ECONOMIC RESEARCH
FEDERAL RESERVE BANK OF ST. LOUIS

WORKING PAPER SERIES

Innovation, Diffusion, and Trade: Theory and Measurement

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Working Paper Number	2014-042A
Creation Date	November 2014
Citable Link	https://doi.org/10.20955/wp.2014.042
Suggested Citation	Santacreu, A.M., 2014; Innovation, Diffusion, and Trade: Theory and Measurement, Federal Reserve Bank of St. Louis Working Paper 2014-042. URL https://doi.org/10.20955/wp.2014.042

Published In	Journal of Monetary Economics
Publisher Link	https://doi.org/10.1016/j.jmoneco.2015.06.008

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Innovation, Diffusion, and Trade: Theory and Measurement

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May 2014

Abstract

I develop a multicountry-model in which economic growth is driven mainly by domestic innovation and the adoption of foreign technologies embodied in traded intermediate goods. Fitting the model to data on innovation, output per capita, and trade in varieties for the period 1996-2007, I estimate the costs of both domestic innovation and adopting foreign innovations, and then decompose the sources of economic growth around the world. I find that the adoption channel has been especially important in developing countries, and accounts for about 65% of their "embodied" growth. Developed countries grow mainly through the domestic innovation channel, which explains 85% of their "embodied" growth. A counterfactual exercise shows that if all countries reached the same research productivity, then (i) the world's steady-state growth rate would double, and (ii) developing countries would close the gap in terms of both growth rate and income per capita.

*Contact: anamaria.santacreu@insead.edu. I am very grateful to Jonathan Eaton for his support and guidance. I am also grateful to Diego Comin, Antonio Fatas, Mark Gertler, Denis Gromb, Boyan Jovanovic, Sam Kortum, Demian Pouzo, Kim Ruhl, and Gianluca Violante as well as to seminar participants at NYU, the Federal Reserve Bank, Wharton University of Pennsylvania, Boston College, the IMF, University of Texas, CREI, Universitat Autonoma de Barcelona, Universidad Carlos III, London Business School, University of British Columbia, Toulouse School of Economics, and INSEAD. I am responsible for any errors. Financial support by CICYT grant ECO2008-04669 is gratefully acknowledged.

1 Introduction

In the last decade, some developing countries in Asia and Europe grew faster than average. While their research intensity was lower than that of developed economies, they were expanding their variety of imports. In fact, innovations tend to concentrate in a few developed countries, which grow and import varieties at a lower rate than do developing economies. Endogenous growth theories show innovation to be the main engine of growth. Yet in a cross section of developed and developing countries, the correlation between research intensity (a rough measure of innovation) and economic growth is negative or nonsignificant. Fast-growing countries that expand their range of imported varieties may benefit from foreign innovations embodied in those varieties. Several empirical studies have documented this benefit (Coe, Helpman, and Hoffmaister (1997)). However, structural models that quantify these connections are limited. In this paper, I present an endogenous growth model of innovation and adoption through trade in varieties to measure the effect of foreign sources of innovations on "embodied" economic growth.

Theories about the effects of innovation, imported products, and growth date back at least to Romer (1987) and Rivera-Batiz and Romer (1991), but empirical work based on these models 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 last decade's increase in the ratio of trade to gross domestic product (GDP) stems from the extensive and not the intensive margin of trade—that is, from 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]

I develop a multicountry dynamic general equilibrium model in which countries undertake research to develop new products and exploit the advances of others by importing their products. In contrast with a large literature exploring the reduced-form relationship between trade and growth—for instance, Feyrer (2009) uses a time varying geographic instrument to establish a robust causal relationship between trade and income—both are equilibrium outcomes in my analysis. Imports and growth are connected by technological innovations and their international diffusion through trade. Economic growth is driven

[1]Broda, Greenfield, and Weinstein (2008) show that, for an 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.

by technology accumulation.[3] In addition to 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 research and development (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 technology diffusion through trade is endogenous.[4]

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 and different research productivity induce persistent income differences.[5] More interestingly, countries grow at different rates during the transition 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 this transition path. Countries at early stages of development (and thus farther from the technological frontier) grow by adopting the new foreign technologies embedded in the intermediate goods that they import. In contrast, countries at later stages of development (and thus relatively close to the technological frontier) grow by developing new technologies through R&D.

The model is fitted to 30 countries grouped, for tractability, into three types: emerging, less innovative OECD, and more innovative OECD countries. I use data on innovation, GDP per capita, and bilateral trade at the product level over the period 1996–2007 and employ Bayesian techniques to estimate the structural parameters. Using the estimated parameters, I distinguish worldwide sources of growth in terms of "disembodied" versus "embodied" growth, and then decompose the latter into domestic innovation and adoption of foreign innovations through trade, which are the model's main growth channels. 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

[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 process 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 simplifying (though admittedly extreme) 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.

of embodied growth for developed countries. Indeed, about 65% of embodied growth in emerging economies can be explained by foreign innovations—especially from the most innovative OECD countries.[6]

Finally, I conduct counterfactual experiments to study how the steady state would change if all the countries reached the same research productivity and then if they all faced the same barriers to adoption. I find that if all countries reached the same research productivity, then the steady-state growth rate of the world would double and the developing countries would close the gap not only in growth rates but also in levels of income per capita. Convergence of barriers to adoption would have a smaller (but still significant) positive impact on the world's economic growth and on the research intensity in each country.

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 (2010a) 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, 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 a third literature stream to use 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. It has been widely established that trade allows countries to adopt innovations developed abroad. Along these lines, Coe, Helpman, and Hoffmaister (1997) find that the TFP of developing countries 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. Bøler, Moxnes, and Ulltveit-Moe (2012) use Norwegian firm-level data on R&D and trade in intermediates to develop a model they estimate structurally and find that both imports

[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.

[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.

and R&D investment are key to explaining firm-level productivity growth.

Fourth, 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 (2010b) 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 accounts for this mechanism by stipulating that the innovation process includes learning from imports. Kasahara and Rodrigue (2008) find that importing intermediate goods improves plant performance in a sample of Chilean manufacturing panel data, which is in line with the results of my paper when extended to a cross-section of countries.

In a fifth stream of related literature, Atkeson and Burstein (2010) develop a model of heterogeneous firms that use both process and product innovation to assess the effect of changes in trade costs on welfare. They analyze entry and exit decisions of firms regarding the export market and find that the effect of decreases in trade on welfare are offset by the response of product innovation. In focusing only on exports, they fail to account for the additional channel of technology diffusion that is embodied in the imported varieties. This is the main channel of my model, and it has implications for welfare when one considers Dixit–Stiglitz preferences and for aggregate productivity when one considers an Ethier production function. Through technology diffusion, decreases in trade costs have a positive effect on aggregate TFP.

