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Digital intensity, trade costs and exports' quality upgrading

Raphaël Chiappini[1] | **Cyrielle Gaglio**[2]

[1]BSE, CNRS, UMR 6060, Univ. Bordeaux, Pessac, France

[2]Department of Economics and Management, Finland, and Sciences Po, OFCE, University of Helsinki, Helsinki, France

Correspondence
Raphaël Chiappini, BSE, CNRS, UMR 6060, Univ. Bordeaux, Avenue Léon Duguit, F-33600 Pessac, France.
Email: raphael.chiappini@u-bordeaux.fr

Abstract

This paper studies the relationships between digitalisation, trade costs, quality upgrading and trade flows, using an extended version of a gravity model. Based on information from various sources of data, we estimate these relationships sequentially for a sample of 18 manufacturing and 14 service sectors in 40 countries over the period 2000–2014. Using input–output tables from World Input–Output Database, we define an original measure of digitalisation at the country-sector level that reflects the use of digital inputs into a country's production function. Using trade databases from the CEPII and OECD, we estimate a series of gravity models of trade augmented with this measure of digitalisation. Our results show that sectoral digital intensity positively affects sectoral exports. We provide evidence that this result is not ruled out by other possible factors, such as internet adoption or participation in a global value chain. A heterogeneous analysis also reveals that the effect of digital intensity is stronger for manufacturing trade and for trade between emerging economies. We explore two possible mechanisms explaining this positive relationship. First, we find that digital intensity facilitates trade between countries by reducing communication and transport costs. Second, we show that digital intensity improves the quality of exported products.

KEYWORDS
digital intensity, export upgrading, gravity model, trade costs, trade flows

1 | INTRODUCTION

The waves of recent globalisation are a result of the fragmentation of production processes along global value chains (GVCs) combined with fast-paced technological change. The fragmentation of production processes is in itself far from being a new phenomenon (Gereffi & Lee, 2012) and has shaped globalisation: it has grown since the 1980s and contributed, in the 1990s and early 2000s, to the unprecedented development of GVCs and thus to the growth of world trade (Gaulier et al., 2020). However, rapid technological advances (such as cheaper telecommunications and more powerful personal computers) have reduced the communication, coordination and transaction costs of the complex activities associated with GVCs (Forman et al., 2005; Gooris & Peeters, 2016; OECD, 2013). Thus, along with trade and financial liberalisation and the expansion of markets at the international level, technological changes have also contributed 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-sized 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 production revolution, with implications for productivity, employment, skills, income distribution, trade, welfare and the environment, and this 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, since digital technologies require substantial investments, the role of public authorities would be to effectively support investments in these technologies. In terms of implications for trade, these digital technologies (and their constant improvements) enhance trade opportunities by reducing trade costs such as cultural and language barriers (Baldwin, 2019), but also the cost of organisation for multinational firms. At the same time, they accelerate the pace of trade between locations. An 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 on the location of production and the organisation of production within GVCs, that is 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 (including trade costs, the lowering of which aims 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 (Fan et al., 2015; Manova & Zhang, 2012), previous studies have remained somewhat quiet on the relationship between digital technologies and product quality. Among the few studies that have examined this relationship, it is once again the uses, and more specifically the adoption of ICTs, that are at the heart of the studies. 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 (which refers to a cost-reduction effect), but that the average quality of their exports decreases after internet adoption (which refers to a 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 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 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 (Choi, 2010; Freund & Weinhold, 2002). While previous studies justify the impact of internet adoption on trade by showing that its diffusion reduces trade costs, they do not test this hypothesis empirically. Visser (2019), by studying exports from 162 countries to 175 destinations for the period 1998–2014, finds that increasing the number of broadband subscriptions decreases the impact of language distance on trade. This result holds for both intensive and extensive trade margins. 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) as well as for SMEs (Sun, 2021). Kitenge and Lahiri (2022) complement the analysis by Visser (2019) by constructing a bilateral measure of internet adoption for a large sample of countries for the period 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. On the contrary, 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 an increase in the number of internet users mainly stimulates exports from developing economies to developed markets, while Aker and Mbiti (2010) indicate

[1]Trade costs remain 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%–2.3%, while the analysis by 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 customs systems, can reduce these significant trade costs.

that the adoption of mobile telephony can have a significant effect on the export behaviour of African farmers by reducing their search costs. Therefore, this strand of the literature focuses only on the adoption and diffusion of ICTs and not on digitalisation per se.

In such a context, the intensification of the fragmentation of international production processes has offered a variety of intermediate inputs that are less expensive and/or of better quality. Some of these inputs are purely digital, while others have become digitised. Even if the digitalisation of economies is a modern marker of changes in our modes of production, consumption or communication, and paves the way for new forms of sharing, creation, collaboration or innovation (Gaglio & Guillou, 2018a), the effect of digitalisation 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 focused mainly on either the adoption and diffusion of ICTs or the uses of digital technologies.

Given the importance of digitalisation in trade and countries' competitiveness, this paper aims to assess the relationships between digitalisation at the country-sector level, trade costs, quality upgrading and trade flows. Digitalisation can be a driver in simultaneously reducing trade costs and improving product quality. We develop an original measure of digitalisation—called digital intensity—that, unlike existing ones, does not reflect the use of digital technologies. Our digital intensity measure reflects the use of digital inputs into a country's production function. We define this measure as the intermediate consumption of a country-sector in digital inputs (i.e. digital goods and services) over the intermediate consumption of the same country-sector in market inputs. We isolate digital inputs from other market inputs to quantify digitalisation and expect that these digital inputs can be used to expand the scope of production but also of differentiation. Therefore, our measure allows us to draw conclusions about both trade costs and quality upgrading. Using WIOD, CEPII, and OECD data, we estimate an extended version of a trade gravity model augmented with 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 18 manufacturing and 14 service sectors in 40 countries between 2000 and 2014. While there is clear evidence of the digitalisation of countries, few quantitative studies have focused on the introduction of digital inputs into production functions and their impacts on trade.

