Knowledge Diffusion and Trade Across Countries and Sectors

Jie Cai, Nan Li and Ana Maria Santacreu*

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Abstract

Countries and sectors interact through knowledge spillovers and international trade flows. These interactions drive differences in income per capita and innovation not only across countries, but also across sectors within a country. We develop and quantify a model of innovation, knowledge diffusion and trade that can explain these differences. Using data on intersectoral patent citations, R&D expenditures and international trade flows, we calibrate the model and perform several counterfactual exercises. Decreases in trade costs or increases in the speed of diffusion reallocate resources across countries and sectors, generating a distributional effect on aggregate innovation and growth.

Keywords: Technology Diffusion; R&D; Intersectoral linkages; Patent; Citations; Trade

JEL Classification: F12, O33, O41, O47

*Cai: Shanghai University of Finance and Economics, cai.jie@mail.shufe.edu.cn; Li, International Monetary Fund, address: 700 19th Street NW, Washington DC 20431, email: nanli1@gmail.com; Santacreu, Federal Reserve Bank of St. Louis, email: am.santacreu@gmail.com. We are grateful for Jonathan Eaton, Dan Treffler, Lorenzo Caliendo, and participants of the brown bag seminar at the Saint Louis Fed for helpful discussions.

1 Introduction

The world has increasingly become a highly interconnected network of countries and sectors which not only trade goods and services between each other, but at the same time, exchange ideas with one another. For example, when trade costs are reduced in a given sector for the exports from China to U.S., not only does competition increase and potentially profits of the U.S. producers in the same sector go down, but this also leads to (i) cost reduction for sectors that purchase the product as intermediate input; (ii) profit distribution changes across sectors in U.S. which may affect cross-sectoral R&D allocation and innovation distribution; (iii) more investment in innovation in China in the same sector due to higher market share and profit; (iv) profit opportunity and higher innovation incentive in China in the related sectors; and (v) direct (within-sector) or indirect (across-sector) knowledge diffusions between China and the U.S. In a highly interconnected world as we live in now, changes to one sectors can have far-reaching implications for other sectors both in the product space and in the technology space.

Recently, a growing strand of the trade literature has examined how the benefits of trade liberalization may spread across sectors, through production input-output linkages (such as Caliendo and Parro 2014). However, sectors are also linked along a different dimension—knowledge complementarities. Indeed, technological advances never happens in isolation (David, 1991; Rosenberg, 1982). Knowledge in one area can be adapted to enhance innovation in another, and much alike the cross-sectoral production input-output linkages, the adaptability across sectors are far from uniform. Therefore, in a world with interlinked multiple sectors, when changes in trade costs alter the knowledge composition of the economy, the latter also conditions trade patterns and aggregate growth (as shown in the empirical research by Hausmann, Hwang and Rodrik, 2007; Hidalgo, Klinger, Barabasi and Hausmann, 2007). Furthermore, although trade flow often serves as a vehicle or a catalyst for knowledge diffusion (Alvarez, Buera and Lucas, 2014), they do not necessarily follow the same pattern or intensity. The literature so far has either treated these two as separate issues or has modeled them together as one channel (e.g. more trade necessarily implies more knowledge spillovers).

This paper analyzes quantitatively the rich interplay between cross-country, cross-sector trade and knowledge diffusion. We first develop a multi-sector and multi-country model of trade with Bertrand competition, which determines the level of technology in a sector-country pair, and then introduce a process of endogenous innovation and technology diffusion across sectors and countries to model the evolution of technologies over time. We use cross-country intersectoral patent citations to discipline the direction and intensity in which knowledge in a particular sector is utilized in the innovation of other sectors. This allows us to directly uncover the intersectoral knowledge input-output relationships. The model is able to reproduce the distribution of technology level and of R&D intensity across sectors and countries. Furthermore, change sin trade costs and the strength of knowledge spillovers have an impact on R&D intensity at the country level by changing its allocation across sectors within a country. R&D is reallocated to sectors in which the country has a comparative advantage. [Jie: Therefore, trade liberalization strenthens countries' comparative advantage and enhances the static gain from Richardian type of trade, on top of greater dynamic gain from trade due to higher overall R&D investment. In contrast, knowledge diffusion enables faster productivity convergence and makes countries more similar, which dampens the static gain from trade. Nevertheless, knowledge diffusion provides strong enough dynamic gain, because countries can innovate with access to larger foreign knowledge pool.]

To highlight that not only aggregate R&D investment, but also the distribution of R&D across sectors, matters for growth, we start by documenting two novel observations. When characterizing each sector by its measure of "knowledge applicability"—which evaluates a sector's importance as a knowledge supplier to both its immediate and indirect downstream application sectors using cross-sector patent citation data, we find: (i) Richer countries tend to import and export disproportionately more in sectors with high knowledge applicability; (ii) Countries whose export (or import) structures are more *biased* towards applicable sectors invest more in R&D (as a share of GDP). Given the intrinsic heterogeneous knowledge applicability across sectors and its impact on future innovation, the allocation of R&D expenditures across sectors would affect the aggregate innovation and growth. To understand how trade plays a role in directing R&D and transferring ideas among multiple sectors, we need a structural framework of trade, innovation and knowledge spillovers with realistic feature of intersectoral linkages both on the knowledge spillover dimension and on the factor demand dimension.

We then develop a general equilibrium model of trade in intermediate goods, sectoral heterogeneity and input-output linkages, in which technology evolves endogenously through a process of innovation and international diffusion. A final producer combines the output of all the sectors in the domestic economy under perfect competition. In addition, there are two types of producers within each sector: a sector final producer that operates under perfect competition and sells the good to the final producer in the country, and intermediate firms that use labor to produce traded varieties that are then sold to the sector producer of other sectors and/or countries. These firms operate under Bertrand competition and are heterogeneous in their productivity. Finally, innovators in each sector invest final output to come up with a new idea to produce a variety. These ideas can diffuse internationally and across sectors according to an exogenous process of diffusion. The novel feature of this model is that sectors and countries are connected not only through trade in varieties but also through knowledge spillovers. These two channels interact in a way that allows us to explain differences in innovation and income per capita across sectors and countries. Decreases in trade costs or increases in the speed of diffusion increase sector productivity and innovation, and this allows us to reproduce the empirical facts previously documented.

Different from Eaton and Kortum 1996 and Eaton and Kortum 1999 , Buera and Oberfield 2016, and Atkeson and Burstein 2010, in our model, changes in trade costs have a direct effect on the incentives to innovate. The reason is that we assume that entrepreneurs investing into R&D belong to a particular sector. Within that sector, however, the innovation effort applies to any good in the continuum. Incentives to do R&D are driven by expected profits from selling the good to the same sector either domestically or abroad.[1] In a one sector model, trade affects expected profits positively through an increase in market size and negatively because there is an increase competition faced by the firms in the domestic market, It turns out that these two effects cancel out. In a multi-sector model, however, after a trade liberalization, countries allocate more R&D towards the sector in which they have comparative advantage. Our probabilistic formulation and the continuum of goods guarantees that there is some innovation done in every sector in the economy.

We calibrate the model to data on intersectoral patent citations, investment in R&D and international trade to match our novel empirical facts. Following Eaton and Kortum 2002 , we derive a theoretical gravity equation, which we then estimate to uncover the trade cost parameters. The estimation procedure adds fixed effects which, together with data on R&D and patent citation, allow us to recover the technology parameters (Santacreu 2015). We then perform several counterfactual exercises.

Despite of its complexity, the model comes with the benefit of tractability, as we build upon the Ricardian trade model of Eaton and Kortum 2002 with Bertrand Competition (Bernard, Eaton, Jensen, and Kortum 2003). The innovation and international technology diffusion processes are modeled in a similar fashion as in Eaton and Kortum 1996 and Eaton and Kortum 1999. The diffusion lags—backed by empirical observations—have an exponential distribution. All these features allow us to estimate the set of parameters based on observables in trade and citation data from steady-state relationships.

[1]This assumption is what a recent paper by Somale 2014 calls targeted research. Different from his model, however,we consider international technology diffusion as an additional source of technological progress. Furthermore, we provide a quantitative analysis of the effect of trade and technology diffusion on the reallocation of R&D across industries.

Related Literature Our paper merges and extends several strands of existing literature. The first is the literature on innovation, diffusion and international trade. Eaton and Kortum 1996 and Eaton and Kortum 1999 posit technological innovations and their international diffusion through trade as potential channels of embodied technological progress. Santacreu 2015 develops a model in which trade allows countries to adopt innovation developed abroad, and thus diffusion does not take place without trade. Our main departure from these previous works is that we allow knowledge diffusion and trade to operate separately, even though common economic forces may contribute to the development of both and diffusion and trade may benefit and reinforce each other. In addition, we extend these studies into multi-sector environment in which sectors interact both in the product space and in the technology space.

The second is the multi-sector trade literature which extends Eaton and Kortum (2002) trade model to multiple sectors (Chor, 2010; Costinot, Donaldson and Komunjer, 2012). A recent growing body of research in this area also explores the trade and growth implications of interdependence across different sectors through intermediate input-output relationships (Eaton, Kortum, Neiman and Romalis, 2011; Caliendo and Parro 2014). Our paper differs in several dimensions. First, our focus is on innovation and knowledge diffusion. Second, besides the factor demand linkages, this paper also simultaneously consider the intrinsic interconnections of technologies embodied in different sectors, which turns out to be significant and relevant when studying innovation and diffusion. Related to the current work, Cai and Li (2016) study knowledge spillovers across sectors within a country and how trade costs affect the distribution of endogenous knowledge accumulation across sectors. Different from our paper, however, cross-sector knowledge diffusion is not considered across countries and material input demand linkages across sectors are absent. [Jie: Levchenko and Zhang (2016) provide evidence of relative productivity convergence across 72 countries over 5 decades: productivity grew systematically faster in initially relatively less productive sectors. These changes have had a significant impact on trade volumes and patterns, and a modest negative welfare impact.]

Led by Hidalgo, et al. (2007), several papers have shown that producing goods with strong synergy with each other can improve growth, as it is easier to adapt existing ideas and enter new sectors (e.g. Hausmann and Klinger, 20007, Kali et al, 2012, Hauswman et al, 2007). However, these studies mostly adopt the regression based approach which is hard to establish causality and to examine the general equilibrium implications of changing trade structure. Moreover, none of these studies consider at the same time the product complementarity along the intermediate input-output dimension.

The rest of the paper proceeds as follows. Section 2 documents several empirical observations that motivate our study. Section 3 presents the model. Section 4 describes the steady state and Section 5 presents the calibration. Finally section 8 concludes.

2 Motivating Facts

This section presents the facts that motivate our model and calibration exercise.

2.1 Data and Measurement

Knowledge Applicability The 2006 edition patent citation database provided by U.S. Patent and Trade Office (USPTO) is used to trace the direction and intensity of knowledge flows within and across sectors, and to construct indices of knowledge applicability for each sector.[2] In the dataset, patents are organized by their technical features and each patent belongs to a technology field according to the International Patent Classification (IPC), which is then mapped into industry sectors.

