From Ideas to Trade

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Abstract

This paper studies the role of technology in international trade. Using patent data to capture technological know-how, we show that countries differ technologically in two dimensions: the stock of technology, and its allocation across the economy. The literature has taken into account the role of the former, but neglected the latter. We build on the seminal work of Eaton and Kortum (2002) and develop a Ricardian model that incorporates the allocation of technology as a determinant of bilateral trade. Our model predicts that, as in the previous literature, the exporter's stock of technology has a positive impact on exports while the relative input costs have a negative one. In addition, our model predicts that the covariance between the allocation of technology and relative input costs affects trade. In particular, a more even distribution of technology benefits countries with lower input costs (since their exports are determined by these and not technological differences) and viceversa. To test our model we create a novel dataset of international historical patents and use these to construct our technology variables. Our empirical results confirm the model's predictions and indicate that technological innovation matters for trade through both the stock of patents and their allocation across the economy.

Keywords: Ricardian model, Comparative advantage, Technology, Patents

JEL Classification: F10, F11, O31

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1 Introduction

The role of technology as a key driver of bilateral trade has been a central topic ever since David Ricardo's 1817 model. According to traditional Ricardian theory countries differ technologically in two dimensions: the amount of technology that they have (*stock*), usually associated to the notion of absolute advantage, and how they distribute that technology across their sectors (*allocation*). These country differences in the allocation of technological capabilities define the principle of comparative advantage that will determine who exports which good. Countries benefit by specializing in those goods in which they are relatively better at, and exchanging them for the other goods. Eaton and Kortum (2002), henceforth EK, develops a general equilibrium model that extends the two-countries/two-goods Ricardian framework to many countries and many goods, capturing how the opposing forces of technology and geographic barriers affect bilateral trade. EK's seminal contribution, as well as the posterior Ricardian literature[1], while capturing the role of the stock of technology on exports, assumes that the allocation of technology across sectors is equal (dispersion-wise) for every country.[2]

In this paper we show that the dispersion of technological capabilities indeed varies substantially across countries, and that this variation plays an important role in bilateral trade. Figure 1 showcases our main argument by providing evidence, using patents as a proxies for technological know-how, that countries differ both in the stock and allocation of technology and how these are related to exports. The left panel plots the stock of technology, measured by the count of patents, against exports (as a share of the world's) for many countries and years. Each dot represents a country-year, from a pool of 84 countries over the period 1985-2000. The positive association between the stock of technology and trade is not surprising at all and is embedded in most models of trade an innovation[3]. The right

[1] With the notable exception of Costinot, Donaldson, and Komunjer (2012).

[2] Technology can be more or less evenly distributed across industries, but it is the same for all countries.

[3] Models that explain the role of technology in trade, like EK, predict that countries with a higher stock of technology will export more. In addition, studies about the role of international trade in innovation, show that both higher exports (through larger markets, see Lileeva and Trefler (2010) and Bustos (2011))

panel of Figure 1, shows the relationship between the allocation of technology and exports, and reveals two new stylized facts in the trade literature that served to motivate our work. First, that the allocation of patenting activity varies dispersion-wise across countries and years. At any point in time, some countries exhibit a very even distribution of technological know-how across their sectors while others show the opposite (all know-how concentrated in a few industries). Second, that the allocation of patenting activity is highly correlated with bilateral trade. In particular, using the familiar Gini coefficient to measure dispersion of patenting activity across sectors in the economy, we show that countries with a more uneven allocation of know-how (high Gini) also export less. Even though these graphs provide simple correlations and we have not yet controlled for other determinants of innovation and trade, they seem to suggest that cross-country both differences in the stock and the allocation of technological know-how (not accounted for in EK's multi-good and multi-country Ricardian model) might matter for exports.

The aim of this paper is to study how cross-country differences in technology affect bilateral trade. In particular, as suggested by Figure 1, do both the stock and the allocation of technology have an effect on exports? In what ways? To answer these questions, several challenges need to be overcome. The main one is to reconcile the theory with the empirics. Most empirical studies of the effect of innovation on bilateral exports are either specific to a country (and/or sector) or exhibit no clear theoretical grounds. While it has been shown that the gravity equation can be derived from various models, these are rarely used to guide the analysis. A second challenge is finding a theoretical model that is able to explain the empirical regularities observed but at the same time is simple enough to be tested. To date the theory has failed to predict trade in a world where both the stock and

and imports (through increased competition, see Bloom, Draca, and Van Reenen (2015) and Steinwender (2015)) lead to higher innovation. Therefore, both channels predict a positive correlation between the stock of technology and trade.

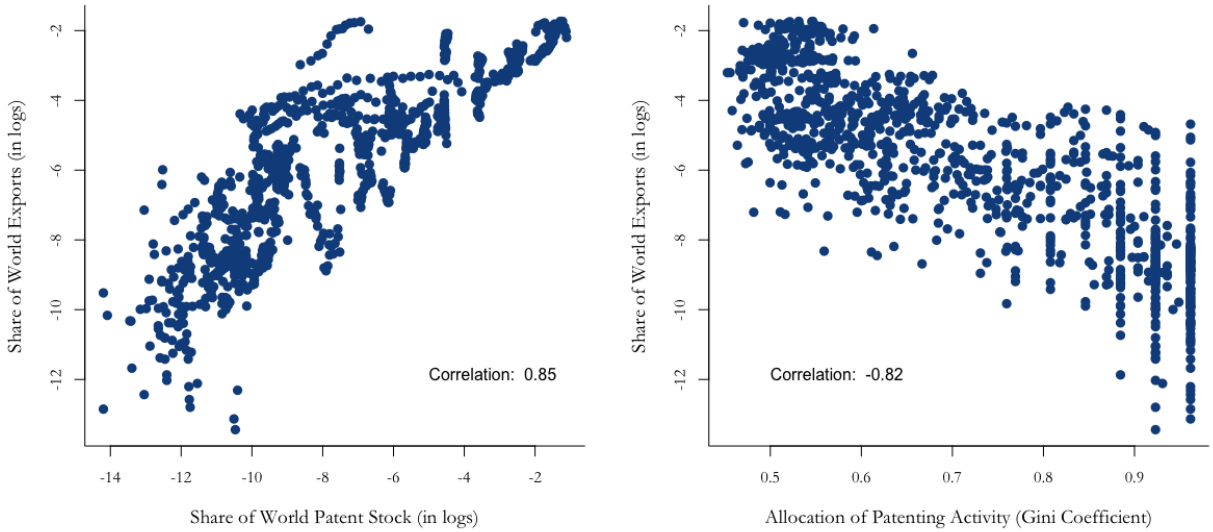


Figure 1: Trade and Patents.

the allocation of technology vary from one country to another[4]. Finally, most studies that use theoretical models lack data on technology to test their predictions. For instance, in EK and many subsequent papers that use their Ricardian model, the effect of technology on trade is trapped inside a country fixed effect dummy rather than estimated in isolation to other effects. In other studies, technological levels are derived as a residual of the model so it cannot be properly tested. Therefore, in order to test the theory, we need measures of technology that are independent of the model and allow us to test its predictions.

We build on Eaton and Kortum (2002) and develop a Ricardian model where the process of innovation determines both the stock *and* allocation of technology in each country. Specifically, bilateral exports depend on the stock of technology, the relative input costs, and the allocation of technology. The first two have a direct effect on trade, while the latter combines with input costs to form comparative advantage (determined by the covariance between relative input costs and the allocation of technological capabilities). Like in the

[4]An exception to this is Costinot, Donaldson, and Komunjer (2012). Note that Eaton and Kortum (2002) do have a technological dispersion parameter in their model, but it is assumed to be the same for all countries. Thus, the only technological difference between them arises from the overall stock of ideas.

EK model, our model predicts that a higher stock of technology and lower relative input costs foster exports. Unlike in the EK model, differences in the allocation of technology play an important role through their effect on comparative advantage. Our model predicts that countries with higher relative input costs benefit by a more uneven allocation of know-how across sectors. The rationale behind it is that countries that don't have a cost advantage need a technological advantage to sell. The opposite is true for low relative input cost countries, since comparative advantage will be determined mainly by these (and not technology). In addition, an interesting feature of our framework is that when we impose a common allocation of technology across countries the model simplifies to the EK model. This allows for a direct comparison and assessment of the gains of our more general framework. We derive a gravity equation and study how changes in a country's costs and technology affect trade flows.

On the empirical side, the main difficulty lies in finding measures of the key technological variables (stock and allocation) needed to test the predictions of our model. These should accurately reflect technological capabilities, be independent of exports, and consistent with the theory. There are a few measures of revealed comparative advantage in the literature that try to capture Ricardian technology[5]. These, however, lack theoretical foundations and cannot truly represent the drivers of exports (in a Ricardian spirit) since they are unable to separate causes of exports from consequences.[6] In order to test effects of technological innovation on bilateral exports we create a novel dataset of historical patents (the longest to date) and use these to construct measures of the stock and allocative dispersion of technology by country and year. Specifically, we take patent grants at the United States Patent and Trademark Office (USPTO) from 1836 to 2000 and add geographic location (country of origin) based on the inventor's residence.[7] We use patent counts by country and year as our

[5]The most famous one is Balassa's 1989 Index of revealed comparative advantage

[6]An exception to this is provided by Costinot, Donaldson, and Komunjer (2012) and Leromain and Orefice (2014), who develop measures of comparative advantage isolating exporter-specific characteristics that might drive trade flows.

