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Specialization Dynamics, Convergence, and Idea Flows

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Abstract: This paper studies the dynamic evolution of the patterns of Ricardian compara- tive advantage from the perspective of knowledge diffusion. The theoretical analysis builds knowledge diffusion into a quantifiable model of trade by allowing for industry-level produc- tivity to evolve through a spatial flow of ideas. This may take place through four channels: Firms could upgrade their technology via meetings with domestic producers and foreign sell- ers, and meetings are both intra- and interindustry. This theoretical framework yields a law of motion of industry-level productivity across countries, capturing strong interdependence in the evolution of Ricardian comparative advantage. I calibrate the model to a large sample of countries. My 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 suggests that international and interindustry channels play a major role in knowledge diffusion. The framework yields additional quantitative implications. Analysis of the knowledge-diffusion network facilitates the identification of the countries or country–industry pairs that contribute most to global productivity growth. The calibrated model also suggests that dynamic gains from trade through knowledge diffusion are economically significant, amounting to at least one third of static gains from trade.

Keywords: International trade, specialization dynamics, convergence, industrial productivity, comparative advantage, knowledge diffusion, economic growth.

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Dynamique de spécialisation, convergence et flux d'idées

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Abstract : Cet article étudie l'évolution dynamique des modèles d'avantage comparatif ricardien du point de vue de la diffusion des connaissances. Il repose sur un modèle théorique de diffusion des connaissances permettant à la productivité industrielle d'évoluer grâce aux flux spatiaux d'idées. Cette diffusion s'effectue par quatre canaux : les entreprises peuvent améliorer leur technologie par le biais d'interactions avec des producteurs nationaux et des vendeurs étrangers, et ces interactions sont à la fois intra- et inter-industrielles. Ce cadre théorique produit une loi de mouvement de la productivité industrielle dans tous les pays, qui crée une forte interdépendance dans l'évolution des avantages comparatifs ricardiens. Le modèle est calibré sur un large échantillon de pays. Les résultats illustrent une tendance nette des données : Il existe une forte convergence de la productivité au niveau sectoriel et une mobilité substantielle des schémas de spécialisation. Un exercice de décomposition basé sur la loi théorique du mouvement suggère que les canaux internationaux et inter-industriels jouent un rôle majeur dans la diffusion des connaissances. Le modèle calibré fait apparaître d'autres résultats empirique intéressants. L'analyse du réseau de diffusion des connaissances facilite l'identification des paires de pays - secteurs qui contribuent le plus à la croissance de la productivité mondiale. De plus, les gains dynamiques découlant du commerce via la diffusion des connaissances sont très significatifs, et représentent au moins un tiers des gains statiques du commerce.

Mots-clefs : Commerce international, dynamique de spécialisation, convergence, productivité industrielle, avantage comparatif, diffusion des connaissances, croissance économique.

1 Introduction

The last few decades have seen dramatic shifts in the patterns of industrial specialization in the global economy. In an influential paper, Rodrik (2013b) demonstrates a strong convergence in manufacturing productivity across countries, with countries that are initially less productive catching up faster. Perhaps relatedly, many countries have seen large changes in the composition of their exports in less than two decades,[3] suggesting substantial mobility in international specialization patterns (Hanson et al., 2016). Convergence in productivity and more broadly the dynamics of comparative advantage have profound implications for economic growth and therefore cross-country income distribution. Given its impact on the world economy, understanding the drivers of specialization dynamics is clearly an important pursuit.

This paper studies the dynamic evolution of the patterns of Ricardian comparative advantage[4] from the perspective of knowledge diffusion. In an interdependent world, knowledge diffusion is ubiquitous. It is hardly bounded by country borders or industry classifications.[5] To understand and assess the nexus between the complex structure of knowledge diffusion and specialization dynamics, I build a dynamic model featuring both international and interindustry flows of ideas. The cross-sectional setting is a fully fledged multi-country multi-industry Ricardian model of international trade with multiple factors and input–output linkages as in Caliendo and Parro (2014) and Levchenko and Zhang (2016). Industrial productivity, as well as national factor endowments, shapes specialization patterns across countries. Knowledge diffusion is modeled as in Buera and Oberfield (2016). Firm-to-firm interactions brings about exchange of knowledge and therefore productivity growth. International trade determines the structure of firm-to-firm interactions, and, as a result, flows of ideas go hand in hand with flows of goods. I allow additionally for ideas to flow within and across different industries. Thus, I am able to integrate four channels of idea flows: Each firm could upgrade technology through meetings with domestic producers as well as foreign exporters, and knowledge diffusion is both intra- and interindustry. The theoretical framework yields a law of motion of industry-level productivity across countries, capturing strong interdependence of evolution in the Ricardian comparative advantage.

[3]For instance, China's top export industry shifted from children's toys to computers within less than twenty years (Hanson, 2012). Similarly, South Korea managed to establish its leading position in the shipbuilding industry from zero production in two decades. Frequent turnover of main export industries is not just confined to Eastern Asian miracle economies. African countries have also witnessed substantial mobility in their specialization for the last two decades (Easterly and Reshef, 2010).

[4]Despite the fact that the Ricardian comparative advantage has been converging across countries, global trade volume has increased dramatically in the last five decades due to declining trade costs and increasing fragmentation of production across borders.

[5]International trade makes it possible for people across the world to be exposed to new products and ideas created elsewhere in the world. Moreover, interdisciplinary and interindustry exchange of ideas is increasingly important and has become one of the defining features of the modern economy. For example, The rapid development of the information and communication technology in the last twenty years has a profound impact on virtually all sectors of the economy, much beyond its own narrowly defined industry (Acemoglu et al., 2016).

Importantly, the law of motion of industry-level productivity is amenable to empirical implementation.[6] Using production and trade data, I calibrate this structural model of knowledge diffusion to a sample of 32 OECD and 40 non-OECD countries. The calibrated model reproduces strong convergence in Ricardian comparative advantage and its magnitude is in line with what is observed in the data. The model also matches well the convergence pattern in the data for reduced-form, broader measures of comparative advantage. To the best of my knowledge, this is the first structural work on trade and growth that quantitatively captures cross-country convergence in industry-level productivity. The quantitative exercise demonstrates that knowledge diffusion serves as a plausible candidate to quantitatively explain convergence in industry-level productivity or, more broadly, Ricardian comparative advantage (Rodrik, 2013b; Levchenko and Zhang, 2016). Furthermore, the calibrated model generates substantial mobility in specialization especially among non-OECD countries. This is consistent with the empirical findings by Proudman and Redding (2000), Redding (2002), and Hanson et al. (2016).

My empirical framework provides a natural way to decompose global knowledge diffusion into different channels. According to my quantification, international knowledge diffusion on average contributes about two thirds to global productivity growth, playing a much more important role than domestic knowledge diffusion. Interindustry knowledge diffusion, a channel that has recently received attention from the innovation-based growth literature (Cai and Li, 2014), contributes about 60% to total knowledge diffusion. The decomposition results underscore the importance of studying cross-industry knowledge flows which enable us to study industries' technological relatedness in relation to global productivity growth (Hidalgo et al., 2007). By allowing idea flows to take place in the technological space in conjunction with the geographical space, the model offers a more comprehensive description of the complex form of knowledge diffusion, thereby shedding light on the drivers of productivity convergence.

This paper also contributes to the large quantitative literature on the gains from trade. Using the calibrated law of motion of industrial productivity, I compute the dynamic gains from trade as additional increase in real income when a country starts drawing insights from foreign exporters and enjoys higher productivity growth. On average, the additional gains amount to *at least* 8% of real GDP. To put it in context, the standard static gains from trade are on average about 20% of real GDP even taking into account input–output linkages.[7] This suggests that the dynamic welfare gains originally proposed by Buera and Oberfield (2016) are quite substantial. If we split the sample into non-OECD and OECD economies, the dynamic gains from trade are much larger among non-OECD economies, on average accounting for about 12% of real GDP, double the average dynamic gains from trade among

[6]Although the central focus of the paper is the endogenous evolution of industry-level productivity, like Levchenko and Zhang (2016), I also allow production endowments to change over time.

[7]The static gains from trade depend on the elasticity of substitution in final consumption and the trade elasticity. 20% is in line with the numbers reported in Costinot and Rodríguez-Clare (2014). The static gains from trade are much smaller if I pick a relatively large estimate of trade elasticity as in Levchenko and Zhang (2016), in which case the dynamic gains from trade exceed the static gains from trade.

OECD economies. The asymmetry is due to the fact that knowledge diffusion plays a much larger role in boosting productivity growth in developing countries. This suggests that static trade models tend to greatly underpredict the gains from trade for countries that are far away from the world productivity frontier.

Moreover, the model maps the directly observable trade network to an underlying network of knowledge diffusion. The global diffusion network keeps track of the share of knowledge that each country–industry pair receives from other country–industry pairs. Employed with the full structure of idea flows, I propose different methods to identify the country or country–industry pair that contributes most to the global knowledge diffusion. Using the reduced-form centrality measure, I find that while such advanced economies as the United States and Germany top the list of "key players," major emerging-market economies including China and India play an increasing role in mediating knowledge diffusion. To understand substitutability of a country in the global diffusion network, I also propose a counterfactual centrality measure. It is defined as the percentage decrease of global productivity growth upon removing a given country in the world trade network.[8] For example, the counterfactual analysis suggests that removing Japan from the world trade would have caused the largest decline of productivity growth by 5.81% from 1990 to 2010. Interestingly, China, the leading emerging-market economy, disappears from the list of top ten non-OECD economies ranked by this centrality measure. There is only a 1% decline of global productivity growth when China is assumed to be autarkic. The contrasting findings under different centrality measures can be reconciled by the fact that industry-level productivity is relatively low in China. Therefore, many countries would achieve higher productivity growth by importing from more expensive, but also more productive, exporters outside China.

In sum, while a growing body of work documents specialization dynamics and particularly the underlying convergence in Ricardian comparative advantage, most papers in the literature have nevertheless been silent on the sources of dynamic evolution of comparative advantage. This paper attempts to fill this void by providing a quantitative exploration from the perspective of knowledge diffusion through international trade.

1.1 Relation to the Literature

From a modeling point of view, this paper is closely related to the recent theoretical literature on "idea flows." In this class of models, agent-to-agent interaction is the engine of growth (Lucas and Moll, 2014; Perla and Tonetti, 2014). Each period, an agent is randomly matched with another agent in the economy and potentially adopts new insight from the matched agent. Economic growth is thereby characterized as a traveling wave of productivity

[8]This centrality measure does not admit a simple closed-form solution, because I must account for the endogenous change of trade patterns and evolution of industry-level productivity when a country is excluded from the sample. This measure is closely related to the notion of "key players" in the literature on social networks (Zenou, 2016).

distribution within the economy. Extending this framework into the open-economy setting, a series of theoretical papers study how dynamic gains from trade arise from learning from foreign sellers (Alvarez et al., 2013), the timing of technology adoption (Perla et al., 2015), and dynamic selection effects due to entry-exit decisions (Sampson, 2016a). My model builds upon Buera and Oberfield (2016), which itself stems from Kortum (1997) and Alvarez et al. (2013). The key departure from this literature is opening up the industry dimension.[9] Agents across different industries are allowed to meet each other and exchange insights. The traveling wave of an industry is therefore determined by productivity distributions of those industries from which this industry draws insights.

The cross-sectional setting of my model closely follows Caliendo and Parro (2014) and Levchenko and Zhang (2016). Following Eaton and Kortum (2002), a large literature employs quantifiable trade models to study how Ricardian comparative advantage shapes international trade. Shikher (2011) and Costinot et al. (2012) first extend the Eaton–Kortum framework into a multi-industry setting. Caliendo and Parro (2014) and Levchenko and Zhang (2016) further enrich the framework by incorporating realistic input–output linkages (Acemoglu et al., 2012) and multiple factors of production. Though their theoretical predecessors are dynamic growth models (Kortum, 1997; Eaton and Kortum, 1999), most of the existing structural trade models are static. A recent exception is Somale (2014), which studies the complex two-way relationship between productivity growth and trade pattern in an innovation-based framework. My work adds to this literature by endogenizing industry-level trade patterns through the lens of knowledge diffusion.

This paper draws insights from the literature that examines the economic consequences of the technological relatedness of industries spurred by Jaffe (1986). Based on a coexport structure, Hidalgo et al. (2007) conceptualize and operationalize the notion of the "product space" and document strong path dependence in trade patterns. Follow-up work by Kali et al. (2012) reveals the structure of the product space in relation to growth acceleration using cross-country regressions. Cai and Li (2014) builds into an innovation-based growth model industrial linkages of knowledge creation. Using patent citation data, they demonstrate that industrial linkage is important in explaining firms' R&D behavior. Cai et al. (2016) further extend their earlier work into a multi-country setting. Similarly, they allow knowledge diffusion across borders and industries, but their theoretical and quantitative exercise is based on the balanced growth paths on which trade patterns are stable.

This paper is also related to the literature on international technology diffusion.[10] This strand of literature studies the extent to which technology diffuses across borders via imports, exports, and foreign direct investment. The seminal paper by Coe and Helpman (1995) documents that a country's R&D expenditures have large effects on the productivity of its trade partners. Acharya and Keller (2009) provide more recent evidence that technology transfers

[9]Sampson (2016b) offers a multi-industry framework of idea flows, but his contribution is primarily theoretical and the paper focuses on steady-state trade patterns.

[10]Keller (2004) provides an excellent review.

through international trade. As an influential paper, Keller (2002) also integrates four channels of knowledge diffusion in a reduced-form empirical framework. He examines the spillover effects of R&D expenditures on industry-level productivity and finds substantial contribution from interindustry spillovers. The existing cross-country empirical studies primarily rely on industry-level R&D data to measure knowledge stock; as a result, analysis is restricted to a sample of industrialized economies. On the other hand, micro-level studies have established a causal link between imports of intermediate inputs and domestic productivity growth across emerging-market economies such as Indonesia (Amiti and Konings, 2007; Blalock and Veloso, 2007), Chile (Kasahara and Rodrigue, 2008), India (Topalova and Khandelwal, 2011), and Hungary (Halpern et al., 2015). Closest in spirit to this paper, Zhang (2016) documents substantial dynamic gains from input imports, suggesting that knowledge diffusion plays an important role in boosting productivity growth. Taking a macro approach, I base my empirical exercise on a dynamic quantifiable trade model, which allows me to conduct cross-country empirical analysis with a tight connection to the theory.

The rest of the paper is structured as follows. Section 2 presents the motivating evidence: specialization dynamics and convergence. Section 3 describes the model, solves the instantaneous equilibrium, and derives the law of motion of industry-level productivity. Section 4 describes sample construction and the two-step estimation strategy. Section 5 presents main results and demonstrates the model's internal validity. Section 6 discusses the model's quantitative implications. Section 7 concludes.

2 Motivating Facts

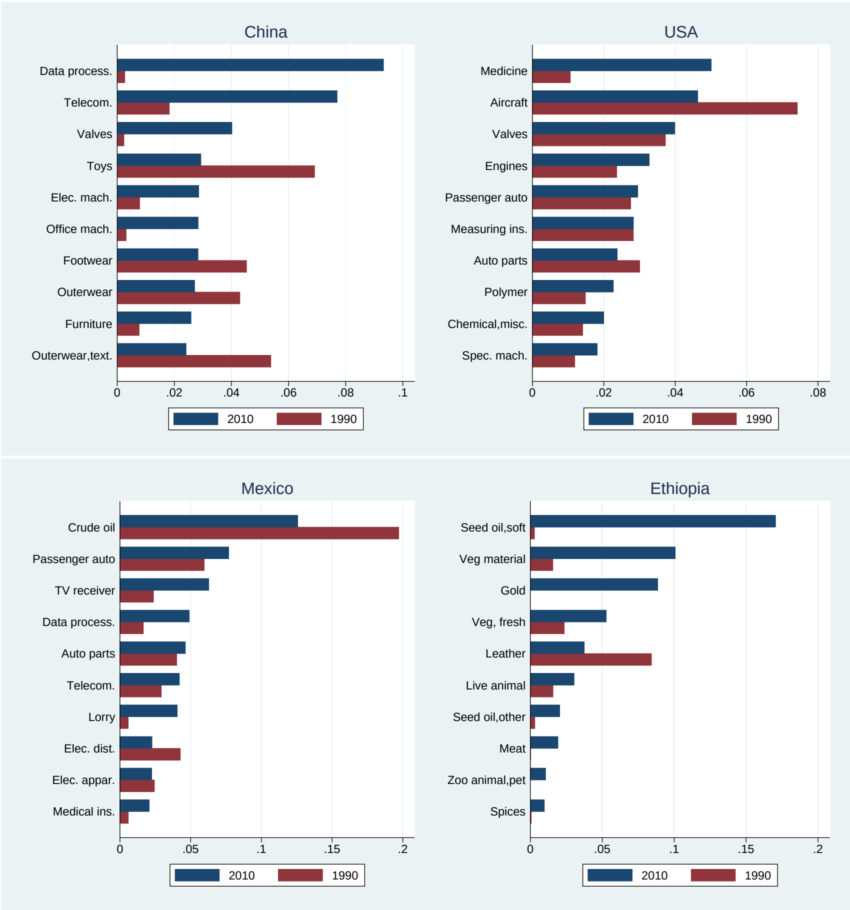
2.1 Specialization Dynamics

The first set of facts concern changes in specialization patterns across countries. Earlier work by Redding (2002) examines evolution of seven OECD countries' export baskets. Armed with an empirical framework of distribution dynamics, he finds substantial mobility in specialization. This finding is further extended by Hanson et al. (2016) in a gravity-equation framework. In a 20-year window, they find the turnover rate of the top 5% of industries to be about 60%. Figure 1 plots four representative countries' export shares[11] of the top 10 export industries in 2010 and compares them with their export shares in 1990. Consistent with the literature, there is substantial turnover among emerging-market economies and developing countries. The US export basket is relatively stable, but the change of export shares is also quite prominent for the top two industries. Figure 2 conducts an exercise similar to that in Hanson et al. (2016). The small values on the diagonal suggest that many of leading export

[11] Export share is admittedly a crude measure, but this pattern is robust under more sophisticated measures of export capabilities. Another criticism is that change in gross exports may simply reflect change in vertical specialization, but I find a similar degree of change in specialization using trade in value-added data (TiVA) from OECD-WTO.

industries in 2010 exported very little or not at all in 1990.

Figure 1: Export Share: 1990 versus 2010



Notes: (1) The data source is Comtrade (3-digit SITC, Rev. 2); (2) I choose the top 10 industries in terms of export share in 2009–2011 and compare their export shares in 1989–1991. The only exception is that I omit coffee industry in Ethiopia (export share drops from 61% to 34%) for better scaling.

2.2 Convergence

Despite the longstanding theoretical prediction, it is only very recently[12] that the quest for evidence on cross-country convergence has delivered sharp empirical results. Rodrik (2013a) documents that, within the manufacturing sector, countries tend to achieve higher productivity growth if the initial level of productivity is relatively low.[13] Closely related to this, the recent trade literature documents convergence patterns for a variety of measures of comparative advantage, such as the revealed comparative advantage index (RCA), export capability

[12]In an earlier work, Hwang (2006) documents cross-country convergence in unit values using product-level international trade data.