This paper makes four contributions to filling this gap in our knowledge. First, it provides an analysis of the relationship between digitalisation 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 service sectors and a stronger effect of digital intensity on exports between 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 of the relationship 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. 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 closely 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 by disentangling the effects of exporting and importing countries by both sector and income levels. However, we find no evidence that the sectoral digital intensity of the importing country has a significant effect on trade flows. Fourth, from a purely methodological point of view and contrary to previous studies, our paper directly addresses the issue of endogeneity, which could bias the results by relying on an identification strategy using instrumental variables (IVs) such as 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 DIGITALISATION

2.1 | The measures of digital intensity

In the context of increasing the penetration of (new) digital technologies into production processes, we assume that digitalisation means that the production function of a sector in a country uses more digital inputs than in the past. Digitalisation 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. Digitalisation can also be the result of an increase in new firms entering the market, whose production functions are much more digitised than those of incumbents. In such a context, two effects must be distinguished. (i) At the country 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 & Westlake, 2017). (ii) At the sector level, we expect the pace of technological change to create between-sector differences.

Given the importance of digitalisation in trade and countries' competitiveness, there have been many attempts to quantify this phenomenon, especially in the institutional literature (Calvino et al., 2018; European Commission, 2017; IMF, 2018; OECD, 2019; UNCTAD, 2019). As part of its digital decade policy programme, the European Commission has defined a micro-based digital intensity index that measures the share of firms using digital technologies (out of 12)[2] in a specific country. Values are ranked between 0 and 12 and then split into four levels: between 0 and 3, the digital intensity index is considered 'very low'; between 4 and 6, 'low'; between 7 and 9, 'high'; and between 10 and 12, 'very high'. For each of these four levels, the digital intensity index estimates the share of firms using monitored digital technologies. The higher the index, the higher the digital intensity of the firm. Established in 2020, the most recent digital intensity measure illustrates two main findings: on the one hand, most European firms have a low digital intensity index; on the other hand, only Finland and Denmark stand out from other European countries by having 5% of firms with a very high level of digital intensity (the European average is 2%), which implies a significant investment in digital technologies and infrastructures in these two countries.

The European Commission's measure reflects the use of digital technologies while we seek to capture the use of digital inputs. Our measure of digital intensity reflects the incorporation

[2]These digital technologies vary between different survey years. In the latest versions (in 2018 and 2020), digital technologies cover, for example: 'employment of ICT specialists; fast broadband; having a website; a website has sophisticated functionalities; use of 3D printing; sending invoices suitable for automated processing; use of industrial or service robots; analysing big data internally from any data source or externally'. For more details on this micro-based digital intensity index, see: https://ec.europa.eu/eurostat/fr/web/products-eurostat-news/-/ddn-20211029-1.

of digital inputs into a country's production function. We define digital intensity at both the country and country-sector level (using input–output tables, see Section 3.3) as specified below:

$$DI_{it} = \frac{IC_{it}^{\omega}}{IC_{it}^{\Omega}} \qquad DI_{ikt} = \frac{IC_{ikt}^{\omega}}{IC_{ikt}^{\Omega}} \quad \text{with } \omega \in \Omega$$

where DI_{it} and DI_{ikt} represent the measures of digital intensity either at the country i or at the country-sector ik level for a specific year t. IC_{it}^{ω} and IC_{ikt}^{ω} refer to the intermediate consumption of a country or a country-sector in digital inputs ω (i.e. digital goods and services), IC_{it}^{Ω} and IC_{ikt}^{Ω} refer to the intermediate consumption of the same country or country-sector in market inputs Ω. As discussed above, we isolate digital inputs from other market inputs to quantify the digitalisation of country's production function and separate digital-producing sectors from digital-using ones (van Ark et al., 2016, 2019). We identify digital inputs based on the definition of the digital sector proposed by the OECD: 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).

Using input–output tables, our approach to measuring digitalisation focuses on intermediate consumption (such as Calvino et al., 2018; van Ark et al., 2016, 2019), which means that we estimate the value of digital goods and services consumed as inputs into a production function. Our measures of digital intensity are in line with one of the key indicators developed by the OECD (Calvino et al., 2018), called purchases of ICT intermediates, which relies on the composition of the consumption of intermediate goods and services to assess the digital intensity of sectors. Unlike Calvino et al. (2018) who distinguish a share of intermediate purchases of ICT goods from a share of intermediate purchases of ICT services, we establish a common measure that covers the entire digital sector. Furthermore, we define digital intensity at both the country and country-sector level, whereas they set their indicator only at the sector level by calculating an average over a dozen countries. Like theirs, our measure does not cover inputs that are embedded in other inputs. In our first two measures, a country indifferently consumes digital and market inputs that are produced by itself (which refers to the domestic component) or by other countries (which refers to the imported component).