The method to construct the applicability measure is discussed in detail in Cai and Li (2014) and here we content ourselves by outlining the main idea. We start by adding up citations made from (and to) patents that belong to the same IPC sector to generate a *cross-sector* citation matrix $(c^{ij})_{J\times J}$, where c^{ij} denotes the number of citations to sector i made by j. We then apply the iterative algorithm developed by Kleinberg (1998) to the citation matrix and construct an index, called *authority weight* (aw), to capture the 'knowledge applicability' of each sector (i.e. the extent to which they enable the creation of knowledge in all sectors). The algorithm simultaneously generates another index, hub weight (hw), which characterizes the extent to which the sector relies on knowledge from other sectors. Formally,

$$\begin{aligned} aw^i &= \lambda^{-1}\sum_{j\in J} W^{ji} hw^j \qquad (1)\\ hw^i &= \mu^{-1}\sum_{j\in J} W^{ij} aw^j \end{aligned}$$

where λ and μ are the Euclidean norms of vectors $(aw^i)_{i\in J}$ and $(hw^i)_{i\in J}$, respectively. W^{ji} corresponds to the number of citations received by patents in sector i from patents in sector j, c^{ji}. We calculate the time-variant aw^i_t for each IPC sector based on rolling window subsamples, pooling citations from the previous 10 years for each year during 1985-2006.[3]

[2] The updated NBER patent database is available at: https://sites.google.com/site/patentdataproject/Home. It contains detailed patent and citation information, including the patent application year, grant year, the technological area to which it belongs, the nationality of patent inventors, the patent assignees, the citations made and received and by each patent, etc.

[3] The ranking for most sectors does not change drastically over the sample period, although the quality

Applicability Bias of a Country's Trade Pattern Countries' export structures are measured based on an updated version of the UN-NBER World Trade Flows dataset (see Feenstra et al, 2005), which harmonizes COMTRADE annual bilateral trade flow data for SITC sectors over the 1978-2013 period. To rank these industrial sectors according to their knowledge applicability, we employ the IPC–SITC concordance provided by World Intellectual Property Organization (WIPO) to generate the aw for each 2-digit SITC sector.

Based on the sector-specific knowledge applicability measure (aw^i), we measure the applicability bias of a country's export (import) structure by the cross-sector correlation between aw^i and the share of export (import) by the country in the respective sectors, x_c^i:

$$\rho_c = Corr\{\ln(aw^i), \ln(x_c^i)\}$$

where x_c^i is the share of export (import) in sector i in total export (import) value of country c.

2.2 Observations

Fact 1: *R&D intensities are persistently heterogeneous across sectors, with highly applicable sectors being more R&D intensive.*

It has been well established in the innovation and growth literature that there are large and persistent cross-sector differences in R&D intensity (Klenow [1996], Ngai and Samaniego [1996], Nelson [1988]). Cai and Li (2015) find that the innate characteristics of the technology embodied in the sector–knowledge applicability—explains the large and persistent variations in R&D intensity across sectors (as shown in Figure I)

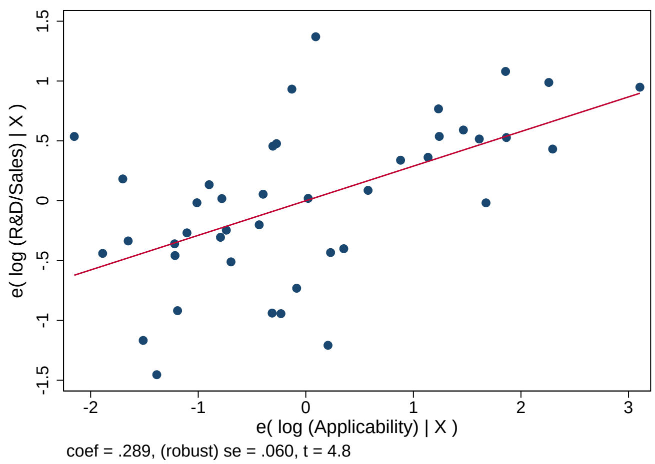
Fact 2: *Richer countries export (or import) disproportionately more in highly knowledge applicable sectors.*

As demonstrated in Figure II, there is a significantly positive relationship between a countries' knowledge applicability bias of the export and import structure and real GDP per capita, even after controlling for standard development accounting variables, such as human capital (h_c) and capital-output ratio (k_c/y_c) and the natural reserve rent (r_c).

Fact 3: *Countries that export (or import) disproportionately more in highly knowledge applicable sectors invest more in R&D (as share of GDP).*

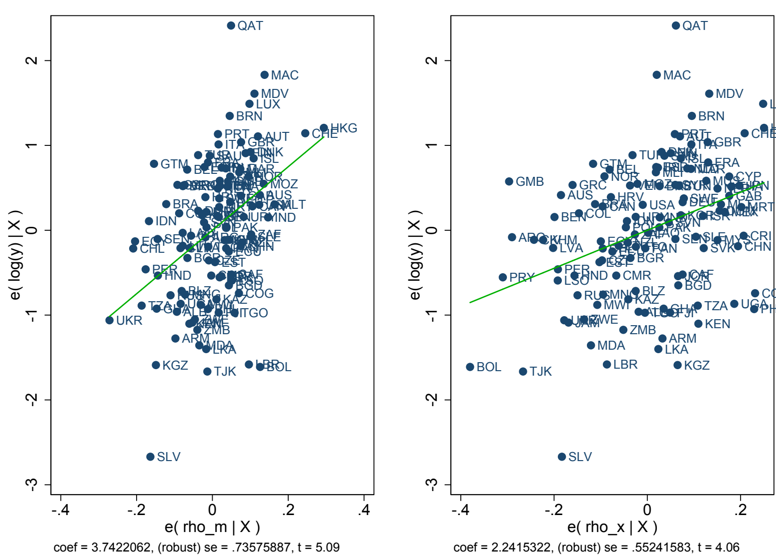
of our measure decreases close to the end of the sample as a result of citation lags. The average correlation of the ranking across different decades is about 0.90.

Figure I: Sectoral R&D intensity and applicability



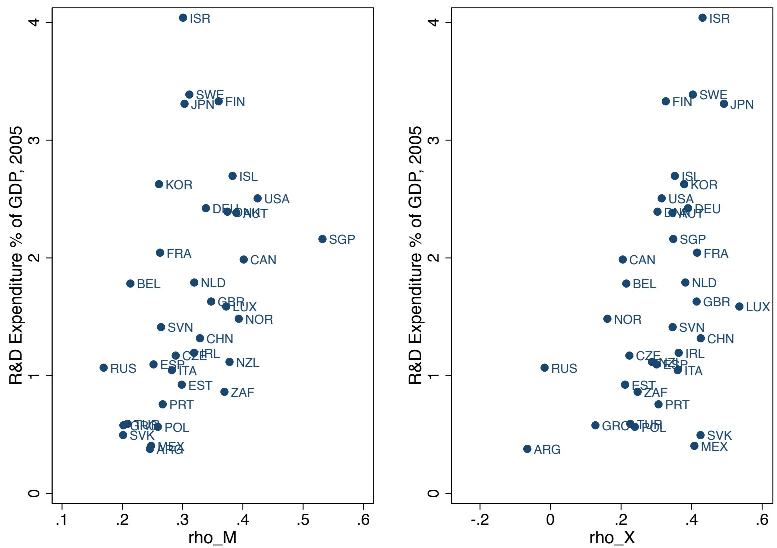
Notes: The figure shows the partial regression plot for $\ln(aw)$ from the following regression that links sectoral R&D intensity to sector-specific knowledge applicability, controlling for sectoral market size (measured by sales), profitability (value of shipment divided by labor compensation) and self-applicability: $\frac{R\&D^i}{Sales^i} = \underset{(0.060)}{0.289}\ln(aw^i) - \underset{(0.069)}{0.040}\ln(sales^i) + \underset{(0.041)}{0.059}\ln(prof^i) - \underset{(0.035)}{0.085}\ln(self\_app^i)$, where R&D intensity is the total R&D expenditure divided by total sales among firms in U.S. Compustat over the period 1970-2000. The applicability measure is constructed based on cross-sector patent citation network (NBER Patent Dataset, 1976-2002). The solid line represents the fitted values.

Figure II: GDP per capita and ρ_c



Notes: This figure displays the partial regression plot based on the following regressions, using data in 2005: $\ln(y_c) = \underset{(0.736)}{3.74}\rho_c^M + \underset{(0.267)}{3.63}\ln(h_c) - \underset{(0.188)}{0.10}\ln(k_c/y_c) + \underset{(0.673)}{0.82}r_c + \varepsilon_c$, $\ln(y_c) = \underset{(0.552)}{2.24}\rho_c^X + \underset{(0.273)}{3.65}\ln(h_c) - \underset{(0.176)}{0.05}\ln(k_c/y_c) + \underset{(0.718)}{1.72}r_c + \varepsilon_c$, where ρ_c^M and ρ_c^X are the knowledge applicability bias of country c's import and export structure respectively.

Figure III: (Normalized) R&D Expenditure and ρ_c



Notes: Data Source: R&D expenditure data are from OECD Main Science and Technology Indicators Database.

Figure III shows that countries with higher level of R&D intensity also tend to import and export disproportionately more in sectors with highly applicable knowledge.[4]

3 The Model

We develop a general equilibrium model of trade in intermediate goods, sectoral heterogeneity and input-output linkages, in which technology evolves endogenously through a process of innovation and international diffusion. The model builds upon the Ricardian trade model of Eaton and Kortum 2002 with Bertrand Competition (Bernard, Eaton, Jensen, and Kortum 2003). The innovation and international technology diffusion processes are modeled as Eaton and Kortum 1996 and Eaton and Kortum 1999.

There are N countries and J sectors. Countries are denoted by i and n and sectors are denoted by j and k. Labor is the only factor of production and we assume it to be mobile across sectors within a country but immobile across countries. In each country, there is a consumer who consumes a non-traded final good and saves. A perfectly competitive final producer combines a composite output of all J sectors in the domestic economy with a Cobb-Douglas production function.

[4]The same pattern emerges when we use business enterprise expenditure on R&D instead of gross R&D expenditure which includes government and research institutes.

In each sector there is a producer of a composite good that operates under perfect competition and sells the good to the final producer and to intermediate producers from all sectors in that country. Intermediate producers use labor to produce varieties that are traded and are used by composite producer of that sector, either domestic or foreign These firms operate under Bertrand competition and are heterogeneous in their productivity. Trade is Ricardian.

Finally, the technology of each sector-country pair evolves endogenously through a process of innovation and international and intersectoral technology diffusion. The innovation process follows the quality-ladders literature in that the new innovations increase the quality of a sector-country pair. Trade is balanced in every period.

3.1 Consumers

In each country there is a measure of L_n representative households who choose consumption optimally to maximize their life-time utility

$$U_{nt} = \sum_{t=0}^{\infty} \beta^t u\left(C_{nt}\right)$$

where $\beta \in (0,1)$ is the stochastic discount factor, and C_{nt} represents consumption of country n at time t. The households own all the firms and finance R&D activities by the entrepreneurs.

