Innovation, Diffusion, and Trade: Theory and Measurement

Santacreu, Ana Maria

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Ana Maria Santacreu*

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Abstract

Growth and imports are correlated across countries, but the mechanisms underlying this relationship are not well understood. I develop a multi-country model in which imports and growth are connected by technological innovations and their international diffusion through trade. Fitting the model to data on innovation, productivity, and trade in varieties, I find that most of the growth–imports correlation is explained by these two mechanisms. I also find that the trade channel has been particularly important in developing countries, accounting for about three-fourths of their growth. Finally, I run counterfactuals analysis.

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1 Introduction

Although the positive correlation between imports and growth is well established, the mechanisms underlying this relationhip are not well understood. Theories about the effects of imports on growth date back at least to Romer (1987) and Rivera-Batiz and Romer (1991), but empirical work has been limited owing mostly to lack of data. The disaggregated trade data that has more recently become available for many countries yield new stylized facts. In particular, it appears that much of the increase in trade-to-GDP ratio in the last decade stems from the extensive and not the intensive margin of trade — that is, the number rather than the quantity of goods traded.[1] During this period, developing countries that expanded their range of imports grew much faster than average. For instance, China and India grew at an average annual rate of 8% over 1994–2003 against a world average of 2%; at the same time, their growth in imported varieties was 5 times that of developed economies.[2] It therefore seems that understanding the relation between growth in GDP and growth in imports requires an emphasis on the extensive margin of trade.

I develop a dynamic general equilibrium model in which imports and growth are connected by technological innovations and their international diffusion through trade. The engine of economic growth is growth in productivity, which is driven by technology accumulation.[3] On top of an exogenous process of "disembodied" productivity growth, there are two sources of "embodied" productivity growth. First, in the spirit of the new growth theory, countries accumulate domestic technologies when their firms invest in R&D and innovate. Second, because technology is assumed to be embodied in intermediate goods, countries adopt foreign technologies embedded in the intermediate goods they import. In the model, both innovation and adoption are endogenous processes. Firms in each country invest in R&D to produce new technologies, and each new technology is then used to produce an intermediate good. Domestic final producers buy and use the new intermediate good immediately whereas foreign final producers must first adopt it, which requires investing resources over time (e.g., in learning). Hence, the speed of diffusion of technologies through trade is endogenous.[4]

[1]Broda, Greenfield, and Weinstein (2008) show that, for the average country, the extensive margin explains more than 75% of the increase in this ratio. Hummels and Klenow (2002) also perform this decomposition for exports and find that the extensive margin explains two thirds of the increase in trade.

[2]Broda, Greenfield, and Weinstein (2008) find that, for developing countries, the extensive margin explains almost all of productivity growth. Santacreu (2006) finds that more than 60% of Ireland's growth during 1994–2003 was driven by an increase in the variety of imported goods from highly innovative OECD countries.

[3]A large literature studies whether differences in growth rates are driven mainly by differences in factor accumulation (capital, in particular) or in total factor productivity (TFP) (see Young (1991)). Other authors who study the role of trade in explaining growth-rate differences have focused on capital accumulation (Ventura (1997)). Easterly and Levine (2001) and Klenow and Rodriguez-Clare (2005) show that differences in TFP drive differences in growth rates across countries.

[4]Consistently with recent evidence (Comin and Hobijn (2004)), diffusion is modeled as a slow pro-

I analyze both the model's steady state and its transition dynamics. In steady state, international technology diffusion through trade ensures that all countries grow at the same rate, but barriers to foreign technology adoption induce persistent income differences.[5] More interestingly, countries grow at different rates during the transition phase (from a low technology, developing economy to a high technology, developed one). I find that innovation and adoption through imports affect a country's productivity growth differently depending on its position on the transition path. Countries at early stages of development, and so further away from the technological frontier, grow by adopting the new foreign technologies embedded in the intermediate goods they import. In contrast, countries at later stages of development and close to the technological frontier, grow by developing new technologies through R&D.

The model is fitted to 37 countries grouped into five regions: Asia, developing Europe, developed Europe, Japan and Korea, and the United States. I use data on innovation, productivity, and trade at the product level over 1994–2003 and employ Bayesian techniques to estimate the structural parameters. I find that embodied productivity explains 67% to 80% of the correlation between growth in imports and growth in GDP per capita over the sample period. Furthermore, I find that adoption of foreign technologies through trade is an important source of embodied growth for developing countries, whereas domestic innovation is the main source of embodied growth for developed countries. Indeed, about 75% of embodied growth in Asia can be explained by foreign innovations, especially from the United States and Japan. These two countries are also the main sources of foreign technology for other regions.[6]

Finally, I conduct counterfactual experiments to study the link between trade and growth by changing various exogenous parameters. I find that, following a decrease in barriers to adoption, countries at earlier stages of development initiate the transition and convergence toward the income levels of developed countries. Countries closer to the technological frontier, however, need policies that spur innovation in order to keep growing.

This paper builds on several streams of literature. The first one concerns endogenous growth fueled by technology embodied in new goods, as in Romer (1987). Goldberg, Khandelwal, Pavcnik, and Topalova (2010) provide empirical evidence that conventionally measured TFP increases with imported varieties. My model also considers an exogenous component of TFP that represents disembodied technology as in Greenwood, Hercowitz,

cess whose speed depends on the resources invested by the adopters. Eaton and Kortum (1999) find that international diffusion is much slower than domestic diffusion; I make the extreme and simplifying assumption that domestic diffusion is free and instantaneous.

[5] Rodriguez-Clare and Klenow (1997) review models of international diffusion of technology that predict a common constant growth rate.

[6] Cameron, Proudman, and Redding (2005) analyze a panel of UK manufacturing industries, and find that innovation and technology transfers are the main sources of productivity growth for countries lagging behind the technology frontier.

and Krusell (1997).

Second, I follow Eaton and Kortum (1996, 1999) in positing technological innovations and their international diffusion through trade as potential channels of embodied technological progress.[7] In my model, however, the pace of innovation and the speed of diffusion are both endogenous. Comin and Gertler (2006) and Comin, Gertler, and Santacreu (2009) also model endogenous diffusion in a business cycle model for a closed economy. I adapt their framework to an open-economy model.

The lack of direct measures of adoption has led to the use of indirect ones, such as trade in intermediate goods (Rivera-Batiz and Romer (1991); Eaton and Kortum (2001) and Eaton and Kortum (2002)) or international patenting (Eaton and Kortum (1996, 1999)).[8] Because this paper aims to understand the trade–growth connection, I use trade as an indirect measure of diffusion. Trade allows countries to adopt innovations developed abroad. Along these lines, Coe, Helpman, and Hoffmaister (1997) find that, for developing countries, TFP is related to the stock of R&D carried out by their trading partners. My paper extends this literature by taking explicit account of the mechanisms connecting trade and growth.

This paper also relates to the literature on trade in varieties (Feenstra (1994); Broda and Weinstein (2006); Broda, Greenfield, and Weinstein (2008)). I follow their methodology to construct a measure of the extensive margin of trade, but I model explicitly the firms' incentives for R&D and adoption. Goldberg, Khandelwal, Pavcnik, and Topalova (2009) find that, once allowed by trade liberalization in India during the 1990s, access to foreign inputs raised productivity levels, and thereby generated static gains from trade.[9] Furthermore, they show that new foreign inputs also lowered the cost of innovation, which enabled the creation of new varieties and hence dynamic gains from trade. My model allows for this mechanism by introducing learning from imports in the innovation process.

The paper proceeds as follows. Section 2 examines the data, and Section 3 presents the model. Sections 4 and 5 study the steady state and transition dynamics, respectively. Sections 6 to 8 explain the estimation procedure and report the results. Section 9 reports on the counterfactual experiments, and Section 10 concludes.

2 A First Look at the Data

This section presents some stylized facts based on correlations among trade, innovation, and productivity. I use data for a sample of 37 countries divided into three groups according to their level of income and economic growth: (i) high-income, slow-growing

[7] Keller (2004) surveys empirical studies of innovation and diffusion.

[8] Comin and Hobijn (2004) provide direct measures of adoption for many countries over a long sample period; however, they do not distinguish between domestic and imported technologies.

[9] Halpern, Koren, and Szeidl (2009) estimate a model of importers in Hungarian micro data and find that importing all foreign varieties would increase firm productivity by 12%.

countries (developed Europe, Japan and Korea, and the United States); (ii) low-income, fast-growing countries (developing Europe and Asia); and (iii) low-income, slow-growing countries (Africa and Latin America). These groups also differ markedly in terms of innovation and imports. For instance, developed countries are more innovative and expand the variety of their imports less than average. No developing country does much innovation; however, those that grow faster than average expand the variety of their imports whereas the others do not.

First, we observe that the average growth rate of income per capita is positively correlated with the expansion in import variety (Figure 1).[10] The average is taken over 1994–2003. The red circles in the figure represent less developed countries in Asia, Europe, Africa, and Latin America; the blue circles represent developed countries in Europe, Japan, and the United States. I use bilateral trade data (at the 6-digit level of disaggregation), from UN COMTRADE, and define a variety as a 6-digit product from a specific source of exports. Growth in imported varieties is computed as in Broda, Greenfield, and Weinstein (2008), adjusting for quality and symmetry bias. Output growth is growth in real GDP per capita, taken from the Penn World Table and adjusted by the extensive margin of intermediate imports as in Feenstra (1994) and Broda, Greenfield, and Weinstein (2008). The United States, Japan, and Germany are at one end of the spectrum, with less import variety and lower economic growth; China, Vietnam, and India are at the other end. Although the link between the two variables is clear, we cannot infer causality.

Second, we observe that developed countries— which are closer to the technological frontier—innovate more. A proxy for innovation is research intensity, the fraction of GDP invested in R&D. Indeed, figure 2 shows a positive correlation between GDP and research intensity. A more direct way to measure innovation is to look at the number of products developed in a country. Owing to lack of data, I use the number of goods exported by a country as a proxy for the number of innovations in that country. We observe a positive correlation between the number of goods a country exports and its research intensity measured as the fraction of workers employed in R&D (Figure 3).

