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New Developments in International Production Networks: Impact of Digital Technologies[*]

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Abstract: *We conducted a standard gravity exercise using worldwide disaggregated trade data to shed light on the influence of the spread of digital technologies on network trade. We found that growing investment in industrial robots in relatively lagging countries, together with imported digitally deliverable services, is enhancing bilateral network trade flows in East Asia, but not necessarily in other parts of the world. This suggests that exploring complementarities between machines and human resources in production blocks supported by better service-link connectivity may allow newly developed economies to retain and expand the international division of labour.*

Keywords: international production networks, digital technologies, gravity analysis

JEL classification: F14, F23

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1. Introduction

Since the 1990s, East Asia (including Northeast and Southeast Asia) has led the world in aggressively utilising the mechanics of international production networks (Ando and Kimura, 2005), also known as the 'second unbundling' (Baldwin, 2016). Although the degree of participation in production networks differs widely across countries, the widening and deepening of production networks have continuously been observed in this region (Obashi and Kimura, 2016, 2017). Even during the slow trade era in 2011–2016, parts and components trade within East Asia grew steadily, and trade in assembled end products also expanded thanks to growing incomes and market integration in the region (Obashi and Kimura, 2018).

Digital technologies have now arrived in East Asia, and these are sure to have a multifaceted impact on the international division of labour. Eventually, a fundamentally different type of international division of labor may emerge, that is, cross-border services outsourcing or the 'third unbundling'. However, policymakers in the region are currently concerned with what will happen in their international production networks.

To conceptualise the impact of digital technologies on newly developed economies, it is useful to identify the two faces of digital technology, as suggested by Baldwin (2016): information technologies and communication technologies.[1] While both are derived from the same technologies, they have quite different implications for the international division of labour. Information technologies – including artificial intelligence (AI), robots, machine learning, and industry 4.0 – make data processing faster, economise the number of tasks, accelerate the substitution of humans by machines, and are thus likely to generate concentration forces for economic activities. Consequently, some 're-shoring' may occur, where certain production blocks in newly developed economies return to advanced economies. On the other hand, communication technologies – including the Internet, smartphones, and 5G – overcome physical distance, reduce matching costs, encourage the division of labour, and therefore generate dispersion forces for economic activities. Indeed,

[1] The original idea of information and communication technologies is found in Aghion, Bloom, and Van Reenen (2014) in the context of intra-firm governance. Baldwin (2016) applied this concept to the international division of labour.

communication technologies are penetrating even newly developed economies amazingly quickly, leading to a proliferation of new businesses. Thus, it seems possible that while information technologies reduce jobs in newly developed economies, communication technologies create jobs.

However, things may not be so simple. Although information technologies overall accelerate the substitution of humans by machines, at the level of production blocks or tasks, complementarity between humans and machines also emerges. The cutting out of production blocks in the second unbundling is constrained by technological and managerial conditions. During the transition from the first unbundling to the second, we observed some persistent attachments between skilled and unskilled labour in both advanced and newly developed economies. As a production block typically comprises a combination of different productive factors, it is not feasible to make a production block purely skilled labour-intensive or purely unskilled labour-intensive. This is why there are shortages of unskilled labour in advanced economies and of skilled labour in newly developed economies. A similar effect is expected in the substitution of humans by machines at an even finer level. It is difficult for newly developed economies to compete with advanced economies on the frontiers of digital innovation, at least in the short run. How can they therefore attract or keep production blocks within their territories? A natural solution is to seek complementarity with information technologies. Virtually all newly developed economies in East Asia, including China, Malaysia, Thailand, the Philippines, and Indonesia, are trying to encourage the introduction of robots in production processes.[2] Is this an irrational idea that eliminates comparative advantages, or a meaningful step to retaining production blocks? This is an empirical question.

[2] For example, the introduction of AI and robotics is one of the main pillars of Thailand 4.0. The Board of Investment is providing a 13 year–maximum corporate income tax exemption for investment in target industries, the use of AI, and robotics, which makes such incentives more likely to be approved. See Thailand Board of Investment (2016), *Thailand's Automation & Robotics*. Bangkok. https://www.boi.go.th/upload/content/BOI-brochure%202016-automation-20170615_14073.pdf; Office of the Prime Minister, Board of Investment, Investment Services Center (2019), *Thailand Promotes AI, Robotics Technology to Spur Industry 4.0 Readiness*. Bangkok. 21 May. https://www.boi.go.th/upload/content/no76_2562_5ce64eb915fa9.pdf; South China Morning Post (2017), 'Development Plan for Robotics Gets Nod in Thailand', 30 August. https://www.scmp.com/news/asia/southeast-asia/article/2108938/development-plan-robotics-gets-nod-thailand.

Statistical data are still too incomplete to conduct comprehensive empirical studies on the use of digital technologies in newly developed economies. However, a casual data exercise captures some signs of an important transition. This paper looks at international trade within production networks and conducts a standard gravity equation exercise to identify the possible trade-enhancing effects of digital technologies on the operation of international production networks – the second unbundling. Regarding ‘network trade’, we focus on trade in manufactured parts and components in particular and, more broadly, trade in capital and manufactured consumption goods. We highlight trade within East Asia, which is centred on network trade, as compared with trade in other parts of the world.

To capture the impact of information and communication technologies, we introduce three indicators: the use of industrial robots, individuals’ Internet use, and imported digitally deliverable services. To some extent, these reflect multiple aspects of information and communication technologies, although they are weighted differently. Our major findings are that the use of industrial robots seems to be important in combination with imported digitally deliverable services, even though the penetration of robots is still limited in proportion. Our tentative interpretation is that newly developed economies in East Asia seem to keep or even expand production blocks by exploiting the complementarity between information technologies and indigenous resources. Communication technologies also seem to play a complementary role in maintaining production blocks.

This paper is organised as follows: section 2 outlines the channels through which digital technologies affect network trade, section 3 explains our empirical strategy using the gravity framework and describes the three indicators to capture the digital transformation in relation to network trade, section 4 presents the estimation results, and section 5 concludes.

2. Effects of Digital Technologies on Network Trade

The effects of digital technologies on network trade emerge through at least three channels. The first is supply, where information technologies may strengthen or alter the location advantages for internationalised production activities. The second channel is service links, as communication technologies may change ways of overcoming distances. The third channel is demand, as communication technologies may develop new markets for consumption goods.

2.1. First Channel: Information Technologies and Location Advantages

The introduction of information technologies in manufacturing production processes leads to industrial automation, which may change the nature of complex tasks performed by workers. By enhancing the complementarity or substitutability of labour and machines, introducing information technologies may strengthen or alter the location advantages for internationalised production activities, either enhancing or reducing network trade.

The current study focuses on whether investment in information technologies in newly developed economies strengthens the economies' location advantages, retaining production blocks and expanding network trade. Newly developed economies tend to lag behind advanced economies in terms of the degree of utilisation of information technologies, such as industrial robots. If newly developed economies can strengthen their location advantages by introducing more information technologies in a way that exploits the complementarity between machines and labour, they will be able to retain production blocks.

On the other hand, if advanced economies rely more on information technologies, and the substitutability of labour in newly developed economies by machines in advanced economies dominates, some production blocks may return from newly developed economies to advanced economies; that is, it may induce reshoring. In our empirical investigation (described in section 3.3), we examine whether investing more in information technologies in relatively lagging economies expands network trade, while controlling for network-shrinking or reshoring forces.

2.2. Second Channel: Communication Technologies and Service-Link Cost

Communication technologies will reduce the cost of service links that connect and coordinate remotely placed production blocks in the second unbundling. They enable multinational firms to track and monitor cargos moving from one production block to another more easily, and to operate longer and more complex supply chains across borders. In addition, communication technologies might increase the quality and availability of a wide range of imported intermediate services that further reduce the service-link cost, facilitating the operation of production networks (World Trade Organization, 2018).[3][4]

The more a country uses communication technologies in a way that reduces the service-link cost, the more it is tightly integrated into production networks thanks to strengthened service links. Thus, while information technologies in relatively lagging economies retain production blocks within those countries (through the first channel), communication technologies could play a complementary role in retaining production blocks and in expanding network trade.

