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Idea Flows and the Dynamics of Comparative Advantage

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Abstract

This paper studies the dynamic evolution of the patterns of Ricardian comparative advantage from the perspective of knowledge diffusion. The theoretical analysis builds knowledge diffusion into a quantifiable model of trade by allowing for industry-level productivity to evolve through a spatial flow of ideas. This theoretical framework yields a law of motion of industry-level productivity across countries, capturing strong interdependence in the evolution of Ricardian comparative advantage. We calibrate the model to 78 countries spanning from 1991 to 2017. Our quantitative results capture important patterns in the data: There is strong convergence in industry-level productivity and substantial mobility in specialization patterns. A decomposition exercise based on the theoretical law of motion facilitates the identification of the key players that contribute most to global productivity growth. We also draw a rich set of quantitative implications on the gains from trade, welfare elasticity of diffusion, and policy issues including the targeted ban of international trade.

Keywords: International trade, knowledge diffusion, economic growth, comparative advantage

JEL Classification: F10, F43, O33, O47

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1 Introduction

It has been long argued that international trade facilitates cross-border diffusion of knowledge (Keller, 1998, 2002, 2004, 2021; Santacreu, 2015; Bloom et al., 2016; Savvides and Zachariadis, 2005). The ongoing US-China technology war, the US chip ban in particular, underscores the role of industry in trade-induced knowledge diffusion. It is important to account for the heterogeneity across industries and interindustry linkages in a framework that attempts to understand the pattern of international knowledge diffusion.[1] Going beyond the geopolitics, perhaps more importantly, the past five decades have witnessed substantial changes in international specialization patterns, accompanied by strong convergence in underlying productivity across tradable industries. Convergence in productivity and more broadly specialization dynamics have profound implications for economic growth and cross-country income differences. Through the lens of knowledge diffusion, an investigation of the evolution of comparative advantage calls for the industry dimension to be put into play.

In this paper, we incorporate the industry dimension into a model of knowledge diffusion through international trade as in Buera and Oberfield (2020). The quantitative framework features a multi-industry and multi-country dynamic setting in which knowledge diffuses across countries and industries, bringing about a complex *trade-induced* diffusion structure at the country-industry level that evolves over time. The diffusion structure can be described by the law of motion of industry-level productivity (Ricardian comparative advantage) which hinges on trade specialization. Since trade is determined by Ricardian comparative advantage, the underlying dynamics are driven by the two-way relationship between trade specialization and (evolving) comparative advantage.[2]

We estimate the law of motion of industry-level productivity based on a balanced sample of 78 countries,[3] including 36 OECD and 42 non-OECD economies and 15 manufacturing industries spanning from 1991 to 2017. Our estimation proceeds in two steps. We first follow Levchenko and Zhang (2016) using the trade and production data based on the cross-sectional trade model to estimate industry-level productivity across countries. Based on those productivity measures, we then estimate the key diffusion parameters in the law of motion of productivity. The estimated parameters of diffusion intensity vary substantially across industries but with tight confidence intervals. The quantitative model delivers the convergence in productivity across countries. The quantitative results imply an annual rate of productivity convergence of 0.9% across countries, amounting to about one-third of what we observe in the data. We compute the static and dynamic gains from international trade, the former of which is due to specialization whereas the latter of which stems from knowledge diffusion. The dynamic gains from trade are on average about two-thirds of the static gains from trade but with a much lower dispersion across countries.

The estimated law of motion of productivity yields a natural decomposition of the sources of diffusion-based productivity growth by country and industry. Interestingly, we find that Japan

[1]Interindustry linkages in the innovation and diffusion have been well investigated in the closed-economy setting; see, for example, Cai and Li (2019) and Acemoglu et al. (2016).

[2]In an innovation-based open-economy growth model, Somale (2021) also formalizes and quantitatively investigates the two-way relationship between trade and technology.

[3]More specifically, there are 78 economies consisting of countries and (combined) regions. We follow the World Bank definition that the term "country" does not imply political independence but refers to any territory for which authorities report separate social or economic statistics. For more details, see Table A1 in the Appendix. Throughout the paper, China refers to mainland China.

has played consistently a leading role in global knowledge diffusion, surpassing the contribution of the US throughout the sample period. For example, Japan's machinery and electronics industry contributed to 5.13% of global productivity growth from 1994 to 2017. Our analysis provides some quantitative insights into the strategic importance of Japan highlighted in the ongoing policy and political discussions about the US-China chip war.[4]

The diffusion intensity plays a crucial role in the quantitative analysis, as noted by Buera and Oberfield (2020). We examine the welfare consequences across countries by varying the diffusion intensity of a given industry from its estimated level. Growth in real GDP across countries is particularly sensitive to the diffusion intensity of the transport equipment industry. A 10% drop in diffusion intensity of this industry leads to a decline in real GDP growth by about 4.4% across countries from 1994 to 2017. Interestingly, we find that diffusion intensity is not always positively correlated with welfare. For example, Japan's real GDP would be otherwise higher if the diffusion intensity of the machinery and electronics industry were lower. This is because lower intensity of diffusion can slow down the erosion of Japan's strong comparative advantage in this industry. Our analysis provides concrete examples of the business-killing effect: stronger knowledge diffusion can be welfare-reducing for some countries. Further, as emerging market economies like China and India rely more on international knowledge diffusion, we also document that they are more sensitive in their GDP response to a change in diffusion intensity.

Moreover, we assess the welfare implications of a targeted technology ban on China. We simulate how the trade restrictions on machinery and electronics, the industry that features prominently in the looming US-China tech war and is also identified in our quantitative analysis as the most important industry in global knowledge diffusion, affects global welfare. We find a unilateral export restriction from the US to China of varying degrees of strictness imposes a much greater welfare loss on China than on the US, with the magnitude of the loss being relatively moderate. For example, even in the extreme scenario of a complete ban on exports from the US to China in this industry, China's real GDP drops by about 0.5% where the loss to the US is 0.07%. China's welfare loss will experience a five- to six-fold increase when all the G7 countries coordinate such a targeted technology ban on China. The welfare implications for the rest of the world hinge on the degree of strictness of the unilateral trade restrictions. Under a low level of restrictions, the spillover effects are positive, whereas, under a high level of restrictions, the spillover effects turn negative.

This paper, featuring a multi-industry extension of Buera and Oberfield (2020), joins the idea-flows literature that examines the dynamics of productivity distribution through learning from (random) meetings with other agents from the economy.[5] Alvarez et al. (2013) incorporate the diffusion mechanism as in Alvarez et al. (2008), which is a variant of Kortum (1997), into a standard Ricardian model to demonstrate the persistent productivity-enhancing effect of international trade. Building on Perla and Tonetti (2014), Perla et al. (2015) develop a growth model of diffusion and technology adoption with firm heterogeneity to show both theoretically and quantitatively how opening up to trade induces more rapid technology adoption, thus bringing about higher economic

[4]For more details about Japan's position in the global semiconductor industry, see the report by Semiconductor Industry Association (2021).

[5]For earlier contributions, see Jovanovic and Rob (1989) and Kortum (1997), and also see Luttmer (2007); Luttmer et al. (2012), Lucas and Moll (2014), and Perla and Tonetti (2014) for models of economic growth through idea flows in a closed-economy setting. For an overview of this literature in a broader domain of dynamic economic environments, see Buera and Lucas (2018).

growth. In a closely related study, Sampson (2016) considers entrants learn from incumbent firms and highlights how the dynamic selection effect is amplified under trade liberalization through the free entry condition. Unlike Perla et al. (2015) and Sampson (2016), Buera and Oberfield (2020) abstract from firm heterogeneity and focus on how trade shapes the composition of insights from which ideas are drawn.

We depart from the existing work of idea flows by introducing the industry dimension. Closely related to our work is a recent paper by Góes and Bekkers (2022) which also extends Buera and Oberfield (2020) to a multi-industry setting. Our analysis differs from theirs in two important ways: First, whereas Góes and Bekkers (2022) focus their quantitative analysis on various decoupling scenarios, our paper takes a broader inquiry into the evolution of Ricardian comparative advantage, with one of the quantitative implications on the targeted technology ban. In their simulation of a decoupling that takes place only in the electronic equipment industry, they also document a relatively modest loss for China. Second, we provide a more detailed account of the productivity dynamics for 78 countries and 15 manufacturing industries, compared with 10 regions and 6 sectors in Góes and Bekkers (2022). This is achieved through a period-by-period estimation of industry-level productivity based on the cross-sectional equilibrium of the Ricardian model. Third, with the large panel of productivity estimates, we estimate the law of motion by flexibly allowing the diffusion parameters to vary across industries, whereas Góes and Bekkers (2022) base their estimation on the aggregate GDP series with the diffusion intensity to be uniform across industries. Last, we proxy the interindustry diffusion intensity by the patent citation matrix instead of the production input-output linkage and also explicitly take into account the role of R&D in our quantitative analysis.

This paper adds to the vast literature on international technology diffusion. Eaton and Kortum (1999) provide a quantitative framework of innovation and diffusion in an open-economy setting and their framework has been extended by Lind and Ramondo (2022) to incorporate international trade. In an important recent study, Cai et al. (2022) build explicitly the industry dimension and allow for diffusion to take place across industries. They structurally estimate the cross-country cross-industry diffusion intensity based on the patent citation data as in Caballero and Jaffe (1993). In contrast, our framework focuses exclusively on diffusion through international trade. This somewhat restrictive assumption makes the data requirement for quantitative exercise much less demanding (especially for the non-OECD economies) and also yields a potentially tighter connection between the theory and data. Moreover, our paper contributes to the open-economy growth literature where trade is the vehicle of knowledge diffusion (Rivera-Batiz and Romer, 1991; Coe and Helpman, 1995; Coe et al., 1997; Santacreu, 2015) by incorporating the industry dimension.[6]

Our quantitative results are related to the strand of literature on the dynamics of comparative advantage. Redding (2002) documents substantial dynamics in specialization patterns across countries. Hanson et al. (2015) corroborate this finding using more disaggregated data for a much larger set of countries and document strong convergence in export capability. This convergence pattern is also documented in Levchenko and Zhang (2016) based on the model implied measures of Ricardian comparative advantage and in Rodrik (2013) based on labor productivity data in the manufacturing sector. Our results suggest trade-induced knowledge diffusion to be a quantitatively important channel that underlies the convergence in industry-level productivity.

[6]Keller (2002) provides the reduced-form evidence of trade-induced knowledge diffusion at the industry level. For an overview of the earlier empirical literature, see Keller (2004).

The rest of the paper is structured as follows. We introduce the model and provide an analytical characterization of the law of motion of industry-level productivity in the next section. In Section 3, we describe our quantitative analysis and provide the basic estimation results. We discuss the quantitative implications of the model in Section 4 and offer concluding remarks in the last section.

2 The Model

The model has two main components. The cross-sectional setting is a multi-industry multi-country Hechscher–Ohlin–Ricardian framework with input-output linkages, which closely follows Caliendo and Parro (2014) and Levchenko and Zhang (2016). The evolution of industry-level productivity is modeled as in Buera and Oberfield (2020): The diffusion of ideas through international trade is the engine of productivity growth. The two-way relationship between international trade and productivity growth is captured separately by the two components of the model: At each moment of time, the trade pattern is determined by cross-country industry-level productivity; along the time dimension, productivity growth is shaped by the pattern of international trade. By incorporating the industry dimension into Buera and Oberfield (2020), we are able to investigate knowledge diffusion in a richer setting and derive the law of motion for *industry-level* productivity that is amenable to empirical implementation.

In our model, the world consists of N countries indexed by n or n'. There are $(I+1)$ industries indexed by i or i' among which the first I industries produce tradable goods and the $(I+1)^{\text{th}}$ industry produces nontradable goods. Time is continuous, infinite, and indexed by t.

2.1 The Cross-Sectional Setup

2.1.1 Demand

The final goods are produced by combining the output from $(I+1)$ industries of the following form[7]

$$Y_{n,t} = \left[\Pi_{i=1}^{I}\left(Y_{n,t}^{i}\right)^{\omega^{i}}\right]^{\phi_n}\left(Y_{n,t}^{I+1}\right)^{1-\phi_n},$$

where $Y_{n,t}$ is the output of the final goods in country n and $Y_{n,t}^{i}$ is the composite intermediate good input from industry i; ω^{i} is the share parameter of tradable industries satisfying $\sum_{i=1}^{I}\omega^{i}=1$; ϕ_n is Cobb–Douglas share of the tradable sector and $1-\phi_n$ is the share of the non-tradable sector. Denote by $E_{n,t}$ country n's expenditures at time t and by $P_{n,t}$ the corresponding composite price index. Standard derivation yields

$$Y_{n,t}^{i} = \omega^{i}\phi_n\frac{E_{n,t}}{P_{n,t}^{i}}, \quad i=1,2,...,I, \tag{1}$$

$$Y_{n,t}^{I+1} = (1-\phi_n)\frac{E_{n,t}}{P_{n,t}^{I+1}}, \tag{2}$$

where $P_{n,t}^{i}$ is the price index for industry i in country n, satisfying $P_{n,t}=\left[\Pi_{i=1}^{N}\left(\frac{P_{n,t}^{i}}{\omega^{i}\phi_n}\right)^{\omega^{i}}\right]^{\phi_n}\left(\frac{P_{n,t}^{I+1}}{1-\phi_n}\right)^{1-\phi_n}$. The final goods can be used for three purposes: consumption ($C_{n,t}$), capital investment ($I_{n,t}$), and

[7] To simplify the notation, we suppress the time subscript t in our presentation of the cross-sectional setup.