Third, we observe that developing countries that grow faster than average expand more the variety of their imports (Figure 1). This is the case for Asia and some countries in Europe. At the same time, there are countries in Africa and Latin America with initial levels of income similar to those in Asia and developing Europe but that either failed to expand the variety of their imports or saw their innovation stagnate (Figure 1).

The empirical evidence suggests that countries farther from the technology frontier may grow faster than average by adopting foreign technologies embedded in the goods

[10] One could argue that exports are no less important than imports in explaining the development experienced by Asia and Eastern Europe. However, the correlation computed between productivity growth and growth in exported varieties is only 0.4, whereas it is almost 0.8 between productivity growth and growth in imports.

they import. Countries closer to the technology frontier grow mainly by innovating and pushing this frontier.

3 The Model

I develop a multi-country growth model in which technological progress is driven by endogenous innovation and the adoption of new technologies. In each country there is a set of available technologies produced by both domestic and foreign intermediate producers. Labor is the only factor of production, and it is used to produce traded intermediate goods. Intermediate goods are combined to produce a non-traded final good, which is used for consumption, domestic innovation and adoption of foreign innovations. Time is discrete and indexed by $t = 0, 1, \ldots$, and there are I countries in the world, indexed by $n = 1, 2, \ldots I$. Each period of time is divided into two stages. In the first stage, production and consumption takes place, while taking each country's technologies as given. In the second stage, innovation and adoption of technologies takes place, determining the technologies available in the next time period.

3.1 Production and Consumption

3.1.1 Intermediate Production

In each country n, the total labor supply L_n is employed by a continuum of monopolistically competitive firms to produce intermediate goods indexed by $j \in [0, Z_{nt}]$, where Z_{nt} represents the mass (or, alternatively, the number) of available products. I assume intermediate goods to be differentiated by source of exports; that is, countries exogenously specialize in different sets of goods (Armington assumption). As is standard practice in the literature, I define variety nj as the intermediate good j produced in country n.[11] Each firm produces a different good according to a CRS (constant returns to scale) production function

$$y_{njt} = l_{njt}, \tag{1}$$

where y_{njt} is the quantity of variety nj produced and l_{njt} is the amount of labor employed in its production. Note that all intermediate producers in a country have the same productivity regardless of which good they produce.

The producer of variety nj takes as given the demand by the final producer in each country $i = 1, 2, ..., I$ and sets a price that is a constant markup over the marginal cost. Prices can differ across countries because markets are segmented owing to iceberg

[11] The Armington assumption allows us to define a variety nj as a good j from a particular country n. In this sense, good j produced in country n is a different variety from good j produced in country k.

transport costs: for products shipped from country n to country i, the transport cost is $d_n^i > d_n^n = 1$ for $i \neq n$. The marginal cost is given by domestic wages because labor is the only factor of production. Hence the price in country i of variety nj is

$$p_{njt}^i = \frac{\sigma}{\sigma - 1} \omega_{nt} d_n^i, \tag{2}$$

where $\frac{\sigma}{\sigma-1}$ is the markup (σ will be determined in Section 3.1.2) and w_{nt} is the wage in country n.

The profit of the producer of variety nj is

$$\pi_{njt} = \sum_{i=1}^{I} (p_{njt}^i - \omega_{nt}) x_{njt}^i = \frac{1}{\sigma - 1} \sum_{i=1}^{I} p_{njt}^i x_{njt}^i, \tag{3}$$

where x_{njt}^i is the demand for variety nj by the final-good producer in country i, to be determined in the next section.

3.1.2 Final Production

In each country i, a perfectly competitive firm (henceforth final producer) uses traded intermediate goods—both domestic and foreign— to produce a non-traded final good, Y_{it}. Varieties are combined according to the CES (constant elasticity of substitution) production function

$$Y_{it} = e^{a_{it}} \left(\sum_{n=1}^{I} \int_{j=0}^{A_{nt}^i} b_{njt}^i (x_{njt}^i)^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}}, \tag{4}$$

where A_{nt}^i is the mass of intermediate goods that country i imports from country n, b_{njt}^i are the so-called Armington weights and represent the share of country i's spending on variety nj, $\sigma > 1$ is the elasticity of substitution across varieties (which are perfect substitutes when $\sigma \to \infty$), and a_{it} is an exogenous TFP shock following the AR(1) process

$$a_{it} = \bar{g}t + \rho a_{i,t-1} + u_{it}, \tag{5}$$

where the steady-state growth rate, $\bar{g} \in (0, 1)$, $\rho \in (0, 1)$, and $u_{it} \sim N(0, \sigma_u^2)$.

The engine of economic growth is growth in productivity, which itself is driven by technological progress. Technology is embodied in intermediate goods traded across countries and potentially used by final producers in all countries. This is captured by the CES production function, which introduces a so-called love-for-variety effect: holding expenditures constant, using a wider range of varieties corresponds to increased productivity (Ethier 1982). The shock process a_{it} introduces an additional channel of technological progress, which I refer to as disembodied technology (Greenwood, Hercowitz, and Krusell 1997); it captures the unexplained component of productivity growth given $\bar{g}$ the steady state growth rate.

The final producer chooses x^i_{njt} to maximize his profit Π_{it},

$$\Pi_{it} = P_{it} Y_{it} - \sum_{n=1}^{I} \int_{j=0}^{A^i_{nt}} p^i_{njt} x^i_{njt} \, dj, \tag{6}$$

where P_{it} is the price index for the final good, which takes the CES form

$$P_{it} = \left(\sum_{n=i}^{I} \int_{j=0}^{A^i_{nt}} (b^i_{njt})^{\sigma} \left(p^i_{njt}\right)^{1-\sigma} dj \right) .^{\frac{1}{1-\sigma}} \tag{7}$$

This equality implies the following demand for variety nj:

$$x^i_{njt} = (b^i_{njt})^{\sigma} \left(\frac{p^i_{njt}}{P_{it}} \right)^{-\sigma} Y_{it}. \tag{8}$$

Total spending by country i on variety nj is then

$$p^i_{njt} x^i_{njt} = (b^i_{njt})^{\sigma} \left(\frac{p^i_{njt}}{P_{it}} \right)^{1-\sigma} P_{it} Y_{it}. \tag{9}$$

3.1.3 Households

In each country $n = 1, \dots, I$, a representative household consumes the final good, supplies labor inelastically, and saves. The household maximizes life-time expected utility

$$E_t \sum_{s=t}^{\infty} \beta^s \log(C_{ns}) \tag{10}$$

subject to the budget constraint

$$P_{nt} C_{nt} = \omega_{nt} L_{nt} + \Pi^T_{nt} + R_{nt} B_{nt} - B_{n,t+1}. \tag{11}$$

Here C_{nt} is consumption, $\beta \in (0,1)$ is the discount factor, ω_{nt} is the wage, Π^T_{nt} are the total profits of all firms in country n, B_{nt} is total loans the household extended at time $t-1$ and that are payable at time t, and R_{nt} is the risk-free rate. The household chooses consumption, labor supply, and loans to maximize (10) subject to (11).

3.2 Innovation and Adoption

In each time period's second stage, innovation and adoption of technologies determine the technology available in each country at time $t+1$. New technologies are introduced endogenously through an innovation process, and each new technology is then used to produce an intermediate good under monopolistic competition. Intermediate goods can immediately be sold to the domestic final producer. However, to sell the good in a foreign market, it has to be adapted first.

3.2.1 Innovation

In each country $n = 1, \dots, I$, a continuum of start-ups invest the final good to undertake R&D. Start-ups are ranked according to their efficiency: a start-up with productivity k introduces a new technology at the stochastic rate

$$\alpha_n^r \gamma_r T_{nt} Y_{nt}^{-\gamma_r} k^{\gamma_r - 1},$$

where $\alpha_n^r T_{nt}$ is R&D productivity and $\gamma_r \in (0,1)$ is a parameter of diminishing returns to R&D.[12] The fraction of total output invested in R&D, $\frac{y_{nt}^r}{Y_{nt}}$, measures research intensity in country n. If y_{nt}^r units of final output are invested in R&D, then the mass of newly introduced technologies is

$$E_t Z_{n,t+1} - Z_{nt} = \int_{k=0}^{y_{nt}^r} \alpha_n^r \gamma_r T_{nt} Y_{nt}^{\gamma_r} k^{\gamma_r - 1}\, dk = \alpha_n^r T_{nt} \left(\frac{y_{nt}^r}{Y_{nt}} \right)^{\gamma_r}, \tag{12}$$

There are two components of R&D productivity. First, a country-specific parameter α_n^r captures policies and institutions affecting the country's innovative environment (patent protection, education, etc.). Second, a spillover effect is determined by the total number of technologies available, $T_{nt} = Z_{nt} + \sum_{i \neq n} A_{it}^n$, where Z_{nt} is the stock of technologies introduced domestically through innovation in country i up to period t. That is, innovators "learn" from the available range of technologies, both domestic Z_{nt} (learning by doing) and foreign $\{A_{it}^n\}$ (learning by using imports). This assumption is consistent with the "variety in, variety out" model of Goldberg, Khandelwal, Pavcnik, and Topalova (2009) and has two implications: first, countries in which more varieties are available have a lower R&D cost; second, countries expanding the variety of their imports (growing $\{A_{nt}^i\}$) lower their R&D cost.[13]

Each start-up chooses how much final output to invest in R&D in order to maximize expected profits. Free entry determines the level of investment in R&D, which is given by the break-even condition

$$\alpha_n^r \gamma_r (\gamma_r - 1) T_{nt} Y_{nt}^{\gamma_r} k^{\gamma_r - 2} V_{nt} = P_{nt}, \tag{13}$$

[12] This functional form is similar to the innovation process in Eaton and Kortum (1996, 1999). The main difference is that innovators employ labor in their model whereas in my model they invest final output.

