New Developments in International Production Networks: Impact of Digital Technologies

Fukunari Kimura*

Keio University and the Economic Research Institute for ASEAN and East Asia (ERIA)

Ayako Obashi

Aoyama Gakuin University

May 2019

Abstract

This paper tries to identify the impact of digital technologies on network trade, particularly in East Asia. A standard gravity exercise is conducted with the worldwide disaggregated data of network trade, which consists of trade in manufactured parts and components, capital goods, and consumable goods, in order to find possible influence of the introduction of digital technologies represented by the by-industry use of industrial robots, individual's internet use, and imported digitally deliverable services. We find that the introduction of robots, together with imported digitally deliverable services, seems to enhance trade in manufactured parts and components as well as consumable goods in East Asia, but not necessarily in other parts of the world. This suggests that the exploration of complementarity between machines and human resources in production blocks supported by better connectivity may allow newly developed economies to retain and expand the division of labor, rather than suffering from massive "reshoring" in which factories would go back to advanced economies.

* Corresponding Author: Fukunari Kimura, Professor, Faculty of Economics, Keio University, 2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan. Phone: +81-3-5427-1290. Fax: +81-3-5427-1578. E-mail: fkimura@econ.keio.ac.jp.

1. Introduction

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

And now, digital technologies arrive in East Asia. The impact of digital technologies on the international division of labor will surely be multifaceted. Eventually, we may have a fundamentally different type of international division of labor, i.e., the third unbundling or cross-border services outsourcing. However, an immediate concern of the policymakers in the region is what would happen in their international production networks.

To conceptualize the impact of digital technologies on newly developed economies, we believe it useful to identify two faces of digital technologies as suggested by Baldwin (2016): information technologies and communication technologies.[1] Both are derived from same technologies but may have quite different implication for the international division of labor. Information technologies represented by artificial intelligence, robots, machine learning, and industry 4.0 achieve faster data processing, economize the number of tasks, accelerate substitution for human by machines, and thus is likely to generate concentration forces for economic activities. Because of it, we may experience "re-shoring," i.e., some production blocks now located in newly developed economies may go back to advanced economies. On the other hand, communication technologies centered by the internet, smartphones, and 5G overcome physical distance, reduce matching costs, encourage the division of labor, and therefore generate dispersion forces for economic activities. Indeed, the penetration of communication technologies is amazingly fast even in newly developed economies, which make a series of new businesses mushrooming. So, can we say that information technologies would reduce jobs while communication technologies would create works in newly developed economies?

[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) applies the concept for the international division of labor.

Things may not be so simple though. Information technologies overall accelerate substitution for human by machines, but at the level of production blocks or tasks, complementarity between human and machines also emerges. Cutting out a production block in the second unbundling is constrained by technological and managerial conditions. When we experienced a transition from the first unbundling to the second unbundling, we observed some sticky attachments between skilled and unskilled labor in both advanced and newly developed economies. A production block typically has a combination of different productive factors; it is not feasible to make a production block purely skilled labor-intensive or purely unskilled labor-intensive. That is why we always complain the shortage of unskilled labor in advanced economies and that of skilled labor in newly developed economies. A similar thing is expected when we experience in the substitution between human and machines in an even finer micro level. From the viewpoint of newly developed economies, it is not easy to compete with advanced economies at the very frontier of digital innovation, at least in the short run. Then, how can they attract or at least keep production blocks within their territories? A natural solution would be to seek complementarity with information technologies. Virtually all East Asian newly developed economies including China, Malaysia, Thailand, the Philippines, and Indonesia try to encourage the introduction of robots in production processes.[2] Is it a stupid idea that opposes to comparative advantage or a meaningful step to seek the way to retain production blocks? This is an empirical question.

Statistical data are still immature to conduct comprehensive empirical studies on the usage of digital technologies in newly developed economies. However, some signs of an important transition may be captured by a casual data exercise. This empirical paper concentrates on network trade and conducts a standard gravity equation exercise in order to identify the possible trade-enhancing effects of digital technologies on the operation of international production networks or the second unbundling. "Network trade" is defined in this paper as (i) manufactured parts and components, (ii) capital goods, and (iii) consumable goods while trade in primary goods and processed materials is excluded.

---

[2] For example, in Thailand, the introduction of artificial intelligence (AI) and robotics is one of the main pillars of Thailand 4.0. The Board of Investment is providing 13-year-maximum corporate income tax exemption for investment in the target industries in which the usage of AI and robotics makes such incentives more likely to be approved (https://www.boi.go.th/upload/content/BOI-brochure%202016-automation-20170615_14073.pdf ,https://www.boi.go.th/upload/content/no76_2562_5ce64eb915fa9.pdf, https://www.scmp.com/news/asia/southeast-asia/article/2108938/development-plan-robotics-gets-nod-thailand).

Trade within East Asia, which is centered by network trade, is highlighted in comparison 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, individual's internet use, and imported digitally deliverable services. These to some extent reflect multiple aspects of information and communication technologies though the weights between them are different. Our major findings are the first indicator, 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 exploring the complementarity between information technologies and indigenous resources. The role of communication technologies also seems to be complementary in the effort of keeping production blocks.

The paper plan is as follows: the next section outlines the channels through which digital technologies affect network trade. Section 3 explains our empirical strategy using the gravity framework and describe the three indicators to capture the digital transformation in relation to network trade. Section 4 presents estimation results. And section 5 concludes the paper.

2. Effects of digital technologies on network trade

The effects of digital technologies on network trade would emerge at least through three channels.

The first is on the supply side. Information technologies may change location advantages for production blocks. Here, substitutability and complementarity between human and machines matter. If substitutability dominates, we may observe massive "re-shoring," i.e., some production blocks may go back from newly developed economies to advanced economies. To keep production blocks to stay, newly developed economies must seek for the room for complementarity between machines and labor. Cutting out a production block goes with technological and managerial constraints. From here, some substitutability would emerge.

The second channel is on service links. Communication technologies may change the way of overcoming distances. Communication technologies would reduce the cost of service links that connect remotely placed production blocks in the second unbundling. In addition, they might encourage the use of cross-border service outsourcing, a part of which would be interpreted as the third unbundling. These elements would also affect the pattern of international division of labor.

The third channel is on the demand side. Communication technologies may develop new markets for consumable goods. Through the internet, small businesses and individual consumers can participate in matching platforms. New demands would be created by communication technologies.

Our three measures on digital technologies may not be perfect indicators for capturing these three channels. However, with a bold simplicity, we may be allowed to interpret the use of robots as reflecting the first channel, imported digitally deliverable services as the second channel, and individual's internet use as the third channel. And we find that the pattern of evolving network trade in East Asia seems to be supported by the first channel complemented by the second channel.

3. Data and methodology

We begin by explaining our empirical strategy using the gravity framework in the next subsection. We then describe the variables that are used to capture the digital transformation over time as well as data on network trade in the following subsections. We also provide data overview on these variables.

3.1. Gravity analysis with the usage of digital technologies

To examine the extent to which changes in digital technologies are linked with changes in network trade, we estimate a gravity model with time-varying origin-industry and destination-industry fixed effects. Specifically, we consider exports from country i to country j of industry k, $Trade_{ijk}$, as a function of origin-industry-specific factors that represent the export supply capacity, S_{ik}, destination-industry-specific factors that make up for the import demand, M_{jk}, and the ease of exporter i's access to the market of industry k in destination j, t_{ijk}:

$$Trade_{ijk} = S_{ik} M_{jk} t_{ijk},$$

where we omit time indexes for simplicity. We introduce variables for the usage of digital technologies as part of the industry-specific bilateral trade costs of t_{ijk}.

The standard procedure for estimating a gravity equation like above is to take the natural logarithms of all terms and obtain a log-linear form that can be estimated using the ordinary least square (OLS):

$$\ln Trade_{ijk} = \ln S_{ik} + \ln M_{jk} + \ln t_{ijk}.$$

To control for so-called multilateral trade resistance, we include origin-industry and destination-industry dummy variables (Anderson and van Wincoop, 2003). The industry-specific bilateral trade costs are assumed to take the form:

$$t_{ijk} = dist_{ij}^{\delta_1} \cdot \exp(\delta_2 cont_{ij} + \delta_3 lang_{ij} + \delta_4 colony_{ij}) \cdot digi_{ijk}^{\delta_5},$$

where $dist_{ij}$ is bilateral distance, and $cont_{ij}$, $lang_{ij}$, and $colony_{ij}$ is a dummy variable indicating contiguity, common official or primary language, post-1945 colonial relationship, respectively.[3] Of our special interest is $digi_{ijk}$, which captures the usage of digital technologies.