2.3. Third Channel: Communication Technologies and Digital Connectivity

Communication technologies give rise to new demands. For example, small businesses and individual consumers can use the Internet to participate in matching platforms. Greater usage of communication technologies in countries on both the demand and supply sides will enhance digital connectivity and lower communication and matching costs, resulting in increased international trade (Freund and Weinhold, 2002, 2004). The network trade examined here is no exception.

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[3] Indeed, a recent study shows that imports of digitally deliverable services are key inputs into the production of goods for export. For example, about two-thirds of digitally deliverable services imported by the European Union are used to produce goods for export (Meltzer, 2014).

[4] Such cross-border service outsourcing, part of which is interpreted as the third unbundling, would alter the nature and pattern of the international division of labor (this is beyond the scope of the current paper).

3. Data and Methodology

We begin by describing how to construct industry-level network trade data and three variables measuring digital transformation over time, and provide a data overview of those variables. We then explain our empirical methodology using the gravity framework.

3.1. Data for Network Trade

Next we examine industry-level bilateral data of network trade amongst a maximum of 104 countries, from 2011 to 2017. To construct the network trade data by industry, we take the following three steps: first, we obtain bilateral trade data at the most disaggregated level of the Standard International Trade Classification, Revision 4 (SITC Rev. 4) from the United Nations (UN) Comtrade Database. The number of sample countries is constrained by the trade data availability. We can obtain continuously reported import statistics (or mirror data as needed) for 104 countries, including 17 East Asian countries in the Regional Comprehensive Economic Partnership (RCEP) region: the 10 Association of Southeast Asian Nations member countries, China, Japan, the Republic of Korea, Australia, New Zealand, India, and Taiwan.[5] We use the data from 'Other Asia, not elsewhere specified (code 490)' for Taiwan.[6]

Second, we narrow the collected trade data to those of network trade, using the production stage indicators of the Research Institute of Economy, Trade and Industry Trade Industry Database (RIETI–TID).[7] As we are examining network trade, we focus on trade occurring within international production networks based on the cross-border unbundling of manufacturing production processes. Such network trade encompasses manufactured parts and components and assembled end products. Although we can

[5] For a complete list of the 104 countries, see Appendix A.

[6] In principle, trade data for territories in Asia but not specified by country could end up under 'Other Asia, nes' (code 490); however, in practice, only Taiwan's trade is included under this code (except for certain countries such as Saudi Arabia, which report all their exports to unknown countries) (see the UN Statistics Database. https://unstats.un.org/unsd/tradekb/Knowledgebase/Taiwan-Province-of-China-Trade-data.

[7] The RIETI–TID website (http://www.rieti-tid.com/) provides aggregated data for the export and import values of selected countries, regions, and country groups, organised by industry (13 sectors), product category (five production stages), and year (from 1980 to the present). We use the RIETI–TID's production stage indicators and apply them to the disaggregated bilateral trade data obtained from UN Comtrade to enable us to conduct a more detailed data analysis.

identify the most disaggregated SITC Rev. 4 codes for ‘manufactured parts and components’ using the RIETI–TID production stage indicators, the assembled end products are included only as part of the ‘capital goods’ and ‘(manufactured) consumption goods’ codes. Given this data constraint, we employ both broad and narrow definitions of network trade: under a broader definition of network trade, we look at the trade data of the SITC Rev. 4 codes classified as either ‘manufactured parts and components’, ‘capital goods’, or ‘consumption goods’; under a narrower definition, we focus on those classified as ‘manufactured parts and components’ only.[8]

Third, we reorganise the network trade data at the most disaggregated level of SITC Rev. 4 into industrial categories so we can examine network trade in relation to industrial robot usage (described below). The industrial categories used by the International Federation of Robotics (IFR) (2018), the source of the robot data, are based on the International Standard Industry Classification (ISIC) Rev. 4 two-digit codes. We create a many-to-one mapping from the most disaggregated SITC Rev. 4 codes of either ‘manufactured parts and components’, ‘capital goods’, or ‘consumption goods’ to the industrial categories based on ISIC Rev. 4.[9]

Ultimately, we have a square matrix of network trade consisting of 104 x 103 country pairs x 7 years x 14 industry categories at maximum. However, we exclude from our sample the country pairs with no trade throughout the period under study. The 14 industrial categories are listed in Appendix B. We examine all 14 industries under the broader definition of network trade, while under the narrower definition, we focus on 10 industries covering the SITC Rev. 4 codes of ‘manufactured parts and components’.

[8] We exclude the RIETI–TID product category of processed raw materials from our definition of network trade because they are mostly (semi-)processed materials used as intermediates for chemicals, iron and metal products, and petroleum and coal products.

[9] As there is no publicly available direct correspondence table from SITC Rev. 4 to ISIC Rev. 4, we use multiple correspondence tables in combination: first, we correspond SITC Rev. 4 to ISIC Rev. 3 using a conversion table from Harmonized System 2007 to SITC Rev. 4 (see UN Trade Statistics, Correspondence Tables. https://unstats.un.org/unsd/trade/classifications/correspondence-tables.asp), together with a conversion from Harmonized System 2007 to ISIC Rev. 3 (see World Integrated Trade Solution, Product Concordance. https://wits.worldbank.org/product_concordance.html). We then use a conversion from ISIC Rev. 3 to ISIC Rev. 4 (see Eurostat, Correspondence Tables. https://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_LINK&StrNomRelCode=ISIC%20REV.%203.1%20-%20ISIC%20REV.%204&StrLanguageCode=EN).

Table 1: Overview of Network Trade by Trade Flow Type

		Number of observations			Trade propensity	Mean trade value ($'000)	Proportion of 'narrow' network trade
		Total	Trade>0	Trade=0			
Intra-East Asian trade	Broad definition						
	2011	3,808	3,405	403	0.89	361,384	..
	2014	3,808	3,448	360	0.91	390,189	..
	2017	3,808	3,551	257	0.93	429,868	..
	Narrow definition						
	2011	2,720	2,041	679	0.75	238,046	0.39
	2014	2,720	2,094	626	0.77	264,609	0.41
	2017	2,720	2,161	559	0.79	305,223	0.43
East Asian exports to outside	Broad definition						
	2011	20,216	15,274	4,942	0.76	93,771	..
	2014	20,216	15,498	4,718	0.77	100,127	..
	2017	20,216	15,898	4,318	0.79	103,922	..
	Narrow definition						
	2011	14,440	8,105	6,335	0.56	34,149	0.19
	2014	14,440	8,328	6,112	0.58	35,682	0.19
	2017	14,440	8,496	5,944	0.59	37,920	0.20
East Asian imports from outside	Broad definition						
	2011	20,076	12,334	7,742	0.61	36,369	..
	2014	20,076	12,833	7,243	0.64	40,831	..
	2017	20,076	13,560	6,516	0.68	41,021	..
	Narrow definition						
	2011	14,340	6,094	8,246	0.42	17,115	0.23
	2014	14,340	6,337	8,003	0.44	18,750	0.23
	2017	14,340	6,742	7,598	0.47	18,233	0.22
Extra-East Asian trade	Broad definition						
	2011	99,512	61,970	37,542	0.62	40,739	..
	2014	99,512	63,687	35,825	0.64	42,822	..
	2017	99,512	65,212	34,300	0.66	42,743	..
	Narrow definition						
	2011	71,080	30,848	40,232	0.43	15,736	0.19
	2014	71,080	31,511	39,569	0.44	16,431	0.19
	2017	71,080	32,595	38,485	0.46	16,018	0.19

Notes: East Asia is defined as the Regional Comprehensive Economic Partnership. Our sample includes 17 East Asian and 87 other countries listed in Appendix A. See the text for how finely disaggregated trade data is grouped into network trade under the broad and narrow definitions.

Source: Authors' calculation using the Standard International Trade Classification Revision 4 bilateral trade data (United Nations Comtrade Database).

Table 1 presents basic statistics for network trade at the industry level, by type of trade flows, both broadly and narrowly defined, in 2011, 2014, and 2017. For example, the first row of the table shows the following figures for intraregional network trade (broadly defined) in the RCEP region in 2011: the total number of observations at the exporter-importer-industry level; the number of observations of non-zero trade flows; the number of observations of zero flows; trade propensity, defined as a proportion of non-zero trade flows; and the mean trade value in thousand United States dollars (in nominal prices). The rightmost column shows the proportion of network trade, narrowly defined, to that broadly defined for each year.