[7]For patents previous to 1975 we went through the digitalised patents available in Google via Reed Tech and collected all the necessary information. The procedure we followed is described in detail under the Data

measure for the stock of knowledge for every country and year. To measure dispersion in the allocation of technology we estimate the dispersion parameter of the Eaton and Kortum (2010) idea-generating model that serves as the microfoundation for EK. Our estimated dispersion parameters are in the range of EK and other previous estimates in the literature, like Costinot, Donaldson, and Komunjer (2012) and Simonovska and Waugh (2011).

Since our measures of technological innovation are consistent with the theory, we can use them to test our theoretical predictions. We use data on bilateral exports, patents, input costs, income, expenditures, and the usual bilateral pair characteristics for 84 developed and developing countries in the period 1983-2000 to test our model. Our empirical results support our model's theoretical predictions. Technological innovation matters for trade through both the stock of patents and their allocation across industries. In line with traditional Ricardian literature, a higher technological stock fosters exports while higher (relative) input costs dampen them. In addition, we confirm our model's predictions that the covariance between input costs and dispersion in the allocation of technology explains part of the variation in bilateral exports. This implies that previous literature was neglecting an important determinant of comparative advantage (and therefore exports): the allocation of technological capabilities. In particular, a more uneven allocation of technology across sectors benefits countries with higher relative input costs. Our results also suggest interesting policy implications as they contradict the popular idea that diversification is a dominant strategy. To our knowledge, this is one of the few papers in the literature that provides a complete test of a Ricardian model [8].

This paper contributes to an extensive literature concerned with the role of technological advance on international trade that goes back to David Ricardo's famous 1817 model. Recent extensions of the classical theory include EK's general equilibrium multi-country setting, and the multi-sector extensions of Caliendo and Parro (2014), Chor (2010), Costinot, Donaldson, and Komunjer (2012), and Shikher (2011). The latter develops a model that introduces factor endowments and leads to a HO-Ricardian hybrid. Our paper departs from

section.

[8] Costinot, Donaldson, and Komunjer (2012) also test the Ricardian model)

this literature in three main respects. First, to construct our technology measures we use data on patents which reflect (technological) productivity better than other indicators like wholesale prices[9]. Second, rather than estimating the dispersion in the allocation of technology as a parameter (like in EK), we test its effect on bilateral trade. Finally, since our model was constructed to embed the benchmark EK model, these can be easily compared and the gains from adding technological allocation can be easily assessed. This paper is also related to empirical studies concerned with both testing the Ricardian model and constructing comparative advantage measures. Examples of the these include Kerr (2013), Simonovska and Waugh (2011), Levchenko and Zhang (2016), Leromain and Orefice (2014), and Bolatto (2013). Our technological allocation measures differ to those in the literature in that they are derived from the theory that microfounds our Ricardian model.

The rest of the paper is organised as follows. Section 2 develops our theoretical framework. Section 3 describes our data sources, the construction of our variables, and discusses our empirical specification. We derive a gravity equation from our theoretical model and we use it as the estimating equation. Section 4 tests our model using panel data. Our empirical results confirm our theoretical predictions, suggesting that both the stock and the allocation of knowledge play a fundamental role in bilateral trade. Several robustness tests are performed to assess our results. Finally, Section 5 concludes and suggests implications for policy.

2 Theoretical Framework

We develop a simple Ricardian model of innovation and trade that builds on Eaton and Kortum (2002) and incorporates all country technological heterogeneities. Like previous studies, the model accounts for differences in the technological stock across countries. Unlike previous studies, it also accounts for differences in how countries allocate their technological stock across industries.

[9]Some studies have used R&D data to measure patent stock, but not dispersion.

2.1 Model Setup

The world economy consists of N countries indexed by $i = 1, ..., N$ and a continuum of goods indexed by $j \in [0, 1]$. Under constant returns to scale, the cost of producing one unit of good j is $c_i/z_i(j)$, where z_i denotes the number of units of the good produced by one unit of inputs (efficiency), and c_i is the input cost in country i. Geographic barriers are introduced by means of an iceberg cost $d_{ni} > 1$, the cost of delivering one unit from i to n. Perfect competition makes the price that country i charges in country n for one unit of good j equal to the cost of delivering one unit in n.

$$p_{ni}(j) = \left(\frac{c_i}{z_i(j)}\right) d_{ni}$$

The actual price that buyers in country n will pay for good j is the lowest across all sources: $p_{nj} = \min_i\{p_{ni}(j)\}$. Country i's efficiency in producing good j is the realization of a random variable z_i (drawn independently for each j) from its country-specific Frechet probability distribution $F_i(z) = e^{-Tz^{-\theta}}$. Buyers in country n buy from the cheapest source, so the probability that country i provides a good at the lowest price in country n is:

$$\begin{aligned}
\pi_{ni} &= Pr(P_{ni}(j) \leq min_{k\neq i} P_{nk}(j)) \\
&= Pr\left(\frac{c_i d_{ni}}{Z_i} \leq \min_{k\neq i} \frac{c_i d_{nk}}{Z_k}\right) \\
&= \Pi_{k\neq i}^{N} E\left(Pr\left(Z_k \leq z_i \frac{c_k d_{nk}}{c_i d_{ni}} \middle| z_i\right)\right) \qquad (1)
\end{aligned}$$

2.2 Technology

The distribution of efficiencies provides the key to understanding the role of technology in trade. In particular, the Frechet distribution is governed by two parameters, T and θ, that depict two aspects of the countries' technological capabilities: the stock and the allocation.

2.2.1 Stock of technology: T

T represents the overall stock of technology, or the amount of knowledge present in a country[10]. A higher T increases the likelihood that goods produced by country i are more efficient (require less labor per unit). Statistically, T governs the location of the distribution. Figure 2 shows that increases in T will shift the Frechet distribution to the right, making higher efficiency productivity draws for all goods more likely.

2.2.2 Allocation of technology: θ

The parameter θ represents dispersion in the allocation of technology, or in simpler terms, how evenly or unevenly technology is distributed across industries[11]. It measures dispersion in the labor requirement (efficiency) across goods. As shown in Figure 3, θ determines the shape of the distribution. A high θ means that all of the input requirements (or efficiencies) drawn from the conuntry-specific Frechet distribution are close to the mean: the country is similarly productive in all of its sectors.[12] In other words, a high θ means that technology is evenly distributed across sectors, while a low θ implies the opposite (a high variance in technological know-hows across industries).

In this model a country will sell a good only if it is the lowest cost supplier. The position of the Frechet curve for each country, determined by the country's T and θ, will determine the efficiency draws and thus the export probability. The more "to the right" the Frechet curve is, relative to the Frechets of the rest of the world, the more productive the country will be in all the goods it produces and the more likely it will be export these. Therefore, shifts in the T and/or θ parameters can serve to increase a country's exports. But what does it mean, in practice, for a country to change T or θ? Although in this model these are assumed to arrive to countries exogenously, in reality countries have the ability to choose how they allocate their knowledge. As time goes by countries accumulate more technology,

[10] In EK, T is the absolute advantage parameter.

[11] In EK, θ represents the *force* of comparative advantage.

[12] So it is neither exceptionally bad nor exceptionally good in anything.

i.e. by means of R&D, therefore raising T.[13] What happens with θ depends on how this new technology is allocated across the different industries. If it goes to industries that were already technology abundant relative to the rest, then θ will decrease and the difference in efficiencies across industries will become even more pronounced. A low θ thus refers to a very uneven allocation of technology across sectors. On the contrary, allocating the newer technology towards industries with technological scarcity will bring all efficiencies closer. But helping the most inefficient sectors, which will raise θ, comes at the expense of punishing the most productive ones.

Eaton and Kortum (2002) assume the distribution of country i's efficiency Z_i is $F_i(z) = e^{-T_i z^{-\theta}}$. Since θ is fixed, countries only differ in their stock of technology T (absolute advantage) and the world can be perfectly described by Figure 2. Countries draw their efficiencies from similar distributions (in shape), and so their differences arise from some distributions being shifted to the right due to a larger stock of technology. The theoretical contribution of our paper is to allow countries to differ in how they distribute their technology across their industries. By introducing a country-specific allocation parameter θ_i, the world will looks like Figure 4. The probability of exporting will depends on *both* country-specific stock and the allocation of technology, so it is not so obvious what countries ought to do to "move to the right" and become more productive than the rest of the world.

