The Effect of ICT on Trade: Does Product Complexity Matter?

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Abstract: We use a gravity model of trade to investigate the effect of internet use on aggregate trade flows. We apply a structural gravity model using up-to-date PPML estimation techniques to a sample of bilateral exports of 120 countries over the period 2000–2014. In contrast to previous studies, we segment countries according to their degree of product complexity and estimate the model for each segment. The results show that internet use increases trade, and the segmentation by product complexity is more sensitive to internet use than segmenting by level of income. The main results also indicate that countries trade more if similar levels of ICT use are coupled with similar degrees of product complexity in the trading countries.

Keywords: Economic Complexity Index, Gravity Model of Trade, Structural PPML

JEL codes: F14

1. Introduction

There is no doubt that ICTs and increasing trade flows are key drivers of the *New Globalization* (Baldwin 2016). Nonetheless, trade liberalization comes with high entry costs to foreign markets, so only the most productive firms are able to engage in trade (Melitz 2003). Information and Communication Technologies (ICT) contribute to firms' internationalization by reducing the transaction costs linked to uncertainty (Abramovsky and Griffith 2006) and increasing the efficiency of the logistics process (World Bank 2016). This results in lower trade costs and higher trade flows. Data corroborate the relevance of both ICTs and trade in the new wave of globalization: according to World Bank data, from 2000 to 2014 exports increased from 26.1 to 30.2 as a percentage of GDP, while internet users as a percentage of the total population grew from almost 7 to 40[1].

Both ICTs and trade are dynamic factors evolving with economic change, and governed by knowledge. In fact, both access to and transmission of knowledge has been completely transformed in less than 40 years. In 1969, Arrow argued that individuals and nations did not have the same opportunities to transmit knowledge. In contrast to Arrow´s (1969) findings, the *New Globalization* is characterized not only by an unprecedented growth in trade flows, but also by a near-total elimination of the cost of moving ideas, due to the introduction of ICTs (Baldwin 2016). As a result, tacit and codified knowledge are becoming increasingly important in the production process, but knowledge stocks differ across countries (Hausmann et al. 2014). Hence, not only is the increase in trade flows relevant in itself, but the way in which knowledge has shaped countries' trade specialization is also key.

Differences in knowledge across countries are related to other cross-country differences, and we argue that they need to be considered when studying the impact of ICTs on trade. The existence of cross-country differences affects productivity and becomes fundamental to an understanding of trade patterns (Trefler 1993a; Caselli and Coleman 2001). Still, the literature addressing the effects of ICTs on trade (Freund and Weinhold 2004; Vemuri and Siddiqi 2009; Lin 2015, among others) has not yet considered cross-country differences in terms of knowledge. The studies find a positive effect of ICTs on trade without segmenting countries; as such, they do not consider the disparities in technology

[1] This data is taken from the World Development Indicators (WDI) collected by the World Bank.

diffusion nor do they treat ICTs as general purpose technologies (GPTs), as proposed by Helpman and Trajtenberg (1998). Those authors stated that viewing ICTs as GPTs entails low adoption rates in the initial phases. In addition, research on ICT diffusion shows disparities in the diffusion of ICTs between countries (Baliamoune-Lutz 2003; ITU 2017, among others), and this should be taken into account when analysing the effect of ICTs on trade. A few studies have identified cross-country differences derived from the disparities in ICT diffusion (Márquez-Ramos and Martínez-Zarzoso 2005; Clarke and Wallsten 2006; Abeliansky and Hilbert 2017). In these studies, income per capita is the variable that potentially captures the asymmetric diffusion of ICTs. However, income per capita differences are the result of an interaction between different supply and demand factors related to cross-country differences. Among these factors, knowledge emerges as the main supply-side explanatory factor (Comin and Mestieri 2014). The theory of endogenous growth emphasizes the importance of knowledge as an economic growth determinant (Romer 1990; Grossman and Helpman 1991; Aghion and Howitt, 1992). Indeed, knowledge explains much of the variation in income per capita (Howitt 2000; Hanushek et al. 2017). In recent contributions, Yushkova (2014) and Wang and Li (2017) show that technological and knowledge differences matter in explaining the effects of ICTs on trade in a cross-sectional setting using data for 2011 and 2013, respectively.

The abovementioned research shows some evidence of a positive effect of ICTs on trade and underlines the importance of knowledge in explaining cross-country differences in technology diffusion and also the relevance of time dynamics in evaluating the effect of new ICTs on trade. Departing from Yushkova (2014) and Wang and Li (2017), we extend this research by using panel data and estimating a structural gravity model that considers third country effects and models unobserved heterogeneity in a more comprehensive manner; as a result, the identification strategy relies on a fully specified model.

The objective of this study is to shed some light on the asymmetric effects of ICTs on trade; to do so, we follow the novel approach of considering product complexity differences between countries. In contrast to previous studies, we segment countries by knowledge using the Economic Complexity Index estimated by Hausmann et al. (2014). In addition, panel data techniques allow us to control for time invariant unobserved heterogeneity and to capture cross-country variations over time and the GPT nature of ICTs. To this end, we use a structural gravity model of bilateral trade using the estimator proposed by Larch et al. (2018), estimated for a sample of 120 countries over the period 2000–2014, with internet use as a proxy for ICTs.

The main results indicate that differentiating by degree of knowledge produces more heterogeneous coefficients for the target variables than when differentiating by income level, indicating the relevance of economic complexity as a factor affecting the relationship between ICTs and trade. Our findings also indicate that countries trade more if similar levels of ICT use are coupled with similar degrees of product complexity in the trading countries.

The rest of this paper is organized as follows: section 2 summarizes the literature review while section 3 presents some stylized facts concerning product complexity and sets out the research hypotheses. Section 4 presents the empirical analysis, including the model specification, data description and the estimation strategy. Section 5 is devoted to the presentation and discussion of results and, finally, section 6 outlines the conclusions.

2. Literature review

The existing related literature indicates that increasing ICT use—in particular internet use—positively affects firms' performance (Cardona et al. 2013). However, the question of how ICTs have contributed to increasing trade flows remains largely unexplored in the literature. An efficiency increase is always cited as the most important impact of ICTs (Cardona et al. 2013; ITU 2017, among others). This efficiency increase due to ICT usage actually affects specific cases, such as the banking system (Salim et al. 2010) or agricultural output (Salim et al. 2016). Efficiency is strongly linked to international trade, because entry costs to foreign markets are high and only a minority of firms can engage in such trade (Melitz 2003). ICTs contribute to reducing different components of trade costs, especially transactional components, which account for a large part of total trade costs. As found by different authors, ICTs reduce transaction costs such as search costs (Venables 2001; Abramovsky and Griffith 2006). ICTs also contribute to cutting costs related to inventories and transportation routes, so that firms can improve the efficiency of their supply chains and logistic operations (World Bank 2016). Hence, decisions about ICTs are fundamental to fostering the internationalization of firms (Correa-Lopez and Domenech 2012).

The literature analysing the impact of ICTs on trade has mainly focused on country-level studies. The gravity model is the standard methodology used in the literature. This framework has allowed researchers to include not only ICTs, but an additional set of geographical and institutional determinants as proxies for trade costs, and has contributed to an exhaustive explanation of trade barriers. In general, prior studies have focused on only one type of ICT, with the percentage of internet subscriptions being the most commonly-used variable.