3.2 Final production

Domestic final producers use a composite output from every domestic sector j in country n at time t, Y_{nt}^j, to produce a non-traded final output Y_{nt} according to the following Cobb-Douglas production function

$$Y_{nt} = \prod_{j=1}^{J} \left(Y_{nt}^j\right)^{\alpha_n^j}, \tag{2}$$

with α_n^j the share of sector production on total final output, and $\sum_{j=1}^{J} \alpha_n^j = 1$.

Final producers operate under perfect competition. Their profits are given by:

$$\Pi_{nt} = P_{nt} Y_{nt} - \sum_j P_{nt}^j Y_{nt}^j$$

where P_{nt} is the price of the final produce, and P_{nt}^j is the price of the composite good produced in sector j from country n.

Under perfect competition, the price charged by the final producers to the consumers is equal to their marginal cost, that is

$$P_{nt} = \prod_{j=1}^{J} \left(\frac{P_{nt}^{j}}{\alpha_n^{j}} \right)^{\alpha_n^{j}},$$

The demand by final producers for the sector composite good is given by:

$$\alpha_n^{j} P_{nt} \frac{Y_{nt}}{Y_{nt}^{j}} = P_{nt}^{j}$$

3.3 Intermediate producers

In each sector j there is a continuum of intermediate producers indexed by $\omega \in [0,1]$ that use labor, $l_{nt}^{j}(\omega)$, and a composite intermediate good from every other sector k in the country, $m_{nt}^{jk}(\omega)$ to produce a variety ω according to the following constant returns to scale technology[5]

$$q_{nt}^{j}(\omega) = z_n^{j}(\omega)[l_{nt}^{j}(\omega)]^{\gamma_n^{j}} \prod_{k=1}^{J} [m_{nt}^{jk}(\omega)]^{\gamma_n^{jk}}, , \tag{3}$$

with $\gamma_n^{j} + \sum_{k=1}^{J} \gamma_n^{jk} = 1$. Here γ_n^{kj} is the share of materials from sector k used in the production of intermediate ω is sector j, and γ_n^{j} is the share of value added.

Firms are heterogeneous in their productivity $z_n^{j}(\omega)$.

The cost of producing each intermediate good ω is

$$c_{nt}^{j}(\omega) = \frac{c_{nt}^{j}}{z_{nt}^{j}(\omega)}$$

where c_n^{j} denotes the cost of input bundle. In particular, given constant returns to scale:

$$c_n^{j} = \Upsilon_n^{j} W_{nt}^{\gamma_n^{j}} \prod_{k=1}^{J} (P_n^{k})^{\gamma_n^{jk}}$$

with $\Upsilon_n^{j} = \prod_{k=1}^{J} (\gamma_n^{jk})^{-\gamma_n^{jk}} (\gamma_n^{j})^{-\gamma_n^{j}}$ and W_{nt} is the nominal wage rate. Intermediate producers operate under Bertrand competition.

[5]The notation in the paper is such that every time there are two subscripts or two superscripts, the right one corresponds to the source country and the left one corresponds to the destination country.

3.4 Composite intermediate goods (Materials)

Each sector j produces a composite good combining domestic and foreign varieties from that sector. Composite producers operate under perfect competition and buy intermediate products ω from the minimum cost supplier.

The production for a composite good in sector j in country n is given by the CES function, as in Ethier 1982,

$$Q^j_{nt} = \left(\int r^j_{nt}(\omega)^{1-1/\sigma^j} d\omega \right)^{\sigma^j/(\sigma^j-1)}, \tag{4}$$

where $\sigma^j > 0$ is the elasticity of substitution across intermediate good from sector j, and $r^j_{nt}(\omega)$ is the demand of intermediate goods from the lowest cost supplier in sector j.

The demand for each intermediate good ω is given by

$$r^j_{nt}(\omega) = \left(\frac{p^j_{nt}(\omega)}{P^j_{nt}} \right)^{-\sigma^j} Q^j_{nt}$$

where

$$P^j_{nt} = \left(\int p^j_{nt}(\omega)^{1-\sigma^j} d\omega \right)^{\frac{1}{1-\sigma^j}}, \tag{5}$$

The sector composite producer uses varieties from its own sector, but only from the lower cost producer, since there is perfect competition.

Composite intermediate goods are used as materials for the production of the intermediate goods and as final goods in the final production.

$$Q^j_{nt} = Y^j_{nt} + \sum_{k=1}^{J} \int m^{jk}_n(\omega) d\omega$$

3.5 International trade

We follow Bernard, Eaton, Jensen, and Kortum 2003 and assume Bertrand competition. Trade in goods is costly. In particular, there are iceberg transport costs from shipping a good in sector j from country i to country n, d^j_{ni}.The p'th most efficient producer of variety ω from sector j in country i can deliver a unit of good to country n at the cost:

$$c^j_{pni}(\omega) = d^j_{ni} \frac{c^j_i}{z_{pi}(\omega)}$$

With Bertrand competition, as with perfect competition, composite producers in each sector and country buy from the lowest cost supplier. The cost of a good ω in country n is given by

$$c_{1n}^{j}(\omega) = min_i \left\{ c_{1ni}^{j}(\omega) \right\}$$

In addition, Bertrand competition implies that the price charged by the producer will be the production cost of the second lowest producer

$$c_{2n}^{j}(\omega) = min \left\{ c_{2ni*}^{j}(\omega), min_{i \neq i*} \{ c_{1ni}^{j}(\omega) \} \right\}$$

where $i*$ satisfies $c_{1ni*}^{j}(\omega) = c_{1n}^{j}(\omega)$. The low cost supplier will not want to charge a mark-up above $\bar{m}^{j} = \sigma^{j}/(\sigma^{j} - 1)$. Hence,

$$p_{n}^{j}(\omega) = min \left\{ c_{2n}^{j}(\omega), \bar{m}^{j} c_{1n}^{j}(\omega) \right\}$$

Ricardian motives for trade are introduced as in Eaton and Kortum 2002, since productivity is allowed to vary by sector and country. The productivity of producing intermediate good ω in country i and sector j is drawn from a Frechet distribution with parameter T_{i}^{j} and shape parameter θ^{j}. A higher T_{i}^{j} implies a higher average productivity of that sector-country pair, while a lower θ^{j} implies more dispersion of productivity across varieties in that sector. From here

$$F(z_{i}^{j}) = Pr \left[Z \leq z_{i}^{j} \right] = e^{-T_{i}^{j} z^{-\theta^{j}}}$$

and,

$$Pr \left[p_{ni,t}^{j} < p \right] = 1 - e^{-T_{it}^{j} \left(d_{ni}^{j} c_{it}^{j} / p \right)^{-\theta^{j}}}$$

Because each sector j in country n buys goods from the second cheapest supplier, the cost of good ω in sector j and country n is $p_{nt}^{j}(\omega) = min \left\{ p_{nit}^{j}(\omega) \right\}$. Then, $c_{nt}^{j}(\omega)$ are realizations from G_n

$$G_{n}^{j}(p) = 1 - \prod_{i=1}^{N} \left(Pr \left[p_{nit}^{j} > p \right] \right) = 1 - \prod_{i=1}^{N} e^{-T_{it}^{j} \left(d_{ni}^{j} c_{it}^{j} / p \right)^{-\theta^{j}}} = 1 - e^{-\Phi_{nt}^{j} p}$$

with $\Phi_{nt}^{j} = \sum_{i=1}^{N} T_{it}^{j} (d_{ni}^{j} c_{it}^{j})^{-\theta^{j}}$ each country n and sector j accumulated technology. From here, we can obtain the distribution of prices of goods in sector j in country n as

$$P_{nt}^{j} = A^{j} \left(\Phi_{nt}^{j} \right)^{-1/\theta^{j}}, \tag{6}$$

with $A^{j} = \left[\frac{1 + \theta^{j} - \sigma^{j} + (\sigma^{j} - 1) \left(\bar{m}^{j} \right)^{-\theta^{j}}}{1 + \theta^{j} - \sigma^{j}} \Gamma \left(\frac{2\theta^{j} + 1 - \sigma^{j}}{\theta^{j}} \right) \right]^{1/(1-\sigma^{j})}$ and assuming $\sigma^{j} < (1 + \theta^{j})$.

3.6 Expenditure shares

The probability that country i is the low cost supplier of a good in sector j that is to be exported to sector j in country n is

$$\pi^j_{nit} = \frac{T^j_{it}\left(c^j_{it}d^j_{ni}\right)^{-\theta^j}}{\Phi^j_{nt}}, \tag{7}$$

with $\Phi^j_{nt} = \sum_{i=1}^{M} T^j_{it}\left(c^j_{it}d^j_{ni}\right)^{-\theta^j}$. This is the fraction of goods that country n buy from sector j in country i. That probability is also the fraction of goods that sector j in country i sells to any sector in country n. In particular, the share that sector j in country n spends from sector j in country i is

$$\pi^j_{nit} = \frac{X^j_{nit}}{X^j_{nt}} = \pi^j_{nit}, \tag{8}$$

Therefore,

$$X^j_{nit} = \pi^j_{nit} X^j_{nt}$$

with X^j_{nit} the expenditures of country n from sector j in country i and X^j_{nt} the total expenditures of country n from sector j. Substituting the expression for π^j_{nit}we have

$$X^j_{nit} = \frac{T^j_{it}\left(c^j_{it}d^j_{ni}\right)^{-\theta^j}}{\Phi^j_{nt}} X^j_{nt}$$

From here, we can get to an expression that is similar to a gravity equation at the sector level (source sector):

$$\frac{X^j_{nit}}{X^j_{nnt}} = \frac{T^j_{it}\left(c^j_{it}d^j_{ni}\right)^{-\theta^j}}{T^j_{nt}\left(c^j_{nt}\right)^{-\theta^j}}, \tag{9}$$

Taking logs:

$$log\left(\frac{X^j_{nit}}{X^j_{nnt}}\right) = log\left(T^j_{it}\left(c^j_{it}\right)^{-\theta^j}\right) - log\left(T^j_{nt}\left(c^j_{nt}\right)^{-\theta^j}\right) - D^j_{ni}, \tag{10}$$

which can be estimated with fixed effects

$$log\left(\frac{X^j_{nit}}{X^j_{nnt}}\right) = S^j_{it} - S^j_{nt} - D^j_{ni}, \tag{11}$$

where $S^j_{it} = \log\left(T^j_{it}\left(c^j_{it}\right)^{-\theta^j}\right)$ and $D^j_{ni} = \sum_k \rho^j_k D_k$, D_1 to D_6 are distance dummy variables equal to one if the population weighted distance countries n and i is between 0 and 375 kilometers, 375 and 750 kilometers, 750 and 1500 kilometers, 1500 and 3000 kilometers, 3000 and 6000 kilometers, and above 6000 kilometers, respectively; D_7 to D_{10} are dummy variables indicating if countries n and i share common language, common border, belong to the same free trade agreement and costumes union. ρ_k^j is the sensitivity of sector j's trade flow to the k^{th} trade barrier.