The paper proceeds as follows. Section 2 examines the data, and Section 3 presents the model. Section 4 studies the steady state and transition dynamics. Section 5 describes the estimation procedure. Section 6 decomposes the sources of economic growth and assesses their relative contributions. Section 7 describes (and reports results from) my counterfactual experiments, and Section 8 concludes.

2 A First Look at the Data

This section presents some stylized facts based on correlations among the extensive margin of trade, innovation, and GDP per capita (abbreviated a "pc" in the figures). I use data for a sample of 30 countries for the period 1996–2007.[10] These countries account for 80%

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

[10] For the sample of countries being analyzed, the period of time is chosen based on data availability for the measure of innovation and for the level of disaggregation of bilateral trade in varieties.

of world GDP and 85% of world trade.

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 version 8 of the Penn World Table (PWT). Finally, research intensity is measured by a country's R&D expenditures as a fraction of its GDP (based on data from the World Bank's World Development Indicators).

Figure 1 indicates that there is a positive correlation between growth in GDP per capita and growth in the extensive margin of trade computed using the Hummels–Klenow decomposition (a similar pattern is obtained when using growth in the number of imported varieties). Countries that have increased the number of imported intermediate goods faster are countries that have grown faster during the period of analysis. That said, these countries are not especially innovative. Figure 2 reveals domestic innovation, as measured by R&D intensity (the fraction of GDP that is allocated to R&D), is concentrated in a handful of rich countries; this distribution indicates that innovation and growth are but weakly correlated. Fast-growing countries that import intermediate products at a rapid pace may benefit from the foreign innovations embodied in those products.

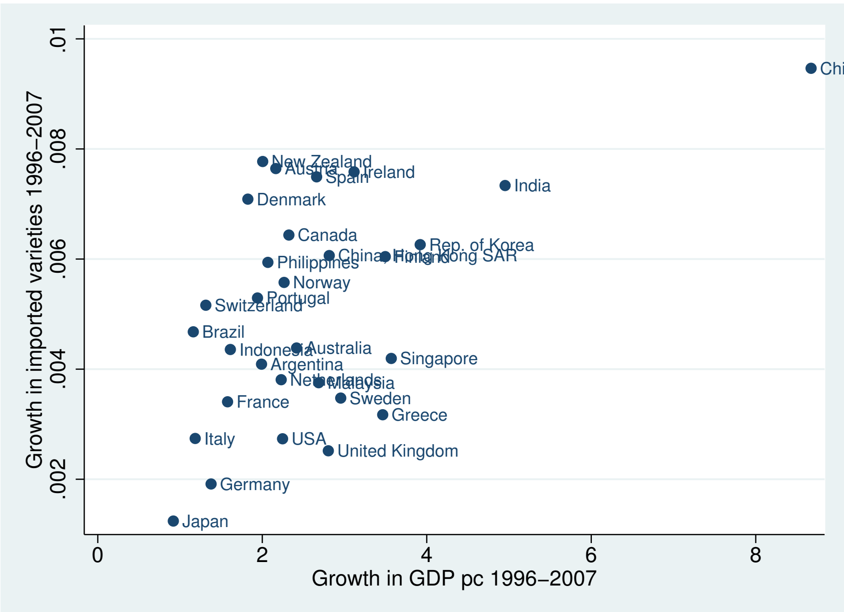

Figure 1: Growth and the Extensive Margin of Imports

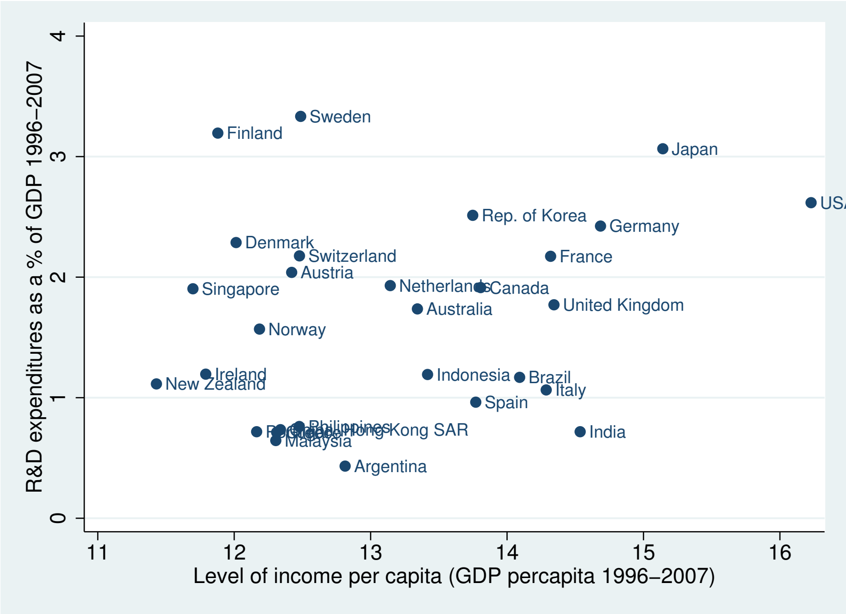

Figure 2: Innovation and income per capita

Figure 3 offers evidence in favor of that hypothesis. A scatter plot of the correlation between a country's growth and the R&D content of its imports (measured as the fraction of R&D embodied in those imports) shows a positive correlation between the two measures. This channel was especially important for developing countries during the period of analysis.

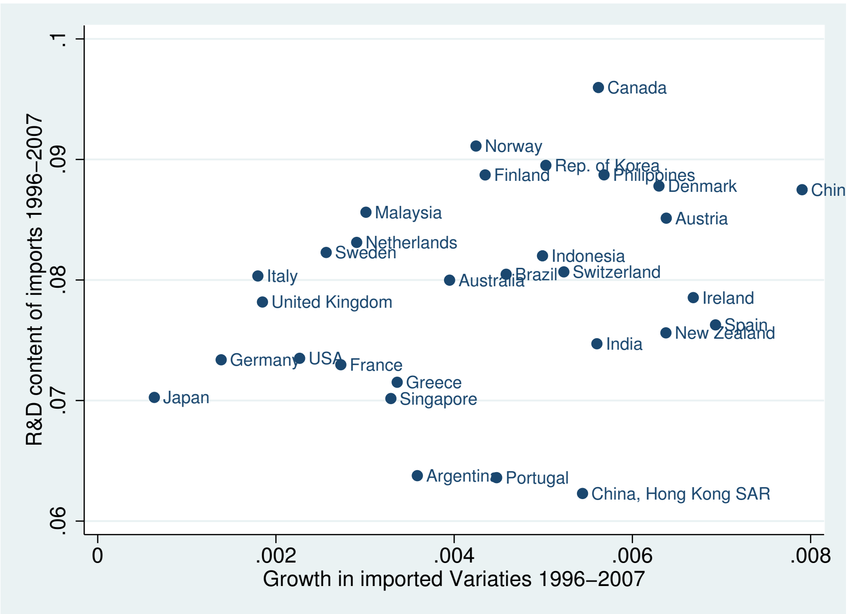

Figure 3: Growth and the R&D content of imports

Taken together, the empirical evidence suggests that developing countries—which are farther from the technology frontier—may exceed average growth rates by adopting the foreign innovations embedded in goods that they import. Developed countries, which are closer to the technology frontier, grow mainly by doing their own innovation and hence by pushing that frontier. The main goal of this paper is to decompose the sources of "embodied" economic growth into domestic factors (i.e., domestic innovation) and foreign factors (i.e., foreign innovation adopted through trade in varieties).