The seminal paper by Freund and Weinhold (2002) focus on the exports of services from the United States to 31 countries in 2000 and find a positive relationship between internet hosts and trade. In a later study, Freund and Weinhold (2004) analyse the effect of the internet on trade between 54 countries during cross sections from 1995 to 1999, and replicate the positive effect of ICTs. Vemuri and Siddiqi (2009) study a sample of 63 countries trading during the period 1985-2005 and find a positive and significant effect of the internet on exports. Márquez-Ramos and Martínez-Zarzoso (2010) focus on trade between 13 exporter and 167 importer countries in 2000. Using an index of technological innovation that weights ICT, they find a positive and non-linear effect of ICTs on trade. Chung et al. (2013) analyse trade between Asia-Pacific countries from 1997 to 2006 and find a positive effect of the internet and fixed line phones on trade. Liu and Nath (2013) also find a positive effect of ICTs on trade for a sample of 40 emerging countries from 1995 to 2010. Lin (2015) reports a positive effect of internet use on trade using a sample of 200 countries in the period 1990-2006. Recent research has also considered the ICT impacts on trade at the regional level. Bensassi et al. (2015) analyse the effect of capital stock of ICT on exports from Spanish regions during the period 2003–2007 and find a positive effect. Barbero and Rodriguez-Crespo (2018) study the effect of broadband infrastructure on regional trade in European Union and report a positive relationship between both variables in 2007 and 2010.

A major shortcoming of the reviewed literature is the assumption that the effects are similar for all trade relationships. Failing to account for cross-country differences is implicitly equivalent to assuming similar diffusion patterns of ICTs. However, the diffusion of ICTs is characterized by the existence of persistent asymmetric digitalization levels between and within countries (Baliamoune-Lutz 2003; ITU 2017, among others). Cross-country differences in the adoption of ICTs lead to disparities that affect both the exporter and the importer country. These differences must be taken into account in order to accurately evaluate ICT effects on trade.

Of the limited number of studies that do account for cross-country differences when analysing ICT effects on trade, most take income levels as the factor that determines these differences. Using a sample covering 62 developed and developing countries in 1999, Marquez-Ramos and Martinez-Zarzoso (2005) find that technology, measured through the Technological Achievement Index (TAI), has an effect on trade, which is greater for developing countries. Clarke and Wallsten (2006) find that internet users coefficients are larger for exports from low- to high-income countries in 1999, using a sample of 52 high-income and 46 low- and middle-income countries. Portugal-Pérez and Wilson (2012) analyse a sample of 101 developed and developing countries during the period 2004–2007 and find a positive effect of an ICT infrastructure index on trade, with higher coefficients for developing countries. Abeliansky and Hilbert (2017) find a positive effect of the quality and quantity of telecommunication subscriptions on trade. These authors distinguish by income levels and types of ICTs using a sample of 122 countries during the period 1995–2008, finding that the quality of broadband infrastructure is more important for the trade patterns of developing countries, while the number of subscriptions matters more for developed countries. Lastly, Rodriguez-Crespo et al. (2018) find a positive relationship between three types of ICT and trade for the period 2000–2013, and how this relationship varies by country income levels.

Other studies have focused on differences in technology, as they are more closely related to the diffusion of ICTs. Yushkova (2014) analyses the impact of ICTs on trade for 40 OECD countries, segmented by the technological content of exports. Her cross-sectional data for 2011 shows a positive effect of ICTs on exports, with greater coefficients for high-technology exports.

Using GDP per capita or the technological content of products to account for cross-country differences in digitalization may be suboptimal; a more suitable strategy is to account for differences in the underlying factors of the growth process. The endogenous growth theory considers cross-country differences in knowledge as one of the main explanatory factors for economic growth (Romer 1990; Grossman and Helpman 1991; Aghion and Howitt 1992). Human capital is the principal knowledge-related factor (Comin and Mestieri 2014), and is also fundamental to explaining labour productivity differences between countries and the future evolution of growth (Barro and Lee 1996). Knowledge capital explains a large part of the variations in GDP per capita (Howitt 2000; Hanushek et al. 2017). Knowledge is defined as one of the main supply-related factors for the diffusion of technology in countries (Comin and Mestieri 2014) and it is fundamental for current production processes, which are governed by technology (Baldwin and Venables 2013). Furthermore, tacit knowledge leads to an increase in product sophistication (Hausmann and Hidalgo 2011); knowledge-intensive products are considered more complex and require more sophisticated production processes than products with low knowledge content. Accordingly, the related literature has recently defined different approaches to study and measure product complexity[2]. Lapatinas (2019) identifies an indirect effect of the internet on economic growth through an increasing degree of product sophistication.

The growing evidence attesting to the importance of knowledge highlights the need to include this variable in the analysis in order to capture differences at a country level. Trade theory has progressively incorporated knowledge and learning as an additional factor to explain trade patterns. In contrast to the early contribution of Ricardo (1891), where technology was exogenous and could not be improved over time, Grossman and Helpman (1995) introduce endogenous technology in their literature review about technology and trade. These authors find that knowledge and trade affect each other, and knowledge can be endogenous: countries can improve knowledge through a learning process. Hausmann and Hidalgo (2011) define the attributes of product diversity and ubiquity. Looking at diversity, countries with higher per capita GDP seem to have introduced more products in their export basket than poor countries. However, in terms of ubiquity, that is, the number of countries specialized in making a particular product, it can be seen that only a minority of countries can produce that product. Hausmann and Hidalgo (2011) explain differences in ubiquity relating to intrinsic knowledge-based differences between countries. Accordingly, differences in knowledge affect countries' trade performance (Hausmann and Hidalgo 2011).

The literature on ICT effects on trade has recently incorporated knowledge as an explanatory factor, but this new line of research has yet to reach its full potential. In one of the most recent studies in the literature, Wang and Li (2017) study the role of cross-

[2] Interested readers can see Minondo and Requena (2013) for a full list of product complexity measures.

country differences in ICT potentially influencing the ICT effects on trade. Using data for 152 countries and 86 industries in 2013, these authors show how countries with higher ICT development hold a comparative advantage in knowledge-intensive industries. This study constitutes a new line of research in relation to the previous literature.

Although Wang and Li (2017) provide fundamental information on the role of knowledge in ICT effects on trade, their results are cross-sectional. Considering ICTs as GPTs requires the incorporation of a time dimension to evaluate their economic impacts (Helpman and Trajtenberg 1998). Unlike cross-sectional data, panel data techniques allow the researcher to capture heterogeneity across agents and estimate dynamic effects changing over time (Greene 2011). In this study, we assign a key role to panel data: we estimate ICT effects on trade accounting not only for differences in income, but also differences in the degree of knowledge between countries. To the best of our knowledge, no studies to date have addressed the degree of knowledge in order to explain ICT effects on trade, or compared these results with those obtained by considering income levels. We aim to shed light on this matter with a novel contribution to this promising new line of research.

3. Product Complexity and main research hypotheses

3.1 Measuring product complexity

In the previous section, we stated that an important aspect related to exports is the change in the composition of countries´ export basket. In this regard, Figure A1 shows the growing importance of product categories with high knowledge content, such as machinery and chemicals, from 1996 to 2014 in the United States. In contrast, Figure A2 shows the opposite trend during the same period in South Africa, where product categories involving less intensive knowledge input, such as stone and minerals, represent an important share of total exports. Given the changes in the composition of the export basket across countries with respect to the knowledge content of products, it is important to evaluate the role of knowledge in countries' trade, and also the role of ICTs in expanding knowledge flows (Peri 2005).