R&D investment ($R_{n,t}$). We have $E_{n,t} = P_{n,t}(C_{n,t} + I_{n,t} + R_{n,t})$ for each country. In this paper, we focus on the diffusion process and abstract from endogenous factor accumulation and innovation, so in the subsequent analysis, $I_{n,t}$ and $R_{n,t}$ are treated as exogenously given.

2.1.2 Production

In each industry i, there is a unit mass of intermediate goods indexed by $\nu^i \in [0,1]$. Each variety of intermediate good, ν^i, is produced by combining labor, capital, and composite intermediate goods. Production technology is of the Cobb-Douglas form:

$$q^i_{n,t}(\nu^i) = z^i_{n,t}(\nu^i)[\ell^i_{n,t}(\nu^i)]^{\gamma^{iL}_{n,t}}[k^i_{n,t}(\nu^i)]^{\gamma^{iK}_{n,t}} \prod_{i'=1}^{I+1} [m^{ii'}_{n,t}(\nu^i)]^{\gamma^{ii'}_{n,t}},$$

where $q^i_{n,t}(\nu^i)$ is the output of variety ν^i; $z^i_{n,t}(\nu^i)$ is the productivity level; $\ell^i_{n,t}(\nu^i)$ and $k^i_{n,t}(\nu^i)$ are labor and capital; $m^{ii'}_{n,t}$ is composite intermediate goods from industry i'; Cobb–Douglas coefficients $\gamma^{iL}_{n,t}$ and $\gamma^{iK}_{n,t}$ are the labor and capital shares; $\gamma^{ii'}_{n,t}$ is the input share of intermediate goods from industry i', capturing the important input–output (I–O) linkage emphasized by the recent macroeconomic literature (Carvalho, 2014). Production technology follows constant returns to scale (CRS), which requires $\gamma^{iL}_{n,t} + \gamma^{iK}_{n,t} + \sum_{i'=1}^{I+1} \gamma^{ii'}_{n,t} = 1$ for any country n and any time t. According to the production function, the unit cost of an input bundle, $c^i_{n,t}$, can be defined as

$$c^i_{n,t} = \left(\frac{w_{n,t}}{\gamma^{iL}_{n,t}}\right)^{\gamma^{iL}_{n,t}} \left(\frac{r_{n,t}}{\gamma^{iK}_{n,t}}\right)^{\gamma^{iK}_{n,t}} \prod_{i'=1}^{I+1} \left(\frac{P^{i'}_{n,t}}{\gamma^{ii'}_{n,t}}\right)^{\gamma^{ii'}_{n,t}}, \tag{3}$$

where $w_{n,t}$ is the wage rate and $r_{n,t}$ is the rental rate. The wage and rental rates are country-specific.

Composite goods in each industry are produced by combining a continuum of varieties within the same industry using the constant-elasticity-of-substitution (CES) technology

$$Q^i_{n,t} = \left[\int_0^1 s^i_{n,t}(\nu^i)^{(\sigma^i-1)/\sigma^i} d\nu^i\right]^{\sigma^i/(\sigma^i-1)},$$

where $s^i_{n,t}(\nu^i)$ is the intermediate input of variety i and σ^i is the elasticity of substitution. Standard derivation yields

$$s^i_{n,t}(\nu^i) = \left(\frac{p^i_{n,t}(\nu^i)}{P^i_{n,t}}\right)^{-\sigma^i} Q^i_{n,t} \quad \text{with} \quad P^i_{n,t} = \left[\int_0^1 p^i_{n,t}(\nu^i)^{1-\sigma^i} d\nu^i\right]^{1/(1-\sigma^i)},$$

where $p^i_{n,t}(\nu^i)$ is the price of variety ν^i in country n. Composite goods in each industry can be either used as composite intermediate inputs in production at the variety level or as input for the production of final goods. Production technology of the composite goods is identical across countries. This implies that international trade only takes place at the variety level, which will be specified in the next subsection.

2.1.3 International Trade

Trade cost is of the iceberg form (Samuelson, 1954). It requires shipping $d^i_{nn',t}$ units of goods from country n' to deliver one unit of good to country n. The triangle inequality is assumed to always hold: $d^i_{nn'',t} d^i_{n''n',t} \geq d^i_{nn',t}$ for any country n, n', n'' and industry i. This implies that reexport is always more costly than direct export in the model. Consequently, entrepôts such as Singapore and Hong Kong are excluded in the empirical implementation of the model. For the nontradable sector, $d^{I+1}_{nn',t} = \infty$ for any n, n' such that $n \neq n'$. Domestic trade is assumed to be frictionless, so $d^i_{nn,t} = 1$ for any n and i.

The product market is assumed to be perfectly competitive. Each variety of intermediate inputs is purchased from the supplier with the lowest unit cost adjusted by trade cost. Recall that $c^i_{n,t}$ is the unit cost of an input bundle of industry i in country n. Therefore, the price of the intermediate good ν^i in country n is given by

$$p^i_{n,t}(\nu^i) = \min \left\{ \frac{c^i_{1,t} d^i_{n1,t}}{z^i_{1,t}(\nu^i)}, \frac{c^i_{2,t} d^i_{n2,t}}{z^i_{2,t}(\nu^i)}, ..., \frac{c^i_{N,t} d^i_{nN,t}}{z^i_{N,t}(\nu^i)} \right\}.$$

Following Eaton and Kortum (2002), we assume the variety-level productivity, $z^i_{n,t}$, is a random variable from a Fréchet distribution independently drawn across varieties, industries, and countries:

$$F^i_{n,t}(z) = \exp(-\lambda^i_{n,t} z^{-\theta^i}),$$

where $F^i_{n,t}$ is country n's productivity distribution in industry i; the location parameter, $\lambda^i_{n,t}$, governs the mean of the distribution; θ^i measures the dispersion of the distribution. Denote by $\pi^i_{nn',t}$ the share of expenditure that country n spends on the imports from country n' in industry i. Exploiting the probabilistic structure, standard derivation yields

$$\pi^i_{nn',t} = \frac{\lambda^i_{n',t}(c^i_{n',t} d^i_{nn',t})^{-\theta^i}}{\sum_{n''=1}^N \lambda^i_{n'',t}(c^i_{n'',t} d^i_{nn'',t})^{-\theta^i}}, \tag{4}$$

where the denominator captures "multilateral resistance" coined by Anderson and van Wincoop (2003), the fact that bilateral trade flows are shaped by economic variables beyond those of the bilateral trading partners in a multilateral world. The industry-level price index is also a function of multilateral resistance.

$$P^i_{n,t} = \left[\Gamma\left(1 + \frac{1-\sigma^i}{\theta^i}\right)\right]^{1/(1-\sigma^i)} \left(\sum_{n'=1}^N \lambda^i_{n',t}(c^i_{n',t} d^i_{nn',t})^{-\theta^i}\right)^{-1/\theta^i}, \tag{5}$$

where $\Gamma(\cdot)$ is the Gamma function. The usual regularity condition, $\theta^i + 1 > \sigma^i$, is imposed, so the price index is well defined.

It should be noted that the location parameter of the Fréchet distribution, $\lambda^i_{n,t}$, varies across time. When turning to the time dimension of the model, we will introduce the diffusion process developed by Buera and Oberfield (2020) to endogenize the dynamics of the industry-level productivity.

2.1.4 Market Clearing and Instantaneous Equilibrium

Denote country n's total trade deficit by $D_{n,t}$, which is taken as exogenously given. The world total trade deficit has to be balanced out, so $\sum_{n=1}^{N} D_{n,t} = 0$ for any t. Country n's total expenditure is then given by

$$E_{n,t} = w_{n,t}L_{n,t} + r_{n,t}K_{n,t} + D_{n,t}, \tag{6}$$

where $L_{n,t}$ and $K_{n,t}$ is labor and capital endowment. By definition, the trade deficit is the difference between total imports and exports

$$D_{n,t} = \sum_{i=1}^{I}\sum_{n'=1}^{N} \left(P^i_{n,t}Q^i_{n,t}\pi^i_{nn',t} - P^i_{n',t}Q^i_{n',t}\pi^i_{n'n,t}\right) \tag{7}$$

Recall that composite goods in each industry can be either used as intermediate inputs for variety-level production or combined to final goods, so the product market clearing condition in each industry is given by

$$P^i_{n,t}Q^i_{n,t} = \sum_{i'=1}^{I+1}\gamma^{i'i}_{n,t}\sum_{n'=1}^{N} P^{i'}_{n',t}Q^{i'}_{n',t}\pi^{i'}_{n'n,t} + P^i_{n,t}Y^i_{n,t} \tag{8}$$

Given the Cobb–Douglas production technology, the share of labor and capital income are given by $\gamma^{iL}_{n,t}$ and $\gamma^{iK}_{n,t}$, respectively. Therefore, we have

$$w_{n,t}L^i_{n,t} = \gamma^{iL}_{n,t}\sum_{n'=1}^{N} P^i_{n',t}Q^i_{n',t}\pi^i_{n'n,t} \quad \text{and} \quad r_{n,t}K^i_{n,t} = \gamma^{iK}_{n,t}\sum_{n'=1}^{N} P^i_{n',t}Q^i_{n',t}\pi^i_{n'n,t}, \tag{9}$$

where $L^i_{n,t}$ and $K^i_{n,t}$ are industry-level labor and capital inputs. Market-clearing conditions for the labor and capital markets further require[8]

$$\sum_{i=1}^{I+1} L^i_{n,t} = L_{n,t} \quad \text{and} \quad \sum_{i=1}^{I+1} K^i_{n,t} = K_{n,t}. \tag{10}$$

At each moment of time t, given labor and capital endowments $\{L_{n,t}, K_{n,t}\}_{n=1}^{N}$, trade deficits $\{D_{n,t}\}_{n=1}^{N}$, bilateral industry-level trade costs $\{d^i_{nn',t}\}_{n=1,n'=1,i=1}^{N,N,I}$, and industry-level productivity $\{\lambda^i_{n,t}\}_{n=1,i=1}^{N,I+1}$, an instantaneous equilibrium is characterized by the vectors $\{r_{n,t}, w_{n,t}, E_{n,t}\}_{n=1}^{N}$, $\{P^i_{n,t}, L^i_{n,t}, K^i_{n,t}, c^i_{n,t}, Y^i_{n,t}, Q^i_{n,t}\}_{n=1,i=1}^{N,I+1}$, and $\{\pi^i_{nn',t}\}_{n=1,n'=1,i=1}^{N,N,I}$ such that Equations (1)–(10) hold for any country n and industry i.

2.2 The Dynamic Setup

2.2.1 A General Diffusion Process

We start with a brief description of a general diffusion process originally formulated by Buera and Oberfield (2020). Consider a continuum of firms whose productivity distribution follows the

[8] We do not distinguish production workers (or capital) from R&D workers (or capital), based on the implicit assumption that the factors are perfectly mobile and equally productive in the two activities. Remunerations of R&D activities are paid in the form of final goods and are determined exogenously.

cumulative distribution function F_t at time t. At each moment, a firm f from F_t has a certain probability to be matched with another firm g which is randomly drawn from a mass of firms with the productivity distribution G_t. The random matching is modeled as a Poisson process with an arrival rate η_t. At this point, we do not impose restrictions on where and what firm g produces. Firm g can be a domestic firm or a foreign firm. It may compete with firm f in the same industry, or it may produce in a different industry. Firm f learns from firm g but learning is subject to friction. In particular, we follow Buera and Oberfield (2020) to assume that the productivity associated with the idea firm f draws from firm g is given by $z_h x^\beta$, where z_h is a random draw from a Pareto distribution following $H(z_h) = 1 - z_h^{-\theta}$ with the shape parameter θ, x is firm g's productivity, and $\beta \in [0, 1)$ captures the intensity of diffusion. The smaller β is, the noisier the diffusion process is. In the limiting case, for $\beta = 0$, the diffusion process is entirely driven by the random shock. Firm f adopts the new idea if the productivity associated with the new idea $z_h x^\beta$ is greater than its own productivity z. This diffusion process yields the following law of motion

$$\frac{d \ln F_t(z)}{dt} = -\eta_t z^{-\theta} \int_0^\infty x^{\beta\theta} dG_t(x).$$

To ensure the integral not diverge to infinity, we impose the regularity condition that $\lim_{x\to\infty} x^{\beta\theta+\epsilon}(1- G_t(x)) = 0$ for any t and some $\epsilon > 0$. If we further assume that the initial distribution of F is Fréchet as in Buera and Oberfield (2020), then $F_t(z) = \exp(-\lambda_t z^{-\theta})$ with the location parameter λ_t following the law of motion

$$\frac{d\lambda_t}{dt} = \eta_t \int_0^\infty x^{\beta\theta} dG_t(x). \tag{11}$$

We now turn to the specification of G_t in the context of our multi-industry trade model.

2.2.2 Channels of Diffusion

With the industry dimension in our setting, we consider both intra and interindustry knowledge diffusion. Knowledge diffusion takes place within a country and across borders. As a benchmark, we assume productivity dispersion not to vary across industries: $\theta^i = \theta$ for any i. Later we will discuss how to relax this assumption.