[13] As a consequence, countries may shift from being adopters to innovators, thereby increasing the number of goods that they produce and export. Acemoglu, Aghion, and Zilibotti (2002) considers this process a shift from an "investment-growth strategy" (adoption) to an "innovation-shift strategy" (innovation). That reasoning is also in line with the results of Hallward-Driemeier (2000), who in data from five Asian countries observes that—prior to entry into export markets—productivity gains are associated with higher imports.

where V_{nt} is the market price for an innovation (to be determined). The start-ups invest final output up to the point where marginal revenue is equal to marginal cost. Successful start-ups use the new technology to produce an intermediate good; that is, they join the pool of intermediate-good producers in period $t+1$.

3.2.2 Adoption

Each intermediate good that is produced with the new technology must be adopted before it can be used by the final producer. I assume that adoption is instantaneous and free within countries but slow and costly across countries. Thus, whereas a country's final producer can use all the domestic intermediate goods produced, using foreign intermediate goods involves an adoption process: an adopter in country i invests final output to adapt the product to that country's specifications. Out of Z_{nt} goods available in country n, $Z_{nt+1} - A^i_{nt}$ remain to be adopted by the final producer in country i. An adopter in country i invests a quantity h^i_{nt} of final output to adapt the $Z_{nt+1} - A^i_{nt}$ technologies, which are then adopted at the stochastic rate

$$\varepsilon^i_{nt} = \alpha^A_i \frac{A^i_{nt}}{Z_{n,t+1}} \left(\frac{h^i_{nt}}{Y_{it}}\right)^{\gamma_a}. \tag{14}$$

Here α^A_i is a country-specific parameter reflecting barriers to adoption of new technologies, as in Parente and Prescott (2002) (a higher value of this parameter implies lower barriers to adoption); and $\gamma_a \in (0,1)$ is the elasticity of adoption with respect to investment in adoption.[14] The number of newly adopted technologies is then given by

$$E_t A^i_{n,t+1} - A^i_{nt} = \varepsilon^i_{nt}(Z_{n,t+1} - A^i_{nt}). \tag{15}$$

This specification is similar to that in Nelson and Phelps (1966) and Benhabib and Spiegel (1994).

Equation (15) exhibits four main features. First, it has the same microfoundations as the innovation process, with diminishing returns to investment in adoption. Second, the cost of adoption is measured in terms of the importer's final output. So when the cost of adoption decreases, the demand for final output in the destination country increases, thereby increasing income; thus countries with decreasing adoption costs (increasing rate of adoption) see their income increase. Third, the cost of adoption resembles a fixed cost of penetrating a foreign market. Fourth, as the destination country starts to import goods, it becomes familiar with the exporter's products (increase in $\frac{A^i_{nt}}{Z_{n,t+1}}$), and so less

[14]Policies that affect this parameter include increasing investment in education, an improvement in telecommunications infrastructure that facilitates communication across countries, and trade policies. Eaton and Kortum (1996) and Benhabib and Spiegel (1994) analyze the dependence of the probability of adoption on different factors, including human capital; they find that human capital has a positive and significant impact on the likelihood of adoption.

final output is needed to start exporting the good. Interactions among the countries allow the importer to learn about the source and this leads, ceteris paribus, to an increase in the probability of adoption.[15]

Observe that the existence of a continuum of intermediate goods means that the probability of adoption ε_{nt}^{i} is also the fraction of technologies adopted.[16]

To gain a better understanding of the adoption process, I substitute equation (14) into equation (15) to find the growth rate of adopted technologies:

$$g_{A_{int}} = \frac{E_t(A_{nt+1}^{i} - A_{nt}^{i})}{A_{nt}^{i}} = \alpha_i^A \left(\frac{h_{nt}^{i}}{Y_{it}}\right)^{\gamma_a} L_{it} \left(1 - \frac{A_{nt}^{i}}{Z_{nt+1}}\right).$$

The growth rate in the number of goods that country i imports from country n at time t depends on four factors: (i) barriers to adoption, α_i^A; (ii) investment in adoption, h_{nt}^{i}; (iii) elasticity of adoption, γ_a; and (iv) relative backwardness, $1 - \frac{A_{nt}^{i}}{Z_{nt+1}}$. In countries that are farther from the exporter's technological frontier (lower $\frac{A_{nt}^{i}}{Z_{n,t+1}}$), an increase in the variety of imports has a greater impact on the growth in the variety of imports.[17] Two key assumptions in the adoption mechanism are nonstandard. First, investment in adoption is measured in terms of the importing country. Second, adoption measures the "ability" to import a new technology, which implies that adoption is irreversible. Adopters choose the amount of output to invest in adoption to maximize the expected profits from selling the good to the final producer in different countries (to be determined).

3.2.3 Value Functions

Domestic innovation and adoption of foreign innovations are both endogenous processes. Adopters and innovators decide how much final output to allocate to each activity based on the relative values of innovating and adopting a new technology.

The value W_{nt}^{i} of adopted technologies from country n by country i at time t is given by the present discounted value from selling that good:

$$W_{nt}^{i} = \pi_{nt}^{i} + \beta E_t W_{n,t+1}^{i}, \tag{16}$$

[15] A different way to model the process of adoption is to assume that investment in adoption pays off after a random time period. Higher investment in adoption results in a shorter expected waiting time for the next variety (Klette and Kortum (2004); Koren and Tenreyro (2007)).

[16] Cummins and Violante (2002) focus on the adjustment of productivity growth to technological innovations. They estimate that the gap between average productivity and the productivity of the best technology rose from 15% in 1975 to 40% in 2000. This finding is consistent with technology diffusion models that claim learning about new technologies can generate long implementation lags because resources are channeled into the process of adapting current production structures to accommodate the new technology.

[17] Empirically, countries that are expanding their range of imports rapidly are relatively backward countries that are also experiencing higher-than-average growth rates.

where π^i_{nt} denotes profits and $W^i_{n,t+1}$ the continuation value.

The value of technologies invented in country n at time t that have yet to be adopted by country i is

$$J^i_{nt} = \max_{Y^i_{nt}}\{-P_{it}h^i_{nt} + \beta E_t(\varepsilon^i_{nt}W^i_{n,t+1} + \beta(1-\varepsilon^i_{nt})J^i_{n,t+1})\}. \tag{17}$$

At time t, the adopter invests the quantity h^i_{nt} to adapt the technologies to the specifications of country i. At $t+1$, adoption is successful with probability ε^i_{nt} and the firm obtains the value of an adopted technology, $W^i_{n,t+1}$; with probability $1-\varepsilon^i_{nt}$, adoption is not successful and the firm obtains the continuation value $J^i_{n,t+1}$.

The value V_{nt} for an innovation in country n is the expected value of selling the good in each potential market:

$$V_{nt} = \sum_{i=1}^{I} J^i_{nt} \tag{18}$$

with $J^n_{nt} = W^n_{nt}$.

3.3 Trade Balance

The model is closed with the trade balance equation. I assume financial autarky, thereby trade is balanced every period. In other words, the total value of exports in one country must equal the total value of its imports:

$$\sum_{i=1}^{I}\int_{j=0}^{A^i_{nt}} p^i_{njt}x^i_{njt}\,dj = \sum_{n=1}^{I}\int_{j=0}^{A^n_{it}} p^n_{ijt}x^n_{ijt}\,dj. \tag{19}$$

3.4 Equilibrium

This section defines a symmetric equilibrium—namely, the equations in which all the firms within a country behave symmetrically. The countries themselves are asymmetric, however, and are defined by the parameters $\{\alpha^R_i, \alpha^A_i, L_i, d^i_n\}$.

For all i and n, a general symmetric equilibrium is defined as an exogenous stochastic sequence $\{a_{it}\}^\infty_{t=0}$, an initial vector $\{A^i_{n0}, Z_{i0}\}$, a set of parameters $\{\sigma, \gamma_a, \gamma_r, \rho\}$ that are common across countries, a set of parameters $\{\alpha^R_i, \alpha^A_i, L_i, d^i_n\}$ that differ across countries, a sequence of aggregate prices and wages $\{P_{it}, V_{it}, R_{it}, \omega_{it}\}^\infty_{t=0}$, a sequence of intermediate good prices $\{p^i_{nt}\}^\infty_{t=0}$, a sequence of aggregate quantities $\{Y_{it}, y^r_{it}, h^i_{nt}\}^\infty_{t=0}$, quantities of intermediate goods $\{x^i_{nt}, y_{nt}\}^\infty_{t=0}$, a sequence of value functions and profit $\{\pi^i_{nt}, W^i_{nt}, J^i_{nt}\}^\infty_{t=0}$, and laws of motion $\{A^i_{n,t+1}, Z_{i,t+1}\}^\infty_{t=0}$ such that:

- the state variables $\{A^i_{n,t+1}, Z_{i,t+1}\}_{t=0}^{\infty}$ satisfy the laws of motion in equations (15) and (22);

- the endogenous variables solve the producers' and households' problems in equations (24) – (30);

- feasibility is satisfied in equations (20) and (21); and

- prices are such that all markets clear.

Next, I present the set of equations needed to solve the model.

Resource Constraint

Final output is used for consumption, innovation, and adoption of foreign innovations:

$$Y_{it} = C_{it} + \sum_{n \neq i}^{I} (Z_{it} - A^n_{it}) h^n_{it} + (Z_{it} - Z_{it-1}) y^r_{it}. \tag{20}$$

Final Production

$$Y_{it} = e^{a_{it}} \left(\sum_{n=1}^{I} A^i_{nt} b^i_{nt} (x^i_{nt})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}. \tag{21}$$

Law of Motion for Innovation

$$E_t Z_{i,t+1} - Z_{it} = \alpha^r_i T_{it} \left(\frac{y^r_{it}}{Y_{it}} \right)^{\gamma_r}. \tag{22}$$

Law of Motion for Adoption

$$E_t A^i_{n,t+1} - A^i_{nt} = \varepsilon^i_{nt} (Z_{n,t+1} - A^i_{nt}). \tag{23}$$

Households

$$\frac{1}{\beta} \frac{C_{i,t+1}}{C_{it}} = \frac{P_{it}}{P_{i,t+1}} R_{i,t+1}. \tag{24}$$

Final Producers

$$x^i_{njt} = (b^i_{njt})^{\sigma} \left(\frac{p^i_{njt}}{P_{it}} \right)^{-\sigma} Y_{it}. \tag{25}$$

Intermediate Producers

In equilibrium, all the intermediate producers in a country behave symmetrically. They use the same amount of labor and supply the same amount of intermediate good to a given country i: $x^i_{njt} = x^i_{nt}$ for all j. Summing over all A^i_{nt} intermediate goods that country n exports to country i yields

$$\sum_{i=1}^{I} A^i_{nt} l^i_{nt} = L_n.$$

.