We would like to point out three features of the recent evolution of network trade: first, trade propensity for each trade flow type rises steadily from 2011 to 2017. At the industry level, more countries appear to be exporting to more trading partner countries within production networks. Second, the mean trade value increases most noticeably for intra-East Asian trade. Third, and in contrast, the mean values of East Asian imports from countries outside the region and of trade amongst extra-regional countries stay sluggish or even trend downward from 2014 to 2017. This sluggishness is especially obvious under the narrow definition.

3.2. Variables Affecting the Spread and Utilisation of Digital Technologies

We employ three variables to measure the digital transformation, as described below. Although these may not be perfect indicators for capturing the three channels through which digital technologies affect network trade, we can interpret them simply as follows: (i) the use of industrial robots by industry as reflecting the first channel, (ii) a country's dependence on imported digitally deliverable services as reflecting the second channel, and (iii) individuals' Internet use by country as reflecting the third channel.

Use of Industrial Robots by Industry

To approximate the degree of investment in information technologies and the resulting, potential industrial automation, we construct the first variable based on the operational stock data of industrial robots.[10] Descriptive statistics on industrial robots are published annually, accompanied by the IFR's online World Robotics database.[11] As the first variable, we employ the robot density measure, defined by the IFR (2018)

[10] According to International Organization for Standardization code 8373: 2012, an industrial robot is an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, that can be either fixed in place or mobile for use in industrial automation applications (IFR, 2018). Robots are reprogrammable, autonomous, and characterised by a high degree of dexterity, unlike machine tools designed to perform very specific tasks (OECD, 2019).

[11] As far as we know, the current paper is the first to utilise the IFR data for industrial robots in the empirical trade literature. The IFR data have been used in only a few economics studies to explore the impact of robots on labour markets (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2019, 2020).

as the number of installed robots in operation (i.e. stock) per 10,000 persons employed. The robot density can be compared between countries and industries as well as being used for longitudinal comparisons over time.

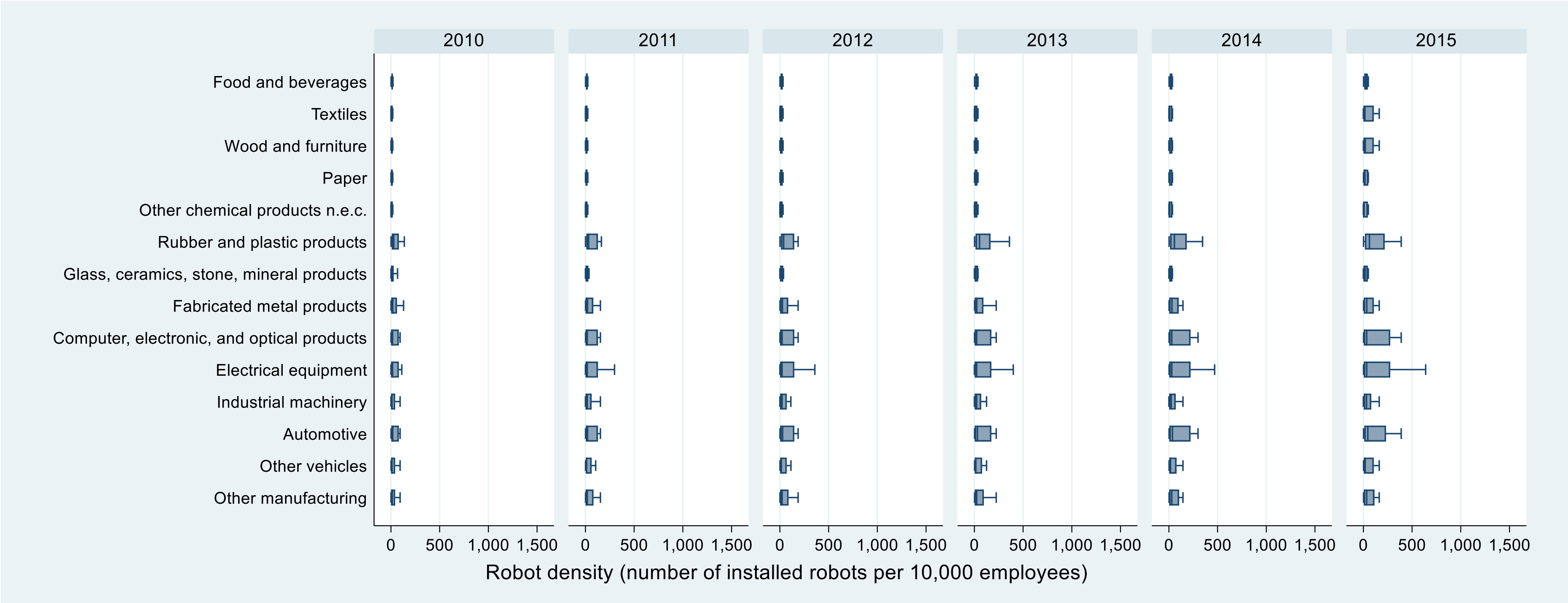
Data for the stock of industrial robots by country and industry are available from the World Robotics database. As for employment data, we obtain data for total employment by country and industry from the Organisation for Economic Co-operation and Development (OECD) Structural Analysis database and from the UN Industrial Development Organization Industrial Statistics database. Since data on both robots and employment are organised at the industry level, according to ISIC Rev. 4, we can calculate the robot density measure for 14 industries (listed in Appendix B) in the countries under study from 2010 to 2016. However, given the scarcity of employment data (especially for non-OECD countries), we augment the by-industry robot density data with the robot density data for the manufacturing industries overall. These data, collected manually from the IFR documents (2018), are relatively widely available for non-OECD countries. Ultimately, we obtain a robot density data set for 48 of the 104 sample countries.[12]

The box plots in Figure 1 show the distributions of robot density across East Asian countries in the RCEP region, compared by industry during the 1-year lagged sample period, from 2010 to 2015.[13] Figure 2 complements Figure 1 by showing the corresponding basic statistics for countries outside the RCEP region for comparison purposes. Among countries outside the RCEP region (Figure 2), the central tendency of robot density is strikingly high in the automotive sector, followed by the rubber and plastic products sector. In the other sectors – including electrical equipment; computer, electronic, and optical products; and other machinery sectors – investments in industrial robots are generally limited to a smaller magnitude, even in 2015.

[12] Appendix A highlights the 48 countries with available robot density data.

[13] Because of the scarcity of employment data, we refrain from including the box plots for 2016, in which the OECD Structural Analysis database only enables us to calculate the robot density for a limited number of industries in Japan and Australia.

Figure 1: Robot Density Across Industries and Years – East Asian Countries of the Regional Comprehensive Economic Partnership Region