Then we estimate the augmented gravity equation as follows:

$$\ln Trade_{ijkt} = \beta_1 I_{ikt} + \beta_2 I_{jkt} + \beta_3 \ln dist_{ij} + \beta_4 cont_{ij} + \beta_5 lang_{ij} + \beta_6 colony_{ij} + \beta_7 digi_{ijkt-1} + \varepsilon_{ijkt},$$

where I_{ikt} and I_{jkt} are time-varying origin-industry and destination-industry dummy variables of individual effects. For the digital technology variable, we take a lag of one year to reduce the incidence of reverse causality. The equation is estimated for the network trade that is supposed to include trade of manufactured parts and components, capital goods, and consumable goods. The estimation is also conducted by disaggregated trade flows: intraregional trade flows within East Asia; exports by East Asian countries to countries outside the region; imports by East Asian countries from countries outside the region; and trade among countries outside the region.

We primarily use OLS as the estimation methodology but check whether the estimation results obtained using OLS are robust to the adoption of Poisson pseudo-maximum likelihood (PPML) estimation. As shown in Santos Silva and Tenreyro (2006), it is a common perception in the empirical trade literature that the PPML estimator provides consistent estimates of the original nonlinear gravity equation as long as the gravity model contains the correct set of explanatory variables.

3.2. Trade data by production stage and network trade

We look at (industry-level) bilateral trade flows among 97 countries, for which we can obtain continuously reported import statistics (or mirror data as needed) based on the Standard International Trade Classification, Revision 4 (hereafter SITC Rev. 4) from 2011 to 2017, from the UN Comtrade.[4] The 97 countries include 17 East Asian countries of our interest; namely, ten ASEAN member countries, (mainland) China, Japan, Republic of Korea, Australia, New Zealand, India, and Taiwan.[5] As for Taiwan, we treat data for

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

[4] See the UN Comtrade website (https://comtrade.un.org/).

[5] For a complete list of 97 countries, see Appendix A.

'Other Asia, not elsewhere specified (code 490)' as that for Taiwan.[6] Amongst the East Asian countries of interest, the SITC Rev. 4-based import statistics are not reported by the Philippines in 2011–2016, Cambodia, Laos, Thailand, and Taiwan in 2017. We fill these missing import data by using the corresponding mirror data.[7]

Connecting trade data at the most disaggregated level of SITC Rev. 4 with the production stage indicators that are originally employed in the RIETI Trade Industry Database (RIETI-TID)[8], we sort out the trade data by production categories according to the stages of the production process: primary goods; processed raw materials; manufactured parts and components; capital goods; and consumable goods, the latter three of which are thought to (partially) constitute the network trade.

As the network trade, we focus on trade occurring within international production networks based on the cross-border unbundling of manufacturing production processes. Such network trade under our perception would encompass manufactured parts and components and the assembled end products. Although we can identify 'manufactured parts and components' using the RIETI-TID production stage indicators, the assembled end products within production networks are included only as part of 'capital goods' and 'consumable goods.' Given these circumstances, we would particularly like to look at trade in manufactured parts and components as the network trade.

Manufactured parts and components as defined in the RIETI-TID are mostly those used in the machinery sectors such as electrical machinery, general machinery, and transport equipment.[9] Also, most of the capital goods as defined in the RIETI-TID are those

---

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

[7] Notice that even though we use the mirror data, the trade data among Cambodia, Laos, Thailand, and Taiwan in 2017 is still missing in our data set.

[8] 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 that are organized by industry (13 sectors), product category (five production stages), and year (from 1980 to the latest year). We make use of the RIETI-TID's production stage indicators and apply them to the disaggregated bilateral trade data obtained from the UN Comtrade so as to enable us to conduct a data analysis at a finer level.

[9] Not only manufactured parts and components but also processed raw materials are product categories of intermediate goods in the RIETI-TID. The processed raw materials, however, are not included in the network trade of our interest because they are mostly (semi-)processed raw materials used as intermediates for chemicals, iron and metal products, and petroleum and coal products.

classified under the general machinery, electric machinery, transport equipment, and precision machinery. Consumable goods as defined in the RIETI-TID consist of not only food and textiles, but also including transport equipment, chemicals, and household electric appliances.

In order to connect the production stage-level trade data based on the SITC Rev. 4 with the data for digital utilization and employment by industries (to be described below), we need to correlate the most disaggregated SITC Rev. 4 codes to the 2-digit industrial categories of the International Standard Industry Classification (ISIC) Rev. 4, which are used in the sources of data on robots and employment. To do so, we first correspond SITC Rev. 4 to ISIC Rev. 3 using the one conversion table from HS 2007 to SITC Rev. 3 and the other from HS 2007 to ISIC Rev. 3.[10] We then make use of the conversion table from ISIC Rev. 3.1 to ISIC Rev. 4[11] to have data organized at the 2-digit industrial categories of the ISIC Rev. 4. For the 2-digit industrial categories, we consider 14 industries in total: namely, food and beverages (D10T12); textiles (D13T15); wood and furniture (D16); paper (D17T18); other chemical products n.e.c. (D20T21); rubber and plastic products (D22); glass, ceramics, stone, mineral products (D23); fabricated metal products (D25); computer, electronic and optical products (D26); electrical equipment (D27); industrial machinery (D28); automotive (D29); other vehicles (D30); and other manufacturing (D31T33).[12]

Ultimately, we potentially have a square matrix consisting of 97 x 96 country pairs x 7 years x 14 ISIC industry categories = 912,576 observations at the maximum. Our sample size, however, is 892,122 (= 9,105 country pairs x 7 years - 12 country pairs) x 14 ISIC categories) because only 9,105 country pairs have some trade transactions with the partner country during the period 2011-2017. We omit the country pairs that have no trade throughout the period. In addition, bilateral trade data among Cambodia, Laos, Thailand, and Taiwan (that is, 12 country pairs) in 2017 are missing even after we augmented the import statistics with the mirror data.

---

[10] The conversion table from HS 2007 to SITC Rev. 3 is available at the UNSD webpage (https://unstats.un.org/unsd/trade/classifications/correspondence-tables.asp) and that from HS 2007 to ISIC Rev. 3 is at the webpage of the World Bank (https://wits.worldbank.org/product_concordance.html).

[11] The conversion table from ISIC Rev. 3.1 to ISIC Rev. 4 is available at the Eurostat webpage (https://ec.europa.eu/eurostat/ramon/relations/index.cfm?TargetUrl=LST_LINK&StrNomRelCode=ISIC%20REV.%203.1%20-%20ISIC%20REV.%204&StrLanguageCode=EN).

[12] ‘D’ stands for ‘division’ (of industrial categories) and ‘T’ stands for ‘to.’

Table 1 presents basic statistics for the network trade at the ISIC 2-digit industry level, in 2011, 2014, and 2017, by product category and by the type of trade flows. For example, the first row of the table shows the following figures for intraregional trade of manufactured parts and components within East Asia in 2011: the total number of observations at the origin-destination-industry level; the number of observations of non-zero trade flows; the number of observations of zero flows; trade propensity, which is defined as a proportion of non-zero trade flows; the mean trade value in thousand US dollars (in nominal prices); and trade composition, which is defined as a proportion of each product category in the overall network trade of a certain flow type in a given year.

We would point out three features of the recent evolution of network trade: first, the trade propensity figures rise steadily from 2011 to 2017 for respective trade flow types of respective product categories. At the industry level, more countries appear to be starting to export to more trading partner countries within production networks. Second, the mean trade values trend upward uniformly for intra-East Asian trade of all the products. As reflected in the changes in trade composition, intra-East Asian trade of parts and components expands to the greatest extent, followed by that of consumable goods. Third, the mean values of the East Asian imports from countries outside the region and those of the trade among extra-regional countries stay sluggish or even trend downward from 2014 to 2017. The sluggishness is especially true for the trade in parts and components and capital goods. Reflecting this, it is noticeable that the proportion of consumable goods in the East Asian imports from extra-regional countries continues to rise.

3.3. Variables for the spread and utilization of digital technologies

We use three variables capturing the digital transformation over time: (i) the use of industrial robots and information technologies by firms; (ii) the country's dependence on imported digitally deliverable services; and (iii) individual's internet use and digital connectivity between countries.