3.7 Endogenous growth: Innovation and international technology diffusion

We model the innovation process within each industry j as in Kortum 1997. Innovation follows the quality-ladders literature, in that a blueprint (i.e., an idea) is needed to produce an intermediate good. Ideas are developed with effort and they increase the efficiency of production of an intermediate good. In each sector j and country n, there are entrepreneurs that invest final output to come up with an idea. Within each sector, research efforts are targeted at any of the continuum of intermediate goods. In each country n and sector j, ideas are drawn at the Poissson rate λ_{nt}^j. That is, if a fraction of final output s_{nt}^j is invested into R&D by the entrepreneur, then ideas are created at the rate

$$\lambda_{nt}^j \left(s_{nt}^j\right)^{\beta_r}$$

with $\lambda_{nt}^j = \lambda_n^j T_{nt}^j$ and λ_n^j a scaling parameter that captures the productivity of innovation in sector j of country n, and $\beta_r \in (0,1)$ a parameter of diminishing returns to investing into R&D. This process is microfounded in Eaton and Kortum 1996 and Eaton and Kortum 1999 and it ensures that there is a balanced growth path without scale effects.

Note that the productivity of innovation varies across sectors and countries. Innovators belong to a particular sector j but, within each sector, their research effort is targeted at any of the goods in the continuum.

Ideas from sector j and country n may become an intermediate product in that sector/country. The efficiency $q^j(\omega)$ with which it enables good ω to be produced in sector j is drawn from the Pareto distribution $H(q) = 1 - q^{-\theta^j}$. An idea applies to only one good in the continuum. The good ω to which it is associated is drawn from the uniform distribution $[0, 1]$;

In equilibrium, only the best idea for each input in each country and sector it is actually used to produce an intermediate good in any sector and/or country. The efficient technology $z_i^j(\omega)$ for producing good ω in country i is the best idea for producing it yet discovered. A new idea is never adopted unless it surpasses the current state of the art $z_i^j(\omega^j)$. Following

Eaton and Kortum 2006, the best technologies available in a country are realizations of a random variable that has a Frechet distribution:

$$F_n^j(z) = \exp[-T_n^j z^{-\theta}]$$

That is, the quality distribution of successful ideas inherit the distribution of productivity of the intermediate goods produced in a country. We elaborate more on this point later, when we introduce the incentives of an innovation.

Once an idea has arrived in sector j and country n there is no forgetting.

New ideas created in each sector j and country n increase its average productivity, T_n^j. Ideas may also diffuse slowly and exogenously to other sectors and/or countries. If an idea is discovered at time t in country i and sector k, then it diffuses to country n and sector j at time $t + \tau_{ni}^{jk}$. We assume that the diffusion lag τ_{ni}^{jk} has an exponential distribution with parameter ε_{ni}^{jk} (this is the speed of diffusion), so that $Pr[\tau_{ni}^{jk} \leq x] = 1 - e^{-\varepsilon_{ni}^{jk} x}$.

Through diffusion, technology in a country/sector is composed by the technologies developed in all sectors and countries. That is, $T_n^j = \sum_i \sum_k T_{ni}^{jk}$. Therefore, the flow of ideas diffusing to country n and sector j is given by the accumulation of the past research effort of each sector k in country i that has already been diffused, according to

$$\dot{T}_{nt}^j = \sum_{i=1}^{N} \sum_{k=1}^{J} \varepsilon_{ni}^{jk} \int_{-\infty}^{t} e^{-\varepsilon_{ni}^{jk}(t-s)} \lambda_i^k \left(s_{is}^k\right)^{\beta_r} ds, \tag{12}$$

with $\lambda_{is}^k = \lambda_i^k T_{is}^k$. If $\varepsilon_{ni}^{jk} \to \infty$, then there is instantaneous diffusion. If $\varepsilon_{ni}^{jk} \to 0$, then there is no diffusion. The growth of the stock of knowledge in a particular sector j and country n at time t depends on the past research effort that has been done by each other sector k in country i up to time t, and that has diffused at the rate ε_{ni}^{jk}.

3.7.1 The incentives to innovate

There is free entry into innovation. Entrepreneurs finance R&D issuing equity claims to the households. These claims pay nothing if the entrepreneur is not successful in introducing a new technology in the market, and it pays the stream of future profits from selling the good in a particular sector either domestically or abroad, if the innovation succeeds. The price for a research success by an entrepreneur in a particular sector is the expected flow of profits that will last until a new success or a foreign producer may produce the good at a lower cost. Because of the probabilistic distribution of productivity, entrepreneurs will be indifferent on what product ω to devote its efforts, since in expectation, all products with a sector deliver the same expected profit. As in the quality ladders literature, we focus on a situation in which all products within an industry are targeted with the same intensity. Following the quality-ladders literature, a new idea will interact with the set of existing technologies in a particular sector and country if $Q > Z_n^j$, which occurs with probability

$$Pr[Q > Z_n^j] = \int_0^\infty Pr[Q > z] dF_n^j(z) = 1/T_n^j$$

This introduces a competitive effect, by which the larger the number of existing technologies in a sector/country, the lower the probability that the new idea lowers the cost there.

Then, the distribution of Q conditional on $Q > Z_n^j$ is

$$Pr[Q \leq q | Q > Z_n^j] = e^{-T_n^j q^{-\theta^j}}$$

Therefore, conditional on joining the set of best technologies, the quality of a new idea has the same distribution of the quality of existing technologies.

A local innovator will lower cost in sector j of country n if:

$$c_n^j(\omega)/q \leq min_i \left\{ c_i^j(\omega) d_{ni}^j / z_i^j(\omega) \right\}$$

Therefore, using the results of the international trade section, the profits of an innovator in sector j in country n are

$$\Pi_{nt}^j = \sum_{i=1}^{M} \frac{\pi_{int}^j X_{it}^j}{(1+\theta^j) T_{nt}^j}$$

Rearranging, we obtain

$$\Pi_{nt}^j = \frac{1}{(1+\theta^j) T_{nt}^j} \sum_{i=1}^{M} X_{it}^j \pi_{int}^j, \tag{13}$$

The value of an idea that has been developed in country n and sector j is the expected present discounted value of the stream of future profits

$$V_{nt}^j = \int_t^\infty \left(\frac{P_{nt}^j}{P_{ns}^j} \right) e^{-\rho(s-t)} \Pi_{ns}^j ds, \tag{14}$$

Note that the incentive to innovate depends on the value of an innovation, which depends on: (i) the probability of the new technology lowering the cost of production there, $\frac{1}{T_n^j}$, and (iii) the expected profits from selling the good to each potential country-sector, $\frac{X_{in}^j}{1+\theta^j}$.

The first order condition for innovation is:

$$\beta_r \lambda_{nt}^j V_{nt}^j \left(s_{nt}^j\right)^{\beta_r - 1} = P_{nt} Y_{nt}, \tag{15}$$

3.8 Trade Balance

WE assume that trade is balanced every period. Total imports in country n are given by:

$$\sum_{i=1}^{M} \sum_{k=1}^{J} X_{nit}^k = \sum_{i=1}^{M} \sum_{k=1}^{J} \pi_{nit}^k X_t^k = \sum_{k=1}^{J} X_{nt}^k \sum_{i=1}^{M} \pi_{nit}^k, \tag{16}$$

Then,

$$IM_{nt} = \sum_{k=1}^{J} X_{nt}^k \sum_{i=1}^{M} \pi_{nit}^k$$

Total exports in country n are given by:

$$EX_{nt} = \sum_{i=1}^{M} \sum_{k=1}^{J} X_{int}^k = \sum_{i=1}^{M} \sum_{k=1}^{J} \pi_{int}^k X_{it}^k$$

Trade balance implies

$$EX_{nt} = IM_{nt}$$

4 Endogenous growth in steady-state

In our model, all countries and sectors grow at the same rate in steady-state. Nominal variables grow at the rate of nominal wages, and nominal wages grow at the same rate in every country. Therefore, we can express all the variables normalized by wages of country M, W_M. We also normalize the technology variable and express it as $\hat{T}_n^j = T_n^j / T_M^J$. Unless we specify otherwise, all variables with a hat correspond to the original variable normalized by W_M. All the hat variables are constant in steady state.

(1) Probability of imports

$$\hat{\pi}_{ni}^j = \hat{T}_i^j \frac{\left(\hat{c}_i^j d_{ni}^j\right)^{-\theta^j}}{\hat{\Phi}_n^j}, \tag{17}$$

where $\hat{T}_n^j = \frac{T_n^j}{T_M^J}$ and $\hat{\Phi}_n^j = \frac{1}{T_M^j} \frac{\Phi_n^j}{W_M^{-\theta^j}}$

(2) Import shares

$$\hat{X}_{ni}^{j} = \pi_{ni}^{j} \hat{X}_{n}^{j}, \tag{18}$$

(3) Cost of production

$$\hat{c}_{n}^{j} = \Upsilon_{n}^{j} \hat{W}_{n}^{\gamma_{n}^{j}} \prod_{k=1}^{J} (\hat{P}_{n}^{k})^{\gamma_{n}^{jk}}, \tag{19}$$

(4) Intermediate good prices in each sector

$$\hat{P}_{n}^{j} = A^{j} \left(\hat{\Phi}_{n}^{j} \right)^{-1/\theta^{j}}, \tag{20}$$

(5) Cost distribution

$$\hat{\Phi}_{n}^{j} = \sum_{i=1}^{M} T_{i}^{j} \left(d_{ni}^{j} \hat{c}_{i}^{j} \right)^{-\theta^{j}}, \tag{21}$$

(6) Price index

$$\hat{P}_{n} = \prod_{j=1}^{J} \left(\frac{\hat{P}_{n}^{j}}{\alpha_{n}^{j}} \right)^{\alpha_{n}^{j}}, \tag{22}$$

(7) Labor market clearing condition

$$\hat{W}_{n} L_{n} = \sum_{i=1}^{J} \gamma_{n}^{j} \sum_{i=1}^{M} \pi_{in}^{j} \hat{X}_{i}^{j}, \tag{23}$$

(8) Sector production

$$\hat{X}_{n}^{j} = \sum_{k=1}^{J} \gamma_{n}^{kj} \sum_{i=1}^{M} \hat{X}_{i}^{k} \pi_{in}^{k} + \alpha_{n}^{j} \hat{Y}_{n}, \tag{24}$$

where $\hat{Y}_{n} = \frac{P_{n} Y_{n}}{W_{M}}$.

(9) Final production

$$\hat{Y}_{n} = \hat{W}_{n} L_{n} + \sum_{j=1}^{J} \sum_{i=1}^{M} \pi_{in}^{j} \hat{X}_{i}^{j}, \tag{25}$$

(10) Resource constraint

$$\hat{Y}_n = \hat{C}_n + \sum_{k=1}^{J} s_n^k \hat{Y}_n, \tag{26}$$

(11) R&D expenditures

$$\beta_r \lambda_n^j \hat{V}_n^j \left(s_n^j\right)^{\beta_r - 1} = 1, \tag{27}$$

4.1 The mechanism

The model generates endogenously differences in innovation and income per capita across sectors and countries. Technology evolves endogenously through innovation and international technology diffusion. Changes in technology have an effect on the pattern of trade in the country, which changes the incentives to innovate through the effect on expected future profits. Therefore, countries and sectors in which technology diffusion is faster or in which international trade costs are lower have higher incentives to innovate, hence higher productivity and income per capita. The static trade model interacts with the dynamic part to identify the stock of knowledge, wages and growth rates. Heterogeneity in the production side at the country and sector level together with international and intersectoral heterogeneity in the knowledge linkages drives heterogeneity in the stock of knowledge in steady-state. This translates into variation in income per capita across countries.