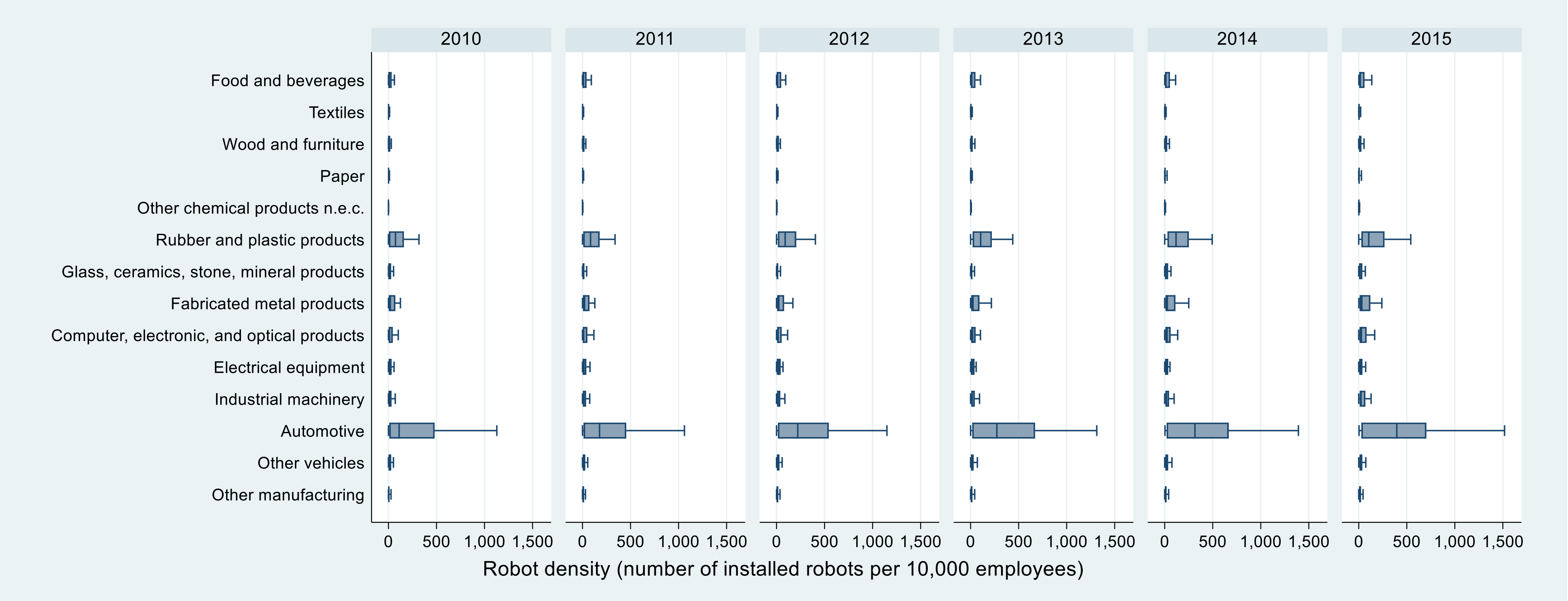


n.e.c. = not elsewhere classified.

Notes: The 12 East Asian countries of the Regional Comprehensive Economic Partnership region are included in the above box plots, as shown in Appendix A. The International Standard Industrial Classification codes corresponding to 14 industry categories are listed in Appendix B. Outliers beyond either whisker of each box plot are omitted. The horizontal axis is re-scaled to be comparable with Figure 2.

Sources: Authors' calculation using data on robots from the International Federation of Robotics (2018), *World Robotics*; and employment from the Organisation for Economic Co-operation and Development Structural Analysis Database and United Nations Industrial Development Organization Industrial Statistics Database.

**Figure 2: Robot Density Across Industries and Years –
Countries Outside the Regional Comprehensive Economic Partnership Region**



n.e.c. = not elsewhere classified.

Notes: The above box plots include 36 countries, as shown in Appendix A. The International Standard Industrial Classification codes corresponding to 14 industry categories are listed in Appendix B. Outliers, beyond either whisker of each box plot, are omitted.

Sources: Authors' calculation using data on robots from the International Federation of Robotics (2018), *World Robotics*; and employment from the Organisation for Economic Co-operation and Development Structural Analysis Database and United Nations Industrial Development Organization Industrial Statistics Database.

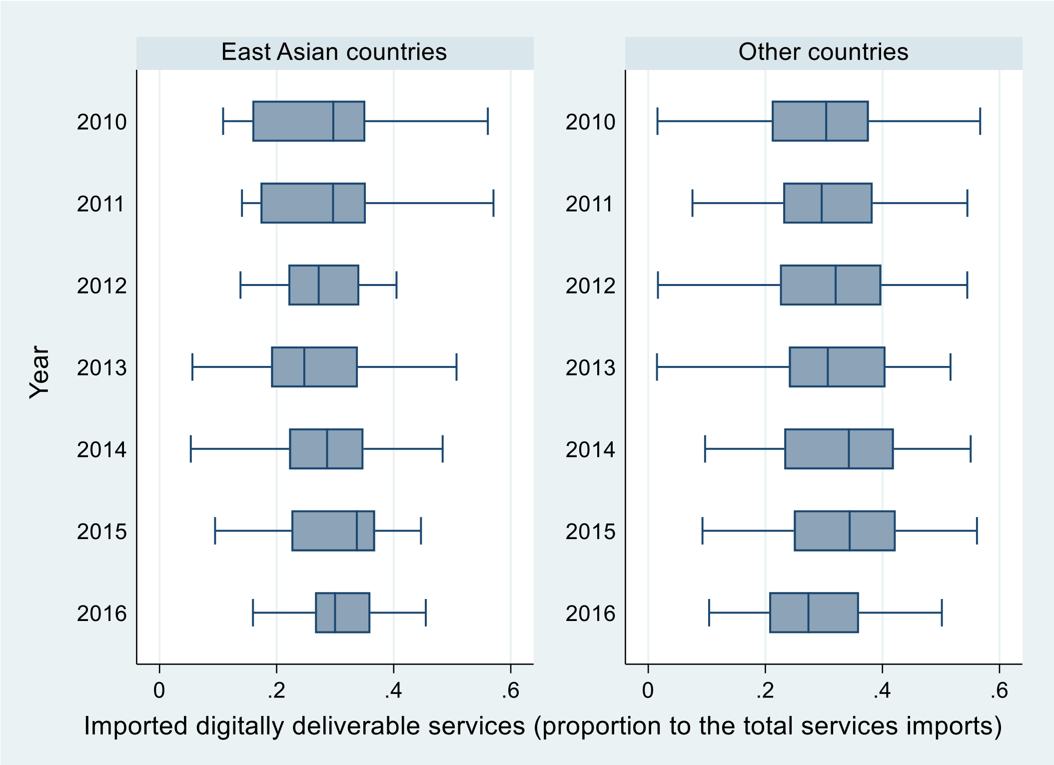
In contrast, East Asian countries within the RCEP region (Figure 1) appear to invest in industrial robots more broadly, and the central tendency of robot density increases steadily across various sectors over the years. In general, the degrees of investment in industrial robots in the automotive sector and in the rubber and plastic products sector are noticeably high in both the RCEP region and the rest of the world. More interestingly, the central tendency of robot density increases most significantly in the electrical equipment sector and in the computer, electronic, and optical products sector, from 2010 onward. These electric and precision machinery sectors appear to lead the RCEP region in the greater utilisation of industrial robots and information technologies.

Countries' Dependence on Imported Digitally Deliverable Services

The second variable is a country's dependence on imported digitally deliverable services relative to total services imports from the world, which reflects the degree to which the country utilises communication technologies to reduce the service-link cost. Data for imports of digitally deliverable services as well as total services imports are obtained from UN Comtrade. In accordance with the UN Conference on Trade and Development (2015), we define digitally deliverable services as those potentially, but not necessarily, delivered digitally. These correspond to the following categories of the Extended Balance of Payments Services Classification 2002: communications services (3), insurance services (5), financial services (6), computer and information services (7), and other business services (9).

The box plots of Figure 3 show the changes in imported digitally deliverable services over time as a proportion of total services imports across East Asian countries in the RCEP region and across the rest of the sample countries in the 1-year lagged sample period from 2010 to 2016. The central tendency of the relative magnitude of imported digitally deliverable services does not increase monotonically, but still tends to move upward overall until 2015. The figures for 2016 show a different tendency, possibly because the number of countries included to depict the box plot is quite limited, as mentioned in the footnote of the figure.

Figure 3: Imported Digitally Deliverable Services Across Years – East Asian (Regional Comprehensive Economic Partnership) and Other Countries



Notes: The above box plots includes 16 East Asian countries of the Regional Comprehensive Economic Partnership and 77 other countries in 2010–2013. The sample size is slightly smaller in 2014 and 2015. For 2016, only six East Asian and 19 other countries are included due to the data limitations. Outliers beyond either whisker of each box plot are omitted.

Source: Authors' calculation using the services trade data from the United Nations Comtrade Database.