By symmetry, and as we can see from the expression

$$p^i_{nt} = \frac{\sigma}{\sigma-1}(\omega_{nt} d^i_n), \tag{26}$$

the price index and the profits are equal across intermediate producers; that is, $p^i_{njt} = p^i_{nt}$ for all j and $\pi^i_{njt} = \pi^i_{nt}$ for all j.

Investment in Innovation

Investments in innovation and adoption are chosen to maximize V_{it} and J^i_{nt}. Start-ups in country i invest in R&D up to the point where the marginal benefit equals the marginal cost. By equation (13), if Y^R_{it} units of final output are invested in R&D then

$$\int\limits_{k=0}^{Y_{r\,it}} \alpha^r_i \gamma_r T_{it} Y^{\gamma_r}_{it} k^{\gamma_r - 1} V_{it}\, dk = \gamma_r \alpha^r_i \left(\frac{y^r_{it}}{Y_{it}}\right)^{\gamma_r - 1} \frac{T_{it} V_{it}}{Y_{it}} = 1, \tag{27}$$

where

$$V_{it} = W^i_{it} + \sum_{n \neq i} J^n_{it}, \tag{28}$$

$$W^i_{nt} = \pi^i_{nt} + \beta E_t \frac{1}{1+g_{A_{int}}} W^i_{n,t+1},$$

$$J^i_{nt} = \left\{ -P_{it} Y^i_{nt} + \beta E_t \left(\varepsilon^i_{nt} \frac{1}{1+g_{A_{int}}} W^i_{n,t+1} + \beta(1-\varepsilon^i_{nt}) \frac{1}{1+g_{A_{int}}} J^i_{n,t+1} \right) \right\}. \tag{29}$$

Investment in Adoption

The adopter in country i uses final output to adapt technologies from country n until marginal benefit equals marginal cost:

$$\gamma_a \alpha^A_i \left(\frac{h^i_{nt}}{Y_{it}}\right)^{\gamma_a - 1} \frac{A^i_{nt}}{Z_{n,t+1}} \frac{W^i_{n,t+1} - J^i_{n,t+1}}{Y_{it}} = 1. \tag{30}$$

Observe that the marginal benefit of adoption increases with the productivity of adoption and also with the difference between the value of adopted and yet-to-be-adopted technologies (i.e., between W_{nt}^i and J_{nt}^i).

Trade Balance

$$\sum_{i=1}^{I} A_{nt}^i p_{nt}^i x_{nt}^i = \sum_{n=1}^{I} A_{it}^n p_{it}^n x_{it}^n. \tag{31}$$

Market-Clearing Conditions

$$\int_{j=0}^{Z_{nt}} l_{njt}\, dj = L_n, \tag{32}$$

$$y_{njt} = \sum_{i=1}^{I} x_{njt}^i. \tag{33}$$

4 The Steady State

The economy has a balanced growth path in which all countries grow at the same rate but differ in their income per capita. The common growth rate is guaranteed by international diffusion; in contrast, differences in income per capita are driven by the country-specific parameters $\{\alpha_i^r, \alpha_i^A, L_i, \{d_n^i\}_{n\neq i}\}$, which can be identified from the system's initial conditions. If instead the parameters are common across countries, then all countries reach the same steady state—both in levels and in growth rates—and differ only in their speeds of convergence.

In steady state, the endogenous variables grow at a constant rate. Therefore, by equation (20) and equations (22) and (23), the number of adopted technologies and of invented technologies (A_{nt}^i and Z_{nt}, respectively) grow at the same rate along the balanced growth path. By equation (14), the rate of adoption ε_{nt}^i is constant (this rate is obtained using the survival analysis techniques explained in Appendix D). From the resource constraint (20), it is evident that the quantity of output allocated to adoption and innovation grows at the rate of final output.

Solving for the steady state requires an algorithm to compute relative wages. Taking advantage of the recursive structure of the model, I proceed as follows. First, from the law of motion for newly adopted technologies and the prediction that the rate of adoption ε_{nt}^i is constant, the steady-state value of the fraction of technologies from country n that have been adopted by country i between t and $t+1$ can be obtained as $\frac{A_n^i}{Z_n(1+g_z)} = \frac{\varepsilon_n^i}{g_a+\varepsilon_n^i}$. We can use this equality to derive the ratio $\frac{A_n^i}{A_k^i}$ and an expression for $\frac{Z_n}{Z_k}$. We can approximate the ratio $\frac{Z_n}{Z_k}$ by the ratio of the number of varieties exported. Finally, the trade-balanced equation (31) is used to obtain relative wages.

5 Transition Dynamics

Differences in growth rates across countries arise in the transition and depend on differences in investment in innovation and adoption, which ultimately depend on differences in income per capita. For countries in early stages of development, adoption is cheaper than innovation and so more resources are invested in adopting foreign technologies; catching-up allows these countries to grow faster than average. As they start importing more goods, the productivity of R&D increases in response to the spillover effect, increasing the attractiveness of innovation; hence, they start allocating more resources to innovation. In short, countries located at different points on the transition path invest and adopt at different rates and therefore grow at different rates. Developed countries are mainly innovators, while developing countries are mainly adopters of foreign innovations.

The model is solved by log-linearizing around the steady state. The variables are stationarized so that they are constant in steady state. There are two trends in the model: the first is given by the growth rate of disembodied technology, which is exogenous; the second is endogenous and depends on the growth rate of newly developed technologies g_z. I use Dynare to solve and estimate the structural parameters.[18]

6 Empirical Strategy

Section 5 has described a fully specified structural stochastic model with interdependencies across countries. In this section, I fit the model to annual data on innovation, productivity, and imports, for the period 1995–2003. I then use the structural nature of the model to conduct a counterfactual analysis in order to understand the main mechanisms in the connections between growth and imports. The small sample size (only nine years of data) and the rich structure of the model require the use of non-classical estimation methods in order to obtain consistent estimates. I use Bayesian techniques to estimate the relevant parameters of the model, as described in Schorfheide (1999).[19]

6.1 Bayesian Estimation

Bayesian estimation is a mix between classical estimation and calibration. Relative to just using calibration, Bayesian estimation allows us to confront the model with the data in a statistical sense. Relative to classical estimation there are three advantages. First, Bayesian estimation has better properties when the sample size is relatively small (which is the case in this paper). Second, it allows us to estimate a fully specified model with fairly flexible stochastic processes. Correct estimates of these models and processes

[18] The set of log-linearized equations is available upon request.

[19] The Dynare program (see (Juillard 1996)) is used to solve and estimate the model. The code is available upon request.

enable a study of the system's transition dynamics that captures cross-country growth rates differences, as observed in the data. And third, classical inference might not provide consistent results in multi-country models with interdependencies, as argued by Canova and Ciccarelli (2009). They show that Bayesian methods are necessary to estimate multi-country VAR models with spillover effects across regions, especially when examining issues related to income convergence or evaluating the effects of regional policies. In those models GMM (generalized method of moments) estimators of QML (quasi-maximum likelihood) and minimum distance estimators, do not provide consistent results.[20]

Next, I describe briefly the main steps to follow when estimating a model with Bayesian techniques. First, we need to specify prior probability distributions for the parameters of interest. The priors are then combined with the likelihood density, which is confronted to the data in order to obtain the posterior distribution of these parameters. Second, the likelihood density is approximated by a kernel density function, using MCMC simulation methods. This method works if all the variables are observable in the data, but usually this is not the case in dynamic stochastic general equilibrium (DSGE) models generally (and in my model in particular) which involve unobservable variables—including, for example, the number of newly innovated technologies, the total amount of output invested in adoption and the shock processes. To establish the likelihood density in these cases, we must obtain a state-space representation of the model and apply the Kalman filter. In a final step, the Metropolis Hasting algorithm is used to derive the posterior distribution of the parameters.

6.2 Data and Priors

For tractability, I allocate the 37 countries to five regional groups with common characteristics (similar innovation intensity, extensive margins of trade, and productivity): the United States, Japan, European countries with R&D investment above the median, European countries with R&D investment below the median, and Asia.[21]

6.2.1 Data

The model is fitted to annual data for the period 1996–2005, because 1995 is the first year for which data at a high level of disaggregation are available for a large sample of countries.[22] The observable variables are the annual growth in imported varieties, output growth, and the fraction of workers employed in R&D. There are 135 observations corresponding to nine years, five regions, and three observable variables.

[20]Another good reference on the evolution of DSGE modelling and the need to use Bayesian estimation in these models can be found in Fernández-Villaverde (2010).

[21]See Appendix A for the countries grouped within each region.

[22]For the sample of countries studied in the analysis, there are only 8 years of very disaggregated trade data available.

Bilateral trade data are obtained from the UN COMTRADE database. I follow the HS-1996 classification, which lists goods at the 6-digit level of disaggregation, and restrict the analysis to intermediate products (see Appendix B). Output is measured as GDP per capita adjusted via purchasing power parity (PPP) to constant 2005 prices; the data are from the World Bank's World Development Indicators and this measure is adjusted to account for the extensive margin of trade (see Appendix C). Finally, the research intensity of a country is measured by the fraction of workers employed in R&D (again based on data are from the World Bank's World Development Indicators).