Use of industrial robots and information technologies by firms

The first variable is the stock of operational robots, namely, the number of industrial robots in use, which approximates the usage of information technologies by firms. An industrial robot is defined by ISO 8373: 2012 as an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications (IFR, 2018). Robots are by no means the only form of automation; the older example includes the automation of machine tools thanks to technologies such as Computer Numerical

Control (CNC) introduced in the early 1960s. Although machine tools are designed to perform very specific tasks, robots are reprogrammable, autonomous and characterized by a high degree of dexterity (OECD, 2019). As such, the introduction of industrial robots in production processes will change the nature of the tasks performed by workers in a complex manner and may strengthen or alter the location advantages for internationalized production activities, through affecting the complementarity or substitutability between machines and labor. Furthermore, the introduction of industrial robots may enhance or discourage network trade.

International trade within production networks are occurring between production blocks that are hosted by different countries of different location advantages. The diversity of location advantages can be approximated by differences in the level of economic development across countries. Indeed, network trade, in particular, that of manufactured parts and components, evolves centering on East Asia between newly developed economies and advanced economies. Meanwhile, newly developed economies tend to lag behind advanced economies in terms of the degree of investment in industrial robots. Given these together in mind, we can sort out possible directions of the effects of the introduction of industrial robots on network trade as follows.

First, when only advanced economies as one side of network trade introduce more industrial robots, the network exports from newly developed economies to advanced economies would be diminished. This is because the substitutability between machines in advanced economies and labor in newly developed economies dominates and thereby some production blocks may go back from newly developed economies to advanced economies, that is, reshoring may be induced. Such reshoring implies a decrease in network trade. The trade flow in an opposite direction may decrease or increase, depending on the trade-diminishing effect of reshoring and the trade-enhancing effect of the strengthened location advantages of advanced economies.

Second, when only newly developed economies as one side of network trade introduce more industrial robots, the network trade in both directions would expand. This is because newly developed economies strengthen the location advantages in a way of enjoying on the complementarity between machines and labor and thereby production blocks will be kept to stay in those countries.

Lastly, if both advanced economies and newly developed economies involving in network trade introduce industrial robots, the relative magnitude of the first force to the second force does matter. Nevertheless, the possibility of reshoring will be diminished as newly developed economies as well as advanced economies introduce industrial robots.

Hence, in order to identify the positive effects of industrial robots on network trade in the gravity analysis, we take the minimum of robot density for each pair of countries since we are interested particularly in whether newly developed economies invest in industrial robots as discussed above. The newly developed economies of our interest tend to have a relatively lower degree of investment in industrial robots, and therefore, using the minimum of robot density enables us to focus on whether newly developed economies as either side of network trade introduce more industrial robots.

Descriptive statistics on industrial robots are published annually, accompanied by the online database of World Robotics, by the International Federation of Robotics (IFR). As far as we know, the current paper is the first to utilize the IFR data of industrial robots in the empirical trade literature. The IFR data has been used only in few studies in the economics field to explore the impact of robots on labor market (Graetz and Michaels, 2015; Acemoglu and Restrepo, 2016, 2017). To measure the degree of investment in industrial robots and the resulting, potential industrial automation, we use the robot density measure according to IFR (2018). The robot density is defined as the number of multipurpose industrial robots in operation per 10,000 persons employed, and can be compared between countries and industries as well as longitudinal comparisons over time.

To calculate the robot density, we obtain data for the total employment by country and industry from the OECD Structural Analysis (STAN) database while data for the stock of operational robots by country and industry is available at the World Robotics database. Both data on robots and employment are organized at the industry level, according to the latest version of ISIC Rev. 4. We can calculate the robot density measure at the 2-digit level of the ISIC Rev. 4 for respective countries across years.

Because data on employment by industry is (basically) available only for OECD countries at the STAN database, we can calculate the robot density at the industry level for those OECD countries only. Among 17 East Asian countries, for example, the by-industry robot density can be calculated for Japan, Korea, Australia, and New Zealand only, unless we refer to another source of data on employment for the rest of (non-OECD) countries.[13] For now, given the employment data limitation issue, we augment the by-

[13] We could instead refer to the UNIDO INDSTAT database to obtain the by-industry employment data for non-OECD countries. Since data for the stock of operational robots by industry is available not only for OECD but for many of non-OECD countries, we can calculate the robot density by industry for a wider range of countries once we obtain by-industry employment data. Among East Asian countries, for example, data for the stock of operational robots by industry is available for Indonesia, Malaysia, the Philippines, Singapore, Taiwan, and Thailand, in addition to Japan, Korea, Australia, and New Zealand. We will deal with this data issue in the process of a future revision of the current paper.

industry robot density data with the robot density data for the overall manufacturing industries that can be (manually) collected from the documents of IFR (2018). The latter data is available throughout the (1-year lagged) sample period 2010–2016 for five ASEAN countries (Indonesia, Malaysia, Philippines, Singapore, and Thailand), China, and India. We ultimately get the augmented version of data on robot density for 12 out of 17 East Asian countries. By a similar way, we can have the augmented data on robot density for 36 out of 80 countries outside East Asia.

The box plots of Figure 1 show the distributions of robot density across East Asian countries that are compared across industries from 2010 to 2015. Because of the employment data limitations, we refrain from including the box plots for 2016, in which the STAN database only enables us to (originally) calculate the robot density of a limited number of industries for Japan and Australia. Figure 2 complements Figure 1, showing the corresponding basic statistics for countries outside East Asia for a comparison purpose.

First, among countries outside East Asia, the central tendency of robot density is strikingly high in the automotive sector, followed by the rubber and plastic products sector. Compared to these two sectors, however, investments in industrial robots are generally limited to a smaller magnitude in the rest of sectors including electrical equipment, computer, electronic and optical products and other machinery sectors, even in 2015.

In contrast, East Asian countries appear to invest in industrial robots more broadly and the central tendency of robot density increases steadily across various sectors over the recent several years. The general degrees of investments in industrial robots in the automotive sector and the rubber and plastic products sector are noticeably high for in East Asia as well as in the rest of the world. More interestingly, the central tendency of robot density increases most significantly in the electrical equipment sector and the computer, electronic and optical products sector, from 2010 onward. These electric and precision machinery sectors appear to lead the East Asian region in the more utilization of industrial robots and information technologies by firms.

Country's dependence on imported digitally deliverable services

In order to confirm the impact of industrial robots, or information technologies, on network trade, we consider an extent to which an exporting country is tightly integrated into international production networks. In particular, we focus on a complementary role of communication technologies in keeping the production blocks to stay. Communication technologies would reduce the cost of service links that connect and coordinate remotely placed production blocks: they would enable multinational firms to track and monitor cargos moving from a 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 (WTO, 2018).[14] The more the origin country of a certain bilateral trade flow within production networks depends on imported digitally deliverable services, the more likely the country is tightly integrated in production networks thanks to the strengthened service links. Further, keeping the production blocks to stay, the origin country might enhance the exports of manufactured parts and components or the assembled end products through the production networks.

We therefore use the origin country's dependence on imported digitally deliverable services relative to the total services imports as a proxy for the probability that the production blocks are kept to stay in the origin country. We introduce this proxy as an interaction term with the minimum robot density for a pair of countries, in addition to including the minimum robot density independently, in the gravity equation. By doing so, we can check whether the investments in more industrial robots especially by newly developed economies enhance network trade, conditional on the (origin) countries involving network trade retain the production blocks.

Data for the imports of digitally deliverable services as well as the total services imports are obtained from the UN Comtrade. Digitally deliverable services are defined as those potentially delivered digitally, though not necessarily, according to UNCTAD (2015). They relate to the following categories of the Extended Balance of Payments Services Classification (EBOPS) 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 distributions of imported digitally deliverable services as a proportion to the total services imports across East Asian countries and the rest of the sample countries in the period 2010–2016. 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. Note that the figures for 2016 show a different tendency possibly because the number of countries included to depict the box plot for 2016 is quite limited, as mentioned in the footnote of the figure.

[14] Indeed, a recent study shows that imports of digitally deliverable services are key inputs into the production of goods to be exported. For example, about two thirds of digitally deliverable services imported by the EU are used to produce goods to be exported (Meltzer, 2014).