Individuals' Internet Use by Country

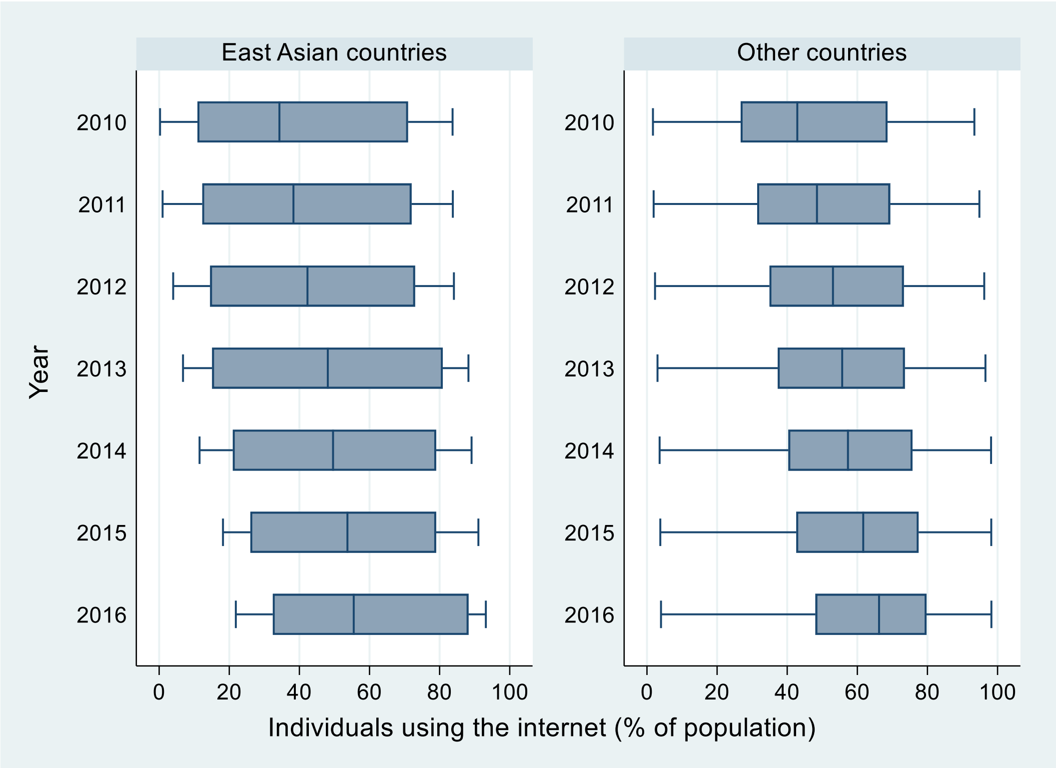
To examine the role of communication technologies in enhancing digital connectivity, we use data for Internet usage by individuals as the third variable. These data have been widely used in the related literature (e.g. Freund and Weinhold, 2002, 2004) because of their availability for a wide range of countries and wide time period. Although this variable captures only one aspect of individuals' usage of communication technologies, it correlates very strongly to business and household usage of broadband, access to computers, and wireless and fixed broadband subscriptions (González and Ferencz, 2018).

Data for the share of the population using the Internet for various countries can be obtained from the OECD.Stat database of ICT Access and Usage by Households and Individuals. The only exception is Taiwan, for which we instead refer to the recent

Individual/Household Digital Opportunity Survey conducted by the Taiwan National Development Council (2017).

The box plots of Figure 4 show the distributions of individuals' Internet use across East Asian countries in the RCEP region and across other countries in the 1-year lagged sample period from 2010 to 2016. Changes in the median and quantile range indicate that the central tendency moves steadily from left to right for both groups of countries. In particular, the first quantile and lowest value of the left whisker of the box plot rises substantially, suggesting an increasing usage of communication technologies across the RCEP region. On the other hand, non-negligible countries are left behind by the advancement of communication technologies outside the RCEP region, although the central tendency moves upward.

Figure 4: Individual's Internet Use Across Years – East Asian (Regional Comprehensive Economic Partnership) and Other Countries



Notes: All the 17 East Asian countries of the Regional Comprehensive Economic Partnership and 87 other countries, as listed in Appendix A, are included in the above box plots for respective years. Outliers beyond either whisker of each box plot are omitted.

Sources: Authors' calculation using the Internet usage data from OECD.Stat, and the National Development Council (2017).

3.3. Gravity Analysis of Network Trade with Variables on Digital Technologies

We examine the extent to which variations in the spread and utilisation of digital technologies are linked with variations in network trade flows. To do so, we estimate gravity equations for bilateral trade flows at the industry level. The gravity equation has long played a central role in the empirical trade literature. As summarised in Fally (2015), there are now two main approaches to account for differences in market thickness across importer and exporter countries, that is, multilateral resistance (Anderson and van Wincoop, 2003): (i) estimating a general, reduced-form gravity equation by introducing exporter and importer fixed effects to control for market-size effects and multilateral-resistance effects in a simple way; and (ii) imposing more constraints or structure on the gravity equation. Various theoretical features of trade models have been used to generate the latter 'structural gravity' equations (Anderson, 2011).

Fally (2015) showed that estimating 'general gravity' using the Poisson pseudo-maximum likelihood (PPML) with exporter and importer fixed effects is consistent with the equilibrium constraints imposed by 'structural gravity'. The equivalence between 'general gravity' and 'structural gravity' holds for the industry- or product-level gravity model (e.g. Anderson and Yotov, 2010) as well. Given recent trends in the gravity literature, in the current paper, we regress a reduced-form gravity equation defined at the industry level using the PPML as well as ordinary least squares (OLS) with fixed effects as a simple tool, rather than imposing restrictions relying on a specific theoretical model.

Formally, Head and Mayer (2014) defined 'general gravity' as when, for each exporter i and importer j, trade flows X_{ij} can be written as

$$X_{ij} = exp\left[e_i + m_j - \theta lnD_{ij}\right],$$

where e_i is invariant across importers and m_j is invariant across exporters. D_{ij} captures trade costs from i to j, and the parameter θ reflects the elasticity of trade flows to trade cost. Adding industry and year subscripts (k, t) and taking the natural logarithms of all terms, the above equation becomes

$$lnX_{ijkt} = e_{ikt} + m_{jkt} - \theta lnD_{ijkt}.$$

We estimate the industry-level bilateral network trade flows, introducing a set of exporter-industry-year and importer-industry-year dummy variables. Not only do these dummies account for the multilateral-resistance issue, they also capture industrial outputs and other time-varying country and industry-specific effects whose data are rarely available, especially for newly developed economies.

Our interest focuses on the covariates not captured by either the exporter-industry-year or importer-industry-year dummies, that is, those captured by the trade cost variable (lnD_{ijkt}). We consider the three channels through which digital technologies affect network trade by broadly interpreting lnD_{ijkt} as reflecting not only trade costs but also any exporter-importer, exporter-importer-year, exporter-importer-industry, and exporter-importer-industry-year effects. The trade cost variable is often assumed to be a linear combination of the log of bilateral distance ($dist_{ij}$), dummy variables indicating contiguity ($cont_{ij}$), common official language ($lang_{ij}$), and so on.[1] Following convention, we incorporate the three channels linearly as part of lnD_{ijkt}.

With respect to the first channel, we are interested in examining whether greater investment in industrial robots and information technologies in newly developed economies, on either the exporter or importer side, strengthen their location advantages and expand network trade. To do so, we employ the logarithmic value of the minimum robot density for a pair of countries ($ln\ robot_{ijkt}$). Although we focus on variations in the robot density of relatively lagging economies by taking the minimum value, individual effects of robot usage in each country are well controlled by the exporter-industry-year and importer-industry-year dummies.

With respect to the second channel, we are interested in the complementary role of communication technologies in retaining production blocks and enhancing network trade. Specifically, we examine whether greater investment in industrial robots and information technologies in newly developed economies expands network trade, conditional on their tight integration into international production networks. To do so, we introduce an interaction term of the exporter country's dependence on imported

[1] All variables regarding country pair-wise trade costs are obtained from the Centre d'Études Prospectives et d'Informations Internationales GeoDist database (http://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=6).

digitally deliverable services as a proportion of total services imports, interacted with the minimum robot density for a pair of countries ($ln\, robot_{ijkt} \times service_{it}$). The exporter country's service import variable ($service_{it}$) is itself controlled by exporter-industry-year dummies.

With respect to the third channel, we are interested in examining whether strengthened digital connectivity through the increased use of communication technologies enhances trade. In line with Freund and Weinhold (2002, 2004), we take the minimum share of the population using the Internet within a pair of countries to construct a proxy for digital connectivity ($connectivity_{ijt}$).