To understand how knowledge diffusion and international trade can have an effect on the reallocation of R&D across sectors, we now derive the steady-state of the model, in which all variables grow at a constant rate. International and intersectoral diffusion guarantees that T_n^j growth at a common rate across sectors and countries. Denote the common growth rate as $\frac{\dot{T}_n^j}{T_n^j} = g_T$. From the resource constraint in equation (26), the fraction of final output that is invested into R&D, s_n^j, is constant in steady-state. This result and the expression for the value of an innovation implies that, in steady-state

$$\hat{V}_n^j = \frac{\hat{\Pi}_n^j}{\rho - g_T}$$

since by the definition of profits in steady-state,

$$\hat{\Pi}_n^j = \frac{\sum_{i=1}^{M} \hat{X}_i^j \pi_{in}^j}{(1+\theta^j)\hat{T}_n^j}$$

with $\hat{\Pi}_n^j = \frac{\Pi_n^j T_M^J}{W_M}$. Note that trade has a positive effect on the value of an innovation because now the innovator can access a larger market.

We can now use the expression for the value of an innovation together with the optimal investment into innovation to obtain an expression for R&D intensity in steady-sate:

$$\hat{V}_n^j = \frac{1}{(1+\theta^j)\hat{T}_n^j}\sum_{i=1}^{M} X_i^j \hat{\pi}_{in}^j \frac{1}{\rho - g_T}$$

$$\beta_r \lambda_n^j \frac{1}{(1+\theta^j)}\frac{1}{\rho}\sum_{i=1}^{M} \hat{X}_i^j \pi_{in}^j = s_n^{j\,1-\beta_r}$$

Then,

$$s_n^j = \left(\beta_r \lambda_n^j \frac{1}{(1+\theta^j)}\frac{1}{\rho - g_T}\sum_{i=1}^{M} \hat{X}_i^j \pi_{in}^j\right)^{\frac{1}{1-\beta_r}}$$

Noting that $\sum_{i=1}^{M} X_i^j \hat{\pi}_{in}^j$ is the value of production of sector j in country n which we can denote $\hat{Y}_n^j$, we can rewrite the optimal investment into R&D as

$$s_n^j = \left(\beta_r \lambda_n^j \frac{1}{(1+\theta^j)} 1\rho \hat{Y}_n^j\right)^{\frac{1}{1-\beta_r}}$$

Trade affects optimal investment into R&D at the sectoral level to the extent that it affects the reallocation of production into particular sectors. This result differs from previous papers in the literature that find that trade has no impact on R&D intensity. In our paper, R&D reallocates towards sectors in which the country has comparative advantage, through $\hat{Y}_n^j$.

Substituting into the growth rate of technologies of new technologies in equation (41)

$$g_T = \sum_{i=1}^{N}\sum_{k=1}^{J} \frac{\varepsilon_{ni}^{jk}}{g_T + \varepsilon_{ni}^{jk}} \lambda_i^k \frac{\hat{T}_i^k}{\hat{T}_n^j} \left(s_i^k\right)^{\beta_r}$$

$$1 = \sum_{i=1}^{N}\sum_{k=1}^{J} \frac{\varepsilon_{ni}^{jk}/g_T}{g_T + \varepsilon_{ni}^{jk}} \lambda_i^k \frac{\hat{T}_i^k}{\hat{T}_n^j} \left(\frac{1}{\rho - g_T}\beta_r \lambda_i^k \frac{1}{(1+\theta^k)}\sum_{n=1}^{M} \hat{X}_i^k \pi_{ni}^k\right)^{\frac{\beta_r}{1-\beta_r}}$$

$$g_T \hat{T}_n^j = \sum_{i=1}^{N}\sum_{k=1}^{J} \frac{\varepsilon_{ni}^{jk}}{g_T + \varepsilon_{ni}^{jk}} (\lambda_i^k)^{\frac{1}{1-\beta_r}} \hat{T}_i^k \left(\frac{1}{\rho - g_T}\beta_r \frac{1}{(1+\theta^k)}\sum_{n=1}^{M} \hat{X}_i^k \pi_{ni}^k\right)^{\frac{\beta_r}{1-\beta_r}}$$

The steady-state growth rate of the stock of knowledge depends positively on the speed of diffusion, the expected profits (note that it depends on trade costs through their effect on trade shares in the equation for profits) and negatively on the dispersion parameter. Following Eaton and Kortum 1999, the Frobenius theorem guarantees that there is a unique balanced growth path in which all countries and sectors grow at the same rate g_T. The expression for the growth rate can be expressed in matrix form as:

$$g_T T = \Delta(g_T) T$$

If the matrix $\Delta(g_T)$ is definite positive, then there exists a unique positive balanced growth rate of technology $g_T > 0$ given research intensities. Associated with that growth rate is a vector T (defined up to a scalar multiple), with every element positive, which reflects each country/sector relative level of knowledge along that balanced growth path.

5 Welfare Analysis: Gains from Trade

Welfare in our model is determined by the real wage. We can obtain an expression for the real wage in country i as

$$\frac{W_i}{P_i} \propto \prod_{j=1}^{M} \left(\frac{W_i}{P_i^j} \right)^{\alpha_i^j}$$

Using the first order condutions for prices and import shares, it can be shown that

$$\frac{W_i}{P_i^j} = \left(\frac{T_i^j}{\pi_{ii}^j} \right)^{1/\theta^j} \frac{W_i}{c_i^j} \propto \left(\frac{T_i^j}{\pi_{ii}^j} \right)^{1/\theta^j} \prod_{k=1}^{j} \left(\frac{W_i}{P_i^k} \right)^{\gamma_i^{jk}}$$

Therefore,

$$\frac{W_i}{P_i} \propto \prod_{j=1}^{M} \left(\left(\frac{T_i^j}{\pi_{ii}^j} \right)^{\alpha_i^j/\theta^j} \prod_{k=1}^{j} \left(\frac{W_i}{P_i^k} \right)^{\alpha_i^j \gamma_i^{jk}} \right) \tag{28}$$

Note that this formula resembles the standard welfare formula in Arkolakis, Costinot, and Rodríguez-Clare 2012. In a one sector version of our model, in which $j = 1$ and, γ_i^{jk}=0, $\alpha_i^j = 1$, equation 28 becomes

$$\frac{W_i}{P_i} \propto \left(\frac{T_i}{\pi_{ii}} \right)^{1/\theta} \tag{29}$$

This is the standard formula for welfare gains from trade that has been used in the literature and it depends on the aggregate productivity, the home trade shares and the trade elasticity.

Our formula for welfare in equation 28 is dynamic. Dynamics are driven by the evolution of the stock of ideas captures in T_i^j. In this sense, our formula is the multi-sector version of the one derived in Buera and Oberfield 2016.

It can be shown that welfare in each country n is a weighted average of the ACR formula in equation 29 for each sector, and the weights depend on the production parameters α_j^j, γ_n^j and γ_n^{jk}. More specifically,

$$\log\left(\frac{W_n}{P_n}\right) \propto \sum_{j=1}^{M} w_n^j \log\left(\frac{T_n^j}{\pi_{nn}^j}\right)^{1/\theta^j}$$

with w_j the weights. Taking growth rates of the previous expression

$$\Delta\log\left(\frac{W_n}{P_n}\right) \propto \sum_{j=1}^{M} w_n^j \left(\Delta T_n^j + \frac{1}{\theta^j}\Delta\pi_{nn}^j\right) \tag{30}$$

Equation 30 describes the main components of welfare in a particular country. A country's welfare change after a trade liberalization depends on what sectors benefit more from such liberalization and the comparative advantage of the country in those sectors. Sectors that experience a larger increase in their technology level T_n^j or a larger decrease in the home trade share π_{nn}^j will experience a larger increase in welfare. If the country has a comparative advantage in those sectors, the effect on welfare in that country will be large.

6 Quantitative Analysis

We perform our quantitative analysis in steady-state. In Appendix C we describe the calibration approach that we follow to recover all the parameters of interest.

6.1 Gravity Equation at the Sector Level

Here we run gravity equations at the sector level as in Eaton and Kortum 2002 to obtain an estimate of the average productivity T_i^j. We set $\theta = 4$ in this exercise. We have also run gravity equation at the sector level using $\theta = 8.28$ and a sector specific θ^j from Caliendo and Parro 2014. We find that the technology parameters estimated under different θ are highly correlated, as it has been documented in Levchenko and Zhang 2016.[6]

In particular, the calibration of technology parameters for $\theta = 4$ and $\theta = 8.28$ is 0.97, whereas the correlation of the technology parameter when θ is common and when we use the θ from Caliendo and Parro 2014 is 0.67. Figure IV plots the Kernel Density of the technology parameters under the three values of θ.

[6] We are now looking into retail price data from the ICP 2011 program from the United Nations to obtain a sector specific dispersion parameter that does not rely on tariff data. Our plan is to follow Simonovska

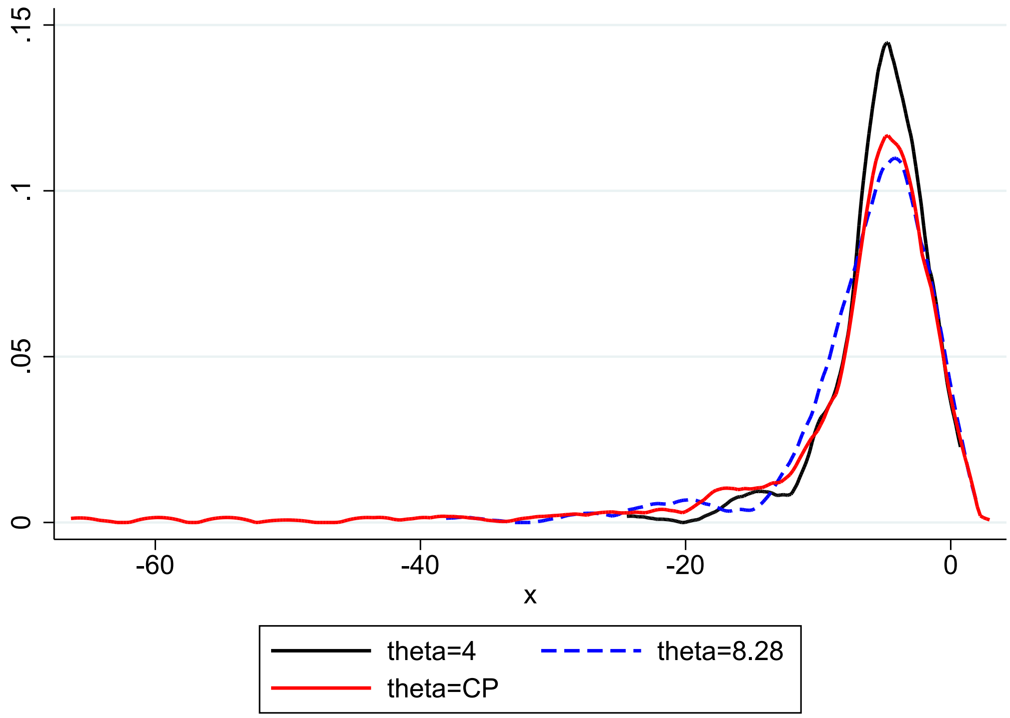


Figure IV: Technology at the Sectoral Level (different θ

For the purpose of this first calibration, we assume that θ is common across countries and set it equal to 4. Figure V shows, for a few sectors, that there is a positive relation between the R&D intensity across countries and the technology level. The strength of the correlation differs across sectors. Also, in our estimation, the US displays the largest technology level across all sectors and countries. Slovenia is the country with the lowest technological advantage.