[13]In the growth literature, unconditional convergence refers to a negative correlation between the initial level of a variable of interest and its growth rate without conditioning on any country-specific characteristics. A negative correlation with conditioning is conditional convergence. In this paper, I consider both conditional convergence in a pooled regression with country fixed effects and unconditional convergence in regressions by industry without country fixed effects. The model captures both types of convergence.

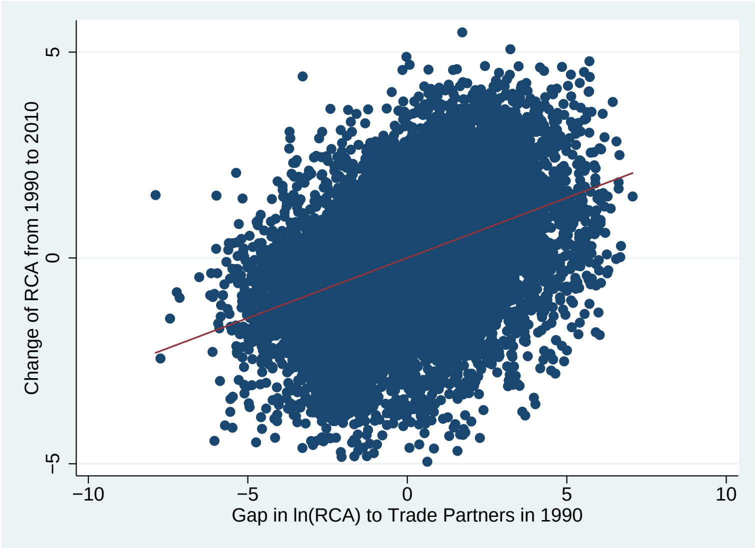
Figure 2: Transition Matrix from 1990 to 2010

		Percentile in 1990				
		0-5	5-10	10-15	15-25	25-100
Percentile in 2010	0-5	**0.33**	0.07	0.04	0.06	0.50
	5-10	0.25	**0.21**	0.10	0.12	0.33
	10-15	0.10	0.19	**0.13**	0.16	0.43
	15-25	0.04	0.09	0.11	**0.18**	0.58
	25-100	0.01	0.02	0.03	0.09	**0.84**

Notes: (1) The data source is Comtrade (3-digit SITC, Rev. 2); (2) Industries are ranked according to the revealed comparative advantage index. The ijth entry is the share of the ith percentile industries in 2009–2011 that were in jth percentile in 1989–1991; (3) Due to skewness in export share, industries with RCA below the 25th percentile export very little, if not zero. Therefore, percentiles are not equally divided.

constructed from a gravity equation (Hanson et al., 2016), and industry-level TFP derived from structural gravity equations (Levchenko and Zhang, 2016). Figure 3 illustrates convergence from a slightly different point of view. I plot industry-level RCA growth in the tradable sector from 1990 to 2010 against the gap between a country's RCA and the average RCA of its trade partners weighted by import share in 1990. There is clearly a positive relationship between the growth rate and the initial gap, meaning that a country tends to experience faster export growth in industries where it falls far behind its trade partners. That being said, a country's export capability converges to not only the world technology frontier, a salient pattern that has been documented in the literature, but also the average level of its trade partners. International technology diffusion through trade partners seems to be a plausible explanation of this convergence pattern. In the next section, I build a model of knowledge diffusion to quantitatively assess how various channels of technology diffusion could give rise to convergence.

Figure 3: Convergence to Trade Partners



Notes: (1) The data source is Comtrade (3-digit SITC, Rev. 2); (2) Gap in $\ln(RCA)$ to trade partners is obtained as the average difference in $\ln(RCA)$ between a country and its trade partners weighted by import share; (3) The RCA index is calculated as a three-year average (1989–1991, 2009–2011); (4) I control for industry and country fixed effects.

3 Model

The model has two main components. The cross-sectional setting is a multi-industry multi-country Hechscher–Ohlin–Ricardian framework with industrial linkages, which closely follows Caliendo and Parro (2014) and Levchenko and Zhang (2016). Dynamics of industry-level productivity is modeled in line with Buera and Oberfield (2016). Diffusion of ideas is the engine of productivity growth. The two-way relationship between international trade and productivity growth is separated into two dimensions: 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 (2016), I am able to investigate a rich set of knowledge diffusion and derive the law of motion for industry-level productivity that is amenable to empirical implementation.

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

3.1 Cross-sectional Setup

To simplify the notation, I suppress the time subscript t in presenting the cross-sectional setup when this causes no confusion.

3.1.1 Demand

Goods from $I+1$ industries are combined into final goods which are used for investment and consumption. The combination is of the form

$$Y_n(Y_n^1, Y_n^2, ..., Y_n^{I+1}) = \left[\sum_{i=1}^{I} \left(\omega_n^i\right)^{1-\kappa} \left(Y_n^i\right)^{\kappa}\right]^{\phi_n/\kappa} \left(Y_n^{I+1}\right)^{1-\phi_n},$$

where Y_n is the output of final goods in country n and Y_n^i is the goods from industry i; ω_n^i is the share parameter of tradable goods and $\sum_{i=1}^{I} \omega_n^i = 1$ for any country n; ϕ_n is Cobb–Douglas share of tradable goods. The elasticity of substitution across tradable goods is constant and given by $1/(1-\kappa)$. A representative consumer in country n is faced with the following per-period decision problem

$$\max_{Y_n^1, Y_n^2, ..., Y_n^{I+1}} Y_n(Y_n^1, Y_n^2, ..., Y_n^{I+1}) \quad \text{subject to} \quad \sum_{i=1}^{I+1} P_n^i Y_n^i \leq E_n,$$

where P_n^i is the industry-level price index and E_n is per-period total expenditure. Standard derivation yields

$$Y_n^i = \frac{\omega_n^i P_n^{i\,\frac{\kappa}{\kappa-1}}}{\sum_{i'=1}^{I} \omega_n^{i'} P_n^{i'\,\frac{\kappa}{\kappa-1}}} \cdot \frac{\phi_n E_n}{P_n^i}, \quad i = 1, 2, ..., I, \tag{1}$$

$$Y_n^{I+1} = \frac{(1-\phi_n)E_n}{P_n^{I+1}}. \tag{2}$$

3.1.2 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 using labor, capital, and composite intermediate goods. Production technology is of Cobb–Douglas form:

$$q_n^i(\nu^i) = z_n^i(\nu^i)[\ell_n^i(\nu^i)]^{\gamma_n^{iL}} [k_n^i(\nu^i)]^{\gamma_n^{iK}} \prod_{i'=1}^{I+1} [m_n^{ii'}(\nu^i)]^{\gamma_n^{ii'}},$$

where $q_n^i(\nu^i)$ is the output of variety ν^i; $z_n^i(\nu^i)$ is the productivity level; $\ell_n^i(\nu^i)$ and $k_n^i(\nu^i)$ are labor and capital; $m_n^{ii'}$ is composite intermediate goods from industry i'; Cobb–Douglas coefficients γ_n^{iL} and γ_n^{iK} are the labor and capital shares; $\gamma_n^{ii'}$ 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 $\gamma_n^{iL} + \gamma_n^{iK} + \sum_{i'=1}^{I+1} \gamma_n^{ii'} = 1$ for any country n.

According to the production function, the unit cost of an input bundle, c_n^i, can be defined as

$$c_n^i = \left(\frac{w_n}{\gamma_n^{iL}}\right)^{\gamma_n^{iL}} \left(\frac{r_n}{\gamma_n^{iK}}\right)^{\gamma_n^{iK}} \prod_{i'=1}^{I+1} \left(\frac{P_n^{i'}}{\gamma_n^{ii'}}\right)^{\gamma_n^{ii'}}, \tag{3}$$

where w_n is the wage rate and r_n is the rental rate.

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

$$Q_n^i = \left[\int_0^1 q_n^i(\nu^i)^{(\sigma^i-1)/\sigma^i} d\nu^i\right]^{\sigma^i/(\sigma^i-1)},$$

where σ^i is the elasticity of substitution. Standard derivation yields

$$q_n^i(\nu^i) = \left(\frac{p_n^i(\nu^i)}{P_n^i}\right)^{-\sigma^i} Q_n^i \quad \text{with} \quad P_n^i = \left[\int_0^1 p_n^i(\nu^i)^{1-\sigma^i} d\nu^i\right]^{1/(1-\sigma^i)},$$

where $p_n^i(\nu^i)$ 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 combined to final goods. Production technology of composite and final goods is identical across countries. This implies that international trade only occurs at the variety level, which will be specified in the next section.

3.1.3 International Trade

Trade cost is of the iceberg form (Samuelson, 1954). It requires shipping $d_{nn'}^i$ units of goods from country n' to deliver one unit of good to country n. The triangle inequality is assumed to always hold: $d_{nn''}^i d_{n''n'}^i \geq d_{nn'}^i$ for any country n, n', n'' and industry i. This implies that reexport is always more costly than direct export in the model. Consequently, such trade hubs as Singapore and Hong Kong are excluded in the empirical implementation of the model. For the nontradable sector, $d_{nn'}^{I+1} = \infty$ for any n, n' such that $n \neq n'$. Domestic trade is assumed to be frictionless,[14] so $d_{nn}^i = 1$ 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_n^i 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

$$p_n^i(\nu^i) = \min\left\{\frac{c_1^i d_{n1}^i}{z_1^i(\nu^i)}, \frac{c_2^i d_{n2}^i}{z_2^i(\nu^i)}, ..., \frac{c_N^i d_{nN}^i}{z_N^i(\nu^i)}\right\}.$$

Following Eaton and Kortum (2002), variety-level productivity, z_n^i, is a random draw from

[14] The recent work by Ramondo et al. (2016) suggests that assuming full integration for each country may not be innocuous.

a Fréchet distribution:

$$F_n^i(z) = \exp(-\lambda_n^i z^{-\theta^i}),$$

where F_n^i is country n's productivity distribution in industry i; the location parameter, λ_n^i, governs the mean of the distribution; θ^i measures the dispersion of the distribution. Denote by $\pi_{nn'}^i$ the share of expenditure that country n spends on the imports from country n' in industry i. Exploiting the probabilistic structure, standard derivation yields

$$\pi_{nn'}^i = \frac{\lambda_{n'}^i (c_{n'}^i d_{nn'}^i)^{-\theta^i}}{\sum_{n''=1}^N \lambda_{n''}^i (c_{n''}^i d_{nn''}^i)^{-\theta^i}}, \tag{4}$$

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.

$$P_n^i = \left[\Gamma\left(1 + \frac{1-\sigma^i}{\theta^i}\right)\right]^{1/(1-\sigma^i)} \left(\sum_{n'=1}^N \lambda_{n'}^i (c_{n'}^i d_{nn'}^i)^{-\theta^i}\right)^{-1/\theta^i}, \tag{5}$$

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.

Note that the location parameter, λ_n^i, varies across time. When turning to the time dimension of the setup, I will introduce the diffusion process developed by Buera and Oberfield (2016) to further endogenize and dynamize the industry-level productivity distribution.

3.1.4 Market Clearing and Instantaneous Equilibrium

Denote country n's total trade deficit by D_n. Like Caliendo and Parro (2014), I allow international lending and borrowing, and trade deficits are exogenously given.[15] The world total trade deficit has to be balanced out, so $\sum_{n=1}^N D_n = 0$. Country n's expenditure is therefore given by

$$E_n = w_n L_n + r_n K_n + D_n, \tag{6}$$

where L_n and K_n is labor and capital endowment.

By definition, the trade deficit is the difference between total imports and exports

$$D_n = \sum_{i=1}^{I+1} \left(P_n^i Q_n^i - \sum_{n'=1}^N P_{n'}^i Q_{n'}^i \pi_{n'n}^i \right). \tag{7}$$

Recall that composite goods in each industry can be either used as intermediate inputs for

[15]The paper does not model the international capital market, so it is silent on the sources of global trade imbalances. Reyes-Heroles (2016) offers a recent explanation for trade imbalances based on a dynamic multi-industry model of international trade in which households' intertemporal decisions and international capital market are explicitly modeled.

variety-level production or combined to final goods, so the product-market-clearing condition in each industry is given by

$$P_n^i Q_n^i = \sum_{i'=1}^{I+1} \gamma_n^{i'i} \sum_{n'=1}^{N} P_{n'}^{i'} Q_{n'}^{i'} \pi_{n'n}^{i'} + P_n^i Y_n^i \tag{8}$$

Given the Cobb–Douglas production technology, the share of labor and capital income are given by γ^{iL} and γ^{iK}, respectively. Therefore, I have

$$w_n L_n^i = \gamma^{iL} \sum_{n'=1}^{N} P_{n'}^i Q_{n'}^i \pi_{n'n}^i \quad \text{and} \quad r_n K_n^i = \gamma^{iK} \sum_{n'=1}^{N} P_{n'}^i Q_{n'}^i \pi_{n'n}^i, \tag{9}$$

where L_n^i and K_n^i are industry-level labor and capital inputs

Market-clearing conditions for the labor and capital markets further require

$$\sum_{i=1}^{I+1} L_n^i = L_n \quad \text{and} \quad \sum_{i=1}^{I+1} K_n^i = K_n. \tag{10}$$

At each moment of time t, given labor and capital endowments $\{L_n\}_{n=1}^N$ and $\{K_n\}_{n=1}^N$, trade deficits $\{D_n\}_{n=1}^N$, bilateral industry-level trade costs $\{d_{nn'}^i\}_{n=1,n'=1,i=1}^{N,N,I+1}$, and industrial productivity measures $\{\lambda_n^i\}_{n=1,i=1}^{N,I+1}$, an instantaneous equilibrium is characterized by $\{r_n\}_{n=1}^N$, $\{w_n\}_{n=1}^N$, and $\{P_n^i\}_{n=1,i=1}^{N,I+1}$ such that consumers maximize utility (Equation 1, 2), firms maximize profit (Equation 3), decisions on international trade are made optimally (Equation 4, 5), product markets clear (Equation 6–8), and factor markets clear (Equation 9–10). In short, Equation 1–10 hold[16] for any country n and industry i.

3.2 Dynamic Setup

3.2.1 A General Diffusion Process

I start with a brief description of a general diffusion process originally formulated by Buera and Oberfield (2016). To make it concrete, consider that firms participate in a trade fair. Each moment of time, a domestic firm f with productivity z drawn from a productivity distribution $F_{n,t}^i$ has a certain chance randomly meeting another firm g in the trade fair. This is formally modeled as a Poisson process. At this point, I do not impose restrictions on where and what firm g produces. Firm g could be a domestic firm or an international firm. It could compete with firm f in the same industry, or it may produce in a different industry. Its productivity z_G is drawn from a productivity distribution $G_{n,t}^i$. This distribution evolves over time and potentially varies across countries and industries. I will explicitly specify $G_{n,t}^i$ when turning to explaining different channels of knowledge diffusion. Firm f adopts the technology

[16]Among these equations, N equations are redundant due to the identity for each country, $E_n = \sum_{i=1}^{I+1} P_n^i Y_n^i$. The proof can be found in Appendix B.1.

or idea from g if it is productivity improving.

However, technology adoption usually requires localization and customization, so it inherently involves randomness. To capture the noisiness in adoption, Buera and Oberfield (2016) introduce another random draw, z_H, from an exogenous, time-invariant Pareto distribution H^i. In particular, the actual productivity of adopting technology from firm g is given by a Cobb–Douglas combination of z_G and z_H, $z_G^{\beta^i} z_H^{1-\beta^i}$. The adoption parameter β^i captures the degree of determinacy in knowledge diffusion. If $\beta^i = 1$, adoption of new ideas is deterministic; if $\beta^i = 0$, the quality of new ideas is purely determined by exogenous noise.[17] The new idea is adopted if and only if $z_G^{\beta^i} z_H^{1-\beta^i}$ is greater than the productivity level of the existing technology z. Following the derivation in Buera and Oberfield (2016), this diffusion process yields[18] the productivity distribution $F_{n,t}^i = \exp(-\lambda_{n,t}^i z^{-\theta^i})$ which coincides with the Fréchet distribution I assume in the cross-section setting. In this sense, the general diffusion process endogenizes the industrial productivity distribution. The industry-level productivity parameter $\lambda_{n,t}^i$ follows the law of motion[19]

$$\frac{d\lambda_{n,t}^i}{dt} = \eta \int_0^\infty x^{\beta^i \theta^i} dG_{n,t}^i(x),$$

where η is the normalized rate of random meetings with firms drawn from distribution $G_{n,t}^i$ and θ^i is the shape parameter in the Pareto distribution H^i divided by $1-\beta^i$. The lower θ^i is, the more likely it is to get a very large random draw from H^i, which implies more dispersion in the productivity distribution and thus strong forces of comparative advantage.

Since a firm could meet many different groups of firms in the trade fair, it draws ideas from different productivity distributions. Let each firm draw new ideas from source s with distribution $G_{n,t}^{i,s}$ at a normalized rate η^s. New ideas from different sources arrive independently of each other. The adoption parameter β^i is assumed to be industry specific but source invariant. Therefore, I can write the general law of motion of industry-level productivity under multiple sources as

$$\frac{d\lambda_{n,t}^i}{dt} = \sum_s \eta^s \int_0^\infty x^{\beta^i \theta^i} dG_{n,t}^{i,s}(x). \tag{11}$$

3.2.2 Channels of Idea Flows

I integrate four channels of idea flows: Knowledge diffuses within a country and across borders through international trade. It takes place within the same industry and across industries. As a benchmark, I start with the assumption that productivity dispersion does not vary across industries: $\theta^i = \theta$.

[17] Notice that there is no upper bound on z_H, so it is possible that an idea adopted by a new firm delivers even higher productivity than where it is originally crafted.

[18] Details of the derivation can be found in Appendix B.2.

[19] In what follows, x in the integral always denotes the variety-level productivity draw.

In the model, intraindustry knowledge diffusion[20] takes the form of random meetings among producers within the same industry. For example, in my trade-fair analogy, electronics producers in China could meet and adopt technology from other electronics producers who sell to the Chinese market. Denote by $\tilde{\eta}_{n,t}^{i}$ the Poisson intensity at which a producer in industry i and country n randomly meets another seller in the same industry. Assuming that each active seller in the domestic market is drawn with equal probability, I obtain the source distribution of this channel as

$$G_{n,t}^{i}(z) = \int_{0}^{z} \sum_{n'=1}^{N} \prod_{n''\neq n'} F_{n'',t}^{i}\left(\frac{c_{n'',t}^{i} d_{nn''}^{i}}{c_{n',t}^{i} d_{nn'}^{i}} x\right) dF_{n',t}^{i}(x),$$

where $\prod_{n''\neq n'} F_{n'',t}^{i}\left(\frac{c_{n'',t}^{i} d_{nn''}^{i}}{c_{n',t}^{i} d_{nn'}^{i}} x\right) dF_{n',t}^{i}(x)$ can be interpreted as the (infinitesimal) probability that a firm with productivity x from country n' is the cheapest seller in country n.