To measure the amount of knowledge incorporated into countries´ export basket, we use a measure of product complexity. The intuition underlying product complexity is that products requiring more sophisticated inputs are denoted as more complex. Hausmann et al. (2011, 2014) have produced an Economic Complexity Index (henceforth, ECI), with the aim of measuring the amount of complexity in countries´ export basket. In *The Atlas of Economic Complexity*, Hausmann et al. (2011, 2014) present the methodology used to create the ECI; we provide a brief description below[3].

Let us define a matrix *M*, which takes a value of 1 if a country *c* produces the product *p*, and 0 otherwise. We can use this matrix M_{cp} to create two measures of country capabilities: ubiquity and diversity. Product diversity (D) refers to the number of products that a country is connected to, while ubiquity (U) refers to the number of countries that a product is connected to. Equations (1) and (2) show the analytical measures of ubiquity and diversity:

$$D = k_{c,0} = \sum_{p} M_{cp} \qquad (1)$$

$$U = k_{p,0} = \sum_{c} M_{cp} \qquad (2)$$

To obtain an accurate measure of both attributes, following a recursive interaction, the expressions D and U are used to correct each other. Equations (3) and (4) present a recursive expansion of expressions (1) and (2), which takes into account the average diversity and ubiquity for all countries,

$$D = k_{c,N} = \frac{1}{k_{c,0}} \sum_{p} M_{cp} * k_{p,N-1} \qquad (3)$$

$$U = k_{p,N} = \frac{1}{k_{p,0}} \sum_{c} M_{cp} * k_{c,N-1} \qquad (4)$$

Equation (5) results from inserting equation (4) into (3) and rewriting the final expression as,

$$k_{c,N} = \sum_{c'} \widetilde{M_{cc'}}\ k_{c',N-2} \qquad (5)$$

where $\widetilde{M_{cc'}} = \sum_{p} \frac{M_{cp} M_{c'p}}{k_{c,0} k_{p,0}}$

3 For a complete description, we refer readers to Technical Box 2.1 (Hausmann et al. 2011, page 24).

In the case of $k_{c,N} = k_{c,N-2} = 1$, $\widetilde{M_{cc'}}$ is the eigenvector of expression (5). However, this eigenvector is a vector of ones, which may not be informative when it comes to explaining countries' intrinsic trade capabilities. As a consequence, we take the eigenvector with the second largest eigenvalue. Given that this eigenvector captures the largest proportion of variance, Hausmann et al. (2011) define ECI as follows:

$$ECI = \frac{\mathrm{K} - < \mathrm{K} >}{stdev(K)} \qquad (6)$$

where $\vec{K}$ is the eigenvector of $\widetilde{M_{cc'}}$ that captures the largest share of the variance, $<>$ denotes the average and $stdev$ the standard deviation. This normalized measure of the ECI is a consistent way of measuring the amount of knowledge incorporated in a country's export basket.

By using the ECI, we can provide a different perspective about how ICT use influences trade flows. Previous studies evaluating the effect of ICTs on trade have accounted for differentials in ICT diffusion through income differentials (Márquez-Ramos and Martínez-Zarzoso 2005; Clarke and Wallsten 2006; Abeliansky and Hilbert 2017). However, as we pointed out above, income per capita does not capture knowledge accurately. Hence, we can gain more insight into the impact of ICTs on trade if we segment by knowledge differentials, to which end we use the ECI. To the best of our knowledge, this is the first study on the effect of ICTs on trade that considers differences in knowledge. It is important to highlight that the ECI is consistent with the existence of income differentials between countries (Hausmann and Hidalgo 2011; Minondo and Requena 2013).

3.2 Research Hypotheses

In this study, we test three hypotheses, H1–H3. The first, H1, aims at validating previous findings, whereas H2 and H3 reflect the value added of the study.

H1: Internet use has a positive effect on trade

Previous studies find a positive effect of ICTs on trade due to a reduction in trade costs enabled by ICTs (Freund and Weinhold 2002, 2004; Clarke and Wallsten 2006; Lin 2015, Abeliansky and Hilbert 2017, among others).

H2: The effect of ICTs on trade differs according to the degree of product complexity in the trading countries

In the literature about ICT effects on trade, income per capita has traditionally been the indicator used to segment countries (Márquez-Ramos and Martínez-Zarzoso 2005; Abeliansky and Hilbert 2017). However, cross-country variations in income per capita are not the cause, but rather the result of different supply and demand factors. Among all these factors, knowledge is the main one and explains a large part of the cross-country differences in income per capita (Aghion 2003; Hanushek et al. 2017). Hence, given that ICTs increase the speed of knowledge flows dissemination (Peri 2005), we expect differences in knowledge to capture a large part of the ICT diffusion when segmenting by level of income.

H3: Countries trade more if they have similar access to ICTs, but this depends on the type of products produced.

ICTs help to lower both fixed and variable trade costs and hence expand countries' trade flows. In addition, there are productivity differentials across sectors that affect the nature of the comparative advantage (Levchenko and Zhang 2012). It is expected that countries specialized in high-complexity products will have production structures that can incorporate value added into the intermediate inputs. In contrast, countries specialized in producing less complex goods may not have production structures that incorporate value added into the product. Given that ICTs increase productivity and it differs across sectors, the effect of ICTs on trade is expected to be asymmetric depending on the degree of complexity of the products produced.

4. Empirical analysis

The gravity model is the main methodology used to theoretically and empirically analyse international trade, and this methodology has been used in the previous literature to explain ICT effects on trade (Márquez-Ramos and Martínez-Zarzoso 2005 and 2010; Lin 2015, among others). The gravity equation (7) is our baseline model for studying ICT effects on trade and is rigorously rooted in previous studies: among others, the theoretical framework outlined by Anderson and Van Wincoop (2003) and the panel gravity equation presented by Baltagi et al. (2014). We have augmented the gravity model with variables representing internet use in the origin and the destination countries. The theoretically-based model is given by,

$$X_{ijt} = \frac{GDP_{it}}{\Pi_{it}} \frac{GDP_{jt}}{\Omega_{jt}} * IU_{i,t-1} * IU_{j,t-1} * DIST_{ij} \\ * \exp\left(RTA_{ij,t-1} * COL_{ij} * COMLANG_{ij} * CONT_{ij}\right) \qquad (7)$$

where subscripts i, j and t refer to exporter country, importer country and time, respectively. $IU_{i,t-1}$ and $IU_{j,t-1}$ are internet users in countries *i* and *j*, respectively, during the previous year. GDP_{it} and GDP_{jt} refer to exporter and importer countries' Gross Domestic Product. $DIST_{ij}$ is the bilateral distance that separates *i* and *j*.

The remaining explanatory variables are the usual gravity controls. $RTA_{ij,t-1}$ takes a value of 1 if both i and j are members of a specific regional trade agreement and 0 otherwise. COL_{ij} takes a value of 1 if i and j share a colonial past, and 0 otherwise. $COMLANG_{ij}$ takes a value of 1 if i and j share a common language and 0 otherwise. $CONT_{ij}$ takes a value of 1 if *i* and *j* are adjacent countries and 0 otherwise.

Finally, Π_{it} and Ω_{jt} refer to time-varying multilateral resistance terms (henceforth, MRTs). Anderson and Van Wincoop (2003) define MRTs as the third-country unobservable characteristics, such as policies, regulations or tariffs that can potentially affect the bilateral trade relationship between *i* and *j*. The omission of MRTs from the gravity equation leads to biased estimators (Head and Mayer 2014). As a major shortcoming, time-varying MRTs show collinearity with both GDP and internet variables. We discuss this problem in section 4.2.2.