3 The Model

I develop a multicountry 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 nontraded final good, which in turn is used for consumption, domestic innovation, and adoption of foreign innovations. Time is discrete and indexed by $t = 0, 1, \ldots$; 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 take place, and I take each country's technologies as given. In the second stage, innovation and adoption of technologies takes place, which determines 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 $j \in [0, Z_{nt}]$; here Z_{nt} represents the mass (or, alternatively, the number) of available products. I assume that intermediate goods are differentiated by source of exports—in other words, countries exogenously specialize in different sets of goods (this is the Armington assumption). As is standard practice in the literature, variety nj is defined as the intermediate good j produced in country n.[11] Each firm produces a different good according to the 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

[11] The Armington assumption allows us to define a variety nj as a good j from a particular country n. Thus good j produced in country n differs from good j produced in country k.

country $i = 1, 2, \ldots, I$ 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" 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, since labor is the only factor of production. Hence the price in country i of variety nj is

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

where $\frac{\theta}{\theta-1}$ is the markup (θ will be described in Section 3.1.2) and ω_{nt} is the wage in country n.

The profit of the producer of variety nj is

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

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 the final producer) uses traded intermediate goods—both domestic and foreign— to produce a nontraded final good Y_{it}. Varieties are combined according to the CES (constant elasticity of substitution) production function

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

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

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

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

Economic growth is driven by technological progress. Technology is embodied in intermediate goods traded across countries and potentially used by final producers in all countries. This dynamic is captured by the CES production function, which introduces a "love-for-variety" effect: holding expenditures constant, using a wider range of varieties corresponds to increased output per capita—that is, to increased productivity as in(Ethier

1982).[12] The shock process a_{it} introduces an additional channel of technological progress, which I refer to as disembodied technology (Greenwood, Hercowitz, and Krusell 1997); thus a_{it} captures the unexplained component of productivity growth, with $\bar{g}$ the steady-state growth rate.

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

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

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

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

The maximization problem implies the following demand for variety nj:

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

Total spending by country i on variety nj is then

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

3.1.3 Households

In each country $n = 1, \ldots, I$, 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 the firms (final and intermediate good producers) in country n, B_{nt} denotes total loans the household extended to innovators and adopters at time $t - 1$ and that are payable at time t, and R_{nt} is the risk-free rate. The household chooses

[12] Because labor is the only factor of production in this model, output per capita and productivity are the same thing. The empirical stylized facts on the correlation of growth and the extensive margin of imports can also serve as a measure of productivity computed as the Solow residual, where labor and capital are factors of production. Building a model to analyze the correlation in terms of TFP would imply adding capital, which would introduce an additional state variable and complicate the analysis. So, in this paper, output per capita and productivity are the same variable.

consumption, labor supply, and loans to maximize (10) subject to (11).

3.2 Innovation and Adoption

So far, I have described the production process of each economy, while assuming a given set of available technologies or intermediate goods. Yet the number of intermediate goods evolves over time according to an endogenous process of innovation and adoption that I describe next. 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 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, selling the good in a foreign market requires that the good first be adopted by that market. Domestic adopters invest foreign resources so that they can sell the good in each potential destination with a certain probability.

3.2.1 Innovation

In each country $n = 1, \ldots, I$, innovators develop new prototypes of an intermediate good (i.e., an idea). They then sell the right to use this idea to an adopter who converts it into a new intermediate good to be used by domestic and foreign final producers, as described next. Specifically, each innovator p invests the final good to undertake R&D and introduce a new technology. The innovator finances this technology with loans from households.[13]

Let y^r_{pnt} be the total amount of final output invested in R&D by innovator p from country n at time t, and let Z^p_{nt} be total stock of innovations. Let φ^r_{nt} be a productivity function that the innovator takes as given. The innovation technology is as follows:

$$E_t Z^p_{n,t+1} - Z^p_{nt} = \varphi^r_{nt} y^r_{pnt}. \tag{12}$$

It is assumed that φ^r_{nt} depends on aggregate conditions, which are taken as given by the innovators. In particular,

$$\varphi^r_{nt} = \frac{\alpha^r_n T_{nt}}{Y^{\gamma_r}_{nt} \left(y^r_{nt}\right)^{1-\gamma_r}};$$

here $\gamma_r \in (0,1)$ is the elasticity of R&D with respect to new technology creation, and $Y^{\gamma_r}_{nt} \left(y^r_{nt}\right)^{1-\gamma_r}$ is a "congestion" term that raises the cost of developing new products as total R&D increases (see Comin and Gertler (2006)). This congestion term depends on

[13]This process is similar to the innovation process described by Eaton and Kortum (1996, 1999). The main difference is that innovators employ labor in their model whereas innovators invest final output in this model. I use final output because then the law of motion of newly invented technologies depends on the fraction of output allocated to R&D, which is the measure of research intensity used to fit the model in the empirical analysis.

Y_{nt}, which guarantees the existence of a balanced growth path. In addition, 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 to the country, $T_{nt} = Z_{nt} + \sum_{i \neq n} A_{it}^n$, where Z_{nt} is the stock of technologies introduced domestically through innovation in country n up until period t. That is, the innovator "learns" 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 (2010b) and has two implications. First, countries in which more varieties are available have a lower R&D cost; second, countries can lower their R&D costs by expanding the variety of their imports (increasing $\{A_{nt}^i\}$) .[14]

Let V_{nt} be the price at which an innovator can sell the right of using a new product to an adopter. This is the value of an unadopted prototype for an intermediate good, and as I describe later, it is given by the expected profits to the adopter from selling the good to each potential market (domestic and foreign). Free entry in innovation determines the level of investment in R&D, which is given by the break-even condition

$$E_t \left[V_{nt+1} \right] = \frac{P_{nt}}{\varphi_{nt}^r}. \tag{13}$$

The innovator invests final output up to the point where marginal revenue is equal to marginal cost. Successful technologies join the pool of intermediate-good producers in period $t+1$.