By adding an industry dimension to Buera and Oberfield (2016), I am able to investigate a much richer set of diffusion channels beyond intraindustry interactions. Motivated by the recent empirical evidence on interindustry linkages in innovation (Cai and Li, 2016; Acemoglu et al., 2016), I explicitly allow firm-to-firm meetings to be interindustry. For example, Chinese electronics producers can meet and potentially adopt insights from German machinery exporters. Formally, in the model, I allow firms in industry i to learn from active sellers in the domestic market from another industry i'. New ideas arrive with the rate $\tilde{\eta}_{n,t}^{ii'}$. The source distribution is then given by

$$G_{n,t}^{ii'} = \int_{0}^{z} \sum_{n'=1}^{N} \prod_{n''\neq n'} F_{n'',t}^{i'}\left(\frac{c_{n'',t}^{i'} d_{nn''}^{i'}}{c_{n',t}^{i'} d_{nn'}^{i'}} x\right) dF_{n',t}^{i'}(x).$$

Collecting these channels together and using Equation 11, I obtain the law of motion of industry-level productivity:[21]

[20] Social learning has long been argued crucial to the understanding of productivity growth. A growing body of empirical work confirms learning from information neighbors as an important factor of technology adoption (Bandiera and Rasul, 2006; Conley and Udry, 2010). Case studies of Argentinian industries by Artopoulos et al. (2013) suggest domestic knowledge diffusion could significantly impact a country's comparative advantage through learning from export pioneers. Moreover, a large literature studies international technology diffusion through imports at the industry level. This channel is found important for both high-tech industries like capital equipment (Eaton and Kortum, 2001) and traditional sectors like agriculture (Gisselquist and Jean-Marie, 2000).

[21] Detailed derivation can be found in Appendix B.2.

$$
\begin{aligned}
\frac{d\lambda^i_{n,t}}{dt} = & \overbrace{\eta^i_{n,t}\pi^i_{nn,t}{}^{1-\beta^i}\lambda^i_{n,t}{}^{\beta^i}}^{\text{domestic intraindustry diffusion}} + \overbrace{\eta^i_{n,t}\sum_{n'\neq n}\pi^i_{nn',t}{}^{1-\beta^i}\lambda^i_{n',t}{}^{\beta^i}}^{\text{international intraindustry diffusion}} \\
& + \overbrace{\sum_{i'\neq i}\eta^{ii'}_{n,t}\pi^{i'}_{nn,t}{}^{1-\beta^i}\lambda^{i'}_{n,t}{}^{\beta^i}}^{\text{domestic interindustry diffusion}} + \overbrace{\sum_{i'\neq i}\eta^{ii'}_{n,t}\sum_{n'\neq n}\pi^{i'}_{nn',t}{}^{1-\beta^i}\lambda^{i'}_{n',t}{}^{\beta^i}}^{\text{international interindustry diffusion}}, \quad (12)
\end{aligned}
$$

where $\eta^i_{n,t} \equiv \Gamma(1-\beta^i)\tilde{\eta}^i_{n,t}$, and $\eta^{ii'}_{n,t} \equiv \Gamma(1-\beta^i)\tilde{\eta}^{ii'}_{n,t}$. In the equation above, $\pi_{nn',t}$ is directly observed in trade data and $\lambda^i_{n,t}$ can be estimated from production and trade data. The main objective of my empirical exercise is to obtain diffusion parameters, $\eta^i_{n,t}$, $\eta^{ii'}_{n,t}$, and β^i. In the most general setting, there are too many diffusion parameters, so I impose further assumptions on those parameters in the empirical specification.

It might already be noticed that intraindustry domestic knowledge diffusion is observationally equivalent at the industry level to an alternative formulation through the standard narrative of learning by doing (Young, 1991). Therefore, unlike the development economics literature using microeconomic data (Foster and Rosenzweig, 1995), I do not distinguish learning by doing from knowledge diffusion, so the empirical interpretation of this channel encompasses both mechanisms. Moreover, unlike Buera and Oberfield (2016), I only consider the channel called *learning from sellers* in their original model. Since exporters must also sell in their own domestic market due to the triangle inequality of trade cost, by taking into account learning from domestic sellers, the industry-level diffusion process already captures the idea that domestic producers could learn from each other. Having additional learning channels may potentially improve the prediction of the model, but as suggested by my empirical results, focusing on "learning from sellers" already captures the salient features in the trade data.

I close this part by discussing the earlier simplifying assumption: $\theta^i = \theta$ for any i. According to Caliendo and Parro (2014), there is substantial variation in industrial productivity dispersion across industries. In the presence of heterogeneous θ^i, when producers in industry i with little productivity dispersion (high θ^i) adopt ideas from producers in industry i' with substantial productivity dispersion (low $\theta^{i'}$), the recipient industry's productivity distribution tends to be largely shaped by the extreme values drawn from the source distribution. It can be formally shown that the diffusion process becomes degenerate if and only if $\theta^{i'} \leq \beta^i\theta^i$. Therefore, to relax the assumption on homogeneous θ^i, I have to assume that the diffusion process is adjusted for industrial dispersion so as to maintain the analytical tractability of the model. In particular, an adjustment parameter $\tau_{ii'}$ is introduced into interindustry diffusion. When producers in industry i draw a new insight z_G from productivity distribution G of industry i' as well as a random noise z_H from the exogenous distribution H, the actual productivity of this new insight is given by $z_G^{\tau^{ii'}\beta^i} z_H^{1-\beta^i}$ with $\tau^{ii'} = \theta^{i'}/\theta^i$. Under this assumption of dispersion adjustment, the law of motion of industrial productivity (Equation 12) will be unchanged even when productivity dispersion is not uniform across industries.[22]

3.2.3 Evolution of Endowment

To complete the dynamic setting of the model, I specify the laws of motion of labor and capital. The population growth rate $\chi_{n,t}$ is country specific and time varying:

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

The equation of capital accumulation is given by

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

where $I_{n,t}$ is investment and $\delta_{n,t}$ is the depreciation rate. Since international borrowing and lending is allowed in this model, domestic saving is not necessarily equal to domestic investment. The following accounting identity always holds.

$$D_{n,t} = P_{n,t}(I_{n,t} - S_{n,t}),$$

where $S_{n,t}$ is the domestic saving, and $P_{n,t}$ is the price index of final goods given by

$$P_{n,t} = \left(\sum_{i=1}^{N} \omega_n^i \left(\frac{P_{n,t}^i}{\phi_n} \right)^{\frac{\kappa}{\kappa-1}} \right)^{\frac{\kappa-1}{\kappa}\phi_n} \left(\frac{P_{n,t}^{I+1}}{1-\phi_n} \right)^{1-\phi_n}.$$

As in Levchenko and Zhang (2016), the model features both Ricardian and Heckscher–Ohlin motives for international trade. However, since the main theme of the paper targets productivity dynamics, the evolution of the endowment structure is treated exogenous. At each moment of time, consumers treat saving rates, trade deficits, and investment rates as given. By abstracting away from the complex intertemporal consumption-saving decision, a country's investment level goes hand in hand with its total output. This simplifying assumption makes it feasible to conduct a variety of counterfactual analyses on the Ricardian side of the model.

4 Empirical Specification and Data

4.1 Sample Construction

My sample construction mainly follows Levchenko and Zhang (2016). The baseline sample consists of 72 countries and regions among which 42 are non-OECD economies. Unlike

[22]The proof can be found in Appendix B.3.

innovation-based growth models, an empirical implementation of this model does not require industry-level R&D data. Hence, a much larger set of non-OECD countries is included in the sample. Data from OECD economies typically have longer time span. Since my second-stage estimation requires a balanced panel, I use data from 1990 to 2010 to maximize the number of countries. As a robustness check, similar analysis will also be performed in a longer time span from 1970 to 2010, but most countries in the former Soviet Union will no longer be included. Although the trade and production data is at the annual frequency, I choose the length of each period to be five years to ensure that productivity estimates and calibration of diffusion parameters are not contaminated by short-term business fluctuations. Therefore, the baseline sample is a four-period balanced panel. All the variables are averaged within each period. The sample contains 17 tradable industries. They are slightly aggregated up from two-digit ISIC (revision 3) manufacturing industries.[23]

My sample is constructed from two main data sources.[24] Bilateral trade variables are obtained from the UN Comtrade database and further aggregated up from four-digit SITC to two-digit ISIC. Production variables including industry-level output, value added, and wage bills come from the UNIDO INDSTAT2 (2015 edition) database. Country-specific variables like wage and rental rates, labor supply, and capital stock are taken from the Penn World Table (version 8.1).

4.2 Empirical Specification

My empirical specification has two stages. The first stage uses the gravity structure in each instantaneous equilibrium to estimate industry-level trade costs $d^i_{nn',t}$, industry-level productivity parameters $\lambda^i_{n,t}$, and other cross-sectional structural variables. Estimation of industry-level productivity parameters $\lambda^i_{n,t}$ further consists of two steps. The first step is to estimate productivity parameters relative to a benchmark country, the United States, following the procedure originally proposed by Shikher (2012). The second step is to estimate US industry-level productivity parameters (λ^i_{US}) taking into account the mechanism of Ricardian selection (Finicelli et al., 2013). The second stage calibrates the diffusion parameters $\eta^i_{n,t}$, $\eta^{ii'}_{n,t}$ and β^i. This stage requires solving the instantaneous equilibrium every period and applying model-implied trade and production variables to the law of motion of industry-level productivity.

4.2.1 First Stage: Trade and Production Variables

The first stage estimates trade costs and industry-level productivity. The estimation strategy is to exploit the gravity structure of international trade arising from each instantaneous equilibrium. The subscript t is omitted if doing so does not cause confusion. I first derive

[23] In the appendix, Table A1 reports the sample coverage, and Table A2 describes industries.

[24] The details of sample construction are relegated to Appendix C. Table A3 outlines construction of key variables and data sources.

the empirical version of the gravity equation from the model. Equation 4 implies

$$\ln\left(\frac{\pi^i_{nn'}}{\pi^i_{nn}}\right) = \ln\left(\lambda^i_{n'} {c^i_{n'}}^{-\theta^i}\right) - \ln\left(\lambda^i_n {c^i_n}^{-\theta^i}\right) - \theta^i \ln(d^i_{nn'}). \tag{13}$$

As in Eaton and Kortum (2002), I define the competitiveness measure S^i_n as the industry-level productivity parameter adjusted by the unit cost of an input bundle. That is, $S^i_n \equiv \lambda^i_n {c^i_n}^{-\theta^i}$. The bilateral trade cost is of the form

$$\ln(d^i_{nn'}) = Dist_{nn'} + GravityVar_{nn'} + Exp^i_{n'} + \varepsilon^i_{nn'}, \tag{14}$$

where $Dist_{nn'}$ captures the impact of bilateral distance on trade cost and the impact is discretized by categorizing distance in miles into six intervals, [0, 375), [375, 750), [750, 1500), [1500, 3000), [3000, 6000), [6000, maximum). $GravityVar_{nn'}$ includes a set of gravity variables capturing such effects on trade cost as having a common border, sharing the same language, and belonging to a common currency union or free trade area. I also include the industry-level exporter fixed effect $Exp^i_{n'}$, forcefully advocated by Waugh (2010), to generate implications more consistent with data than the approach using importer fixed effects. The last term $\varepsilon^i_{nn'}$ is an error term orthogonal to all the importer and exporter fixed effects and bilateral observables mentioned above.

Combining Equations 13 and 14, I obtain

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

where $(\ln S^i_{n'} - \theta^i Exp^i_{n'})$ and $(-\ln S^i_n)$ can be captured by two fixed effects. Since we take the United States as the benchmark country, the competitiveness measure relative to it can be obtained from the importer fixed effects,

$$\frac{S^i_n}{S^i_{US}} = \frac{\lambda^i_n}{\lambda^i_{US}} \left(\frac{c^i_n}{c^i_{US}}\right)^{-\theta^i}. \tag{16}$$

In the benchmark estimation, I pick θ^i to be four, the same value across industries ($\theta^i \equiv \theta$). In the robustness check, I will report results using other values of θ^i, including industry-specific estimates from Caliendo and Parro (2014). According to the expression above, to obtain estimates of relative productivity parameters, $\lambda^i_n/\lambda^i_{US}$, what remains to estimate are relative unit costs c^i_n/c^i_{US}. As a benchmark, I assume I–O shares are country invariant. Using Equation 3, I have

$$\frac{c^i_n}{c^i_{US}} = \left(\frac{w_n}{w_{US}}\right)^{\gamma^{iL}} \left(\frac{r_n}{r_{US}}\right)^{\gamma^{iK}} \prod_{i'=1}^{I} \left(\frac{P^{i'}_n}{P^{i'}_{US}}\right)^{\gamma^{ii'}} \left(\frac{P^{I+1}_n}{P^{I+1}_{US}}\right)^{\gamma^{i(I+1)}}, \tag{17}$$

where all the Cobb–Douglas coefficients can be calculated using production data and I–O tables. The I–O shares are calibrated to US values in the benchmark exercise, while country-specific I–O tables will be used as a robustness check. Relative wage rates and relative rental rates are obtained from the Penn World Table. The relative price indices in the nontradable sector are obtained from the International Comparison Program. To obtain relative price indices in tradable industries, I follow Shikher (2012). Using Equation 4 and 5, I can show

$$\frac{\pi^i_{nn}}{\pi^i_{US\,US}} = \frac{S^i_n}{S^i_{US}} \left(\frac{P^i_n}{P^i_{US}}\right)^{\theta}. \tag{18}$$

Collecting Equations 16–18, I finally have

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

where all the relative terms on the right-hand side are either estimated or directly measurable.[25] For the nontradable sector, estimation of relative productivity parameters is even 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} is obtained from Equations 17 and 18, and P^{I+1}_n/P^{I+1}_{US} can be directly obtained from data.

Estimation of Equation 15 also yields the relative competitiveness measure $S^i_{n'}/S^i_n$ for every country pair. Plugging this back into Equation 13, I obtain a panel of trade costs $d^i_{nn'}$. Trade-cost estimates will be used as exogenous parameters in the second-stage calibration. Based on estimation of the gravity equation at the annual frequency, Figure 4 shows how average trade costs decline during the postwar era and the trend is generally downward across most industries. The unbalanced panel of trade-cost estimates exhibits a similar pattern, with a slight increase of the median trade cost from the 1960s to the 1980s due to compositional changes.[26] The only anomaly is that the trade cost of the petroleum/fuel industry picked up early 2000s, which is most likely to be driven by the 2000s' energy crisis.

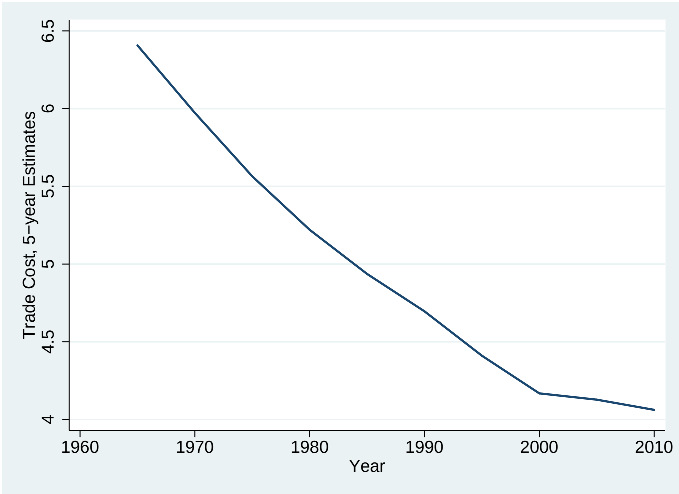
The second step of the first-stage estimation is to estimate US industry-level productivity parameters λ^i_{US}. By aggregating up output, capital, production and nonproduction worker hours, and materials from four-digit SIC to two-digit ISIC, I first estimate four-factor productivity, TFP^i_{US}, of tradable industries (Bartlesman and Gray, 1996). US TFP in the nontradable sector is obtained by combining information from the NBER-CES database and the Penn World Table. However, the observed TFP may overestimate a country's underlying

[25]As a cross validation, I compare the first-stage TFP estimates with those reported in Fadinger and Fleiss (2011). In a similar Ricardo–Heckscher–Ohlin framework but with monopolistic competition, they also obtain industry-level TFP estimates relative to the United States. The cross-sectional comparison is based on 1996 data and the correlation is above 0.5 for the vast majority of industries.

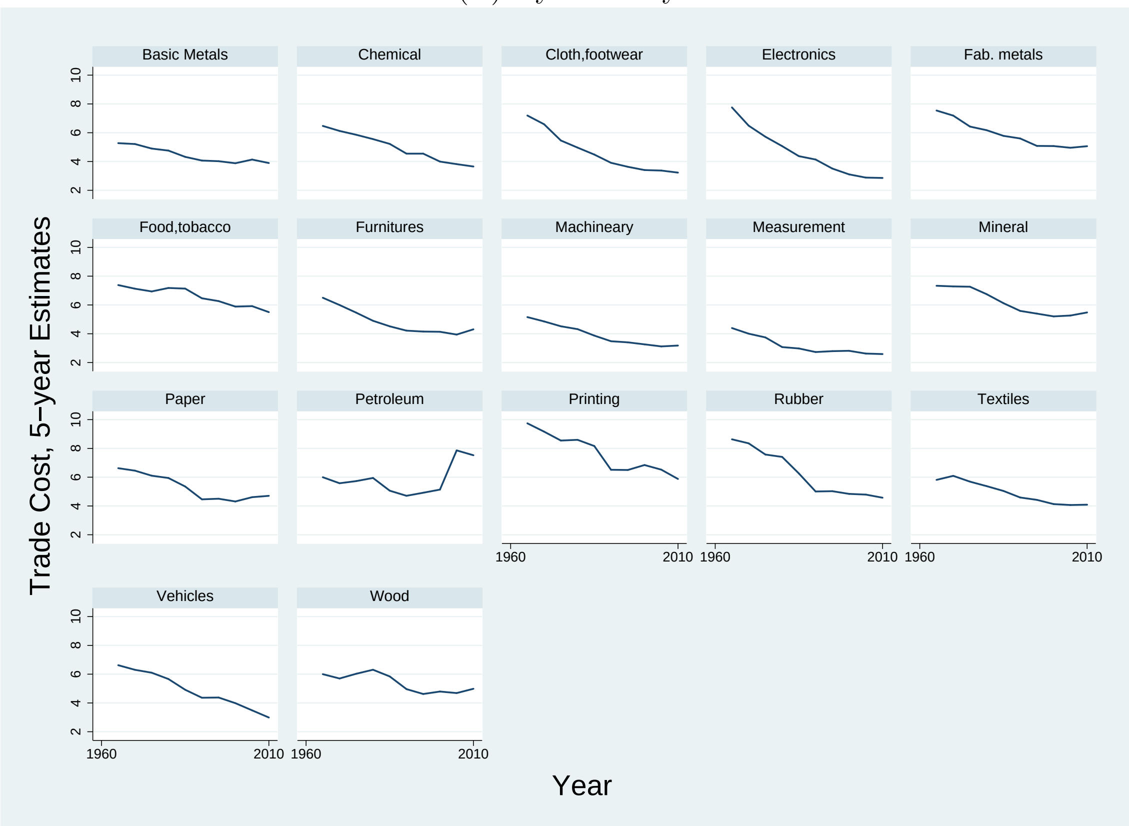
[26]Many country pairs with greater geographic separation started international trade during this sample period.

Figure 4: Evolution of Median Trade Costs from 1960 to 2010

(A) Full Sample



(B) By Industry



Notes: The median trade cost is calculated using a balanced five-year panel of trade-cost estimates.

productivity level because trade openness forces many unproductive domestic producers to exit the market. According to Finicelli et al. (2013), the true productivity level needs to be adjusted by the share of domestic absorption[27]

$$\lambda_{US}^{i} = (TFP_{US}^{i})^{\theta}\pi_{US\,US}^{i}. \tag{20}$$

Combining Equations 19 and 20, I obtain for every period the estimates of productivity parameters across all countries and industries.