6.2.2 Shocks

To obtain invertibility in the likelihood function, the maximum likelihood approach requires as many shocks as there are observable variables. Given three series of observable variables, I introduce three series of shocks (one for each region): a neutral technology shock a_i in final production, an i.i.d. shock a^{α}_{it} to innovation productivity, and a measurement error in the growth rates of imported varieties.

The structural shocks and measurement errors incorporated in the estimation are:

$$a_{it} = \rho_i a_{i,t-1} + u_{it}$$

with $u_{it} \sim N(0, \sigma^2_{u,i})$;

$$\xi_{it} \sim N(0, \sigma^2_i);$$

and

$$g^{\text{obs}}_{it} = g_{it} e^{me_{it}}$$

with $me_{it} \sim N(0, \sigma^2_{me,i})$, where me denotes the measurement error and $i = 1, \ldots, 5$.

6.2.3 Parameters

A set of parameters is treated as fixed in the estimation (these are also known as strict priors or calibrated parameters). These parameters cannot be identified from the data. They are obtained from other studies or from steady-state relations, and they are reported in Table 1 and Table 2.

The "iceberg" transport cost, d^i_n, varies across pairs of countries and is proportional to distance. This parameter's value is chosen to match the intensive margin of trade.

The steady-sate growth rate of domestic and foreign technologies is the same and common across countries. Following Eaton and Kortum (1996), I use the Frobenious theorem and the steady-state relation for the growth of new technologies derived in Appendix E to obtain a value of 0.012 for this parameter. If we assume a steady-state growth rate of

0.02 for the regions in the analysis, as it is standard in the empirical literature, the results on the growth rate of new technologies imply that 60% of the growth rate in steady-state is accounted for by embodied technology; the remaining 40% is explained by a residual or disembodied technology (thus, $\bar{g} = 0.08$), which is uncorrelated with the mechanisms of the model (education, the organization and structure of the market, etc, are potential candidates).[23]

The productivity of the innovation process, α_i^R, is set to satisfy equation (12) using the data on R&D intensity, the number of exports as a proxy for the number of newly produced technologies, and the number of imports as a measure of the spillovers from foreign technologies. The results show that Asia and less innovative Europe have the lowest productivity of innovation (0.0086 and 0.0186, respectively) whereas more innovative Europe, the United States, and Japan have highest R&D productivity (0.0237, 0.0288, and 0.0368, respectively).

The rate of adoption, α_i^A, is obtained using the survival techniques explained in Appendix D; the values are listed in Table 1. For the average country, it takes three and a half years to start importing a good that has been developed elsewhere. Asia and Europe take, on average, more than four years to start importing a good, whereas Japan and the United States take between two and three years. Other studies that have quantified the speed of adoption are Eaton and Kortum (1999) and Comin and Hobijn (2004). The former study uses international patent data to measure international diffusion; the latter uses direct measures of technology for many countries and a long time period. To my knowledge, this paper is the first to estimate hazard rates of adoption using trade data.

The parameters to be estimated are the elasticity of substitution across intermediate goods, σ; the elasticity of adoption, γ_a; the extent of diminishing returns in the innovation process, γ_r; and the standard deviations, σ_i, of the neutral technology shock and innovation productivity shocks. The Bayesian approach has the benefit of adding some weight on the priors of the researchers and some weight on the data over the sample period. By changing the standard deviation of the distribution on the priors, a measure of tightness, we can change the relative weights on the priors and the data in determining the posterior distribution for the parameters. In the limit, a diffuse or non-informative distribution puts more weight on the data. The prior mean and standard deviation are reported in Table 3 for the structural parameters and in Table 4 for the shock processes.

I assume a Gamma distribution for the elasticity of substitution across intermediate goods, with mean 3 and standard deviation 0.15. Estimates of this parameter in the trade and industrial organization literature typically range from 3 to 10, and it differs across goods, as shown by Broda, Greenfield, and Weinstein (2008) who report lower

[23] These results are in line with what Greenwood, Hercowitz, and Krusell (1997) found for the United States. Although the Greenwood, Hercowitz, and Krusell (1997) analysis is for the United States, we can assume the same value for all the regions because technology diffusion guarantees that, in steady state, embodied productivity growth is the same across countries.

elasticities for more differentiated goods. Therefore, to use a single value for σ amounts to a simplifying assumption. The prior for α_i^A, the cost of adoption in each region, is distributed Gamma with mean 2 and standard deviation 0.15. The mean is set to match the hazard rates in Table 1, which determine the rate of adoption. The prior for γ_r, the diminishing returns in the innovation process, is set to a Beta distribution with mean 0.1 and standard deviation 0.15.[24] The elasticity of adoption with respect to effort, γ_a, is assumed to follow a Beta distribution with mean 0.4 and standard deviation 0.05.[25] Finally, I assume an Inverse Gamma distribution for the standard deviation of the shocks, which guarantees a positive variance.

6.3 Estimation Results

Tables 3 and 4 report the estimation results. They contain the prior and posterior mean of the estimated parameters as well as 95% confidence intervals.

The posterior mean for the elasticity of substitution σ across intermediate goods is 3.5. Broda, Greenfield, and Weinstein (2008)'s estimate is 3.4 for a sample of 73 countries. The value I obtain lies between those obtained in microeconomic and in macroeconomic studies.

The posterior mean for the elasticity of innovation γ_r is 0.8; this is close to the estimates of Comin and Gertler (2006) and Griliches (1990), which range between 0.8 and 0.9. Eaton and Kortum (1999) find a much lower value (about 0.02) when using labor as the input to the innovation function. Finally, the posterior mean for the elasticity of adoption γ_a is 0.35, half of what Comin and Gertler (2006) obtain for a closed economy. This is expected, since adoption is slower across countries than within a country.

Next, Table 5 compares the standard deviation of several variables in our model and with that in the data. Using the estimated parameters and standard deviations of the shocks, I run 1,000 draws from the shocks in the model and then compute the standard deviation of the simulated variables. Overall, the results are in line with the data.

I then compute correlations between growth in imports and real GDP per capita growth, between R&D intensity and real GDP per capita growth, and between R&D intensity and growth in imports (Table 6). As in the data, R&D and trade are negatively correlated across countries; the same is true for R&D and productivity growth. Countries

[24] Eaton and Kortum (1999) find a value of about 0.2 for this parameter; Griliches (1990), using the number of new patents as a proxy for technological change, obtains estimates ranging from 0.5 to 1.

[25] This parameter has been calibrated by Comin and Gertler (2006) and also by Comin, Gertler, and Santacreu (2009); they find that a reasonable value in a closed-economy model is 0.8. Because there are no good measures of adoption expenditures or adoption rates, they use as a partial measure the development costs incurred by manufacturing firms to make the goods usable (this is a subset of R&D expenditures) and then regress the rate of decline of the relative price of capital with respect to the partial measure of adoption costs. The idea is that the price of capital moves countercyclically with the number of new adopted technologies and is thus a measure of embodied adoption. The regression yields a constant of 0.8.

that invest less in R&D typically diversify their imports and grow at higher rates. The model also captures the positive correlation between growth in imports and GDP per capita, since countries that have diversified their imports are also growing faster. This model captures the signs of the relations as well as their magnitude. In the data, the correlation between growth and trade is 0.54 while the model predicts 0.57. For R&D–trade and R&D–growth correlations, respectively, the empirical values are -0.26 and -0.15 while the model's predictions are -0.21 and -0.16.

6.4 Speed of Convergence

The model has predictions for the speed of convergence that are consistent with the findings of the empirical growth literature. Note however that this literature relies on reduced form models. Hence, my model of endogenous innovation and adoption adds structure to the traditional analysis while remaining consistent with their main predictions.

In particular, I study how long it would take each region to reach levels of US income per capita. For this, I use the estimated value of the structural parameters and the standard deviation of the shocks to simulate the model for 1,000 periods.

The last three columns of Table 10 summarize the model implications for convergence. In the data, Asia's income per capita in 1996 was 25% of that in the United States. Japan is at the other extreme, with 80%. Europe lies in between: less innovative Europe is closer to Asia while more innovative Europe is closer to Japan.

Columns 4 and 5 show each region's distance to the technological frontier once they are halfway to the new steady state. Asia would improve its position by 68%, reaching a 42% income per capita of that in the United States, and this would take 40 years. Japan, which is closer to the United States, would take only 15 years but improves by 22%. Countries that lag behind (Asia and less innovative Europe) take longer to close the gap, but their percentage improvement is greater. As the convergence theory predicts, the gap narrows more slowly when it is close to the steady state.

Figure 4 displays the evolution of relative income per capita in Asia, Europe (less and more innovative), and Japan with respect to the United States. The initial period is 1996, when the relative income per capita with respect to the United States was 25% in Asia, 37% in less innovative Europe, 75% in more innovative Europe, and 80% in Japan. The figure shows that convergence to the steady state is faster at early stages but slows down when approaching the steady state, as the empirical growth literature estimates.

Note that the technological frontier is always moving forward because of global innovation. In steady state, countries close the gap with the frontier but there is no (complete) catching-up in their levels of income per capita. These results can be explained by differences in policies and institutions, which are captured by the country-specific parameters (Klenow and Rodriguez-Clare (2005)).

7 Decomposition of Productivity Growth

In this section I compute the contribution of domestic and foreign innovation to productivity growth in each region, as predicted by the model, and compare the results with the available data.

7.1 Embodied versus Disembodied Productivity

In the model, economic growth is decomposed into: (i) embodied growth, captured by an expansion in the number of intermediate goods (through innovation and international diffusion); and (ii) disembodied growth, captured by an exogenous TFP shock.[26] Taking the estimated series of the TFP shock together with data on output growth from the empirical analysis, I compute the contribution of each source of growth (Table 7).

Embodied growth has contributed about 78% of the productivity growth in Asia and less innovative Europe, and about 67% of such growth in the United States, Japan, and more innovative Europe. That is, the main mechanisms of the model (innovation and international diffusion) are able to capture, on average, three-fourths of economic growth in the regions of analysis. The remaining one-fourth cannot be explained by the mechanisms of the model.