Finally, we construct a baseline equation to be estimated for the three channels through which digital technologies affect network trade, as follows:

$$lnX_{ijkt} = e_{ikt} + m_{jkt} + \beta_1 \ln dist_{ij} + \beta_2 cont_{ij} + \beta_3 lang_{ij} + \beta_4 connectivity_{ijt-1} + \beta_5 ln\, robot_{ijkt-1} + \beta_6 (ln\, robot_{ijkt-1} \times service_{it-1}) + \varepsilon_{ijkt},$$

where three variables corresponding to the three channels are lagged by 1 year to reduce the incidence of reverse causality. e_{ikt} and m_{jkt} are accounted for by exporter-industry-year and importer-industry-year dummies. Basic statistics for the variables in the estimating equation are summarised in Table 2.

Table 2: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Number of observations
Exporter-importer (*i-j*) variables					
ln(Distance)	8.6561	0.8901	4.0879	9.9010	1,005,284
Contiguity	0.0231	0.1502	0	1	1,005,284
Common language	0.0908	0.2873	0	1	1,005,284
Exporter-importer-year (*i-j-t*) variables					
Digital connectivity	39.4439	22.8986	0.2500	98.1367	1,005,284
Exporter-importer-industry-year (*i-j-k-t*) variables					
Trade value, in thousand USD	57,828	895,906	0	191,528,186	1,005,284
ln(Trade value, USD)	13.4980	3.4634	6.9088	25.9783	606,105
ln(Minimum robot density)	2.4146	1.3472	0.0132	7.3256	182,662
x imported digitally deliverable services	0.8122	0.5644	0.0008	3.8575	152,286

USD = United States dollars.
Sources: Authors' calculation using data for the Standard International Trade Classification Revision 4 bilateral trade (United Nations Comtrade Database), robots (International Federation of Robotics [2018], *World Robotics*), employment (Organisation for Economic Co-operation and Development Structural Analysis Database; United Nations Industrial Development Organization Industrial Statistics Database), services trade (United Nations Comtrade Database), Internet usage (OECD.Stat; National Development Council [2017] for Taiwan), and trade cost measures (Centre d'Études Prospectives et d'Informations Internationales GeoDist).

We primarily estimate the above equation and its variants using OLS, but check whether the estimation results obtained using OLS are robust to the adoption of the PPML estimation. As shown in Santos Silva and Tenreyro (2006), it is a common perception in the gravity literature that the PPML estimator provides consistent estimates of the underlying gravity equation and is robust to different patterns of heteroskedasticity and measurement error. Moreover, as suggested by Fally (2015), the OLS estimator even with appropriate fixed effects tends to be biased, putting more weight on larger economies, and not consistent with structural gravity.

4. Estimation Results

As is clear from Table 2, although the digital connectivity variable is available for all sample countries throughout the period, the sample size decreases significantly once the minimum robot density variable is introduced.[2] Taking the exporter country's service import variable into consideration further reduces the sample size. We thus first regress industry-level bilateral network trade flows against digital connectivity and a set of conventional trade cost variables with exporter-industry-year and importer-industry-year dummies. The estimated coefficients obtained using OLS, accompanied by the corresponding robust standard errors clustered by exporter-importer-year combinations in parentheses, are reported in column [1] of Table 3. The digital connectivity variable, as well as other explanatory variables, is estimated to be statistically significant with an expected sign.

Including the minimum robot density variable together with the digital connectivity variable causes a multicollinearity issue, as seen in column [2] of Table 3. The estimated coefficient for digital connectivity turns negative in contrast to that in column [1], although the minimum robot density is estimated as expected. In column [3], on the other hand, we exclusively employ the minimum robot density and find that the estimated coefficient for the minimum robot density is relatively stable against the inclusion of the other interrelated variable of digital connectivity.

[2] Nevertheless, at least in the RCEP region, the reduced sample covers all of the advanced economies and most of the newly developed economies that actively participate in regional and global production networks. This includes 12 out of 17 countries, namely, five Association of Southeast Asian Nations countries (Indonesia, Malaysia, the Philippines, Singapore, and Thailand), China, Japan, the Republic of Korea, Australia, New Zealand, India, and Taiwan.

Table 3: The Impact of Digital Technologies on Network Trade (Broadly Defined)

	[1]	[2]	[3]	[4]	[5]
Method	OLS	OLS	OLS	OLS	PPML
Dependent variable	ln(Trade)	ln(Trade)	ln(Trade)	ln(Trade)	Trade
Explanatory variables					
Digital connectivity	0.0125***	-0.00426***			
	(0.000529)	(0.000919)			
ln(Minimum robot density)		0.0452***	0.0383***	0.0278***	0.0220**
		(0.00811)	(0.00814)	(0.00719)	(0.00881)
ln(Distance)	-1.314***	-1.218***	-1.211***		
	(0.00772)	(0.0111)	(0.0109)		
Contiguity	0.528***	0.243***	0.241***		
	(0.0401)	(0.0441)	(0.0443)		
Common language	0.844***	0.361***	0.363***		
	(0.0209)	(0.0299)	(0.0300)		
Exporter-industry-year dummies	Yes	Yes	Yes	Yes	Yes
Importer-industry-year dummies	Yes	Yes	Yes	Yes	Yes
Exporter-importer-year dummies				Yes	Yes
Number of observations	606,004	176,026	176,026	175,581	182,228
Number of country pairs	103x102	48x47	48x47	48x47	48x47
Number of industrial sectors	14	14	14	14	14
Adjusted R-squared	0.785	0.860	0.860	0.895	
R-squared					0.977

OLS = ordinary least squares, PPML = Poisson pseudo-maximum likelihood.

Notes: See the text for our broad definition of network trade. Estimated coefficients are accompanied by robust standard errors in parentheses: clustered standard errors by exporter-importer-year pairs in columns [1], [2], and [3]; robust standard errors without clustering in [4] and [5]. Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Sources: Authors' calculation using data for the Standard International Trade Classification Revision 4 bilateral trade (United Nations Comtrade Database), robots (International Federation of Robotics [2018], *World Robotics*), employment (Organisation for Economic Co-operation and Development Structural Analysis Database; United Nations Industrial Development Organization Industrial Statistics Database), Internet usage (OECD.Stat; National Development Council [2017] for Taiwan), and trade cost measures (Centre d'Études Prospectives et d'Informations Internationales GeoDist).

Ideally, we would consider both variables together to examine two different channels of the trade impact of digital technologies; however, we instead introduce exporter-importer-year dummies, in addition to the exporter-industry-year and importer-industry-year dummies. The exporter-importer-year dummies absorb not only the digital connectivity under study, but also the three trade cost variables included in the previous equations. In addition, the dummies capture other time-varying exporter-importer effects, including the wage differential between a pair of countries and the existence of preferential trade agreements between the countries. We therefore expect that introducing exporter-importer-year dummies will yield a more accurate estimation of the minimum robot density, although we must abandon examining digital connectivity.

The estimated coefficient for the minimum robot density reported in column [4] indicates the robustness of its effects on network trade against the inclusion of exporter-importer-year dummies: the industry-level bilateral network trade (of non-zero values) increases by 2.78 percentage points when the minimum robot density, which reflects the usage of industrial robots in relatively lagging economies, increases by 1 percentage point, with other things unaltered. This result is confirmed by the estimates obtained using the PPML and reported in column [5]. The difference in the sample size between columns [4] and [5] is accounted for by zero-value bilateral trade flows, even at the industry level. Considering zero flows as well as trade relationships of non-zero values with the PPML, network trade increases by 2.20 percentage points when the minimum robot density increases by 1 percentage point. Since exporter-importer-year dummies are included in columns [4] and [5], the reported robust standard errors are no longer clustered.