2.3 A small model with country-specific allocation of technology

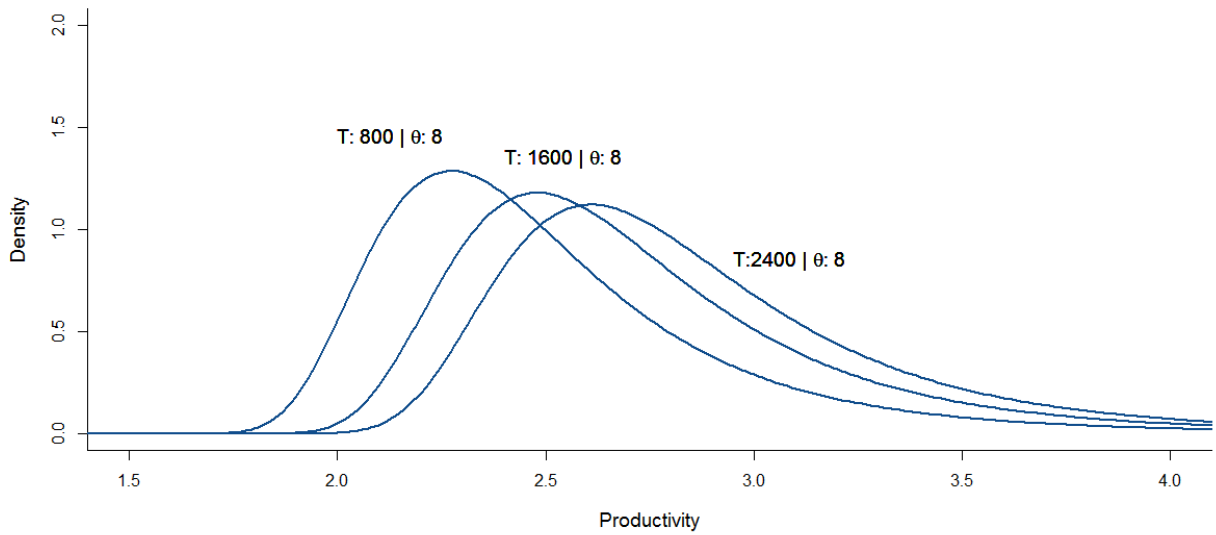
To develop some intuition on the role of country differences in the allocation of technology, we will focus on a model with only two countries, Home and Foreign, and assume z_i is lognormally distributed:

$$z_i \sim LN(\mu_i, \sigma_i^2)$$

where $i \in \{\text{Home}, \text{Foreign}\}$. Here μ_i captures the technological stock of country i while σ_i^2 represents the variance in the allocation of technology. A higher σ_i^2 gives a more uneven distribution of technology across sectors in country i. In the spirit of Dornbusch, Fischer,

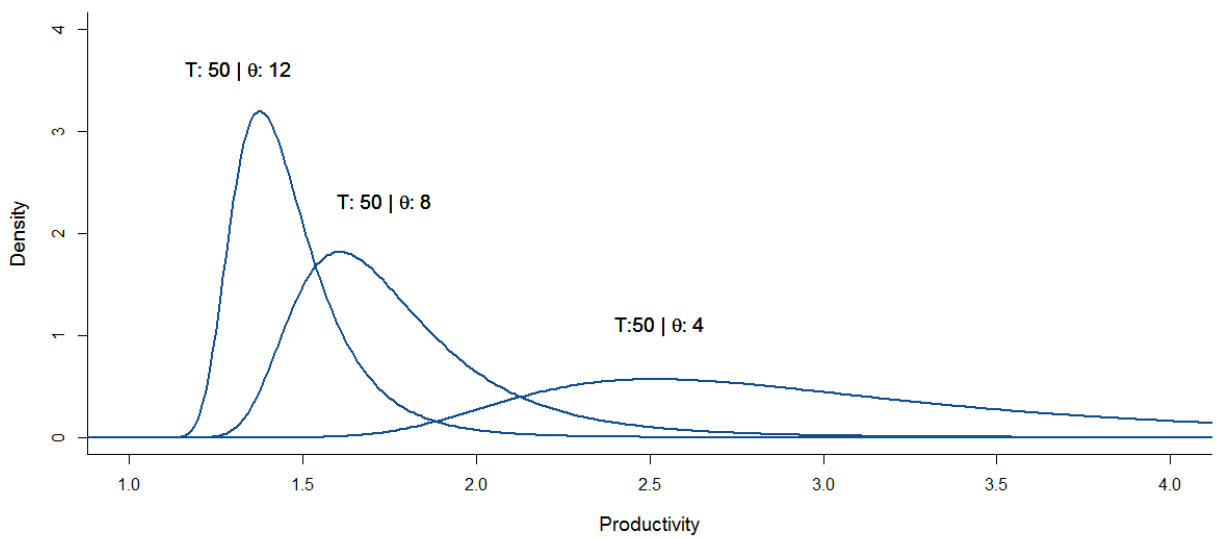
[13] T can never decrease in this model since it refers to the stock of ideas rather than physical capital.

Figure 2: T



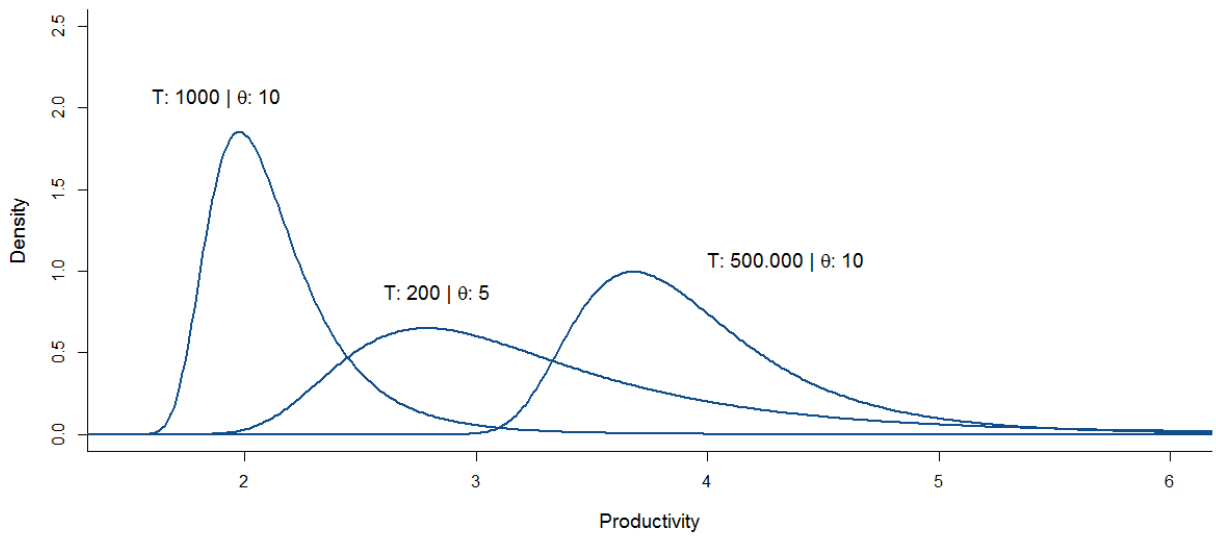
Changes in the stock of technology (T), holding allocation (θ) fixed.

Figure 3: θ



Changes in the allocation of technology (θ), holding the stock (T) fixed.

Figure 4: T and θ



Changes in both the stock and allocation of technology.

and Samuelson (1977), we can order sectors based on decreasing comparative advantage from the perspective of Home, which defines the downward sloping curve $A(j)$.

$$\begin{aligned} j &= P\left(\frac{z_H}{z_F} > A(j)\right) \\ &= 1 - \Phi\left(\frac{\ln A(j) - (\mu_H - \mu_F)}{\sqrt{\sigma_H^2 + \sigma_F^2}}\right) \end{aligned}$$

In equilibrium there is a cutoff sector j^* such that Home produces goods $j \in [0, j^*]$ defined by

$$\frac{w_H}{w_F} = A(j^*)$$

so that

$$j^* = 1 - \Phi\left(\frac{\ln w_H - \ln w_F - (\mu_H - \mu_F)}{\sqrt{\sigma_H^2 + \sigma_F^2}}\right) \tag{2}$$

What happens to the range of goods produced at Home when σ_H^2 increases (or technology becomes more unevenly distributed across sectors)? It depends on the equilibrium relative wage that appears in the numerator of equation (2).

If we impose CES preferences then each country spends a fraction j^* of their income in goods produced at Home. Total spending in equilibrium has to equal total wages at Home

$$w_H L_H = j^* w_H L_H + j^* w_F L_F \tag{3}$$

Starting from a symmetric case where $L_H = L_F$, it can be shown that (2) and (3) imply

$$\frac{\partial j^*}{\partial \sigma_H^2} > 0 \iff \ln w_H - \ln w_F > \mu_H - \mu_F \iff \mu_H < \mu_F$$

so a more uneven allocation of technology across sectors (higher σ_H^2) raises the range of goods produced at Home if and only if Home is a technological follower (has less technological stock than Foreign). The intuition behind this result is as follows. Home is on average more expensive than Foreign and thus produces in equilibrium a narrower range of goods. As a result, an increase in σ_H^2 dampens the effect of the technological stock and therefore increases the range of goods produced by the technological follower. Notice however that the effect depends on the initial values of σ_H^2 and σ_F^2.

