5) uses the log transformation of the variables, our measure of quality is already in logarithm form. In Table 6, we provide the results of estimating equation (5) using the OLS estimator. All estimations include exporter-year and importer-sector-year fixed effects.

Our results confirm the positive link between the increased use of digital inputs and the improved quality of exported products. This result is robust to adding the different controls. Moreover, following Ndubuisi and Owusu (2021), our results also provide evidence of a strong link between GVC participation (backward and forward) and export quality upgrading.

5 Robustness checks

In this section, we present several robustness tests conducted to check the sensitivity of our results to alternative econometric specifications. We used an alternative estimator, the OLS estimator, and employed only domestic digital inputs as a measure of sectoral digital intensity. We also used an IV identification strategy to account for a potential endogeneity problem in our setting.

[17] The weights are constructed using the value of exports of each 6-digit product within each sector.

Table 6: Digital intensity and quality upgrading

	(1)	(2)	(3)	(4)
DI_{ikt}	0.00159**	0.00161**	0.00130**	0.00139**
	(0.000645)	(0.000645)	(0.000643)	(0.000652)
D_{ij}		-0.0595***	-0.0591***	-0.0624***
		(0.00941)	(0.00921)	(0.00946)
$contig_{ij}$		0.0520**	0.0570**	0.0522**
		(0.0260)	(0.0257)	(0.0261)
$colony_{ij}$		0.0610*	0.0666**	0.0584*
		(0.0325)	(0.0317)	(0.0325)
COL_{ij}		0.0275	0.0240	0.0263
		(0.0353)	(0.0345)	(0.0360)
$GVCB_{ikt}$			0.138***	0.142***
			(0.0495)	(0.0493)
$GVCF_{ikt}$			0.0347***	0.0354***
			(0.00798)	(0.00795)
INT_{ijt}				0.0548
				(0.0368)
Constant	0.469***	0.937***	0.866***	-0.920
	(0.00711)	(0.0764)	(0.0767)	(1.226)
Observations	392,054	392,054	388,592	387,983
R-squared	0.285	0.288	0.263	0.289
Exporter-year FE	YES	YES	YES	YES
Importer-sector-year FE	YES	YES	YES	YES

Note: Standard errors, clustered at the exporter-importer level, are given in parentheses.
Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.1 Regressions using the OLS estimator

In Table 7, we estimate the gravity model only on the intensive margin (strictly positive trade flows) using a log transformation of the export variable and the OLS estimator. The results are very similar to those found in Table 2 and provide evidence of a positive relationship between sectoral digital intensity and sectoral exports. Note that the estimated coefficients for sectoral digital intensity are lower than those estimated in Table 2.

5.2 Regressions using only domestic digital inputs

One criticism that could be made of our approach is that our measure of digital intensity is based on both domestic and imported digital inputs. Thus, one might expect reverse causality, as imports of digital inputs could be the result of increased insertion into GVCs. To address this important issue, we test the sensitivity of our results to a measure of digital intensity that is constructed only from domestic digital inputs (DI^d_{ikt}).

Table 7: Robustness check – Estimation results using OLS

	(1)	(2)	(3)
DI_{ikt}	0.0104***	0.00894***	0.00905***
	(0.00135)	(0.00141)	(0.00142)
DI_{jkt}	0.00191	0.000324	0.000353
	(0.00130)	(0.00129)	(0.00129)
$GVCB_{ikt}$		0.933***	0.930***
		(0.189)	(0.190)
$GVCB_{jkt}$		1.071***	1.065***
		(0.134)	(0.134)
$GVCF_{ikt}$		0.336***	0.333***
		(0.0291)	(0.0290)
$GVCF_{jkt}$		0.0815***	0.0809***
		(0.0207)	(0.0207)
FTA_{ijt}	0.177**	0.176**	0.182**
	(0.0774)	(0.0776)	(0.0775)
D_{ij}	-1.426***	-1.428***	-1.434***
	(0.0513)	(0.0514)	(0.0526)
$contig_{ij}$	0.376***	0.377***	0.383***
	(0.119)	(0.119)	(0.118)
$colony_{ij}$	0.268*	0.267*	0.261*
	(0.137)	(0.137)	(0.137)
COL_{ij}		0.451***	0.440***
		(0.115)	(0.117)
INT_{ijt}			0.251**
			(0.111)
Constant	20.57***	19.87***	11.51***
	(0.438)	(0.446)	(3.630)
Observations	422,164	422,164	418,119
R-squared	0.717	0.720	0.719
Exporter-year FE	YES	YES	YES
Importer-year FE	YES	YES	YES
Sector FE	YES	YES	YES