4.2.2 Second Stage: Diffusion Parameters

The second stage calibrates the diffusion parameters. To proceed, I assume that each diffusion parameter can be written as a product of country- and industry-specific terms: $\eta_{n,t}^{i} = \eta_{n,t}\eta^{i}$, $\eta_{n,t}^{ii'} = \eta_{n,t}\eta_{t}^{ii'}$. In the benchmark exercise, I further impose three assumptions: The diffusion parameter β^{i} is industry invariant ($\beta^{i} = \beta$); the arrival rate is the same across countries ($\eta_{n,t} = \eta_{t}$); interindustry knowledge linkages are proportional to production I–O linkages. Therefore, I end up with only two parameters to calibrate in each period, a diffusion intensity parameter η_{t} capturing average global productivity growth, and an adoption parameter, $\beta \equiv \beta^{i}$, capturing dispersion in industry-level productivity growth. Later, I will check the robustness of the benchmark setting by relaxing each of these assumptions.

Calibration of β and η works as follows. First, I take an initial guess at the diffusion parameters. Given the first-period estimates of productivity parameters λ_{n,t_0}^{i}, I solve the instantaneous equilibrium for bilateral trade shares.[28] Using the law of motion of the productivity parameters (Equation 12), I obtain $\lambda_{n,t}^{i}$ for the next period. Then, given the predicted productivity parameters, I solve the next-period instantaneous equilibrium. Iterating this process until the last period of the sample, I obtain a full panel of bilateral trade shares and production variables. Diffusion and parameters are updated until the model-implied country-level TFP growth rates are close enough to the data. Since the calibration exercise does not draw any industry-level information, I will use predicted industry-level productivity measures and trade patterns to test the model for internal validity.

The evolution of the endowment structure is treated as exogenous. In each period, total labor supply $L_{n,t}$ is obtained from the data. The capital series is constructed using the equation of capital accumulation and exogenous investment rates from the Penn World Table. Exogenous trade deficits $D_{n,t}$ are introduced as a wedge between a country's total income and expenditures.

[27]Note that TFP_{US}^{i} needs to be exponentiated, because the mean of a Fréchet distribution with $F(z) = \exp(-\lambda z^{-\theta})$ is proportional to $\lambda^{1/\theta}$.

[28]Details of the solution algorithm can be found in Levchenko and Zhang (2016).

5 Empirical Results

5.1 Baseline Results

Panel I of Table 1 reports the goodness of fit under a full panel of estimated industry-level TFP. The target variables for each cross-sectional equilibrium are country-level labor and capital. The implied trade pattern matches the actual trade pattern well. Correlation is consistently above 0.85, and median and mean trade shares are quite close. Panel II reports the goodness of fit under my baseline calibration. The first-period TFP is chosen as the estimated TFP from the data, so goodness of fit for 1990–1995 stays the same. It is expected that as the number of iterations increases, it becomes difficult for the model to match the data. However, correlation between bilateral trade share is still consistently above 0.75.

I now turn to the model's key implication, convergence in Ricardian comparative advantage. Figure 5 compares the pattern of convergence in RCA implied by the model with data. It can be clearly seen that the simulated trade data also exhibits strong convergence. Industries with little export volume in 1990 enjoy much higher export growth in the next two decades. To establish the pattern of convergence more formally, I regress the growth rate of the variable of interest on the initial value of that variable and a set of fixed effects,

$$\triangle \ln X = \alpha \ln X_{t_0} + \mathit{FixedEffects} + \varepsilon. \tag{21}$$

There are many measures of comparative advantage. I consider three alternatives for X: Industry level TFP, the central variable of interest, precisely capturing Ricardian comparative advantage; the RCA index,[29] a measure that is directly observable and widely used; and export capability index[30] proposed by Hanson et al. (2016). I also include bilateral trade shares (not taking the logarithm) to check if convergence occurs on a bilateral base. To ensure robustness, I consider four calibration strategies. Methods I and II fully solve the model iteratively and apply model-implied trade shares to the law of motion of industry-level TFP. Methods III and IV directly apply actual trade shares to update industry-level TFP. Methods I and III fix β to be time invariant, while Methods II and IV allow a time-specific β.

Table 2 presents regression results over cross-sectional observations of a 20-year window. The first row reports convergence coefficients of the actual trade and productivity data. They are all estimated negative and statistically significant, which echoes earlier findings in the literature. The second row reports the convergence coefficients of my baseline calibration using Method I. The adoption parameter β is calibrated to be 0.301. Given parsimony of the parameters in my calibration exercise, it is surprising to see that the model-implied convergence coefficients are remarkably close to the actual data. OECD countries tend to

[29] The results are robust if symmetric or weighted RCA indices are used (Yu et al., 2009).

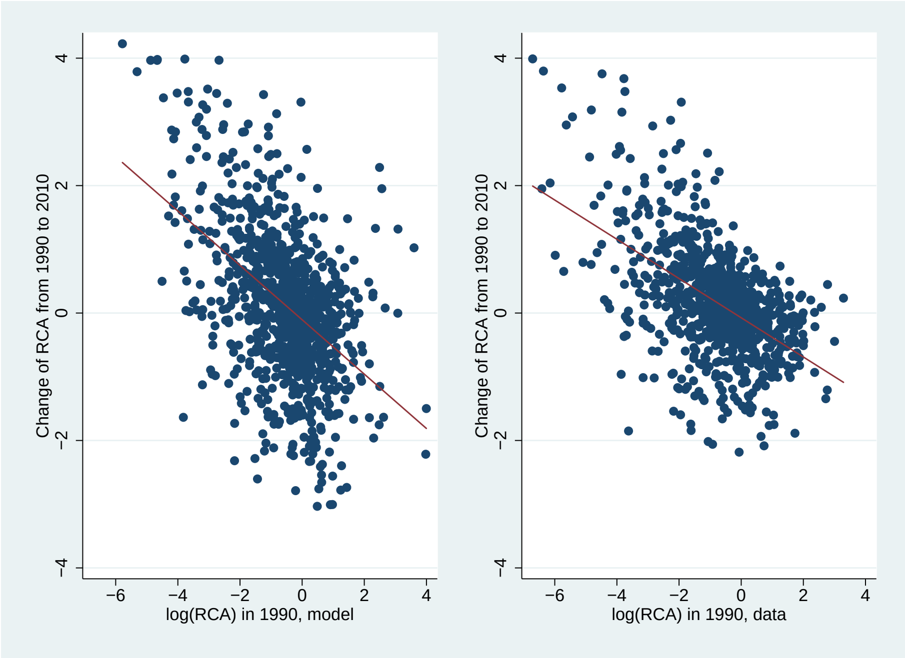
[30] Formally, it is obtained as the exporter fixed effect by running the standard gravity model by industry and time.

Table 1: Goodness of Fit

Period	Data Mean	Model Mean	Data Median	Model Median	Corr.
		Panel I: Actual TFP			
Wage (2005 US $)					
1990-1995	6,165	5,071	4,647	3,995	0.96
1996-2000	6,451	5,337	4,759	4,407	0.96
2001-2005	6,651	5,344	4,728	3,958	0.94
2006-2010	6,934	5,993	5,053	4,116	0.93
Rent					
1990-1995	0.18	0.16	0.17	0.16	0.66
1996-2000	0.18	0.15	0.16	0.14	0.61
2001-2005	0.19	0.14	0.16	0.13	0.40
2006-2010	0.20	0.12	0.17	0.12	0.05
Bilateral Trade Share					
1990-1995	4.5e-3	3.8e-3	0	0	0.89
1996-2000	5.2e-3	4.4e-3	1.5e-5	1.7e-5	0.91
2001-2005	4.9e-3	4.2e-3	4.0e-5	3.7e-5	0.89
2006-2010	4.6e-3	3.9e-3	3.7e-5	1.3e-5	0.87
Domestic Absorption Share					
1990-1995	0.61	0.66	0.67	0.75	0.91
1996-2000	0.55	0.62	0.59	0.69	0.92
2001-2005	0.51	0.56	0.54	0.63	0.92
2006-2010	0.47	0.52	0.50	0.59	0.90
		Panel II: Model-implied TFP			
Wage (2005 US $)					
1990-1995	6,165	5,127	4,647	4,044	0.97
1996-2000	6,451	5,350	4,759	4,302	0.97
2001-2005	6,651	5,717	4,728	4,485	0.96
2006-2010	6,934	5,872	5,053	4,517	0.94
Rent					
1990-1995	0.18	0.16	0.17	0.16	0.67
1996-2000	0.18	0.19	0.16	0.16	0.73
2001-2005	0.19	0.21	0.16	0.18	0.77
2006-2010	0.20	0.24	0.17	0.20	0.72
Bilateral Trade Share					
1990-1995	4.5e-3	3.8e-3	0	0	0.89
1996-2000	5.2e-3	4.7e-3	1.5e-5	0.9e-5	0.86
2001-2005	4.9e-3	4.5e-3	4.0e-5	3.2e-5	0.83
2006-2010	4.6e-3	4.0e-3	3.7e-5	1.6e-5	0.78
Domestic Absorption Share					
1990-1995	0.61	0.66	0.67	0.75	0.91
1996-2000	0.55	0.64	0.59	0.70	0.62
2001-2005	0.51	0.64	0.54	0.70	0.42
2006-2010	0.47	0.66	0.50	0.71	0.27

Note: Goodness of fit is reported for the baseline sample. Panel I reports simulation using actual TFP estimates. Panel II reports simulation using industry-level TFP series obtained from Method I.

Figure 5: Convergence in RCA: Model versus Data



have lower convergence rates than non-OECD countries in the data. This fact is also well captured by the model. In the sample of non-OECD countries, the convergence rate matches almost perfectly with the data, while in the sample of OECD countries, the model slightly underpredicts the convergence rate. It should also be noticed that this convergence pattern is not an artifact of my calibration exercise: In the baseline calibration, no country-specific or industry-specific trend is fed into the model. The results are largely unchanged under different calibration methods. Under Method II, β takes different values across periods:[31] $\beta_{90-95} = 0.169$, $\beta_{95-00} = 0.119$, $\beta_{00-05} = 0.500$, suggesting that knowledge diffusion becomes less noisy in the post-2000 episode. Method IV suggests a similar picture: $\beta_{90-95} = 0.158$, $\beta_{95-00} = 0.009$, $\beta_{00-05} = 0.484$. However, Method IV raises the concern that the value of β seems to be sensitive to calibration strategy. Therefore, I redo the benchmark exercise by fixing β to 0.5 or 0.7 and report the results in the last two rows. They further confirm the finding that the convergence pattern delivered by the model is quite robust.

Another important implication of the model concerns the turnover of export industries. Following Proudman and Redding (2000), I construct a transition matrix in terms of industry-level TFP. To account for industrial variation, I normalize the TFP estimates by the 90th percentile for each industry. I then rank 17 tradable industries by their normalized TFP measures. In each subtable of Table 3, the ijth element in a transition matrix represents the conditional probability that a group-i industry in 1990 moves to the jth group in 2010. More concretely, according to the first subtable in Table 3, if an industry is among the top four industries in 1990, this industry is expected to remain top four after 20 years with

[31] I denote the adoption parameter over a time window from year y_0 to y_1 by $\beta_{y_0-y_1}$.

Table 2: Convergence: Model versus Data

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	RCA Index	TFP	TFP	TFP	Trade Share	Export Capability
Sample	Full	Full	OECD	Non-OECD	Full	Full
Data	-0.310	-0.258	-0.243	-0.342	-0.065	-0.248
	(0.023)***	(0.037)***	(0.062)***	(0.054)***	(0.011)***	(0.024)***
Method I	-0.395	-0.287	-0.186	-0.358	-0.072	-0.363
($\beta = 0.285$)	(0.035)***	(0.022)***	(0.033)***	(0.028)***	(0.009)***	(0.040)***
Method II	-0.394	-0.282	-0.177	-0.352	-0.071	-0.361
	(0.035)***	(0.021)***	(0.032)***	(0.027)***	(0.009)***	(0.040)***
Method III	-0.383	-0.257	-0.158	-0.325	-0.066	-0.351
($\beta = 0.240$)	(0.035)***	(0.021)***	(0.031)***	(0.027)***	(0.009)***	(0.041)***
Method IV	-0.385	-0.268	-0.181	-0.331	-0.068	-0.357
	(0.036)***	(0.022)***	(0.038)***	(0.027)***	(0.009)***	(0.042)***
Method I	-0.396	-0.286	-0.179	-0.357	-0.071	-0.358
Fix $\beta = 0.5$	(0.035)***	(0.022)***	(0.031)***	(0.027)***	(0.009)***	(0.040)***
Method I	-0.389	-0.283	-0.170	-0.355	-0.073	-0.358
Fix $\beta = 0.7$	(0.036)***	(0.021)***	(0.029)***	(0.027)***	(0.009)***	(0.040)***
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Importer FE					Yes	
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	967	992	483	509	83,464	952

Notes: (1) Growth rate of each variable is calculated between 1990–1995 and 2005-2010. The table only reports the convergence parameter α specified in Equation 21; (2) Top and bottom 1% observations in terms of growth rate are dropped; (3) Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

probability 49%. Diagonal terms in a transition matrix indicate persistence in specialization, while off-diagonal terms capture mobility in specialization.

Table 3: Transition Probability in TFP: Model versus Data

		Data					Model			
Non-OECD Countries										
		2010 Rank					2010 Rank			
		1-4	5-8	9-12	13-17			1-4	5-8	9-12	13-17
1990 Rank	1-4	0.49	0.21	0.15	0.14	1990 Rank	1-4	0.74	0.22	0.04	0.00
	5-8	0.29	0.33	0.25	0.13		5-8	0.15	0.49	0.31	0.04
	9-12	0.14	0.33	0.29	0.24		9-12	0.03	0.19	0.38	0.41
	13-17	0.06	0.11	0.25	0.59		13-17	0.07	0.08	0.22	0.64
OECD Countries										
		2010 Rank					2010 Rank			
		1-4	5-8	9-12	13-17			1-4	5-8	9-12	13-17
1990 Rank	1-4	0.51	0.22	0.18	0.09	1990 Rank	1-4	0.89	0.11	0.00	0.00
	5-8	0.27	0.38	0.25	0.10		5-8	0.05	0.79	0.16	0.00
	9-12	0.11	0.29	0.30	0.30		9-12	0.01	0.07	0.73	0.20
	13-17	0.09	0.09	0.21	0.61		13-17	0.04	0.03	0.09	0.84

Notes: Each transition matrix is constructed using 1990–1995 and 2005–2010 sample.

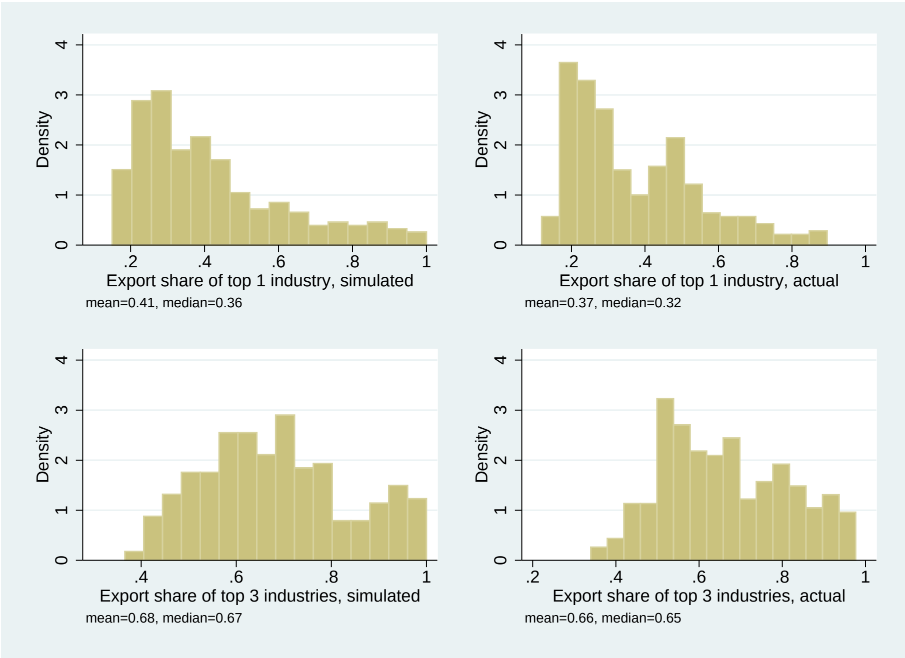
Comparing the two transition matrices in each panel of Table 3, I find that the model predicts substantial mobility in specialization despite the fact that the actual turnover rate is even higher. For non-OECD countries, the model's prediction about catch-up from the bottom is in line with what is observed in the data. It captures well the dynamic patterns of those industries that are initially at the bottom of the distribution. The model tends to underpredict the fraction of industries that fall back in ranking because I do not introduce negative TFP shocks to my calibration. The model delivers less mobility in specialization among OECD countries, because the innovation channel, an important mechanism for productivity growth on the frontier, is not incorporated in the model. The results once again suggest that this model of knowledge diffusion is more applicable to emerging-market economies, precisely the group of countries that receive little attention from empirical assessment of innovation-based growth models.[32]

Moreover, the calibration exercise suggests that knowledge diffusion could reconcile two salient but seemingly contradictory features in the trade data: hyperspecialization and strong mean reversion in comparative advantage (Hanson et al., 2016). The upper panel in Figure

[32]The contrasting findings for these two country groups underscore the insight in Acemoglu et al. (2006) that countries switch to an innovation-based growth strategy only when they get close to the world technology frontier.

6 plots the distribution of the export share of the top export industry over 72 countries. Consistent with the actual data, the calibrated model implies that the top industry accounts for about 37%, more than a third, of a country's total export volume. The lower panel plots the distribution for the export share of the top three export industries. On average, top three export industries amount to two thirds of the export volume. Therefore, in a world where productivity growth is driven by knowledge diffusion, high skewness in comparative advantage, namely, hyperspecialization, is perfectly compatible with strong convergence in Ricardian comparative advantage.