2.4 Full model with country-specific comparative advantage

When the allocation of technological know-how θ_k is country-specific, the probability that country i provides a good at the lowest price in country n is:

$$\begin{aligned}
\pi_{ni} &= P(p_{ni}(j) \leq \min_{k \neq i} p_{nk}(j)) \\
&= P\left(\frac{c_i d_{ni}}{z_i(j)} \leq \min_{k \neq i} \frac{c_k d_{nk}}{z_k(j)}\right) \\
&= \int_0^\infty \Pi_{k \neq i}^N e^{-T_k \left(\frac{c_k d_{nk} z_i}{c_i d_{ni}}\right)^{-\theta_k}} \theta_i T_i z_i^{-\theta_i - 1} e^{-T_i z_i^{-\theta_i}} dz_i \\
&= \int_0^\infty e^{-\sum_{k=1}^N T_k \left(\frac{c_k d_{nk} z_i}{c_i d_{ni}}\right)^{-\theta_k}} \theta_i T_i z_i^{-\theta_i - 1} dz_i
\end{aligned} \tag{4}$$

In the appendix we show that the term inside the integral can be replaced by

$$\sum_{k=1}^N T_k \left(\frac{c_k d_{nk} z_i}{c_i d_{ni}}\right)^{-\theta_k} = \sum_{k=1}^N T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k} z_i^{-\theta_i} + \varepsilon$$

where the expectation of the approximation error $E(\varepsilon)$ is second order. This approximation treats the sum with heterogeneous θ_k as if it were a sum with a fixed θ_i, since differences in the exponents will tend to cancel out.[14] With this approximation, we can simplify expression (4) to get

$$\pi_{ni} = \frac{T_i}{\sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k}} \tag{5}$$

The term in the denominator is a measure of world competitiveness relative to country i. It reflects how much cheaper (in terms of input and transport costs) the rest of the world is relative to i. Intuitively, exporter i will be more successful if its technological stock is higher relative to world competitiveness. Since in this model π_{ni} is also the fraction that country n spends in goods from i, equation (5) becomes:

$$\frac{X_{ni}}{X_n} = \frac{T_i}{\sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k}} \tag{6}$$

The left hand side variable is normalized bilateral imports: i's imports from n adjusted by home purchases. We can think of (6) as the model's gravity equation as it relates normalized bilateral trade to the stock of technology, and relative input and transport costs (like wages and geographic distance). Taking logs and expanding with respect to the θ_k parameters up to a first order we get

$$\ln \frac{X_{ni}}{X_n} = \ln T_i - \ln \left(\sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta} \right) + \sum_{k=1}^{N} \alpha_k \ln \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right) (\theta_k - \theta) \tag{7}$$

where α_k is the relative standing of country k in world competitiveness

$$\alpha_k = \frac{T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k}}{\sum_{j=1}^{N} T_j \left(\frac{c_j d_{nj}}{c_i d_{ni}}\right)^{-\theta_j}}$$

Equation (7) summarizes our model. Bilateral trade is related to the exporter's technological stock (first term), a world competitiveness index (relative to i, second term), and a comparative advantage term. Note that, if all countries have the same allocation parameter,

[14] See appendix for an analysis of the accuracy of this approximation.

$\theta_k = \theta \; \forall k$, the last term equals zero and our model simplifies to the benchmark Eaton and Kortum (2002).[15] This is an advantage of our setup, compared to others, as it allows for easy comparison between the models.

The EK model, contained in the first two terms, provides a gravity equation to study the effect of trade costs, represented by geography and technology, on the pattern of trade. In particular, it predicts that exports from country i are larger when it has more absolute advantage relative to world competitiveness. That is, country i will export more to country n the more technology it accumulates and the higher the trade costs of the rest of the countries (relative to i).[16] The only role of the technological allocation parameter θ is in shaping the elasticity of imports with respect to input costs and geographic barriers. Note that an increase in the relative cost of any given country k will have a similar effect (henceforth, the EK effect) on i as the model imposes a common (world) allocation of technology θ for every country. In other words, in the EK model, it doesn't matter from the perspective of i's exports to n which competitor k experiences an increase in relative costs. Similarly, any increase in the world allocation parameter (θ) will benefit all exporters equally. But, as we already anticipated in the introduction and will show in section 3, the allocation of technological know-how (measured with patenting data) varies significantly across countries and these differences turn out to be important determinants of bilateral trade.

The key feature of our model is, compared to the standard EK gravity, the additional (third) term of equation (7). The comparative advantage term helps us to better understand the effect of both a change in a country's relative costs and a change in the allocation parameter on exports by introducing an effect that has been neglected so far in the literature: that a country's exports also depend on its relative world standing regarding costs and technology. So any changes in a competitor's k input costs or technological allocation (i.e. they become more technologically specialized or diversified) will affect i's exports to n. With regard to relative costs, the baseline EK effect still holds and is captured by our world

[15] $\ln \frac{X_{ni}}{X_n} = \ln T_i - \ln \left(\sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}} \right)^{-\theta} \right)$

[16] The trade costs have an exporter specific component (input costs) and a bilateral pair component (i.e. geographic distance).

competitiveness (second) term. An increase in k's costs relative to i will benefit i's exports to n. However, there is an additional effect coming from the comparative advantage (third) term so the overall effect can be augmented or dampened depending on the magnitude of parameter θ_k. The effect will be larger when θ_k is large, that is, when dispersion in know-how is smaller (technology is more evenly distributed across the economy). Since country k's force of comparative advantage is weaker any given change in k's costs has a larger effect on i's exports.

Our model captures, through the comparative advantage term, how the country-specific allocation of technology co-varies with relative costs. We can see from equation (7) that the effect of an increase in θ_k depends on the sign of the log of relative costs. If country k is relatively less competitive (has higher costs relative to i), then the log term is positive. An increase in θ_k, or a more even allocation of technology across the economy in k, increases exports from i to n (at the expense of k's exports to n). Intuitively, a larger θ_k dampens the force of technology in comparative advantage and increases the effect of a difference in relative costs. This effect was already present in the two country model of Section 2.3. A reduction in technological dispersion increases exports of the country that is relatively less expensive. In the multicountry case, we also observe that this effect is larger when α_k is big: an increase in θ_k favors country i's exports, especially if country k is highly competitive relative to the world's average competitiveness index. The opposite is true when θ_k decreases, or technology becomes more unevenly distributed across the (relatively) more expensive country's economy.

In summary, our model has two main predictions. First, like in the EK model, a higher stock of technology and lower relative input costs increase bilateral exports. Second, unlike in the EK model, the allocation of technological know-how across the economy also matters for trade. In particular, a more uneven allocation of technology benefits countries that have higher relative input costs by increasing their export probability.

When is country k relatively more expensive than country i? The answer was already provided in the two country model of Section 2.3, which suggested that in a two country world with log-normal productivity, the country with a higher stock of technology was relatively

less expensive. If we assume labor is the only input in production, the equilibrium in the multicountry model is given by

$$w_i L_i = \sum_{n=1}^{N} \pi_{ni} w_n L_n$$

We can solve the model in closed form if we assume no trade barriers, so that $d_{ni} = 1$ for all country pairs, and a common allocation parameter θ for all countries. In that case we get:

$$\frac{w_n/T_n^{1/\theta}}{w_i/T_i^{1/\theta}} = \left(\frac{T_n^{1/\theta}/L_n}{T_i^{1/\theta}/L_i}\right)^{-\frac{1}{1+\theta}}$$

so that if country n has higher absolute advantage measured by $T_n^{1/\theta}$ then it will be more competitive in terms of productivity adjusted labor costs.

3 Data Description

We build a unique panel dataset containing measures of the stock of technology T, the dispersion in the technological allocation θ, bilateral trade, input costs, trade costs, and other bilateral characteristics (like shared language or border) for 84 developed and developing countries, from 1980 to 2000.[17] We follow Eaton and Kortum (2010) in understanding technology as the outcome of a process that starts with an idea, and therefore use patent data to measure the technological stock and dispersion. These two are then used to construct the absolute and comparative advantage variables T and θ in a theory-consistent way, which constitutes one of the main contributions of this paper. For the rest of the variables we follow the literature in choosing widely used measures and databases. To measure trade we use UN COMTRADE bilateral imports. Data on GDP per capita by country and year is from the World Bank's World Development Indicators (WDI). Our measures of trade costs (geographic distance, common language, border, common currency, common colonizer, etc.) by bilateral pair are from CEPII gravdata dataset. Finally, we use data on wages by country

[17] A list of all countries can be found in the Data Appendix.

and year from the International Labour Organization (ILO). Below we describe the sources of the technological data and the construction of the key variables.

3.1 Patent Data

Patent grants at the USPTO are our indicator of technological capabilities of countries. Data on patenting activity covering the period 1975-2000 was obtained from the "Patent Network Dataverse" developed by the Institute for Quantitative Social Science at Harvard University (Lai et al., 2011) using original data from the USPTO. This database contains all patents granted at the USPTO to resident and non-resident inventors along with their address information, which we used to determine and assign the origin of the patent.[18] To identify older patent grants (pre 1975) at the USPTO we developed an algorithm that retrieves the location information of optically recognised (OCR) historical patent documents. Since 2006 the USPTO started a series of no-cost agreements with Reed Tech and Google to digitalise all available patent documents dating back to 1790, making OCR patent documents available to anyone free of charge.[19] This algorithm finds references to geographic locations (country names) within patent documents to later evaluate the likelihood that a reference is indeed the location of an inventor/assignee in a specific patent. Our algorithm is analogous to the one used in Petralia, Balland, and Rigby (2016) but for international patents.[20]

To sum up, for each patent in USPTO since 1836 we were able to retrieve information on: the country of origin, the year it was granted, the patent class, and number of citations. The latter is used, in line with the innovation literature, as a measure of patent quality. Quality dispersion will result crucial for our empirics since they will identify technological

[18]This assumes that the knowledge is where the inventor. If a patent has several inventors in different locations then we assigned an entire patent count to each country. Results do not change if a proportional fraction is assigned to each country instead.

