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Digitalization, AI Intensity, and International Trade

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The study presents a simple model that incorporates data factors into production, demonstrating that both digitalization and artificial intelligence (AI) intensities contribute to facilitating international trade. Empirically, we find for every 1% increase in a country's AI intensity that its exports rise by 1.01% to 1.30%. Furthermore, while trade elasticity of digital intensity is around 0.85 to 2.03, the trade elasticity of AI and digital intensities combined is about 43% of the trade cost elasticity. Finally, our results suggest that AI and digitalization play an equally important role as production technology in explaining the distribution of trade flows across countries.

Key Words: Artificial Intelligence; Digital Intensity; International Trade.
JEL Classification Numbers: F12, F13.

1. INTRODUCTION

People's daily life is affected by the growing popularity of artificial intelligence (AI) and digitalization. Facial recognition allows one to log in to smart phones and computers, search information, and order products through the Internet. Businesses also collect data about customers' purchase histories. AI-enabled technology is likely to have a large influence on a country's production level and international trade flows. Given that economic activity is largely conducted on a digital basis, the world is entering a digital economy dominated by AI and information and communication technology (ICT) (e.g., van Ark, 2016).

Numerous empirical studies have examined the effects of digitalization on international trade in terms of development of the bandwidth/Internet/mobile phones. They generally used the intensity of bandwidth/internet adoption in a country as an ICT variable, referred to as digitalization (e.g., Clarke

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and Wallsten, 2006; Freund and Weinhold, 2002, 2004; Demirkan et al., 2009; Vemuri and Siddiqi, 2009; Choi, 2010; Mattes et al. (2012); Liu and Nath, 2013).[1] Among others,[2] Mattes et al. (2012) find that international trade in the EU is promoted when both trading partners have revealed advanced ICT endowments, because ICT development (i.e., digitalization) can reduce transaction costs in international trade.[3] However, few studies have focused on the impact of AI on international trade. This study is to address this gap in literature by providing a theoretical framework of AI and data and then empirically estimating the contributions of AI, in addition to production technology and digitalization, to international trade.

By leveraging AI, companies are able to embrace intelligent, efficient, and sustainable production practices, thereby bolstering their competitiveness and fostering innovation.[4] In this model, when we refer to AI, we mean the utilization of technologies such as machine learning to process big data. To accomplish this, a digital infrastructure called digitization is required for communication and raw data collection. Such non-rival raw data are processed by AI algorithms guided and programmed by humans to transform them into a usable data factor.[5] To address the role of data and AI in modern production, we first develop a model of international trade, consisting of a positive feedback loop between the output and data. In this model, on the one hand, data are substitutive to the production factor, labor, as in the traditional Cobb-Douglas production function. On the other hand, data is also a by-product of production that are complementary to firm's productivity. When a country ramps up digitalization by improving its digital infrastructure, this study contends that firms in that country tend to collect and access more raw data in their production, which are

[1]Mattes et al. (2012) use ICT Development Index as the ICT variable.

[2]Choi (2010) finds that a doubling of Internet usage in a country leads to lead to a 2∼4% rise in services trade by using data of 151 countries from 1990 to 2006. Vemuri and Siddiqi (2009) show that ICT infrastructure and the Internet availability help promote international trade in 64 countries in 1985-2005.

[3]Also see Freund and Weinhold (2002), who find that a 10% increase in the Internet abroad is associated with about a 6% increase in the level of U.S. imports and about a 4% increase in the level of U.S. exports in 1995-1999.

[4]First, through the analysis of large amounts of production data and operational metrics, AI technology can identify potential bottlenecks and efficiency issues and provide optimization recommendations. Second, AI can analyze vast amounts of market data, user feedback, and competitive information to provide valuable insights and innovative directions to product design teams. Furthermore, AI can simulate and optimize product performance, thus speeding up the development cycle and lowering costs, and detect products' quality issues in real-time, so that a firm is able to take appropriate corrective actions when anomalies occur.

[5]Through technologies like machine learning, AI can extract patterns and insights from vast amounts of data, assisting humans in making better decisions and creating greater value, particularly in production.

then transformed into more data factors for production especially when the country happens to have larger AI intensity. Thus, higher AI intensity and greater digitalization lead to higher output and more international trade.

Second, we examine the elasticity of AI and digitalization on international trade flows based on the gravity equation derived from our theoretical framework. We find that a 1% increment in a country's AI intensity increases the country's export value by 1.01% to 1.30%. The trade elasticity of digitalization is about 0.85 to 2.03, while the trade elasticity of AI and digitalization together is around 43% of the trade cost elasticity, suggesting that improvement in digital infrastructure and AI significantly affects a country's export value. Furthermore, we decompose the contributions of production technology (net out production cost), digitalization, and AI intensity to the distribution of international trade flows across countries. We find that 47% of the variation in international trade flows are explained by the differences of production technology across countries. The remaining 53% contributes to the differences in AI and digitalization across countries. Our estimated results suggest that AI and digitalization together play an equally important role as production technology in explaining the distribution of international trade flows across countries.

The rest of this paper proceeds as follows. Section 2 sets up the model. Section 3 shows the equilibrium. Section 4 explains the sources of data. Section 5 provides empirical models and results. Section 6 concludes.

2. THE MODEL

Machinery (capital) drove the automation of manual labor in the first (machinery) industrial revolution, expanding the production function from primarily consisting of labor (and farmland) to also include capital. However, in the emerging (AI) industrial revolution, data are driving the automation of knowledge work. Data are increasingly being utilized as inputs in the production process, frequently complementing traditional production factors like labor and physical capital. Thus, in the modern economy, data play a pivotal role in enhancing productivity and fostering innovation by enabling informed decision-making, optimizing operations, and improving product and service quality (e.g., McAfee and Brynjolfsson, 2012). Given the pivotal role of data in decision-making, innovation, productivity, and economic growth across various sectors, some studies in the literature thus consider data as a form of capital, often referred to as "data capital", within the production function.