Individual's internet use and digital connectivity between countries

To look at the role of communication technologies, we employ measures of the internet usage by individuals at the country level. The individual's internet use data has been widely used in the related literature because of its availability for a wide range of countries with a wide time period coverage. Although the variable captures only an aspect of the usage of communication technologies by individuals, it is known to correlate very strongly with business and household usage of broadband, access to computers, and wireless and fixed broadband subscriptions (González and Ferencz, 2018).

In the gravity analysis, by taking the minimum of the share of population using the internet between a pair of countries, we construct a proxy for the potential digital connectivity between the two countries through communication technologies, in line with Freund and Weinhold (2002, 2004). The higher internet penetration in countries on both supply and demand sides will lower communication and matching costs, which would result in an increase in network trade as well as ordinary trade.

Data for the share of population using the internet for various countries can be obtained from the OECD.Stat database of the ICT Access and Usage by Households and Individuals.[15] Only an exception is Taiwan, for which we instead refer to the recent Individual/Household Digital Opportunity Survey conducted by the Taiwan National Development Council (NDC, 2017).

The box plots of Figure 4 show the basic statistics for the individual's internet use in the (1-year lagged) sample period 2010–2016, for East Asian countries and the rest of the sample countries. Data for the individual's internet use is available for all the 97 countries throughout the period. Changes in the median and the quantile range indicate that the central tendency of distribution steadily moves from left to right for both East Asian and other countries. In particular, the first quantile and the lowest value of the left whisker of the box plot rises substantially among East Asian countries, suggesting an increasing usage of communication technologies across the region. On the other hand, there exist non-negligible countries left behind from the advancement of communication technologies outside East Asia though the central tendency tends upward.

4. Estimation results

Our baseline estimation results are reported in Tables 2 and 3. Table 2 shows the estimated coefficients, accompanied by the corresponding robust standard errors in parentheses that are obtained using OLS with a proxy for the digital connectivity through communication technologies between the origin and destination countries. A set of

[15] See the OECD.Stat website (https://stats.oecd.org/).

explanatory variables in the usual gravity analysis are also included as a proxy for country pair-wise trade costs. The leftmost column of the table shows the estimates for industry-level bilateral flows of the overall network trade of our interest, including all three product categories: manufactured parts and components, capital goods, and consumable goods. The second, third, and fourth column shows the corresponding estimates for industry-level bilateral trade flows of manufactured parts and components, capital goods, and consumable goods, respectively.

As a proxy for the digital connectivity through communication technologies, we employ the minimum value of the percentage of individuals using the internet to the overall population between the origin and destination countries, as described in section 3.3. The coefficient for the minimum internet use variable, as well as the conventional pair-wise gravity covariates, is estimated in an expected direction with statistical significance: the overall industry-level bilateral trade value increases by 1.37% when the minimum internet use rises by one percentage point, with other things unaltered. A similar trade-enhancing effect of the rise in the minimum internet use is also observed for all the disaggregated product categories of the network trade.

While the minimum internet use variable captures the digital connectivity through communication technologies, the (minimum) robot density measure approximates the degree of investment in industrial robots, and more generally the usage of information technologies by firms (in newly developed economies). We ideally consider both variables together to capture the two different aspects of digital technologies. However, we cannot include the both variables simultaneously because of collinearity issue. In what follows, we exclusively employ the (minimum) robot density measure, focusing on the impact of information technologies on network trade. Notice that the minimum internet use variable is country-specific in nature. We are interested more in examining whether and how differences in the utilization of digital technologies among countries and industries and how their transformation over time is related to changes in the bilateral network trade at the industry level. In this regard, the robot density measure collected at the country-industry level is more preferred.

In Table 3 (and in the following estimated results), as a proxy for the usage of information technologies by firms, we employ the logarithmic value of the minimum number of installed robots per 10,000 employees for a pair of countries so as to capture whether newly developed economies on either exporter or importer side of the network trade introduce more industrial robots, as described in section 3.3. As is clear from comparing the number of observations reported in Table 3 with those in Table 2, relying on the robot density data restricts the sample country coverage: the reduced sample includes 12 out of 17 East Asian countries of interest, namely, five ASEAN countries (Indonesia, Malaysia, Philippines, Singapore, and Thailand), China, Japan, Korea, Australia, New Zealand, India. Nevertheless, the sample still covers all the advanced economies and most of the newly developed economies that are actively participating in the regional and global production networks in East Asia.

As for the OLS estimation results in the four rightmost columns of Table 3, the coefficients for the minimum robot density variable, as well as the conventional pair-wise gravity covariates, are estimated to be significant with expected signs: a percentage increase in the minimum robot density implies that the industry-level bilateral trade value increases by 2.53–5.37%. The corresponding PPML estimation results are reported in the three rightmost columns of the table. By the adoption of PPML estimation, the estimated coefficient for the minimum robot density variable turns to be negative and loses statistical significance for manufactured parts and components; the coefficient turns to be negative and significant at the 5% significance level for capital goods. An exception is consumable goods, for which the sign and significance of the estimated coefficient for the minimum robot density variable is robust to the PPML adoption.[16]

Next, we look into the trade effect of the minimum robot density for respective product categories of network trade, by disaggregating trade flows into intraregional trade in East Asia and other trade flows. Tables 4 and 5 report the estimation results for respective disaggregated trade flows obtained using OLS and PPML, respectively. We obtain robust estimation results under both OLS and PPML as summarized in the following three points.

First of all, both the OLS and PPML estimated coefficients for the minimum robot density are positive and significant for East Asian intraregional trade in manufactured parts and components and that in consumable goods, unlike the other trade flows. It appears that investments in more industrial robots by East Asian newly developed economies strengthen the location advantage and keep the production blocks to stay in those countries, leading to an increase in the trade of manufactured parts and components and the assembled consumable goods within the regional production networks. This finding is consistent with the data observations as presented in sections 3.2 and 3.3: East Asian intraregional trade of parts and components and consumable goods expands steadily; in the meantime, East Asian countries actively invest in more industrial robots broadly across sectors, centering on the electric and precision machinery sectors.

Second, for East Asian exports of manufactured parts and components to countries outside the region, in contrast to the first point, both the OLS and PPML estimated

[16] Conducting the PPML estimation for non-zero trade values only yields qualitatively similar results.

coefficients for the minimum robot density are negative and significant. It appears that East Asian advanced economies expand exports of parts and components destined to extra-regional countries that are reluctant to invest in industrial robots. In the case of the exports by East Asian newly developed economies to extra-regional countries, on the other hand, the East Asian newly developed economies appear to become oriented more to regional production networks while they invest in more industrial robots and strengthen the location advantage. Whatever the case may be, the networking of cross-border transactions of parts and components that is driven by the more utilization of information technologies appears to be limited to the East Asian region.

Third, the coefficients for the minimum robot density are also estimated to be negative and significant as for the trade of manufactured parts and components and capital goods between countries outside East Asia. In a country pair where industrial robots have been introduced in either of the countries and the minimum robot density has also risen, trade of parts and components and capital goods appears to decrease due possibly to reshoring or to an increasing dependence on domestic sourcing and production. Indeed, as observed in section 3.2, trade in parts and components and capital goods among extra-regional countries sluggish.

In addition, we obtain different estimation results regarding the minimum robot density under OLS and PPML for some trade flows. For East Asian exports of consumable goods to countries outside the region, for example, the coefficient for the minimum robot density is estimated to be statistically insignificant under OLS but to be positive and significant under PPML. Compared to the OLS estimates, the PPML estimates reflect trade flows with smaller values, which are more likely to be engaged by newly developed economies than by advanced economies. Given this in mind, it appears that East Asian newly developed economies tend to increase the exports of consumable goods destined to extra-regional countries as the East Asian countries introduce more industrial robots in their production.

To confirm the positive impact of information technologies on network trade, we introduce an interaction term of the (logarithmic value of) minimum robot density with the origin country's dependence on imported digitally deliverable services (as percentages in the total services imports from the world), in addition to a set of covariates employed in the previous tables. Table 6 reports the estimation results obtained using OLS and PPML by including the interaction term. Here, we focus on the East Asian intraregional trade of manufactured parts and components and consumable goods for which we detect the trade-enhancing effect of the minimum robot density as reported in Tables 4 and 5.

For the East Asian intraregional trade of manufactured parts and components, the OLS estimates indicate with statistical significance that a rise in the minimum robot density alone will have adverse effects on trade but will enhance trade together with a higher dependence of the origin country on imported digitally deliverable services. It can be interpreted as suggesting that the investments in more industrial robots by East Asian newly developed economies enhance intraregional trade of manufactured parts and components within the production networks that are driven by communication technologies only when the production blocks are maintained as they were. The OLS estimate for the interaction term is robust to adopting the PPML, but not for the single minimum robot density variable.