3.2.2 Adoption

Next, I characterize the process by which newly developed intermediate goods are adopted over time—that is, by which each Z_{nt} is transformed into A_{nt}^i. Each intermediate good produced with the new technology must be adopted before it can be used by the final producer. The adoption process is undertaken by the intermediate producer seeking to sell the good in domestic and foreign markets. 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 (i.e., $Z_{nt} = A_{nt}^n$), using foreign intermediate goods involves an slow adoption process. During each period of time, adopters succeed in adopting only a subset of the new intermediate goods available (i.e.,

[14] Under this specification, countries may shift from being adopters to innovators, thereby increasing the number of goods that they produce and export. Acemoglu, Aghion, and Zilibotti (2002) view this process as 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 using data from five Asian countries observes that—prior to entry into export markets—productivity gains are associated with higher imports.

$Z_{nt} > A^i_{nt}$ for all $i \neq n$).

I follow Comin and Gertler (2006) in assuming that adopters buy the right to a new technology from innovators. The adopters then make the technology usable for final producers by investing resources. Adopters fund the expenses of adoption with loans from households. Once the good has been adopted, it is sold to the final producers who use it as an input. There is a positive correlation between the rate of adoption and investment in adoption: an adopter in country n becomes successful in making a product usable for final production in country i in any given period t with a probability ε^i_{nt} , which is increasing in the amount of final output that the adopter spends, y^i_{nt}. An adopter who is not successful may try again in the subsequent period. This formulation captures the slow process of adoption. I assume that, during this process, the adopter invests final output from the foreign market in which she wants to sell the product.

I also assume the following functional form for the stochastic rate of adoption:

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

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. The term $\gamma_a \in (0,1)$ is the elasticity of adoption with respect to investment in adoption.[15]

Equation (14) 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, and thereby increases 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 $\frac{A^i_{nt}}{Z_{n,t+1}}$); hence less 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.[16]

Note that the existence of a continuum of intermediate goods means that the proba-

[15] Policies that affect the parameter α^A_i include increasing investment in education, improving telecommunications infrastructure so as to facilitate communication across countries, and liberalizing trade policies. Eaton and Kortum (1996) and Benhabib and Spiegel (1994) analyze how the probability of adoption depends on different factors, including human capital; they find that human capital has a positive and significant effect on the likelihood of adoption.

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

bility of adoption ε^i_{nt} is also the fraction of technologies adopted.[17]

Let W^i_{nt} be the value to an adopter in country n successfully adopting a technology to be sold to country i. This value is the present discounted value of profits from selling that good:

$$W^i_{nt} = \pi^i_{nt} + \beta E_t W^i_{n,t+1}, \tag{15}$$

where π^i_{nt} denotes profits and $W^i_{n,t+1}$ the continuation value. Then, the value of technologies invented in country n at time t that have yet to be adopted by country i is

$$J^i_{nt} = \max_{Y^i_{nt}} \{-P_{it} y^i_{nt} + \beta E_t(\varepsilon^i_{nt} W^i_{n,t+1} + (1-\varepsilon^i_{nt}) J^i_{n,t+1})\}. \tag{16}$$

At time t, the adopter invests the quantity y^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 adopter chooses y^i_{nt} to maximize (16) subject to (14). At the margin, each adopter decides to invest in adoption until the marginal cost (one unit of final output) equals the discounted marginal benefit:

$$P_{it} = \gamma_a \alpha^A_i \left(\frac{y^i_{nt}}{Y_{it}}\right)^{\gamma_a - 1} \frac{A^i_{nt}}{Z_{n,t+1}} \frac{W^i_{n,t+1} - J^i_{n,t+1}}{Y_{it}}. \tag{17}$$

Overall, the number of newly adopted technologies is then given by

$$E_t A^i_{n,t+1} - A^i_{nt} = \varepsilon^i_{nt}(Z_{n,t+1} - A^i_{nt}). \tag{18}$$

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 y^i_{nt} of final output to adapt the $Z_{nt+1} - A^i_{nt}$ technologies, which are then adopted at the stochastic rate ε^i_{nt}. This specification is similar to that in Nelson and Phelps (1966) and Benhabib and Spiegel (1994).

To gain a better understanding of the adoption process, I substitute equation (14) into equation (18) to find the growth rate of adopted technologies:

$$g_{A_{int}} = \frac{E_t(A^i_{nt+1} - A^i_{nt})}{A^i_{nt}} = \alpha^A_i \left(\frac{y^i_{nt}}{Y_{it}}\right)^{\gamma_a} \left(1 - \frac{A^i_{nt}}{Z_{nt+1}}\right).$$

[17] 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.

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, y_{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 effect on growth in the variety of imports.[18]

There are two key assumptions in the adoption mechanism. 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.

3.2.3 Value Functions

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

$$V_{nt} = \sum_{i=1}^{I} J_{nt}^i, \tag{19}$$

where $J_{nt}^n = W_{nt}^n$. Note that this is the price that adopters (intermediate producers) are willing to pay to use a new technology invented by the innovator in equation (13).

3.3 Trade Balance

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

$$\sum_{i \neq n}^{I} \int_{j=0}^{A_{nt}^i} p_{njt}^i x_{njt}^i \, dj = \sum_{i \neq n}^{I} \int_{j=0}^{A_{it}^n} p_{ijt}^n x_{ijt}^n \, dj. \tag{20}$$

3.4 Equilibrium

This section defines a symmetric equilibrium: a set of equations according to which all firms within a country behave symmetrically. However, the countries themselves are asymmetric, and are characterized by the parameters $\{\alpha_i^R, \alpha_i^A, L_i, d_n^i\}$.

For all i and n, a general symmetric equilibrium is defined as an exogenous stochastic sequence $\{a_{it}\}_{t=0}^{\infty}$, an initial vector $\{A_{n0}^i, Z_{i0}\}$, a set of parameters $\{\beta, \theta, \gamma_a, \gamma_r, \rho\}$ that are common across countries, a set of parameters $\{\alpha_i^R, \alpha_i^A, L_i, d_n^i\}$ that differ across countries,

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

a sequence of aggregate prices and wages $\{P_{it}, V_{it}, R_{it}, \omega_{it}\}_{t=0}^{\infty}$, a sequence of intermediate-good prices $\{p_{nt}^i\}_{t=0}^{\infty}$, a sequence of aggregate quantities $\{Y_{it}, y_{it}^r, y_{nt}^i\}_{t=0}^{\infty}$, quantities of intermediate goods $\{x_{nt}^i, y_{nt}\}_{t=0}^{\infty}$, a sequence of value functions and profit $\{\pi_{nt}^i, W_{nt}^i, J_{nt}^i\}_{t=0}^{\infty}$, and laws of motion $\{A_{n,t+1}^i, Z_{i,t+1}\}_{t=0}^{\infty}$ such that the following statements hold:

- The state variables $\{Z_{i,t+1}, A_{n,t+1}^i\}_{t=0}^{\infty}$ satisfy the laws of motion in equations (23) and (18).
- The endogenous variables solve the producers' and households' problems in equations (25)–(32).
- Feasibility is satisfied in equations (21) and (22).
- Prices are such that all markets clear.