In this study, internet users is the policy variable and several studies include this as an explanatory variable (Freund and Weinhold 2002; Freund and Weinhold 2004; Clarke and Wallsten 2006; Abeliansky and Hilbert, 2017, among others). The interaction of internet users and the distance can be interpreted as the attenuation of distance due to Internet usage. Seminal examples of the basic gravity model mainly include GDP and distance, which show a positive and negative relationship with trade, respectively. Apart from distance, we include the common control variables used in the literature for proximity, institutional legacies and free trade agreements. This set of control variables is not only in line with seminal gravity equations (Bergstrand 1989; Frankel 1997), but also with the subsequent advances in empirical international trade. In addition to internet use, these control variables complement the trade cost specification and capture other potential trade barriers.

Proximity is one of the elements potentially impacting trade flows and the reason is fairly obvious. Countries tend to concentrate their trade flows with adjacent countries because trade barriers are lower (Eaton and Kortum 2002). We also control for institutional legacies with colonial ties and the existence of a common language. Institutions help reduce transaction costs (Rodrik 2011) and have a positive impact on trade performance (Levchenko 2007; Nunn and Trefler 2014). Free trade agreements and custom unions result in greater trade flows when tariffs are abolished as a result of trade liberalization, and their effects must be incorporated into the gravity equation (Baier and Bergstrand 2007).

4.1. Data and variables

We use an unbalanced panel with 120 countries trading over the period 2000–2014. A list of all the countries can be found in Table A1 in the Appendix. The total number of observations is almost 150,000.

We gather the data from different international organizations. Bilateral exports at aggregate level come from UN Comtrade, while GDP and internet data come from the World Bank. Finally, distance and control variables come from the Centre d´Études Prospectives et d'Informations Internationales (CEPII). Tables A2 and A3 in the Appendix show the description of the variables and the summary statistics, respectively. Finally, the Economic Complexity Index (henceforth, ECI) comes from Hausmann et al. (2014). The ECI is computed at country level and can be interpreted as follows: A higher ECI implies that countries are specialized in products with greater complexity, which are more knowledge intensive, while a lower ECI is related to countries specialized in non-knowledge-intensive products. Countries with an average ECI greater than zero are classified as countries specialized in high-complexity products, whereas an average ECI below zero is related to specialization in low-complexity products. Table A4 in the Appendix shows the list of countries and their average ECI computed from 2000 to 2014.

4.2. Estimation strategy

4.2.1. Endogeneity

Endogeneity is a persistent problem in empirical international trade, which results in biased estimates. Trade policy is endogenous, and empirical estimations have not traditionally tackled the endogeneity problem (Baier and Bergstrand 2007). Trefler (1993b) finds that when trade protection is considered endogenous, the coefficients are around 10 times higher than in the exogenous case. Baier and Bergstrand (2007) study the effect of trade agreements and find three major causes for endogeneity: measurement errors, reverse causality and omitted variable bias.

The relationship between technology and trade is potentially endogenous, and some studies report the existence of reverse causality. Grossman and Helpman (1995) demonstrate not only that technology affects trade, but the causality also runs in the other direction and trade affects technology. As several authors argue, international trade stimulates technology adoption (Caselli and Coleman 2001; Lileeva and Trefler 2010; Bustos 2011; Rodrik 2011).

Other researchers have also found omitted variable bias in the relationship between ICTs and trade (Freund and Weinhold 2002; Clarke and Wallsten 2006; Liu and Nath 2013). In this case, there are unobservable omitted country characteristics that affect the empirical relationship and cannot be captured by the set of explanatory variables. These characteristics may be related to institutional, political or geographical determinants.

To address endogeneity, we follow two steps: first, we take lags of potentially endogenous variables, as suggested by different authors (Vemuri and Siddiqi 2009; Alvarez et al. 2018). Lagging variables that are potentially subject to endogeneity issues treats these variables as predetermined, and they become unaffected by shocks happening during the current period. This statement is in line with the consideration of ICTs as GPTs, because firms need to adapt their inputs after the introduction of the new technology (Helpman and Trajtenberg 1998). Hence, the effects of ICTs on trade shocks are expected to occur in the future rather than immediately, because of the learning process that firms undergo.

In addition, we follow Greene (2011) and implement the methodology proposed by Hausman and Taylor (1981). This econometric technique consists of a three-step instrumental variable regression, which allows us to create an alternative between fixed and random effects estimators. In the first step, a fixed effects model is estimated on the time-varying variables. In the second step, the first-step estimation results are used to construct group means of the within-group residuals. In the third and final step, these group means are used as instrumental variables for the explanatory variables, and the estimation is similar to a 2SLS one.

Moreover, we follow Trefler (1993b) and consider trade policy as endogenous. Endogenous trade policy implies the consideration of trade agreements as endogenous to avoid biased estimates (Baier and Bergstrand 2007). Potentially endogenous trade agreements are incorporated into the gravity equation and, using the approach detailed above, we introduce the variable measuring trade agreements lagged one period.

4.2.2 Multilateral resistance terms and structural gravity

How to capture MRTs is a major challenge in the specification of the gravity equation (Yotov et al. 2016). In a cross-sectional context, Feenstra (2016) claims that the introduction of fixed effects is the easiest and the most efficient solution to capture MRTs. Accordingly, the literature has used control variables to explain MRTs, but the introduction of panel data with an additional dimension may entail problems. Head and Mayer (2014) define a structural gravity equation, where MRTs are a pivotal element. The authors state that time-invariant fixed effects do not capture MRTs and advocate using exporter-time and importer-time fixed effects with the aim of being consistent with the structural gravity equation.

Unfortunately, ICT variables also vary by exporter-time and importer-time, as do constructed MRTs. As a result, capturing MRTs with control variables presents collinearity issues with the policy variables, but failing to capture MRTs correctly represents a *gold-medal mistake* (Baldwin and Taglioni 2007).

We can find several solutions to the challenge of capturing MRTs in the gravity equation by addressing the problem of collinearity. Martínez-Zarzoso and Márquez-Ramos (2019) introduce time-varying controls for MRTs that change every five years. Given that third-country unobservable characteristics may be related to changes in laws, policies or institutions that do not occur immediately, this way of modelling MRTs is consistent with the real world. Bacchetta et al. (2012) criticize the introduction of exporter-time and importer-time control variables due to the existence of collinearity issues and propose the use of time-invariant controls to capture MRTs for short panels. Finally, Baier and Bergstrand (2009) propose the Bonus Vetus approach, a novel gravity estimator that does not rely on control variables to capture MRTs, but rather on a Taylor approximation for the bilateral trade costs components (distance and trade agreements, among others).

An important debate has centred on how to estimate the gravity equation being consistent with the structural gravity model. In this case, the pseudo-poisson maximum likelihood (henceforth, PPML) suggested by Santos-Silva and Tenreyro (2006) is the preferred alternative for several reasons. First, it solves two prevalent problems related to the gravity equation: the heteroskedasticity derived from the logarithmic transformation and the existence of zero values for the dependent variable (Santos-Silva and Tenreyo 2006). The second reason is the resemblance between PPML and the roots of the structural gravity equation using fixed effects to control for MRTs (Fally 2015). Finally, Beverelli et al. (2018) state that the nature of the PPML estimator allows researchers to perform iterative estimations closer to the structural gravity equations. In a recent survey of gravity estimations, Kabir et al. (2017) emphasize the importance of using PPML in order to achieve a consistent gravity estimation.