For the East Asian intraregional trade of consumable goods, on the other hand, the OLS estimation yields no statistically significant results regrading the minimum robot density and its interaction term. Nevertheless, the corresponding PPML estimates would suggest that the more utilization of information technologies in East Asian newly developed economies enhance their exports of the assembled consumable goods through the regional production networks driven by communication technologies, conditional on the production blocks being kept to stay in those countries.

5. Conclusion

This paper investigated the possible trade-enhancing effects of digital technologies on the operation of international production networks. With a special interest on the usage 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 East Asian newly developed economies enhance the trade of manufactured parts and components and the assembled consumable goods within the regional production networks. In addition, such trade-enhancing effects of information technologies were found to realize in combination with a higher dependence of the origin country on imported digitally deliverable services driven by communication technologies. The role of communication technologies appears to be complementary in reducing the service link cost and in keeping production blocks as they were thanks to the strengthened service links. These findings can be interpreted as indicating that East Asian newly developed economies seem to retain production blocks and enhance the network trade that they engage in by exploring the complementarity between information technologies and indigenous resources.

We do not necessarily recommend strong government intervention for introducing information technologies in newly developed economies. However, some mild promotion together with investing in the soft and hard infrastructure for communication technologies seems to make sense. With more empirical evidences, we must write up workable development strategies with pro-actively utilizing digital technologies.

References

IFR (2018) *World Robotics Industrial Robots 2018*, International Federation of Robotics.

Acemoglu, D. and P. Restrepo (2016) "The Race Between Machine and Man: Implications of Technology for Growth, Factor Shares and Employment," NBER Working Paper No. 22252.

Acemoglu, D. and P. Restrepo (2017) "Robots and Jobs: Evidence from US Labor Markets," NBER Working Paper No. 23285.

Aghion, P., N. Bloom, and J. Van Reenen (2014) "Incomplete Contracts and the Internal Organization of Firms," *Journal of Law, Economics, and Organization*, 30(Suppl.1): 37-63.

Anderson, J. E. and E. van Wincoop (2003) "Gravity with Gravitas: A Solution to the Border Puzzle," *American Economic Review*, 93(1): 170–92.

Ando, M. and F. Kimura (2005) "The Formation of International Production and Distribution Networks in East Asia," in T. Ito and A. K. Rose (eds.), *International Trade in East Asia (NBER-East Asia Seminar on Economics, Volume 14)*, The University of Chicago Press, pp.177-213.

Baldwin, Richard. (2016) *The Great Convergence: Information Technology and the New Globalization*. Cambridge, MA: The Belknap Press of Harvard University Press.

Freund, C. and D. Weinhold (2002) "The Internet and International Trade in Services," *American Economic Review Papers and Proceedings*, 92 (2): 236-240.

Freund, C. and D. Weinhold (2004) "The Effect of the Internet on International Trade," *Journal of International Economics*, 62: 171-189.

Graetz, G. and G. Michaels (2015) "Robots at work," IZA Discussion Papers, No.8938, Institute of Labor Economics. http://ftp.iza.org/dp8938.pdf.

González J. L. and J. Ferencz (2018) "Digital Trade and Market Openness," OECD Trade Policy Papers 217, OECD Publishing.

Meltzer, J. P. (2014) "The Importance of the Internet and Transatlantic Data Flows for US and EU Trade and Investment," Brookings Institution. www.brookings.edu/research/the-importance-of-the-internet-and-transatlantic-data-flows-for-u-s-and-eu-trade-and-investment/.

NDC (2017) *Individual/Household Digital Opportunity Survey in Taiwan*, Taiwan National Development Council.

Obashi, A. and F. Kimura (2016) "The Role of China, Japan, and Korea in Machinery Production Networks," *International Economic Journal*, 30(2): 169-190.

Obashi, A. and F. Kimura (2017) "Deepening and Widening of Production Networks in ASEAN," *Asian Economic Papers*, 16(1): 1-27.

Obashi, A. and F. Kimura (2018) "Are Production Networks Passé in East Asia? Not Yet," *Asian Economic Papers*, 17(3): 86-107.

OECD (2019) "Determinants and impact of automation: An analysis of robots' adoption in OECD countries," OECD Digital Economy Papers, No. 277, OECD Publishing, Paris. https://doi.org/10.1787/ef425cb0-en.

Santos Silva, J.M.C. and S. Tenreyro (2006) "The Log of Gravity," *Review of Economics and Statistics*, 88(4): 641-658.

UNCTAD (2015) "International Trade in ICT Services and ICT-enabled Services: Proposed Indicators from the Partnership on Measuring ICT for Development." (TN/UNCTAD/ICT4D/03).

WTO (2018) *World Trade Report 2018: The future of world trade: How Digital Technologies are Transforming Global Commerce*, WTO, Geneva. https://doi.org/10.30875/f309483f-en.

Appendix A. 97 sample countries including 17 East Asian countries of interest.

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

Notes: 97 countries included in our sample are listed in an alphabetical order. Among them, 17 East Asian countries of our interest are indicated in bold face.

Table 1. Overview of network trade by product category and by trade flow type.

		Number of observations			Trade	Mean trade value	Trade
		Total	Trade>0	Trade=0	propensity	(thousand $)	composition
Intra-East Asian trade	Parts and components						
	2011	2,720	2,041	679	0.75	238,046	0.47
	2014	2,720	2,094	626	0.77	264,609	0.48
	2017	2,600	2,039	561	0.78	315,527	0.51
	Capital goods						
	2011	2,176	1,648	528	0.76	206,094	0.33
	2014	2,176	1,674	502	0.77	209,695	0.31
	2017	2,080	1,631	449	0.78	222,150	0.29
	Consumable goods						
	2011	3,808	3,230	578	0.85	73,583	0.20
	2014	3,808	3,287	521	0.86	81,357	0.21
	2017	3,640	3,185	455	0.88	90,917	0.21
East Asian exports to outside	Parts and components						
	2011	13,440	7,586	5,854	0.56	36,143	0.26
	2014	13,440	7,808	5,632	0.58	37,666	0.26
	2017	13,440	7,936	5,504	0.59	39,923	0.26
	Capital goods						
	2011	10,752	6,545	4,207	0.61	61,545	0.36
	2014	10,752	6,616	4,136	0.62	66,242	0.36
	2017	10,752	6,804	3,948	0.63	69,269	0.37
	Consumable goods						
	2011	18,816	13,335	5,481	0.71	37,368	0.38
	2014	18,816	13,460	5,356	0.72	39,503	0.38
	2017	18,816	13,750	5,066	0.73	40,161	0.37
East Asian imports from outside	Parts and components						
	2011	13,290	5,883	7,407	0.44	18,342	0.33
	2014	13,290	6,110	7,180	0.46	20,153	0.33
	2017	13,290	6,256	7,034	0.47	19,017	0.32
	Capital goods						
	2011	10,632	5,183	5,449	0.49	23,909	0.35
	2014	10,632	5,372	5,260	0.51	25,358	0.33
	2017	10,632	5,491	5,141	0.52	24,358	0.33
	Consumable goods						
	2011	18,606	10,005	8,601	0.54	12,351	0.32
	2014	18,606	10,468	8,138	0.56	15,064	0.34
	2017	18,606	10,657	7,949	0.57	14,910	0.35
Outside-East Asia trade	Parts and components						
	2011	61,600	28,173	33,427	0.46	17,898	0.28
	2014	61,600	28,733	32,867	0.47	18,633	0.27
	2017	61,600	29,992	31,608	0.49	18,120	0.27
	Capital goods						
	2011	49,280	24,996	24,284	0.51	21,764	0.27
	2014	49,280	25,693	23,587	0.52	22,622	0.27
	2017	49,280	26,564	22,716	0.54	22,621	0.27
	Consumable goods						
	2011	86,240	48,803	37,437	0.57	21,026	0.45
	2014	86,240	50,169	36,071	0.58	22,200	0.46
	2017	86,240	51,839	34,401	0.60	22,349	0.46

Notes: 17 East Asian and 80 other countries listed in Appendix A are included in our sample. See the text for our way of grouping finely disaggregated trade data into three product categories of network trade.
Source: Authors' calculation using the SITC Rev. 4 bilateral trade data (UN Comtrade).