Note: Standard errors, clustered at the exporter-importer level, are given in parentheses.
Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In Table 8, we provide the results for domestic digital intensity. In column (1), we estimate the baseline equation using only domestic digital inputs as the measure of sectoral digital intensity. In column (2), we present the results for the relationship between domestic digital intensity and trade costs. In column (3), we present the results for export quality. We find that our results are robust to the use of the domestic digital intensity measure, as we find very similar results to the previous ones, both qualitatively and quantitatively.

Table 8: Robustness check – Only domestic digital inputs

	(1) Baseline	(2) Trade costs	(3) Quality
DI^{d}_{ikt}	0.0231***	-0.0298**	0.00390***
	(0.00276)	(0.0150)	(0.000727)
DI^{d}_{jkt}		0.00226	
		(0.00257)	
D_{ij}	-0.697***	-0.782***	-0.0624***
	(0.0434)	(0.0424)	(0.00946)
FTA_{ijt}	0.383***	0.350***	
	(0.0965)	(0.0884)	
$contig_{ij}$	0.482***	0.508***	0.0522**
	(0.0759)	(0.0919)	(0.0261)
$colony_{ij}$	0.125	0.182**	0.0584*
	(0.0915)	(0.0835)	(0.0325)
COL_{ij}	0.196**	0.321***	0.0262
	(0.0970)	(0.104)	(0.0360)
$GVCF_{ikt}$	0.973**	0.798*	0.166***
	(0.464)	(0.464)	(0.0497)
$GVCB_{jkt}$	0.376	0.325	
	(0.381)	(0.352)	
$GVCF_{ikt}$	0.661**	0.590**	0.0355***
	(0.285)	(0.250)	(0.00796)
$GVCF_{jkt}$	0.122***	0.127***	
	(0.0373)	(0.0364)	
INT_{ijt}	0.692***	0.705***	0.0548
	(0.222)	(0.211)	(0.0368)
$DI^{d}_{ikt} * D_{ij}$		0.00639***	
		(0.00169)	
$contig_{ij} * DI^{d}_{ikt}$		-0.00560	
		(0.00607)	
$colony_{ij} * DI^{d}_{ikt}$		-0.00559	
		(0.00429)	
$DI^{d}_{ikt} * COL_{ij}$		-0.0118**	
		(0.00569)	
Constant	-6.449	-6.151	-0.940
	(8.170)	(7.715)	(1.226)
Observations	576,273	576,273	387,983
R-squared			0.290
Exporter-year FE	YES	YES	YES
Importer-year FE	YES	YES	NO
Sector FE	YES	YES	NO
Importer-sector-year FE	NO	NO	YES

Note: Standard errors, clustered at the exporter-importer level, are given in parentheses.
Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3 Regressions using instrumental variables

The main limitation of our previous results is related to the fact that digital intensity may itself be enhanced by increased trade. Indeed, the adoption of increasingly more digital tools, which is expected to increase digital intensity, could be the consequence of increasing international exposure and relationships for the firm to cope with. In this case, reverse causality could exist, and the estimation of the gravity model could be biased. Note that using the domestic component of the digital intensity in Section 5.2 lessens this phenomenon but does not eliminate it completely.