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

Resource Constraint

$$Y_{it} = C_{it} + \sum_{n \neq i}^{I} (Z_{it} - A_{it}^n) y_{it}^n + (Z_{it} - Z_{it-1}) y_{it}^r. \tag{21}$$

Final Production

$$Y_{it} = e^{a_{it}} \left(\sum_{n=1}^{I} A_{nt}^i b_{nt}^i (x_{nt}^i)^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}. \tag{22}$$

Law of Motion for Innovation

$$E_t Z_{i,t+1} - Z_{it} = \alpha_i^r T_{it} \left(\frac{y_{it}^r}{Y_{it}} \right)^{\gamma_r}. \tag{23}$$

Law of Motion for Adoption

$$E_t A_{n,t+1}^i - A_{nt}^i = \varepsilon_{nt}^i (Z_{n,t+1} - A_{nt}^i). \tag{24}$$

Households

$$\frac{1}{\beta} \frac{C_{i,t+1}}{C_{it}} = \frac{P_{it}}{P_{i,t+1}} R_{i,t+1}. \tag{25}$$

Final Producers

$$x_{njt}^i = (b_{njt}^i)^{\theta} \left(\frac{p_{njt}^i}{P_{it}} \right)^{-\theta} Y_{it}. \tag{26}$$

Intermediate Producers

$$\sum_{i=1}^{I} A_{nt}^{i} p_{nt}^{i} x_{nt}^{i} = \omega_{nt} L_{n}. \tag{27}$$

$$p_{nt}^{i} = \frac{\theta}{\theta - 1} (\omega_{nt} d_{n}^{i}), \tag{28}$$

Investment in Innovation

$$E_t \left[V_{nt+1} \right] = \frac{P_{nt}}{\varphi_{nt}^{r}}, \tag{29}$$

with

$$\varphi_{nt}^{r} = \frac{\alpha_{n}^{r} T_{nt}}{Y_{nt}^{\gamma_r} \left(y_{nt}^{r} \right)^{1-\gamma_r}}$$

and

$$V_{nt} = W_{nt}^{n} + \sum_{i \neq n} J_{nt}^{i}, \tag{30}$$

$$W_{nt}^{i} = \pi_{nt}^{i} + \beta E_t \frac{1}{1 + g_{A_{int}}} W_{n,t+1}^{i},$$

$$J_{nt}^{i} = \left\{ -P_{it} Y_{nt}^{i} + \beta E_t \left(\varepsilon_{nt}^{i} \frac{1}{1 + g_{A_{int}}} W_{n,t+1}^{i} + \beta (1 - \varepsilon_{nt}^{i}) \frac{1}{1 + g_{A_{int}}} J_{n,t+1}^{i} \right) \right\}. \tag{31}$$

Investment in Adoption

$$\gamma_a \alpha_i^{A} \left(\frac{y_{nt}^{i}}{Y_{it}} \right)^{\gamma_a - 1} \frac{A_{nt}^{i}}{Z_{n,t+1}} \frac{W_{n,t+1}^{i} - J_{n,t+1}^{i}}{Y_{it}} = 1. \tag{32}$$

Trade Balance

$$\sum_{i=1}^{I} A_{nt}^{i} p_{nt}^{i} x_{nt}^{i} = \sum_{n=1}^{I} A_{it}^{n} p_{it}^{n} x_{it}^{n}. \tag{33}$$

Market-Clearing Conditions

$$y_{nt} = \sum_{i=1}^{I} A_{nt}^{i} x_{nt}^{i}. \tag{34}$$

4 The Steady State and Transition Dynamics

4.1 Steady State

The economy has a balanced growth path in which all countries grow at the same rate but differ in their levels of 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 were common across countries, then all countries would reach the same steady state—both in levels and in growth rates—and would differ only in their speeds of convergence.

In steady state, the endogenous variables grow at a constant rate. So by equation (21) and equations (23) and (24), 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. From the resource constraint (21), 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 since the rate of adoption ε_{nt}^i is constant, it follows that the steady-state value of the fraction of technologies from country n that have been adopted by country i between times t and $t+1$ can be obtained as $\left(\frac{A_n^i}{Z_n(1+g_z)}\right) = \left(\frac{\varepsilon_n^i}{g_a+\varepsilon_n^i}\right)$. We can use this equality to derive the ratio $\left(\frac{A_n^i}{A_k^i}\right)$ and an expression for $\left(\frac{Z_n}{Z_k}\right)$. Finally, the trade balance equation (33) is used to obtain relative wages.[19]

4.2 Transition Dynamics

Differences in growth rates across countries arise in the transition and depend on differences in their investment in innovation and adoption, which ultimately depend on country differences in income per capita. The model predicts the following transition dynamic results, which accord with the empirical evidence from Section 2. 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 their R&D increases in response to the spillover effect, increasing the attractiveness of innovation; hence, developing countries 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, whereas 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 will be 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 g_z of newly developed

[19]The steady-state algorithm is available upon request.

technologies. I use Dynare to solve and estimate the structural parameters.[20]

5 Empirical Strategy

Section 3 described a fully specified structural stochastic model with interdependencies across countries. In this section I fit the model to annual data on innovation, GDP per capita, and imports for the period 1996–2007. I then use the structural nature of the model to conduct a counterfactual analysis. The small sample size (twelve 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 estimate the model's dynamics with Bayesian techniques described in Schorfheide (1999).[21]

5.1 Bayesian Estimation

Bayesian estimation is a mix of classical estimation and calibration. Relative to using ony 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 one to estimate a fully specified model with fairly flexible stochastic processes. Correct estimates of these models and processes enable a study of the system's transition dynamics that captures the cross-country growth rate differences observed in the data. 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 multicountry vector autoregressive models with spillover effects across regions, especially when examining issues related to income convergence or evaluating the effects of regional policies. In such models neither generalized method of moments estimators of quasi-maximum likelihood nor minimum distance estimators are able to provide consistent results.[22]

Next, I describe briefly the main steps to follow when estimating a model with Bayesian techniques. We must first specify prior probability distributions for the parameters of interest. The priors are then combined with the likelihood density, which is compared with the data in order to obtain the posterior distribution of these parameters. Second, the likelihood density is approximated by a kernel density function, derived via Markoc Chain Monte Carlo simulation methods. This approach works if all the variables are observable in the data; however, this is seldom the case in dynamic stochastic gen-

[20]The set of log-linearized equations is available from the author upon request.

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

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

eral equilibrium (DSGE) models generally such as this one, which involve unobserved 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–Hastings algorithm is used to derive the posterior distribution of the parameters.