For instance, Carriére-Swallow and Haksar (2019) propose that data serve a synthesizing role in the modern economy, functioning not only as a means of information transmission among economic agents, but also playing a crucial role as a production factor in the production function. In this production function with data as inputs, "data enables the creation of knowledge, which can be directed toward the ongoing production of an existing good or in the development of a new product or service. . . . Data has thus come to represent a necessary input into the development and production of a wide range of new products." (p.10). Drawing from the insights of the Romer (1990) model, Jones and Tonetti (2018) emphasize that the non-rivalry of ideas leads to increasing returns and suggest that the production of a product is a collaborative process involving high-quality ideas and labor. In their model, data is the exclusive production factor that enhances the quality of ideas, thus indirectly becoming a component of their model's production function. This is because production relies on the quality of ideas, akin to the ideas generated by researchers in the Romer model (1990).

Taking insights from the literature (e.g., Carriére-Swallow and Haksar, 2019; Farboodi and Veldkamp, 2019; McAfee and Brynjolfsson, 2012) into account, we presume that firms in each country use labor factor to produce goods, and that there will also be some specific by-products from the production, such as raw data. The raw data can be constructed by AI workers into useful data, known as the data factor in production. This mechanism that constructed data is a factor of production while raw data is a by-product of production, thus forming a positive loop between production and data.

This current model includes a manufacturing sector and a digital sector, and the manufacturing sector is in perfect competition, while the digital sector is in monopolistic competition. Each firm in country i produces a continuum of goods and independently draws its productivity from this Fréchet distribution as $F(z) = e^{-T_i z^{-\theta}}$ for $z \geq 0$, where T_i denotes country i's total stocks of technologies (e.g., Eaton and Kortum, 2001, 2002). Suppose further that country has an exogenously given labor force L_i, and $i \in [1, N]$. Here labor is a factor of production for a continuum of goods $\mu \in [0, 1]$. Thus, the production function in the manufacturing sector is given as

$$x_i(\mu) = z(\mu) l_{im}(\mu)^{1-\phi} d_i(\mu)^{\phi}, \quad 1 > \phi \geq 0, \tag{1}$$

where $l_{im}(\mu)$ represents manufacturing workers employed by firm μ in producing goods while $d_i(\mu)$ denotes a measure of data generated and used by firm μ in country i.[6]

When manufacturing workers produce products, they also generate relevant by-products, namely, raw data. Reasonably, the amount of raw data in a country positively relates to the amount of a country's output, which

[6]Some studies in literature perceive data as a production factor (e.g., Varian, 2018; Wagner, 2020).

also positively relates to a its digital infrastructure development. The better a country's digital infrastructure is developed, the more efficient the data collection and management processes become. However, it still requires digital workers to transform relevant data into a structured and useful dataset that acts as a key factor for production.

While the development of AI algorithms can be regarded as a fixed cost, the annotation and labeling tasks serve as variable costs in data processing. These digital workers are responsible for annotating, labeling, and transforming vast amounts of raw data into usable information, often referred to as the data factor, which can then be fed into specialized AI algorithms. It is widely recognized that automation and artificial intelligence often require higher skill levels compared to many manufacturing activities. However, in reality, the majority of AI-related jobs are low-skilled yet experience exponential growth. For example, OpenAI, an AI company, employs over 50,000 data annotators in Kenya to label data for training ChatGPT, one of the most powerful AI chatbots developed by OpenAI. In contrast, OpenAI has an in-house team of 375 AI experts. It is important to note that these outsourced data annotators, who perform low-skilled tasks, receive an hourly wage of approximately \$1.32 to \$2 (Perrigo, 2023). Another example is China, where it is estimated that there are more than 10 million people currently engaged in data labeling, but the number of AI talents in the country is only around 50,000 (Qiao and Lu, 2019). Similar to assembly lines in the manufacturing sector, data annotation jobs can be considered the cognitive equivalent of an assembly line in the AI era (e.g., Croce and Musa, 2019). Therefore, for the sake of simplicity, we simplify the labor classification to one type.

We argue that the variable costs are positively related to the digital infrastructure of a country, as such digital infrastructure serves as a conduit for data. Thus, the labor requirement for the data (factor) generation of firm μ in country i is:

$$l_i(\mu) = f_i + \frac{d_i(\mu)}{\varphi_i}, \quad \forall i, \mu, \tag{2}$$

where f_i is the fixed cost that represents country i's endowment of AI talents engaged in developing AI algorithms, and φ_i is variable cost of data processing for firm μ in country i, $\forall \mu$. Here, the data digitization rate φ_i increases with the investment into AI algorithms, which we will explain in detail below.

2.1. Equilibrium

In the digital sector, with equation (2), the profit function for firm μ in the digital sector is as $\pi_d(\mu) = c_{id}(\mu)d_i(\mu) - w_i(f_i + \frac{d_i(\mu)}{\varphi_i})$, where w_i is wage and $c_{id}(\mu)$ represents the unit price of processed data for firm μ in country

i. Alternatively, we may assume that firms can employ a third-party, such as AI marketplaces or cloud computing giants (e.g., Amazon, Alibaba, etc.), and pay for the data utilization costs.[7] The profit maximization of the digital service is given by $\max_{d_i(\mu),f_i} \pi_d(\mu),\ \forall\mu$. Taking the first order condition of the profit maximization with respect to $d_i(\mu)$, we obtain an optimal unit price of obtaining the data factor in country i:

$$c_{id} = \frac{1}{1-\varepsilon_a^{-1}}\frac{w_i}{\varphi_i}, \quad \forall\mu, \tag{3}$$

where $\varepsilon_a > 1$ is an elasticity of demand for the constructed data.