While Table 3 shows the estimates for industry-level bilateral flows of network trade, broadly defined (see section 3.1), Table 4 shows the corresponding estimates for network trade, as narrowly defined. Network trade as narrowly defined consists only of trade in manufactured parts and components in 10 of 14 industries. The trade-enhancing effect of the minimum robot density is also observed for narrowly defined network trade, except for the PPML estimate reported in column [5] of Table 4, which loses statistical significance at the 10% significance level, although it is still estimated to be positive. Because the OLS estimates tend to be biased, weighting trade flows with larger values more, we interpret this result as indicating that narrow network trade flows with relatively large values increase with a rise in the minimum robot density, while those with relatively small values are not significantly affected by the minimum robot density.

Table 4: The Impact of Digital Technologies on Network Trade (Narrowly Defined)

	[1]	[2]	[3]	[4]	[5]
Method	OLS	OLS	OLS	OLS	PPML
Dependent variable	ln(Trade)	ln(Trade)	ln(Trade)	ln(Trade)	Trade
Explanatory variables					
Digital connectivity	0.0126***	0.00158			
	(0.000634)	(0.00109)			
ln(Minimum robot density)		0.0259***	0.0293***	0.0438***	0.00219
		(0.00977)	(0.00977)	(0.0109)	(0.0105)
ln(Distance)	-1.190***	-1.170***	-1.173***		
	(0.00845)	(0.0120)	(0.0118)		
Contiguity	0.460***	0.200***	0.201***		
	(0.0390)	(0.0452)	(0.0452)		
Common language	0.655***	0.302***	0.302***		
	(0.0225)	(0.0313)	(0.0313)		
Exporter-industry-year dummies	Yes	Yes	Yes	Yes	Yes
Importer-industry-year dummies	Yes	Yes	Yes	Yes	Yes
Exporter-importer-year dummies				Yes	Yes
Number of observations	303,108	113,312	113,312	113,184	131,889
Number of country pairs	103x102	48x47	48x47	48x47	48x47
Number of industrial sectors	10	10	10	10	10
Adjusted R-squared	0.758	0.829	0.829	0.863	
R-squared					0.983

OLS = ordinary least squares, PPML = Poisson pseudo-maximum likelihood.

Notes: See the text for our narrow definition of network trade. Estimated coefficients are accompanied by robust standard errors in parentheses: clustered standard errors by exporter-importer-year pairs in columns [1], [2], and [3]; robust standard errors without clustering in [4] and [5]. Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Sources: Authors' calculation using data for the Standard International Trade Classification Revision 4 bilateral trade (United Nations Comtrade Database), robots (International Federation of Robotics [2018], *World Robotics*), employment (Organisation for Economic Co-operation and Development Structural Analysis Database; United Nations Industrial Development Organization Industrial Statistics Database), Internet usage (Organisation for Economic Co-operation and Development Statistics; National Development Council [2017] for Taiwan), and trade cost measures (Centre d'Études Prospectives et d'Informations Internationales GeoDist).

Table 5: The Impact of Information Technologies on Broad Network Trade – Comparison Between East Asian (Regional Comprehensive Economic Partnership) Intraregional Trade and Other Trade Flows

Trade flows	Intra-East Asian trade		East Asian exports to outside		East Asian imports from outside		Extra-East Asian trade	
Method	OLS	PPML	OLS	PPML	OLS	PPML	OLS	PPML
Dependent variable	ln(Trade)	Trade	ln(Trade)	Trade	ln(Trade)	Trade	ln(Trade)	Trade
Explanatory variables								
ln(Minimum robot density)	0.0805***	0.0588***	-0.0323**	-0.0122	0.0386**	-0.0707***	-0.0523***	-0.0847***
	(0.0249)	(0.0226)	(0.0139)	(0.0135)	(0.0167)	(0.0175)	(0.0114)	(0.0171)
Exporter-industry-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer-industry-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-importer-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	12,622	12,710	34,992	36,579	34,254	36,572	94,105	96,768
Number of country pairs	12x11	12x11	12x36	12x36	36x12	36x12	36x36	36x36
Number of industrial sectors	14	14	14	14	14	14	14	14
Adjusted R-squared	0.903		0.901		0.873		0.871	
R-squared		0.962		0.993		0.938		0.894

OLS = ordinary least squares, PPML = Poisson pseudo-maximum likelihood.

Notes: See the text for our broad definition of network trade. Estimated coefficients are accompanied by robust standard errors in parentheses. Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Sources: Authors' calculation using data for the Standard International Trade Classification Revision 4 bilateral trade (United Nations Comtrade Databse), robots (International Federation of Robotics [2018], *World Robotics*), and employment (Organisation for Economic Co-operation and Development Structural Analysis Database; United Nations Industrial Development Organization Industrial Statistics Database).

Next, we look into the trade effect of the minimum robot density by disaggregating trade flows, as follows: intraregional trade flows within East Asia or the RCEP region; exports by East Asian countries to countries outside the region; imports by East Asian countries from countries outside the region; and trade amongst countries outside the region. Table 5 shows the estimated coefficients for the minimum robot density on network trade, broadly defined, for respective disaggregated trade flows. For each trade flow type, the estimate obtained with the exporter-industry-year, importer-industry-year, and exporter-importer-year dummies, using OLS and PPML, respectively, is reported. Table 6 complements Table 5 by presenting the corresponding estimates for network trade, narrowly defined.

We obtain robust estimates for the minimum robot density using both OLS and PPML; this is summarised as follows. First, both the OLS and PPML estimated coefficients are positive and significant for East Asian intraregional network trade, both broadly and narrowly defined, unlike the other trade flows. Similar positive results are also found for East Asian imports from extra-regional countries, but only with OLS. Second, and in contrast, both the OLS and PPML estimates are negative and significant for trade between countries outside East Asia, both broadly and narrowly defined. Similar negative results are also obtained for East Asian exports to extra-regional countries, although the PPML estimate for broadly defined network trade is statistically insignificant.

Table 6: The Impact of Information Technologies on Narrow Network Trade – Comparison Between East Asian (Regional Comprehensive Economic Partnership) Intraregional Trade and Other Trade Flows

Trade flows	Intra-East Asian trade		East Asian exports to outside		East Asian imports from outside		Extra-East Asian trade	
Method	OLS	PPML	OLS	PPML	OLS	PPML	OLS	PPML
Dependent variable	ln(Trade)	Trade	ln(Trade)	Trade	ln(Trade)	Trade	ln(Trade)	Trade
Explanatory variables								
ln(Minimum robot density)	0.0353*	0.0407*	-0.0620***	-0.0325**	0.0847***	0.000597	-0.0306**	-0.190***
	(0.0213)	(0.0246)	(0.0198)	(0.0150)	(0.0218)	(0.0333)	(0.0150)	(0.0207)
Exporter-industry-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer-industry-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-importer-year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	8,587	9,106	21,179	26,263	21,359	25,770	62,014	70,267
Number of country pairs	12x11	12x11	12x36	12x36	36x12	36x12	36x36	36x36
Number of industrial sectors	10	10	10	10	10	10	10	10
Adjusted R-squared	0.876		0.870		0.841		0.830	
R-squared		0.969		0.973		0.898		0.891

OLS = ordinary least squares, PPML = Poisson pseudo-maximum likelihood.

Notes: See the text for our narrow definition of network trade. Estimated coefficients are accompanied by robust standard errors in parentheses. Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Sources: Authors' calculation using data for the Standard International Trade Classification Revision 4 bilateral trade (United Nations Comtrade Databse), robots (International Federation of Robotics [2018], *World Robotics*), and employment (Organisation for Economic Co-operation and Development Structural Analysis Database; United Nations Industrial Development Organization Industrial Statistics Database).

Greater investment in industrial robots by newly developed economies in East Asia appears to strengthen the countries' location advantages and retain the production blocks in those countries, leading to increased trade within the regional production networks. This finding is consistent with the data observations presented in sections 3.1 and 3.2: as East Asian intraregional network trade expands steadily, East Asian countries are actively investing in more industrial robots broadly across sectors, while focusing on the electric and precision machinery sectors where regional production networks have greatly developed.

In stark contrast, network trade appears to decrease in country pairs outside East Asia where industrial robots have been introduced in one of the countries and the minimum robot density has also risen. This may be due to reshoring or an increasing dependence on domestic sourcing and production. Indeed, as observed in section 3.1, network trade amongst extra-regional countries is sluggish.