To address this issue, we implement IV regressions. The main idea is to find instruments correlated with digital intensity but exogenous to trade flows at the country-sector level. In a first-stage regression, the variable that captures the digital intensity of the exporting sector in the exporting country (DI_{ikt}) is regressed on this set of excluded instruments, the other covariates, and exporter-year and importer-year fixed effects. In a second-stage regression, the fitted values of DI_{ikt} obtained are used to estimate the gravity model presented in equation (3) following a two-stage least squares (2SLS) estimation.

Our IV identification strategy draws inspiration from the approach developed by Acemoglu et al. (2019). We argue that, similar to democracy, digitalization spreads geographically, which means that digital transformation occurs as geographical waves as we witnessed during the industrial revolution. In the context of the fragmentation of production processes along GVCs, we expect that when two countries are nested in the same GVC for the same sector and this sector digitizes in one of the two countries, this will induce a digitalization of the same sector in the partner country. Moreover, it is very unlikely that the digital intensity of a given sector of the neighbours affects exports of that given sector in the country under consideration through any channel other than the level of digital intensity of that specific sector in that country if country-time fixed effects are controlled for.

Consequently, we use an inverted-distance-weighted measure of the sectoral digital intensity of all other countries in the sample as the excluded instrument for the sectoral digital intensity level of country i at time t. The instrument is expressed as specified in equation (6):

$$Z_{ikt} = \frac{\sum_{j \neq i}^{J} \frac{1}{D_{ij}} DI_{jkt}}{\sum_{j \neq i}^{J} \frac{1}{D_{ij}}} \tag{6}$$

We use the first and second lags of variable Z_{ikt} as instruments. It is important to note that three assumptions must be verified to ensure the accuracy of our IV identification strategy. First, the instruments must be correlated with the endogenous variable (DI_{ikt}). This relevance condition can be easily tested with a robust F-statistic test. Second, the exclusion restriction assumption requires that the digital intensity of a given sector in country i's neighbours affects country i's exports in a given sector only through its impact on country i's digital intensity level in that specific sector. However, since this assumption cannot be tested, we assume that it holds. Note that even if the first two assumptions are verified, the IV strategy identifies only a local average treatment effect (LATE) and not an average treatment effect (AVE), as in our previous results. The use of IV regressions only identifies the ATE for complying country-sector pairs (i.e., country-sector pairs that are affected by the instruments). Although it is highly unlikely that the effect in complying countries is different from the average effect, we cannot test this. Third, it is important to note that the PPML estimator is subject to the incidental parameter problem in the case of the IV (Anderson and Yotov, 2020). Therefore, in a first approach, we rely on OLS to estimate the gravity model using the IV. Then, in a second approach, we apply the methodology proposed by Lin and Wooldridge (2019) and introduce a control function into our PPML estimation because we have roughly continuous variables. The main idea is to obtain the residuals from the first-step regression using the IV strategy, introduce them into the gravity model (i.e., into the second-step estimation) and estimate it using the PPML and bootstrapped standard errors.

In Table 9, we provide the estimation results for IV regressions. In columns (1) and (2), we estimate linear regressions, while in column (3), we present nonlinear results. We observe that the p-value associated with the F-statistics for the excluded instruments is zero in all IV regressions. Therefore, we can reject the null hypothesis that our instruments are weak. The Kleibergen-Paap rk LM test reveals that the minimum canonical correlation between our endogenous variable and our instruments is significantly different from zero. These results therefore indicate that the sectoral digital intensity of country i's neighbours has a strong influence on the level of sectoral digital intensity of country i and that the relevance condition seems to be satisfied. For the IV control function, the Wald test of the residuals in the first stage suggests that our digital intensity measure is endogenous because we can reject the null hypothesis that the effect of residuals in the second stage is significantly different from zero. Finally, we find quantitatively and qualitatively similar results to those found in Tables 2 and 6, which confirms our previous conclusions.