[19]Even though the earliest patent available dates back to 1790, coverage between 1790 and 1836 is scattered and not reliable. This is because a fire at the USPTO destroyed file histories of thousands of patents and pending applications in 1836. For more information see https://www.google.com/googlebooks/uspto.html, and http://www.uspto.gov/learning-and-resources/electronic-bulk-data-products.

[20]See our Data Appendix for further detail.

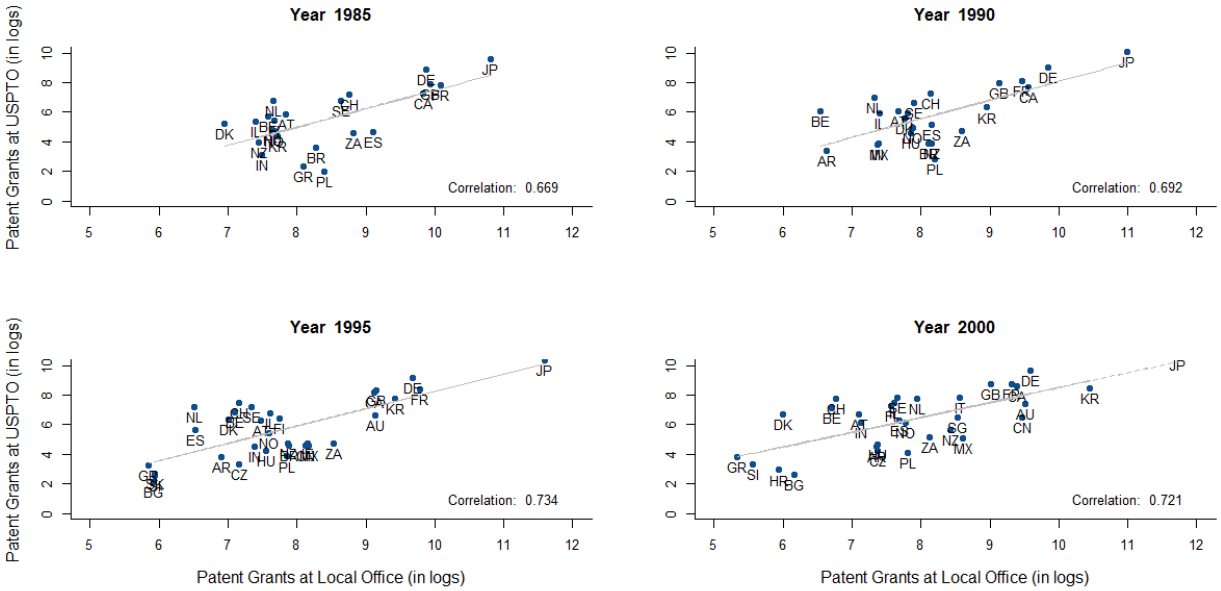
dispersion, as we show below. Note that, to avoid a home bias effect, we leave US patents out of the analysis and focus on foreign patents in the US. We chose to use data on patents at USPTO rather than individual patent offices for easier comparison between countries (same criteria for everyone), more reliability, and the availability of scanned historic patents. In the next section we show that patents at the USPTO are a good measure of the countries' technological innovation and describe the evolution of foreign patents in time.

3.1.1 Patent Descriptives

The usefulness of patent grants at USPTO as a measure of the countries technological innovation relies on two assumptions: that patents indeed capture technological progress, and that the patenting behaviour of countries is similar at home and abroad (USPTO). The first one has been widely debated in the literature of innovation, which concludes that patents and R&D expenditures are the best available proxies of technological innovation. Since patents are an output rather than an input measure, they represent best the countries' technological stock. The second claim deserves closer look. Figure 5 compares patent grants at USPTO with grants at the local (home) office since 1980. The comparison for earlier dates can be seen in Figure 11 in the Appendix. There is a strong correlation between the two patenting activities: countries that patent more at home also patent more abroad, in particular at USPTO.

The historic evolution of patent grants is depicted by Figures 6 and 7. Foreign patent grants at the USPTO have increased drastically since the 1830's, as seen in Figure 6, with a clear change of pace around the 1950's. They went from a negligible 3% to a modest 15% of the total patent grants between mid and end of the 19th century, and later jumped to represent more than 40% of overall patents in USPTO by the end of the 20th century. The exponential increase in foreign grants at USPTO can be partially attributed to the contribution of Japan as a key player in the world production of technological knowledge. In fact, as shown in Figure 7 below, Japan climbed from producing less than 3% of all patent grants in the 1950's to producing nearly 50% by the turn of the century. The countries that

Figure 5: Grants at local office vs. USPTO



Source: Own elaboration based on USPTO and WIPO statistics.

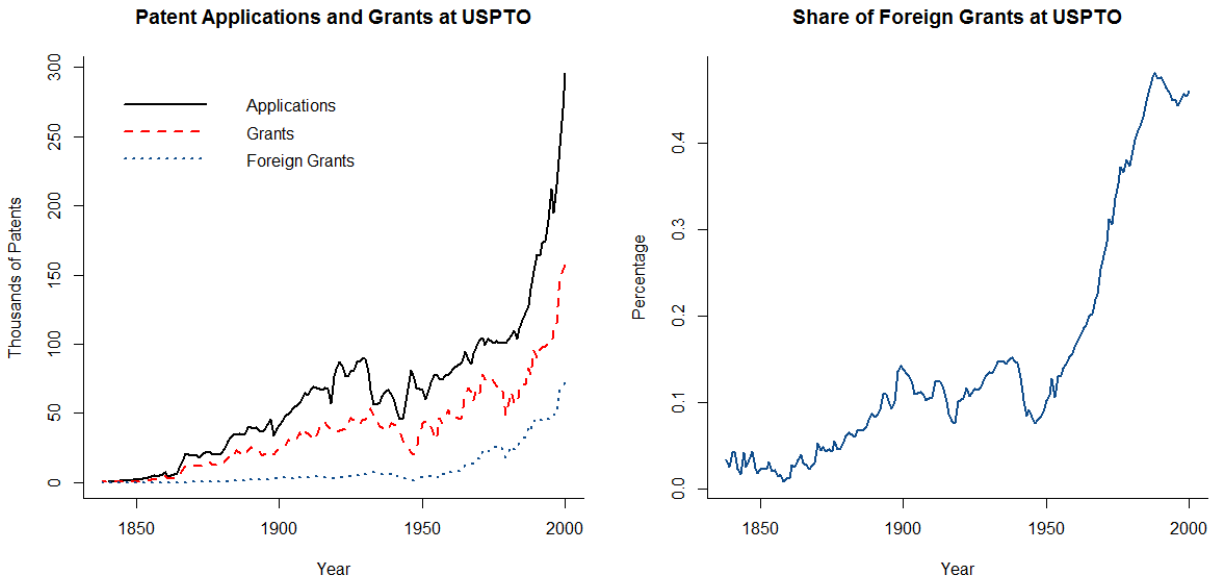
consistently patent the most over the entire time period are Japan, Germany, Great Britain, France, and Canada.

3.1.2 Measures of T and θ

We construct our measures of technological stock (T) and allocation (θ) by combining the patent data with a general equilibrium model of technological change from Eaton and Kortum (2010). This idea-generating model provides the microfoundation of the Frechet distributions we assume in the main model, yielding a theory-consistent approach to estimating the distribution parameters T and θ that will allow to construct our technological variables of interest.

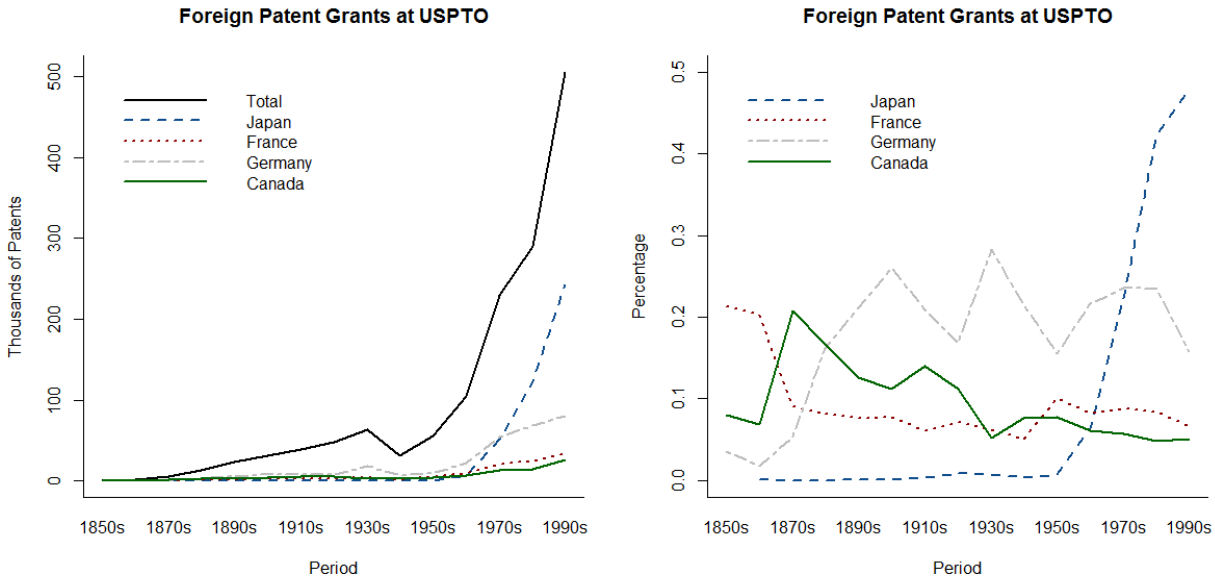
According to Eaton and Kortum (2010) an idea is the core of technology and can be described as "a recipe to produce some good j with some efficiency q (quality of the idea) at some location i". In this model, ideas arrive to researchers as a Poisson process with an intensity (arrival rate) that depends on both current research effort and the history of arrival

Figure 6: Patent Applications and Grants at the USPTO



Source: Own elaboration based on USPTO and WIPO statistics.