Figure 6: Share of Top Export Industries

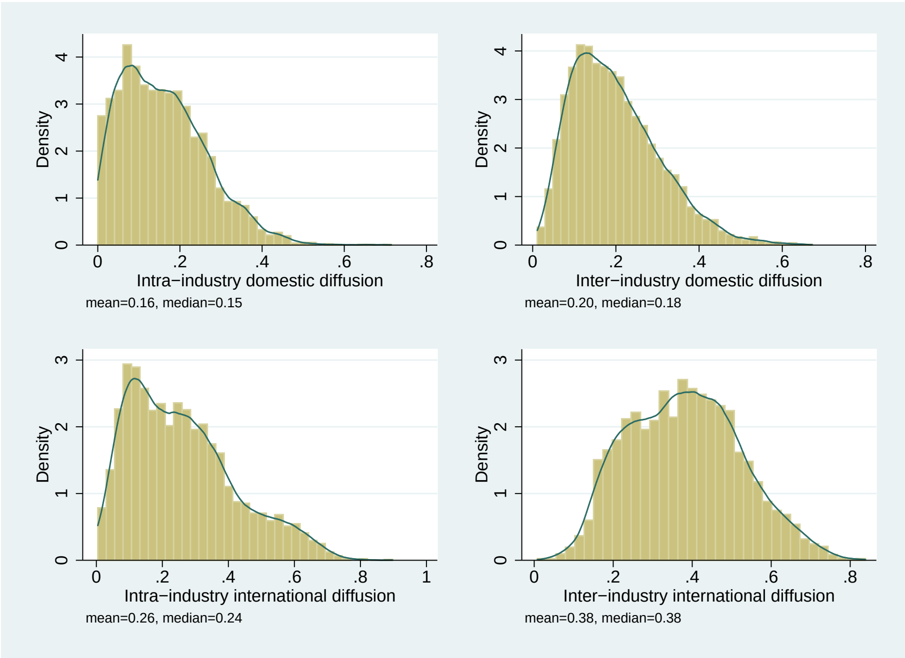


Given the assumptions on diffusion parameters, the law of motion of industry-level productivity can be rewritten as

$$\frac{d\lambda_{n,t}^{i}}{dt} = \eta_t \left(\gamma^{ii} {\pi_{nn,t}^{i}}^{1-\beta} {\lambda_{n,t}^{i}}^{\beta} + \gamma^{ii} \sum_{n'=1}^{N} {\pi_{nn',t}^{i}}^{1-\beta} {\lambda_{n',t}^{i}}^{\beta} + \sum_{i' \neq i} \gamma^{ii'} {\pi_{nn,t}^{i'}}^{1-\beta} {\lambda_{n,t}^{i'}}^{\beta} + \sum_{i' \neq i} \gamma^{ii'} \sum_{n'=1}^{N} {\pi_{nn',t}^{i'}}^{1-\beta} {\lambda_{n',t}^{i'}}^{\beta} \right), \tag{22}$$

where, in the baseline calibration, γ^{ij} are the input–output coefficients in the US I–O table. This equation can be used to decompose productivity growth into four different channels: intra- and interindustry idea flows within and across borders. Although diffusion parameters are not country specific, decomposition of productivity growth still varies across countries because each country has different trade partners, thereby different learning opportunities. Figure 7 illustrates the decomposition of productivity growth. The domestic knowledge diffusion on average accounts for about 36% of the overall industry-level productivity growth, while the rest, 64% of the productivity growth, can be attributed to international knowledge diffusion. In other words, producers tend to learn more from foreign sellers in the domestic markets than from their domestic fellow producers. Under the assumption that interindustry diffusion intensity is proportional to I–O coefficients, I find that interindustry knowledge diffusion can explain about 58% of the overall productivity growth. This suggests that ignoring interindustry knowledge linkages may substantially bias the prediction of productivity dynamics at the industry level.

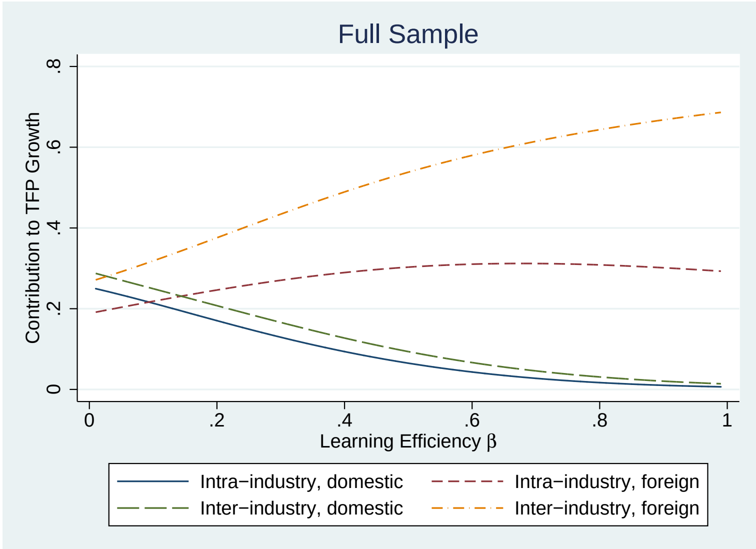
Figure 7: Contribution to Productivity Growth: 1990–2010



The decomposition of productivity growth is very similar between OECD and non-OECD economies (see Figure A1 in the appendix). At first glance, this may seem counterintuitive because rich countries tend to trade more with rich countries, thus having better sources of learning. However, rich countries also have higher domestic productivity, so this balances out international knowledge diffusion and makes the contribution of each channel similar in developing countries. Decomposition by industry (see Figure A2) reveals that although the structure of knowledge diffusion varies substantially across industries, international knowledge diffusion consistently plays a dominant role in boosting productivity growth.

One might suspect that β plays little role in understanding the dynamics of comparative advantage because, according to Table 2, different values of β lead to similar rates of convergence in comparative advantage. However, as is evidenced in Figure 8, the contribution of each channel of knowledge diffusion to productivity growth crucially depends on β. The contribution of domestic knowledge diffusion decreases with β. This is a direct consequence of the diffusion specification as in Buera and Oberfield (2016). As the diffusion becomes more noisy, high-quality ideas from foreign exporters get heavily discounted and sources with different quality of ideas become less distinguishable from each other.

Figure 8: Contribution to Productivity Growth versus β



5.2 Robustness Check

The first set of robustness checks concerns the choice of diffusion matrices. In the first panel of Table 4, I report the convergence pattern using country-specific, time-variant I–O tables as diffusion matrices. Compared with the benchmark simulation, the results are highly robust. Moreover, since the pattern of interindustry knowledge diffusion could be different from what is suggested by production I–O tables, I also construct a matrix of interindustry knowledge flow in light of Cai and Li (2014). Each element in the diffusion matrix is defined as the share of patent citation from industry i to j. The simulated model slightly outperforms the one using I–O tables.

The second robustness check concerns the sample choice. Table 5 reports the results of convergence from 1970 to 2010. The downside of extending to a longer sample period is that I end up with only 55 countries, among which 25 are OECD countries. The results are generally consistent with those obtained from the benchmark sample. The model predicts lower rates of convergence in TFP than the data, partly because some important sources of idea flows like Germany are no longer in the sample and neither are many technology recipients such as Eastern European countries.[33] Column (5) reports convergence results in import share, an indirect reduced-form measure of a country's export capability. The rate of convergence suggested by the model is remarkably similar to that of the data. Table

[33]For similar reasons, the bilateral trade share tends to be overestimated. The issue becomes increasingly severe over time because those emerging-market economies that are excluded from the sample play an increasingly important role in global trade.

Table 4: Convergence: Alternative Diffusion Matrices

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	RCA Index	TFP	TFP	TFP	Trade Share	Export Capability
Sample	Full	Full	OECD	Non-OECD	Full	Full
Data	-0.310	-0.252	-0.239	-0.320	-0.066	-0.248
	(0.023)***	(0.037)***	(0.062)***	(0.053)***	(0.011)***	(0.024)***
			Country-specific I–O Table			
Method I	-0.398	-0.304	-0.200	-0.372	-0.076	-0.362
($\beta = 0.318$)	(0.036)***	(0.021)***	(0.037)***	(0.026)***	(0.010)***	(0.038)***
Method II	-0.399	-0.295	-0.191	-0.362	-0.078	-0.366
	(0.036)***	(0.020)***	(0.034)***	(0.026)***	(0.010)***	(0.039)***
Method III	-0.387	-0.276	-0.175	-0.342	-0.072	-0.343
($\beta = 0.244$)	(0.036)***	(0.020)***	(0.036)***	(0.026)***	(0.009)***	(0.037)***
Method IV	-0.393	-0.280	-0.175	-0.349	-0.074	-0.347
	(0.036)***	(0.021)***	(0.034)***	(0.027)***	(0.009)***	(0.038)***
			Patent Citation Matrix			
Method I	-0.368	-0.282	-0.194	-0.334	-0.065	-0.322
($\beta = 0.416$)	(0.036)***	(0.023)***	(0.040)***	(0.028)***	(0.009)***	(0.040)***
Method II	-0.366	-0.282	-0.192	-0.336	-0.065	-0.320
	(0.036)***	(0.024)***	(0.040)***	(0.028)***	(0.009)***	(0.040)***
Method III	-0.360	-0.251	-0.171	-0.300	-0.063	-0.310
($\beta = 0.397$)	(0.036)***	(0.022)***	(0.038)***	(0.027)***	(0.009)***	(0.039)***
Method IV	-0.356	-0.273	-0.202	-0.313	-0.061	-0.316
	(0.037)***	(0.021)***	(0.045)***	(0.028)***	(0.009)***	(0.041)***
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Importer FE					Yes	
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	967	992	483	509	83,464	952

Notes: (1) Growth rate of each variable is calculated for 1990–1995 and 2005–2010. The table only reports the convergence parameter α specified in Equation 21; (2) Top and bottom 1% observations in terms of growth rate are dropped; (3) TFP estimates are based on country-specific I–O tables; (4) Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

6 compares convergence in TFP by industry.[34] For a majority of industries, the rate of convergence is comparable. For industries that are heavily endowment-driven like Coke and petroleum products, the model fails to capture a lack of convergence in the data, which suggests that alternative mechanisms might be at work in these industries.

The third set of robustness checks concerns different methods of estimating the baseline industry-level TFP. Table A4 in the Appendix summarize the convergence pattern of the variables of interest under five alternative estimates of industry-level TFP. The first panel reports the convergence pattern of the alternative TFP estimates from data. The second panel reports for comparison the convergence pattern of simulated TFP from the model where the first-period TFP is obtained from corresponding alternative specifications. The last panel reports convergence in trade patterns suggested by the model. In Column (1), I reestimate the main gravity equation using the Poisson pseudo-maximum likelihood method (PPML) proposed by Silva and Tenreyro (2006) to address the issue of "zeros" in bilateral trade flows. Accordingly, bilateral trade costs are also obtained from PPML regressions. Columns (2)–(5) reestimate the model using country-specific and time-variant I–O tables.[35] In Columns (2) and (3), I maintain the baseline setting that the trade elasticity is the same across industries and simulate the model using both OLS and PPML TFP estimates. According to Caliendo and Parro (2014), trade elasticity varies substantially across industries, so Columns (4) and (5) are based on TFP estimates using their industry-specific θ^i. Overall, the model delivers a similar degree of convergence in TFP as data in terms of both statistical and economic significance. It might be noticed that the simulated model in Columns (4) and (5) suggests much stronger convergence in trade variables. This is due to the fact that some industries have very high trade elasticity (for example $\theta^i = 50$ for petroleum industry), which leads to more outliers of λ^i in the first-stage estimation. The convergence rate largely agrees with the data if these outliers are dropped.[36]

I further allow the diffusion parameter to be industry specific. The convergence results are comparable to the benchmark simulation. Table 7 reports calibrated industry-specific β^i under two methods. Interestingly, β^i is very similar across industries, ranging from 0.280 to 0.455. This suggests that the baseline calibration, which assumes an industry-invariant β, is a reasonable approximation.

[34] I also report convergence in RCA by industry in Table A5 in the Appendix.

[35] The country-specific I–O tables are constructed from the WIOD database (Timmer et al., 2015). Details can be found in the appendix.

[36] In light of Levchenko and Zhang (2016), I also reestimate the model using alternative interest rates: marginal product of capital (Caselli and Feyrer, 2007), full financial integration, and WDI lending rates. The baseline results are essentially unchanged.

Table 5: Convergence: 1970–2010

Variable Sample	(1) RCA Index Full	(2) TFP Full	(3) TFP OECD	(4) TFP Non-OECD	(5) Import Share Full
Data	-0.500	-0.596	-0.533	-0.665	-0.746
	(0.028)***	(0.048)***	(0.054)***	(0.075)***	(0.045)***
			Benchmark		
Method II	-0.493	-0.356	-0.287	-0.454	-0.752
	(0.038)***	(0.025)***	(0.045)***	(0.030)***	(0.049)***
Method IV	-0.482	-0.334	-0.263	-0.432	-0.732
	(0.036)***	(0.025)***	(0.044)***	(0.030)***	(0.050)***
			Country-specific I–O Tables		
Method II	-0.492	-0.363	-0.287	-0.439	-0.747
	(0.037)***	(0.025)***	(0.043)***	(0.029)***	(0.049)***
Method IV	-0.485	-0.340	-0.260	-0.419	-0.729
	(0.038)***	(0.025)***	(0.042)***	(0.030)***	(0.050)***
			Patent Citation Matrix		
Method II	-0.479	-0.357	-0.294	-0.455	-0.723
	(0.037)***	(0.029)***	(0.048)***	(0.038)***	(0.050)***
Method IV	-0.473	-0.340	-0.277	-0.443	-0.733
	(0.039)***	(0.029)***	(0.048)***	(0.038)***	(0.053)***
Country FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
No. of Obs.	782	732	377	355	908

Notes: (1) Growth rate of each variable is calculated for 1970–1975 and 2005–2010. The table only reports the convergence parameter α specified in Equation 21; (2) Top and bottom 1% observations in terms of growth rate are dropped; (3) TFP estimates are based on country-specific I–O tables; (4) Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Convergence in TFP by Industry: 1970–2010

	(1) Data	(2) Benchmark	(3) WIOD	(4) Patent	Obs.
Food, tobacco	-0.388	-0.417	-0.369	-0.482	51
	(0.082)***	(0.042)***	(0.042)***	(0.040)***	
Textiles	-0.344	-0.540	-0.516	-0.502	49
	(0.162)**	(0.069)***	(0.072)***	(0.070)***	
Apparel, footwear	-0.458	-0.104	-0.091	-0.085	35
	(0.137)***	(0.015)***	(0.014)***	(0.013)***	
Wood	-0.188	-0.441	-0.409	-0.478	48
	(0.088)**	(0.038)***	(0.037)***	(0.033)***	
Paper	-0.349	-0.543	-0.659	-0.533	49
	(0.072)***	(0.041)***	(0.032)***	(0.041)***	
Printing, publishing	-0.126	-0.011	-0.017	-0.008	49
	(0.098)	(0.002)***	(0.003)***	(0.002)***	
Coke, petroleum	0.157	-0.779	-0.652	-0.908	51
	(0.143)	(0.035)***	(0.050)***	0.015)***	
Chemical	-0.360	-0.357	-0.292	-0.313	43
	(0.089)***	(0.033)***	(0.031)***	(0.031)***	
Rubber, plastic	-0.461	-0.267	-0.281	-0.215	48
	(0.090)***	(0.033)***	(0.034)***	(0.028)***	
Nonmetallic mineral	-0.339	-0.163	-0.149	-0.164	47
	(0.064)***	(0.023)***	(0.022)***	(0.022)***	
Basic metals	-0.118	-0.429	-0.449	-0.408	42
	(0.100)	(0.023)***	(0.027)***	(0.022)	
Fabricated metal	-0.159	-0.172	-0.143	-0.122	48
	(0.068)**	(0.016)***	(0.015)***	(0.014)***	
Machinery, equipment	-0.311	-0.568	-0.597	-0.483	41
	(0.125)**	(0.047)***	(0.048)***	(0.053)***	
Electronics	-0.370	-0.349	-0.415	-0.274	40
	(0.114)***	(0.045)***	(0.052)***	(0.041)***	
Medical, precision	0.069	-0.026	-0.029	-0.012	33
	(0.171)	(0.013)**	(0.014)**	(0.006)**	
Vehicles	-0.230	-0.393	-0.409	-0.279	46
	(0.152)	(0.031)***	(0.031)***	(0.026)***	
Other manufacturing	-0.310	-0.075	-0.078	-0.055	47
	(0.140)**	(0.024)***	(0.026)***	(0.017)***	

Notes: (1) Calibration (Method III) is performed on the sample from 1970 to 2010 estimated using country-specific TFP (2) Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Industry-specific Diffusion Parameter β^i

	(1) Method I	(2) Method III		(3) Method I	(4) Method III
Food, tobacco	0.361	0.364	Textiles	0.368	0.383
Apparel, footwear	0.284	0.337	Wood	0.299	0.424
Paper	0.284	0.402	Printing	0.349	0.305
Coke, petroleum	0.312	0.448	Chemical	0.443	0.353
Rubber, plastic	0.421	0.331	Non-metallic	0.289	0.379
Basic metals	0.387	0.343	Fabricated metal	0.312	0.317
Machinery, equipment	0.455	0.336	Electronics	0.320	0.306
Medical, precision	0.347	0.307	Vehicles	0.451	0.304
Other manufacturing	0.280	0.334			

Notes: (1) Calibration is performed on the baseline sample (2) β^i is industry specific but time invariant

The implied decomposition of each channel's contribution to TFP growth is similar across different specifications and samples. The calibrated model consistently suggests that international knowledge diffusion contributes about 60–70% to TFP growth while domestic knowledge exchange contributes the other 30–40%. The only exception is when I use the patent-citation matrix as the diffusion matrix (see Figure A3). In this case, international knowledge diffusion explains almost 80% of productivity growth, because the adoption parameter β is calibrated highest under this specification.[37] Moreover, interindustry diffusion also plays a larger role because off-diagonal terms are much larger in the patent-citation matrix than in the production I–O tables.

Various specifications also yield comparable transition matrices. The model tends to underpredict transition probability in TFP, but for non-OECD countries, the model produces closer predictions to the data. Table A6 compares transition matrices over the longer sample period from 1970 to 2010 and suggests a similar finding. Given how well the convergence pattern has been reproduced in the model, it calls for additional channels to explain dynamics in industrial productivity beyond convergence.

[37]The data are obtained from Method III ($\beta = 0.397$) using the patent-citation matrix.

6 Implications

6.1 "Key Players" in Knowledge Diffusion

The calibrated model suggests a complex network of industry-level knowledge diffusion. By putting industries into play, complexity arises from both the international and interindustry dimensions. For example, textile producers in Pakistan could draw insights and benefit from machinery exporters in Germany through imports and interindustry spillovers. Therefore, each country–industry pair potentially draws insights from $N \times I$ sources (N countries, I industries). Denote the direct knowledge contribution from industry i' in country n' to industry i in country n by $\alpha_{nn'}^{ii'}$. I obtain $\alpha_{nn'}^{ii'}$ using Equation 22 and, by construction, $\sum_{n',i'} \alpha_{nn'}^{ii'} = 1$. If each country–industry pair is treated as a node, then the matrix $\alpha \equiv \{\alpha_{nn'}^{ii'}\}_{NI\times NI}$ is the adjacency matrix of a weighted, directed network.

To find "key players," that is, countries or country–industry pairs that contribute most to global productivity growth through knowledge diffusion, I define centrality measures[38] in the global diffusion network. The first centrality measure is simply defined as a country or country–industry pair's average direct contribution to world productivity growth:

$$C_n^{Direct} = \frac{\sum_{n',i,i'} \alpha_{n'n}^{i'i}}{\sum_{n,n',i,i'} \alpha_{n'n}^{i'i}}; \quad C_{n,i}^{Direct} = \frac{\sum_{n',i'} \alpha_{n'n}^{i'i}}{\sum_{n,n',i,i'} \alpha_{n'n}^{i'i}}.$$

Table 8 reports the top five OECD country's contributions to global knowledge diffusion from 1990 to 2010. I also report the weighted-average contribution of which weights are given by industry-level output share. It can be seen from the table that the simple average yields rankings similar to those of the weighted average, but the share of contribution varies substantially. The weighted-average centrality measure suggests that the United States and Germany contribute to almost 40% of global knowledge diffusion. For comparison, I include five major emerging-market economies ("BRICS") in the table, among which China's contribution is very close to those leading OECD countries. Similar rankings can be obtained under two alternatives of the diffusion matrix: country-specific production I–O tables and the patent-citation matrix. In the Appendix, Table A7 reports contributions to TFP growth by period. Clearly, China plays an increasingly important role in global knowledge diffusion. By the end of the sample, China's contribution to global TFP growth surpassed major industrialized economies like the United Kingdom, Italy, and France, and approached Japan, the third main contributor to idea flows for the last two decades.