To the extent that intermediate consumption is the sum of a domestic and an imported component, we define additional measures that focus only on the domestic component, meaning that a country consumes only digital and market inputs that it has produced itself. In doing so, we pay attention to the domestic component rather than the imported component to differentiate countries in the pace of their digital transformation, especially in the development of their digital-producing sectors. These domestic digital intensity measures[4]—DI_{it}^{d} and DI_{ikt}^{d}—are defined as specified below:

$$DI_{it}^{d} = \frac{IC_{it}^{\omega_d}}{IC_{it}^{\Omega_d}} \qquad DI_{ikt}^{d} = \frac{IC_{ikt}^{\omega_d}}{IC_{ikt}^{\Omega_d}} \qquad \text{with } \omega_d \in \Omega_d,\ \omega_d < \omega \text{ and } \Omega_d < \Omega$$

[3]International Standard Industrial Classification (ISIC).

[4]We use this restricted measure only in robustness checks (see Section 5.2).

where ω_d and Ω_d refer to the domestic digital and market inputs, respectively. We restrict our analysis to the manufacturing sector and each of its branches as well as the service sectors (i.e. transport and storage; accommodation and food service activities; information and communication; financial and insurance activities; real estate activities; professional, scientific and technical activities).

We expect the measures of digital intensity to have a positive effect on trade in simultaneously reducing trade costs and improving product quality. Digital inputs can be used to expand the scope of production but also of differentiation; some of these inputs are purely digital, while others have become digitised. When digital intensity increases, it may mean that the economy uses more computers, more software and/or more IT services compared to other inputs. Either the inputs go digital (e.g. a firm buys accounting software instead of using an accounting service),[5] or firms created in the sector have a production process containing more digital inputs (Gaglio & Guillou, 2018b). When digital intensity decreases, the opposite changes will prevail.

2.2 | Patterns of digitalisation

2.2.1 | Differences by country

In Figure 1, we present the measure of the total digital intensity (i.e. manufacturing + service sectors) and rank countries according to their level in 2014,[6] the latest year available in the data: <8%, between 8% (inclusive) and 12%, between 12% (inclusive) 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%). These 17 countries form a heterogeneous mix, but idiosyncratic policies 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. Given such a context, Asian countries increased their digital VA (producer side) in 2014 from their 2000 levels. Finland has been at the forefront of the digital revolution after the rapid downfall of Nokia by improving the quality of its transmission networks, focusing on open access to public data, and also developing digital technologies 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 20 years. Sweden has focused on the deployment of digital technologies (artificial intelligence, cybersecurity solutions, and as a leader in the Internet of Things) to households and firms, which has enabled firms to integrate GVCs associated with manufacturing sectors to digitise them.

The other countries have a digital intensity of <12% or <8%: for example, India (7.8%), Russia (6.8%), Lithuania (6.2%) and Turkey (4.3%). European countries fall somewhere in between but

[5]A limitation to this is that we capture only inputs that are subject to a market transaction, which implies that we exclude digital inputs that are produced internally by a firm.

[6]Figure A1 in Appendix 1 presents the same elements for the domestic digital intensity measure.

FIGURE 1 Digital intensity by country in 2014 (in %). *Note*: See the domestic digital intensity measure in Figure A1.
Source: WIOD—Authors' calculations.

are characterised by strong heterogeneity in their digital transition: Finland (14.9%), Germany (12.4%), France (12.2%), Spain (8.8%), Belgium (8.1%), Luxembourg (6.8%), Latvia (6.3%), etc. In the European context, the digitalisation of countries is framed by national digital support programmes (which they have individually launched) mixed with common European digital policies (to support citizens and firms in the digital decade).[7] Thus, countries have experienced different trends over time.

2.2.2 | Differences by country-sector

A few salient characteristics emerge from these measures of digital intensity. First, digital-producing sectors are also mainly digital-using sectors, meaning that digital inputs are largely consumed by the digital sectors themselves. On the manufacturing side, on average over all

[7]Europe is very active in digital regulation. Between 2011 and 2017, 19 national digital support programmes were launched, including Catapult in the UK, Industrie du futur in France, Industrie 4.0 in Germany and Smart Industry in the Netherlands (European Commission, 2018). At the same time, various common European digital policies have emerged, from eEurope action plans to the General Data Protection Regulation or the creation of the digital single market. One of the most recent aims to boost high-performance computing, artificial intelligence, cybersecurity and advanced digital skills throughout society.

FIGURE 2 Average of digital intensity by sector (in %).
Source: WIOD—Authors' calculations.

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, publishing activities consume 19.1% of digital inputs, information services activities 42.7%, motion picture and television programme production 50.4%, and telecommunications 53.1%. In our econometric approach (see Section 3), we estimate an extended version of a trade gravity model augmented with our digital intensity measures by excluding these digital sectors to avoid overestimating the digitalisation of countries.

Second, except for Luxembourg, Ireland and Malta, digital inputs are used/consumed more in service sectors than in manufacturing (see Figure 1). One explanation relates to the dual decline faced by most European countries (which make up a large part of our sample) and the United States, which have experienced a decline in the share of the manufacturing in their economies, coupled with a decline in ICT prices (especially prices of digital goods in the manufacture of computer, electronic and optical products). Another explanation is related to the expansion of platform activities: these are the new players in the digital economy that have replaced traditional industrial activities in sectors as varied as transport, retail, music industry, and accommodation and food service activities. Among manufacturing sectors, the 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, which is in line with the conclusions made by European Commission (2017), Calvino et al. (2018) and van Ark et al. (2019).