Table 9: Robustness check – IV regressions

	(1) OLS IV- Baseline	(2) OLS IV- Quality	(3) IV PPML Control function
DI_{ikt}	0.0282***	0.00730***	0.0343973***
	(0.00178)	(0.000301)	(0.0036052)
DI_{jkt}	-0.00119		-0.0123511***
	(0.00164)		(0.0032113)
FTA_{ijt}	0.274***		0.35817***
	(0.0796)		(0.11446)
D_{ij}	-1.362***	-0.0562***	-0.7157***
	(0.0504)	(0.00948)	(0.0433)
$contig_{ij}$	0.407***	0.0577**	0.4642***
	(0.113)	(0.0258)	(0.07792)
$colony_{ij}$	0.249*	0.0563*	0.13489
	(0.130)	(0.0325)	(0.09131)
COL_{ij}	0.439***	0.0326	0.18660*
	(0.114)	(0.0369)	(0.09937)
$GVCB_{ikt}$	2.233***	-0.343***	3.3736***
	(0.129)	(0.0325)	(0.3599)
$GVCB_{jkt}$	2.337***		3.1792***
	(0.127)		(0.37907)
$GVCF_{ikt}$	0.252***	-0.0319***	0.5859***
	(0.0259)	(0.00671)	(0.10183)
$GVCB_{jkt}$	0.0400*		3.1792***
	(0.0204)		(0.37907)
INT_{ijt}	0.303**	0.0826	1.0537***
	(0.146)	(0.0504)	(0.2844189)
Observations	366,280	334,606	498,577
R-squared	0.214	0.013	
Exporter-year FE	YES	YES	YES
Importer-year FE	YES	NO	YES
Importer-sector-year FE	NO	YES	NO
F-test of excluded instruments (p-value)	0.000	0.000	0.000
Kleibergen-Paap rk LM statistic (p-value)	0.000	0.000	
Wald test of the first-stage residuals (p-value)			0.000

Note: Standard errors, clustered at the exporter-importer level, are given in parentheses for columns (1) and (2). Bootstrapped standard errors (1,000 replications) are given in column (3).

Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6 Conclusion

This paper explores the relationships between digitalization at the country-sector level, trade costs, quality upgrading and trade flows for a sample of 40 countries, 18 manufacturing and 14 services industries for the period of 2000-2014. Our original contributions are threefold. (i) We construct an original measure of digital intensity of the country-sector level that reflects the use of digital inputs in the production function of a country. (ii) We offer a broad analysis as we disentangle the effects by sector and income level of the exporting and importing country. (iii) From a purely methodological point of view, our paper directly tackles the issue of endogeneity which could bias the results by using an identification by instrumental variables inspired by the work of Acemoglu et al. (2019).

Our findings show, first, that sectoral digital intensity increases exports. We show that although both manufacturing and services are affected by this positive link, the effect is significantly greater for manufacturing. We also provide evidence of a stronger effect of sectoral digital intensity on exports from emerging economies. Second, we find no evidence of a significant effect of the sectoral digital intensity of the importing country on trade flows. Third, we find evidence of a mitigating effect of sectoral digital intensity on the negative impact of geographical distance on exports. Sectors with the highest levels of digital intensity appear to defy gravity. We also show that sectoral digital intensity reduces the benefits of sharing common languages. Fourth, we show that an increase in sectoral digital intensity is associated with an increase in the quality of exported products. Therefore, digitalization is a key driver of export flows; it facilitates trade between countries by lowering communication and transport costs but also increases exported product quality.

In this paper, we have juxtaposed two concepts that, although considered central in economic debates, are each recognized as statistical challenges. For GVCs, this is due to interlinked cross border relations at the firm level (Nielsen, 2018), and for digitalization, this is due to the misclassification of platform activities and the measurement of price changes for digital goods and services (IMF, 2018). Beyond the fact that they both present statistical challenges, GVCs and digitalization have the common consequence of increasing interdependence between countries. By sharing a global market, countries have become increasingly connected to each other. This connection has been reinforced by the presence of a fragmentation of production processes along GVCs. The more a country is integrated into GVCs, the more it is dependent on the other links in the chain. Despite the fact that globalization has strengthened international relations between countries, this has been accompanied by far-reaching structural changes. The last change is associated with the digitalization of economies, and similar to the previous changes, this structural change has also reinforced the interdependence between countries. Because the production, distribution and supply chains are minimally computerized, the GVCs for the production of ICT goods are more closely intertwined (Ghodsi et al., 2021). For instance, in the electronics sector, some Southeast Asian countries are involved in the assembly of components into finished products and participate in low-VA activities at the end of the production chain, but they depend as much on the preliminary design and manufacturing stages occurring in the United States, Japan and Korea as on the components imported into the supply chain. Southeast Asian countries act as countries that assemble and re-export but do not add much value from their export revenues. However, electronic components (especially semiconductors), in addition to being inputs used in ICT goods, are used in the production of other goods such as automobiles, medical equipment and aeronautical equipment.