Taking the first-order condition of the profit maximization above with respect to f_i, we obtain an optimal investment in AI algorithms as f_i^* that satisfies an equilibrium $\varphi_i(f_i^*) = (\xi + f_i^*/d_i^*)^{-1}$,[8] where ξ is an arbitrary constant. Here, $d_i^*(\mu) = (\varepsilon_a - 1)f_i^*$ is the optimal amount of constructed data in long-run equilibrium. As a result, full investment in AI leads to an optimal data digitization rate $\varphi_i(f_i^*) = (\xi+(\varepsilon_a-1)^{-1})^{-1}$. However, in real practice, on account of factors such as a shortage of talent in AI algorithms and other limitations, not all countries can invest sufficient resources into AI. That is, in this model of one wage, we simplistically presume that the supply of AI algorithms workers in each country is inelastic, such that $f_i \leq f_i^*,\ \forall i$. It stands to reason that the closer a country's AI resources are to its optimal level of AI, the higher the data digitization rate of enterprises in that country will be. Thus, AI-intensive countries tend to process data more efficiently as $\varphi'(r_{ia}) > 0$ and $\frac{d\ln\varphi(r_{ia})}{d\ln r_{ia}} = 1$, where $r_{ia} = f_i/L_i$ denotes a country's AI intensity whereby it allocates such a proportion of workers to develop AI algorithms and $r_{ia} \leq r_{ia}^* = f_i^*/L_i$.[9]

As argued above, a country's digital infrastructure plays a significant role in facilitating the efficient processes of data collection and management. The efficiency of a country's data pipelines is directly proportional to its per capita digital infrastructure, which enables firms in that country to access and manage a greater amount of data by-products from their production processes. Therefore, it is reasonable to assume that a country's data digitization rate is influenced not only by the availability of its AI algorithm talent but also by the level of digital infrastructure it possesses. Thus, we

[7]In fact, some academics have provided algorithms for free (Varian, 2018).

[8]Plugging the solution in equation (3) into the profit maximization function, we obtain $\max_{f_i} w_i(\frac{1}{\varepsilon_a-1}\frac{d_i(\mu)}{\varphi_i(f_i)} - f_i)$. Taking the first order condition of it with respect to f_i, we obtain a general solution as $\varphi_i(f_i) = (\xi + f_i/d_i)^{-1}$, where xi is an arbitrary constant.

[9]As implied in equations (2) and (3), we have $r_{ia} \equiv f_i/L_i = (f_i/d_i)(d_i/L_i) = (f_i/d_i)\phi(1-\varepsilon_a^{-1})\varphi_i$, suggesting that $f_i/d_i = r_{ia}[\phi(1-\varepsilon_a^{-1})\varphi_i]^{-1}$. Plugging this relation into $\varphi_i = \varphi(f_i) = (\xi - f_i/d_i)^{-1}$, we obtain $\varphi_i = \xi^{-1}\phi^{-1}(1-\varepsilon_a^{-1})^{-1}r_{ia}$, which implies that $\varphi'(r_{ia}) > 0$ and $\frac{d\ln\varphi(r_{ia})}{d\ln r_{ia}} = 1,\ \forall f_i \leq f_i^*$.

argue that $\varphi_i'(k_i) > 0$, where $k_i = K_i/L_i$ is defined as country i's digital intensity and K_i as digital infrastructure processed by country i.

2.2. Digital Intensity and AI intensity

The above analysis, as implied in equation (3), suggests a markup in AI data processing that increases with both AI intensity and digital intensity as $m_i(r_{ia}, k_i) = \xi r_{ia}^{-\gamma} k_i^{-(1-\gamma)}$,[10] where we assign an arbitrary parameter $1 > \gamma > 0$ to represent the share of AI workers' contribution to the markup and $\xi = \gamma^{-\gamma}(1-\gamma)^{-(1-\gamma)}$. Thus, equation (3) can be rewritten as

$$c_{id} = \xi r_{ia}^{-\gamma} k_i^{-(1-\gamma)} w_i, \quad \forall i, \mu. \tag{4}$$

In general, ceteris paribus, firms in countries with higher digital intensity tend to access and manage more raw data due to the greater efficiency of their data pipelines. Additionally, a country's AI intensity is crucial in improving the accuracy and efficiency of analyzing and structuring data from raw data. While higher digital infrastructure intensity in a country assists firms in accessing more raw data, higher AI intensity in a country significantly improves the efficiency and accuracy of analyzing, structuring, and transforming raw data into useful data. Therefore, both digital intensity and AI intensity contribute to a lower cost of data processing, as equation (4) indicates.

3. THE GRAVITY MODEL

Assume there exists an iceberg type transportation cost of goods across borders as $\tau_{in} \geq 1$ and $\tau_{ii} = 1, \forall i, n$. In equations (1) and (4), the unit price of output x_{in} in country n imported from country i is:

$$p_{in}(\mu) = \frac{\lambda (r_i a)^{-\gamma} k_i^{-(1-\gamma)^{\phi}} w_i \tau_{in}}{z(\mu)}, \tag{5}$$

where $\lambda \equiv [\phi^{\phi}(1-\phi)^{1-\phi}\xi]^{\phi}$ is a constant. Given a constant elasticity substitution utility function, the exact price index in country n is $p_n = \left[\int_0^1 p_{in(\mu)^{1-\sigma}} d\mu\right]^{\frac{1}{1-\sigma}}$. The price index in country n becomes $p_n = \Upsilon \Phi_n^{-\theta^{-1}}$, where $\Upsilon \equiv \left[\Gamma(1 + \frac{1-\sigma}{\theta})\right]^{(1-\theta)^{-1}}$ and Γ is a Gamma function. We get $\Phi_n = \sum_{i=1}^{N} T_i[\lambda(r_{ia}^{-\gamma} k_i^{-(1-\gamma)})^{\phi} w_i \tau_{in}]^{-\theta}$. Equation (5) implies that the application of AI and data help reduce the overall production cost.[11] This

[10] As implied in equation (3), we have $m_i(r_{ia}, k_i) = \frac{1}{1-\varepsilon_a^{-1}} \frac{w_i}{\varphi(r_{ia}, k_i)}$. Given $\varphi'(r_{ia}) > 0$ and $\varphi'(k_i) > 0$, it is easy to obtain $m_i'(r_{ia}) < 0$ and $m_i'(k_i) < 0$, respectively.