5.2 Data and Priors

5.2.1 Data

For tractability, I allocate the 30 countries to three groups with common characteristics (similar innovation intensity, extensive margins of trade, and productivity): emerging markets (EM), less innovative OECD countries (OECD−), and more innovative OECD countries (OECD+).[23]

The model is fitted to annual data for the period 1996–2007; this is because 1996 is the first year for which R&D expenditure data and highly disaggregated trade data are available for a large sample of countries. The observable variables are the annual growth in imported varieties (bilateral trade, where growth is computed as the change in the number of varieties and corresponds to ΔA^i_{nt} in the model), GDP per capita growth, and R&D expenditures as a percentage of GDP (as measured in Section 2). There are 432 observations corresponding to twelve years, three groups, and twelve observable variables.

Mapping the model to the data requires three main adjustments. First, determine whether innovation and adoption costs are capitalized into the economy's investment or instead are expensed—that is an intangible investment that is not measured in the country's value added. McGrattan and Prescott (2010) argue that activity associated with an expanding number of products is expensed and not capitalized in national accounts. Also, Atkeson and Burstein (2010) treat entry into domestic and foreign markets as being expensed. When estimating the model I therefore use a measure of GDP that corresponds to the final output net of innovation and adoption costs:

$$Y_t^{\mathbf{obs}} = Y_t - Y^r_{it} - \sum_{n \neq i} Y^i_{nt}.$$

Second, I use the measure of GDP that contains the Feenstra adjustment for terms of trade, as reported in the PWT. This is a better measure of production; it measures real GDP on the output side, corrected for the terms of trade and then using PPP prices for each year.[24]

The third adjustment applies when comparing the model's price indices and their

[23]See Appendix A for a list of the countries by group.

[24]This measure corresponds to the "cgdpo" variable (current-price real GDP) in version 8 of the PWT.

counterparts in the data. The CES production function exhibits the love-for-variety effect (i.e., the introduction of new varieties through domestic innovation or adoption of foreign innovations tends to reduce the model's price indices) but this is not captured in the data. I apply the method of Alessandria and Choi (2007) and Ghironi and Melitz (2005) to construct a price index in which average prices are weighted by the number of varieties.

5.2.2 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 group of countries): a neutral technology shock a_i in final production, a shock ξ_{it} to the productivity of R&D in equation (12), and a measurement error $\varepsilon_{in,t}$ 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

$$g^{\text{obs}}_{int} = g_{int} e^{\varepsilon_{in,t}}$$

with $\varepsilon_{in,t} \sim N(0, \sigma^2_{\varepsilon_{in}})$, where me denotes the measurement error and $i, n = 1, \ldots, 3$.

5.2.3 Parameters

A set of parameters is treated as fixed in the estimation (these are also known as "strict priors" or calibrated parameters). They are obtained from previous studies, from steady-state relationships implied by the model, and from trade and R&D data through the use of gravity equations as explained in this section later.

The parameters obtained from previous studies are the discount factor β, the elasticity of substitution θ, the growth rate $\bar{g}$ of output in steady state, and the elasticity of adoption γ_a. These parameters cannot be identified from the data used in the empirical analysis. I set $\beta = 0.9$, which implies an annual interest rate of 4%. I choose a value of 4 for the elasticity of substitution θ between differentiated goods. Estimates of this parameter in the trade and industrial organization literature typically range from 3 to 10 and differ across goods; see Broda, Greenfield, and Weinstein (2008), who report lower elasticities for more differentiated goods. In robustness analyses I find that the results are robust to changes in this parameter within the rage found in the empirical literature. To estimate the growth rate of new technologies, I follow Eaton and Kortum (1996) in using the Frobenius theorem, as explained in Appendix D; I obtain a value of 0.012 for this parameter. If we assume a steady-state growth rate of 0.02 for the country groups being analyzed, as is standard in the empirical literature, then 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 and hence that the remaining 40% is explained by a residual or disembodied technology (so $\bar{g} = 0.08$) that is uncorrelated with the mechanisms of the model (candidates education as well as the organization and structure of the market).[25] The elasticity of adoption, γ_a, is 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 that 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, which I use in my calibration of γ_a.

Next, I describe how to obtain the calibrated parameters for distance, d_n^i, and the elasticity of innovation (γ_r) using trade and R&D data and a gravity equation approach. Following Eaton and Kortum (2002), I first derive a gravity equation as implied by my model. This equation relates bilateral trade volumes to the characteristics of the trading partners, and of the geography between them as follows

$$X_{nt}^i = A_{nt}^i \left(\frac{\omega_{nt} d_n^i}{P_{it}} \right)^{1-\theta} Y_{it}.$$

Normalizing by the importer's home sales, X_{it}^i, yields

$$\frac{X_{nt}^i}{X_{it}^i} = \frac{A_{nt}^i}{Z_{it}} \left(\frac{\omega_{nt} d_n^i}{\omega_{it}} \right)^{1-\theta}.$$

Rearranging, we have

$$\frac{X_{nt}^i}{X_{it}^i} = \frac{A_{nt}^i}{Z_{nt}} \frac{Z_{nt} \omega_{nt}^{1-\theta}}{Z_{it} \omega_{it}^{1-\theta}} \left(d_n^i \right)^{1-\theta}.$$

Now, taking logs allows us to obtain

$$\log \frac{X_{nt}^i}{X_{it}^i} = S_{nt} - S_{it} - (\theta - 1) \ln d_n^i + u_{nt}^i. \tag{35}$$

[25] These results are in line with what Greenwood, Hercowitz, and Krusell (1997) find for the United States. We can assume the same value for all the country groups because technology diffusion guarantees that, in steady state, embodied productivity growth is the same across countries.

where $S_{nt} = \ln Z_{nt} - (\theta - 1) \ln \omega_{nt}$. We can view S_{nt} as a measure of the source country n's competitiveness. A country n is more competitive if it is more technologically more advanced (higher Z_{nt}) and the lower the cost of production (lower wage ω_{nt}).

Equation (35) constitutes the basis of my estimation. The left-hand-side (LHS) is estimated using data for domestic production from UNIDO and bilateral trade from UN COMTRADE for the 30 countries in Section 2 (data for domestic production are obtained from CEPII). I then follow Eaton and Kortum (2002) to estimate the gravity equation using (on the right-hand-side (RHS)) exporter and importer fixed effects in addition to proxies for geographic barriers as suggested by the literature (data obtained from CEPII geography variables):

$$\log d_n^i = d_k + l + b + ta,$$

where d_k (k=1,...,6) is the effect of geographic distance between i and n lying in the kth interval ($[0, 375)$;$[375, 500)$;$[750, 1500)$;$[1500, 3000)$; $[3000, 6000)$; and [6000,maximum)). The term b is a dummy variable for sharing a border, l is a dummy variable for using the same language, and ta is a dummy for the existence of a trade agreement. I estimate equation (35) for every year and report the results for the average year in Table B.1.