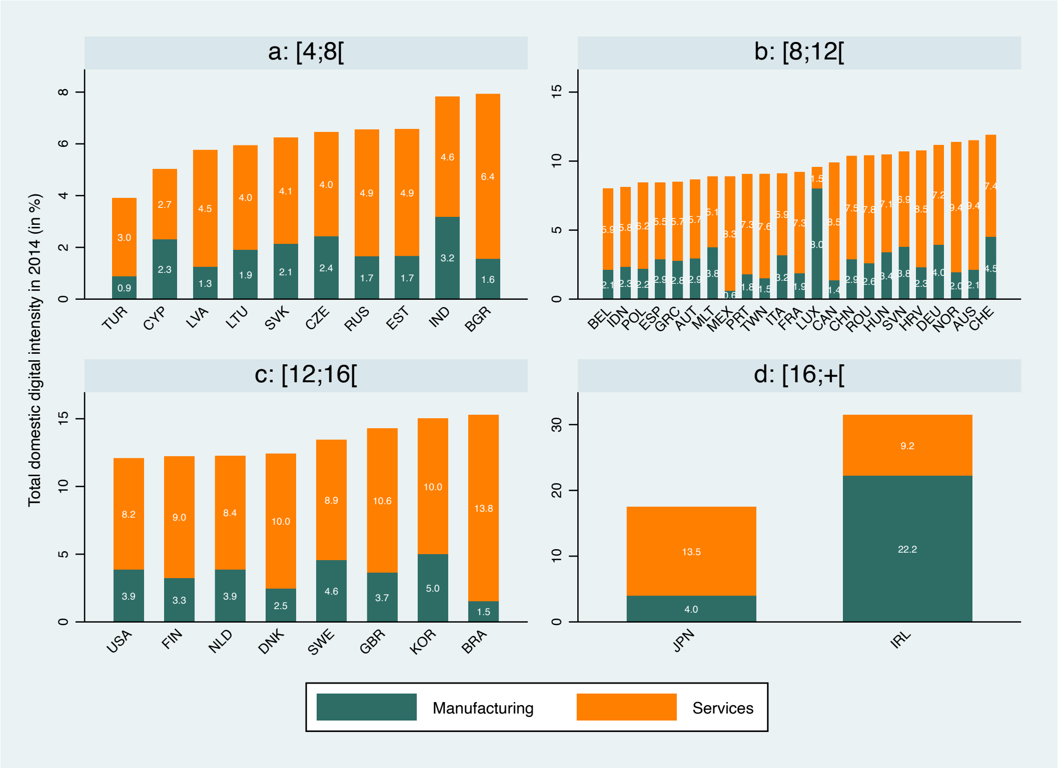
Despite the fact that economies are going digital, there remains a digital divide. Even though the COVID-19 pandemic has prompted countries to expand the digitalization of their services, digital transformation differs from one country to another. As a result of the pandemic, the Bruegel Institute[18] recently established a comparative analysis of European countries in terms of resource allocation in national recovery and resilience plans. One of its allocations concerns the share of digitalization in these plans. Although the sums committed are intended to make the digital decade a reality, there are major disparities between the member states. For example, Germany has dedicated 14.7 billion euros to the digital transition (52.5% of its total plan), while Poland has dedicated "only" 7.7 billion euros to this transition (21.4%). More generally, the EU is extremely heterogeneous in its digital transition. Even though it is very active in terms of digital regulation and aims to pool certain digital expenses at the European level, each member country began its transition at different times and has developed specific national programs.