Equation (8) is estimated by applying the PPML estimator with exporter-time and importer-time effects to equation (7). *Ln* denotes the natural logarithm of a specific variable.

$$X_{ijt} = \beta_0 + \beta_1 \ln IU_{i,t-1} * \ln DIST_{ij} + \beta_2 \ln IU_{j,t-1} * \ln DIST_{ij} + \beta_3 \ln DIST_{ij} + \beta_4 RTA_{ij,t-1} + \beta_5 COL_{ij} + \beta_6 COMLANG_{ij} + \beta_7 CONT_{ij} + \pi_{it} + \varphi_{jt} + \varepsilon_{ijt} \quad (8)$$

Equation (2) incorporates additional components into the gravity equation. $\ln IU_{i,t-1} * \ln DIST_{ij}$ and $\ln IU_{j,t-1} * \ln DIST_{ij}$ refer to the interaction between internet use in the exporter and importer country with the distance, respectively. These interaction terms allow us to evaluate how the effect of internet use varies with the distance, similar to an elasticity. π_{it} and φ_{jt} are the exporter-time and importer-time effects. These effects absorb the effect of time-varying variables (i.e.: GDP and GDP per capita).

5. Main Results

5.1. Comparing different gravity estimators

In this section, we present and compare different gravity estimators in order to select the most suitable specification. Table 1 shows the main results. All the specifications consider internet use and trade agreements as endogenous, and these variables are 1-year lagged. In the specifications where GDP coefficients are estimated, GDP is also endogenous. Columns 1-4 refer to different versions of PPML. Column 1 is the structural gravity equation (2) following Zylkin's (2016) estimation technique. Column 2 follows the same estimation technique as in column (1) but introducing pair fixed effects, which entails removing the time-invariant bilateral variables. Column 3 is also a PPML estimation, but using time-invariant fixed effects to be able to identify the internet use variables. Column 4 includes time-variant exporter and importer fixed effects each varying 5 years, in line with Martinez-Zarzoso and Marquez-Ramos (2019).

Columns 5 and 6 complement the previous estimations. Column 4 presents the Hausman and Taylor (1981) estimation to tackle endogeneity bias using time-invariant country fixed effects[4]. Finally, column 5 refers to the Bonus Vetus OLS estimation proposed by Baier and Bergstrand (2009)[5].

[4] Given that the xthtaylor Stata command does not provide estimations for exporter-time and importer-time effects due to the high number of variables, we just introduce exporter and importer fixed effects.
[5] As Beverelli et al. (2018) claim, the Bonus Vetus is only compatible with centred estimations using logarithms in the dependent variable. In this regard, Bonus Vetus is not compatible with PPML.

Table 1. Comparison of different gravity estimators, 2000–2014

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	*Structural PPML Time-variant MRT*	*Structural PPML Time-variant MRT pair FE*	*PPML time-invariant MRT*	*PPML time-variant MRT*	*Hausman and Taylor Time-invariant MRT*	*Bonus Vetus POLS*
Dependent variable	X_{ijt}	X_{ijt}	X_{ijt}	X_{ijt}	$ln\, X_{ijt}$	$ln\, X_{ijt}$
$\ln IU_{i,t-1} * \ln DIST_{ij}$	0.023***	0.042***				
	(0.007)	(0.012)				
$\ln IU_{j,t-1} * \ln DIST_{ij}$	0.156***	0.018*				
	(0.007)	(0.010)				
$\ln IU_{i,t-1}$			0.075***	0.146***	0.086***	0.327***
			(0.024)	(0.023)	(0.007)	(0.004)
$\ln IU_{j,t-1}$			0.102***	0.166***	0.062***	0.145***
			(0.019)	(0.019)	(0.006)	(0.004)
$\ln GDP_{it}$			0.788***	0.446***	1.022***	1.176***
			(0.081)	(0.070)	(0.028)	(0.004)
$\ln GDP_{jt}$			0.762***	0.413***	0.728***	0.918***
			(0.079)	(0.062)	(0.027)	(0.004)
$\ln DIST_{ij}$(*)	-1.335***		-0.635***	-0.633***	-1.612***	-1.463***
	(0.029)		(0.009)	(0.009)	(0.039)	(0.011)
$RTA_{ij,t-1}$(*)	0.606***	0.059***	0.585***	0.593***	0.099***	0.408***
	(0.018)	(0.022)	(0.019)	(0.019)	(0.018)	(0.019)
COL_{ij}(*)	0.268***		0.283***	0.286***	0.651***	0.783***
	(0.024)		(0.027)	(0.027)	(0.186)	(0.033)
$COMLANG_{ij}$(*)	0.100***		0.078***	0.078***	1.048***	0.798***
	(0.023)		(0.024)	(0.024)	(0.083)	(0.022)
$CONT_{ij}$(*)	0.494***		0.489***	0.489***	0.729***	0.717***
	(0.022)		(0.024)	(0.024)	(0.160)	(0.034)
Intercept			-20.031***	0.502	-17.616***	-51.432***
			(2.691)	(1.724)	(0.932)	(0.165)
Exporter FE	No	No	Yes	No	Yes	No
Importer FE	No	No	Yes	No	Yes	No
Time FE	No	No	Yes	Yes	Yes	No
Exporter-time FE	Yes	Yes	No	Yes§	No	No
Importer-time FE	Yes	Yes	No	Yes§	No	No
Pair FE	No	Yes	No	No	No	No
R-squared	0.896	0.996	0.883	0.879	0.788	0.645
Observations	143,783	143,783	138,988	138,988	138,988	138,988

Notes: Robust standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1. POLS corresponds to Pooled Ordinary Least Squares, PPML to pseudo-poisson maximum likelihood, BV to Bonus Vetus and FE to Fixed Effects. (*) denotes the Bonus Vetus transformation for the bilateral variables in column (6) using the Baier and Bergstrand (2009) methodology. The R-squared in Column 5 has been calculated following Carrére (2006), such as R2= 1- (SSR/TSS), where SSR is the sum of squared residuals and TSS the total sum of squares. § time denotes 5-year periods. Internet users in the exporter and the importer country and regional trade agreements are considered as endogenous variables in the HT estimator.

We now discuss the results obtained using the different estimators, since each has different implications for the explanatory variables. Our policy variable, internet use, is positive and significant in all scenarios, even when it is modelled as an interaction with the distance variables in columns (1) and (2). The coefficients of internet use range between 0.03 and 0.26 and show a positive effect of internet use on trade, in line with the literature.

The results also confirm the basic theory of gravity, where GDP and distance are positive and negative, respectively, in all cases. The other gravity control variables, namely regional trade agreements, common language, common colonial past, common border and common continent are always positive and significant across specifications. The coefficients yielded by the structural gravity estimations in column (1) are in general higher in magnitude for all the variables apart from common colonial past; the exception is internet use, for which the magnitude is lower for the exporter and higher for the importer than in column (2), where bilateral fixed effects have been added. The results in column 5, where the coefficients of the target variables are considered as endogenous[6] show fairly stable coefficients, when we capture the MRTs using time-invariant country fixed effects.

We select the structural PPML estimator with exporter-time and importer-time effects and bilateral gravity controls, shown in column (1), as the preferred technique due to its resemblance to the structural gravity model, as pointed out by Head and Mayer (2014) and Kabir et al. (2017)[7]. In addition, the PPML estimator allows us to mitigate heteroskedasticity in trade flows.

5.2. Comparing the results segmenting by income and complexity

In this section, we estimate the effects of ICTs on trade, distinguishing first by product complexity and then, for comparative purposes, by income per capita. For this purpose, we use the structural PPML estimator (Zylkin 2016; Larch et al. 2018) for the period 2000-2014 (Column 1 at Table 1).