Third, most of the inputs used in the digital service sectors are domestic. The relationship is less true for digital goods, for which imports may be important. Therefore, a highly digitised economy is likely to have a thriving digital services sector. Moreover, a transition is underway in Europe: the shift of digital value creation from digital manufacturing to digital services.

3 | EMPIRICAL APPROACH, DATA SOURCES AND SAMPLE

3.1 | Gravity model

3.1.1 | Model specification

We rely on a theory-consistent estimation of the trade gravity model to quantify the effect of digitalisation on international trade flows. Since the pioneering work of Anderson (1979), this equation has become the workhorse model for exploring the relationship between international trade flows and policy variables of interest (Head & 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 demonstrate the importance of controlling the model for relative trade costs because trade flows between two countries are determined not only by the trade barriers separating the two countries, but also by the average trade barrier between each country and 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 & Kortum, 2002) or models with heterogeneous firms (Chaney, 2008; Melitz, 2003).

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

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

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

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

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

where D_{ij} is the distance in kilometres between the country of origin i and the country of destination 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 language, 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):

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

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 measure of digital intensity of each of the two countries in sector k, $GVCB_{ikt}$ and $GVCB_{jkt}$ are the measures of backward GVC participation of the two countries in sector k, while $GVCF_{ikt}$ and $GVCF_{jkt}$ are the measures of forward GVC participation. Following 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. 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 specific stages of the production process. We add these measures of participation in GVCs for two reasons. First, we want to distinguish the impact of the digital intensity measure from participation in GVCs. Indeed, since our measure involves the use of imported digital inputs, it is important to control for countries' participation in GVCs. Second, participation in GVCs and exports are closely related phenomena. Altun et al. (2022) have shown that both backward and forward GVC participation are associated with increased high-tech exports. The analyses by Jangam and Rath (2021) and Ndubuisi and Owusu (2021) also found that participation in GVCs enables countries to improve their exports. We therefore expect a positive impact between participation in GVCs and bilateral trade flows. 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. The full description of the different variables and associated descriptive statistics are reported in Tables A4 and A5.

3.1.2 | Collinearity issues

The aim of this paper is to show that digital intensity affects exports. However, there is some concern that our measures of digital intensity are too collinear with measures of participation in GVCs, especially since our measures are also based on input–output tables. The overall correlation rate between our digital intensity measure at the sector level and the backward GVC participation measure is negative and equal to −0.1156, while the correlation rate between our digital intensity measure at the sector level and the forward GVC participation measure is also negative and equal to −0.0736.[8] There is therefore no systematic association between digital intensity and participation in GVCs.

3.1.3 | Estimation method

Following standard practice in the international trade literature, we estimate the model using the PPML estimator developed by Santos Silva and Tenreyro (2006). There are three reasons for choosing this approach. First, disaggregated data entail numerous number of zero-value observations (29% in our study)[9] and if these zeros are not randomly distributed, a selection bias occurs if zeros are dropped from the sample using a log-linearisation method. Second, Santos Silva and Tenreyro (2006) provide evidence that this estimator outperforms OLS in the presence of heteroscedasticity, while Head and Mayer (2014) show that the PPML estimator remains consistent in the case of over-dispersion in the data. Therefore, Anderson and Yotov (2010) argue that the use of the PPML estimator to assess 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 & Mayer, 2014).

3.2 | Quality inference

One channel through which digital intensity might affect trade patterns is export quality upgrading. Indeed, 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 liberalisation allows firms to access a wider variety of inputs to produce their final product, and this wider variety increases firm productivity (Ethier, 1982; Halpern et al., 2015). Several empirical studies have confirmed the existence of a positive link between imports of intermediate inputs and firm productivity, particularly in the case of French firms (Bas & Strauss-Kahn, 2015). The second channel is called the innovation effect, in which imported intermediate inputs incorporate foreign technologies that could be absorbed by firms to produce new varieties of final products (Kugler & Verhoogen, 2009). Other empirical studies have shown a positive link between imports of intermediate inputs and export upgrading. For example, Manova and Zhang (2012) show 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 better quality and higher export prices for firms in sectors where the scope for differentiation is broad. Using Chinese firm-level data, Zhu and Tomasi (2020) confirm that foreign sourcing improves export quality. Consequently, the use of digital inputs (domestic or/and imported) should improve export quality.

[8]See the correlation matrix in Table A3.

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

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 allows us to infer the quality of product h exported by country i to country j at time t as specified in Equation (4):

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

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-destination-product-year can be estimated as the residual of the following OLS regression as specified in Equation (5):

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

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 $\hat{\phi}_{ijht} = \frac{\hat{\varepsilon}_{ijht}}{\sigma-1}$. We set the value of σ at 3, which represents the median of the elasticity of substitution found for developed economies in Broda et al. (2017). While most studies rely on firm-level data to implement the method proposed by Khandelwal et al. (2013), some recent analyses have relied on product-level data. For example, Ndubuisi and Owusu (2021) or Fiankor et al. (2020) used product at the 6-digit level of HS[10] classification of the BACI database and the method of Khandelwal et al. (2013) to infer product quality. Other papers focused on a particular product to implement the method, such as Curzi and Huysmans (2022) for cheese and Emlinger and Lamani (2020) for Cognac.