[11] A vast amount of literature has already documented that the adoption of digital technologies, such as AI algorithms, help improve firm productivity (e.g., Draca et al.,

could be reflected in real-world practices such as shorter production cycles, decreased inventory, lower defect rates, and reduced energy consumption (e.g., Osnago and Tan, 2016; Freund and Weinhold, 2002; Clarke and Wallsten, 2006; Liu and Nath, 2013; and Xing, 2018).

Let country i's total exports to country n be denoted by x_{in}. The total output in country i is then $Y_i = \sum_{n=1}^{N} X_{in}$. Country n would buy a particular good from country i only when country i is the cheapest source. This probability is determined by country i's contribution to country n's price parameter Φ_n. The share of country i's total exports to country n then becomes

$$X_{in} = \frac{T_i[\lambda(r_{ia}^{-\gamma} k_i^{-(1-\gamma)})^{\phi} w_i \tau_{in}]^{-\theta}}{\Phi_n} Y_n.[12] \tag{6}$$

Equation (6) implies a trade elasticity with respect to trade cost as $\varepsilon_\tau \equiv -\frac{d\ln X_{in}}{d\ln \tau_{in}} = \theta$. It also implies a trade elasticity with respect to digital intensity, namely, digitalization, as $\varepsilon_k \equiv \frac{d\ln X_{in}}{d\ln k_i} = (1-\gamma)\phi\theta$ and a trade elasticity with respect to AI intensity as $\varepsilon_a \equiv \frac{d\ln X_{in}}{d\ln r_{ia}} = \gamma\theta\phi$ for all countries.

In contrast to other studies, this paper suggests that both digitalization and AI help a country improve its firms' effective productivity and subsequently enable them to undertake more output and international trade as well. It is worth verifying these hypotheses by empirically examining whether the parameters (ϕ, γ) in (6) are significantly greater than zero, and it is also worth estimating the size of these parameters. The estimated size of these parameters will help clarify the role of digitalization and AI in production, especially their contribution to international trade.

Following the model of Eaton and Kortum (2001, 2002), in which all tradable activities are confined to the manufacturing sector and the utility function of consumers is based on the continuum of manufacturing goods, this model also does not take service goods into account. Indeed, trade in services has been growing in importance and has become a significant share of international trade, especially in financial, legal, consulting, marketing, distribution, and telecommunications sectors.[13] However, it is important to note that despite the increasing share of trade in services in international trade, especially with the significant improvement in cross-border tradability through the utilization of AI technologies, not all services are easily tradable. Moreover, many business services primarily function as in-

2009; Syverson, 2011; Gal et al., 2019; Grimes et al., 2011; Czernich et al., 2011; and Grimes et al., 2011). Here, we presume that AI indirectly improves firm productivity through its capability of transforming raw data into the data factor.

[12]The derivation is similar to that of Eaton and Kortum (2002).

[13]According to the World Trade Organization (WTO), trade in services accounted for around 24% of global trade in 2020.

termediary facilities, providing production support to manufacturing goods rather than directly targeting end consumers (e.g., Lo and Yang, 2020).

In the context above, AI has enhanced the role of these services in providing production support for manufacturing goods. Therefore, for the sake of simplification, in this model we attribute all intangible factors, including data and business services, to the digital sector, even though business services are not explicitly included in this simplified model. Overall, we assume that these intangible factors, enhanced by AI, primarily serve as intermediating facilities for manufacturing firms, providing production support rather than being directly consumed.

4. DATA

For our analyses we employ the country-level trade flows data from the CEPII database. This dataset includes traditional gravity variables such as distance between the sourcing and destination countries, some dummy variables indicating whether the sourcing and destination countries have common languages, common religion, and whether both have joined the World Trade Organization (WTO).

We use country-level measures of digitalization from the World Bank database. Digital intensity (k_{it}) is measured by the proportion of individuals using the Internet over the population of a country.[14] Countries with a high fraction of population using the Internet reflect high internet usage and thus a high degree of digitalization. In addition to Internet usage, we adopt some alternative measures for digital intensity, such as mobile phone subscriptions (per 100 people) and fixed broadband subscriptions. High mobile phone and fixed broadband subscriptions reflect easy access to the Internet.

The data on AI intensity are collected from the OECD AI Policy Observatory (OECD.AI), which collects scientific publications related to AI which is identified by the Microsoft Academic Graph (MAG) and reports the number of AI publications for each country. The MAG uses a sematic search engine to classify scientific publications into different fields of study. The OECD.AI collects papers detected in the fields classified as either “artificial intelligence” or “machine learning” in the MAG taxonomy. Then the OECD.AI assigned each AI-related papers to the relevant countries based on the authors’ institutional affiliations. However, each paper may have multiple authors who belong to different institutions. To avoid the double-counting problem, the OECD.AI splits one publication equally among each author. Ideally, a country that is endowed with a large amount

[14]Data of individuals using the Internet (% of population) comes from the World Bank.

of AI-related publications is likely to have good fundamentals in developing AI-related technology.[15] However, large countries may have a greater number of AI publications. To control for country size, we calculate the number of AI publications per capita as the measure of a country's AI intensity.

TABLE 1.