There are several ways that the results of this study could be usefully extended. First, the data we mobilize to build our digital intensity measure (i.e., WIOD data) cover only the period of 2000-2014. Our analysis could be extended to a longer time period with more recent data. Especially since digitalization is a constantly evolving process, economies do not digitize at the same pace, and the digitalization of recent years should provide us with additional useful insights. Second, we only examined the impact of digitalization on trade patterns through the value of total exports. Other trade analyses should focus on the national VA contained in trade to isolate the contributions of each economy by excluding the contributions of the other countries involved in the production process. A joint analysis of the VA of the digital sector and that of trade would make it possible to refine the effect of the former on the latter.

[18] For more information, see https://www.bruegel.org/publications/datasets/european-union-countries-recovery-and-resilience-plans/.

A Appendix

Figure A1: Domestic digital intensity by country in 2014 (in %)



Source: WIOD - Authors' calculations.

Table A1: List of countries by income level

Country	Income	Country	Income
Australia	High	India	Emerging
Austria	High	Ireland	High
Bulgaria	Emerging	Italy	High
Brazil	Emerging	Japan	High
Canada	High	Korea	High
Switzerland	High	Lithuania	High
China	Emerging	Latvia	High
Cyprus	High	Mexico	Emerging
Czech Republic	High	Malta	High
Germany	High	Netherlands	High
Denmark	High	Norway	High
Spain	High	Poland	High
Estonia	High	Portugal	High
Finland	High	Romania	Emerging
France	High	Russian Federation	Emerging
United Kingdom	High	Slovakia	High
Greece	High	Slovenia	High
Croatia	High	Sweden	High
Hungary	High	Turkey	Emerging
Indonesia	Emerging	United States	High

Table A2: List of manufacturing and services sectors

Manufacturing sector	Description	Service sector	Description
C10-12	Manufacture of food products, beverages and tobacco products	H49	Land transport and transport via pipelines
C13-15	Manufacture of textiles, wearing apparel and leather products	H50	Water transport
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	H51	Air transport
C17	Manufacture of paper and paper products	H53	Postal and courier activities
C18	Printing and reproduction of recorded media	I	Accommodation and food service activities
C19	Manufacture of coke and refined petroleum products	J59-60	Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities
C20	Manufacture of chemicals and chemical products	J61	Telecommunications
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	J62-63	Computer programming, consultancy and related activities; information service activities
C22	Manufacture of rubber and plastic products	K64	Financial service activities, except insurance and pension funding
C23	Manufacture of other non-metallic mineral products	K65	Insurance, reinsurance and pension funding, except compulsory social security
C24	Manufacture of basic metals	M69-70	Legal and accounting activities; activities of head offices; management consultancy activities
C25	Manufacture of fabricated metal products, except machinery and equipment	M71	Architectural and engineering activities; technical testing and analysis
C26	Manufacture of computer, electronic and optical products	M72	Scientific research and development
C27	Manufacture of electrical equipment	M73	Advertising
C28	Manufacture of machinery and equipment n.e.c.		
C29	Manufacture of motor vehicles, trailers and semi-trailers		
C30	Manufacture of other transport equipment		
C31-32	Manufacture of furniture; other manufacturing		

Note: n.e.c stands for "not elsewhere classified".

Source: WIOD & BACI.