Table 2. The impact of communication technologies on network trade.

Method	OLS			
Products	Overall	Parts and components	Capital goods	Consumable goods
Dependent variable	ln(Trade)	ln(Trade)	ln(Trade)	ln(Trade)
Explanatory variables				
Minimum internet use	0.0137***	0.0135***	0.0167***	0.0156***
	(0.000288)	(0.000426)	(0.000448)	(0.000323)
ln(Distance)	-1.322***	-1.207***	-1.256***	-1.304***
	(0.00360)	(0.00511)	(0.00549)	(0.00399)
Contiguity	0.449***	0.391***	0.451***	0.487***
	(0.0144)	(0.0189)	(0.0207)	(0.0152)
Common language	0.710***	0.522***	0.595***	0.712***
	(0.00928)	(0.0130)	(0.0139)	(0.0103)
Colony	1.249***	1.163***	1.250***	1.181***
	(0.0224)	(0.0302)	(0.0329)	(0.0245)
Origin-industry-year FE	Yes	Yes	Yes	Yes
Destination-industry-year FE	Yes	Yes	Yes	Yes
Number of observations	553,692	282,194	251,952	481,239
Adjusted R-squared	0.793	0.767	0.757	0.755

Notes: See the text for our way of grouping finely disaggregated trade data into three product categories of network trade. 3. Estimated coefficients are accompanied by robust standard errors in parentheses. Asterisks denote statistical significance: *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' calculation using the SITC Rev. 4 bilateral trade data (UN Comtrade), combined with the data for individual's internet usage (OECD.Stat; NDC (2017) for Taiwan) and the country pair-wise trade cost measures (CEPII GeoDist).

Table 3. The impact of information technologies on network trade.

Method	OLS				PPML		
Products	Overall	Parts and components	Capital goods	Consumable goods	Parts and components	Capital goods	Consumable goods
Dependent variable	ln(Trade)	ln(Trade)	ln(Trade)	ln(Trade)	Trade	Trade	Trade
Explanatory variables							
ln(Minimum robot density)	0.0347***	0.0253***	0.0361***	0.0537***	-0.00486	-0.0300**	0.0685***
	(0.00526)	(0.00753)	(0.00869)	(0.00604)	(0.0149)	(0.0134)	(0.0133)
ln(Distance)	-1.213***	-1.175***	-1.225***	-1.229***	-0.629***	-0.571***	-0.634***
	(0.00498)	(0.00676)	(0.00766)	(0.00566)	(0.00933)	(0.0104)	(0.0107)
Contiguity	0.231***	0.195***	0.192***	0.347***	0.308***	0.395***	0.557***
	(0.0171)	(0.0230)	(0.0250)	(0.0191)	(0.0307)	(0.0269)	(0.0251)
Common language	0.333***	0.278***	0.309***	0.345***	0.254***	0.0538**	0.0151
	(0.0134)	(0.0184)	(0.0206)	(0.0156)	(0.0269)	(0.0258)	(0.0270)
Colony	0.615***	0.460***	0.517***	0.605***	-0.00489	0.0297	-0.0363
	(0.0295)	(0.0401)	(0.0453)	(0.0356)	(0.0463)	(0.0526)	(0.0717)
Origin-industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	175,955	113,264	91,327	169,980	132,036	101,483	182,634
Adjusted R-squared	0.860	0.830	0.807	0.814			
R-squared					0.902	0.947	0.887

Note: See notes of Table 2.
Source: Authors' calculation using the SITC Rev. 4 bilateral trade data (UN Comtrade), combined with the data for the stock of operational robots (IFR World Robotics), employment (OECD STAN) and the country pair-wise trade cost measures (CEPII GeoDist).

Table 4. Comparison of the impact of information technologies on network trade between East Asian intraregional trade and other trade flows: OLS estimates.

Method	OLS											
Products	Parts and components				Capital goods				Consumable goods			
Trade flows	Intra-East Asian trade	East Asian exports to outside	East Asian imports from outside	Outside-East Asia trade	Intra-East Asian trade	East Asian exports to outside	East Asian imports from outside	Outside-East Asia trade	Intra-East Asian trade	East Asian exports to outside	East Asian imports from outside	Outside-East Asia trade
Dependent variable	ln(Trade)	ln(Trade)	ln(Trade)	ln(Trade)	ln(Trade)	ln(Trade)	ln(Trade)	ln(Trade)	ln(Trade)	ln(Trade)	ln(Trade)	ln(Trade)
Explanatory variables												
ln(Minimum robot density)	0.0369*	-0.0629***	0.0843***	-0.0378***	0.0433*	-0.0296	0.0583***	-0.0739***	0.0658***	-0.00567	0.0513***	-0.0266***
	(0.0211)	(0.0165)	(0.0180)	(0.0120)	(0.0254)	(0.0188)	(0.0209)	(0.0133)	(0.0170)	(0.0127)	(0.0137)	(0.00981)
ln(Distance)	-0.977***	-0.190***	-0.893***	-1.225***	-1.009***	-0.490***	-0.902***	-1.275***	-0.920***	-0.101*	-0.909***	-1.284***
	(0.0350)	(0.0689)	(0.0692)	(0.0131)	(0.0379)	(0.0712)	(0.0840)	(0.0146)	(0.0287)	(0.0611)	(0.0575)	(0.0107)
Contiguity	-0.560***	0.775***	0.819***	0.246***	-0.428***	0.128	1.483***	0.239***	-0.223***	0.380***	0.387*	0.384***
	(0.0743)	(0.140)	(0.240)	(0.0252)	(0.0736)	(0.101)	(0.243)	(0.0263)	(0.0553)	(0.0909)	(0.208)	(0.0196)
Common language	0.399***	0.437***	0.304***	0.237***	0.197***	0.568***	0.296***	0.319***	0.162***	0.478***	0.354***	0.397***
	(0.0441)	(0.0479)	(0.0468)	(0.0266)	(0.0471)	(0.0535)	(0.0503)	(0.0290)	(0.0325)	(0.0391)	(0.0378)	(0.0222)
Colony	-0.0826	-0.111	0.165***	0.988***	-0.0637	0.197**	0.0520	1.068***	0.169**	0.208***	0.377***	0.933***
	(0.0875)	(0.0713)	(0.0617)	(0.0938)	(0.111)	(0.0774)	(0.0591)	(0.106)	(0.0738)	(0.0576)	(0.0537)	(0.0697)
Origin-industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	8,557	21,166	21,326	62,042	6,353	17,289	17,265	50,243	12,498	33,682	32,245	91,474
Adjusted R-squared	0.876	0.870	0.840	0.831	0.829	0.856	0.812	0.819	0.846	0.859	0.831	0.831

Notes: See notes of Table 2. East Asia here includes 12 (out of 17) countries, due to availability of the robots and employment data. Namely, five ASEAN countries (Indonesia, Malaysia, Philippines, Singapore, and Thailand), China, Japan, Korea, Australia, New Zealand, and India.
Source: Authors' calculation using the SITC Rev. 4 bilateral trade data (UN Comtrade), combined with the data for the stock of operational robots (IFR World Robotics), employment (OECD STAN) and the country pair-wise trade cost measures (CEPII GeoDist).

Table 5. Comparison of the impact of information technologies on network trade between East Asian intraregional trade and other trade flows: PPML estimates.