The first part of Table 2, on the left-hand side, shows the effect of the target variable, internet use, interacted with distance for different combinations of product complexity in the exporter and importer countries. It can be seen that when countries have a comparative

[6] In this specification, the logarithm of internet users in the exporter and the importer country and trade agreements are considered as endogenous.

[7] We prefer to keep the bilateral gravity controls, instead of replacing them with pair FE, because we are interested in keeping the distance coefficient to infer how much the distance effect is reduced due to internet use.

advantage in products of a similar degree of complexity (high-high) and (low-low) in columns (1) and (4), the positive effect of internet use on exports remains positive and significant. Moreover, an increase in internet use reduces the effect of distance. For example, in column (1), a 1% increase in distance reduces exports by 1.45%, more than proportionally, if internet use is set to zero; in contrast, for the average value of internet use in the exporter and importer countries, the distance effect is reduced by 43%[8].

Nevertheless, this is not necessarily the case when the level of complexity differs between exporters and importers. In particular, when the exporter produces low-complexity goods and the importer high-complexity goods (low-high), the effect of internet use on exports for a given distance is shown to be negative and significant. However, the distance coefficient (assuming zero internet use) in column (3) is much lower in magnitude (-0.449) than in the other columns. In this case, the marginal effect of an increase in distance increases with internet use. For instance, a 1% increase in distance for average values of internet use reduces exports by 0.91%. This could be because the differences in internet use between the trading countries magnify trade costs; specifically, trade costs may rise if *buyers* in one country are not able to connect with *sellers* in the other country.

[8] The marginal effect of distance=-1.495+0.186*2.82+0.04*2.69=-0.86; where 2.82 and 2.69 are average values taken from the Appendix.

Table 2. Results with the PPML estimator disaggregating by income and degree of product complexity, 2000–2014

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
Criteria		*Degree of product complexity*				*Income per capita*			
Exporters	*All*	*High*	*High*	*Low*	*Low*	*High*	*High*	*Low*	*Low*
Importers	*All*	*High*	*Low*	*High*	*Low*	*High*	*Low*	*High*	*Low*
$\ln IU_{i,t-1} * \ln DIST_{ij}$	0.023***	0.040***	-0.020	-0.059***	0.100***	0.101***	0.027	0.127***	0.021
	(0.007)	(0.011)	(0.018)	(0.021)	(0.019)	(0.019)	(0.03)	(0.014)	(0.013)
$\ln IU_{j,t-1} * \ln DIST_{ij}$	0.156***	0.186***	0.046***	-0.108***	0.101***	0.184***	0.179***	0.231***	0.065***
	(0.007)	(0.011)	(0.011)	(0.024)	(0.013)	(0.019)	(0.013)	(0.026)	(0.013)
$\ln DIST_{ij}$	-1.335***	-1.495***	-1.086***	-0.449***	-1.777***	-1.767***	-1.406***	-2.127***	-1.031***
	(0.029)	(0.053)	(0.062)	(0.087)	(0.049)	(0.084)	(0.113)	(0.099)	(0.042)
$RTA_{ij,t-1}$	0.606***	0.678***	0.432***	-0.026	0.326***	0.575***	0.588***	0.625***	0.688***
	(0.018)	(0.023)	(0.028)	(0.063)	(0.053)	(0.035)	(0.030)	(0.037)	(0.038)
COL_{ij}	0.268***	0.189***	0.803***	0.695***	1.040***	0.144***	0.748***	0.438***	0.403***
	(0.024)	(0.024)	(0.039)	(0.055)	(0.124)	(0.027)	(0.042)	(0.043)	(0.072)
$COMLANG_{ij}$	0.100***	0.096***	0.258***	0.266***	0.260***	0.214***	0.134***	0.052	0.364***
	(0.023)	(0.027)	(0.031)	(0.057)	(0.060)	(0.032)	(0.035)	(0.035)	(0.044)
$CONT_{ij}$	0.494***	0.529***	0.213***	-0.023	0.052	0.440***	0.978***	0.954***	0.217***
	(0.022)	(0.023)	(0.048)	(0.091)	(0.057)	(0.026)	(0.044)	(0.045)	(0.037)
R-squared	0.896	0.916	0.894	0.682	0.721	0.912	0.959	0.975	0.879
Observations	143 783	33 345	44 095	34 267	32 076	25 607	40 566	34 627	42 983

Notes: All the estimations are done with the structural PPML estimator ppml_panel_sg (Zylkin, 2016). X_{ijt} is the dependent variable for all the regressions. Robust standard errors in parentheses, with *** p<0.01, ** p<0.05, * p<0.1. Columns (2)-(5) analyse the degree of product complexity, while columns (6)-(9) analyse income levels. For columns (6)-(9) the category Low includes all Low- and middle-income countries. The threshold for income is 12,236, in line with the World Bank, while the threshold for product complexity is 0.

In line with previous studies (Freund and Weinhold 2002 and 2004; Clarke and Wallsten 2006; Lin, 2015), we confirm the existence of a positive effect of internet use on trade. The exceptions are columns (3) and (4), where internet use is not significant for the exporter (column 3) and also displays a negative coefficient (column 4). Nevertheless, these cases constitute a minority in the total number of regressions. Hence, our results are in line with the hypothesis *H1*.

The coefficients for internet use tend to be greater when we segment by income than by product complexity. The largest coefficients are for internet users in the importer country, $\ln IU_{j,t-1}$. The highest magnitudes of these coefficients are 0.231 (column 8, income segmentation) and 0.186 (column 2, degree of product complexity). Our results also show the importance of disaggregating by knowledge: internet coefficients in column 9, which are non-significant using income levels for the exporter country (low-low), become positive in column 5. The highest internet use coefficients are for the countries with higher income per capita or that specialize in high-complexity products (high-high). For these countries, the cost of dealing with tacit knowledge is understandably lower (Minondo and Requena 2013) and ICT usage constitutes a real comparative advantage that can boost trade flows. Hence, our results confirm hypothesis *H2*, and results segmenting by knowledge are very close to the segmentation by income levels, albeit only in the case of countries specialized in high-complexity products.

These results show the importance of distinguishing according to income and knowledge in order to explain the effect of internet use on trade. Although the results when we segment by income display positive and significant coefficients for internet use, the segmentation by degree of complexity seems to be more related to the nature of the comparative advantage, which raises the importance of distinguishing between the different types of products traded. Hence, our results also confirm hypothesis H3. According to Levchenko and Zhang (2012), there are productivity differentials within sectors, so that the comparative advantage differs. The coefficients for internet use are also positive and significant for exports between countries with low product complexity. This may be related to the growing number of firms in developing countries that are competing in skill-intensive activities with firms located in developed countries (Minondo and Requena 2013). As stated in Grossman and Helpman (1995), knowledge is fundamental to explaining trade patterns.

The coefficients obtained for control variables are also in line with those in the gravity literature. The variable trade agreements, $RTA_{ij,t-1}$, is always positive and significant except for exports of low-complexity products (column 4). In this case, the variable is negative but significant and the explanation may be the Generalized System of Preferences (GSP): low-complexity products do not belong to the categories of products affected by GSP, mainly manufactured products. Both variables COL_{ij} and $COMLANG_{ij}$, related to institutions, present a positive and significant effect for all cases. $CONT_{ij}$ is also positive and significant, albeit with a few exceptions: columns 4 and 5, in exports from countries with low product complexity. The coefficient is negative and non-significant in column 4, while in column 5 it is positive but non-significant. These cases refer to exports from countries with low product complexity.