Using the estimates from the gravity equation, I obtain a measure for d_n^i. Note that θ and d_n^i are not separately identified because, in equation (35), we have $-(\theta - 1)d_n^i$. I therefore fix $\theta = 4$ to obtain a value for d_n^i. The results suggests that this parameter lies between 1.2 and 1.5.

The estimates for S_{nt} indicate that the United States is the most competitive country, closely followed by Japan, China, and then Germany. The least competitive country is Greece, followed by Portugal (see Table B.2).

To understand what factors explain the ranking of competitiveness, note that

$$S_{nt} = \ln Z_{nt} - (\theta - 1) \ln \omega_{nt}.$$

According to this expression, countries that are technologically more advanced (higher Z_{nt}) or have lower cost of production (lower ω_{nt}) are more competitive. To disentangle the effects of technology and production cost on a country's competitiveness, I use income per capita (Y_{nt}/L_{nt}) as a proxy for wages, (ω_{nt}) and obtain a measure of technology,

$$\ln Z_{nt} = S_{nt} + (\theta - 1) \ln \omega_{nt},$$

using estimates for the source fixed effect that were derived from the gravity equation. Table B.2 shows the ranking of countries according to how technologically advanced they are (Z_{nt}) and how costly is their production of intermediate goods (ω_{nt}). The results show that the most competitive countries from a technological perspective are the advanced economies (France, United Kingdom, Switzerland, Germany, Japan, and the

United States); the least competitive are India, Philippines, Indonesia, China, Argentina, and Brazil—all of which are emerging economies. Norway is an advanced country technologically (high Z_n) but not in terms of its cost of production, since it is the country with the highest GDP per capita and hence with the highest wages. In contrast, China is a competitive country owing to its low cost of production and not because of high technology Z_{nt}.

Next, I calibrate the elasticity of innovation, γ_r, using the estimates for Z_{nt} from the gravity equation combined with the features of the innovation process implied by my model. From equation (12), the term $\log(Z_{nt})$ can be approximated as a linear function of the stock of R&D in country n, R_{nt}, and the total number of varieties imported by country n, $M_{nt} = \sum_{i \neq n} A_{it}^n$. I run the following regression:

$$\log(Z_{nt}) = \gamma_0 + \gamma_1 \log(R_{nt}) + \gamma_2 \log(M_{nt}) + u_{nt}.$$

In this expression, one can approximate $\hat{\gamma}_1 = \gamma_r$ (i.e., the elasticity of innovation in equation (12)).

Table 1: Calibrating the elasticity of innovation

	Z_n
$\log(R_n)$	0.619**
	(0.013)
$\log(M_n)$	1.730**
	(0.022)
** $p < 0.01$	

From the regression results reported in Table 1 (where standard errors are reported in parentheses), I obtain $\gamma_r = 0.62$. This number is consistent with the findings of previous empirical studies. Griliches (1990) uses the number of new patents as a proxy for technological change and obtains estimates ranging from 0.5 to 1.

Figure 4 displays several correlations between competitiveness and its underlying factors, as suggested by the model's gravity equation approach and the resulting calibrated parameters. There is a clear positive correlation between S_{nt} and research intensity (upper left panel), as well as an even stronger correlation between the factor of competitiveness that represents technology, Z_{nt}, and research intensity (upper right panel). Similarly, as shown in the lower left panel, there is a positive correlation between technology and the total number of imported varieties; this is the spillover effect present in the law of motion for newly invented technologies in equation (12).

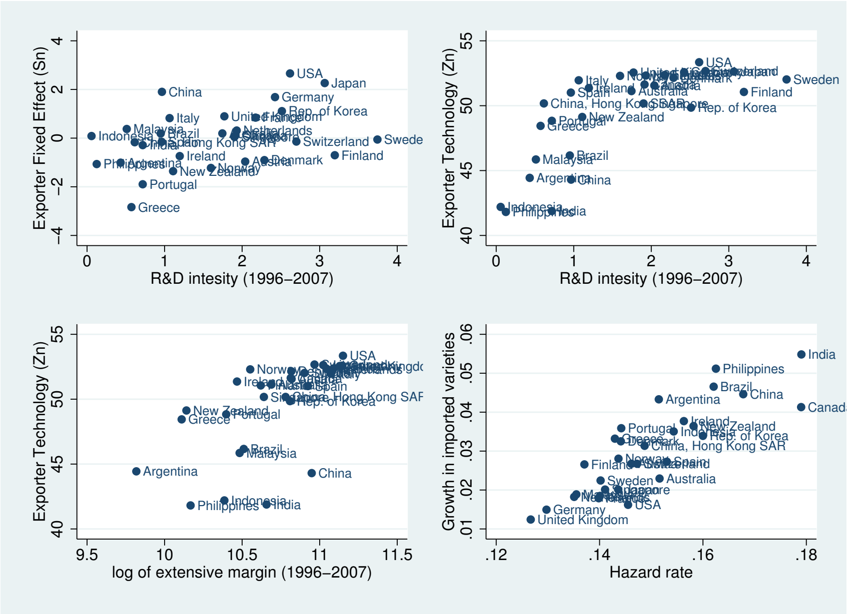

Figure 4: Correlations among Technology, Geography and Trade

Finally, I use the expression for adoption in equation (14), data on the number of imported varieties (A^i_{nt}) and the estimate for technology (Z_{nt}) to obtain the following estimate for ε^i_{nt}, the bilateral probability of adoption:

$$\varepsilon^i_{nt} = \frac{A^i_{nt+1} - A^i_{nt}}{Z_{nt} - A^i_{nt}}.$$

Other papers 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 international costs of adoption by using trade data. The estimates indicate that this value ranges between 0.2 and 0.3, so that it takes between three and five years to start importing a variety that has been developed somewhere else. The lower right panel of Figure 4 shows a clear positive correlation between the probability of adoption and growth in imported varieties over the sample period.

The parameters to be calibrated from steady-state relations are α^r_i and α^a_i. Using the characteristics of the steady-state of the model, I employ an algorithm that takes as input the values of the parameters calibrated so far: the common parameters (β, γ_r, γ_a,θ); and the country–pair specific parameters (ε^i_n,d^i_n) that introduce country-specific variation into the calibrated parameters of interest, α^a_i and α^r_i. From the law of motion for innovation and adoption, we have that the parameters γ_r and α^r_i (on one side) and γ_a and α^a_i (on the other side) are not separately identified. The calibrated parameters are reported in Table C.1.

The parameters to be estimated correspond to the shock processes: the persistence ρ_i of the productivity shocks and also the standard deviations σ_i of both the neutral technology shock and innovation productivity shock. The prior mean and standard deviation are reported in Table C.2. Beta distributions are assumed for those parameters restricted to be between 0 and 1, and Inverse-Gamma distributions are assumed for the variances of the shocks to guarantee a positive support.