Consistent with previous studies, we use the BACI database described in Section 3.3 to estimate Equation (5). Thus, we focus only on manufacturing sectors. Each 6-digit HS code is considered a particular product and we estimate 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, because we are interested in the relationship between digital intensity and export upgrading, we follow Ndubuisi and Owusu (2021) and average the quality measure across importing countries to obtain an exporter-product-specific measure of export quality. Then, we match each 6-digit product with the corresponding 2-digit sector using concordance tables and estimate the following Equation (6):

$$\hat{\phi}_{iht} = \alpha + \eta_1 DI_{ikt-1} + \sum_{n=1}^{6} \zeta_n X_{it-1} + \mu_{ik} + \mu_{ih} + \varepsilon_{iht} \tag{6}$$

where X represents a vector of exporter-time-varying determinants. Following Ndubuisi and Owusu (2021), we retain human capital, backward and forward GVC participation, inflation rate, institutional quality (measured by the rule of law index) and financial development as control variables. Country-product (μ_{ih}) and country-sector (μ_{ik}) fixed effects are introduced

[10] Harmonised System (HS).

to account for characteristics specific to a particular country-sector combination that may influence product quality, and since Equation (5) uses the log transformation of the variables, our measure of quality is in logarithm form. Note also that all variables are lagged by 1 year as suggested by Harding and Javorcik (2012), and that since our variable of interest (i.e. digital intensity) is at the country-sector-year level and the inferred quality is at a more disaggregated level (i.e. the country-product-year level), we cluster standard errors at the country-product-year level (Ndubuisi & Owusu, 2021).

3.3 | Data sources and sample

We combine information from four different sources to build an original dataset for the period 2000–2014. Our sample covers 18 manufacturing sectors and 14 service sectors in 40 countries (see Tables A1 and A2 in Appendix 1).

3.3.1 | Input–output tables

Our main source of data is the World Input–Output Database (WIOD) provided by the European Commission.[11] WIOD is an annual time series of world input–output tables which harmonises a set of national use-resource tables that are connected to each other by bilateral international trade flows. WIOD covers 56 sectors (ISIC, revision 4) and 44 countries (28 European countries, 15 other major economies such as China, Japan and the United States, and a model for the rest of the world) between 2000 and 2014. We use the 2016 version. Values are given in millions of US dollars. As noted by Timmer et al. (2015), the main advantage of 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).

3.3.2 | Export data

We use two trade databases. The first trade database is the Base pour l'Analyse du Commerce International (BACI) provided by the CEPII research center.[12] BACI covers bilateral values (in thousands of US dollars) and quantities (in tons) of world trade flows at HS 6-digit product disaggregation for more than 200 countries and 5000 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 sectors. The second trade database is the International Trade in Services Statistics (ITSS) 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 service sectors.

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

[12]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.

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

3.3.3 | 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 2020.[14] We obtain information on standard gravity variables such as geographical distance, colonial ties, contiguity and FTAs. We rely on the common official language (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.

3.3.4 | Internet variable

In the empirical literature, internet access is often treated as a proxy for connectivity between economic agents, which facilitates bilateral trade (Freund & Weinhold, 2004; Kitenge & Lahiri, 2022). 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 exporter-time and importer-time-varying fixed effects. Therefore, we rely on the two-sided time-varying index developed by Kitenge and Lahiri (2022) 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.

3.3.5 | Other controls

Several controls are added to Equation (6) when estimating the impact of digital intensity on export quality upgrading. The human capital variable is taken from the Penn World Tables version 10.1 (Feenstra et al., 2015). The inflation variable, based on the consumer price index, comes from the World Development Indicators, while the rule of law index is taken from the Worldwide Governance Indicators; both are provided by the World Bank. Finally, financial development is measured using the financial development index developed by the International Monetary Fund. The index ranges from 0 (lowest level of financial development) to 1 (highest level of financial development).

4 | ECONOMETRIC RESULTS

4.1 | Digitalisation and trade flows

4.1.1 | Baseline results

In Table 1, we provide the results of estimating the Equation (3) for various specifications of the gravity model. The determinants of trade are introduced in a stepwise way. The regression

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

TABLE 1 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: ***$p<.01$, **$p<.05$, *$p<.1$.

Abbreviation: PPML, Poisson Pseudo-Maximum Likelihood.

in column (1) includes our digital intensity measures and only the five trade characteristics. Columns (2) and (3) add the variables associated with the measures of GVC participation. Column (4) presents the complete specification, including the internet variable.

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. Thus, we find that an increase of 1 percentage point in sectoral digital intensity of the exporting country leads to an increase of 2.9% in exports. 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 studies 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 Osnago 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. Digital intensity 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 deterrent effect on bilateral trade flows, while sharing a common border, using similar official languages, and having ratified a FTA significantly increase bilateral trade. As expected, the forward GVC participation of both exporting and importing countries has a positive and significant coefficient. A 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) do not fundamentally affect the interpretation and magnitude of the coefficient associated with digital intensity.

4.1.2 | Country and industry heterogeneity

Country heterogeneity

It is important to study whether the impact of digital intensity on trade flows depends on the income levels of the trading partners. In Table 2, we provide the results of estimating Equation (3) for different categories of trade flows based on the income level of the countries involved (see Table A1 in Appendix 1). 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's income classification to determine the nature of bilateral trade flows. 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 an emerging economy if its GDP per capita is between \$1046 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 associated with geographical distance—are high, as in bilateral trade flows between emerging economies. As a result, one mechanism by which sectoral digital intensity potentially affects export flows could be the reduction of communication and transport costs.

Industry heterogeneity

While the literature has shown that internet adoption influences trade in both manufacturing (Clarke & Wallsten, 2006; Freund & Weinhold, 2004; Lin, 2015) and services (Choi, 2010; Freund & Weinhold, 2002), the magnitude of its impact seems to differ depending on the type of sector

TABLE 2 PPML estimation – Country heterogeneity.