Average Digitalization, AI Intensity, and R&D/GDP, by Export Value

Exporter Group	1	2	3	4
Fraction of Individuals Using the Internet over Population(%)	23.5	30.3	34.1	37.08
ln(**Mobile phone subscriptions**)	2.99	3.12	3.24	3.36
ln(**Fixed broadband subscriptions**)	0.48	0.89	1.24	1.69
AI Intensity(%)	5.38	7.06	9.73	11.35
R&D/GDP	0.69	0.99	1.2	1.42

Table 1 reports the distribution of digital intensity, AI intensity, and the ratio of R&D expenditures to GDP across countries with different export values. We first rank countries by their export values. Countries with an export value below the 25^{th} percentile are classified as Group 1; those between the 25^{th} and 50^{th} percentiles are Group 2; those above the 25^{th} percentile but below the 75^{th} percentile are Group 3; and those above the 75th percentile are classified as Group 4.

Table 1 indicates that countries with high export values tend to have high digital and AI intensities, as well as a high R&D intensity. The implication is that both production technology and degree of digitalization as well as AI are important determinants of a country's success in the export market. In the following empirical section, we identify the contributions of AI, production technology and digitalization to international trade.

5. EMPIRICAL MODELS AND RESULTS

5.1. Gravity Equation

Following Eaton and Kortum (2002), we use the two-step approach to estimate the key parameters in the model (θ, ϕ, γ) and construct the productivity index for each exporting country (T_i). From equation (6), we can

[15] Several institutions use AI-related publications as the measure of a country's AI development, such as the China Institute for Science and Technology Policy and Stanford University (Baruffaldi et al., 2020).

calculate the import share from country i to country n:

$$\frac{X_{int}}{Y_{ni}} = \frac{T_{it}[\lambda(r_{iat}^{-\gamma}k_{it}^{-(1-\gamma)})^{\phi}w_{it}\tau_{int}]^{-\theta}}{\Phi_{nt}}. \tag{7}$$

Taking the log of equation (7), the import share equation becomes

$$\ln\left[\frac{X_{int}}{Y_{nt}}\right] = \ln T_{it} - \theta \ln w_{it} + \theta\phi(1-\gamma)\ln k_{it} + \theta\phi\gamma \ln r_{iat} - \theta \ln \tau_{int} - \ln \Phi_{nt}. \tag{8}$$

Let's denote $C_{it} = \ln T_{it} - \theta \ln w_{it} + \theta\phi(1-\gamma)\ln k_{it} + \theta\phi\gamma \ln r_{iat}$ as an exporting capability for country i is in equation (8). Countries with a high exporting capability are likely to have a high export value in the international market. A high exporting capability may result from various factors such as high production technology (T_i), low production cost (w_i), high digital intensity (k_i), or high AI intensity (r_{ia}). In the first stage, as it is similar to the gravity equation in the literature, we estimate equation (8) to get the measures of the exporting capability (C_{it}). In the second stage, we estimate the parameters (θ, ϕ, γ) and recover the country's technology measure, T_i.

We thus use a set of country-year dummy variables to capture the exporting capability equation (θ, ϕ, γ). Equation (8) can be written as:

$$\ln\left(\frac{X_{int}}{Y_{nt}}\right) = C_{it} - \theta \ln \tau_{int} - \ln \Phi_{nt}, \tag{9}$$

where X_{int} is the import value of country n from country i in year t, Y_{nt} is GDP of country n in year t, and τ_{int} is the international trade costs between countries I and n that are usually adopted in the gravity model. The international trade costs include a set of variables such as distance between exporting and importing countries, an indicator variable representing whether countries i and n use the same official language, and so on. Φ_{nt} can be viewed as a kind of multilateral resistance term where country n has a high Φ_{nt} if there are many sourcing countries i in the proximity. Following Baldwin and Harrigan (2011), we use the sourcing country's GDP weighted by the inverse of distance of the sourcing country to the destination country as the measurement of $\ln \Phi_{nt} \equiv \sum_{i \in \Omega_{nt}}^{N} \ln\left(\frac{GDP_{it}}{dist_{in}}\right)$, where Φ_{nt} is the set of sourcing countries that exports to country n in year t in a world of N countries, GDP_{it} is GDP of sourcing country i, and $dist_{in}$ is the distance between sourcing country i and destination country n.

Table 2 reports the estimation result of equation (9). The negative coefficient of distance indicates that a country imports less from distant countries. Countries are likely to import more from countries having the same

TABLE 2.

Estimation Results for the Gravity Equation

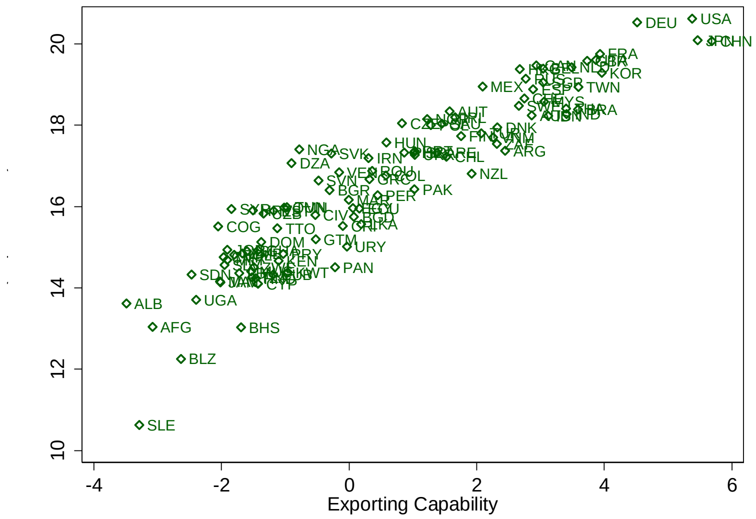
	ln(**Import Share**)
ln(**Distance**)	-1.2757^{***}
	(0.003)
Common Language	0.5774^{***}
	(0.008)
Common Religion	0.2116^{***}
	(0.011)
WTO	0.3164^{***}
	(0.009)
Sibling	0.4784^{***}
	(0.012)
Colonies Relationship	0.8704^{***}
	(0.021)
$\ln(\Omega_{nt})$	-0.0829^{***}
	(0.005)
Constant	2.7033^{***}
	(0.089)
Exporter-Year FE	Yes
Observations	497,636
R-squared	0.676

Note: Standard errors are in parentheses *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

language and religion as the importing countries. The positive coefficient of WTO indicates that the international trade value is high between countries that have both joined the WTO. Countries with sibling or colony relationships also tend to have higher international trade volumes between them. All these results are consistent with the findings in the gravity literature. Finally, the negative coefficients of the multilateral resistance term suggest that importers with numerous sourcing opportunities from neighboring countries tend to have a low import share from any specific country.