Figure 7: Composition of Foreign Patent Grants at the USPTO



Source: Own elaboration based on HistPat and Harvard Patent Dataverse.

of ideas $T(t) = \int_{-\infty}^{t} R(\tau)d\tau$, where $R(\tau)$ is past research effort.[21] Ideas have a quality Q with probability distribution Pareto:

$$P(Q > q) = \begin{cases} \left(\frac{q}{\underline{q}}\right)^{-\theta} & q \geq q \\ 1 & q < q \end{cases}$$

It follows that ideas with quality $Q \geq q$ arrive to researchers with intensity $T(t)q^{-\theta}$. It can be shown that if the distribution of ideas is Pareto, then the distribution of the best ideas is Frechet with parameters T and θ.

The probability that y_i ideas (patents) with quality q_i arrive at a given year is

$$P(Y = y) = \prod_i e^{-T(t)q_i^{-\theta}} \frac{(T(t)q_i^{-\theta})^{y_i}}{y_i!}$$

We obtain values for idea qualities based on citations and proxy T with the stock of patents at time t.

$$T(t) = \sum_{k=1836}^{t} \text{Patents}_k$$

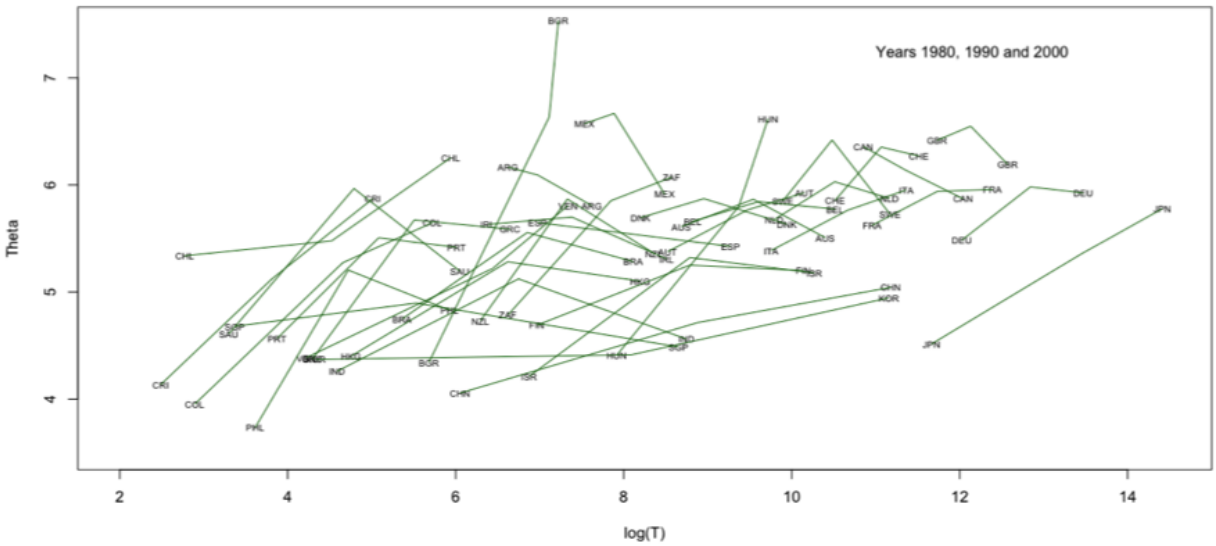
We estimate one Poisson model per country and year, and retrieve $\hat{\theta}_i$. Figure 8 plots these estimated country-specific allocation parameters against the stock of technology for a select group of countries and three points in time (1980, 1990, and 2000)[22]. Note that both the stock and the allocation of technology vary across countries and time. Indeed, there is a positive correlation between T and estimated θ. Initially, countries increase T therefore increasing the probability of exporting. According to the model, this would predict an exponential increase in the arrival rate of new ideas. This exponential growth does not take place in our patent dataset, following a stylized fact that research effort has increased over time but patenting per researcher has stayed relatively constant (Kortum, 1997). The model adjusts this gap by increasing θ, which means that the probability of getting an idea with a given quality is decreasing over time.

Figure 9 plots the estimated θ_i against the technological stock T_i for all countries and all years in our sample. Each dot represents a country-year for a pool of 84 countries

[21] Eaton and Kortum (2010) describe this as a "no forgetting" feature of the model.

[22] The group of countries was chosen due to data availability for the three years.

Figure 8: T and estimated $\hat{\theta}$



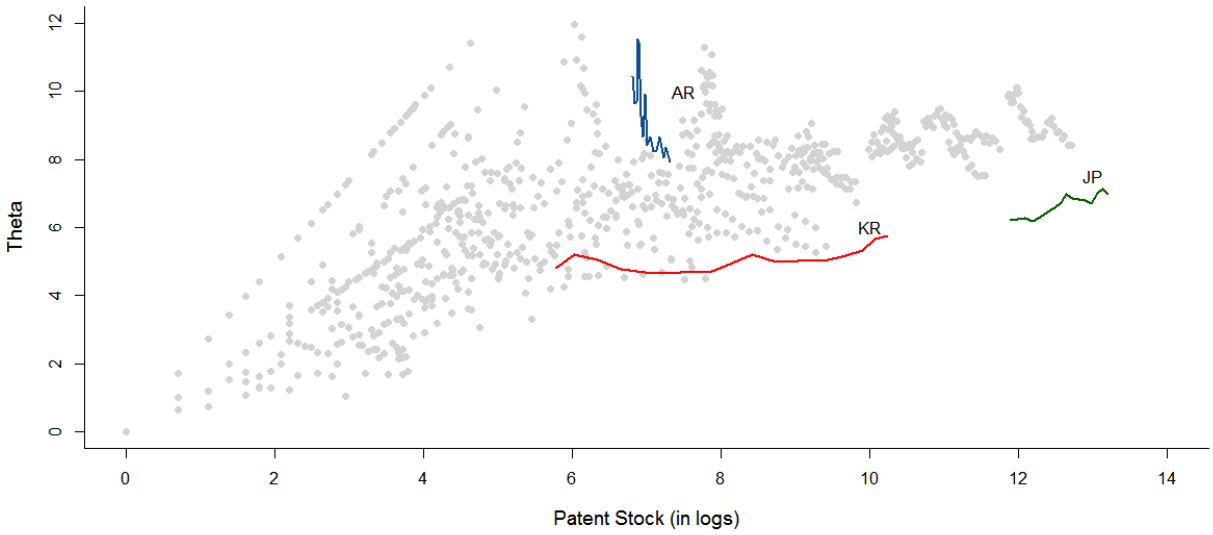
Source: Own elaboration for 50 countries and years 1980, 1990 and 2000.

during the period 1980-2000[23]. We can see that all of our estimates for θ_i lie between 1 and 12, which is consistent with other estimates in the literature[24]. We follow three countries, Argentina, Korea, and Japan in time and also plot their implied country-specific Frechet distributions in Figure 10. Throughout the time period we can see the impressive accumulation of technological stock in Korea, rapidly catching up with the technological leaders on the right hand side. Japan has the highest technological capabilities and has seen a reduction in dispersion, which means that differences in efficiency across sectors are shrinking. Lastly, Argentina has experienced a mild increase in the stock of technology but a sharp reduction of θ (an increase in technological dispersion).

[23]Not all years are available for all countries

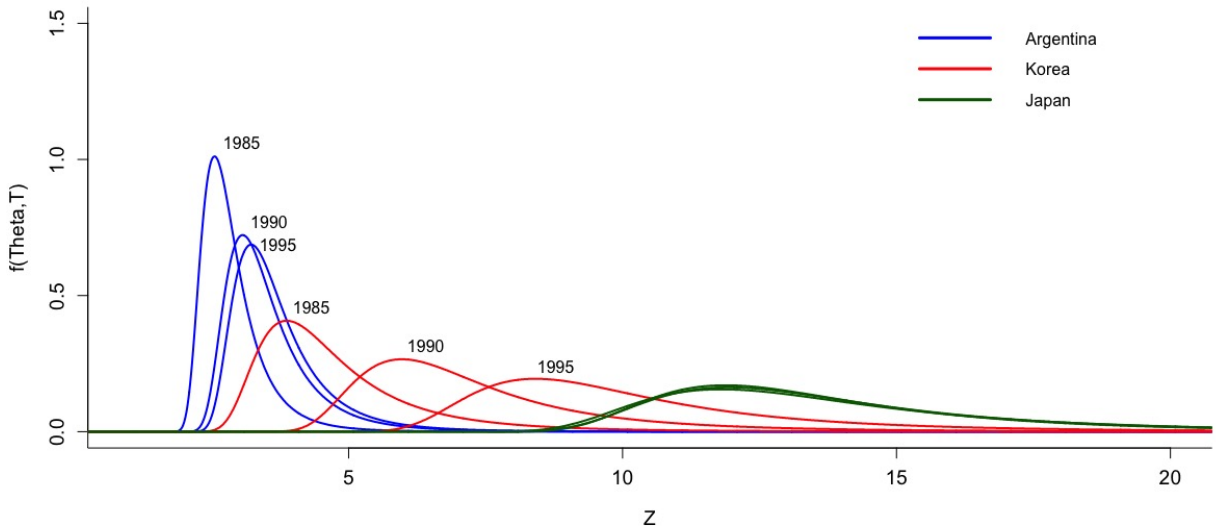
[24]See Eaton and Kortum (2002), Simonovska and Waugh (2011), and Leromain and Orefice (2014) for some examples.