	(1)	(2)	(3)	(4)
	High–high	High–emerging	Emerging–high	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: ***$p<.01$, **$p<.05$, *$p<.1$.

Abbreviation: PPML, Poisson Pseudo-Maximum Likelihood.

examined. Therefore, we also address the issue of sectoral heterogeneity by estimating the gravity models of the manufacturing and services sectors separately. In Table 3, we present the results of this estimation.

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

TABLE 3 PPML estimation—Industry heterogeneity.

	(1)	(2)
	Manuf.	**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: ***$p<.01$, **$p<.05$, *$p<.1$.

Abbreviation: PPML, Poisson Pseudo-Maximum Likelihood.

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 sectors than in the service sectors. This is consistent with the findings associated with internet adoption (Osnago & Tan, 2016). However, we find that the variables capturing COL 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. 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 can therefore have an additional effect on manufacturing exports.

4.2 | Investigating possible channels

4.2.1 | Digitalisation 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 (especially 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 4. 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 COL with the sectoral digital intensity of the exporting country. In column (3), we interact the variables associated with geographical distance and COL 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 (i.e. geographical distance, a common colonial history, COL 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 4 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 between the extreme quartiles is highly significant.[15] 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 the variables DI_{ikt} and 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 language (0.0301) than when they do (0.011). Furthermore, the benefits of using the same official language 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.

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

TABLE 4 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: ***$p<.01$, **$p<.05$, *$p<.1$.

Abbreviation: PPML, Poisson Pseudo-Maximum Likelihood.

Interpretation

Unlike what is observed for internet networks (Kitenge & Lahiri, 2022), the use of digital inputs reduces both the negative impact of geographical distance on exports and the benefits of using the same official language. 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 language 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. The use of more skilled workers in digital services who are more proficient in using foreign languages can also facilitate trade flows (Chiappini & Jégourel, 2021) and lower the importance of sharing a common language. These arguments are very similar to the one developed to explain the impact of internet access on trade (Freund & Weinhold, 2004; Kitenge & Lahiri, 2022; Lin, 2015; Visser, 2019). 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 (Bargain et al., 2023; Fontagné & Hatte, 2013; Martin & Mayneris, 2015).

4.2.2 | Digitalisation and export quality upgrading

In Table 5, we provide the results of estimating Equation (6) using the OLS estimator. All estimations include exporter-product, exporter-sector and year fixed effects.

First, as with previous studies on export upgrading, our results highlight the positive impact of institutional quality (Amighini & Sanfilippo, 2014) and financial development (Ndubuisi & Owusu, 2021) on export upgrading. Second, like Ndubuisi and Owusu (2021), we find a strong link between GVC participation (backward) and export quality upgrading. Third, our results highlight 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. More precisely, we find that an increase of 1 percentage point in digital intensity entails an increase of 0.1% in the quality of exported products. Thus, it confirms that the positive link between digital intensity and export is also driven by an increase in quality of exported products.

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.

5.1 | Regressions using the OLS estimator

In Table 6, 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

TABLE 5 Digital intensity and export quality upgrading.

	(1)	(2)	(3)	(4)
DI_{ikt-1}	0.00111***	0.00111***	0.00103***	0.00108***
	(0.000373)	(0.000373)	(0.000371)	(0.000370)
$GVCF_{ikt-1}$		0.00299	0.00140	0.00207
		(0.00874)	(0.00894)	(0.00908)
$GVCB_{ikt-1}$			0.0563**	0.0578**
			(0.0265)	(0.0266)
$Rule_{ikt-1}$				0.0371***
				(0.00741)
$Inflation_{it-1}$				0.000383*
				(0.000228)
HC_{it-1}				0.0270
				(0.0215)
FD_{it-1}				0.0716***
				(0.0241)
Constant	−0.00404	−0.00504	−0.0212**	−0.185***
	(0.00286)	(0.00410)	(0.00904)	(0.0636)
Observations	1,887,648	1,887,648	1,887,648	1,887,648
R-squared	.362	.362	.362	.362
Exporter-product FE	YES	YES	YES	YES
Exporter-sector FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Standard errors, clustered at the country-sector-year level, are given in parentheses. Significance level: ***$p<.01$, **$p<.05$, *$p<.1$.

very similar to those found in Table 1 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 1.

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}).

In Table 7, 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. We find that our results are robust to the use of the domestic digital intensity measure, as we find results that are very similar to the previous ones, both qualitatively and quantitatively.

TABLE 6 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	.717	.720	.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: ***$p<.01$, **$p<.05$, *$p<.1$.

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

TABLE 7 Robustness check—Only domestic digital inputs.

	(1) Baseline	(2) Trade costs
DI^{d}_{ikt}	0.0231***	−0.0298**
	(0.00276)	(0.0150)
DI^{d}_{jkt}	0.0014	0.00226
	0.0025	(0.00257)
D_{ij}	−0.697***	−0.782***
	(0.0434)	(0.0424)
FTA_{ijt}	0.383***	0.350***
	(0.0965)	(0.0884)
$contig_{ij}$	0.482***	0.508***
	(0.0759)	(0.0919)
$colony_{ij}$	0.125	0.182**
	(0.0915)	(0.0835)
COL_{ij}	0.196**	0.321***
	(0.0970)	(0.104)
$GVCF_{ikt}$	0.973**	0.798*
	(0.464)	(0.464)
$GVCB_{jkt}$	0.376	0.325
	(0.381)	(0.352)
$GVCF_{ikt}$	0.661**	0.590**
	(0.285)	(0.250)
$GVCF_{jkt}$	0.122***	0.127***
	(0.0373)	(0.0364)
INT_{ijt}	0.692***	0.705***
	(0.222)	(0.211)
$DI^{d}_{ikt}{}^{*}D_{ij}$		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
	(8.170)	(7.715)
Observations	576,273	576,273
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: ***$p < .01$, **$p < .05$, *$p < .1$.