Figure 1 depicts a scatter plot showing the relationship between the total export value and a country's exporting capacity. The positive correlation between the exporting capability and export value indicates that countries with a high exporting capability tend to have a high export value. The top four countries with the highest exporting capability are China (CHN), Japan (JPN), the U.S. (USA), and Germany (DEU). These four countries also have the highest export value, but the determinants of good performance in export markets may differ across the four countries. Countries

FIG. 1. Export Value and Exporting Capability



with high technology, high digitalization, or low wage have a high export capability and a high export value as well.

FIG. 2. Wage and Exporting Capability

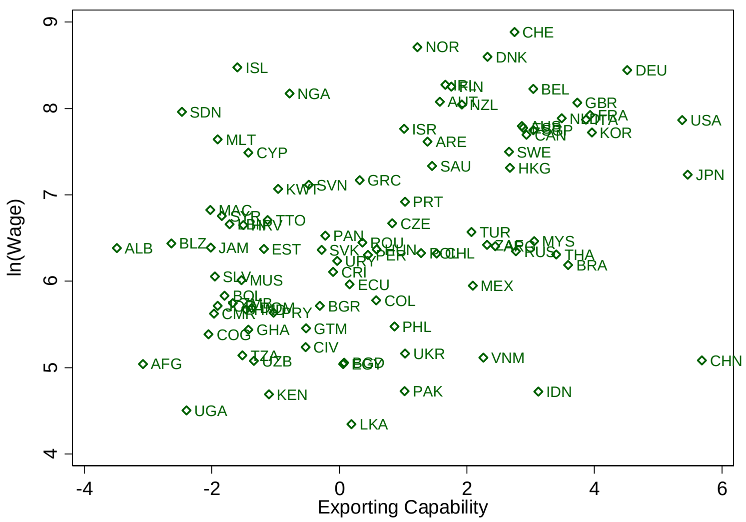


FIG. 3. R&D Expenditure over GDP and Exporting Capability

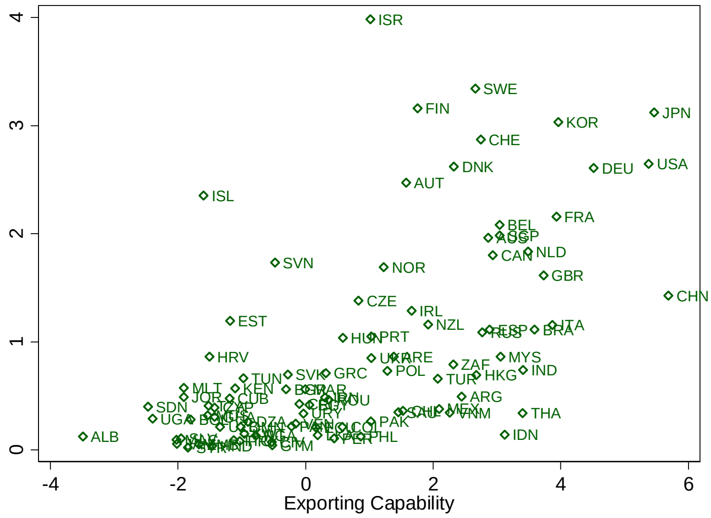
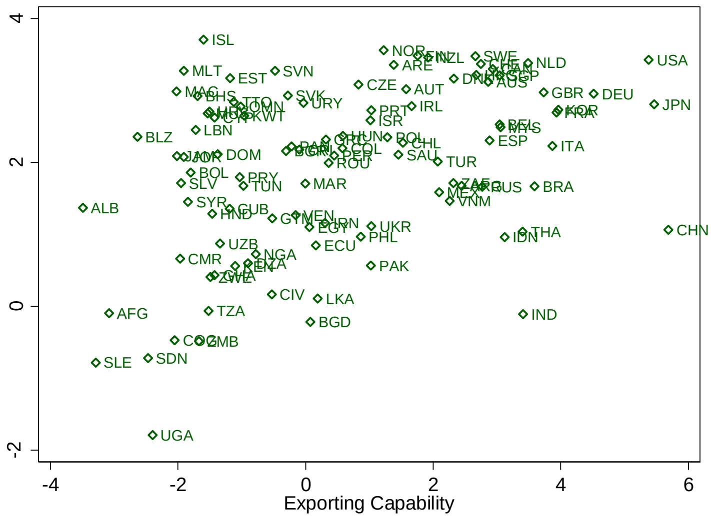


FIG. 4. Individual Internet Usage Intensity and Exporting Capability



Figures 2 and 3 report the scatter relationships between a country's exporting capability and its wage as well as the share of R&D expenditure over GDP (R&D intensity). Among the top four countries with the highest exporting capability, China has a relatively low R&D intensity and a low wage. In contrast, Japan, the U.S., and Germany have a high R&D intensity and a high wage. Figure 4 reports the scatter plot of the exporting capability and the intensity of digitalization. However, compared to Japan, the U.S., and Germany, China has a relatively low intensity of digitalization. These findings suggest that a high exporting capability is likely to result from a low production cost (wage), as in China. In comparison, the high exporting capability is likely to result from high production technology and high digitalization as in Japan, the U.S., and Germany. In the next section, we will decompose the contributions of technology, production costs (wage), and digitalization from the exporting capability.