7.2 Contribution of Domestic and Foreign Innovation to Growth

Table 8 reports the contribution of domestic and foreign innovation to embodied productivity growth. Each entry in the matrix represents the percentage of the embodied productivity growth in the importer country (row) that is explained by innovations of the exporter country (column), averaged over 1996–2005. The diagonal entries measure the contribution of domestic innovation.

The analysis shows that, in Asia and less innovative Europe, more than 75% of total growth can be explained by foreign innovations embodied in imports, especially those from the United States, Japan, and more innovative Europe.[27] In the most innovative regions, 20–30% of embodied productivity stems from domestic innovation. These results are consistent with the empirical evidence: Asia does relatively little innovation but has experienced a rapid increase in imported varieties—especially from the United States and Japan, which are the most innovative regions. By expanding the range of imported varieties from more innovative countries, Asia and less innovative Europe accumulate the technology embodied in the foreign varieties and grow more than average.

[26] We can interpret the TFP shock as capturing all sources of growth not explained by love–for–variety. In that sense, this section is an empirical test of love-for-variety models.

[27] Foreign innovations explain 96% of embodied productivity growth in Asia, and embodied growth constitutes 78% of its total productivity growth. Therefore, 75% of total growth in Asia stems from foreign innovations.

The results off the diagonal in Table 8 can be further decomposed to obtain the contribution of each exporter; Table 9 reports the results. About two thirds of the contribution of foreign sources of innovation in Europe and Asia come from Japan and the United States. Asia and less innovative Europe's innovations contribute less than 10% to embodied productivity growth in the other regions.

The results reported in Tables 8 and 9 use research intensity as a measure of innovation. In Table 10 I conduct the same decomposition, but use the number of exported varieties instead. Table 10 reports, for each importer (row), the share of exports stemming from each exporter (column). The results are similar to those reported in Tables 8 and 9. In Asia, 4% of total imports in varieties comes from less innovative countries in Europe. The United States and Japan together account more than half the imported varieties in each region; Asia and less innovative European countries contribute the least. The results in Tables 9 and 10 are consistent with R&D being embodied in exports, since the main exporters are the main innovators and since both foreign innovation and exports from these countries have the more impact (than do domestic varieties) on the embodied growth of developing countries.

8 Counterfactuals

Finally, I perform three counterfactual exercises. I analyze the effect on world growth rates, research intensity, and income per capita in steady state of: (1) a 25% increase in research productivity, first in the United States and then in Asia; (2) a change in the speed of adoption between Asia and the United States; and (3) an increase in international trade costs between Asia and the United States.

8.1 Increase in Research Productivity

First, I consider a 25% increase in the productivity of research in the United States, $\alpha^R(\text{US})$, and analyze its impact on research intensity in Asia and the United States, the world growth rate, and the relative income per capita of Asia with respect to the United States.

In the new steady state, research intensity in the United States is 1.4% higher. Indeed, an increase in research productivity increases the value of innovation, and more output is invested in research. In Asia, however, research intensity decreases. Higher research productivity in the United States crowds out innovation in its trading partners through a reallocation of resources from innovation to adoption. This is especially true of countries at early stages of development, when the cost of technological adoption is higher than that of innovation. The world growth rate increases by 4% and the relative income per capita of Asia with respect to the United States is 4% higher.

Second, I consider a 25% increase in the productivity of research in Asia, α^R(Asia), and analyze its impact on the same variables.

In the new steady state, research intensity in Asia is 52% higher. In the United States, however, research intensity decreases by 6%. As before, innovation in Asia crowds out innovation in its trading partners. Asian investment in adoption decreases by 52% as resources are reallocated to innovation. Since the United States is Asia's main source of foreign innovation, lower adoption in Asia decreases the value of innovation—and therefore research intensity—in the United States. The 52% increase in research intensity in Asia barely affects the world growth rate, which increases by a mere 0.05%. The relative income per capita of Asia with respect to the United States is 0.55% higher.

This counterfactual analysis shows that increasing innovation in countries closer to the technological frontier, such as the United States, substantially boosts the world growth rate and the speed of convergence to the technological frontier. Developing countries do not contribute substantially to world growth through innovation. Instead, as the next counterfactual shows, a reallocation of resources from innovation to adoption in Asia may be more effective in increasing the world growth rate and accelerating convergence.

8.2 Changes in Asia's Adoption Rate

First, I consider an increase in Asia's adoption rates to US levels. In particular, I set the hazard rates in Table 1 when Asia is the importer to the value when the United States is the importer. Faster adoption increases research intensity in both regions. In the United States, the value of innovation increases in response to increased demand from Asia. In Asia, output rises because of an increase in foreign innovation, which increases the value both of adoption and of innovation; the result is a 6% higher research intensity. Faster adoption speeds up convergence, and Asia reaches a 4% higher (relative to the United States) income per capita. The world growth rate is 7% higher. In countries at early stages of development, faster adoption is more effective than higher innovation at boosting the world growth rate.

Second, I consider a reduction to zero in Asia's rate of adopting US innovations. In the new steady state, research intensity in Asia and the United States is 40% lower, the world growth rate declines 13%, and income per capita in Asia and the United States diverges by 2%.

8.3 Increase in Asia–US Trade Costs

I consider an increase (by 1% and 50%) in Asia–US trade costs (d; see Table 2) and analyze its impact on research intensity and income per capita in the two countries and also on the world growth rate. Overall, research intensity, the world growth rate, and convergence all decrease.

A 1% increase in trade costs reduces research intensity by 8%, resulting in a 15% lower world growth rate. If the trade costs increase to a nearly prohibitive 50%, then research intensity declines by 60% and the world growth rate by 23%. In both cases, Asia's income per capita diverges from US levels.

These results differ from those of Atkeson and Burstein (2007), who report that if all firms in a country export with equal intensity (as in my model), then changes in international trade costs have no steady-state impact on the firm's investment in process innovation.

9 Conclusion

In this paper I develop a dynamic general equilibrium model in which imports and growth are connected by technological innovations and their international diffusion through trade. The engine of growth is growth in productivity, which is itself driven by technology accumulation. I analyze both the model's steady state and its transition dynamics. In steady state, all countries grow at the same rate, but barriers to technology adoption induce persistent income differences. Countries grow at different rates during the transition. I find that innovation and adoption through imports affect a country's productivity growth differently as a function of its position on the transition path. Countries at early stages of development, farther from the technological frontier, grow by adopting the new foreign technologies embedded in the intermediate goods they import. Countries at later stages of development, and close to the technological frontier, instead grow by developing new technologies through R&D.

The analysis has abstracted from a number of interesting issues. For example, the welfare effects of innovation subsidies and the welfare gains—both static and dynamic—of trade costs have important policy implications. These issues are left for future research.

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10 Tables and Graphs

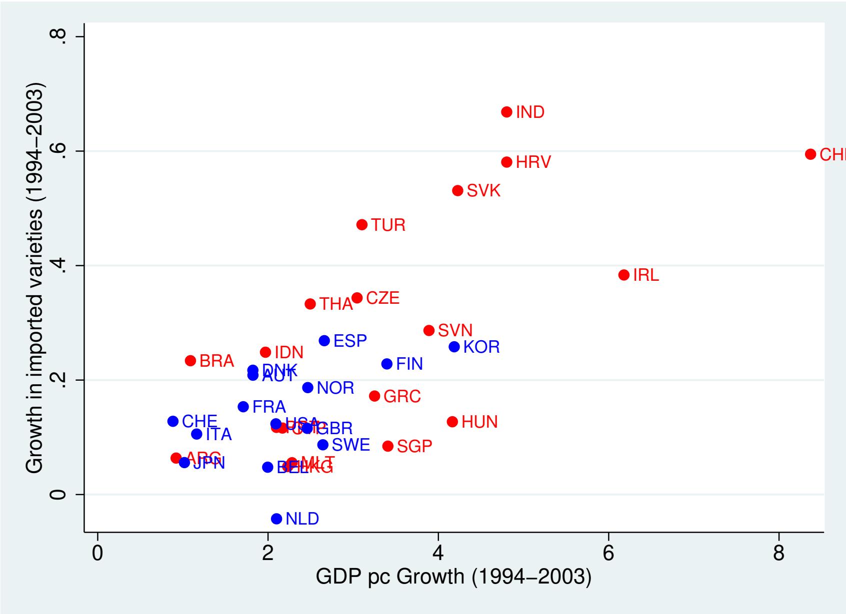

Figure 1: GDP per capita growth and growth in imported varieties (1994–2003)

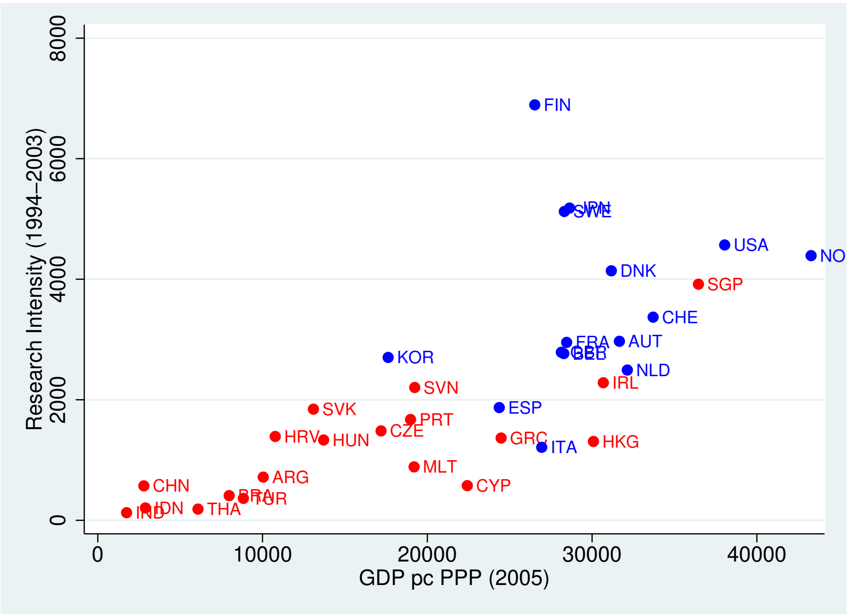

Figure 2: R&D intensity and GDP per capita (1994–2003)