Firms in a given country n and industry i draw insights from the sellers in the home market with the arrival rate $\tilde{\eta}^i_{n,t}$. The conditional probability of a firm in industry i to draw insights from sellers in industry i' is given by $\iota_t^{ii'}$. The matrix $\{\iota_t^{ii'}\}$ governs the structure of intra and interindustry knowledge flows. Thus, the probability for a firm in industry i to be randomly matched with a seller in industry i' from t to $t + dt$ is given by $\tilde{\eta}^i_{n,t}\iota_t^{ii'}dt$. All the active sellers in industry i' in the home market are drawn with equal probability. Therefore, the diffusion-induced productivity growth is given by:[9]

$$
\begin{aligned}
\frac{d\lambda_{n,t}^{i}}{dt} &= \eta_{n,t}^{i}\sum_{i'}\iota_{t}^{ii'}\sum_{n'}\pi_{nn',t}^{i'}\left(\frac{\lambda_{n',t}^{i'}}{\pi_{nn',t}^{i'}}\right)^{\beta^{i}} \\
&= \overbrace{\eta_{n,t}^{i}\iota_{t}^{ii}\pi_{nn,t}^{i}\left(\frac{\lambda_{n,t}^{i}}{\pi_{nn,t}^{i}}\right)^{\beta^{i}}}^{\text{domestic intraindustry diffusion}} + \overbrace{\eta_{n,t}^{i}\iota_{t}^{ii}\sum_{n'\neq n}\pi_{nn',t}^{i}\left(\frac{\lambda_{n',t}^{i}}{\pi_{nn',t}^{i}}\right)^{\beta^{i}}}^{\text{international intraindustry diffusion}} \\
&+ \overbrace{\sum_{i'\neq i}\eta_{n,t}^{i}\iota_{t}^{ii'}\pi_{nn,t}^{i'}\left(\frac{\lambda_{n,t}^{i'}}{\pi_{nn,t}^{i'}}\right)^{\beta^{i}}}^{\text{domestic interindustry diffusion}} + \overbrace{\sum_{i'\neq i}\eta_{n,t}^{i}\iota_{t}^{ii'}\sum_{n'\neq n}\pi_{nn',t}^{i'}\left(\frac{\lambda_{n',t}^{i'}}{\pi_{nn',t}^{i'}}\right)^{\beta^{i}}}^{\text{international interindustry diffusion}},
\end{aligned} \tag{12}
$$

where $\eta_{n,t}^{i} \equiv \Gamma(1-\beta^{i})\tilde{\eta}_{n,t}^{i}$. In the equation above, $\pi_{nn',t}^{i}$ is directly observed in trade data and $\lambda_{n,t}^{i}$ can be estimated from production and trade data. According to Equation (12), productivity growth can be decomposed into four channels. The first channel is through learning from domestic sellers in the same industry. The larger the domestic absorption term $\pi_{nn,t}^{i}$ is, the more firms are learning from home producers.[10] The second channel is through learning from foreign exporters in the same industry. The higher presence of foreign sellers from country n', captured by $\pi_{nn',t}^{i}$, brings about more chances of learning from that country. The third and fourth channels are based on interindustry learning (Cai and Li, 2016; Cai et al., 2022). The mechanism is similar to intraindustry learning and the trade shares continue to play a pivotal role in determining the pattern of diffusion. Further, the industrial productivity adjusted by the trade share, $\left(\frac{\lambda_{n',t}^{i'}}{\pi_{nn',t}^{i'}}\right)$, captures the quality of ideas. The trade pattern impacts the diffusion process not only through the probability of meeting with sellers from different origins but also through the well-known selection mechanism (Costinot et al., 2012; Finicelli et al., 2013).

We now turn to the specification of the arrival rate $\eta_{n,t}^{i}$. The arrival rate depends on the R&D expenditures. The innovation channel is introduced in reduced form as

$$\eta_{n,t}^{i} = \eta {R_{n,t}^{i}}^{\beta^{r}} {\lambda_{n,t}^{i}}^{\beta^{o}}, \tag{13}$$

where $R_{n,t}^{i}$ is the industry-level expenditure $R\&D$ satisfying $\sum_{i=1}^{I} R_{n,t}^{i} = R_{n,t}$. Abstracting from the R&D decisions, we treat $R_{n,t}^{i}$ as given. Moreover, the arrival rate also depends on the initial industry-level productivity, capturing the potential decline of research productivity with development as documented in Bloom et al. (2020).

We close this subsection by discussing the simplifying assumption: $\theta^{i} = \theta$ for any i. According to Caliendo and Parro (2014), there is substantial variation in productivity dispersion across industries. In the presence of heterogeneous θ^{i}, when firms in industry i with little productivity dispersion (high θ^{i}) draw ideas from industry i' with very high productivity dispersion (low $\theta^{i'}$), the recipient industry's productivity distribution will be greatly impacted by the extreme values drawn from the source industry with high dispersion. In Appendix A, we formally show that the law of motion of

[9] The derivation details can be found in Appendix A.

[10] It should be noted that intraindustry domestic knowledge diffusion is observationally equivalent at the industry level to an alternative formulation through learning by doing (Young, 1991). We do not distinguish learning by doing from knowledge diffusion, so the empirical interpretation of this channel encompasses both mechanisms.

industrial productivity under the diffusion process is well-behaved if and only if $\theta^{i'} > \beta^i\theta^i$ for any pair of i and i', that is, productivity dispersion of the source industry cannot be too high. Therefore, to relax the assumption of θ^i being the same across industries, we assume that the diffusion process is adjusted for industrial productivity dispersion so as to maintain the analytical tractability of the model. In particular, an adjustment parameter $\Theta_{ii'}$ is introduced into interindustry diffusion. When a firm in industry i draws a new insight x from productivity distribution G of industry i' as well as a random noise z_h from the exogenous Pareto distribution H, the resulting productivity of this new insight is given by $z_h x^{\Theta^{ii'}\beta^i}$ with $\Theta^{ii'} = \theta^{i'}/\theta^i$. In words, the efficiency of learning is adjusted for the differential in productivity dispersion between the industry pairs. Under this assumption, the law of motion of industrial productivity, Equation (12), continues to hold for heterogeneous θ^i.

2.2.3 Connection with Schumpeterian Creative Destruction

It is worth noting that the law of motion based on the diffusion model can also be reinterpreted through the lens of Schumpeterian creative destruction (Aghion et al., 1998, 2015). In particular, assume new technologies arrive over time following a Poisson process with the arrival rate η governed by the R&D intensity as we specify above. Each new technology draws an existing technology with productivity x from a knowledge pool with productivity distribution $G(\cdot)$. The realized productivity of the new technology is given by $z_c x'^{\beta}$, where z_c, drawn from a Pareto distribution $H(z_c) = 1 - z_c^{-\theta}$, captures the randomness in productivity improvement, x' is an improvement of the existing technology with $x' = \zeta x$ ($\zeta > 1$), and $\beta \in (0, 1)$ captures the fact that it becomes increasingly difficult for the new ideas to sustain exponential productivity growth (Bloom et al., 2020). The new technology will be adopted if its realized productivity exceeds the productivity of the existing technology (for the given variety) in the market. Suppose the productivity distribution for a given country and industry is Fréchet: $F_t(z) = \exp(-\lambda_t z^{-\theta})$. Then, we have

$$\frac{d\lambda_t}{dt} = \eta\zeta^{\beta\theta} \int_0^\infty x^{\beta\theta} dG(x), \tag{14}$$

where the knowledge pool upon which new technologies are built consists of not only the domestic technology frontier but also the foreign technology frontiers and technologies from other industries. This re-interpretation also underscores the R&D activities as adaptive capability (Cohen and Levinthal, 1989; Aghion and Jaravel, 2015; Audretsch and Belitski, 2020). Further, specializing the productivity distribution G as in the previous subsection yields the law-of-motion for productivity that is isomorphic to our baseline specification as in (12).

2.2.4 Evolution of Endowment

To complete the dynamic setting of the model, we specify the laws of motion of labor and capital. The population growth rate $g_{n,t}$ is country specific, time varying, and will be calibrated to the data. We have

$$\frac{dL_{n,t}}{dt} = g_{n,t} L_{n,t},$$

where $g_{n,t}$ is the population growth rate. Capital accumulation follows

$$\frac{dK_{n,t}}{dt} = I_{n,t} - \delta_{n,t} K_{n,t},$$

where $I_{n,t}$ is aggregate investment and $\delta_{n,t}$ is the depreciation rate. Since we focus on the productivity dynamics, the aggregate investment is also modeled exogenously.

3 Quantitative Analysis

3.1 Data and Sample Construction

Our quantitative analysis is mainly based on international trade and production data. The international trade data is from CEPII CHELEM database. The database contains harmonized bilateral trade at the industry level since 1967. The production data is from UNIDO INDSTAT (2020) database. The database contains industrial statistics, gross output in particular, for the 2-digit ISIC (Rev.3) manufacturing industries across countries starting from 1963. To construct our sample, we combine trade and production data, along with an array of auxiliary datasets on R&D, input-output, price, productivity, and patents. For details about data sources and data processing, see Appendix B.

Our trade and production data stretch back to the 1960s, but to include a larger number of emerging market economies, which would allow us to investigate how the diffusion-based growth model applies to the global south, we construct our baseline sample to balance the country coverage and time span. Our sample covers the period from 1991 to 2017. It consists of 78 countries, among which 42 are non-OECD countries. There are 15 tradable industries, which are aggregated from the 2-digit ISIC (Rev. 3) industries. The lists of countries and industries can be found in Tables A1 and A2. To ensure that the productivity estimates and diffusion parameters are not heavily affected by short-term business fluctuations, we choose each period to be three years, and thus the sample covers nine periods. All the variables are averaged within each period.

3.2 Estimation of Industry-Level Productivity

The estimation of industry-level productivity $\lambda^i_{n,t}$, which we outline in this subsection, follows closely Shikher (2012) and Levchenko and Zhang (2016). The main idea is to exploit the gravity structure of international trade arising from each instantaneous equilibrium. Based on the gravity structure, we first estimate industry-level productivity across countries relative to the US. We then use the US productivity measures to compute cross-country industry-level productivity in levels. To simplify notation, we omit the subscript t when doing so does not cause any confusion.

As in Eaton and Kortum (2002), define the competitiveness measure S^i_n as the industry-level productivity parameter adjusted by the unit cost of an input bundle: $S^i_n \equiv \lambda^i_n {c^i_n}^{-\theta^i}$. From Equation (4) and the definition of S^i_n, we can derive

$$\ln\left(\frac{\pi^i_{nn'}}{\pi^i_{nn}}\right) = \ln\left(S^i_{n'}\right) - \ln\left(S^i_n\right) - \theta^i \ln(d^i_{nn'}), \tag{15}$$

with the bilateral trade cost being specified as

$$\ln(d^i_{nn'}) = Dist_{nn'} + GravityVar_{nn'} + Exp^i_{n'} + \varepsilon^i_{nn'}. \tag{16}$$

$Dist_{nn'}$ is a set of dummy variables categorizing the distance in miles into six intervals, [0, 375), [375, 750), [750, 1500), [1500, 3000), [3000, 6000), [6000, maximum). $GravityVar_{nn'}$ is a set of gravity variables capturing whether a country pair shares a common border, the same language, or belong to the same free trade area. We also include exporter-industry fixed effects $Exp^i_{n'}$ as advocated by Waugh (2010). $\varepsilon^i_{nn'}$ is an error term. Combining the two equations above, we obtain

$$\ln\left(\frac{\pi^i_{nn'}}{\pi^i_{nn}}\right) = \ln S^i_{n'} - \theta^i Exp^i_{n'} - \ln S^i_n - \theta^i Dist_{nn'} - \theta^i GravityVar_{nn'} - \theta^i \varepsilon^i_{nn'}, \tag{17}$$

where $(\ln S^i_{n'} - \theta^i Exp^i_{n'})$ and $(-\ln S^i_n)$ can be captured by the exporter-industry and importer-industry fixed effects. We choose the US as the benchmark country, the competitiveness measure relative to the US level can be obtained from the importer-industry fixed effects:

$$\frac{S^i_n}{S^i_{US}} = \frac{\lambda^i_n}{\lambda^i_{US}} \left(\frac{c^i_n}{c^i_{US}}\right)^{-\theta^i}, \tag{18}$$

where θ^i is set to be four, the same value across industries ($\theta^i = \theta = 4$). According to the expression above, to obtain estimates of relative productivity parameters, $\lambda^i_n/\lambda^i_{US}$, what remains to estimate is the relative unit cost c^i_n/c^i_{US}.

Assuming the input shares to be country-invariant, from Equation (3), we have

$$\frac{c^i_n}{c^i_{US}} = \left(\frac{w_n}{w_{US}}\right)^{\gamma^{iL}} \left(\frac{r_n}{r_{US}}\right)^{\gamma^{iK}} \prod_{i'=1}^{I} \left(\frac{P^{i'}_n}{P^{i'}_{US}}\right)^{\gamma^{ii'}} \left(\frac{P^{I+1}_n}{P^{I+1}_{US}}\right)^{\gamma^{i(I+1)}}, \tag{19}$$

where all the Cobb–Douglas coefficients are calibrated to the US level based on its 2004 input-output tables, and cross-validated by the cross-country input shares. Relative wage rates and relative rental rates are obtained from the Penn World Table. The relative price of the nontradable sector is obtained from the International Comparison Program. To obtain the relative prices of tradable industries, as in Shikher (2012) and Levchenko and Zhang (2016), from Equations (4) and (5), we obtain

$$\frac{\pi^i_{nn}}{\pi^i_{US\,US}} = \frac{S^i_n}{S^i_{US}} \left(\frac{P^i_n}{P^i_{US}}\right)^{\theta}. \tag{20}$$

Then, from Equations (18)–(20), we finally have

$$\frac{\lambda^i_n}{\lambda^i_{US}} = \frac{S^i_n}{S^i_{US}} \left(\frac{w_n}{w_{US}}\right)^{\theta\gamma^{iL}} \left(\frac{r_n}{r_{US}}\right)^{\theta\gamma^{iK}} \left(\frac{P^{I+1}_n}{P^{I+1}_{US}}\right)^{\theta\gamma^{i(I+1)}} \prod_{i'=1}^{I} \left(\frac{\pi^{i'}_{nn}}{\pi^{i'}_{US\,US}} \frac{S^{i'}_{US}}{S^{i'}_n}\right)^{\gamma^{ii'}}, \tag{21}$$

where all the relative terms and their exponents on the right-hand side can be either estimated or directly computed.