6. Conclusions

In this paper, we have studied the effect of ICTs on trade using a sample of 120 countries for the period 2000–2014. In contrast with previous studies, we have differentiated between countries according to their degree of knowledge using an indicator of product complexity, the ECI. The percentage of Internet users is the proxy variable used to measure ICTs. Our estimation strategy is the Structural PPML estimator, which allows us to capture MRTs and mitigate heteroskedasticity in trade flows. We compare the results obtained when segmenting by ECI with those based on segmentation by income per capita: internet use coefficients are more similar when segmenting by income levels, whereas the coefficients for product complexity are more sensitive to internet use. Hence, knowledge segmentation better captures the differences in the internet coefficients than segmenting by income per capita. In this regard, internet coefficients are very similar to the case of income when the exporter and importer country present high degrees of product complexity. In addition, internet coefficients are positive and significant for exports between countries with low product complexity.

These results raise important economic policy implications. The internet is fundamental for firms to engage in international trade (Correa-Lopez and Domenech 2012). Given the influence of internet use on trade for countries with similar levels of product complexity, countries could implement policies targeted at reducing the cost of processing tacit knowledge and thus reducing the gap between the North and the South. Beyond the traditional income differences, knowledge provides a basis for the least developed countries to reduce the gap with the most advanced countries. Increasing knowledge may be the key for countries specialized in less complex products to engage in global production networks and boost their competitiveness to meet the challenge of globalization. In this regard, policies should be related to investments in human capital, so that the dissemination of knowledge will positively affect internet use by individuals and, especially, by firms and public administrations. The result will not only be a greater capacity to process tacit knowledge, but also greater trade flows, growth and prosperity.

This analysis is subject to limitations that may be taken into account for future studies. The first one is the use of the ECI as the measure of product complexity. The ECI is based on the number of destinations for certain exported products, and it may be useful to introduce other measures. These potential measures could include quality, as an alternative attribute used to characterize a country´s export basket (Sutton and Trefler 2016). Also, it is important to consider the production of intermediate products in other countries (Timmer et al. 2014). Future studies could examine the most sensitive industries to ICT use in terms of product complexity, in line with Wang and Li (2017).

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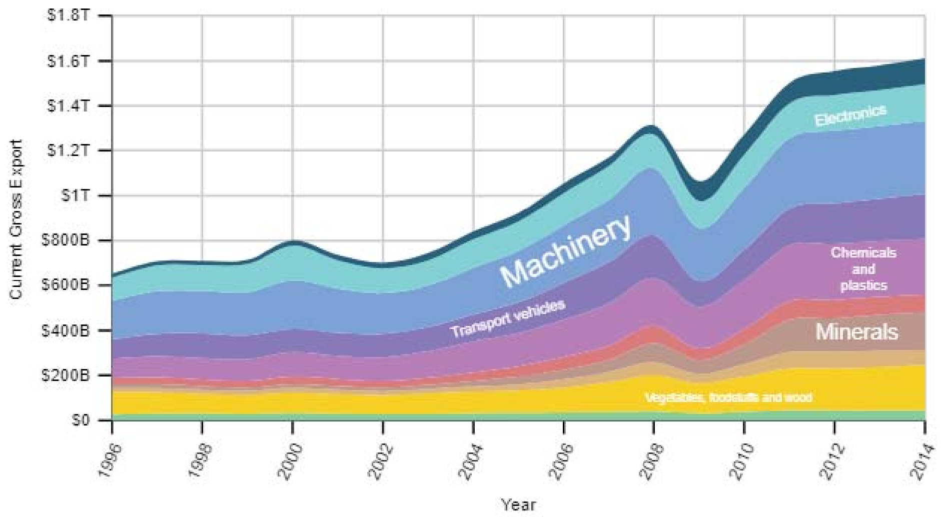
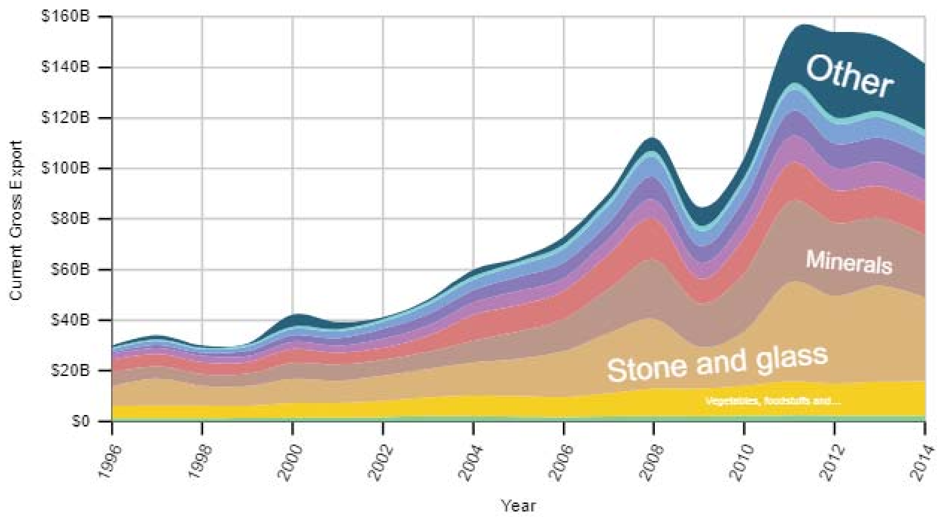
Appendix

Figure A1 Gross exports and product categories for the United States, 1996-2014



Source: The Atlas of Economic Complexity

Figure A2 Gross exports and product categories for South Africa, 1996-2014



Source: The Atlas of Economic Complexity

Table A1 List of countries classified by income levels

Albania	Egypt	Libya	**Saudi Arabia**
Algeria	El Salvador	**Lithuania**	Senegal
Argentina	**Estonia**	Madagascar	**Singapore**
Australia	Ethiopia	Malawi	**Slovakia**
Austria	**Finland**	**Malaysia**	**Slovenia**
Azerbaijan	Fmr Sudan	Mauritania	South Africa
Bangladesh	**France**	Mauritius	**Spain**
Belarus	Gabon	Mexico	Sri Lanka
Belgium	Georgia	Mongolia	Sudan
Bolivia (Plurinational State of)	**Germany**	Morocco	**Sweden**
Bosnia Herzegovina	Ghana	Mozambique	**Switzerland**
Botswana	**Greece**	Namibia	Syria
Brazil	Guatemala	**Netherlands**	TFYR of Macedonia
Bulgaria	Guinea	**New Zealand**	Thailand
Cambodia	Honduras	Nicaragua	Trinidad and Tobago
Cameroon	**Hungary**	Nigeria	Tunisia
Canada	India	**Norway**	Turkey
Chile	Indonesia	Oman	Turkmenistan
China	**Iran**	Pakistan	**USA**
China, Hong Kong SAR	**Ireland**	Panama	Uganda
Colombia	**Israel**	Papua New Guinea	Ukraine
Congo	**Italy**	Paraguay	**United Arab Emirates**
Costa Rica	Jamaica	Peru	**United Kingdom**
Croatia	**Japan**	Philippines	United Rep. of Tanzania
Cuba	Jordan	**Poland**	**Uruguay**
Czech Rep.	Kazakhstan	**Portugal**	**Venezuela**
Côte d'Ivoire	Kenya	**Qatar**	Vietnam
Denmark	**Kuwait**	**Rep. of Korea**	Yemen
Dominican Rep.	**Latvia**	Rep. of Moldova	Zambia
Ecuador	Lebanon	**Russian Federation**	Zimbabwe

Notes: We classify countries by computing the average per capita income during the period 2000-2014, in line with Marquez-Ramos and Martinez-Zarzoso (2005). According to the World Bank, we set a threshold value of US$12,236 to segment income. Countries above the threshold are high-income countries and appear in bold (51). The rest of the countries are low- and middle-income countries (69).