Table 9 reports the top ten country–industry pairs' contributions to global knowledge diffusion. The rankings largely agree with each other under different diffusion matrices. The list is predominantly comprised of four high-tech industries (vehicles, machinery, electronics,

[38] In the context of the global trade network, a variety of centrality measures have been recently proposed to study the structure of international trade in relation to economic growth (Kali and Reyes, 2007; Duernecker et al., 2014; Pinat, 2015).

Table 8: Key Players: Direct Contribution to TFP Growth

Simple Average (%)				Weighted Average (%)			
OECD		"BRICS"		OECD		"BRICS"	
USA	11.29	Brazil	2.16	USA	20.88	Brazil	1.77
Germany	7.52	Russia	1.28	Germany	18.31	Russia	0.70
Japan	6.95	India	1.77	Japan	8.23	India	1.15
Italy	5.26	China	3.78	Italy	5.10	China	5.43
France	4.73	S. Africa	1.13	France	4.88	S.Africa	0.48

Note: This table is based on baseline calibration from 1990 to 2010. Centrality measures are calculated using diffusion parameters obtained from calibration and actual trade and production data. I obtain similar rankings if simulated trade and production data is used.

and measurement) from three major knowledge creators, USA, Japan, and Germany. This table also suggests that the distribution of contribution to knowledge diffusion is extremely skewed. According to the weighted-average centrality, among 1224 (72 countries $\times$ 17 industries) country–industry pairs, the top ten country–industry pairs contribute more than one quarter to global productivity growth.

Table 9: Key Players: Direct Contribution to TFP Growth

Simple Average (%)			Weighted Average (%)		
Country	Industry	Contribution	Country	Industry	Contribution
USA	Measurement	2.23	Japan	Vehicles	3.91
Japan	Vehicles	1.81	USA	Vehicles	3.57
USA	Machinery	1.44	USA	Measurement	2.98
USA	Vehicles	1.40	Japan	Electronics	2.98
USA	Electronics	1.27	USA	Food	2.75
Germany	Machinery	1.11	Japan	Machinery	2.72
Japan	Electronics	1.09	USA	Machinery	1.84
Germany	Vehicles	1.07	USA	Printing	1.75
Germany	Measurement	1.07	Germany	Vehicles	1.74
Japan	Machinery	1.05	USA	Electronics	1.65

Note: This table is based on the baseline calibration from 1990 to 2010. Alternative diffusion matrices yield similar rankings. Centrality measures are calculated using diffusion parameters obtained from calibration and actual trade and production data. I obtain similar rankings if simulated trade and production data are used.

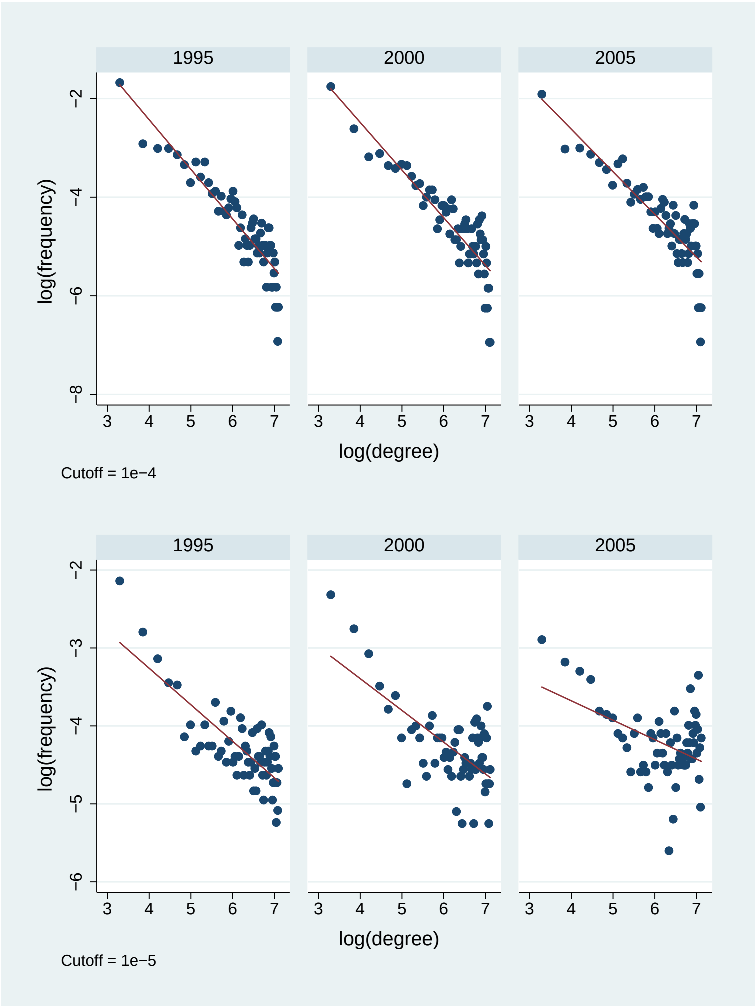
The second centrality measure concerns the extensive margin of global knowledge flows.

Define a country's or country-industry pair's degree centrality as follows

$$C_n^{Degree} = \sum_{n',i,i'} \mathbf{1}_{\alpha_{n'n}^{i'i} \geq \zeta}; \quad C_{n,i}^{Degree} = \sum_{n',i'} \mathbf{1}_{\alpha_{n'n}^{i'i} \geq \zeta},$$

where $\mathbf{1}$ is an indicator function and ζ is a prespecified cutoff.

Figure 9: Degree Distribution of Global Diffusion Network: 1990–2010

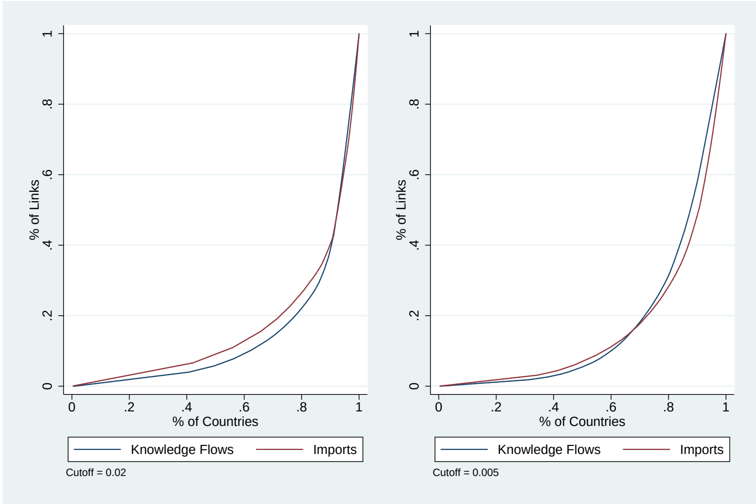


Notes: (1) The diffusion network is constructed using diffusion parameters obtained from the baseline calibration (Method II); (2) The cutoff of 10^{-4} is about the average contribution to global productivity growth and 10^{-5} is the 75-percentile.

The list of "key players" can be found in Table A8. Under this definition, the global diffusion network is reduced to an unweighted directed graph. Figure 9 illustrates the evolution of the global diffusion network. When $\zeta = 10^{-4}$, the approximately linear fitted line in the log–log plot suggests that the degree distribution resembles a scale-free distribution[39] and this line flattens out over time. When I pick a smaller cutoff, $\zeta = 10^{-5}$, the degree distribution

[39]However, it is a not a scale-free network, because the estimated scale parameter (slope of the fitted line) is close to one, not between two and three.

Figure 10: Lorenz Curve of Degree: 1990–2010



Notes: (1) The diffusion network is constructed using diffusion parameters obtained from the baseline calibration (Method II); (2) The average contribution to global productivity growth is about 1.4%; (3) Country-level degree data are pooled together for all three periods.

becomes more interesting. In the last period, the distribution is U-shaped with a very heavy right tail, suggesting that many country–industry pairs play a nonnegligible role in global knowledge diffusion. Following Kali and Reyes (2007), Figure 10 plots the Lorenz curve of degree in knowledge diffusion as well import share for comparison. The global diffusion network is highly asymmetric: knowledge mainly comes from a handful of countries.

The third centrality measure concerns substitutability of a country in the global diffusion network. Suppose that country n completely closes its border. In the absence of trade between country n and the rest of the world, the structure of idea flows changes. A country's importance in knowledge diffusion can be assessed by the change of TFP growth under this counterfactual. Table 10 reports the change of TFP growth from 1990 to 2010 if a given country becomes autarkic. The second and fifth columns are the simple average of counterfactual TFP growth of the rest of the world. Dropping a country from the global trade network always has a negative impact on world TFP growth, although the TFP growth may accelerate for some countries under the counterfactual. Consistent with the first centrality measure, the United States, Germany, and Japan remain the top three countries that have the greatest impact on knowledge diffusion. Interestingly, China, an important contributor to knowledge diffusion, is no longer in the list, mainly due to its relatively low industry-level TFP. Moreover, taking into account the endogenous change in the trade pattern, the counterfactual exercise suggests that substitutability of a country from the perspective of knowledge diffusion is not as high as is traditionally thought, because if a country's trade partner becomes autarkic, this country can always find a second best from the rest of the world. On the other hand, the third and sixth columns indicate that a country's TFP growth is significantly dampened under autarky, and this is even true for developed countries. The average decline of TFP growth of a country is comparable between OECD and non-OECD economies.

Table 10: Key-Player: Counterfactual Change of TFP Growth

Change of TFP Growth from 1990 to 2010 (%)					
OECD	World Average	Own	Non-OECD	World Average	Own
Japan	-5.81	-27.89	Taiwan	-3.50	-25.82
USA	-5.13	-44.70	Brazil	-1.63	-50.60
Germany	-3.75	-57.31	India	-1.42	-47.64
France	-2.82	-54.58	South Africa	-1.38	-54.21
Italy	-2.78	-50.65	Malaysia	-1.37	-33.84
UK	-2.71	-59.05	Russia	-1.37	-63.56
Canada	-2.51	-52.01	Thailand	-1.36	-55.31
Korea	-2.16	-48.09	Indonesia	-1.35	-45.46
Spain	-2.09	-54.34	Ukraine	-1.28	-58.68
Switzerland	-1.96	-26.61	Egypt	-1.25	-60.17
Average	-1.94	-52.15	Average	-1.18	-52.20

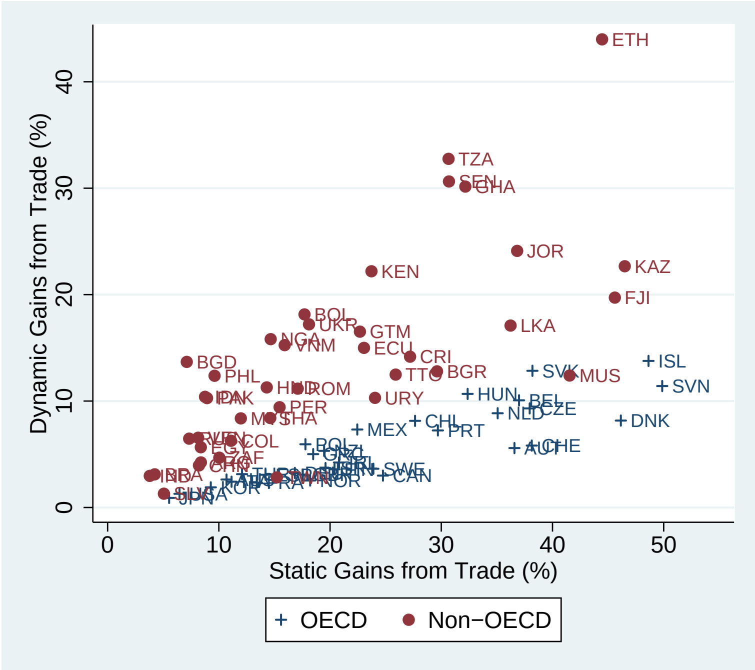
Note: This table computes the percentage change of TFP growth by assuming that one country becomes autarkic. The diffusion parameter is from the method II of the baseline calibration. The world average decline of TFP growth is weighted by PPP-adjusted GDP.

6.2 Dynamic Gains from Trade

Another important implication of the quantitative model is that idea flows give rise to dynamic gains from trade. As opening up to trade exposes a country to exporters with better technology, improved learning opportunity speeds up TFP growth and thus real income growth. To decompose total gains from trade into static and dynamic components, I conduct two thought experiments. I first consider the change of real income for a country to move from autarky to the level of openness of the period 2005–2010. This captures the standard static gains from trade. On average, the static gains from trade are about 20% of a country's real income, which echoes the earlier findings in the literature that static gains from trade are generally modest (Arkolakis et al., 2012; Costinot and Rodríguez-Clare, 2014). Notice that static gains from trade decreases with trade elasticity (θ) and elasticity of substitution ($1/(1-\kappa)$) across industries. Therefore, the static gains from trade become substantially larger if Cobb–Douglas aggregator is used for final consumption goods ($\kappa = 0$). In contrast, if higher trade elasticity is picked in the calibration, then the gains from trade become much smaller.[40]

[40]For example, the gains from trade decline by two thirds if I choose $\theta = 8.28$.

Figure 11: Gains from Trade



Note: (1) The benchmark period is 2000–2005, and diffusion parameters are borrowed from benchmark calibration Method I; (2) The annual discount rate is 3% and the results are robust for the plausible range of annual discount rates (1% to 10%).

The second thought experiment concerns dynamic gains from trade. It is defined as the percentage-point change of a country's real income if this country learns from its trade partners rather than only its domestic producers, conditional on the fact that in both scenarios it opens up to international trade. In other words, the dynamic gains from trade are the additional welfare gains for a country to move from autarky to openness in the sense of knowledge diffusion. Similar to earlier theoretical work (Redding, 1999), I calculate the discounted sum of future real income to measure the dynamic effects of international trade. The dynamic gains from trade amount to, on average, 6.07% of real GDP for OECD economies and 12.34% for non-OECD economies. Non-OECD economies enjoy much higher dynamic gains because of the strong convergence effects. According to the baseline calibration, dynamic gains from trade are about one third of the static gains from trade, but this should be treated as a lower bound. I use the baseline calibrated diffusion parameters ($\beta = 0.285; \eta = 14.18$) for all the future periods, which has the long-run implication that the TFP growth rate of the global economy converges to zero. If η is also allowed to grow (as is suggested by the data), the dynamic gains from trade can be much larger.

7 Conclusion

In this paper, I build a multi-industry model of international trade and knowledge diffusion to investigate the dynamic pattern of Ricardian comparative advantage. Borrowing the strengths from both the trade and growth literature, my model generates quantitative implications on the evolution of Ricardian comparative advantage. The dynamic properties implied by the calibrated model are broadly consistent with two salient features in the data: strong convergence in industry-level productivity and substantial turnover of export industries. The decomposition exercise shows the major roles played by international and interindustry knowledge diffusion. According for its positive effects on productivity growth, the model suggests that gains from trade are at least 40% higher than is implied by a static model of international trade. Analysis based on the global diffusion network further reveals the complex structure of idea flows. In line with the theoretical prediction in Buera and Oberfield (2016), my calibrated model suggests that composition of trade partners matters for the evolution of a country's comparative advantage and its overall economic growth.[41]

This paper can be extended in several dimensions. First, it would be of great interest to incorporate multinational production into this framework. A large literature studies how multinational production affects productivity of domestic firms, but little work has been done at the industry level concerning how knowledge diffuses through multinational production in a dynamic general-equilibrium framework. The main barrier is the availability of data. Even the most comprehensive industry-level database of multinational production covers less than 10 years of data and predominantly consists of OECD countries (Alviarez, 2015; Fukui and Lakatos, 2012). Second, while the assumption of perfectly competitive markets buys tractability of the model, it also eliminates the problem of free-riding that Hausmann and Rodrik (2003) identify as the major hurdle to successful localization of foreign technology in developing countries. Introducing alternative market structures that lead to negative externality of knowledge diffusion is another promising avenue for future research. Last, since firms do not internalize the benefits of idea flows, the door is open for government intervention. Questions on optimal trade and industrial policies call for a richer framework amenable for quantitative policy analysis.

[41]This relates to the discussion of trade and industrial policies. Cross-country regressions by Hausmann et al. (2007) suggest that a country tends to achieve higher economic growth if its export basket is more similar to those of rich countries. Their finding spurs a huge debate on the industrial policy (Lederman and Maloney, 2012). In contrast, this paper suggests that import structure could also be relevant in explaining cross-country growth differentials.