5.2. Technology, Digitalization, and Cost

In the second stage, with equation (7), we estimate the parameters (θ, ϕ, γ) through the following regression model:

$$C_{it} = \alpha Z_{it} - \theta \ln w_{it} + \theta\phi(1-\gamma)\ln k_{it} + \theta\phi\gamma \ln r_{iat} + y_t + \varepsilon_{it}, \qquad (10)$$

where Z_{it} includes some variables that capture country i's production technology, such as the ratio of a country's R&D expenditures over its GDP (R&D/GDP), the number of patents that a country has (ln(Patents)), and a human capital index ($Humcap_{it}$). Recall that k_{it} is the digital intensity of country i in year t, which is measured by the intensity of Internet or mobile phone subscriptions by individuals in country i, and r_{iat} is country i's AI intensity, as described in Section 4. We also include a set of year dummy variables, y_t, to capture global shocks on exporting capability.

Some unobserved production technological shocks correlated with the country-level wage ($\ln w_{it}$). For example, countries with high production technology are endowed with high-quality workers and, thus, high wages. We control for the human capital index to capture the quality of labor and use the labor supply-side variables (population, labor force, and unemployment rate) as instrumental variables for $\ln w_{it}$.

Table 3 reports the estimation results. The first column excludes the measure of digitalization and AI intensity. The coefficients on wage (θ) are around 2, which is lower than the estimated $\theta = 3.6$ in the study by Eaton and Kortum (2002). A low θ represents a high variation of productivity. Considering that Eaton and Kortum (2002) focus on developed countries, we include both developed and developing countries. Therefore, it might be feasible to argue that a relatively low observed in this study is because the comparable advantage competition is stronger across developed and developing countries than that among developed countries.[16]

[16]Antras et al. (2017) use firm-level data to estimate the productivity dispersion parameter (θ) and obtain $\theta = 1.789$. They indicate that productivity dispersion is higher across firms than across countries, and thus they obtain a low θ.

TABLE 3.

Estimation Results of Exporting Capability

	(1)	(2)	(3)	(4)
θ	2.0024***	4.3713***	6.0242***	6.7243***
	(0.423)	(1.742)	(2.885)	(2.588)
ϕ		0.4248***	0.5575***	0.3367***
		(0.061)	(0.075)	(0.033)
γ		0.5431***	0.3962***	0.5730***
		(0.121)	(0.076)	(0.076)
R&D expenditure/GDP	0.0471	0.8838**	0.8739**	0.9726**
	(0.239)	(0.304)	(0.399)	(0.444)
ln(Patents)	0.8200***	0.7440***	0.7510***	0.6669***
	(0.031)	(0.051)	(0.067)	(0.084)
Human Capital Index	0.1948***	0.1445*	0.2508	0.2481***
	(0.048)	(0.086)	(0.155)	(0.128)
Year FE	yes	Yes	yes	yes
Observations	826	732	732	732
Implied trade elasticity with respect to				
D(phi*theta*(1-gamma)		0.85	2.03	0.97
AI(phi*theta*gamma)		1.01	1.33	1.30

Note: Robust standard errors are in parentheses, *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. The measure of digitalization in column (2) is the fraction of individuals who use the Internets. Columns (3) and (4) use mobile phone and fixed broadband subscriptions as the measure of digitalization, respectively.

Columns (2)-(4) report the estimation results based on our model with different measures of digital intensity. The second column reports the estimation results when employing the proportion of individuals using the Internet as the measure of digitalization. The estimate of θ is 4.37 in this case which is larger than the estimated θ in column (1). It indicates that ignoring the effects of digitalization and AI on international trade overstates the contribution of differences in productivity to the trade volumes across countries.

We report the estimated trade elasticity with respect to digital intensity ($\varepsilon_k \equiv \frac{d\ln X_{in}}{d\ln k_i} = \phi\theta(1-\gamma)$) and trade elasticity with respect to AI intensity ($\varepsilon_a \equiv \frac{d\ln X_{in}}{d\ln r_{ia}} = \theta\phi\gamma$) at the bottom of Table 3. Trade elasticity with respect to digital intensity (ε_k) is 0.85, and elasticity with respect to AI intensity (ε_a) is 1.01. Overall, the trade elasticity of digitalization and AI is 1.86 $(0.85 + 1.01)$, which is nearly 43% of the effects of a reduction in trade costs on the international trade volumes ($\theta = 4.37$).[17] This suggests that improvements in digitalization and AI significantly improve a country's exports. Finally, countries with a high R&D ratio over GDP, a large number of patents, and a high human capital index are likely to have a high exporting capability.

TABLE 4.

Correlation Matrix among Technology Indices

	$\ln T1$	$\ln T2$	$\ln T3$
$\ln T1$ (Individuals using the Internet)	1		
$\ln T2$ (Mobile phone)	0.9951	1	
$\ln T3$ (Fixed broadband)	0.9861	0.9911	1

Columns (3)-(4) report the estimation results when using mobile phone subscriptions and fixed broadband subscriptions as a measure of digital intensity, respectively. The estimation results do not present a significant change versus those in column (2). Generally, the estimated θ ranges from 4.37 to 6.72, which does not vary much across different measures of the digitalization. The impacts of the digitalization ($\varepsilon_k + \varepsilon_a$) on trade ranges from 1.86 to 3.36, where mobile phone subscriptions have the largest impact on international trade compared with other measures of digitalization. This may reflect that people are more likely to use the Internet through their smart phones rather than computers in the recent years. Finally, we construct the productivity index ($\ln T_{it}$) from equation (9):

$$\ln T_{it} = C_{it} + \hat{\theta} \ln w_{it} - \hat{\theta}\hat{\phi}(1 - \hat{\gamma}) \ln k_{it} + \hat{\theta}\hat{\phi}\hat{\gamma} \ln r_{iat}. \tag{11}$$

Table 4 shows the correlation matrix among the country-level technology indices constructed from different specifications. The high correlations (0.99) among the technology indices ($\ln T_{it}$) suggest that our measures of country production technology are independent of the measures of digitalization.