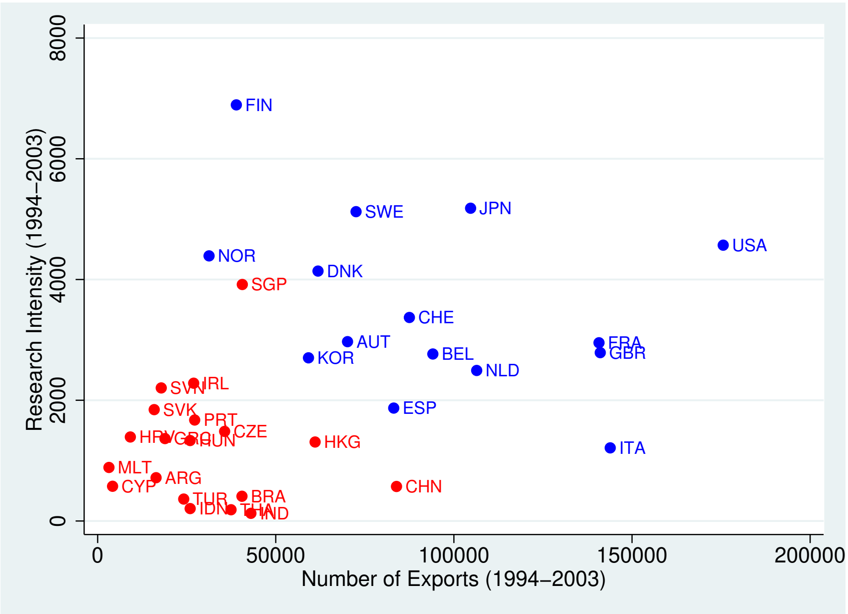

Figure 3: Number of exported goods and R&D intensity (1994–2003)

Table 1: Hazard rates of adoption (ε_{in})

Exporter	Importer	Hazard rate
Europe+	Asia	0.20
Europe−	Asia	0.15
Japan	Asia	0.47
U.S.	Asia	0.31
Asia	Europe+	0.20
Europe−	Europe+	0.27
Japan	Europe+	0.25
US	Europe+	0.25
Asia	Europe−	0.12
Europe+	Europe−	0.26
Japan	Europe−	0.14
US	Europe−	0.22
Asia	Japan	0.81
Europe+	Japan	0.38
Europe−	Japan	0.16
US	Japan	0.25
Asia	US	0.26
Europe+	US	0.75
Europe−	US	0.77
Japan	US	0.20

Key: Europe+ = more innovative Europe; Europe− = less innovative Europe

Table 2: Calibrated parameters

Parameter	Value	Description
β	0.90	Discount factor
$d(\text{Asia}, \text{Europe}-)$	1.30	Iceberg transport costs
$d(\text{Asia}, \text{Europe}+)$	1.30	Iceberg transport costs
$d(\text{Asia}, \text{Japan})$	1.10	Iceberg transport costs
$d(\text{Asia}, \text{US})$	1.30	Iceberg transport costs
$d(\text{Europe}-, \text{Europe}+)$	1.05	Iceberg transport costs
$d(\text{Europe}-, \text{Japan})$	1.40	Iceberg transport costs
$d(\text{Europe}-, \text{US})$	1.30	Iceberg transport costs
$d(\text{Europe}+, \text{Japan})$	1.40	Iceberg transport costs
$d(\text{Europe}+, \text{US})$	1.30	Iceberg transport costs
$d(\text{Japan}, \text{US})$	1.30	Iceberg transport costs
$\bar{g}$	0.02	Disembodied growth in steady state
$\alpha^R(\text{Asia})$	0.0082	Innovation productivity
$\alpha^R(\text{Europe}-)$	0.0186	Innovation productivity
$\alpha^R(\text{Europe}+)$	0.0237	Innovation productivity
$\alpha^R(\text{Japan})$	0.0288	Innovation productivity
$\alpha^R(\text{US})$	0.0368	Innovation productivity

Table 3: Prior and posterior for the structural parameters

Parameter	Prior	Mean	5%	95%
σ	Gamma(3, 0.15)	3.50	3.10	3.74
γ_a	Beta(0.3, 0.15)	0.33	0.10	0.54
γ_r	Beta(0.5, 0.15)	0.82	0.75	0.89

Note: The values in parentheses correspond to the mean and the standard deviation.

Table 4: Prior and posterior for the shock processes

Parameter	Prior	Mean	5%	95%
σ(Asia)	IGamma(0.05,∞)	0.14	0.09	0.20
σ(Europe-)	IGamma(0.05,∞)	0.09	0.05	0.12
σ(Europe+)	IGamma(0.05,∞)	0.13	0.06	0.19
σ(Japan)	IGamma(0.05,∞)	0.08	0.05	0.11
σ(U.S.)	IGamma(0.05,∞)	0.07	0.03	0.11
σ^r(Asia)	IGamma(0.05,∞)	0.06	0.03	0.09
σ^r(Europe-)	IGamma(0.05,∞)	0.05	0.03	0.08
σ^r(Europe+)	IGamma(0.05,∞)	0.09	0.05	0.14
σ^r(Japan)	IGamma(0.05,∞)	0.05	0.03	0.07
σ^r(U.S.)	IGamma(0.05,∞)	0.04	0.03	0.06
me(Asia)	IGamma(0.05,∞)	0.04	0.03	0.06
me(Europe-)	IGamma(0.05,∞)	0.02	0.01	0.02
me(Europe+)	IGamma(0.05,∞)	0.04	0.02	0.06
me(Japan)	IGamma(0.05,∞)	0.03	0.02	0.05
me(U.S.)	IGamma(0.05,∞)	0.03	0.02	0.04

Notes: IGamma = Inverse Gamma. The values in parentheses correspond to the mean and the standard deviation.

Table 5: Comparison of unconditional moments—model versus data

Variable	Model	Data
$g_{\text{R\&D}}$(Asia)	0.0283	0.0330
$g_{\text{R\&D}}$(Europe$-$)	0.0262	0.0227
$g_{\text{R\&D}}$(Europe+)	0.0681	0.0915
$g_{\text{R\&D}}$(Japan)	0.0253	0.0225
$g_{\text{R\&D}}$(US)	0.0489	0.0345
g_y(Asia)	0.0185	0.0168
g_y(Europe$-$)	0.0160	0.0104
g_y(Europe+)	0.0063	0.0112
g_y(Japan)	0.0270	0.0230
g_y(US)	0.0223	0.0125
g_{imports}(Asia)	0.0342	0.0424
g_{imports}(Europe$-$)	0.0072	0.0079
g_{imports}(Europe+)	0.0114	0.0078
g_{imports}(Japan)	0.0183	0.0219
g_{imports}(US)	0.0167	0.0215

Table 6: Comparison of unconditional moments—model versus data

Correlation	Model	Data
(R&D, Trade)	-0.21	-0.26
(Growth, Trade)	0.57	0.54
(Growth, R&D)	-0.16	-0.15

Table 7: Embodied versus disembodied productivity growth in the transition (percentage)

Region	Embodied	Disembodied
Asia	78	22
Europe−	77	23
Europe+	81	19
Japan	70	30
United States	70	30

Table 8: Sources of growth predicted by the model—domestic and foreign innovation

	Source Country				
Destination	Asia	Europe−	Europe+	Japan	US
Asia	4.0	7.8	15.8	21.3	29.1
Europe−	4.7	7.5	17.0	19.9	27.8
Europe+	4.3	8.0	19.6	21.1	28.0
Japan	3.3	7.7	16.0	19.9	29.1
US	4.2	6.8	21.2	20.3	26.5

Table 9: Foreign sources of growth—bilateral contribution predicted by the model

	Source Country				
Destination	Asia	Europe−	Europe+	Japan	US
Asia		10.6	21.3	28.8	39.3
Europe−	6.8		24.5	28.6	40.1
Europe+	7.1	13.0		34.4	45.6
Japan	5.8	13.8	28.5		51.9
US	8.0	13.0	40.3	38.6	

Table 10: Foreign sources of growth—bilateral contribution in the data

	Source Country				
Destination	Asia	Europe−	Europe+	Japan	US
Asia		4.1	19.2	36.3	40.4
Europe−	9.3		37.1	15.9	37.6
Europe+	14.3	15.5		22.9	47.4
Japan	20.0	5.4	22.6		51.9
US	20.9	10.9	31.1	37.1	

Table 11: Speed of convergence

Region	Years to convergence	Relative pc income (1996)	Improvement	Relative pc income (SS)
Asia	40	25%	68%	42%
Europe−	30	37%	62%	67%
Europe+	20	70%	28%	90%
Japan	15	80%	22%	98%
US	Baseline	Baseline	Baseline	Baseline

Key: pc = per capita; SS = steady state.