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A List of Symbols

N, I	number of countries, number of industries
$w_{n,t}, r_{n,t}$	wage rate, rental rate
$s_{n,t}$	saving rate
$D_{n,t}$	trade deficit
$E_{n,t}$	total expenditure
$I_{n,t}$	total investment
$Y_{n,t}, Y^i_{n,t}$	country-level, industry-level demand of final goods
$L_{n,t}, L^i_{n,t}, \ell^i_{n,t}$	country-, industry-, variety-level input of labor
$K_{n,t}, K^i_{n,t}, k^i_{n,t}$	country-, industry-, variety-level input of capital
$P_{n,t}, P^i_{n,t}, p^i_{n,t}$	country-, industry-, variety-level price
$Q^i_{n,t}, q^i_{n,t}$	industry-level, variety level total demand
$c^i_{n,t}$	industry-level unit cost of an input bundle
$F^i_{n,t}$	industry-level productivity distribution (Fréchet)
$G^i_{n,t}$	source distribution of intraindustry knowledge diffusion
$G^{ii'}_{n,t}$	source distribution of interindustry knowledge diffusion
$z^i_{n,t}$	variety-level productivity
$m^{ii'}_{n,t}$	variety-level input of composite intermediate goods from industry i'
$d^i_{nn',t}$	iceberg shipping cost from country n' to n
κ	elasticity of substitution across tradable industries $= 1/(1-\kappa)$
ϕ_n	share of tradable consumption
$\chi_{n,t}$	population growth rate
$\delta_{n,t}$	depreciation rate
β^i	Cobb–Douglas share of learning from other firms
ν^i	variety of industry i
σ^i	elasticity of substitution across varieties
θ^i	dispersion parameter of Fréchet distribution (trade elasticity)
$\tau^{ii'}$	dispersion adjustment parameter in interindustry diffusion
ω^i_n	share parameter of industry i across tradable goods
$\gamma^{iL}_n, \gamma^{iK}_n$	variety-level labor share, capital share
$\gamma^{ii'}_n$	variety-level input share from industry i' to industry i
$\lambda^i_{n,t}$	location parameter of Fréchet distribution (industrial productivity)
$\eta^i_{n,t}$	arrival rate of intraindustry learning from domestic and foreign producers
$\eta^{ii'}_{n,t}$	arrival rate of interindustry learning from domestic and foreign producers
$\pi^i_{nn',t}$	share of expenditure on imports from country n'

B Proofs and Theoretical Extensions

B.1 Instantaneous Equilibrium

Given labor and capital endowment $\{L_n\}_{n=1}^N$ and $\{K_n\}_{n=1}^N$, trade deficits $\{D_n\}_{n=1}^N$, bilateral industry-level trade costs $\{d_{nn'}^i\}_{n=1,n'=1,i=1}^{N,N,I+1}$ instantaneous equilibrium is obtained by solving Equation 1 - 10 for total expenditures $\{E_n\}_{n=1}^N$, wage rates $\{w_n\}_{n=1}^N$, rental rates $\{r_n\}_{n=1}^N$, industrial price levels $\{P_n^i\}_{n=1,i=1}^{N,I+1}$, industrial final demand $\{Y_n^i\}_{n=1,i=1}^{N,I+1}$, industrial unit costs of input bundle, $\{c_n^i\}_{n=1,i=1}^{N,I+1}$, industrial total demand $\{Q_n^i\}_{n=1,i=1}^{N,I+1}$, industrial labor employment $\{L_n^i\}_{n=1,i=1}^{N,I+1}$, industrial capital stock $\{K_n^i\}_{n=1,i=1}^{N,I+1}$, and industrial trade flows $\{\pi_{nn'}^i\}_{n=1,n'=1,i=1}^{N,N,I+1}$. There are in total $N^2(I+1)+6N(I+1)+3N$ unknowns. Equilibrium conditions 1 - 10 consist of $N^2(I+1)+6N(I+1)+4N$ equations, but N equations are redundant, which can be seen as follows

$$
\begin{aligned}
E_n &= w_n L_n + r_n K_n + D_n \\
&= \sum_{i=1}^{I+1}\left(\gamma^{iL}\sum_{n'=1}^{N} P_{n'}^i Q_{n'}^i \pi_{n'n}^i + \gamma^{iK}\sum_{n'=1}^{N} P_{n'}^i Q_{n'}^i \pi_{n'n}^i + P_n^i Q_n^i - \sum_{n'=1}^{N} P_{n'}^i Q_{n'}^i \pi_{n'n}^i\right) \\
&= \sum_{i=1}^{I+1}\left(\gamma^{iL}\sum_{n'=1}^{N} P_{n'}^i Q_{n'}^i \pi_{n'n}^i + \gamma^{iK}\sum_{n'=1}^{N} P_{n'}^i Q_{n'}^i \pi_{n'n}^i - \sum_{n'=1}^{N} P_{n'}^i Q_{n'}^i \pi_{n'n}^i\right) \\
&\quad + \sum_{i=1}^{I+1}\left(\sum_{i'=1}^{I+1}\gamma_n^{i'i}\sum_{n'=1}^{N} P_{n'}^{i'} Q_{n'}^{i'} \pi_{n'n}^{i'} + P_n^i Y_n^i\right) \\
&= \sum_{i=1}^{I+1} P_n^i Y_n^i
\end{aligned}
$$

B.2 Derivation of the Law of Motion of Industrial Productivity

I first derive the law of motion of industry-level productivity in the general diffusion process which follows Buera and Oberfield (2016). New ideas arrive as a Poisson process with the arrival rate $\tilde{\eta}$. A firm draws a new idea of productivity level z_G from a source distribution $G_{n,t}^i(\cdot)$. The new idea is adopted by this firm if and only if $z_G^{\beta^i} z_H^{1-\beta^i}$ is greater than the productivity level of its current technology z, where z_H is random draw from a noise distribution H^i, capturing randomness in knowledge diffusion. This process of adopting new ideas yields the following law of motion of industrial productivity distribution $F_{n,t}^i$

$$
\frac{d}{dt}\ln F_{n,t}^i(z) = -\tilde{\eta}\int_0^\infty \left[1 - G_{n,t}^i\left(\frac{z^{1/\beta^i}}{x^{(1-\beta^i)/\beta^i}}\right)\right] dH^i(x).
$$

Assume that $H^i(\cdot)$ follows a Pareto distribution, $H^i(z) = 1-(z/z_0)^{-\tilde{\theta}^i}$, for $z > z_0$. Let

$\theta^i \equiv \tilde{\theta}^i/(1-\beta^i)$ and normalize $\eta \equiv \tilde{\eta} z_0^{\tilde{\theta}}$ to be a constant. It can be further shown that

$$\lim_{z_0 \to 0} \frac{d}{dt} \ln F^i_{n,t}(z) = -\eta z^{-\theta^i} \int_0^\infty x^{\beta^i \theta^i} dG^i_{n,t}(x),$$

provided that $\lim_{x\to\infty}[1 - G^i_{n,t}(x)]x^{\beta^i\theta^i} = 0$. Therefore, I obtain the industrial productivity distribution $F^i_{n,t}(z) = \exp(-\lambda^i_{n,t} z^{-\theta^i})$, with the law of motion of the key productivity parameter $\lambda^i_{n,t}$ given by $d\lambda^i_{n,t}/dt = \eta \int_0^\infty x^{\beta^i\theta^i} dG^i_{n,t}(x)$.

I now turn to deriving the law of motion of industrial productivity under specific channels in consideration. Recall that the general form of law of motion of industry-level productivity under multiple channels of idea flows is given by

$$\frac{d\lambda^i_{n,t}}{dt} = \sum_s \eta^s \int_0^\infty x^{\beta^i\theta^i} dG^{i,s}_{n,t}(x). \tag{B.1}$$

In light of Buera and Oberfield (2016), I first derive expression of $\int_0^\infty x^{\beta^i\theta^i} dG^{i,s}_{n,t}(x)$ for each channel.

1. Intraindustry knowledge diffusion

$$\begin{aligned}
\int_0^\infty x^{\beta^i\theta^i} dG^i_{n,t}(z) &= \int_0^\infty x^{\beta^i\theta^i} \sum_{n'=1}^{N} \prod_{n''\neq n'} F^i_{n'',t}\left(\frac{c^i_{n'',t} d^i_{nn'',t}}{c^i_{n',t} d^i_{nn',t}} x\right) dF^i_{n',t}(x) \\
&= \sum_{n'=1}^{N} \int_0^\infty x^{\beta^i\theta^i} \exp\left(-\sum_{n''\neq n'} \lambda^i_{n'',t} \left(\frac{c^i_{n'',t} d^i_{nn'',t}}{c^i_{n',t} d^i_{nn',t}} x\right)^{-\theta^i}\right) d\exp\left(-\lambda^i_{n',t} x^{-\theta^i}\right) \\
&= \sum_{n'=1}^{N} \int_0^\infty y^{-\beta^i} \exp\left(-\sum_{n''=1}^{N} \lambda^i_{n'',t} \left(\frac{c^i_{n'',t} d^i_{nn'',t}}{c^i_{n',t} d^i_{nn',t}}\right)^{-\theta^i} y\right) d(\lambda^i_{n',t} y) \\
&= \sum_{n'=1}^{N} \int_0^\infty y^{-\beta^i} \exp\left(-\frac{\lambda^i_{n',t} y}{\pi^i_{nn',t}}\right) d(\lambda^i_{n',t} y) \\
&= \Gamma(1-\beta^i) \sum_{n'=1}^{N} {\pi^i_{nn',t}}^{1-\beta^i} {\lambda^i_{n',t}}^{\beta^i}.
\end{aligned} \tag{B.2}$$

2. Interindustry knowledge diffusion

$$
\begin{aligned}
\int_0^\infty x^{\beta^i\theta^i} dG^{ii'}_{n,t}(z) &= \int_0^\infty x^{\beta^i\theta^i} \sum_{n'=1}^{N} \prod_{n''\neq n'} F^{i'}_{n'',t}\left(\frac{c^{i'}_{n'',t}d^{i'}_{nn'',t}}{c^{j}_{n',t}d^{i'}_{nn',t}}x\right) dF^{i'}_{n',t}(x) \\
&= \sum_{n'=1}^{N} \int_0^\infty x^{\beta^i\theta^i} \exp\left(-\sum_{n''\neq n'} \lambda^{i'}_{n'',t}\left(\frac{c^{i'}_{n'',t}d^{i'}_{nn'',t}}{c^{i'}_{n',t}d^{i'}_{nn',t}}x\right)^{-\theta^{i'}}\right) d\exp\left(-\lambda^{i'}_{n',t}x^{-\theta^{i'}}\right) \\
&= \sum_{n'=1}^{N} \int_0^\infty y^{-\beta^i\theta^i/\theta^{i'}} \exp\left(-\sum_{n''=1}^{N} \lambda^{i}_{n'',t}\left(\frac{c^{i}_{n'',t}d^{i}_{nn'',t}}{c^{i}_{n',t}d^{i}_{nn',t}}\right)^{-\theta^{i}} y\right) d(\lambda^{i}_{n',t}y) \\
&= \sum_{n'=1}^{N} \int_0^\infty y^{-\beta^i\theta^i/\theta^{i'}} \exp\left(-\frac{\lambda^{i}_{n',t}y}{\pi^{i}_{nn',t}}\right) d(\lambda^{i}_{n',t}y) \\
&= \Gamma(1-\beta^i\theta^i/\theta^{i'}) \sum_{n'=1}^{N} {\pi^{i'}_{nn',t}}^{1-\beta^i\theta^i/\theta^{i'}} {\lambda^{i'}_{n',t}}^{\beta^i\theta^i/\theta^{i'}}. \qquad \text{(B.3)}
\end{aligned}
$$

In the benchmark case, $\theta^i = \theta$ for any industry i. Given Equation B.2 and B.3, I obtain the law-of-motion of productivity as Equation 12.

B.3 Adjustment of Industry-level Productivity Dispersion

Consider firms in industry i draw insights from firms in industry i'. Once a new insight is drawn (with arrival rate $\tilde{\eta}$), the actual productivity is given by $z_G^{\tau^{ii'}\beta^i} z_H^{1-\beta^i}$ where z_G is a random drawn from the source distribution $G^{ii'}_{n,t}(\cdot)$ and z_H is drawn from an exogenous distribution $H^i(\cdot)$. With the adjustment parameter $\tau^{ii'}$ of industrial productivity dispersion, the law of motion of industrial productivity can be rewritten as

$$
\frac{d}{dt}\ln F^i_{n,t}(z) = -\tilde{\eta}\int_0^\infty \left[1 - G^{ii'}_{n,t}\left(\frac{z^{1/(\beta^i\tau^{ii'})}}{x^{(1-\beta^i)/(\beta^i\tau^{ii'})}}\right)\right] dH^i(x).
$$

Assume that $H^i(z) = 1-(z/z_0)^{-\tilde{\theta}^i}$. Let $\theta^i \equiv \tilde{\theta}^i/(1-\beta^i)$ and normalize $\eta \equiv \tilde{\eta}z_0^{\tilde{\theta}}$ to be a constant. It can be shown that

$$
\lim_{z_0\to 0}\frac{d}{dt}\ln F^i_{n,t}(z) = -\eta z^{-\theta^i}\int_0^\infty x^{\beta^i\theta^i\tau^{ii'}} dG^i_{n,t}(x),
$$

if $\lim_{x\to\infty}[1-G^i_{n,t}(x)]x^{\beta^i\theta^i\tau^{ii'}} = 0$. Therefore, the industry-level productivity distribution still follows Fréchet with the law of motion of the position parameter $\lambda^i_{n,t}$ given by

$$
\frac{d\lambda^i_{n,t}}{dt} = \eta\int_0^\infty x^{\beta^i\theta^i\tau^{ii'}} dG^i_{n,t}(x). \qquad \text{(B.4)}
$$

Let $\tau^{ii'} = \theta^{i'}/\theta^{i}$. Equation B.3 is modified as follows

$$\int_0^\infty x^{\beta^i\theta^i} dG_{n,t}^{ii'}(z) = \Gamma(1-\beta^i)\sum_{m=1}^{N} {\pi_{nm}^{i'}}^{1-\beta^i} {\lambda_m^{i'}}^{\beta^i} \tag{B.5}$$

which coincide the results under the assumption of homogeneous industrial productivity dispersion.

C Data Description

C.1 Sample

Following Levchenko and Zhang (2016), my sample consists of 72 countries and 17 manufacturing industries. The original data covers from 1963 to 2011. Details of the sample can be found in Table A1 and A2. I treat each five-year window as one period. To maximize the number of countries, especially non-OECD countries, the baseline sample is chosen to start from 1990 and end in 2010, so there are four periods in the baseline sample: 1991-1995, 1996-2000, 2001-2005, and 2006-2010. Within each five-year window, I calculate the median of each trade and production variable.

Table A1: Sample Coverage

Non-OECD	Year	Non-OECD	Year	Non-OECD	Year	Non-OECD	Year
Argentina	80-11	Bangladesh	72-07	Bolivia	63-11	Brazil	80-11
Bulgaria	90-11	China	73-11	Colombia	63-11	Costa Rica	63-11
Ecuador	63-11	Egypt	63-11	El Salvador	63-11	Ethiopia	80-11
Fiji	63-11	Ghana	63-11	Guatemala	63-11	Honduras	63-11
India	63-11	Indonesia	63-11	Jordan	63-11	Kazakhstan	92-11
Kenya	63-11	Malaysia	63-11	Mauritius	63-11	Nigeria	63-11
Pakistan	63-11	Peru	80-11	Philippines	63-11	Romania	90-11
Russia	96-11	Senegal	70-11	S. Africa	63-11	Sri Lanka	63-11
Taiwan	73-11	Tanzania	63-11	Thailand	63-11	Trinidad Tbg	63-10
Ukraine	92-11	Uruguay	63-11	Venezuela	63-11	Viet Nam	91-11
OECD	Year	OECD	Year	OECD	Year	OECD	Year
Australia	63-11	Austria	63-11	Belgium-Lux	63-11	Canada	63-11
Chile	63-11	Czech Rep	93-11	Denmark	63-11	Finland	63-11
France	63-11	Germany	91-11	Greece	63-11	Hungary	90-11
Iceland	63-11	Ireland	63-11	Israel	63-11	Italy	65-11
Japan	63-11	Korea Rep	63-11	Mexico	63-11	Netherlands	63-11
New Zealand	63-11	Norway	63-11	Poland	90-11	Portugal	63-11
Slovakia	93-11	Slovenia	92-11	Spain	63-11	Sweden	63-11
Switzerland	80-11	Turkey	63-11	UK	63-11	USA	58-11

Table A2: Tradable 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
29-30	Office, accounting and computing machinery, other machinery
31-32	Electrical machinery, communication equipment
33	Medical, precision and optical instruments, watches and clocks
34-35	Transport equipment
36	Furniture, other manufacturing

C.2 Trade data

The trade data is obtained from World Trade Flows bilateral data (Feenstra et al., 2005) and further extended using UN comtrade database for post-2000 periods. The original trade sample is organized at the level of 4-digit SITC code (rev. 2). It is aggregated up to the level of 2-digit ISIC code (rev. 3) by using two concordances from 4-digit SITC (rev. 2) to 3-digit ISIC (rev. 2) and from 3-digit ISIC[42] (rev. 2) to 2-digit ISIC[43] (rev. 3). By restricting the sample to 72 countries, about one quarter of the total trade volume is excluded. I also include zero trade flows in the sample whenever PPML is employed in estimation.

C.3 Production data

The production data is obtained from UNIDO INDSTAT 2 database (version 2015). The database includes key production variables at the cross-country industry level: output, value added, and wage bills. Since the database contains information both at the industry level and for the whole manufacturing sector, observations are dropped if the aggregated manufacturing total is more than 20% larger or smaller than the reported total. For countries with missing production data but non-missing trade data, I impute industrial output level using linear interpolation and extrapolation. Observations are dropped if total output (original or imputed) is smaller than total export.

[42]Source: Marc Muendler's personal website, last retrieved: 8/11/2015.
[43]Source: United Nations Statistics Division, last retrieved: 8/15/2015.

Table A3: Construction of Variables and Data Sources

Variables/Parameters	Data Source & Construction Method
Bilateral trade share $\pi^i_{nn',t}$	UN Comtrade & UNIDO INDSTAT2
Trade deficit $D_{n,t}$	UN Comtrade
Trade in value-added	TiVA database (OECD.STAT)
Labor income share γ^{iL}_t	UNIDO INDSTAT2, (wage bill)/(industrial output)
Capital income share γ^{iK}_t	UNIDO INDSTAT2, (value-added − wage bill)/(industrial output)
Input–output coefficients $\gamma^{ii'}_{n,t}$	BEA 1997 I–O accounts (grouped into 2-digit ISIC Rev.3); WIOD
Labor supply $L_{n,t}$	Penn World Table
Capital stock $K_{n,t}$	Penn World Table
Wage rate $w_{n,t}$	Penn World Table, (labor income)/(employment count)
Rental rate $r_{n,t}$	Penn World Table, (total income - labor income)/(capital)
	World Development Indicators; Caselli and Feyrer (2007)
Saving rate $s_{n,t}$	Penn World Table, implied by capital series and depreciation rate
Nontradable price $P^{I+1}_{n,t}$	ICP, interpolate and extrapolate for non-survey years
Tradable exp share ϕ_n	OECD national accounts, (fitting for non-OECD countries)
Trade elasticity θ^i	4; 8.28; Industry-specific (Caliendo and Parro, 2014)
Elasticity of subst. in consumption $\frac{1}{1-\kappa}$	2 (Levchenko and Zhang, 2016); 1 (Caliendo and Parro, 2014)
Elasticity of subst. in production σ^i	2
Tradable consumption share ω^i_n	Levchenko and Zhang (2016)
US industry-level TFP	NBER-CES manufacturing industry database
Other country variables	Penn World Table
Other bilateral variables	CEPII gravity dataset
Industry-level TFP	KLEMS database (EU-, Asia, World- KLEMS)

C.4 Other data

Bilateral variables. CEPII gravity database (Head et al., 2013) provides most of the bilateral gravity variables: bilateral distance weighted by population, dummy variables of contiguity, common official primary language, common currency union, and free trade areas. The database is updated until 2006, so it is extended to incorporate new regional trade agreements[44] and currency unions from 2006 onwards.

Production parameters. For tradable industries, share of wage bill γ^{iL} is obtained by the cross-country median of industry-level wage and salary payment as share of industrial output, and share of rental payment γ^{iK} is obtained by the cross-country median of difference between value added and wage bill as share of output. These variables all come from UNIDO INDSTAT database. For the nontradable industry, γ^{iL} and γ^{iK} are obtained from US 1997 I–O table. I also use US 1997 I–O table to obtain country-invariant I–O coefficients $\gamma^{ii'}$ and cross check γ^{iL} and γ^{iK} of tradable industries obtained from cross-country data.

I also obtain country-specific and time-variant I–O tables from WIOD database (Timmer et al., 2015). Among 72 economies in my sample, 34 economies are included in WIOD database (Brazil, Bulgaria, Canada, China, Czech, Denmark, Finland, France, Germany, Greece, Hungary, India, Indonesia, Ireland, Italy, Japan, Korea, Mexico, Netherlands, Poland, Portugal, Romania, Russia, Solvakia, Slovenia, Spain, Sweden, Taiwan, Turkey, UK, USA). I apply the rest-of-world (ROW) I–O table to the other 38 economies. The database covers

[44]Source: WTO Regional Trade Agreements Database, last retrieved: 6/20/2016.

the period from 1995 to 2011. The data is at 2-digit ISIC level, which is slightly modified to match the industry aggregation of the sample.

Preference parameters. share parameters of tradable goods ω^i is obtained from Levchenko and Zhang (2016). For the share of tradable goods consumption ϕ_n, I first aggregate up consumption shares of current-price durable, semi-durable, and non-durable goods using national accounts from OECD countries.[45] Then I estimate the tradable consumption share of other countries by fitting a linear relationship between the share of manufacturing consumption and GDP per capita. Elasticity of substitution across tradable consumption goods $1/(1-\kappa)$ is given by 2.