Table 5 reports the top five countries with the highest production technology index ($\ln T_{it}$) and the bottom five countries with the lowest technology index.[18] Germany, Switzerland, the U.S., France and the U.K. have the best production technology in the world. Countries with the worst production technology are Malawi, Ethiopia Ghana, Sri Lanka, and Pakistan. On average, the production technology index of the tech-frontier countries is 2.2 times higher than the technology index of the bottom five.

[17]Freund and Weinhold (2004) find that a 10% increase in the growth of web hosts leads to a 0.2% increase in export growth.

[18]We only report the production technology index of the specification using mobile phone subscriptions as the measure of digitalization scale, because $\ln T_{it}$ is highly correlated across specifications.

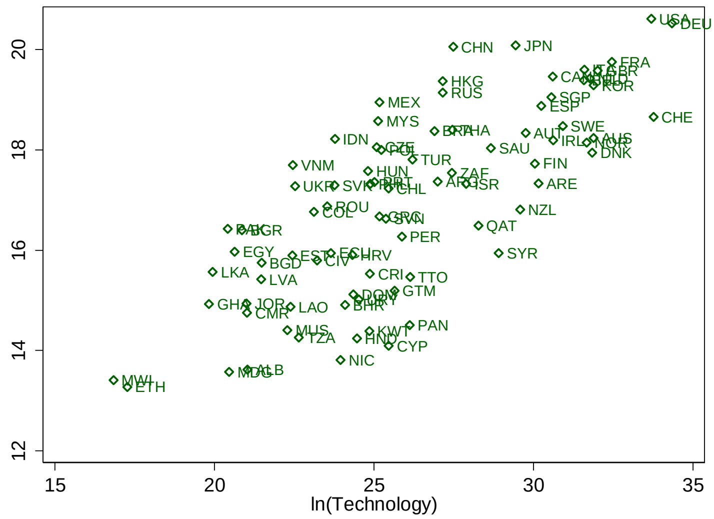
TABLE 5.

Production Technology Index, Top and Bottom Five Countries

Top Five Countries				Bottom Five Countries			
Rank	Country code	Country	$\ln T$	Rank	Country code	Country	$\ln T$
1	DEU	Germany	34.35	1	MWI	Malawi	16.84
2	CHE	Switzerland	33.77	2	ETH	Ethiopia	17.27
3	USA	U.S.	33.70	3	GHA	Ghana	19.83
4	FRA	France	32.46	4	LKA	Sri Lanka	19.95
5	GBR	U.K.	32.02	5	PAK	Pakistan	20.41

Figure 5 shows the production technology index and the export value of each country. Generally, countries with a high production technology index tend to have high export values. For example, the U.S. and Germany have high production technology indices and export values. However, some countries, for example, China, have a high export value, but a middle-level technology index. We argue that China's success in the export market is largely an outcome of its low production costs.

FIG. 5. Country Technology and Export Value



5.3. Decomposition of Exporting Capability

Eaton and Kortum (2002) demonstrate that an exporting country's comparative advantage lies in both high production technology and low wages. By incorporating AI intensity and the degree of digitalization into the production function, we find that both AI intensity and digitalization play crucial roles in explaining international trade flows between countries. Thus, both AI and digital intensities can also be sources of comparative advantage for exporting countries.

In this section we denote exporting capability to assess the contributions of digitalization in order to explain how the exporting capability relates to some traditional determinants (production technology and wage), as shown in Eaton and Kortum (2001, 2002) model. Combining (10) and (11), the exporting capability is expressed as:

$$C_{it} = EK_{it} + \theta\phi(1-\gamma)\ln k_{it} + \theta\phi\gamma \ln r_{iat}, \tag{12}$$

where we define $EK_{it} = \ln T_{it} - \theta \ln w_{it}$. In equation (12), we add digital intensity and AI intensity into the Eaton and Kortum model, where $\theta\phi(1-\gamma)\ln k_{it}$ and $\theta\phi\gamma\ln r_{iat}$ represent the contributions of intensity of digitalization and AI to the exporting capability, respectively.

TABLE 6.

Decomposition of Exporting Capability

EK Components	Intensity of Digitalization($\ln k$)	AI Intensity($\ln h$)
0.47	0.09	0.44
$(0.036)^{***}$	$(0.011)^{***}$	$(0.027)^{***}$

Following Hottman et al. (2016), we regress each component of the right-hand side of equation (12) to get the contribution of each component to the exporting capability. Table 6 reports the results. The EK component $(\ln T_{it} - \theta \ln w_{it})$ can explain 47% of the variation in the exporting capability across countries. The intensity of AI explains 44% of the variation in exporting capability, while digitalization explains 9% of the variation. Overall, the digitalization and AI combined explains nearly 53% of a country's success in the exporting market.

6. CONCLUSIONS

We have developed a theoretical model that incorporates digital data as an input factor in the firm's production function. The costs of generating the data input depend on a country's digital intensity and its AI intensity as well. In addition to traditional gravity variables (such as geographic distance), the exporting country's production technology, and labor costs, this study suggests that both digital intensity and AI intensity impact the bilateral trade flows with different elasticities.

Consistent with our theoretical predictions, our empirical results show that both digital and AI intensities are important determinants of an exporting country's success in the international markets. The trade elasticity of AI and digitization combined is nearly 43% of the trade costs elasticity. Furthermore, we find that 47% of variations in the international trade flows are explained by the difference in production technology across countries, while the remaining 53% of variations are explained by the differences in AI and digitalization across countries. This study suggests that the improvement in digital infrastructure and the increase in AI intensity together are as important as technology upgrading to enhance a country's success in the export market.

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