6.2 The speed of diffusion

To measure the knowledge diffusion speed between using country-sector and used country-sector $\left\{\varepsilon_{ni}^{jk}\right\}$, we resort to the corresponding citation time lags in NBER Patent Citation Database. For a given cited patent, we picked the first citation from a certain citing country-sector, and use the citation lag of first citation as the indicator of knowledge diffusion time lag across countries and sectors. We then discard the repetitive citations because their citation lags overestimate the knowledge diffusion lag. For a citing country-sector (nj) and cited country-sector (ik) quadruplet, we calculate ε_{ni}^{jk} as the inverse of mean citation lag of all first citations during 1976 and 2006. Appendix B described the details.

and Waugh 2014 to obtain an estimate for θ^j.

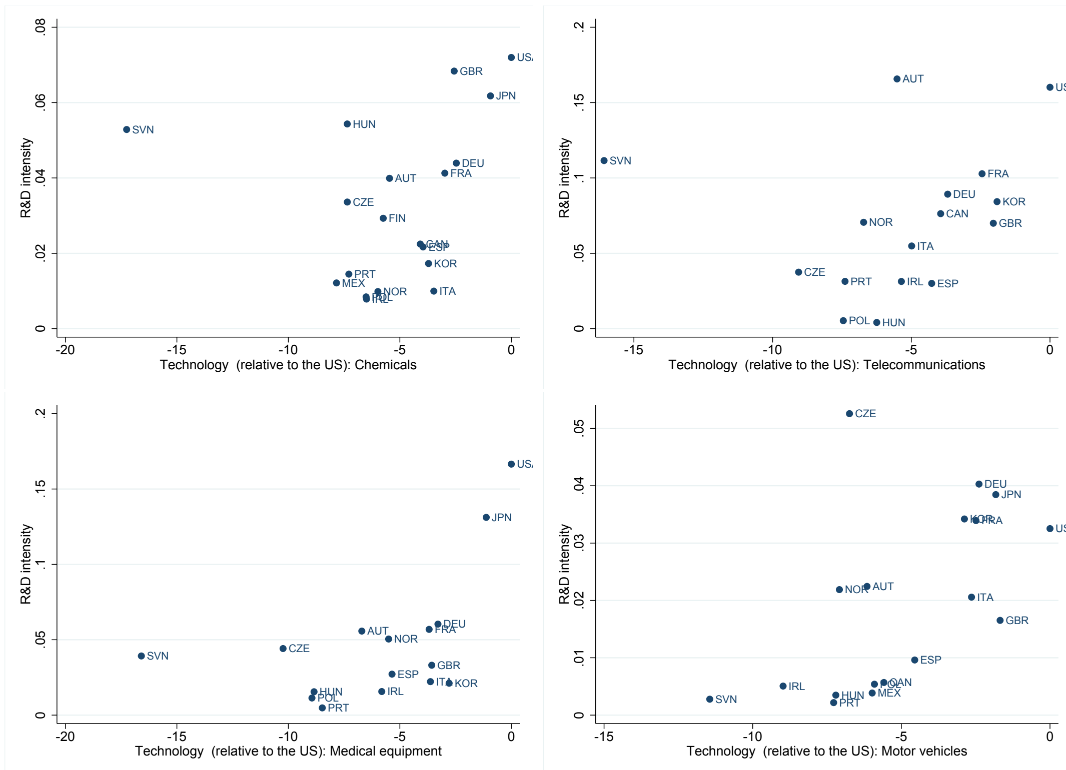


Figure V: Technology at the Sectoral Level

Figure VI shows the historgram of $log(\varepsilon_{nk}^{ij})$. The mean is around 0.35 and it is distributed normally between 0.15 and 0.7. The figure shows thatthere is variation of the mean diffusion lag across country-pairs and sector-pairs.

6.3 Steady-state results

We simulate the model in steady-state using the calibrated parameters on technology, trade barriers, production input-output linkages and the speed of diffusion. All the parameters up to the speed of technology diffusion allow us to obtain relative wages, costs and trade shares in steady-state. Once we have obtained these variables we can use the formula for the growth rate of the economy in steady-state. By assuming that all countries reach a growth rate of 2% in steady-state we can apply the Frobenius theorem and obtain a value for the parameter $\lambda_i^k = \lambda$ which we assume it is identical for each country and sector. The vale that we obtain is 0.0025. We then use the rest of the equations of the model to obtain a value of R&D intensity for each sector and country in our sample. The following figures report relative wages, R&D at the sector-country pair and R&D at the country level both from the data and the simulation of the model (together with the 45 degree line).

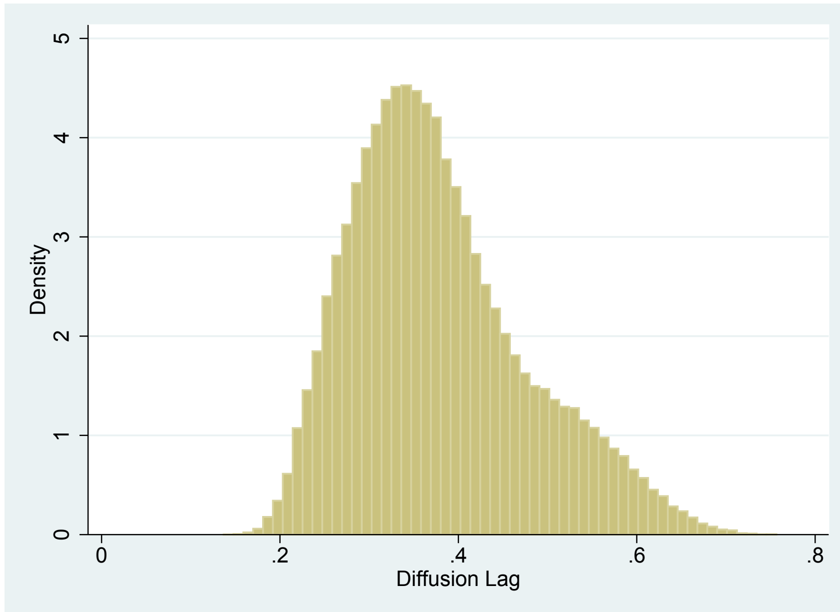


Figure VI: Mean Diffusion Lag

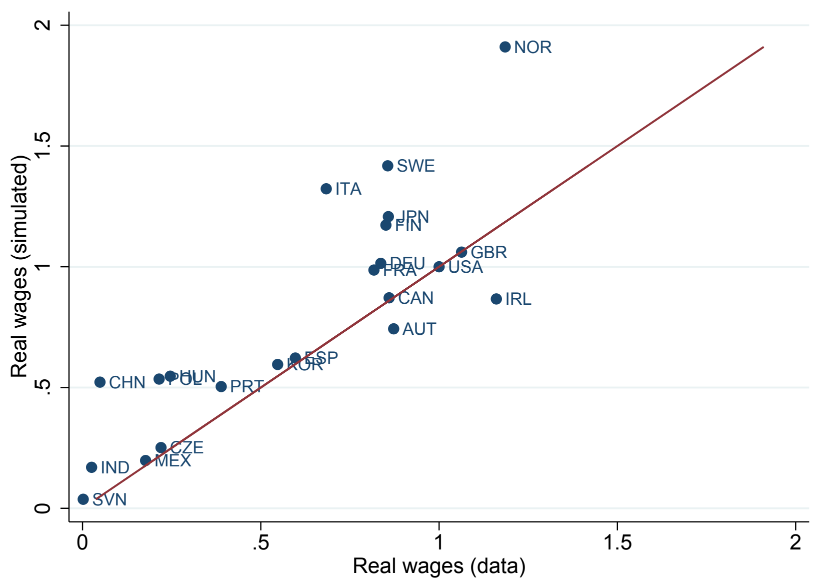


Figure VII: Real Wages

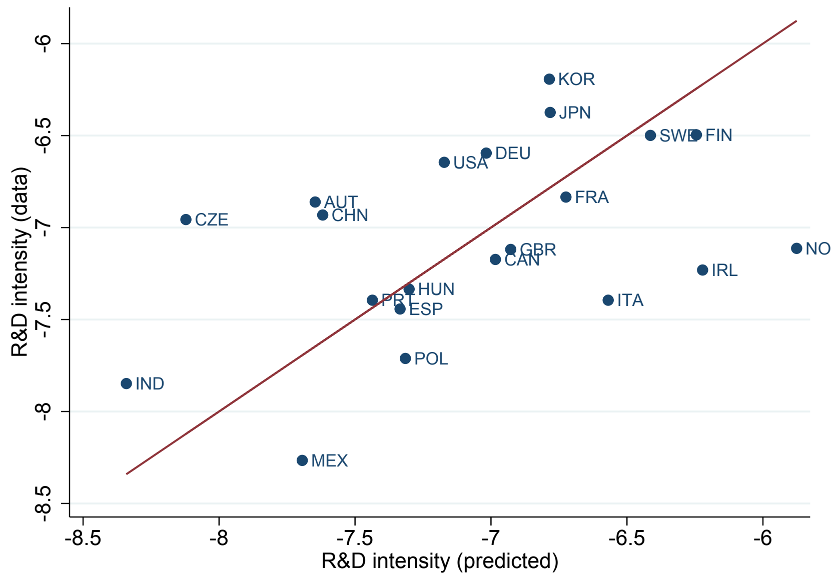


Figure VIII: R&D intensity

7 Counterfactual exercise

We consider a uniform reduction of trade barriers, for each country pair and sector, of 20%. We then report the effect of this policy experiment on aggregate R&D, sectoral R&D across countries and welfare.

7.1 R&D intensity

Contrary to the prediction of most models of international trade and innovation, trade has an effect in R&D intensity in our model, as figure XXX suggests. The effect is asymmetric across countries and sectors, and it depends both on the R&D intensity across sectors within the county, the input-output linkage structure, and the relative comparative advantage (RCA). Almost all countries invest more in their high RCA sectors, and to more extent in the far away countries with high total R&D over GDP ratios, such as Japan and Korea.

7.2 Welfare Analysis

8 Conclusion

Still baking ...