For the nontradable sector, the estimation of relative productivity is similar and simpler. Equation (5) implies

$$\frac{\lambda^{I+1}_n}{\lambda^{I+1}_{US}} = \left(\frac{c^{I+1}_n}{c^{I+1}_{US}} \frac{P^{I+1}_{US}}{P^{I+1}_n}\right)^{\theta},$$

where c^{I+1}_n/c^{I+1}_{US} can be obtained from Equations (19) and (20), and P^{I+1}_n/P^{I+1}_{US} can be directly obtained from the data.

As described above, we obtain S_n^i (relative to the US) from the importer-industry fixed effects in the estimation of Equation (17). For every country pair, we can then compute the relative competitiveness measure $S_{n'}^i/S_n^i$. Plugging this relative measure back into Equation (15), we also obtain the estimates of trade costs $d_{nn'}^i$. Trade-cost estimates will be used later in the counterfactual exercises.

The next step is to estimate the US industry-level productivity λ_{US}^i. We obtain the industry-level factor use and cost share for the tradable industries from the NBER-CES data and for the non-tradable sector from the BLS data. We then estimate the five-factor TFP at the industry level. To account for the Ricardian selection (Finicelli et al., 2013; Costinot et al., 2012), we further adjust the estimated TFP by the share of domestic absorption:

$$\lambda_{US}^i = \left(\Gamma^{-1}\left(\frac{\theta-1}{\theta}\right) TFP_{US}^i\right)^{\theta} \pi_{US\,US}^i. \tag{22}$$

Last, from Equations (21) and (22), we obtain for each period the industry-level estimates of productivity parameters across all countries in our sample.[11]

3.3 Estimation of Diffusion Parameters

We now turn to the estimation of the diffusion parameters. The estimation is based on the law of motion of industry-level productivity (12) and the specification of the arrival rate (13). Discretizing the law of motion, we obtain

$$\Delta\lambda_{n,t}^i = \eta {R_{n,t}^i}^{\beta^r} {\lambda_{n,t}^i}^{\beta^o} \sum_{i'} \iota_t^{ii'} \sum_{n'} \pi_{nn',t}^{i'} \left(\frac{\lambda_{n',t}^{i'}}{\pi_{nn',t}^{i'}}\right)^{\beta^i}, \tag{23}$$

where $R_{n,t}^i$ is country n's R&D expenditure in industry i and period t, normalized by the world GDP in that period, $\lambda_{n,t}^i$ is the estimated industry-level productivity that we have obtained,[12] $\pi_{nn',t}^{i'}$ is the trade share we can directly observe from the data. We set $\beta^r = 0.5$ as the elasticity of successful innovation in Acemoglu et al. (2018). Further, the interindustry diffusion rate $\iota_t^{ii'}$ is specified as

$$\iota_t^{ii'} = \frac{\text{Citation}^{ii'}}{\sum_{i'} \text{Citation}^{ii'}} \times \frac{\frac{1}{N}\sum_n \lambda_{n,t}^i}{\frac{1}{N}\sum_n \lambda_{n,t}^{i'}}$$

where $\text{Citation}^{ii'}$ is patent citation from industry i' (cited industry) to industry i (citing industry) and the second term is the ratio of average productivity in industry i to that in industry i', which is included to control for the mean productivity differences across industries. The patent citation matrix is constructed from the NBER US Patent Citation Data. The parameters that remain to be estimated are $\{\eta, \beta^o, \{\beta^i\}_{i=1}^I\}$. We estimate those parameters based on Equation (23) through weighted non-linear least squares. The weight is given by country n's share of gross output in a

[11] As a cross validation, we compare the TFP estimates with those reported in Fadinger and Fleiss (2011). Based on a Ricardo–Heckscher–Ohlin framework with monopolistic competition, they also obtain industry-level TFP estimates relative to the United States. The cross-sectional comparison between their 1996 estimates and our 1994–1996 estimates yields correlations above 0.5 for 8 tradable industries (out of 14 for which we can match our estimates with theirs).

[12] We scale up industry-level productivity such that $\min_{n,i,t} \lambda_{n,t}^i = 1$. This is to ensure that when β^i varies, the diffusion term λ^{β^i} would vary in the same direction for any estimated λ. An alternative normalization by setting $\max_{n,i,t} \lambda_{n,t}^i = 1$ would yield the same calibration.

given industry i and period t. We compute the standard errors based on the standard Gauss-Newton regression (Davidson and MacKinnon, 2004).

Table 1 presents the baseline estimation results of the key diffusion parameter β^i. The estimates range from 0.4864 (textiles) to 0.9123 (transport equipment) and 0.9272 (furniture and other manufacturing).[13] The median β^i is 0.8009, which is higher than the benchmark $\beta = 0.6$ specified in Buera and Oberfield (2020). The exponent of the initial productivity β^o is estimated to be 0.0525. β^o being smaller than 1 suggests that in the absence of diffusion, the growth rate of productivity decreases with its level.[14]

Before we turn to the quantitative implications, we want to take a look at the goodness of fit for the model. Based on the initial industry-level productivity, we fully solve the cross-sectional general equilibrium of the model and obtain the model-implied trade shares.[15] Using those trade shares, based on the estimated law of motion of industry-level productivity, we can compute the second-period model-implied industry-level productivity. We repeat this procedure period by period and finally obtain a panel of model-implied variables for the entire sample period.

Table 2 compares the actual data and the simulation results. The model-implied factor prices, trade shares, and aggregate GDP growth rate match the data reasonably well. Figure 1 compares the model-implied GDP per capita (relative to the United States) with the data for the last sample period (2015–2017). The simulation results remain highly correlated with the actual data with a correlation of 0.9016.

Moreover, a prominent feature of the productivity data of the tradable sector is the strong convergence over time: industries that start with lower productivity tend to experience faster productivity growth. Formally, we regress the productivity growth on the initial productivity as follows

$$\triangle \ln \left(\lambda_{n,t}^{i}\right)^{\frac{1}{\theta}} = \alpha \ln \left(\lambda_{n,t}^{i}\right)^{\frac{1}{\theta}} + \mu_n + \mu_{it} + \varepsilon_{n,t}^{i}, \tag{24}$$

where the dependent variable is the productivity growth defined as $\triangle \ln \left(\lambda_{n,t}^{i}\right)^{\frac{1}{\theta}} \equiv \ln \left(\lambda_{n,t+\Delta t}^{i}\right)^{\frac{1}{\theta}} - \ln \left(\lambda_{n,t}^{i}\right)^{\frac{1}{\theta}}$. We consider two specifications: a long difference between two periods, 1994–1996 and 2015-2017, and also stacked first differences based on three periods, 1994–1996, 2003–2005, and 2015–2017 (each first difference spanning roughly a decade). We also include the country and industry-year fixed effects (μ_n and μ_{it}).[16]

Table A3 reports the results for the convergence regression based on the actual and model-implied productivity measures. First, as documented in Levchenko and Zhang (2016), convergence in the productivity of tradable industries is highly robust across different specifications and country groups. For the full sample, the annual rate of convergence based on the actual data is approximately 2.5% to 3%, which is higher than the estimated convergence rate in Levchenko and Zhang (2016) but lower than the estimates based on labor productivity measures as in Rodrik (2013).[17]

[13] Fixing $\{\eta, \beta^o\}$ at baseline and re-estimating a uniform diffusion strength $beta^i$ for all industries yields 0.8382.

[14] We do not take a strong stand ex ante on the magnitude of β^o. The fact that the estimated β^o is in $(0, 1)$ is consistent with the findings in Bloom et al. (2020).

[15] The algorithm of solving the general equilibrium follows Levchenko and Zhang (2016).

[16] In the long-difference specification, the industry-year fixed effect boils down to the industry fixed effect.

[17] Rodrik (2013) focuses on the notion of "unconditional" convergence for which the country fixed effect is not included in the regressions. We report the comparison between the data and model based on the estimates for unconditional convergence in Table A3. We also report the results based on the convergence regression by industry in Table A4. The simulated model qualitatively reproduces the convergence pattern (or lack thereof) at the industry

Perhaps not so surprisingly, the non-OECD countries exhibit on average a higher rate of convergence than the OECD countries. Second, the model-implied productivity measures also exhibit a robust convergence pattern with the effect being stronger for the non-OECD countries. Third, the annual rate of convergence implied by the diffusion model is about one-third of the data. It suggests the global diffusion of ideas to be an important channel of productivity convergence but in order to fully explain productivity convergence, there are also other quantitatively important channels to be further incorporated.

3.4 Robustness Checks

We consider a battery of alternative specifications to estimate the main diffusion parameters and report the results in Table 6. In Column (1), the estimates are based on unweighted regressions. The textiles industry is again estimated to have the lowest diffusion parameter whereas the transport equipment industry remains among the industries with the highest β^i. In the next column, we report the estimates based on the regression excluding country-industry pairs that experienced negative TFP growth. The point estimates are highly similar to our baseline setting. We also estimate our model based on the productivity measures that are obtained from the gravity equation through the Poisson pseudo-maximum likelihood (PPML). The estimates reported in Column (3) suggest that PPML-based productivity measures yield on average higher estimates of the diffusion parameters. Last, we allow the diffusion parameters to differ between OECD and non-OECD countries. Because the number of parameters almost doubles, the estimates become less precise, [18] but qualitatively, the basic pattern of the diffusion parameters remains relatively robust and comparable between the two country groups. In what follows, we base our quantitative analysis on the baseline estimates of the diffusion parameters, but the main quantitative implications of the model are robust to the alternative estimates that we have reported here.

4 Quantitative Implications

4.1 Key Players in Global Diffusion of Ideas

In this section, we study how different countries, industries, and country-industry pairs contribute to the global diffusion of ideas. Based on the law of motion of industry-level productivity as in (12), we can compute for each period a matrix of knowledge diffusion at the country-industry level. More specifically, we can define the contribution of country n and industry i to the diffusion induced productivity growth of country n' and industry i', as

$$\psi_{n'n,t}^{i'i} \equiv \frac{\iota_t^{i'i} \pi_{n'n,t}^{i'} \left(\frac{\lambda_{n,t}^{i}}{\pi_{n'n,t}^{i'}} \right)^{\beta^{i'}}}{\sum_{i''} \iota_t^{i'i''} \sum_{n''} \pi_{n'n'',t}^{i''} \left(\frac{\lambda_{n'',t}^{i''}}{\pi_{n'n'',t}^{i'}} \right)^{\beta^{i'}}}.$$

level and delivers a quantitatively similar rate of convergence for industries like transport equipment.

[18] For the residual industry ("other manufacturing"), β^i of the OECD countries hits the specified upper bound.

Then, we can compute the contribution of country n and industry i to the global diffusion by taking a weighted average of $\psi_{n'n,t}^{i'i}$ across countries and industries

$$\psi_{n,t}^{i} \equiv \sum_{n',i'} \frac{Q_{n',t}^{i'} \psi_{n'n,t}^{i'i}}{\sum_{n'',i''} Q_{n'',t^{i''}}},$$

where $Q_{n',t}^{t'}$ is the real industry-level gross output. We can further aggregate up the contribution to the country level or to the industry level.

Figure 2 plots each country's contribution to world productivity growth at the beginning and the end of our sample period. Japan stands out as the most important contributor to global productivity growth through knowledge diffusion. Not surprisingly, OECD industrialized economies in general play a much larger role than the non-OECD economies in knowledge diffusion. Among the non-OECD economies, China's contribution to global knowledge diffusion experienced a three-fold in less than three decades. By the end of our sample period, it has become the most important player in idea flows, contributing to almost 10% of global knowledge diffusion.

To further shed light on the changing landscape of global diffusion, we report in Table 4 the top 10 country-industry pairs in terms of their contribution to global knowledge diffusion. At the beginning of our sample period, the machinery and electronics industry in Japan contributes to a strikingly 10.23% of the world knowledge diffusion. During that period, the machinery and electronics industry plays a dominant role, claiming all the top seven spots in the ranking. During the period of 2015–2017, Japan's machinery and electronics industry remains the top one but its contribution dropped substantially to 3.34%. The chemical industry has also gained much importance over time. Moreover, the rise of China is clearly visible in this table. China's chemical and machinery and electronics industries become the second and third most important contributors among all the country-industry pairs.[19]

We now turn to the source of diffusion-induced productivity growth for each country. In particular, we study the contribution of chemical, machinery/electronics, and transport equipment industries in knowledge diffusion by country. Those three industries are classified by Eurostat as the high- and medium-high-technology industries, and are consistently ranked as the top 3 contributors to global diffusion.[20] Figure 3 depicts the contribution of those high-tech industries. First, the high-tech industries play a dominant role in diffusion, with a contribution of more than 50% for the vast majority and around 70% for some countries. Second, as most of the countries are depicted below the 45-degree line, there is a decline in the high-tech contribution over time, from a cross-country average of 67.62% in 1994–1996 to that of 56.65% in 2015–2017. Third, there is no clear association between the dependence on high-tech industries and the stage of development.

4.2 Decomposing Gains from Trade

The gains from trade in our model can be decomposed into the standard gains from trade in a static Ricardian model and the dynamic gains from trade through productivity growth driven by

[19]Table A5 in the Appendix reports the top 10 countries and country-industry pairs in terms of their contribution to global knowledge diffusion over the entire sample period.