Method	PPML											
Products	Parts and components				Capital goods				Consumable goods			
Trade flows	Intra-East Asian trade	East Asian exports to outside	East Asian imports from outside	Outside-East Asia trade	Intra-East Asian trade	East Asian exports to outside	East Asian imports from outside	Outside-East Asia trade	Intra-East Asian trade	East Asian exports to outside	East Asian imports from outside	Outside-East Asia trade
Dependent variable	Trade	Trade	Trade	Trade	Trade	Trade	Trade	Trade	Trade	Trade	Trade	Trade
Explanatory variables												
ln(Minimum robot density)	0.103***	-0.0303**	-0.00424	-0.190***	0.0281	-0.00758	-0.103***	-0.128***	0.131***	0.0980***	-0.0372*	0.0103
	(0.0258)	(0.0151)	(0.0322)	(0.0208)	(0.0268)	(0.0209)	(0.0193)	(0.0253)	(0.0235)	(0.0266)	(0.0216)	(0.0205)
ln(Distance)	-0.426***	-0.167*	-1.394***	-0.655***	-0.523***	-0.0379	-1.271***	-0.663***	-0.654***	-0.130	-0.307***	-0.703***
	(0.0280)	(0.0968)	(0.117)	(0.0159)	(0.0264)	(0.114)	(0.0924)	(0.0162)	(0.0208)	(0.0904)	(0.0933)	(0.0133)
Contiguity	0.299***	0.223***	0.388	0.442***	0.138**	0.486***	0.137	0.431***	-0.0188	0.555***	0.905***	0.521***
	(0.0736)	(0.0624)	(0.258)	(0.0333)	(0.0582)	(0.0638)	(0.169)	(0.0294)	(0.0523)	(0.0621)	(0.119)	(0.0247)
Common language	0.265***	0.0542	0.472***	0.281***	0.0485	-0.191***	0.0837*	0.112***	-0.0270	-0.124***	0.0238	0.0927***
	(0.0481)	(0.0540)	(0.0768)	(0.0435)	(0.0574)	(0.0475)	(0.0484)	(0.0364)	(0.0366)	(0.0428)	(0.0440)	(0.0352)
Colony	-0.334***	0.230***	0.272***	0.123	0.0386	0.0425	-0.0591	0.291**	0.126**	0.464***	0.497***	0.0131
	(0.0680)	(0.0718)	(0.0727)	(0.102)	(0.0810)	(0.0723)	(0.0801)	(0.118)	(0.0562)	(0.0470)	(0.0720)	(0.131)
Origin-industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination-industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	9,086	26,270	25,777	70,267	6,673	18,943	19,293	54,395	12,682	36,589	36,510	96,768
R-squared	0.968	0.973	0.903	0.891	0.968	0.996	0.953	0.881	0.979	0.995	0.938	0.867

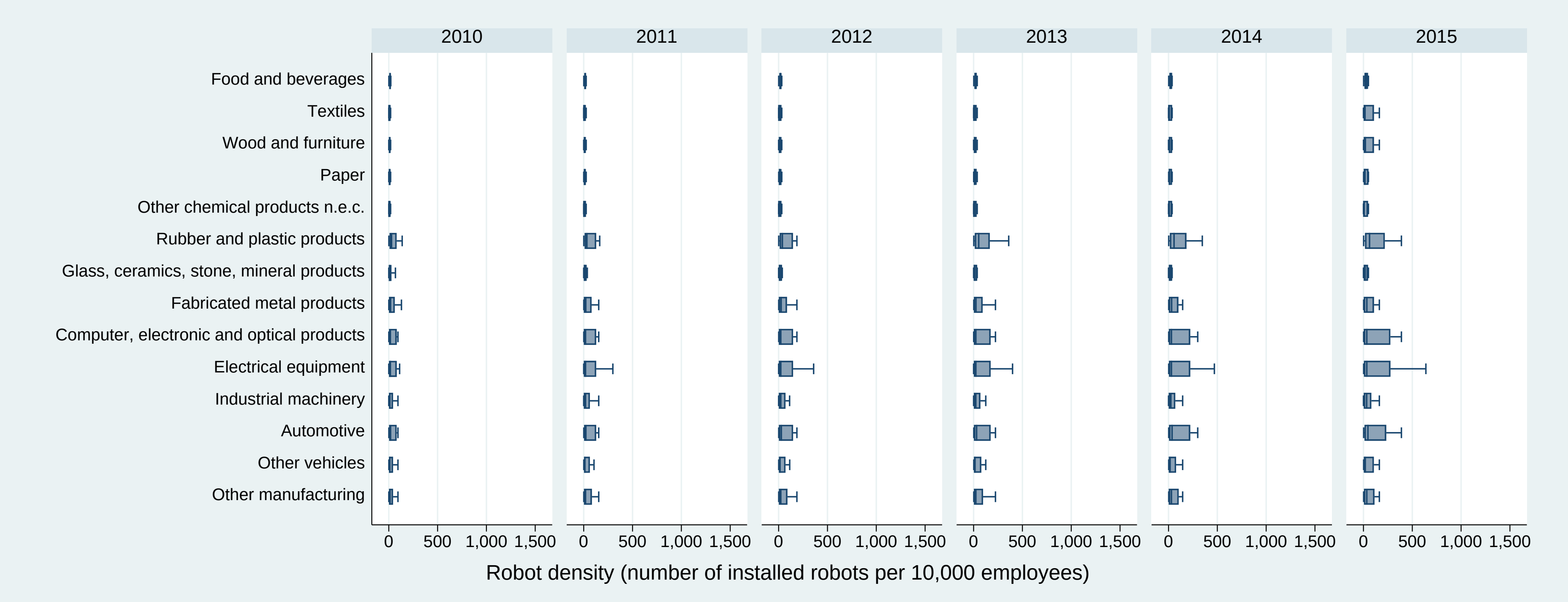
Note: See notes of Table 4.
Source: Authors' calculation using the SITC Rev. 4 bilateral trade data (UN Comtrade), combined with the data for the stock of operational robots (IFR World Robotics), employment (OECD STAN) and the country pair-wise trade cost measures (CEPII GeoDist).

Table 6. The impact of information technologies on East Asian intraregional network trade, reconsidered.

Method	OLS		PPML	
Products	Parts and components	Consumable goods	Parts and components	Consumable goods
Dependent variable	ln(Trade)	ln(Trade)	Trade	Trade
Explanatory variables				
ln(Minimum robot density)	-0.161**	0.00457	-0.0255	-0.255***
	(0.0633)	(0.0439)	(0.0629)	(0.0503)
x imported digitally deliverable services	0.523***	0.125	0.350**	1.014***
	(0.162)	(0.117)	(0.151)	(0.133)
ln(Distance)	-0.945***	-0.891***	-0.434***	-0.672***
	(0.0375)	(0.0309)	(0.0287)	(0.0218)
Contiguity	-0.548***	-0.160***	0.250***	-0.0261
	(0.0794)	(0.0592)	(0.0723)	(0.0528)
Common language	0.336***	0.123***	0.285***	-0.0357
	(0.0478)	(0.0345)	(0.0493)	(0.0395)
Colony	-0.0821	0.205***	-0.373***	0.0932
	(0.0918)	(0.0776)	(0.0697)	(0.0578)
Origin-industry-year FE	Yes	Yes	Yes	Yes
Destination-industry-year FE	Yes	Yes	Yes	Yes
Number of observations	7,739	11,303	8,216	11,466
Adjusted R-squared	0.875	0.847		
R-squared			0.970	0.983

Notes: See notes of Table 4. In addition to a set of covariates employed in Tables 3 to 5, we here include an interaction term of the (log of) minimum robot density with the imported digitally deliverable services (as a proportion to the total services imports from the world).
Source: Authors' calculation using the SITC Rev. 4 bilateral trade data and services trade data (UN Comtrade), combined with the data for the stock of operational robots (IFR World Robotics), employment (OECD STAN) and the country pair-wise trade cost measures (CEPII GeoDist).

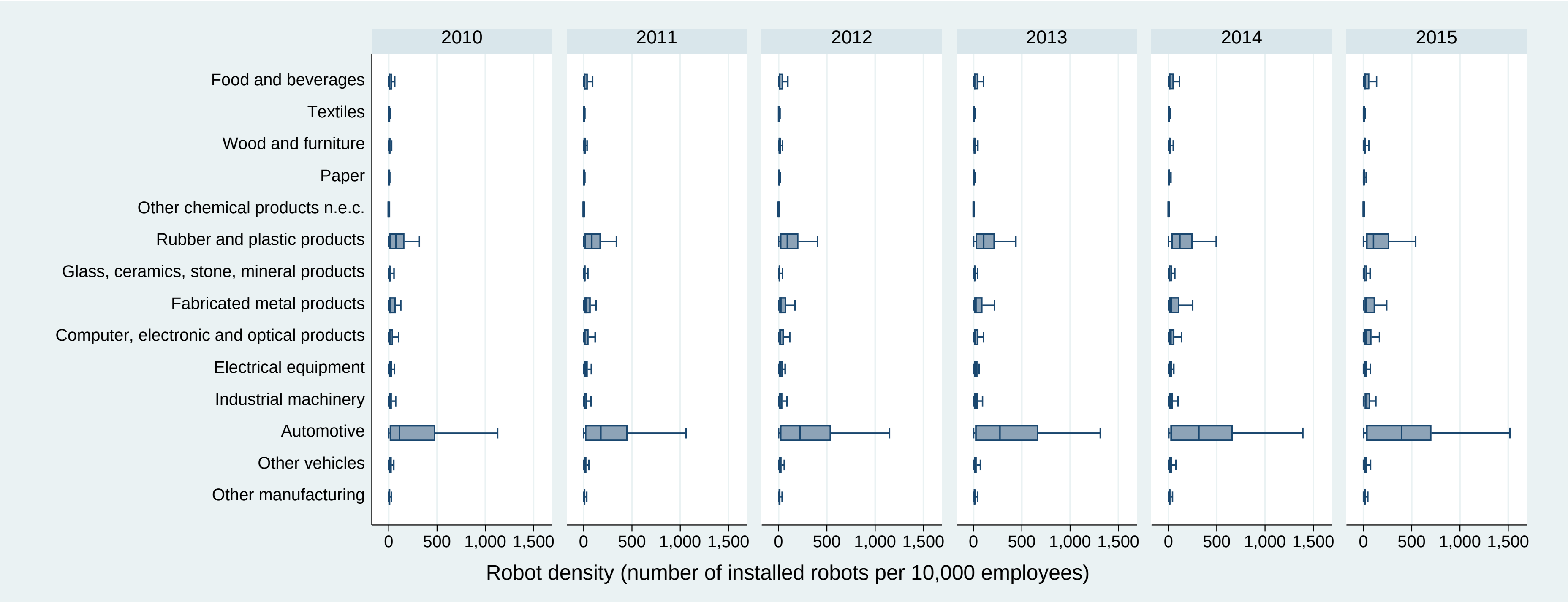
Figure 1. Robot density across industries and time: East Asian countries.