Figure 9: T and estimated $\hat{\theta}$



Source: Own elaboration for 84 countries in the period 1980-2000.

Figure 10: T and estimated $\hat{\theta}$



Source: Own elaboration for based on the T_i and θ_i of Argentina, Korea, and Japan.

4 Estimation Results

To understand the role that the stock and allocation of knowledge play in bilateral trade we estimate the gravity equation (7) derived from our model as follows:

$$\ln Ish_{ni,t} = \beta_0 + \beta_1 AA_{i,t} + \beta_2 WC_{ni,t} + \beta_3 CA_{ni,t} + \epsilon_{ni,t} \tag{8}$$

where Ish_{ni} denotes bilateral imports of country i from country n as a share of i's total spending, AA_i is absolute advantage (or technological stock) of the exporter, WC_{ni} is a world competitiveness index relative to i, and CA_{ni} is country i's comparative advantage when selling to n. Finally, t represents time (in years). All variables are as defined in equation (7) and have been calculated using the data described above.

Our model is a generalized version of Eaton and Kortum (2002), represented by the terms $AA_{i,t}$ and $WC_{ni,t}$. One advantage of this setup is that it allows for a straightforward comparison between the models, so we can assess the relevance of the distribution of knowledge that enters through our term $CA_{ni,t}$. Moreover, this term represents our main contribution as it introduces the two main aspects of classical Ricardian theory to the multi-country setup: that the allocation of technological capabilities is country-specific, and that it matters for bilateral exports. Our theory predicts that β_2 is negative and β_1 and β_3 are positive. Bilateral exports from i to n decrease with i's trading costs (relative to the rest of the world's) and increase with i's technological stock and relative force of comparative advantage. In particular, as we discussed earlier, country i will benefit more from a decrease in a competitor's force of comparative advantage (reduced technological dispersion or a more even distribution of know-how) the cheaper i is relative to its competitors.

Table 1 reports the results of estimating equation (8) for over 2200 country pairs in 18 years, comparing the baseline EK model (first two terms) to our generalized (full) model across different specifications. To keep our econometric model closer to the empirical literature, we include the usual controls. Note that the economic interpretation of the comparative advantage coefficient is not very straightforward. The CA term represents how relative costs covary with technological dispersion, and thus we interpret its coefficient as the elasticity of

exports with respect to the cost-dispersion covariance.

The results in columns (1) and (2) of Table 1 reveal that, after accounting for exporter fixed effects: the absolute advantage, the world competitiveness, and the comparative advantage terms matter for bilateral trade. All coefficients have the expected sign and are highly significant, which supports our model and suggests that the standard EK model was omitting a relevant determinant of exports. Columns (3) and (4) of Table 1 report the results of estimating both models after adding time fixed effects. The coefficient on absolute advantage drops while the others remain virtually unchanged. Finally, columns (5) and (6) of Table 1 report the results of estimating both models after introducing the typical bilateral trade costs determinants from the gravity literature. These allow to control for common shared characteristics constant in time, such as common language, shared border, colonial ties and shared past. The full table of results (including these gravity coefficients) can be seen in the Appendix. The results are very similar to the previous specification and all the gravity variables are significant and have the expected signs. This is our preferred specification. Overall, our results suggest that, in line with the existing Ricardian literature, an increase in the overall stock of technology or a decrease in relative costs of the exporter i increases its exports to n. In addition, we find that the comparative advantage term matters, supporting our augmented (full) model. This evidence suggests that the country-specific allocation of technological know-how is also an important determinant of bilateral trade.

In Table 2 we show that our main finding is robust to alternative specifications and measures of costs. So far we have followed Eaton and Kortum (2002) in using wages to measure costs. One concern with this measure is that wages only capture the labor component of production costs, so now we turn to using the wholesale price index (WPI) as an alternative measure. Columns (1) and (2) of Table 2 report the results of estimating our preferred specification when using wages and WPI, respectively. All coefficients are similar in magnitude, have the expected signs, and are significant. In columns (3) and (4) of Table 2 show the estimation results after adding exporter-time fixed effects with both measures of costs. The comparative advantage term gets absorbed by the fixed effects, but both the

world competitiveness term and the comparative advantage term are statistically significant and have the right signs. Finally, we drop the bilateral controls and exporter-time effects and replace them with bilateral pair fixed effects. Columns (5) and (6) report the results of estimating equation (8) for both measures of costs. As expected, the significance of the comparative advantage effect is diminished, but all results still hold when using wages as the cost measure.

Table 1: Baseline Results

Dependent variable is bilateral imports (as a share of total spending)						
	(1)	(2)	(3)	(4)	(5)	(6)
	EK	full	EK	full	EK	full
Absolute Advantage	0.554***	0.594***	0.245***	0.258***	0.227***	0.238***
	(20.99)	(22.46)	(6.51)	(6.94)	(6.32)	(6.71)
World Competitiveness	-0.105***	-0.0960***	-0.109***	-0.0980***	-0.0784***	-0.0689***
	(-52.19)	(-42.01)	(-52.47)	(-41.45)	(-38.97)	(-30.77)
Comparative Advantage		0.0431***		0.0585***		0.0510***
		(10.06)		(11.64)		(10.94)
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes	Yes
Bilateral controls	No	No	No	No	Yes	Yes
Observations	19230	19230	19230	19230	19230	19230

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Robustness

Dependent variable is bilateral imports (as a share of total spending)						
	(1)	(2)	(3)	(4)	(5)	(6)
Absolute Advantage	0.238***	0.136***	-	-	0.737***	0.602***
	(6.71)	(3.63)			(28.85)	(24.23)
World Competitiveness	-0.0689***	-0.0128***	-0.0709***	-0.0169***	-0.0154***	-0.00278**
	(-30.77)	(-8.83)	(-30.93)	(-9.29)	(-3.02)	(-2.04)
Comparative Advantage	0.0510***	0.0208***	0.0548***	0.0328***	0.0142**	0.00156
	(10.94)	(5.76)	(11.35)	(7.39)	(2.53)	(0.55)
Bilateral controls	Yes	Yes	Yes	Yes	No	No
Exporter-time FE	No	No	Yes	Yes	No	No
Bilateral pair FE	No	No	No	No	Yes	Yes
Cost measure	wages	WPI	wages	WPI	wages	WPI
Observations	19230	15171	19230	15171	19230	15171

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Concluding Remarks

This paper studies the role of technology in international trade. Using patent data to capture technological capabilities, we document that countries differ greatly in both the amount of technology that they have (technological stock, measured as patent counts) and how they allocate it across their economies. In addition, we show that these differences are highly correlated with international trade flows. The modern Ricardian literature has taken into account the effects of a higher technological stock on exports but has neglected the role of the allocation of know-how.

Our main objective is to bring back this technological dimension that is at the core of the original Ricardian theory and the principle of comparative advantage. To do so, we build on the seminal work of Eaton and Kortum (2002) and develop a Ricardian model that incorporates the allocation of technology as a determinant of bilateral trade. Our model predicts that, as in the previous literature, the exporter's stock of technology has a positive impact on exports while the relative input costs have a negative one. In addition, our model predicts that the covariance between the allocation of technology and relative input costs affects trade. In particular, a more even distribution of technology benefits countries with lower input costs (since their exports are determined by these and not technological differences) and viceversa.

The empirical contribution of this paper is that we are able to test the predictions of our model with measures of the key technological variables that represent absolute and comparative advantage, originated from outside of the model and consistent with the theory. We created a novel dataset of international historical patents dating back to 1936 (the longest to date) using an algorithm that could retrieve the location information of patent grants at the USPTO. We use the dataset to construct measures of the stock and allocation of technology that are consistent with the theoretical model. We combine the patent data with data on exports, patents, input costs, income, expenditures, and bilateral pair characteristics for 84 developed and developing exporters in the period 1983-2000.

Our empirical results confirm our theoretical predictions: both the stock and the allo-

cation of technology are important determinants of exports, and countries are affected by their relative world standing in terms of costs and technological stock and dispersion. This finding has important policy implications since it advocates against the popular idea that diversification is better *per se*. The optimal strategy for a country that could change its technological profile depends on where it stands in the world scenario. Low-cost countries are better off competing in costs, and therefore benefit with a more even distribution of technological know-how. The opposite is true for high-cost countries (that are better off competing in technology). Future work should focus on using this model to explain the diversification patterns in export behavior.