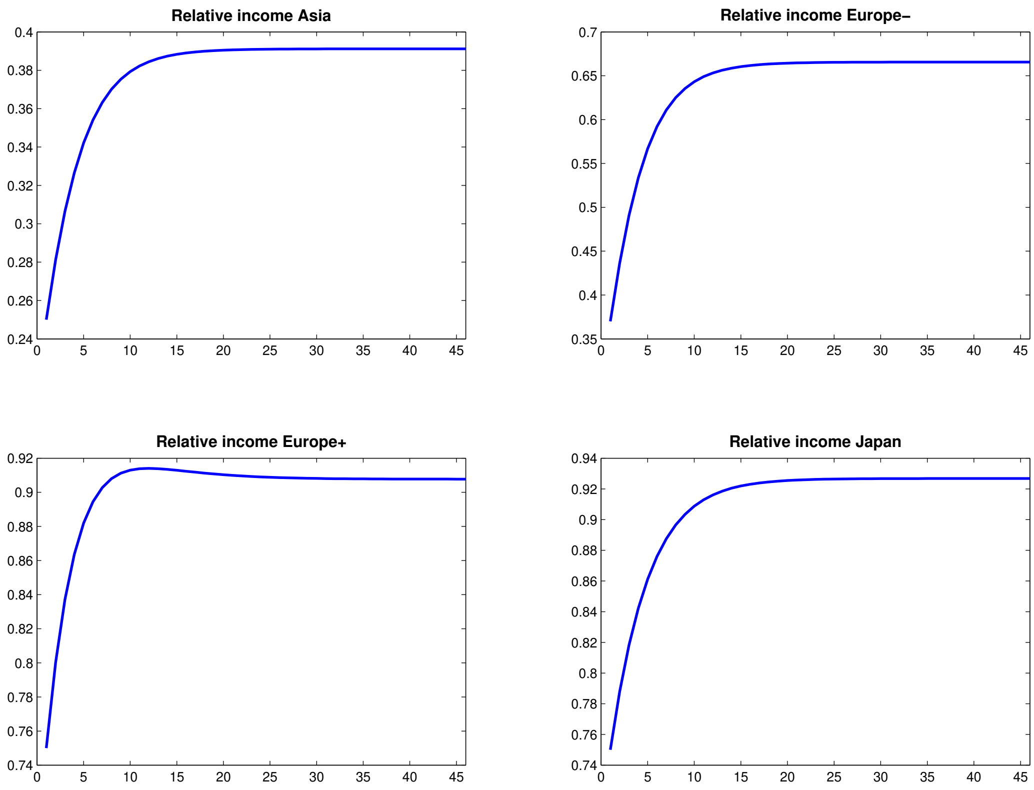

Figure 4: Speed of convergence

Table 12: Increase in US research productivity (25% increase)

Variable	% change
$\Delta r(\text{Asia})$	-3.5%
$\Delta r(\text{US})$	1.4%
Δg^*	3.7%
$\Delta \frac{Y(\text{Asia})}{Y(\text{US})}$	70%

Table 13: Increase in Asian research productivity (25% increase)

Variable	% change
$\Delta r(\text{Asia})$	52%
$\Delta r(\text{US})$	-6%
g^*	0.05%
$\frac{Y(\text{Asia})}{Y(\text{US})}$	40%

Table 14: If Asia adopts at the speed of the United States

Variable	Change
$\Delta r(\text{Asia})$	6.2%
$\Delta r(\text{US})$	0.7%
Δg^*	7.3%
$\Delta \frac{Y(\text{Asia})}{Y(\text{US})}$	3.8%

Table 15: If zero rate of adoption in Asia from the United States

Variable	Change
$\Delta r(\text{Asia})$	-40%
$\Delta r(\text{US})$	-49%
Δg^*	-13%
$\Delta \frac{Y(\text{Asia})}{Y(\text{US})}$	-3%

Table 16: Increase in trade costs between Asia and the United States

Variable	Change ($\tau = 1\%$)	Change ($\tau = 50\%$)
$\Delta r(\text{Asia})$	-7.3%	-58%
$\Delta r(\text{US})$	-8.9%	-56%
Δg^*	-15%	-23%
$\Delta \frac{Y(\text{Asia})}{Y(\text{US})}$	-2%	-44%

A Country List

Table 17: Country List

Region	Country Code	Country Name
Africa	SAU	Saudi Arabia
Asia	CHN	China
Asia	HKG	China, Hong Kong SAR
Asia	IDN	Indonesia
Asia	IND	India
Asia	SGP	Singapore
Asia	THA	Thailand
Less innovative Europe	CYP	Cyprus
Less innovative Europe	CZE	Czech Republic
Less innovative Europe	GRC	Greece
Less innovative Europe	HRV	Croatia
Less innovative Europe	HUN	Hungary
Less innovative Europe	IRL	Ireland
Less innovative Europe	LTU	Lithuania
Less innovative Europe	LVA	Latvia
Less innovative Europe	MLT	Malta
Less innovative Europe	POL	Poland
Less innovative Europe	PRT	Portugal
Less innovative Europe	SVK	Slovakia
Less innovative Europe	SVN	Slovenia
Less innovative Europe	TUR	Turkey
Japan	JPN	Japan
Japan	KOR	Korea
LatinAmerica	ARG	Argentina
LatinAmerica	BRA	Brazil
United States	US	United States
More innovative Europe	AUT	Austria
More innovative Europe	BEL	Belgium
More innovative Europe	CHE	Switzerland
More innovative Europe	DEU	Germany
More innovative Europe	DNK	Denmark
More innovative Europe	ESP	Spain
More innovative Europe	FIN	Finland
More innovative Europe	FRA	France
More innovative Europe	GBR	United Kingdom
More innovative Europe	ISL	Iceland
More innovative Europe	ITA	Italy
More innovative Europe	NLD	Netherlands
More innovative Europe	NOR	Norway
More innovative Europe	SWE	Sweden

B Product Classification

The codes are stipulated by the UN's Broad Economic Categories (BEC) classification, which groups external trade data in terms of the three basic classes of goods in the System of National Accounts (SNA).

1. Capital goods
Sum of categories:
41* Capital goods (except transport equipment)
521* Transport equipment, industrial
2. Intermediate goods
Sum of categories:
111* Food and beverages, primary, mainly for industry
121* Food and beverages, processed, mainly for industry
21* Industrial supplies not elsewhere specified, primary
22* Industrial supplies not elsewhere specified, processed
31* Fuels and lubricants, primary
322* Fuels and lubricants, processed (other than motor spirits)
42* Parts and accessories of capital goods (except transport equipment)
53* Parts and accessories of transport equipment
3. Consumption goods
Sum of categories:
112* Food and beverages, primary, mainly for household consumption
122* Food and beverages, processed, mainly for household consumption
522* Transport equipment, non-industrial
61* Consumer goods not elsewhere specified, durable
62* Consumer goods not elsewhere specified, semidurable
63* Consumer goods not elsewhere specified, nondurable

C Measuring Real GDP

The measure of real GDP used in the empirical analysis was computed while accounting for (i) the effect of differences in the terms of trade across countries and (ii) the extensive margin of trade in the price of imported intermediate goods.

As recently argued by Feenstra, Heston, Timmer, and Deng (2009), the World Development Indicators and Penn World Table (PWT) measure of real GDP represents the ability of a representative agent in the country's economy to purchase goods and services. However, that interpretation of real GDP differs from the one used in growth analysis, where GDP per capita is a measure of productivity. To compute real GDP from the output side, Feenstra, Heston, Timmer, and Deng (2009) correct the PWT measure for differences in the terms of trade across countries. This difference reflects the trading opportunities that countries have (as measured by their ratio of export prices to import prices), and it is shown empirically that the differences can be substantial—especially for small open economies.

To make the measure of real GDP growth from the output side comparable to the real GDP used in my model, an adjustment must be made for the extensive margin of imports. Toward this end, I use the procedure followed in Broda, Greenfield, and Weinstein (2008). The difference between the adjusted and unadjusted calculations gives a measure of the impact of product variety in trade on productivity, or of the gains from trade due to product variety.

D Hazard Rates of Adoption

I use the tools of survival analysis (a.k.a. duration analysis) with censored data. I estimate a nonparametric survival function (using the Kaplan–Meier estimator with right-censored data). Ideally we would know the time at which each good is invented by the exporter and the time at which it is first imported by each destination, but there are several limitations in the data. First, I do not observe the time of invention; instead, I assume that this is given by the first time a source starts exporting a good to any country.

Second, there is left and right censoring in the data. There is left censoring because we do not know whether products exported in 1994 were invented in that year or earlier; there is right censoring because some importers had not adopted, before 2003, all the goods that had been exported. It is easy to fix the problem of right censoring, but left-censored data is more problematic (though it is straightforward to handle if we assume that the hazard rate does not vary with duration). The standard way to deal with left censoring is to drop the spells that started before the window of observation.

E Steady-State growth rate

From the expression $T_{it} = Z_{it} + \sum_{n=1}^{M} A_{nt}^{i}$, the growth rate of intermediate goods in steady state can be obtained as follows,

$$g_i = \frac{\Delta T_i}{T_i} = \frac{\Delta Z_i}{T_i} + \sum_{n=1}^{M} \frac{\Delta A_n^i}{T_i} \tag{34}$$

Substituting equations (12) and (15) into equation (34), productivity growth in steady state can be expressed as a function of the amount of research that has been done around the world:

$$g = g_i = \alpha_i r_i^{\gamma_r} + \sum_{n=1}^{M} \varepsilon_n^i \sum_{s=1}^{t} (1-\varepsilon_n^i)^{-(t-s)} \alpha_{ns} r_{ns}^{\gamma_r} \frac{T_{ns}}{T_{it}} \tag{35}$$

where $r_n = \frac{y_n^r}{y_n}$.

Since $T_{ns} = T_{nt}(1+g)^{(t-s)}$ and $r_{ns} = r_n \forall s$ in steady state, and taking into account that instantaneous diffusion within the country implies that $\varepsilon_{ii} = 1$, we can rewrite equation (34) as

$$g = \sum_{n=1}^{M} \varepsilon_{in} \alpha_n r_n^{\gamma_r} \sum_{s=1}^{M} \left(\frac{(1-\varepsilon_n^i)}{(1+g)} \right)^{-(t-s)} = \sum_{n=1}^{M} \varepsilon_n^i \alpha_n r_n^{\gamma_r} \frac{(1+g)}{g+\varepsilon_n^i} \frac{T_{nt}}{T_{it}} \tag{36}$$

With positive values for γ_r, α_n, ε_{in} and r_n, the Frobenious Theorem guarantees that we can obtain a value for the growth rate g and relative productivity $\frac{T_i}{T_n}$.

It is important to note that, if there were no sources of heterogeneity in the country, that is, if $\alpha_i^R = \alpha^R$, $\alpha_i^A = \alpha^A$, $L_i = L$ and $d_n^i = d\ \forall i, n$, then we would reach a steady state with all the countries investing the same quantity of final output into R&D and adoption, demanding the same amount of intermediate goods, and reaching the same level of income per capita.