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, like democracy, digitalisation spreads geographically, which means that digital transformation occurs in 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 the sector digitises in one of the two countries, this will induce a digitalisation of the same sector in the partner country. Moreover, it is very unlikely that the digital intensity of a given sector of countries in the same region, 2 years ago, affects exports of that 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 define Z_{ikt} as the average domestic digital intensity in a region r,[16] which leaves out the own country (country i) observation as specified in Equation (7):

$$Z_{ikt} = \frac{1}{N_r} \sum_{j \neq i}^{J} DI^{d}_{jkt} \tag{7}$$

where N_r represents the number of countries in region r, leaving out i, the country under scrutiny. To further reduce the likelihood of capturing unobserved confounders, we lag our instrument by two periods, thus combining the spatial lag with a temporal lag. This strategy has also been implemented in other studies on the link between globalisation and inequality (Lang & Tavares, 2018), and on the link between foreign direct investment and health (Chiappini et al., 2022). To probe the robustness of our results, we also use the 2-year lagged value of the average sectoral domestic digital intensity of the three leaders in terms of innovation, namely the United States, Germany and Japan, as an instrument for digital intensity. In this case, it is very unlikely that this instrument directly affect country i's exports 2 years after. A similar strategy has been used in Ndubuisi and Owusu (2021) to instrument GVC participation.

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 region r 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 (ATE), as in our

[16]The different regions are: East Asia and Pacific, Eastern Europe and Central Asia, Latin America, North America and Western Europe.

TABLE 8 Robustness check—IV regressions.

	(1)	(2)	(3)	(4)
	First instrument		Second instrument	
	OLS	PPML-CF	OLS	PPML-CF
DI_{ikt}	0.0273***	0.0354***	0.0537***	0.0438***
	(0.00198)	(0.00488)	(0.00209)	(0.01241)
DI_{jkt}	−0.000180	−0.0011	−0.0219***	−0.0028
	(0.00179)	(0.00353)	(0.00186)	(0.00535)
FTA_{ijt}	0.274***	0.3671***	0.273***	0.3667***
	(0.0792)	(0.10285)	(0.0798)	(0.10291)
D_{ij}	−1.363***	−0.7039***	−1.361***	−0.7050***
	(0.0505)	(0.03847)	(0.0504)	(0.03855)
$contig_{ij}$	0.412***	0.479***	0.406***	0.477***
	(0.112)	(0.06853)	(0.113)	(0.06862)
$colony_{ij}$	0.250*	0,136*	0.252*	0.137*
	(0.130)	(0.0800)	(0.130)	(0.0798)
COL_{ij}	0.438***	0.196**	0.437***	0.1966**
	(0.114)	(0.09339)	(0.114)	(0.09340)
$GVCB_{ikt}$	2.218***	0.5678	2.000***	0.5694
	(0.129)	(0.36434)	(0.128)	(0.37363)
$GVCB_{jkt}$	2.328***	0.4729	2.518***	0.5044
	(0.127)	(0.35536)	(0.129)	(0.35091)
$GVCF_{ikt}$	0.250***	0.7923***	0.255***	0.7915***
	(0.0258)	(0.18206)	(0.0264)	(0.18141)
$GVCF_{jkt}$	0.0396*	0.1271***	0.0509**	0.1288***
	(0.0204)	(0.03831)	(0.0203)	(0.03819)
INT_{ijt}	0.304**	0.8424***	0.304**	0.8427***
	(0.146)	(0.26153)	(0.146)	(0.26135)
Residuals		−0.00468		−0.0135
		(0.0031)		(0.01257)
Observations	364,902	489,500	366,280	498,577
R-squared	.214		.199	
Exporter-year FE	YES	YES	YES	YES
Importer-year FE	YES	YES	YES	YES
F-test of excluded instruments	2877.7***	2181.3***	3633.5***	2762.6***
Kleibergen-Paap rk LM statistic	759.5***			782.2***
Wald test of the first-stage residuals (p-value)		.131		.282

Note: Standard errors, clustered at the exporter–importer level, are given in parentheses for columns (1) and (3). Bootstrapped standard errors (1000 replications) are given in columns (2) and (4). Significance level: ***$p < .01$, **$p < .05$, *$p < .1$.

Abbreviation: PPML, Poisson Pseudo-Maximum Likelihood.

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 & 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 8, we provide the estimation results for IV regressions. In columns (1) and (3), we estimate linear regressions, while in columns (2) and (4), we present nonlinear results. Furthermore, columns (1) and (2) display estimation results using the first instrument based on regional digital intensity (Z_{ikt}), while columns (3) and (4) provide estimations results for the second instrument based on the average of sectoral digital intensity of the United States, Germany and Japan.

We observe that the F-statistics for the excluded instruments is significant and exceed 10 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 the region to which country i belongs 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 not endogenous because we cannot 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 Table 1, which confirms our previous conclusions.