Table A2 List of variables and sources

Variable	Description	Units of measure	Source
X_{ijt}	Bilateral exports from i to j at t.	Current USD	UN-COMTRADE
$IU_{i,t-1}$, $IU_{j,t-1}$	Internet users for *i* and *j* at *t*, 1-year lagged	Percentage of population (per 100 inhabitants)	WB-WDI and ITU
$GDP_{i,t-1}$, $GDP_{j,t-1}$	Gross Domestic Product for *i* and *j* at *t*, PPP adjusted, 1-year lagged	Current USD	WB-WDI
$DIST_{ij}$	Bilateral distance between *i* and *j*	Kilometres	CEPII
$RTA_{ij,t-1}$	Variable that takes value 1 if both countries are members of a specific regional trade agreement and 0 otherwise, 1-year lagged		De Sousa (2012)
COL_{ij}	Variable that takes value 1 if the countries share a colonial past and 0 otherwise		CEPII
$COMLANG_{ij}$	Variable that takes value 1 if the countries share a common language and 0 otherwise		CEPII
$CONT_{ij}$	Variable that takes value 1 if the countries share a common border and 0 otherwise		CEPII

Note: UN corresponds to United Nations, WB "World Bank", WDI "World Development Indicators", ITU "International Telecommunications Union", CEPII "Centre d'Études Prospectives et d'Informations Internationales.

Table A3 Descriptive statistics 2000-2014

A.3.a. Full sample

Variable	Obs	Mean	Std. Dev.
X_{ijt}	164 438	1.01e+09	7.51e+09
$\ln X_{ijt}$	164 438	16.22	3.78
$\ln IU_{i,t-1}$	143 783	2.81	1.51
$\ln IU_{j,t-1}$	143 783	2.64	1.61
$\ln GDP_{i,t-1}$	141 464	26.00	1.62
$\ln GDP_{j,t-1}$	141 286	25.89	1.66
$\ln DIST_{ij}$	164 438	8.61	0.86
$RTA_{ij,t-1}$	143783	0.18	0.38
COL_{ij}	164 438	0.01	0.14
$COMLANG_{ij}$	164 438	0.13	0.34
$CONT_{ij}$	164 438	0.03	0.17

A.3.b. Sample segmented by degree of product complexity

	High degree of product complexity			Low degree of product complexity		
	Obs	**Mean**	**Std. Dev.**	**Obs**	**Mean**	**Std. Dev.**
X_{ijt}	37 443	3.60e+09	1.52e+10	38 819	5.70e+07	2.96e+08
$\ln X_{ijt}$	37 443	19.26	2.89	38 819	13.71	3.55
$\ln IU_{i,t-1}$	34 710	3.55	0.94	30 601	1.96	4.44
$\ln IU_{j,t-1}$	34 710	3.54	0.95	30 601	1.85	4.48
$\ln GDP_{i,t-1}$	34 710	26.62	1.53	29 353	25.31	1.35
$\ln GDP_{j,t-1}$	34 710	26.61	1.54	29 487	25.25	1.40
$\ln DIST_{ij}$	37 443	8.24	1.09	38 819	8.61	0.84
$RTA_{ij,t-1}$	34 710	0.39	0.49	30 601	0.15	0.36
COL_{ij}	37 443	0.03	0.18	38 819	0.00	0.03
$COMLANG_{ij}$	37 443	0.07	0.25	38 819	0.24	0.43
$CONT_{ij}$	37 443	0.05	0.22	38 819	0.04	0.20

Table A4 Countries and average Economic Complexity Index 2000-2014

Countries with high product complexity		Countries with low product complexity			
Japan	2.501	Colombia	-0.024	United Rep. of Tanzania	-1,152
Germany	2.168	Rep. of Moldova	-0.031	Gabon	-1,198
Switzerland	2.099	Tunisia	-0.045	Cameroon	-1,212
Sweden	2.003	Costa Rica	-0.067	Azerbaijan	-1,223
Finland	1.894	Argentina	-0.101	Bangladesh	-1,246
Austria	1.855	Georgia	-0.131	Ethiopia	-1,271
United Kingdom	1.759	Saudi Arabia	-0.168	Turkmenistan	-1,316
Czech Rep.	1.684	Indonesia	-0.197	Mozambique	-1,398
USA	1.641	El Salvador	-0.227	Yemen	-1,416
Rep. of Korea	1.580	Trinidad and Tobago	-0.251	Papua New Guinea	-1,480
Slovenia	1.548	Chile	-0.266	Malawi	-1,485
France	1.513	TFYR of Macedonia	-0.283	Congo	-1,525
Singapore	1.455	United Arab Emirates	-0.312	Libya	-1,558
Slovakia	1.437	Albania	-0.313	Fmr Sudan	-1,576
Ireland	1.437	Egypt	-0.333	Sudan	-1,576
Italy	1.421	Mauritius	-0.369	Mauritania	-1,651
Hungary	1.396	Dominican Rep.	-0.413	Guinea	-1,701
Denmark	1.366	Qatar	-0.414	Nigeria	-1,939
Belgium	1.236	Jamaica	-0.417		
Netherlands	1.077	Australia	-0.419		
Mexico	1.062	Namibia	-0.466		
Spain	1.025	Guatemala	-0.472		
Belarus	1.016	Venezuela	-0.487		
Poland	1.012	Kazakhstan	-0.514		
Israel	0.977	Oman	-0.532		
China. Hong Kong SAR	0.918	Viet Nam	-0.543		
Croatia	0.798	Senegal	-0.567		
Estonia	0.715	Kuwait	-0.586		
Canada	0.710	Botswana	-0.591		
China	0.702	Sri Lanka	-0.607		
Malaysia	0.679	Kenya	-0.608		
Norway	0.649	Morocco	-0.679		
Thailand	0.609	Syria	-0.682		
Latvia	0.594	Zimbabwe	-0.729		
Lithuania	0.581	Peru	-0.746		
Portugal	0.580	Paraguay	-0.768		
Ukraine	0.545	Honduras	-0.793		
Bosnia Herzegovina	0.516	Cuba	-0.803		
Bulgaria	0.448	Iran	-0.860		
Russian Federation	0.403	Pakistan	-0.861		
Panama	0.265	Uganda	-0.944		
Brazil	0.246	Zambia	-0.966		

Turkey	0.246	Nicaragua	-0.974
New Zealand	0.189	Plurinational State of Bolivia)	-0.989
Greece	0.178	Ecuador	-1.039
Lebanon	0.166	Ghana	-1.069
Jordan	0.142	Cambodia	-1.088
India	0.120	Madagascar	-1.110
Philippines	0.040	Côte d'Ivoire	-1.131
South Africa	0.029	Mongolia	-1.137
Uruguay	0.011	Algeria	-1.138

Notes: the threshold marking a country as having high or low product complexity is 0. Countries with an average ECI value above zero are considered as having high product complexity, while countries with an ECI below zero have low product complexity. Source: own elaboration using data from the Economic Complexity Rankings in the Atlas of Economic Complexity: https://atlas.media.mit.edu