Table A3: Correlation matrix

	DI_{ikt}	DI_{jkt}	FTA_{ijt}	D_{ij}	$contig_{ij}$	$colony_{ij}$	COL_{ij}	$GVCB_{ikt}$	$GVCB_{jkt}$	$GVCF_{ikt}$	$GVCF_{jkt}$	INT_{ijt}
DI_{ikt}	1.0000											
DI_{jkt}	0.7810***	1.0000										
FTA_{ij}	0.0221***	0.0198***	1.0000									
D_{ij}	-0.0191***	-0.0229***	-0.7032***	1.0000								
$contig_{ij}$	0.0054***	0.0089***	0.1544***	-0.4087***	1.0000							
$colony_{ij}$	-0.0079***	-0.0039***	-0.0215***	-0.1395***	0.2937***	1.0000						
COL_{ij}	0.0096***	0.0087***	-0.0663***	0.0511***	0.1638***	0.3141***	1.0000					
$GVCB_{ikt}$	-0.1070***	-0.1507***	0.1588***	-0.1491***	-0.0057***	-0.0116***	-0.0120 ***	1.0000				
$GVCB_{jkt}$	-0.1499***	-0.1098***	0.1603***	-0.1517***	-0.0057***	-0.0125***	-0.0125***	0.4553***	1.0000			
$GVCF_{ikt}$	-0.0703***	-0.0833***	0.0856***	-0.0828***	0.0090***	-0.0023*	-0.0071***	0.2609***	0.1877***	1.0000		
$GVCF_{jkt}$	-0.0841***	-0.0732***	0.0852***	-0.0863***	0.0082***	-0.0027**	-0.0055***	0.1913***	0.2655***	0.1294***	1.0000	
INT_{ijt}	-0.0413***	0.0011	-0.2486***	0.2921***	0.0034***	0.0355***	0.0569***	-0.3474***	0.0506***	-0.1437***	0.0332***	1.0000

Table A4: Description and sources of variables

	Description of variables	**Type of variables**	**Source**
Dependent variable			
X_{ijt}	Level of exports from country i to country j in industry k	Continuous	BACI for manufacturing and ITSS for services
Independent variables			
$GVCB_{ikt}$ $GVCB_{jkt}$	Backward GVC participation measure (domestic value added generated from a country-sector's GVC activities through downstream firms as a share of that country-sector's total value added)	Continuous	Wang et al. (2017)
$GVCF_{ikt}$ $GVCF_{jkt}$	Forward GVC participation measure (share of a country-sector's total production of final goods and services involved in GVC activities through upstream firms)	Continuous	Wang et al. (2017)
INT_{ijt}	Individuals with access to the internet in both exporting and importing countries	Continuous	World Bank's WDI
D_{ij}	Natural logarithm of the distance in kilometres between the country of origin i and the destination country j	Continuous	CEPII's gravity database
$contig_{ij}$	Whether two countries share a common border	Binary	CEPII's gravity database
$colony_{ij}$	Whether two countries have ever had a colonial relationship	Binary	CEPII's gravity database
COL_{ij}	Whether two countries use the same official languages	Binary	CEPII's gravity database
FTA_{ij}	Whether two countries have ratified an FTA	Binary	CEPII's gravity database
Digital intensity variables			
DI_{ikt}	Digital intensity measures of country i	Continuous	WIOD
DI_{jkt}	Digital intensity measures of country j	Continuous	WIOD

Table A5: Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
X_{ijt}	609,570	285490.8	2567622	0	3.95e+08
DI_{ikt}	595,185	11.5069	16.46555	.0088832	93.14274
DI_{jkt}	595,575	11.50902	16.3001	.0088832	93.14274
FTA_{ijt}	609,570	.5471628	.4977711	0	1
D_{ij}	609,570	7.953161	1.097272	4.087945	9.802004
$contig_{ij}$	609,570	.0669816	.2499904	0	1
$colony_{ij}$	609,570	.0376003	.1902276	0	1
COL_{ij}	609,570	.0398642	.1956402	0	1
$GVCB_{ikt}$	595,185	.2643925	.1457248	.0144725	.8956174
$GVCB_{jkt}$	595,575	.26266	.1463555	.0144725	.8956174
$GVCF_{ikt}$	595,185	.3036041	.4357144	.0026263	25.43331
$GVCB_{jkt}$	595,575	.3006146	.4362805	.0026263	25.43331
INT_{ijt}	602,880	33.23702	3.336177	22.37257	42.3909

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