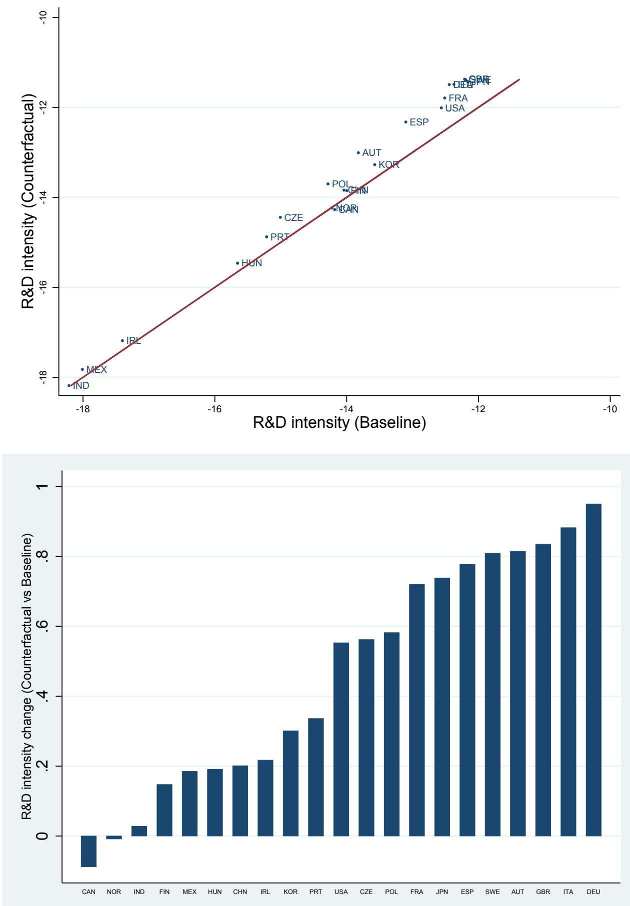
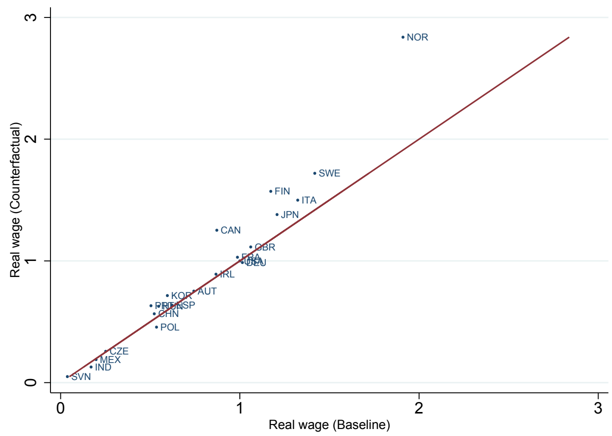


Figure IX: R&D intensity: Counterfactual vs Baseline



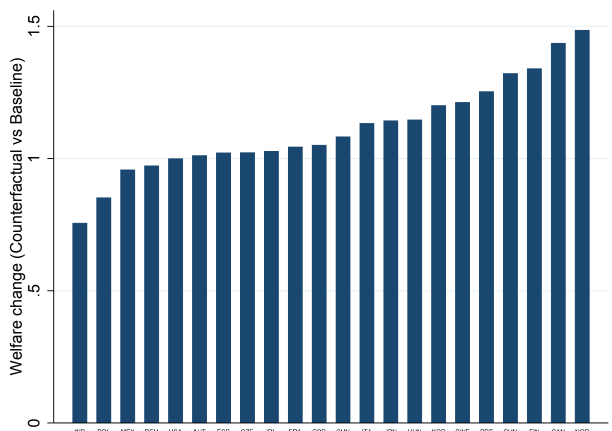


Figure X: Welfare Analysis

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Appendix

A Model Equations

There are 14 endogenous variables and we need 14 equations. The endogenous variables are

$$\{\pi_{in}^j, T_i^j, c_i^j, W_i, P_n^j, X_{ni}^j, X_n^j, P_n, Y_n, \Phi_n^j, C_n, s_n^j, V_n^j\}$$

The corresponding equations are:

(1) Probability of imports

$$\pi_{ni}^j = T_i^j \frac{\left(c_i^j d_{ni}^j\right)^{-\theta^j}}{\Phi_n^j}, \tag{31}$$

(2) Import shares

$$X_{ni}^j = \pi_{ni}^j X_n^j, \tag{32}$$

(3) Cost of production

$$c_n^j = \Upsilon_n^j W_{nt}^{\gamma_n^j} \prod_{k=1}^{J} (P_n^k)^{\gamma_n^{jk}}, \tag{33}$$

(4) Intermediate good prices in each sector

$$P_n^j = A^j \left(\Phi_n^j\right)^{-1/\theta^j}, \tag{34}$$

(5) Cost distribution

$$\Phi_n^j = \sum_{i=1}^{M} T_i^j \left(d_{ni}^j c_i^j\right)^{-\theta^j}, \tag{35}$$

(6) Price index

$$P_n = \prod_{j=1}^{J} \left(\frac{P_n^j}{\alpha_n^j}\right)^{\alpha_n^j}, \tag{36}$$

(7) Labor market clearing condition

$$W_n L_n = \sum_{i=1}^{J} \gamma_n^j \sum_{i=1}^{M} \pi_{in}^j X_i^j, \tag{37}$$

(8) Sector production

$$X_n^j = \sum_{k=1}^{J} \gamma_n^{kj} \sum_{i=1}^{M} X_i^k \pi_{in}^k + \alpha_n^j P_n Y_n, \tag{38}$$

(9) Final production

$$P_n Y_n = W_n L_n + \sum_{j=1}^{J} \sum_{i=1}^{M} \pi_{in}^j X_i^j, \tag{39}$$

(10) Resource constraint

$$Y_n = C_n + \sum_{k=1}^{J} s_n^k Y_n, \tag{40}$$

(11) Innovation

$$\dot{T}_{nt}^j = \sum_{i=1}^{N} \sum_{k=1}^{J} \varepsilon_{ni}^{jk} \int_{-\infty}^{t} e^{-\varepsilon_{ni}^{jk}(t-s)} \alpha_{is}^k \left(s_{is}^k\right)^{\beta^k} ds, \tag{41}$$

(12) R&D expenditures

$$\beta^j \alpha_{nt}^j V_{nt}^j \left(s_{nt}^j\right)^{\beta^j - 1} = P_{nt}, \tag{42}$$

(13) Value of an innovation

$$V_{nt}^j = \int_{t}^{\infty} \left(\frac{P_{nt}^j}{P_{ns}^j}\right) e^{-\rho(s-t)} \Pi_{ns}^j ds, \tag{43}$$

with

$$\Pi_{nt}^j = \frac{1}{(1+\theta^j) T_{nt}^j} \sum_{i=1}^{M} X_{it}^j \pi_{int}^j. \tag{44}$$

B Data

This appendix describes the data sources and construction for the paper. 30 countries are included in our analysis based on data availability: Australia, Austria, Belgium, Canada, China, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, India, Ireland, Italy, Japan, Korea, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovenia, Spain, Sweden, Switzerland, United Kingdom, and United States. When we use R&D data at the sector level, we need to drop China, Sweden, Switzerland, Denmark, and India. The model is calibrated for the year 2005. There are 20 tradable sectors and one aggregate nontradable sector under consideration, which correspond to those in Caliendo and Parro 2014 and are reported in Table **??**.

Bilateral trade flows at the sectoral level Bilateral trade data at sectoral level Data for expenditure by country n of sector j goods imported from country i (X_{ni}^{j}) are obtained from the OECD STAN Bilateral Trade Dataset. Values are reported in thousand U.S. dollars at current prices. Sectors are recorded at the ISIC (rev. 3) 2-3 digit level and were mapped into 2-digit tradable 20 sectors as listed in Table **??**. We use the importer reported exports in each sector as the bilateral trade flows as it is generally considered to be more accurate than the exporter reported exports.

Value added and gross production Domestic sales in sector j, X_{nn}^{j} is calculated as $X_{nn}^{j} = Y_{n}^{j} - \sum_{i \neq n}^{N} X_{in}^{j}$, where both gross production of country n in sector j, Y_{n}^{j} and the total exports from n to i in sector j, $\sum_{i \neq n}^{N} X_{in}^{j}$, are obtained from from OECD STAN Database for Structural Analysis. The database contains data at ISIC 2-digit level that can be easily mapped into our 21 sectors, at current prices and in national currencies. We use the exchange rates provided by OECD to convert the values into U.S. dollar. However, data are missing for China and India, for which we use the INDSTAT (2016 version) provided by United Nations Industrial Development Organization (UNIDO). This database is available for 4-digit ISIC (rev. 3) sectors and we aggregate them into 2-digit ISIC sectors to be consistent with the rest of the countries.

Trade barriers and gravity equation variables Data for variables related to trade costs and used in gravity equations at the country-pair level are obtained from CEPII database at www.cepii.fr/CEPII/en/bdd_modele/bdd.asp.

Wages Average annual wages is reported by OECD Labour statistics at current price in local currency. They are translated into U.S. dolars at the 2005 exchange rates to obtain the variable w_n in the model. However, wage data for China, India, and New Zealand are missing in this database, and are obtained from International Labor Organization (ILO).

R&D data R&D expenditures at the country-sector level are obtained from the database of OECD STAN by ISIC Revision 3 industries. Sectoral R&D data for all sectors in China, India and Sweden and a few sectors in other countries are missing, and we estimate the fitted value using the following approach. First, we run a regression using existing country-sector specific R&D and patent data from USPTO:

$$\log(R_{ij}) = \beta \log\left(PS_{ij}\right) + \mu_i + \gamma_j, \tag{45}$$

where R_{ij} is the R&D expenditure of country i in sector j and PS_{ij} is the patent stock of country i in sector j of year 2005. μ_i and γ_j are country and sector fixed effects. This relation is built on the observations that (a) at steady state, R&D expenditure should be a constant ratio of R&D stock, and (b) innovation input (R&D) is significantly positively related to innovation output (patent). Assuming that (45) also holds for China, India and Sweden, we can obtain the fitted value of their sectoral level R&D expenditure.

$$\log(\widehat{R}_{ij}) = \widehat{\beta} \log\left(P_{ij}\right) + \widehat{\mu}_i + \widehat{\gamma}_j$$

For these three countries, we have information on all the right-hand-side variables except for the country fixed effect, $\widehat{\mu}_i$. This allows us to compute the *share* of R&D in a given sector for each country,

$$\widehat{s}_{ij} = \frac{\widehat{R}_{ij}}{\sum_k \widehat{R}_{ik}} = \frac{PS_{ij}^{\widehat{\beta}} \exp(\widehat{\mu}_i) \exp(\widehat{\gamma}_j)}{\sum_j PS_{ij}^{\widehat{\beta}} \exp(\widehat{\mu}_i) \exp(\widehat{\gamma}_j)} = \frac{PS_{ij}^{\widehat{\beta}} \exp(\widehat{\gamma}_j)}{\sum_j PS_{ij}^{\widehat{\beta}} \exp(\widehat{\gamma}_j)}.$$

We then obtain the aggregate R&D expenditure as percentage of GDP, s_i^{WB}, for country i from the World Bank World Development Indicator Database. The country-sector specific R&D can then be estimated as $\tilde{s}_{ij} = \widehat{s}_{ij} s_i^{WB}$. For the countries with only one or two sectors missing, we estimate the fitted value using the same procedure. To maintain consistency across countries, we correct the OECD data generated total R&D with the World Bank total R&D.

$$\tilde{s}_{ij} = s_i^{WB} * R_{ij}^{OECD} / \sum_k R_{ik}^{OECD}$$

Finally, $\tilde{s}_{ij}$ is the R&D intensity parameters in Equations (15) and (12) that we use in the calibration and counterfactual simulation for country i and sector j.