[20]Table A6 in the Appendix reports the industry ranking based on the contribution to global diffusion over the entire sample period.

knowledge diffusion. To quantify the magnitude of those two sources of gains from trade, we consider two counter-factual exercises. First, we allow the trade costs $d^i_{nn',t}$ to change over time based on the estimates from the gravity equation and fix all the other parameters (including the productivity measures) as of the first period 1991–1993. Second, we allow the productivity measures $\lambda^i_{n,t}$ for the tradable industries to evolve over time according to the law of motion based on the estimated diffusion parameters and fix all the other parameters (including the trade costs) as of the first period 1991–1993. We then fully solve the general equilibrium and obtain the welfare measure (real GDP) for each country period by period.

Figure 4 depicts the static and dynamic gains from trade for each country. The median static gains are 17.50% whereas the median dynamic gains are 10.89%. As is evident in the figure, static gains from trade have a much higher standard deviation of 22.03%, compared to the standard deviation of the dynamic gains from trade being 4.90%.[21] There is no substantial difference in either static or dynamic gains from trade between OECD and non-OECD countries, but it is worth noting that China, according to our quantification, enjoys much larger dynamic gains from trade than the static gains (21.57% versus 2.50%). Another emerging market economy, Viet Nam, also enjoys relatively high dynamic gains from trade (20.41%) whereas its static gains are also quite significant (61.25%). Advanced economies like the US, Japan, France, and Germany in general have relatively modest dynamic gains from trade which account for around 10% of their real GDP.

4.3 Welfare Elasticity of Diffusion Intensity

The diffusion intensity, captured by the diffusion parameter β^i, plays a fundamental role in our model. To understand its quantitative importance, we vary β^i to simulate its effect on aggregate welfare. More specifically, we fully solve the model by setting β^i of a given industry 10% lower than its estimated level (with the diffusion parameter for all other industries to be fixed at the baseline estimates) and obtain the counterfactual growth in real GDP for each country from the period 1994-1996 to 2015-2017.[22] We then compute the welfare elasticity of diffusion intensity as the change in real GDP growth divided by (-10%). We conduct this exercise for each industry and obtain a full panel of elasticity measures at the industry-country level.

Table 5 reports the welfare elasticity for a selection of 6 industries and 12 countries ("BRICS" and "G7" countries).[23] The welfare elasticity of any given industry varies substantially across countries. Emerging market economies like China and India have on average higher elasticity than the advanced economies. This pattern is particularly prominent for the transport equipment industry with the highest average welfare elasticity. As illustrated in Figure 5, the welfare elasticity is negatively correlated with the stage of development (proxied by GDP per capita). The real income growth of emerging market economies is more sensitive to the intensity of knowledge diffusion.

The welfare elasticity always varies substantially across industries.[24] The industry-level average welfare elasticity is positively correlated with the diffusion intensity β^i (correlation=0.54), the im-

[21] The dynamic gains from trade are always positive in our sample but there are countries with negative static gains from trade. In particular, Venezuela's static gains from trade are -8.15% (the most left blue dot in the figure). This is mainly because the trade costs for exports from Venezuela are estimated to experience a sizable *increase* of about 50% over the sample period.

[22] We consider a reduction of β^i by 10% instead of an increase because otherwise β^i would hit its upper bound.

[23] We pick the 5 industries with the highest average elasticities (excluding the residual industry "other manufacturing") and the industry with the lowest average elasticity (apparel and leather).

[24] The industry-level mean and standard deviation are reported in Table A7.

portance of an industry in the final demand ω^i (correlation=0.32), and the Katz-Bonacich centrality of in the input-output network (correlation=0.35) as formally studied in Liu and Tsyvinski (2020). This is consistent with the intuition that industries more important to consumers' final demand or more central in the production network tend to have a greater influence on welfare when the diffusion intensity changes.

It is worth highlighting that the welfare elasticity of diffusion intensity is not always positive, meaning that stronger knowledge diffusion can be welfare-reducing for some countries. This is because when knowledge is easier to diffuse for a given industry, countries with initial comparative advantage will face more competitive foreign sellers over time and this negative business-killing effect can play a dominant role when a country's production is heavily concentrated in that industry. For example, we observe from Table 5 that the welfare elasticity for Japan in the machinery and electronics industry is -0.0109. The industry accounts for 30% of Japan's total manufacturing output at the beginning of the sample period. Moreover, a larger fraction of countries have negative welfare elasticity for the industry of apparel and leather. This is because the industry starts with very high variation in initial productivity. As a result, when its diffusion intensity rises, the business-killing effect is on average much stronger.

4.4 Targeted Restrictions of Technology Trade

The ongoing tension between the US and China concerning trade and technology raises a question about the welfare consequences of targeted restrictions on technology trade. To assess the quantitative implications of such restrictions and their effects on third countries, we vary the trade cost of the exports to China in the machinery/electronics industry (ISIC=29-33) during the entire sample period from 1991 to 2017. We compute the change in real GDP compared to the baseline simulation in the period of 2015-2017 so that the welfare calculation accounts for the cumulative change in productivity that is caused by the policy-induced change in knowledge diffusion. We consider two scenarios: (i) only the US restricts exports of technology goods to China; (ii) all the G7 countries impose the restrictions collectively.

Panel A of Figure 6 illustrates for scenario (i) how the welfare change varies with the degree of the trade restrictions. First, the technology trade restrictions yield welfare losses to both the US and China. The welfare losses are relatively small in magnitude but China's loss is substantially higher than that of the US. When the change in trade cost exceeds a relatively moderate level of about 50%, the US's welfare loss becomes stable, whereas China's welfare loss continues to rise with the degree of restrictions. In the extreme case when the US entirely shut down technology export to China, China would experience a 0.5% welfare loss with a welfare loss to the US by about 0.07%. The sharp difference in welfare loss stems from the fact that China's productivity growth relies significantly more on foreign technology. Second, the spillover effect on the rest of the world is nonlinear. The targeted restrictions of technology trade in fact have a positive effect on the welfare of the rest of the world when the degree of restrictions is relatively moderate. The positive spillover effect peaks when the trade cost of the US exports to China in machinery/electronics increases by about 24%. Panel B of Figure 6 illustrates the welfare consequences for scenario (ii) when the G7 countries impose coordinated technology trade restrictions. The main message remains qualitatively similar, but now the welfare loss for China becomes significantly larger. Compared to the first scenario, China's welfare loss is about five times as large, indicating that the power of coalition is beyond marginal.

5 Concluding Remarks

In this paper, we study knowledge diffusion in a rich multi-country and multi-industry dynamic environment. Theoretically, we incorporate the industry dimension into the diffusion-based growth model of Buera and Oberfield (2020), featuring a two-way relationship between knowledge diffusion and evolving comparative advantage. Empirically, we structurally estimate the diffusion parameters based on the model-implied law of motion of industry-level productivity and data on 78 countries 15 industries from 1991 to 2007.

With the estimated diffusion parameters, we find that about one-third of the cross-country productivity convergence in tradable industries can be attributed to knowledge diffusion through international trade. Further, we employ our quantitative framework to decompose the source of knowledge diffusion and the gains from trade. We identify Japan and US as the main source of knowledge diffusion since the 1990s and China to be an evident outlier in recent decades. The high-tech industries are predominantly the key sources of ideas. We also quantitatively find that the welfare elasticity of diffusion strength is not always positive. In rare cases, business killing effects will dominate the welfare gains from productivity growth driven by knowledge diffusion. With industry dimension in a framework with international trade and knowledge diffusion, this paper also studies the welfare implications of targeted bans on the computer and electronics industry, resembling the recent episode of the US-China trade war.

Our analysis also points to several open questions. First, it is natural to consider how alternative forms of knowledge diffusion, for example, through foreign direct investment or international migration, can be incorporated into the quantifiable models of idea flows. Second, more evidence based on microeconomic studies of technology diffusion can be extremely useful to guide the quantitative analysis at the industry level. Last, and perhaps most importantly, the global diffusion network, with key players being empirically identified, warrants further theoretical exploration.

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Table 1: Estimates of Diffusion Parameters

Industry	β^i	Std. Err.
Food products and beverages, tobacco products	0.8009	(0.0453)
Textiles	0.4864	(13.098)
Wearing apparel, leather, luggage, footwear	0.7345	(0.0214)
Wood products except furniture, straw and plaiting materials	0.7638	(0.0069)
Paper and paper products	0.8482	(0.0078)
Publishing, printing and reproduction of recorded media	0.8156	(0.0503)
Coke, refined petroleum products and nuclear fuel	0.7567	(0.0035)
Chemicals and chemical products	0.7598	(0.0062)
Rubber and plastic products	0.7660	(0.0059)
Other non-metallic mineral products	0.8537	(0.0170)
Basic metals	0.8102	(0.0041)
Fabricated metal products, except machinery and equipment	0.8480	(0.0106)
Machinery, electronics, equipment, medical and optical instruments	0.7776	(0.0039)
Transport equipment	0.9123	(0.0017)
Furniture, other manufacturing	0.9272	(0.0016)

Notes: (i) Estimates of β^i are based on the weighted non-linear least square regression of (23). The weight is the gross output for each country-industry pair. (ii) The sample is a balanced panel of 9360 observations (8 periods $\times$ 78 countries $\times$ 15 industries). (iii) The standard errors are reported in parenthesis. (iv) The constant term η is estimated to be 0.4064.

Table 2: Goodness of Fit

Variable	Data Median	Model Median	Correlation
Wage $w_{n,t}$	0.8328	0.8030	0.7950
Rent $r_{n,t}$	0.0975	0.1061	0.5450
Domestic Absorption $\pi^i_{nn,t}$	0.4372	0.5351	0.7922
Bilateral Trade Share $\pi^i_{nn',t}$	0.0001	0.0001	0.6577
GDP Growth Rate	0.0374	0.0537	0.9885

Notes: (i) This table compares the actual data and simulation results. The simulation results for the model median are obtained by fully solving the general equilibrium of the model period by period with the industry-level productivity measures implied by the estimated law of motion. (ii) The first four rows are based on the sample spanning from 1994–1996 to 2015–2017, covering 8 periods. The last row is based on the annualized GDP growth rate calculated over the same timespan. (iii) The wage rate is in 10,000 USD (2017 PPP-adjusted) and the other variables are in their original levels.

Table 3: Productivity Convergence: Data versus Model

	All Countries		OECD		Non-OECD	
	(1) Data	(2) Model	(3) Data	(4) Model	(5) Data	(6) Model
			Panel A: Long Difference			
Initial Productivity	-0.494***	-0.183***	-0.428***	-0.163***	-0.621***	-0.209***
	(0.069)	(0.017)	(0.057)	(0.018)	(0.111)	(0.025)
N	1,170	1,170	540	540	630	630
			Panel B: Stacked Differences for Two Periods			
Initial Productivity	-0.356***	-0.087***	-0.346***	-0.079***	-0.417***	-0.098***
	(0.036)	(0.009)	(0.031)	(0.010)	(0.059)	(0.013)
N	2,340	2,340	1,080	1,080	1,260	1,260

Notes: (i) This table presents the results of productivity convergence based on the actual data and the model implied productivity measures. (ii) The dependent variable, productivity growth, is computed as the log difference of $(\lambda^i_{n,t})^{1/\theta}$ between 1994-1996 and 2015-2017 for Panel A and as the stacked log difference for three periods, 1994-1996, 2003-2005, and 2015-2017, for Panel B. (iii) The main independent variable, initial productivity, is defined as the log of productivity in 1994-1996 for Panel A and that in 1994-1996 and 2003-2005 (respectively for two first differences) for Panel B. (iv) Country and industry-year fixed effects are included. (5) The standard errors clustered at the country level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Contribution to Knowledge Diffusion: Top 10 Country-Industry Pairs

1994–1996			2015–2017		
Country	Industry	Contribution	Country	Industry	Contribution
Japan	Machinery/electr.	10.23%	Japan	Machinery/electr.	3.34%
United States	Machinery/electr.	4.05%	China	Chemical	3.33%
Switzerland	Machinery/electr.	3.54%	China	Machinery/electr.	2.54%
Germany	Machinery/electr.	2.52%	United States	Chemical	2.41%
Italy	Machinery/electr.	2.09%	Switzerland	Machinery/electr.	2.01%
France	Machinery/electr.	1.91%	Taiwan	Machinery/electr.	1.91%
South Korea	Machinery/electr.	1.71%	Japan	Chemical	1.73%
Japan	Chemical	1.67%	Japan	Transport	1.60%
United States	Chemical	1.66%	South Korea	Chemical	1.49%
Japan	Transport	1.64%	United States	Machinery/electr.	1.45%

Notes: (i) This table reports the top 10 country-industry pairs ranked by their contribution to global knowledge diffusion for the periods of 1994–1996 and 2015–2017. (ii) The contribution is calculated as the average share of knowledge diffusion from a given country-industry pair, weighted by the real output of each recipient country-industry pair. (iii) The quantitative exercise is based on the baseline estimates of diffusion parameters reported in Table 1.