Notes: 12 (out of 17) East Asian countries are included in the above box plots. Namely, five ASEAN countries (Indonesia, Malaysia, Philippines, Singapore, and Thailand), China, Japan, Korea, Australia, New Zealand, and India. Industry categories are those employed in both the IFR World Robotics and OECD STAN database, based on ISIC Rev. 4. Outliers (beyond either whisker of each box plot) are omitted. The horizontal axis is re-scaled to be comparable with Figure 2.

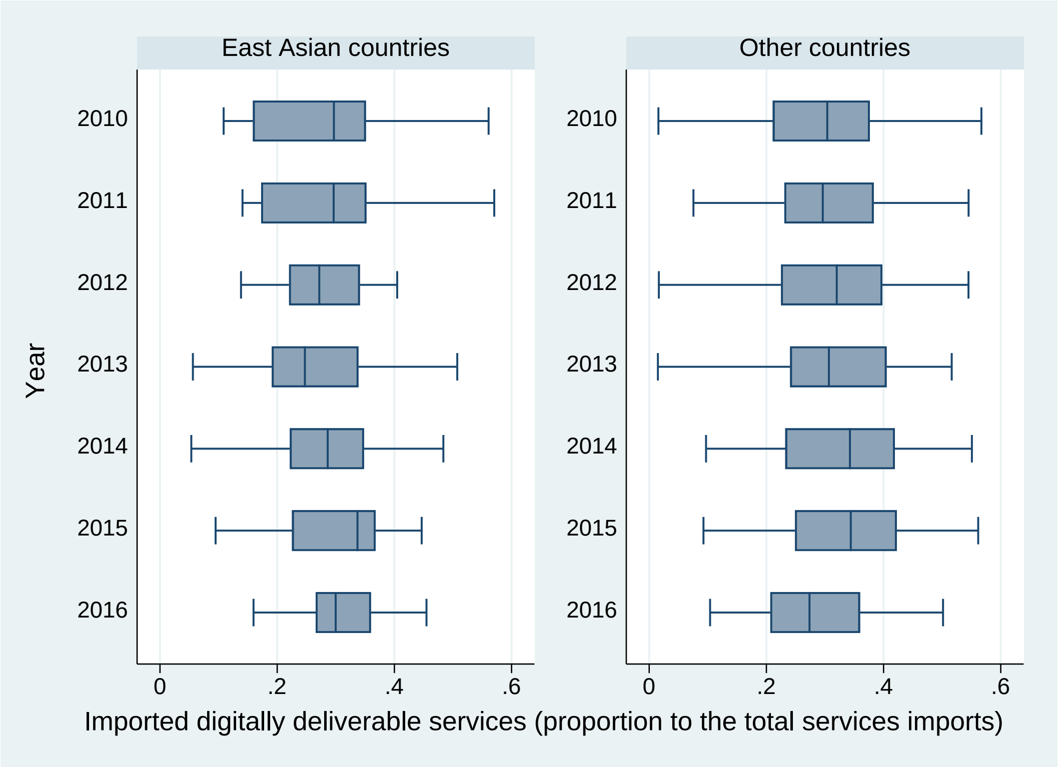
Source: Authors' calculation using the data for the stock of operational robots (IFR World Robotics) and employment (OECD STAN).

Figure 2. Robot density across industries and time: Countries outside East Asia.



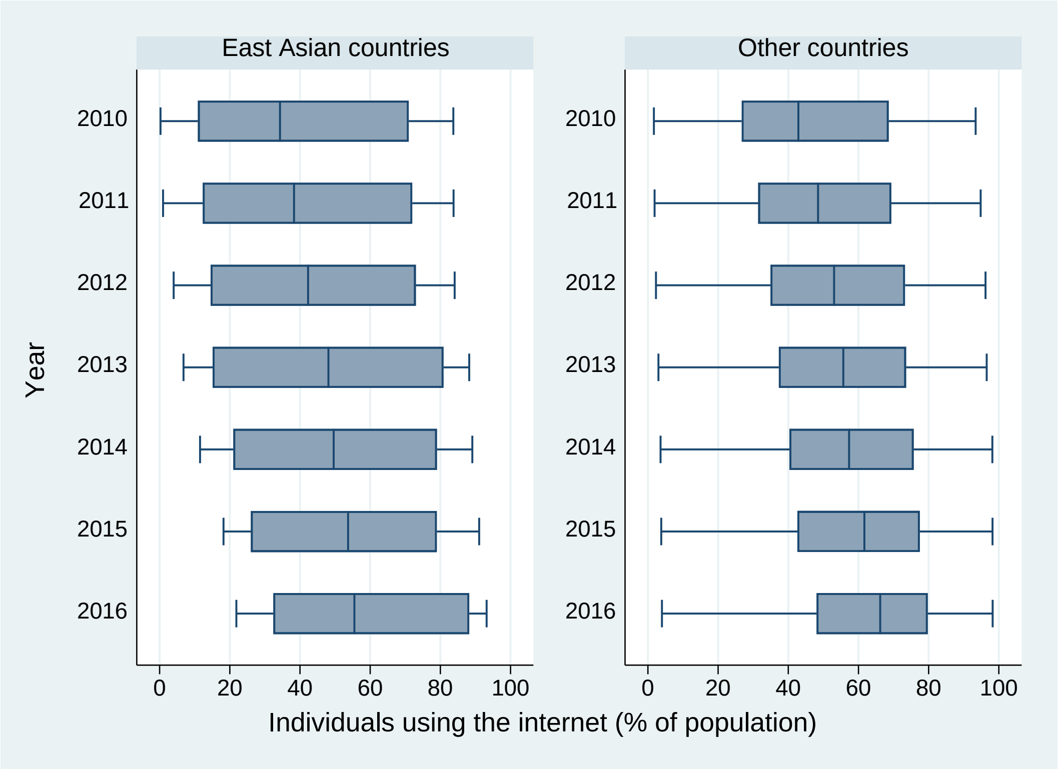
Notes: 36 (out of 80) countries are included in the above box plots. Industry categories are those employed in both the IFR World Robotics and OECD STAN database, based on ISIC Rev. 4. Outliers (beyond either whisker of each box plot) are omitted.
Source: Authors' calculation using the data for the stock of operational robots (IFR World Robotics) and employment (OECD STAN).

Figure 3. Imported digitally deliverable services across time: East Asia vs. other countries.



Notes: 16 (out of 17) East Asian countries and 77 (out of 80) other countries are included in the above box plots in 2010–2013. The sample size is slightly smaller in 2014 and 2015. For 2016, only 6 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 (UN Comtrade).

Figure 4. Individual's internet use across time: East Asia vs. other countries.



Notes: All the 17 East Asian countries and 80 other countries are included in the above box plots of respective years. Outliers (beyond either whisker of each box plot) are omitted.
Source: Authors' calculation using the individual's internet usage data (OECD.Stat; NDC (2017) for Taiwan).