In addition, it appears that advanced economies in East Asia are expanding network exports, especially those of manufactured parts and components (included in the narrow definition of network trade) destined for extra-regional countries that are reluctant to invest in industrial robots. Meanwhile, newly developed economies in East Asia seem to be turning more to regional production networks as they invest in more industrial robots and strengthen their location advantage. Whatever the case, the networking of cross-border transactions of parts and components driven by the active use of industrial robots and more broadly, information technologies, appears to be limited to the East Asian region.

To confirm the trade-enhancing effect of the use of industrial robots and information technologies, we consider the complementary role of communication technologies. In doing so, we include an interaction term of the exporter country's dependence on imported digitally deliverable services, interacted with the minimum robot density. Table 7 shows the estimated coefficients for the minimum robot density and the interaction term on network trade, both broadly and narrowly defined, obtained with the exporter-industry-year, importer-industry-year, and exporter-importer-year dummies, using OLS and PPML. Here, we focus on East Asian intraregional network trade, where we have detected the robust trade-enhancing effect of the minimum robot density in Tables 5 and 6.

Table 7: The Impact of Information Technologies on East Asian (Regional Comprehensive Economic Partnership) Intraregional Network Trade – Complementary Role of Communication Technologies

Trade flows	Intra-East Asian trade			
Network trade definition	Broad		Narrow	
Method	OLS	PPML	OLS	PPML
Dependent variable	ln(Trade)	Trade	ln(Trade)	Trade
Explanatory variables				
ln(Minimum robot density)	-0.136**	-0.306***	-0.150*	-0.331***
	(0.0648)	-0.0978	(0.0842)	(0.0910)
x imported digitally deliverable services	0.620***	0.811***	0.482**	0.787***
	(0.180)	-0.254	(0.238)	(0.237)
Exporter-industry-year dummies	Yes	Yes	Yes	Yes
Importer-industry-year dummies	Yes	Yes	Yes	Yes
Exporter-importer-year dummies	Yes	Yes	Yes	Yes
Number of observations	11,406	11,480	7750	8,226
Number of country pairs	12x11	12x11	12x11	12x11
Number of industrial sectors	14	14	10	10
Adjusted R-squared	0.923		0.898	
R-squared		0.991		0.992

OLS = ordinary least squares, PPML = Poisson pseudo-maximum likelihood.

Notes: See the text for our broad and narrow definitions of network trade. Estimated coefficients are accompanied by robust standard errors in parentheses. Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Sources: Authors' calculation using data for the Standard International Trade Classification Revision 4 bilateral trade (United Nations Comtrade Database), robots (International Federation of Robotics [2018], *World Robotics*), employment (Organisation for Economic Co-operation and Development Structural Analysis Database; United Nations Industrial Development Organization Industrial Statistics Database), and services trade (United Nations Comtrade Database).

Under both the broad and narrow definitions of network trade, the OLS and PPML estimated coefficients for the single minimum robot density variable are negative and significant, whereas the OLS and PPML estimates for the interaction term are positive and significant. These contrasting estimates indicate that a rise in the minimum robot density alone may adversely affect East Asian intraregional network trade, but together with a higher dependence of the exporter country on imported digitally deliverable services will enhance network trade.

This result can be interpreted as suggesting that increased usage of industrial robots and information technologies by newly developed economies in East Asia enhance intraregional network trade when the exporter country uses communication technologies in a way that reduces the service-link cost and is tightly integrated into the production networks. While information technologies would enable these economies to retain production blocks within their national boundaries, this first channel appears to be effective conditional on the second; that is, service-link cost-reducing communication technologies appear to play a complementary role in retaining production blocks and expanding network trade.

5. Conclusion

This paper investigated the possible trade-enhancing effects of digital technologies on the operation of international production networks. With a special focus on the use of digital technologies in newly developed economies, we conducted a standard gravity equation exercise by including indicators to capture digital transformation in relation to the evolution of network trade.

We found that the introduction of more industrial robots into the production in newly developed economies in East Asia enhances the trade of manufactured parts and components and the assembled consumption goods within regional production networks. Our findings can be interpreted as indicating that newly developed economies in East Asia seem to retain production blocks and enhance network trade by exploiting the complementarity between information technologies and indigenous resources. In addition, such trade-enhancing effects of information technologies were found in combination with a higher dependence of the exporter country on imported digitally deliverable services driven by communication technologies. The role of communication technologies appears to be complementary in retaining production blocks by reducing service-link costs or even strengthening service links.

We do not necessarily recommend strong government intervention to introduce information technologies in newly developed economies. However, some mild promotion together with investment in soft and hard infrastructure for communication technologies seems to make sense. We must use empirical evidence to create more workable development strategies to utilise digital technologies proactively.

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Appendix A: 104 Sample Countries, Including 17 East Asian Countries in the Regional Comprehensive Economic Partnership Region

Albania	Fiji	Pakistan
Algeria	Finland	Paraguay
Argentina	France	Peru
Armenia	Georgia	**Philippines**
Aruba	Germany	Poland
Australia	Greece	Portugal
Austria	Greenland	**Rep. of Korea**
Azerbaijan	Guatemala	Rep. of Moldova
Bahrain	Guyana	Romania
Belarus	Hungary	Russian Federation
Belgium	Iceland	Samoa
Belize	**India**	Sao Tome and Principe
Bolivia	**Indonesia**	Saudi Arabia
Bosnia Herzegovina	Ireland	Senegal
Brazil	Israel	**Singapore**
Brunei Darussalam	Italy	Slovakia
Bulgaria	Jamaica	Slovenia
Cambodia	**Japan**	South Africa
Canada	Jordan	Spain
Cape Verde	Kazakhstan	Sri Lanka
Central African Rep.	**Lao PDR**	Sweden
Chile	Latvia	Switzerland
China	Lithuania	**Taiwan**
Colombia	Luxembourg	TFYR of Macedonia
Costa Rica	Madagascar	**Thailand**
Croatia	**Malaysia**	Tunisia
Cyprus	Maldives	Turkey
Czech Rep.	Malta	Uganda
Denmark	Mauritius	United Kingdom
Dominican Rep.	Mexico	United Rep. of Tanzania
Ecuador	**Myanmar**	Uruguay
Egypt	Namibia	US
El Salvador	Netherlands	**Viet Nam**
Estonia	**New Zealand**	
Ethiopia	Norway	

Lao PDR = Lao People's Democratic Republic, Rep. = Republic, TYFR Macedonia = The Former Yugoslav Republic of Macedonia, US = United States.

Notes: The countries are listed in alphabetical order. Data for robot density are available for 48 countries (highlighted in light grey), and the 17 countries in the Regional Comprehensive Economic Partnership region are in bold.

Appendix B: 14 Industrial Categories and Production Stages

		Production stage in RIETI–TID		
Industrial category in World Robotics	(ISIC codes)	Manufactured parts and components	Capital goods	Consumption goods
Food and beverages	(D10T12)	.	.	x
Textiles	(D13T15)	x	.	x
Wood and furniture	(D16)	.	.	x
Paper	(D17T18)	x	.	x
Rubber and plastic products	(D22)	x	.	x
Other chemical products n.e.c.	(D20T21)	.	x	x
Glass, ceramics, stone, mineral products	(D23)	x	.	x
Fabricated metal products	(D25)	x	x	x
Computer, electronic, and optical products	(D26)	x	x	x
Electrical equipment	(D27)	x	x	x
Industrial machinery	(D28)	x	x	x
Automotive	(D29)	x	x	x
Other vehicles	(D30)	x	x	x
Other manufacturing	(D31T33)	.	x	x

ISIC = International Standard Industrial Classification; n.e.c. = not elsewhere classified; RIETI–TID = Research Institute of Economy, Trade and Industry Trade Industry Database.

Notes: Using the RIETI–TID production stage indicators, we can identify the most disaggregated Standard International Trade Classification (SITC) codes of either 'manufactured parts and components', 'capital goods', or 'consumption goods'. There is a many-to-one mapping from the most disaggregated SITC codes to the ISIC industrial categories used by World Robotics. The ISIC codes corresponding to each industrial category are in parentheses. 'D' stands for 'division' (of industrial categories) and 'T' stands for 'to'. The right three columns indicate whether the respective ISIC industries cover some of the SITC codes of each product-stage category.

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