Table 5: Welfare Elasticity of Diffusion Intensity

Industry	food beverage	apparel leather	paper products	fabricated metal	machinery electronics	transport equipment
ISIC Code	15-16	18-19	21	28	29-33	34-35
				BRICS Countries		
Brazil	0.0336	-0.0031	0.0061	0.0161	0.0100	0.4758
China	0.1369	0.0311	0.0725	0.1390	0.0525	0.7314
India	0.0241	0.0155	0.0583	0.1132	0.0327	0.7593
Russia	0.2949	0.0029	0.0409	0.1196	0.0318	0.4763
South Africa	0.0217	0.0013	0.0042	0.0155	-0.0055	0.3721
				G7 Countries		
Canada	0.0301	0.0022	0.0007	0.0345	0.0083	0.3497
France	0.0369	-0.0040	0.0031	0.0147	0.0113	0.3324
Germany	0.0407	0.0009	0.0101	0.0276	0.0155	0.4056
Italy	0.0343	-0.0015	0.0046	0.0125	0.0076	0.3596
Japan	0.0497	-0.0005	0.0085	0.0013	-0.0109	0.2420
United Kingdom	0.0330	-0.0018	0.0118	0.0317	0.0147	0.3300
United States	0.0691	0.0028	0.0072	0.0343	0.0107	0.3053

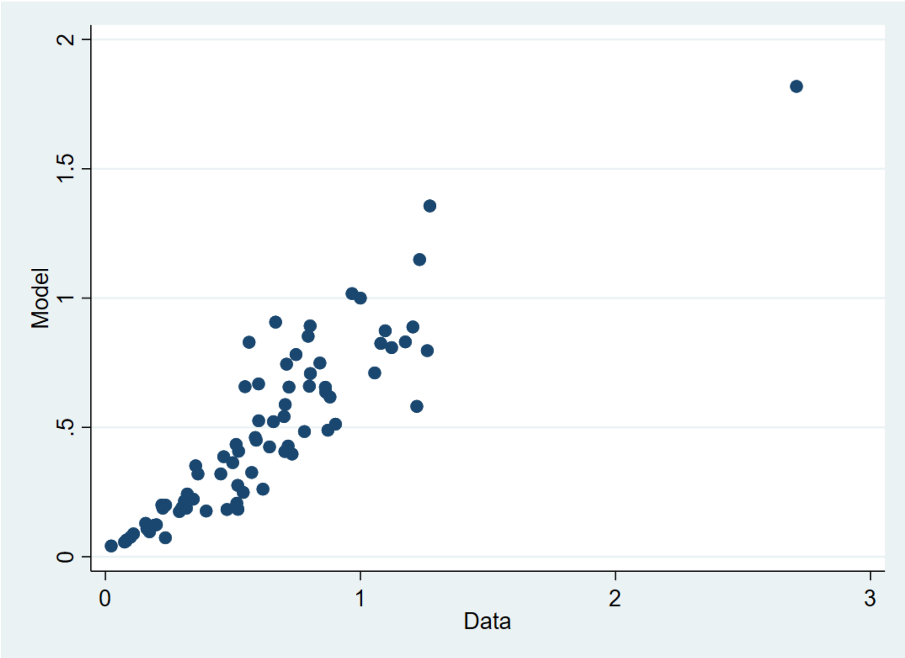
Notes: (i) This table reports the welfare elasticity of diffusion intensity for a select set of industries and countries. (ii) The quantitative exercise is based on the baseline estimates of diffusion parameters reported in Table 1.

Table 6: Estimates of Diffusion Parameters: Robustness Checks

	(1) no weights	(2) excluding negative growth	(3) PPML estimates	(4) country-specific β^i OECD	non-OECD
Food/beverages	0.8386	0.8224	0.9354	0.6722	0.8988
	(0.0073)	(0.0142)	(0.0083)	(82.48)	(0.0281)
Textiles	0.6377	0.6795	0.8721	0.7202	0.5704
	(1.5836)	(0.0848)	(0.0075)	(1.3243)	(1.426×10^3)
Apparel/leather	0.7667	0.7457	0.8732	0.8507	0.8628
	(0.0150)	(0.0115)	(0.0052)	(0.0166)	(0.0361)
Wood products	0.8068	0.7877	0.8839	0.8854	0.9578
	(0.0074)	(0.0032)	(0.0032)	(0.0078)	(0.0048)
Paper products	0.9092	0.8449	0.9166	0.4904	0.9572
	(0.0020)	(0.0068)	(0.0048)	(3.703×10^3)	(0.0061)
Publishing/printing	0.8428	0.8592	0.9416	0.5410	0.3065
	(0.0169)	(0.0077)	(0.0051)	(4.703×10^3)	(9.258×10^4)
Oil products	0.7838	0.7677	0.3119	0.9300	0.9055
	(0.0074)	(0.0027)	(0.0053)	(0.0064)	(0.0062)
Chemical products	0.8248	0.8157	0.8427	0.8925	0.9617
	(0.0049)	(0.0021)	(0.0112)	(0.0074)	(0.0060)
Rubber/plastics	0.8174	0.7621	0.7497	0.8942	0.3634
	(0.0058)	(0.0055)	(0.0104)	(0.0071)	(3.010×10^5)
Other mineral	0.8638	0.8789	0.9900	0.9355	0.9312
	(0.0082)	(0.0047)	(0.0009)	(0.0242)	(0.0181)
Basic metals	0.8486	0.8135	0.8665	0.9173	0.9665
	(0.0044)	(0.0032)	(0.0079)	(0.0064)	(0.0038)
Metal products	0.8896	0.8615	0.9246	0.9513	0.9341
	(0.0026)	(0.0050)	(0.0027)	(0.0099)	(0.0105)
Machinery/electronics	0.7708	0.7758	0.8881	0.8650	0.9321
	(0.0063)	(0.0031)	(0.0035)	(0.0076)	(0.0049)
Transport equipment	0.9256	0.9070	0.9421	0.9853	0.9694
	(0.0007)	(0.0014)	(0.0025)	(0.0023)	(0.0051)
Other manufacturing	0.9541	0.9225	0.9754	0.9900	0.9539
	(0.0006)	(0.0013)	(0.0017)	(0.0017)	(0.0043)
R&D parameter β^r	-0.7506	-0.9199	-1.0024	-0.8722	
	(0.0002)	(0.0004)	(0.0013)	0.0008	

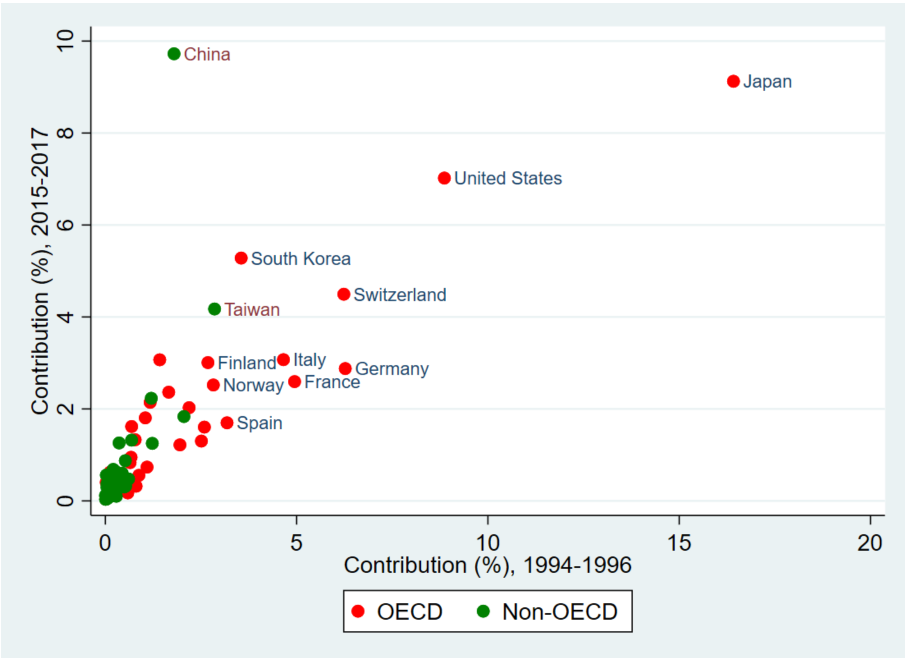
Notes: (i) The reported estimates are based on the non-linear least square regression of (23). (ii) The weight is the gross output for each country-industry pair, except for Column (1) where no weights are applied. (iii) Columns (2) and (3) exclude observations with negative TFP growth with (2) using the productivity estimates based on the OLS estimation of the gravity model and (3) based on the PPML estimation of the gravity model. (iv) Column (4) allows the diffusion parameters β^i to take different values for OECD and non-OECD countries. (iv) The standard errors are reported in parenthesis.

Figure 1: GDP per capita (relative to USA): 2015–2017



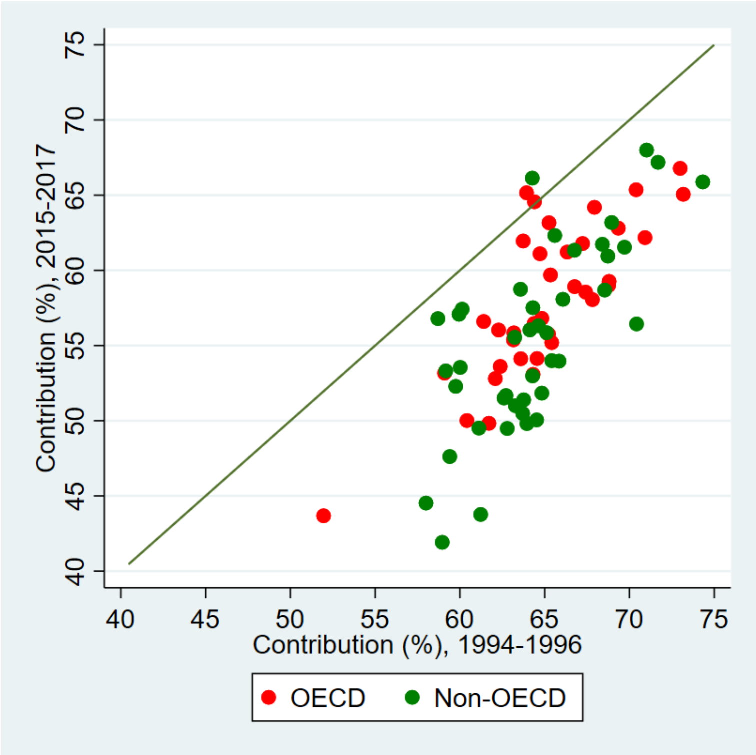
Notes: (i) This scatterplot compares the actual data and simulation results of real GDP per capita for the last period of the model (2015–2017). (ii) GDP per capita is normalized to the USA level (USA level = 1).

Figure 2: Contribution to Global Knowledge Diffusion



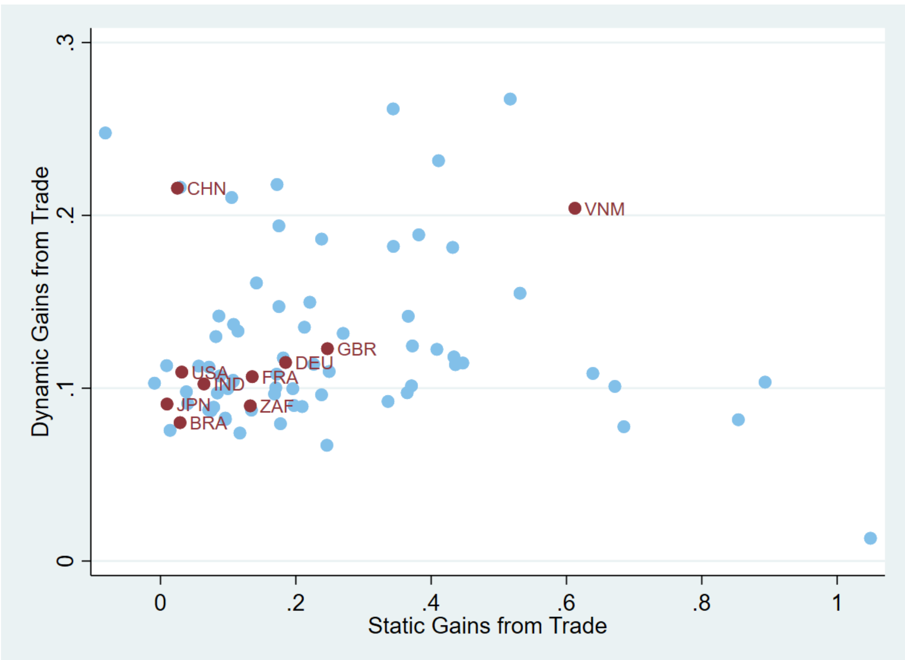
Notes: (i) This figure plots each country's contribution to diffusion-induced productivity growth for the world (weighted by the real output of each recipient country-industry pair) for the periods of 1994–1996 and 2015–2017. (ii) The decomposition exercise is based on the baseline estimate of the diffusion parameter β^i.