Relative cost terms. To calculate cross-country wage rate $w_{n,t}$, I first obtain aggregate labor income by multiplying PPP-adjusted real GDP by labor income share where both variables are available in PWT. If labor income share is missing, I use the share of wage bills in value-added from INDSTAT2 if available and fill out the rest missing observations by interpolation. The total effective employment count is given by the product of the number of persons engaged and average country-level human capital where both variables also come from PWT. For very few countries (such as Ethiopia and Nigeria), I fill out their human capital by fitting a linear relationship between human capital and real GDP per capita. As a crude measure, rental rate $r_{n,t}$ is given by the non-labor income divided by real capital stock. Relative price indices of tradable industries can be obtained from competitiveness measure (estimated as fixed effect in the gravity equation) and domestic absorption rate (obtained from bilateral trade and output data) according to Equation 18. Relative price in the nontradable sector is obtained from the International Comparison Program. I use observations from seven benchmark years (1970, 1975, 1980, 1985, 1996, 2005, and 2011) to fit a linear relationship between nontradable price index and GDP per capita.[46] Before plugging in these relative terms for Equation 19, the last complication arises from the fact that competitiveness estimates may not be available for each industry while it is essential for calculation of relative costs due to input–output linkages. To address this, I scale up input shares of those industries who competitiveness estimates are non-missing proportionally so that the sum of input shares remains equal to one. All variables are normalized by US levels.

US TFP series. US industry-level TFP in the tradable sector is obtained from NBER-CES Manufacturing Industry Database. The TFP series in the nontradable sector is obtained in two steps. I first calculate the nontradable TFP for the benchmark year, 2005, by combining information from NBER-CES database and PWT. Then the time series is obtained by using TFP growth rate in the US nontradable sector from World-KLEMS database.

Country-specific variables: PWT also gives me the following country-specific variables: labor and capital endowment $L_{n,t}$ and $K_{n,t}$, saving rate $S_{n,t}/(w_{n,t}L_{n,t}+r_{n,t}K_{n,t})$, investment rate $I_{n,t}/(w_{n,t}L_{n,t}+r_{n,t}K_{n,t})$, depreciation rate $\delta_{n,t}$, country-level price index $P_{n,t}$, real GDP

[45] Source: OECD Final Consumption Expenditure of Households (Detailed National Accounts, SNA 2008), last retrieved: 6/20/2016.

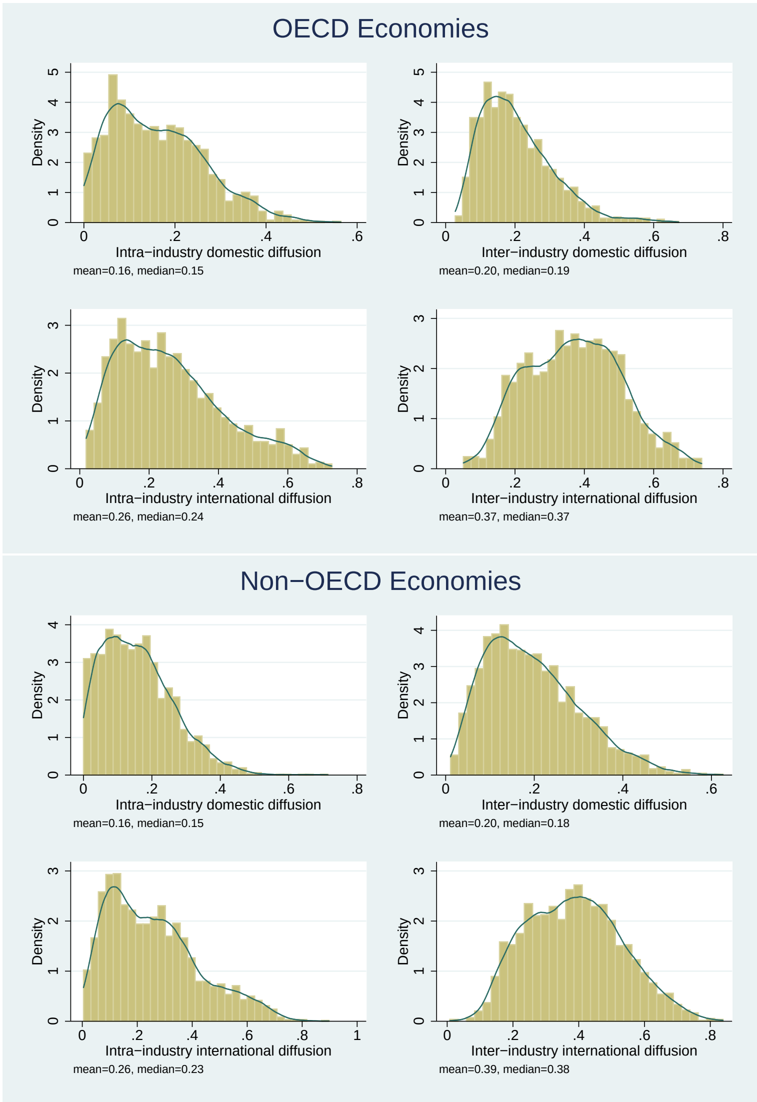
[46] A variety of alternative fitting schemes are discussed in detail by Feenstra et al. (2015).

$Y_{n,t}$, and country-level TFP growth rate.

Patent citation: The NBER US patent citation data (Hall et al., 2001) contains pairwise patent citation information from 1976 to 2006. I construct the citation matrix at 2-digit ISIC level by mapping international patent classification code to US SIC code[47] and then to ISIC code. The time-variant diffusion matrix is simply constructed by calculating the share of interindustry patent citation for each 5-year window.

D Additional Figures and Tables

Figure A1: Contribution to Productivity Growth: OECD versus non-OECD



[47]The concordance can be found in Brian Silverman's personal website, last retrieved: 8/19/2016.

Figure A2: Contribution to Productivity Growth by Industry

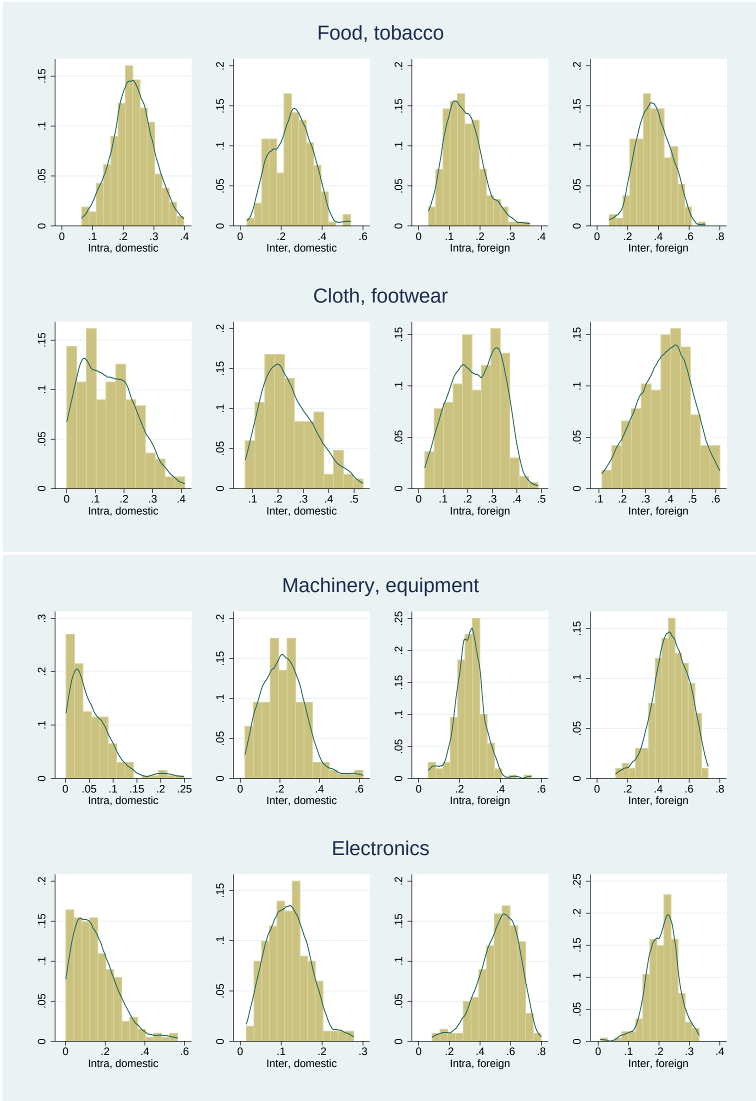


Figure A3: Contribution to Productivity Growth: 1990 - 2010

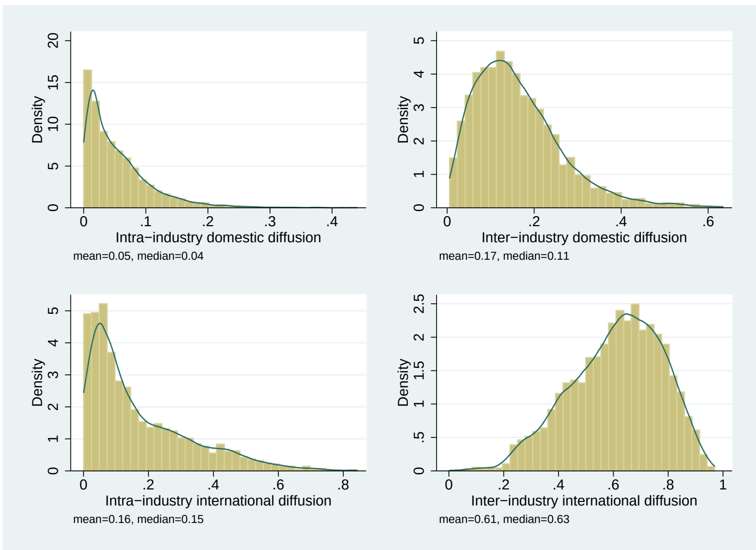


Table A4: Convergence: Alternative Estimates of TFP

	(1)	(2)	(3)	(4)	(5)
		Country-specific Input–output Table			
	Benchmark	$\theta = 4$		Industry-specific θ^i	
	PPML	OLS	PPML	OLS	PPML
			Industry-Level TFP: Data		
Full Sample	-0.309	-0.270	-0.347	-0.172	-0.182
	(0.040)***	(0.037)***	(0.038)***	(0.036)***	(0.060)***
Non-OECD	-0.351	-0.339	-0.389	-0.227	-0.266
	(0.058)***	(0.054)***	(0.054)***	(0.047)***	(0.064)***
OECD	-0.310	-0.254	-0.343	-0.126	-0.064
	(0.059)***	(0.059)***	(0.057)***	(0.051)**	(0.121)
			Industry-Level TFP: Simulation		
Full Sample	-0.337	-0.298	-0.372	-0.191	-0.160
	(0.020)***	(0.021)***	(0.021)***	(0.020)***	(0.013)***
Non-OECD	-0.389	-0.359	-0.426	-0.206	-0.181
	(0.026)***	(0.026)***	(0.028)***	(0.023)***	(0.018)***
OECD	-0.265	-0.214	-0.280	-0.172	-0.129
	(0.033)***	(0.040)***	(0.035)***	(0.035)***	(0.014)***
			Trade Variables: Simulation		
RCA	-0.410	-0.387	-0.384	-0.800	-0.802
	(0.031)***	(0.036)***	(0.031)***	(0.030)***	(0.028)***
π^i_{nm}	-0.102	-0.082	-0.100	-0.124	-0.139
	(0.009)***	(0.009)***	(0.012)***	(0.011)***	(0.010)***
Exp. Capability	-0.420	-0.345	-0.394	-0.876	-0.518
	(0.034)***	(0.039)***	(0.034)***	(0.039)***	(0.030)***

Notes: (1) Growth rate of each variable is calculated between 1990–1995 and 2005-2010. The table only reports the convergence parameter α specified in Equation 21 using Method II; (2) Top and bottom 1% observations in terms of growth rate are dropped; (3) Industry and country fixed effects are included in each regression; (4) Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A5: Convergence in RCA by Industry: 1970 - 2010

	(1) Data	(2) Benchmark	(3) WIOD	(4) Patent	Obs.
Food, tobacco	-0.300	-0.424	-0.453	-0.395	51
	(0.110)***	(0.116)***	(0.115)***	(0.119)***	
Textiles	-0.498	-0.459	-0.459	-0.433	49
	(0.131)***	(0.178)***	(0.170)***	(0.181)**	
Apparel, footwear	-0.603	-0.149	-0.155	-0.142	35
	(0.222)***	(0.164)	(0.164)	(0.162)	
Wood	-0.515	-0.584	-0.588	-0.585	48
	(0.111)**	(0.126)***	(0.124)***	(0.0128)***	
Paper	-0.753	-0.811	-0.894	-0.827	49
	(0.101)***	(0.106)***	(0.104)***	(0.108)***	
Printing, Publishing	-0.423	-0.705	-0.725	-0.714	49
	(0.103)***	(0.137)***	(0.139)***	(0.134)***	
Coke, petroleum	-0.776	-0.627	-0.605	-0.643	51
	(0.166)***	(0.147)***	(0.144)***	(0.152)***	
Chemical	-0.604	-0.548	-0.509	-0.538	43
	(0.073)***	(0.145)***	(0.153)***	(0.151)***	
Rubber, plastic	-0.670	-0.706	-0.714	-0.686	48
	(0.068)***	(0.068)***	(0.066)***	(0.073)***	
Non-metallic mineral	-0.596	-0.511	-0.506	-0.530	47
	(0.057)***	(0.082)***	(0.083)***	(0.082)***	
Basic metals	-0.596	-0.839	-0.842	-0.842	42
	(0.057)***	(0.123)***	(0.124)***	(0.124)***	
Fabricated metal	-0.627	-0.682	-0.666	-0.667	48
	(0.071)**	(0.107)***	(0.108)***	(0.111)***	
Machinery, equipment	-0.517	-0.986	-1.017	-0.905	41
	(0.085)***	(0.102)***	(0.097)***	(0.108)***	
Electronics	-0.490	-0.946	-0.967	-0.925	40
	(0.121)***	(0.102)***	(0.134)***	(0.137)***	
Medical, precision	-0.418	-0.397	-0.409	-0.396	33
	(0.066)***	(0.172)**	(0.171)**	(0.169)**	
Vehicles	-0.577	-0.654	-0.677	-0.593	46
	(0.080)***	(0.090)***	(0.087)***	(0.096)***	
Other manufacturing	-0.639	-0.702	-0.706	-0.697	47
	(0.116)***	(0.148)***	(0.146)***	(0.150)***	

Notes: (1) Calibration (Method III) is performed on the sample from 1970 to 2010 estimated using country-specific TFP (2) Robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table A6: Transition Probability in TFP: Model versus Data

Full Sample

	Data				Model			
	2010 Rank				2010 Rank			
1970 Rank	1-4	5-8	9-12	13-17	1-4	5-8	9-12	13-17
1-4	0.39	0.22	0.17	0.21	0.83	0.14	0.03	0.00
5-8	0.24	0.30	0.20	0.26	0.09	0.63	0.25	0.04
9-12	0.21	0.29	0.26	0.24	0.04	0.14	0.54	0.28
13-17	0.13	0.15	0.29	0.43	0.04	0.08	0.15	0.74

OECD Countries

	Data				Model			
	2010 Rank				2010 Rank			
1970 Rank	1-4	5-8	9-12	13-17	1-4	5-8	9-12	13-17
1-4	0.37	0.26	0.14	0.23	0.90	0.09	0.01	0.00
5-8	0.28	0.27	0.23	0.22	0.04	0.82	0.12	0.02
9-12	0.19	0.31	0.25	0.25	0.02	0.04	0.78	0.16
13-17	0.13	0.13	0.30	0.44	0.03	0.04	0.07	0.86

Non-OECD Countries

	Data				Model			
	2010 Rank				2010 Rank			
1970 Rank	1-4	5-8	9-12	13-17	1-4	5-8	9-12	13-17
1-4	0.40	0.19	0.21	0.20	0.77	0.18	0.05	0.00
5-8	0.20	0.33	0.18	0.30	0.13	0.47	0.35	0.06
9-12	0.23	0.28	0.27	0.23	0.06	0.22	0.34	0.38
13-17	0.13	0.17	0.28	0.42	0.04	0.11	0.21	0.65

Notes: Each transition matrix is constructed using 1970-1975 and 2005-2010 sample.

Table A7: Key Players: Direct Contribution to TFP Growth by Period

Simple Average (%)				Weighted Average (%)			
OECD		"BRICS"		OECD		"BRICS"	
1995 – 2000							
USA	11.25	Brazil	2.23	USA	22.06	Brazil	1.93
Germany	7.94	Russia	1.71	Germany	21.14	Russia	0.97
Japan	7.81	India	1.57	Japan	9.11	India	0.91
UK	4.61	China	2.48	UK	4.61	China	3.64
Italy	4.08	S. Africa	1.04	Italy	4.08	S.Africa	0.43
2000 – 2005							
USA	11.64	Brazil	2.00	USA	20.06	Brazil	1.73
Germany	7.44	Russia	0.97	Germany	17.93	Russia	0.44
Japan	6.76	India	1.75	Japan	7.62	India	1.18
Italy	5.72	China	3.44	Italy	5.27	China	4.72
UK	5.02	S. Africa	1.11	France	5.19	S.Africa	0.42
2005 – 2010							
USA	10.98	Brazil	2.25	USA	19.43	Brazil	1.65
Germany	7.19	Russia	1.16	Germany	14.93	Russia	0.68
Japan	6.29	India	1.99	Japan	7.96	India	1.35
Italy	5.30	China	5.43	Italy	5.50	China	7.93
France	4.71	S. Africa	1.24	France	5.31	S.Africa	0.60

Note: This table covers the period from 1990 to 2010. Centrality measures are calculated using diffusion parameters obtained from the baseline calibration and actual trade and production data. I obtain similar rankings if simulated trade and production data is used.

Table A8: Key Players: Degree Centrality

Cutoff $\zeta = 0.02$				Cutoff $\zeta = 0.005$			
OECD		"BRICS"		OECD		"BRICS"	
USA	0.99	Brazil	0.19	USA	1.00	Brazil	0.44
Germany	0.97	Russia	0.04	Germany	1.00	Russia	0.07
Japan	0.94	India	0.14	Japan	1.00	India	0.26
Italy	0.86	China	0.53	UK	0.99	China	0.86
France	0.84	S. Africa	0.06	France	0.99	S.Africa	0.09

Cutoff $\zeta = 1e - 4$			Cutoff $\zeta = 1e - 5$		
Country	Industry	Degree	Country	Industry	Degree
USA	Measurement	0.99	USA	Measurement	1.00
Germany	Measurement	0.99	Japan	Measurement	1.00
Japan	Measurement	0.97	USA	Vehicles	0.99
UK	Measurement	0.96	UK	Printing	0.99
Japan	Vehicles	0.96	Japan	Vehicles	0.99
France	Measurement	0.95	USA	Other Manuf.	0.99
Switzerland	Measurement	0.95	Germany	Vehicles	0.99
USA	Vehicles	0.95	China	Other Manuf.	0.99
Germany	Vehicles	0.95	Germany	Measurement	0.99
France	Vehicles	0.94	Switzerland	Measurement	0.99

Note: This table covers the period from 1990 to 2010 using the diffusion parameter obtained from the baseline calibration (Method II). Country-level degree measure is normalized by $N = 72$ and industry-level degree measure is normalized by $N \times I = 1224$.