6 | CONCLUSION

This paper studies the relationships between digitalisation at the country-sector level, trade costs, quality upgrading and trade flows for a sample of 18 manufacturing and 14 service sectors in 40 countries over the period 2000–2014. Our original contributions are threefold. (i) We develop an original measure of digitalisation—called digital intensity—at the country-sector level that reflects the use of digital inputs into a country's production function. (ii) We offer a broad analysis as we disentangle the effects by both sector and income level of exporting and importing countries. (iii) From a purely methodological point of view, our paper directly addresses the issue of endogeneity, which could bias the results by relying on an identification strategy using instrumental variables inspired by the work of Acemoglu et al. (2019).

Our findings show 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. We also find no evidence of a significant effect of the sectoral digital intensity of the importing country on trade flows. However, we find evidence of a mitigating effect of sectoral digital intensity on the negative impact of geographical distance on exports. The 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. We show that an increase in sectoral digital intensity is associated with an increase in the quality of exported products. Therefore, digitalisation 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 recognised as statistical challenges. For GVCs, this is due to interlinked cross-border relations at the firm level (Nielsen, 2018), while for digitalisation, 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 digitalisation 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 fragmentation of production processes along GVCs. The more a country is integrated into GVCs, the more dependent it is on the other links in the chain. Even though globalisation has strengthened international relations between countries, this has been accompanied by far-reaching structural changes. The last change is associated with the digitalisation of economies, and, like the previous changes, this structural change has also reinforced the interdependence between countries. Because the production, distribution and supply chains are minimally computerised, 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 to 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.

Although economies are going digital, there remains a digital divide. Even though the COVID-19 pandemic has prompted countries to expand the digitalisation of their services, digital transformation differs from one country to another. As a result of the pandemic, the Bruegel Institute[17] 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 digitalisation 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 € to the digital transition (52.5% of its total plan), while Poland has dedicated 'only' 7.7 billion € to this transition (21.4%). As mentioned previously, Europe is extremely heterogeneous in its digital transition. Even if 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 programmes.

There are several ways in which the results of this study could be usefully extended. First, the data we mobilise to build our digital intensity measure (i.e. WIOD data) cover only the period

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

2000–2014. Our analysis could be extended to a longer time period with more recent data, especially since digitalisation is a constantly evolving process, economies do not digitise at the same pace, and the digitalisation of recent years should provide us with additional useful insights. Second, we examined the impact of digitalisation on trade patterns only 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.

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The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Raphaël Chiappini https://orcid.org/0000-0003-4819-8792
Cyrielle Gaglio https://orcid.org/0000-0002-9724-3273

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APPENDIX 1

FIGURE A1 Domestic digital intensity by country in 2014 (in %). *Note*: A salient fact emerges, among the 17 countries with a digital intensity level >12% (see Section 2.2), 10 remain at the top of the ranking, which means that they produce a large share of the digital inputs they consume. For example, Ireland has a domestic digital intensity of 31.4%.
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		

Abbreviation: n.e.c., not elsewhere classified.

Source: WIOD, BACI & ITSS.

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

* $p < .1$; ** $p < .05$; *** $p < .01$.

TABLE A4 Description and sources of variables.

	Description of variables	Type of variables	Source
Dependent variable			
X_{ijkt}	Level of exports from country i to country j in sector k for specific year t	Continuous	BACI and ITSS
Independent variables			
$GVCB_{ikt}$ $GVCB_{jkt}$	Backward GVC participation measure of the two countries in sector k (domestic VA generated from a country-sector's GVC activities through downstream firms as a share of the total VA of this country-sector)	Continuous	Wang et al. (2017)
$GVCF_{ikt}$ $GVCF_{jkt}$	Forward GVC participation measure of the two countries in sector k (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 who have 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 country of destination j	Continuous	CEPII's gravity database
$contig_{ij}$	Whether the two countries share a common border	Binary	CEPII's gravity database
$colony_{ij}$	Whether the two countries have ever had a colonial relationship	Binary	CEPII's gravity database
COL_{ij}	Whether the two countries use the same official language	Binary	CEPII's gravity database
FTA_{ij}	Whether the two countries have ratified a FTA	Binary	CEPII's gravity database
Digital intensity variables			
DI_{ikt}	Digital intensity measures of country i in sector k	Continuous	WIOD
DI_{jkt}	Digital intensity measures of country j in sector k	Continuous	WIOD

TABLE A5 Summary statistics.

Variable	Obs.	Mean	Std. dev.	Min	Max
X_{ijkt}	609,570	285490.8	2,567,622	0	3.95e+08
DI_{ikt}	595,185	11.5069	16.46555	0.0088832	93.14274
DI_{jkt}	595,575	11.50902	16.3001	0.0088832	93.14274
$GVCB_{ikt}$	595,185	0.2643925	0.1457248	0.0144725	0.8956174
$GVCB_{jkt}$	595,575	0.26266	0.1463555	0.0144725	0.8956174
$GVCF_{ikt}$	595,185	0.3036041	0.4357144	0.0026263	25.43331
$GVCF_{jkt}$	595,575	0.3006146	0.4362805	0.0026263	25.43331
INT_{ijt}	602,880	33.23702	3.336177	22.37257	42.3909
D_{ij}	609,570	7.953161	1.097272	4.087945	9.802004
$contig_{ij}$	609,570	0.0669816	0.2499904	0	1
$colony_{ij}$	609,570	0.0376003	0.1902276	0	1
COL_{ij}	609,570	0.0398642	0.1956402	0	1
FTA_{ijt}	609,570	0.5471628	0.4977711	0	1