Figure 3: Contribute of High-tech Industries to Diffusion by Country



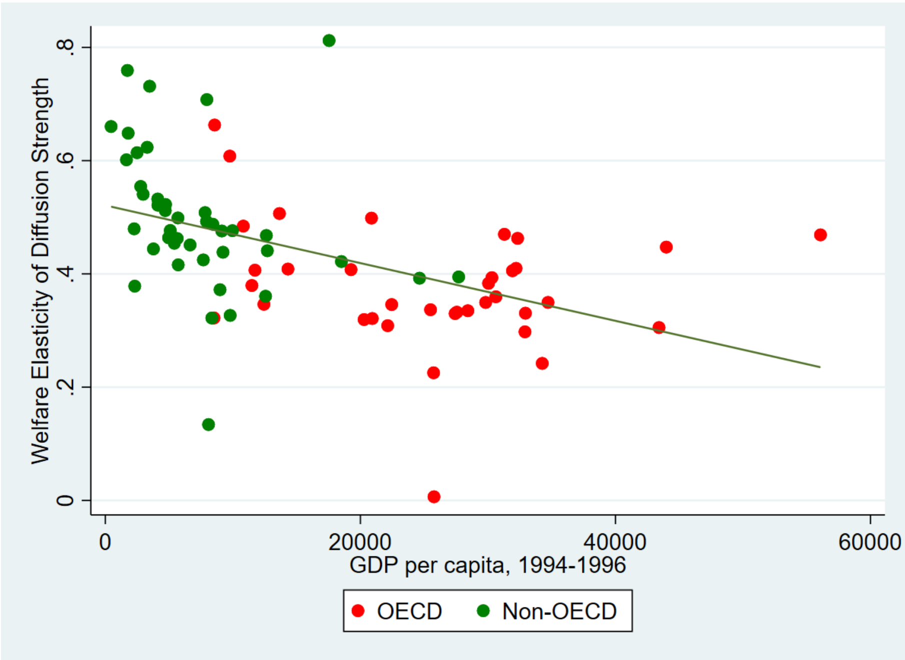
Notes: (i) This figure plots for each country the contribution of high-tech industries (chemical, machinery/electronics, transport) to diffusion-induced productivity growth for the periods of 1994–1996 and 2015–2017. (ii) The decomposition exercise is based on the baseline estimate of the diffusion parameter β^i.

Figure 4: Static and Dynamic Gains from Trade



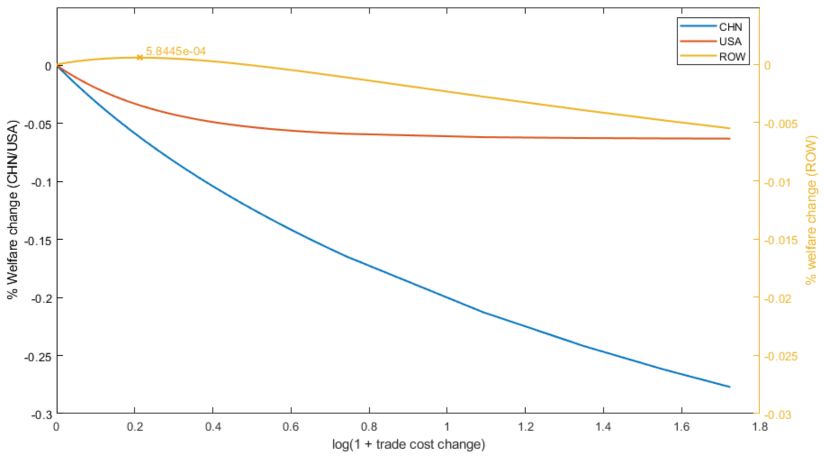
Notes: (i) This scatterplot depicts the static and dynamic gains from trade as the change in real GDP for each country from the period 1994–1996 to the period 2015–2017. (ii) To compute the static gains from trade, we allow trade costs to evolve over time according to the estimates from the gravity equation, while fixing all the other parameters as of the period 1991-1993. To compute the dynamic gains from trade, we allow productivity measures to evolve over time according to the law of motion based on the estimated diffusion parameters, while fixing all the other parameters as of the period 1991-1993.

Figure 5: Welfare Elasticity of Diffusion Intensity (Transport Equipment)

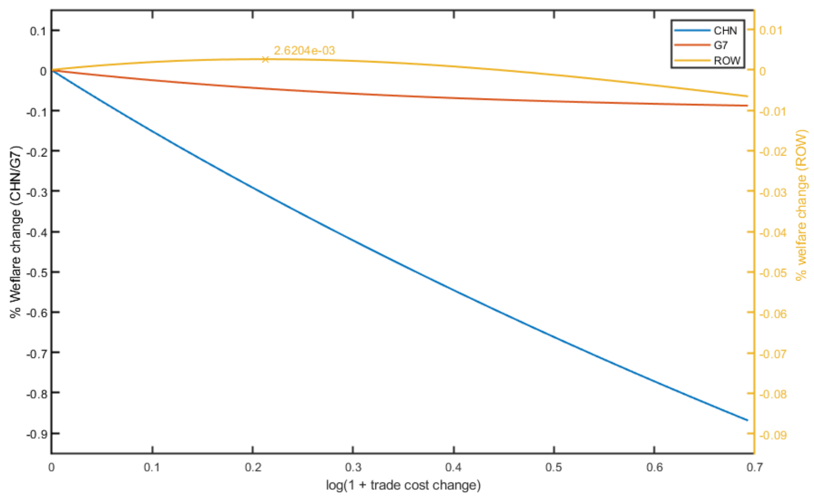


Notes: (i) This scatterplot correlates the welfare elasticity of diffusion intensity for the transport equipment industry with GDP per capita in the period of 1994-1996. (ii) The welfare elasticity calculated based on a 10% reduction of the baseline estimate of the diffusion parameter β^i.

Figure 6: Welfare Implications of Technology Trade Restrictions



Panel A: Restrictions on US Exports to China



Panel B: Restrictions on G7 Exports to China

Notes: (i) The two panels plot the change in real GDP (%) in the period of 2015–2017 due to a hypothetical targeted restriction of exports to China in the high-tech industry of machinery/electronics (ISIC 29-33). (ii) Panel A is the scenario when only the USA imposes the trade restrictions whereas Panel B is the scenario when all G7 countries impose the trade restrictions. (iii) The horizontal axis is the change in trade cost in US/G7 exports of machinery/electronics to China and the change applies to the entire sample period. (iv) The welfare change is based on the benchmark simulation using the baseline estimates of the diffusion parameter β^i and the trade costs.

A The Law of Motion of Industrial Productivity

A.1 Productivity Growth through Knowledge Diffusion

In this subsection, we provide the derivation details for the diffusion-induced productivity growth as in Equation (12). Recall the general form of the law of motion of industry-level productivity as in Equation (11). Specializing that condition to our setting, we obtain

$$\begin{aligned}
\frac{d\lambda_{n,t}^{i}}{dt} &= \tilde{\eta}_{n,t}^{i}\int_{0}^{\infty} x^{\beta^{i}\theta^{i}}\sum_{i'}\iota_{t}^{ii'}\sum_{n'}\prod_{n''\neq n'}F_{n'',t}^{i'}\left(\frac{c_{n'',t}^{i'}d_{nn'',t}^{i'}}{c_{n',t}^{i'}d_{nn',t}^{i'}}x\right)dF_{n',t}^{i'}(x) \\
&= \tilde{\eta}_{n,t}^{i}\int_{0}^{\infty} x^{\beta^{i}\theta^{i}}\sum_{i'}\iota_{t}^{ii'}\sum_{n'}\exp\left(-\sum_{n''\neq n'}\lambda_{n'',t}^{i'}\left(\frac{c_{n'',t}^{i'}d_{nn'',t}^{i'}}{c_{n',t}^{i'}d_{nn',t}^{i'}}x\right)^{-\theta^{i'}}\right)d\exp\left(-\lambda_{n',t}^{i'}x^{-\theta^{i'}}\right) \\
&= \tilde{\eta}_{n,t}^{i}\sum_{i'}\iota_{t}^{ii'}\sum_{n'}\int_{0}^{\infty} x^{\beta^{i}\theta^{i}}\exp\left(-\sum_{n''}\lambda_{n'',t}^{i'}\left(\frac{c_{n'',t}^{i'}d_{nn'',t}^{i'}}{c_{n',t}^{i'}d_{nn',t}^{i'}}x\right)^{-\theta^{i'}}\right)d\left(-\lambda_{n',t}^{i'}x^{-\theta^{i'}}\right) \\
&= \tilde{\eta}_{n,t}^{i}\sum_{i'}\iota_{t}^{ii'}\sum_{n'}\int_{0}^{\infty} y^{-\frac{\beta^{i}\theta^{i}}{\theta^{i'}}}\exp\left(-\sum_{n''}\lambda_{n'',t}^{i'}\left(\frac{c_{n'',t}^{i'}d_{nn'',t}^{i'}}{c_{n',t}^{i'}d_{nn',t}^{i'}}\right)^{-\theta^{i'}}y\right)d(\lambda_{n',t}^{i}y) \\
&= \tilde{\eta}_{n,t}^{i}\sum_{i'}\iota_{t}^{ii'}\sum_{n'}\int_{0}^{\infty} y^{-\frac{\beta^{i}\theta^{i}}{\theta^{i'}}}\exp\left(-\frac{\lambda_{n',t}^{i'}y}{\pi_{nn',t}^{i'}}\right)d(\lambda_{n',t}^{i'}y) \\
&= \tilde{\eta}_{n,t}^{i}\sum_{i'}\iota_{t}^{ii'}\sum_{n'}\int_{0}^{\infty} y^{-\beta^{i}}\exp\left(-\frac{\lambda_{n',t}^{i'}y}{\pi_{nn',t}^{i'}}\right)d(\lambda_{n',t}^{i'}y) \\
&= \tilde{\eta}_{n,t}^{i}\sum_{i'}\iota_{t}^{ii'}\sum_{n'}(\pi_{nn',t}^{i'})^{1-\beta^{i}}(\lambda_{n',t}^{i'})^{\beta^{i}}\int_{0}^{\infty} z^{-\beta^{i}}\exp(-z)\,dz \\
&= \tilde{\eta}_{n,t}^{i}\Gamma(1-\beta^{i})\sum_{i'}\iota_{t}^{ii'}\sum_{n'}(\pi_{nn',t}^{i'})^{1-\beta^{i}}(\lambda_{n',t}^{i'})^{\beta^{i}} \\
&= \eta_{n,t}^{i}\sum_{i'}\iota_{t}^{ii'}\sum_{n'}\pi_{nn',t}^{i'}\left(\frac{\lambda_{n',t}^{i'}}{\pi_{nn',t}^{i'}}\right)^{\beta^{i}},
\end{aligned}$$

where the fourth equality follows from the change of variable $y = x^{-\theta^{i'}}$, the fifth equality follows from $\pi_{nn',t}^{i'} = \frac{\lambda_{n',t}^{i'}(c_{n',t}^{i'}d_{nn',t}^{i'})^{-\theta^{i'}}}{\sum_{n''}\lambda_{n'',t}^{i'}(c_{n'',t}^{i'}d_{nn'',t}^{i'})^{-\theta^{i'}}}$, the sixth equality follows from $\theta^{i} = \theta$ for any i, the seventh equality follows from the change of variable $z = \frac{\lambda_{n',t}^{i'}y}{\pi_{nn',t}^{i'}}$, and the last equality follows from $\eta_{n,t}^{i} \equiv \tilde{\eta}_{n,t}^{i}\Gamma(1-\beta^{i})$. It should be noted that we assume β to be recepient-industry-specific but in principle, we can also allow β to be different across different source industries.

A.2 Allowing θ^i to Vary across Industries

In the benchmark case, $\theta^i = \theta$ for any industry i. According to the derivation in the previous section (the fifth equality in particular), for θ^i that varies across industries, we have

$$\frac{d\lambda^i_{n,t}}{dt} = \tilde{\eta}^i_{n,t} \sum_{i'} \iota^{ii'}_t \sum_{n'} \int_0^\infty y^{-\frac{\beta^i\theta^i}{\theta^{i'}}} \exp\left(-\frac{\lambda^{i'}_{n',t} y}{\pi^{i'}_{nn',t}}\right) d(\lambda^{i'}_{n',t} y). \tag{A.1}$$

Note that the improper integral diverges to infinity if

$$-\frac{\beta^i\theta^i}{\theta^{i'}} \leq -1 \quad \text{or equivalently,} \quad \beta^i\theta^i \geq \theta^{i'}.$$

Therefore, the law of motion of industrial productivity is well defined if and only if $\beta^i\theta^i < \theta^{i'}$ for any pair of i and i'.

Now consider the adjustment parameter $\Theta^{ii'} = \theta^{i'}/\theta^i$ in the diffusion process. Equation (A.1) can simply be rewritten as

$$\begin{aligned}
\frac{d\lambda^i_{n,t}}{dt} &= \tilde{\eta}^i_{n,t} \sum_{i'} \iota^{ii'}_t \sum_{n'} \int_0^\infty y^{-\frac{\Theta^{ii'}\beta^i\theta^i}{\theta^{i'}}} \exp\left(-\frac{\lambda^{i'}_{n',t} y}{\pi^{i'}_{nn',t}}\right) d(\lambda^{i'}_{n',t} y) \\
&= \tilde{\eta}^i_{n,t} \sum_{i'} \iota^{ii'}_t \sum_{n'} \int_0^\infty y^{-\beta^i} \exp\left(-\frac{\lambda^{i'}_{n',t} y}{\pi^{i'}_{nn',t}}\right) d(\lambda^{i'}_{n',t} y),
\end{aligned}$$

where the second equality follows from $\Theta^{ii'} = \theta^{i'}/\theta^i$. The remaining derivation follows the benchmark case and we will again obtain the law of motion as in Equation (12).

B Data Description

Our baseline sample covers 78 countries, 15 manufacturing industries, and a nontradable (non-manufacturing) sector, spanning from 1991 to 2017. Tables A1 and A2 report the list of countries and industries. We exclude entrepôt like Hong Kong and Singapore that our quantitative framework cannot account for. We treat each three-year window as one period and thus the data is organized into nine consecutive periods: 1991–1993, 1994–1996, $\cdots$, 2015–2017. The variables and estimated parameters for each period are computed as the three-year average. In what follows, we describe the data sources and main steps of data processing.

Trade Data. The trade data is obtained from the CEPII CHELEM trade database (2019 version).[25] The database includes harmonized bilateral trade flows from 1967 at the 4-digit ISIC (Rev. 3) level. About 4% of the total trade volume that is not classified into specific industries is discarded. We aggregate the 4-digit to the combined 2-digit level (as in Table A2). We also obtain from the data for each country the industry-level total exports to and imports from the rest of the world.