Patent Citations We use the citation time lags from the U.S. NBER Patent Citation Database to proxy the knowledge diffusion speed from the source country-sector to the application country-sector ε_{ni}^{jk}. For any given cited patent, we picked the first citation from a citing country-sector, and use the citation lag of first citation as the indicator of knowledge diffusion lag across countries and sectors. The repetitive citations are discarded because their citation lags overestimate the knowledge diffusion lag. For a citing country-sector (nj) and cited country-sector (ik) pair, we calculate ε_{ni}^{jk} as the inverse of the average citation lag of all first citations between 1976 and 2006.

However, there are many zeros in the observed citation flows (about 50%of the nj-ik cells) between citing country-sector (nj) and cited country-sector (ik), because not all countries and all sectors apply patents in the U.S. and cite each other. 75% of these zero citation flows happened when either country-sector nj or ik never applied for patents in the U.S. The other 25% appeared when patents do exist in these two country-sector but there are not cross citation between them. For such zero nj-ik cells, no direct measure of knowledge diffusion speed is observed. Moreover, for those nj-ik cells with nonzero citation flows, the observed citation lags can be still biased by their endogenous selection of citing each other at all.

To handle the selection bias, we adopt two-stage Heckman selection approach to estimate $log(\varepsilon_{ni}^{jk})$, correcting for the hazard that nj and ik not only both applied patents in US but also cite each other. The first stage and second stage results are reported in Table A1, robust standard errors are reported and observations are clustered at citing country-sector level. In the first stage, we control for the country pair level relations between citing country n and cited country i: log-scale population weighted distance, common language, common border, being in the same free trade agreement and customs union, and historical colonial relationships; log-scale total patent stocks of citing country-sector ($\log(tps_{nj})$) and cited country-sector ($\log(tps_{ik})$); similarity between citing country i and cited country n's patent stock distribution across sectors; and dummies variables of citing country, cited country, citing sector and cited sector. The country and sector dummies capture the country and sector specific factors, such as geographic and culture distance to US and the length of technology cycle[7], which affect the citation lags in US patent database. The geographic and cultural barriers all have correct and significant signs; larger mass of patent stocks on both ends increase the likelihood of positive citation flow, just like bilateral income in gravity equation; countries with similarity in patent allocation across sectors have approximate industry structure and development stage, hence tend to cite each other.

In the second stage, we drop the colonial relationships from the first stage. Only distance and common border have significant and expected signs. Costumes union has a significant

[7]See Bilir (2014)

wrong sign, but it disappears when varying the set of countries. Therefore, this result supports our assumption that the speed of knowledge diffusion is exogenous, since it depends only on geographic variables.

We calculate the expected $log(\hat{\varepsilon}_{ni}^{jk})$ conditional on being observed, using the post-estimation of heckman selection model. Finally, to avoid 4-dimensional matrix manipulation, we further decompose $log(\hat{\varepsilon}_{ni}^{jk})$ into 2-dimensional fixed effects of FE_n^j, FE_i^k and FE^{jk}, which are good enough to obtain a R^2 of 0.99. In the simulation, we leave out the country-sector fixed effects, FE_n^j, FE_i^k, which capture the country specific relation to US and sector specific length of technology cycle and are unrelated to knowledge diffusion speed across country and sector. Finally, we use $log(\tilde{\varepsilon}_{ni}^{jk}) = distw^{-0.031} exp(FE^{jk})$ in the calibration.

C Calibration

In this section, we describe the procedure that we follow to calibrate all the relevant parameters of our model.

- θ^j: For the dispersion parameter, we try three different values: Following Levchenko and Zhang 2016, we use $\theta = 4$, $\theta = 8.28$ and θ taken from Table A.1 in Caliendo and Parro 2014. The technology parameters estimated under different θ are highly correlated, as in Levchenko and Zhang 2016.

- σ^j: The elasticity of substitution parameter is taken from Broda and Weinstein (2006) for the United States (this parameter is sector specific but not country-specific. We matched SITC rev 3 into ISIC rev 3 and take the mean σ^i of SITC sectors that belong to the same ISIC sector. Data is based on their estimates for period 1990-2001. We do not need this parameter for any of our results.

- γ_n^j and γ_n^{jk} from the I/O tables. Given our production function, the labor share =value added share (as we don't have capital). So γ_n^j is calculated as value added/gross output V_n^j/Y_n^j for each country-sector, γ_n^{jk} is input value of sector k (row sectors) to the gross output of sector j (column sectors) for country n or the share of intermediate consumption of sector j in sector k over the total intermediate consumption of sector k times $1 - \gamma_n^j$.

- β^j is the elasticity of innovation and we can assume that is the same across countries and sectors.

The remaining parameters that we need to calibrate are d_{in}^j, and T_n^j, and the growth rate of the economy.

1. We use bilateral trade gravity equation to estimate the country-sector specific competitiveness and productivity. We follow as close as possible to Caliendo and Parro (2014) with the same set of countries and sectors. In the production side, sectors are connected by Input-output linkages and trade flows, but service is non-tradable. For robustness, we try two methods to estimate country-sector specific productivity level and distance parameters.

- – Method 1

First, we run sector specific gravity equations with constraints on the importer n and export i fixed effects ($\sum_i S_i^j = 1$ and $\sum_n S_n^j = 1$), to obtain importer-exporter-sector speficit distance $D_{ni}^j = \sum_k \rho_k^j \log(D_k)$ and country-sector fixed effects $\{S_i^j\}$ and $\{S_n^j\}$.

$$log\left(\frac{X_{nit}^j}{X_{nnt}^j}\right) = S_i^j - S_n^j - D_{ni}^j \tag{46}$$

$$= S_i^j - S_n^j - \sum_{k=1}^{10} \rho_k^j D_k \tag{47}$$

where D_1 to D_6 are distance dummy variables equal to one if the population weighted distance countries n and i is between 0 and 375 kilometers, 375 and 750 kilometers, 750 and 1500 kilometers, 1500 and 3000 kilometers, 3000 and 6000 kilometers, and above 6000 kilometers; D_7 to D_{10} are dummy variables indicating if countries n and i share common language, common border, belong to the same free trade agreement and costumes union. When $X_{nit}^j = 0$, we enter $log\left(\frac{X_{nit}^j}{X_{nnt}^j}\right)$ as $log\left(\frac{X_{nit}^j*1000+1}{X_{nnt}^j*1000}\right)$.

ρ_k^j is the sensitivity of sector j's trade flow to the k^{th} trade barrier. By allowing sector specific sensitivities, trade libralization in the counterfactual simulation will cause production sturctual change effect, pushing low distance sensitive sectors to remote countries and nontradable service sectors to central countries.

Second, armed with the S_i^j, S_n^j and D_{ni}^j from gravity equations, we then combine Equation (33) to (35) to obtain the country-sector specifc cost c_i^j and productivity T_i^j for three different sets of $\{\theta^j\}$: (I) $\theta = 4$ for all non-service sectors, (ii) $\theta = 8.28$ for all non-service sectors, and (iii) $\{\theta^j\}$ from Caliendo and Parro (2014).

- – Method 2

We compute the D_{ni}^j using the sector specific version of Equation (12) in Eaton and Kortum (2002) and P_i^j on the right hand side of the equation from World Bank International

Consumer Price dataset for 24 countries, using different sets of $\{\theta^j\}$ as in Method 1. Then we calculate c_i^j using (33), and substiute c_i^j into (11) to derive T_i^j, also under different sets of $\{\theta^j\}$.

[Jie: I don't know how to deal with the rest of the calibration, Ana Maria can you finish this part?]

1. Once we have a value for the fixed effects at the exporter level F_n^k we can plug them into equation (5) to obtain Φ_n^j which is a measure of technology progress in a county.

2. Then, we can use (1) to obtain π_{in}^j

3. Then we can use equation (4) and obtain P_n^j.

4. We then plug this into equation (6) to obtain P_n.

5. We now follow Caliendo and Parro and guess a vector of wages and use (7), (8) and (9) to obtain wages, expenditure X_n^j and Y_n^j. We guess vector of wages and update using the labor market clearing condition.

6. Then we can obtain the profits and the value of an innovation using (13)

7. Then use (12) to obtain s_n^j

8. Then, use equation (11) to obtain g and T_n^j using the Frobenious theorem

Table I: Estimation mean diffusion lag

$\log(\varepsilon_{ni}^{jk})$	Heckman	Selection	OLS
$\log(distance_{ni})$	-0.084***	-0.378***	-0.082***
	(0.01)	(0.055)	(0.01)
$Common\_border_{ni}$	-0.035	-0.153	-0.034
	(0.024)	(0.123)	(0.025)
$Common\_language_{ni}$	-0.021	0.065	-0.021
	(0.016)	(0.073)	(0.017)
FTA_{ni}	-0.024	-0.039	-0.024
	(0.029)	(0.082)	(0.029)
CU_{ni}	-0.068**	-0.067	-0.069***
	(0.025)	(0.124)	(0.025)
$Similarity_{ni}$	0.109	0.628***	0.108
	(0.073)	(0.169)	(0.073)
$\log(PS_n^j)$	0.000	0.034***	0.000
	(0.003)	(0.009)	(0.003)
$\log(PS_i^k)$	0.000	0.035***	0.000
	(0.002)	(0.005)	(0.002)
Colony		0.082	
		(0.083)	
Common colony		-0.092	
		(0.100)	
Colony after 1945		-0.027	
		(0.117)	
Same country in history		-0.236	
		(0.160)	
Citing industry dummies	Yes	Yes	Yes
Citing country dummies	Yes	Yes	Yes
Cited industry dummies	Yes	Yes	Yes
Cited country dummies	Yes	Yes	Yes
Number of Observations	415,421	415,421	240,372
Wald chi2	55713.63		
R^2	0.202		

Table II: Industries sample

Sector	ISIC	Industry Description
1	C01T05	Agriculture, Hunting, Forestry and Fishing
2	C10T14	Mining and Quarrying
3	C15T16	Food products, beverages and tobacco
4	C17T19	Textiles, textile products, leather and footwear
5	C20	Wood and products of wood and cork
6	C21T22	Pulp, paper, paper products, printing and publishing
7	C23	Coke, refined petroleum products and nuclear fuel
8	C24	Chemicals and chemical products
9	C25	Rubber and plastics products
10	C26	Other non-metallic mineral products
11	C27	Basic metals
12	C28	Fabricated metal products, except machinery and equipment
13	C29	Machinery and equipment, nec
14	C30	Office, accounting and computing machinery
15	C31	Electrical machinery and apparatus, nec
16	C32	Radio, television and communication equipment
17	C33	Medical, precision and optical instruments
18	C34	Motor vehicles, trailers and semi-trailers
19	C35	Other transport equipment
20	C36T37	Manufacturing n.e.c. and recycling
21	C65T67	service
21	C50T52	service
21	C70T74	service
21	C45	service
21	C75T99	service
21	C60T64	service
21	C55	service
21	C40T41	service