6 Appendix

6.1 Approximation

We use the approximation

$$\sum_k \delta_k z_i^{\theta_i - \theta_k} \approx 1$$

where δ_k is the share of country k in the index of world competitiveness relative to country i

$$\delta_k = \frac{T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k}}{\sum_{j=1}^N T_j \left(\frac{c_j d_{nj}}{c_i d_{ni}}\right)^{-\theta_j}}$$

to integrate

$$\int_0^\infty e^{-\sum_{k=1}^N T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k} z_i^{-\theta_i}} \theta_i T_i z_i^{-\theta_i - 1} dz_i$$

instead of

$$\int_0^\infty e^{-\sum_{k=1}^N T_k \left(\frac{c_k d_{nk} z_i}{c_i d_{ni}}\right)^{-\theta_k}} \theta_i T_i z_i^{-\theta_i - 1} dz_i$$

We want to bound the difference

$$\left| \int_0^\infty e^{-\sum_{k=1}^N T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k} z_i^{-\theta_i}} \theta_i T_i z_i^{-\theta_i - 1} dz_i - \int_0^\infty e^{-\sum_{k=1}^N T_k \left(\frac{c_k d_{nk} z_i}{c_i d_{ni}}\right)^{-\theta_k}} \theta_i T_i z_i^{-\theta_i - 1} dz_i \right| < \varepsilon$$

Instead we will work with

$$\left| \int_{\underline{z}}^{\overline{z}} e^{-\sum_{k=1}^N T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k} z_i^{-\theta_i}} \theta_i T_i z_i^{-\theta_i - 1} dz_i - \int_{\underline{z}}^{\overline{z}} e^{-\sum_{k=1}^N T_k \left(\frac{c_k d_{nk} z_i}{c_i d_{ni}}\right)^{-\theta_k}} \theta_i T_i z_i^{-\theta_i - 1} dz_i \right| < \varepsilon$$

which holds if

$$\int_{\underline{z}}^{\overline{z}} \left| e^{-\sum_{k=1}^N T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k} z_i^{-\theta_i}} - e^{-\sum_{k=1}^N T_k \left(\frac{c_k d_{nk} z_i}{c_i d_{ni}}\right)^{-\theta_k}} \right| \theta_i T_i z_i^{-\theta_i - 1} dz_i < \varepsilon$$

wer impose the integration limits so that the integral does not blow up, but $\underline{z}$ can be made arbitrarily small. This holds if

$$\left| e^{-\sum_{k=1}^N T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k} z_i^{-\theta_i}} - e^{-\sum_{k=1}^N T_k \left(\frac{c_k d_{nk} z_i}{c_i d_{ni}}\right)^{-\theta_k}} \right| < M_\varepsilon$$

where

$$M_\varepsilon \equiv \frac{\varepsilon}{T(\underline{z}^{-\theta} - \overline{z}^{-\theta})}$$

which holds if

$$\left|\frac{e^{-\sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k} z_i^{-\theta_i}} - e^{-\sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk} z_i}{c_i d_{ni}}\right)^{-\theta_k}}}{e^{-\sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k} z_i^{-\theta_i}}}\right| < M_\varepsilon$$

or

$$\left|1 - e^{\sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k} z_i^{-\theta_i} - \sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk} z_i}{c_i d_{ni}}\right)^{-\theta_k}}\right| < M_\varepsilon$$

This holds if

$$\left|1 - e^{-\left|\sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k} z_i^{-\theta_i} - \sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk} z_i}{c_i d_{ni}}\right)^{-\theta_k}\right|}\right| < M_\varepsilon$$

or alternatively

$$-\ln\left(1 + M_\varepsilon\right) < \left|\sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k} z_i^{-\theta_i} - \sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk} z_i}{c_i d_{ni}}\right)^{-\theta_k}\right| < -\ln\left(1 - M_\varepsilon\right)$$

And a first order Taylor expansion gives

$$-\frac{\ln\left(1 + M_\varepsilon\right)}{\ln \underline{z}/\underline{z}^{\theta}} < \left|\sum_{k=1}^{N} T_k \left(\frac{c_k d_{nk}}{c_i d_{ni}}\right)^{-\theta_k} \left|\theta_k - \theta_i\right|\right| < -\frac{\ln\left(1 - M_\varepsilon\right)}{\ln \overline{z}/\overline{z}^{\theta}}$$

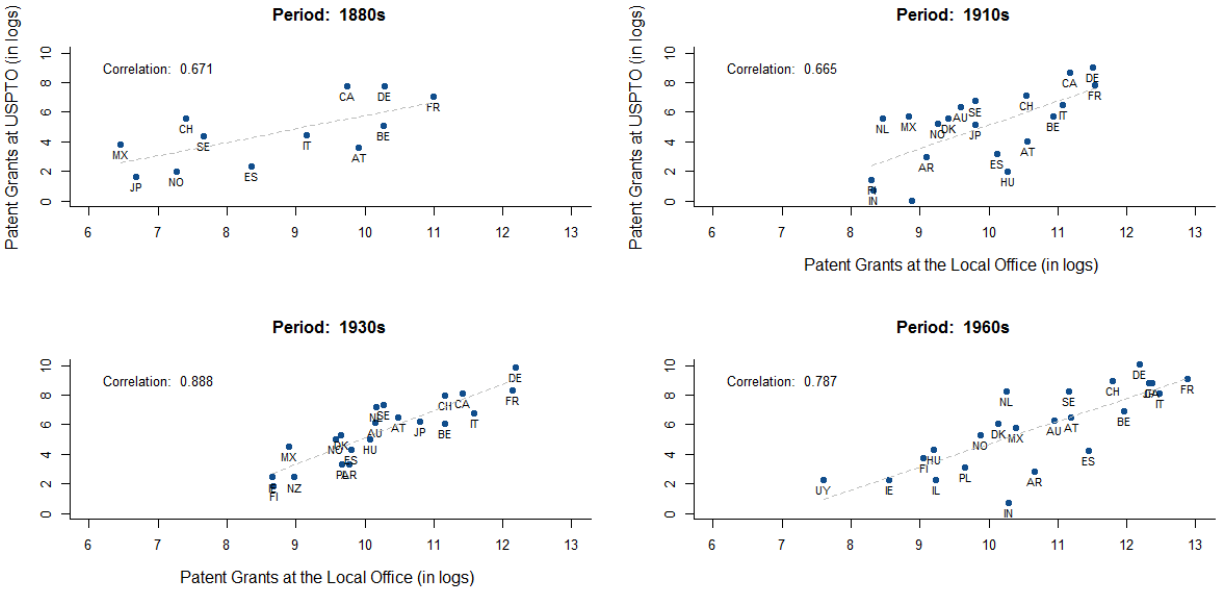
So the approximation will be better when θ_k is close to θ_i.

6.2 Data

We consider all countries with patent and trade data availability, with a few exceptions. We exclude communist and former USSR countries due to unreliable data and large historical gaps, tiny countries (population less than 500 thousand), and US territories due to the home bias effect. This yields a total of 84 countries.

Countries			
Albania	Egypt	Rep. of Korea	Portugal
Argentina	Spain	Lebanon	Paraguay
Australia	Finland	Sri Lanka	Senegal
Austria	France	Morocco	Singapore
Belgium	Gabon	Madagascar	El Salvador
Bangladesh	United Kingdom	Mexico	Suriname
Bulgaria	Ghana	Mali	Slovakia
Bahrain	Guinea	Mauritius	Slovenia
Bolivia	Greece	Malaysia	Sweden
Brazil	Guatemala	Niger	Syria
Canada	Guyana	Nicaragua	Thailand
Switzerland	Honduras	Netherlands	Trinidad and Tobago
Chile	Croatia	Norway	Tunisia
China	Hungary	Nepal	Turkey
Cameroon	India	New Zealand	Tanzania
Colombia	Ireland	Oman	Uganda
Costa Rica	Israel	Pakistan	Uruguay
Cyprus	Italy	Panama	Viet Nam
Czech Rep.	Jordan	Peru	Yemen
Germany	Japan	Philippines	South Africa
Denmark	Kenya	Poland	Zimbabwe

Figure 11: Grants at local office vs. USPTO (pre 1980)



Source: Own elaboration based on USPTO and WIPO statistics.

6.3 Tables

Table 3: Baseline Results - Full Table

	(1)	(2)	(3)	(4)	(5)	(6)
Absolute Advantage	0.554***	0.594***	0.245***	0.258***	0.227***	0.238***
	(20.99)	(22.46)	(6.51)	(6.94)	(6.32)	(6.71)
World Competitiveness	-0.105***	-0.0960***	-0.109***	-0.0980***	-0.0784***	-0.0689***
	(-52.19)	(-42.01)	(-52.47)	(-41.45)	(-38.97)	(-30.77)
Comparative Advantage		0.0431***		0.0585***		0.0510***
		(10.06)		(11.64)		(10.94)
Shared border					1.673***	1.691***
					(21.33)	(21.57)
Common language					0.720***	0.728***
					(7.73)	(7.92)
Have had colonial links					0.266**	0.267**
					(2.89)	(2.87)
Common colonizer					0.794***	0.721***
					(8.40)	(7.74)
Are/were the same country					2.173***	2.172***
					(15.41)	(15.40)
Constant	-9.583***	-9.991***	-7.553***	-7.722***	-8.761***	-8.897***
	(-43.58)	(-44.56)	(-25.19)	(-25.98)	(-30.77)	(-31.46)
Observations	19230	19230	19230	19230	19230	19230
Adjusted R^2	0.572	0.575	0.576	0.580	0.627	0.630

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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