Industrial Statistics. The production data is obtained from the UNIDO INDSTAT2 database (2020 version). The database includes key industrial statistics from 1963 to 2018 for 174 countries. The main variables that we use are (gross) output, value added, and wage bills. Because the original

[25] We thank Alix de Saint Vaulry for kindly providing the access to the data.

data is at the 2-digit ISIC (Rev. 3) level but with various aggregations across different countries, we adapt our industry classification to best accommodate the variation in industry classifications in the data. We drop countries with very few non-missing output values. When output values are missing but value-added or wage bills are non-missing, we impute the output values by assuming that the value-added-output ratio or wage-output ratio changes continuously over time. There are nine countries that have more than 40% output data being imputed: Algeria, Bangladesh, Belarus, Bosnia and Herzegovina, Cameroon, Nigeria, Pakistan, Saudi Arabia, and Venezuela. For about 12% of the data, the total export exceeds the gross output. Following Costinot et al. (2012), we replace those output values based on the highest output-export ratio (among the ratios that are less than one) for a given exporter.

Gravity Variables. The gravity variables are obtained from the CEPII Gravity database. The main variables that we use are population-weighted distance, dummy variables of contiguity, common official primary language, and free trade areas.

Production Parameters. The parameters in the Cobb-Douglas production function are obtained from the 2004 US input-output table provided by the Bureau of Economic Analysis (BEA). The input-output coefficients $\gamma^{ii'}$ are directly taken from the input-output table. γ^{iL} is computed as the ratio of employment compensations to industry output. γ^{iK} is computed as the ratio of the difference between value added and employment compensations to industry output.

Factor Prices. To compute the wage rate $w_{n,t}$ across countries, we first calculate the (non-PPP adjusted) labor income using the data from the Penn World Table (PWT 10.0). For countries with the share of labor compensation missing in PWT (Albania, Algeria, Bangladesh, Pakistan, and Vietnam), we compute the labor income share using the INDSTAT2 data. Because the labor income share computed by the INDSTAT2 data is on average 70% of that computed by PWT (correlation ≈ 0.44), we scale up the values imputed by the INDSTAT2 data accordingly. We then multiply total employment with the human capital index from PWT to compute the the effective endowment of labor. The missing human capital index is imputed by fitting a quadratic function of GDP per capita. The wage rate is then calculated as the labor income divided by the effective endowment of labor. The rental rate $r_{n,t}$ is calculated as the non-labor income (real GDP minus the labor income) divided by capital stock.

Nontradable Price Index. The price index for the nontradable sector $P_{n,t}^{I+1}$ is obtained from the International Comparison Program. We use the data from five survey rounds: 1985, 1996, 2005, 2011, 2017. The nontradable goods consist of housing, water, electricity, gas, health, transport, communication, recreation and culture, education, restaurants and hotels, and construction. We take an average of the price index of those nontradable industries weighted by their nominal expenditure share. For the survey years, we impute the missing values by fitting a quadratic function of GDP per capita, and for the remaining years, we impute the data by linear interpolation. The price index is normalized by the US level.

US TFP. The US industry-level TFP in the tradable sector is calculated using the NBER-CES Manufacturing Industry Database (Becker et al., 2013). We aggregate the data from the 4-digit SIC to the 2-digit ISIC level, and then compute the industry-level TFP based on a simple Cobb-Douglas production function that consists of five factors: non-production workers, production workers, energy, materials, and capital. The US TFP for the nontradable sector is calculated using the TFP and related measures for major industries provided by the Bureau of Labor Statistics (BLS). The nontradable sector TFP is also estimated using a five-factor production function.

R&D Expenditures. The country-level R&D expenditures (as a share of GDP) are obtained from the World Bank. We impute the missing values by fitting a quadratic function of GDP per capita. The OECD Analytical Business Enterprise Research and Development database also provides the R&D expenditures data at the industry level. However, the industry-level data is not available for a large number of non-OECD countries in our sample, so our analysis mainly uses the country-level R&D expenditures.

Preference Parameters. The (country-specific) expenditure share of the tradable sector ϕ_n is obtained from the OECD Final Consumption Expenditure of Households (2019 Archive). The original data is available from 1991. Following Uy et al. (2013), we compute the (manufacturing) tradable expenditure share by summing up the expenditure shares of durable, semi-durable, and non-durable goods. For countries that are not covered by this dataset, we impute their shares by fitting a linear function of GDP per capita. Within the tradable sector, the expenditure share of each industry ω^i is obtained as the share of personal consumption expenditures from the 2004 US input-output table.

Patent Citation. Our patent citation matrix is constructed from the NBER US Patent Citation Data (Hall et al., 2001). The original citation data is available at the 4-letter IPC level, covering the period from 1976 to 2006. We covert the data to the 2-digit ISIC level by using the crosswalks from IPC to SIC codes and then from SIC to ISIC codes. The time-invariant patent citation matrix is constructed analogously as a production input-output table. For each citing and cited industry pair, we compute the pairwise citation count as a share of the total citation count by the citing industry, averaged over time.

Other Country-Level Data. We obtain additional country-level data from PWT. The variables include capital stock $K_{n,t}$, real aggregate GDP $Y_{n,t}$, and population.

Table A1: List of Countries

36 OECD Countries
Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, South Korea, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States.
42 Non-OECD Countries
Albania, Algeria, Argentina, Bangladesh, Belarus, Bolivia, Bosnia and Herzegovina, Brazil, Bulgaria, Cameroon, China, Colombia, Croatia, Cyprus, Ecuador, Egypt, India, Indonesia, Kazakhstan, Kenya, Kyrgyzstan, Macedonia, Malaysia, Malta, Morocco, Nigeria, Pakistan, Peru, Philippines, Romania, Russia, Saudi Arabia, Serbia and Montenegro, South Africa, Sri Lanka, Taiwan, Thailand, Tunisia, Ukraine, Uruguay, Venezuela, Vietnam.

Notes: (1) Colombia officially became an OECD member country in 2020, after the last year of our sample period, so we classify it as a non-OECD country. (2) South Africa refers to a union of five countries: South Africa, Botswana, Lesotho, Namibia, and Eswatini. The trade statistics are reported together for those five countries in the CEPII-CHELEM data. (3) China refers to mainland China. (4) Taiwan refers to Taiwan, China. (5) Serbia and Montenegro separated into two countries in 2006 so we combine the trade and production data for the two countries in the post-2006 period.

Table A2: List of Industries

ISIC (Rev. 3)	Industry Description
15-16	Food products and beverages, tobacco products
17	Textiles
18-19	Wearing apparel, leather, luggage, footwear
20	Wood products except furniture, straw and plaiting materials
21	Paper and paper products
22	Publishing, printing and reproduction of recorded media
23	Coke, refined petroleum products and nuclear fuel
24	Chemicals and chemical products
25	Rubber and plastic products
26	Other non-metallic mineral products
27	Basic metals
28	Fabricated metal products, except machinery and equipment
29-33	Machinery, electronics, equipment, medical and optical instruments
34-35	Transport equipment
36-37	Furniture, other manufacturing
NT	Nontradable sector

Table A3: Unconditional Productivity Convergence: Data versus Model

	All Countries		OECD		Non-OECD	
	(1)	(2)	(3)	(4)	(5)	(6)
	Data	Model	Data	Model	Data	Model
	Panel A: Long Difference					
Initial Productivity	-0.424***	-0.136***	-0.355***	-0.133***	-0.524***	-0.163***
	(0.043)	(0.012)	(0.039)	(0.015)	(0.062)	(0.018)
N	1,170	1,170	540	540	630	630
	Panel B: Stacked Differences for Two Periods					
Initial Productivity	-0.263***	-0.065***	-0.235***	-0.065***	-0.330***	-0.078***
	(0.028)	(0.006)	(0.025)	(0.008)	(0.046)	(0.009)
N	2,340	2,340	1,080	1,080	1,260	1,260

Notes: (i) This table presents the unconditional convergence results of productivity convergence based on the actual data and the model implied productivity measures. (ii) The dependent variable, productivity growth, is computed as the log difference of $(\lambda^i_{n,t})^{1/\theta}$ between 1994-1996 and 2015-2017 for Panel A and as the stacked log difference for three periods, 1994-1996, 2003-2005, and 2015-2017, for Panel B. (iii) The main independent variable, initial productivity, is defined as the log of productivity in 1994-1996 for Panel A and that in 1994-1996 and 2003-2005 (respectively for two first differences) for Panel B. (iv) Industry-year fixed effects are included. (5) The standard errors clustered at the country level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A4: Productivity Convergence by Industry: Data versus Model

	(1) Data	(2) Model
Food/beverages	-0.500***	-0.048***
	(0.103)	(0.016)
Textiles	0.050	-0.000
	(0.170)	(0.000)
Apparel/leather	-0.458***	-0.072***
	(0.121)	(0.019)
Wood products	-0.532***	-0.022***
	(0.131)	(0.008)
Paper products	-0.522***	-0.126***
	(0.072)	(0.041)
Publishing/printing	-0.449***	-0.110***
	(0.089)	(0.021)
Oil products	-0.416***	-0.161***
	(0.138)	(0.036)
Chemical products	-0.245***	-0.074**
	(0.060)	(0.037)
Rubber/plastics	-0.596***	-0.077**
	(0.077)	(0.031)
Other mineral	-0.492***	-0.130***
	(0.087)	(0.024)
Basic metals	-0.487***	-0.096***
	(0.162)	(0.028)
Metal products	-0.462***	-0.215***
	(0.078)	(0.037)
Machinery/electronics	-0.259***	-0.116***
	(0.081)	(0.021)
Transport equipment	-0.407***	-0.328***
	(0.123)	(0.055)
Other manufacturing	-0.402***	-0.439***
	(0.128)	(0.070)

Notes: (i) This table presents the unconditional convergence results of productivity convergence based on the actual data and the model implied productivity measures. (ii) The dependent variable, productivity growth, is computed as the log difference of $(\lambda^i_{n,t})^{1/\theta}$ between 1994-1996 and 2015-2017. (iii) The independent variable, initial productivity, is defined as the log of productivity in 1994-1996. (iv) The standard errors clustered at the country level are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A5: Contribution to Knowledge Diffusion from 1994 to 2017

Top 10 Countries		Top 10 Country-Industry Pairs		
Country	Contribution	Country	Industry	Contribution
Japan	11.29%	Japan	Machinery/electronics	5.13%
United States	7.89%	United States	Chemical products	2.41%
China	4.49%	United States	Machinery/electronics	2.39%
South Korea	4.37%	Switzerland	Machinery/electronics	2.09%
Switzerland	4.32%	Japan	Chemical products	1.96%
Germany	4.28%	China	Chemical products	1.63%
Italy	4.23%	Japan	Transport Equipment	1.62%
France	4.09%	Italy	Machinery/electronics	1.46%
Taiwan	3.48%	Taiwan	Machinery/electronics	1.41%
Norway	3.31%	Finland	Machinery/electronics	1.36%

Notes: (i) This table reports the top 10 countries and country-industry pairs ranked by their contribution to global knowledge diffusion for the sample period from 1994 to 2017. (ii) The contribution is calculated as the average share of knowledge diffusion from a given country-industry pair, weighted by the real output of each recipient country-industry pair and further averaged across eight periods from 1994 to 2017. (iii) The quantitative exercise is based on the baseline estimates of diffusion parameters reported in Table 1.

Table A6: Industry Ranked by Contribution to Knowledge Diffusion

Country	Contribution
Machinery/electronics	27.04%
Chemical products	24.82%
Transport equipment	11.32%
Rubber/plastics	6.92%
Food/beverages	5.62%
Metal products	4.87%
Basic metals	4.77%
Paper products	4.24%
Other mineral	2.47%
Textiles	1.87%
Other manufacturing	1.61%
Apparel/leather	1.57%
Publishing/printing	1.41%
Oil products	0.87%
Wood products	0.60%

Notes: (i) This table reports the ranking of industries by their contribution to global knowledge diffusion for the sample period from 1994 to 2017. (ii) The contribution is calculated as the average share of knowledge diffusion from a given industry, weighted by the real output of each recipient country-industry pair and further averaged across eight periods from 1994 to 2017. (iii) The quantitative exercise is based on the baseline estimates of diffusion parameters reported in Table 1.

Table A7: Welfare Elasticity of Diffusion Intensity by Industry

Industry	Mean	Std. Dev.
Food products and beverages, tobacco products	0.0342	(0.0642)
Textiles	4.57×10^{-7}	(3.51×10^{-6})
Wearing apparel, leather, luggage, footwear	0.0004	(0.0158)
Wood products except furniture, straw and plaiting materials	0.0004	(0.0039)
Paper and paper products	0.0135	(0.0187)
Publishing, printing and reproduction of recorded media	0.0025	(0.0041)
Coke, refined petroleum products and nuclear fuel	0.0079	(0.0207)
Chemicals and chemical products	0.0094	(0.0124)
Rubber and plastic products	0.0016	(0.0013)
Other non-metallic mineral products	0.0115	(0.0097)
Basic metals	0.0076	(0.0226)
Fabricated metal products, except machinery and equipment	0.0438	(0.0356)
Machinery, electronics, equipment, medical and optical instruments	0.0189	(0.0385)
Transport equipment	0.4406	(0.1331)
Furniture, other manufacturing	0.3675	(0.2032)

Notes: (i) This table reports the mean and standard deviation of the welfare elasticity of diffusion intensity by industry. (ii) The quantitative exercise is based on the baseline estimates of diffusion parameters reported in Table 1.