I assume a Beta distribution for the persistence parameter with mean 0.5 and standard deviation 0.15 (the Beta distribution guarantees that the parameter is between 0 and 1). I assume an Inverse Gamma distribution for the standard deviation of the shocks, which guarantees a positive variance of the shocks.

So in the context of my model, the Bayesian estimation approach is useful for estimating the dynamics given by the shock processes. This approach allows me to identify differences in growth rates across countries along the transition path. Other parameters are obtained using the steady-sate relations, which mainly identify differences in cross-country steady-sate levels of the variables and the value of world growth rates. Finally, the parameters for the innovation process and the international costs of adoption are identified using the gravity equation approach, which requires both cross-sectional and time-series variation in the data.

5.3 Estimation Results

In order to to solve the model, I stationarize the variables so that they are constant in steady state. Table C.2 reports the estimation results, which include both the prior and posterior mean of the estimated parameters as well as 95% confidence intervals.

I use the time dimension of the series to estimate the shocks, which allows me to decompose growth in the country groups being analyzed along the transition path. There are twelve observable variables, one for each of the three analyzed groups; hence we need 36 shocks for invertibility. Three of the shocks are productivity shocks (exogenous source of growth in each group), and the rest are measurement errors. I present the prior mean and standard deviations of the shocks in addition to measurement errors. The data allow us to identify these exogenous process, which are then then used to compute the decomposition of growth (see Section 6).

Table C.3a reports second moments of a simulated model that uses the estimated parameters and compares them to the data. I run 10,000 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.

Table C.3.b reports the estimated variance decomposition for the output growth and the R&D intensity in each group of countries using the posterior mean of the parameters. The exogenous TFP shock of the emerging markets explains about 74% of the variability of growth in these countries. The remaining variability is explained by their R&D shock (25%) and by their trading partners' R&D shocks (0.10% by less innovative countries and 0.3% by more innovative OECD countries). In OECD countries (both less and more innovative), however, their exogenous TFP shock explains about 25% and 18% of their growth rates' variability, respectively. The remaining is explained by their R&D shocks. Note that foreign R&D shocks do have an effect on fluctuations in domestic growth rates. The more innovative the country, the higher the effect of its R&D shock on the growth rates of the other countries. Domestic R&D shocks explain most of the fluctuations in the research intensity of each country. The exogenous TFP shock has also an effect, albeit smaller. Taken together, these results suggest that R&D shocks have been an important source of variation of domestic growth rates, especially for OECD countries. In emerging economies, however, fluctuations have come mainly through exogenous TFP shocks.

6 Decomposition of the Sources of Economic Growth

In this section I compute the contribution of domestic and foreign innovation to economic growth in each group of countries, as predicted by the model. The equation used in the decomposition is derived in Appendix E.

6.1 Embodied versus Disembodied Growth

There are two sources of economic growth: "embodied" growth, as captured by an expansion in the number of intermediate goods (through domestic innovation and through international diffusion of foreign innovations through trade in varieties); and "disembodied" growth, as captured by an exogenous TFP shock $e^{a_{it}}$.[26] Taking the estimated series of the TFP shock together with data from the empirical analysis on growth in GDP per capita, I compute the contribution of each source of growth and report the results in Table 2.

Embodied growth has contributed about 50% of the productivity growth in emerging economies and less innovative OECD countries; it has contributed about 64% of such growth in more innovative OECD countries. That is, the main mechanisms of the model (innovation and international diffusion) are able to capture, on average, half of all economic growth in the country groups analyzed. The remaining growth cannot be explained by the mechanisms proposed in the model. These results are consistent with the findings of Greenwood, Hercowitz, and Krusell (1997), who estimate that two thirds of the steady-state growth rate in the United States can be explained by "embodied" sources of growth and the rest by "disembodied" sources of growth. My model predicts

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

long-run convergence in growth across countries and so, to the extent that more innovative countries are close to the steady state, the values shown in Table 2 are in line with the Greenwood, Hercowitz, and Krusell (1997) findings. In developing economies, the contribution of embodied growth is slightly more than 50% and is expected to increase as they approach the steady state.

Table 2: Embodied versus disembodied growth in the transition (percentage)

Group	Embodied	Disembodied
Emerging	52	48
OECD−	53	47
OECD+	64	36

6.2 Contribution of Domestic and Foreign Innovation to Growth

Table 3 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 1996–2007. The diagonal entries measure the contribution of domestic innovation.

The analysis shows that, in emerging economies and less innovative OECD countries, about 65% and 40% of total embodied growth (respectively) can be explained by foreign innovations embodied in imports—especially those from the more innovative countries. In the most innovative countries, 85% of embodied productivity stems from domestic innovation. These results are consistent with the empirical evidence: emerging economies do relatively little innovation but have experienced a rapid increase in imported varieties, especially from the most innovative countries. By expanding the range of imported varieties from more innovative countries, less innovative countries accumulate the technology embodied in the foreign varieties and grow more than average.

Table 3: Sources of growth predicted by the model—domestic and foreign innovation

	Source country		
Destination	Emerging	OECD−	OECD+
Emerging	35.5	19.9	44.6
OECD−	11.7	56.6	33.7
OECD+	7.00	8.50	84.5

Taking the results from Tables 2 and 3 together, we can conclude that some 34% of total growth in emerging economies has been explained by foreign sources of growth, 16% by domestic innovation and 48% by exogenous "disembodied" sources of growth.

Table 4 reports the same decomposition as before but for the case in which all countries have reached the steady state. In this case, there is an increase in the domestic contribution to domestic growth in each country: 85% and 90% of endogenous growth in (respectively) emerging and less innovative OECD countries is explained by domestic innovation. Note that the increase in the contribution of domestic sources of growth is higher for those countries that are farther from the steady state (i.e., for emerging and less innovative OECD countries). Since embodied growth in steady state explains 60% of total growth, it follows that—in steady-state—innovation explains 54% of total growth, 6% is explained by adoption, and the remaining 40% comes from disembodied sources of growth.

Table 4: Sources of growth predicted by the model (steady-state)—domestic and foreign innovation

	Source country		
Destination	Emerging	OECD−	OECD+
Emerging	85	5.0	10
OECD−	3.0	91	6.0
OECD+	1.0	2.0	97

7 Counterfactuals

Finally, I perform two counterfactual exercises to analyze how the steady state of the model would change if: (i) all the countries reached the same research productivity, α_i^r; and (ii) all the countries faced the same barriers to adoption, α_i^a. The results are reported in Table 5.

Table 5: Counterfactual experiments

Variable	**Baseline**	**Same innovation**	**Same adoption**
Y_1^r	0.102	0.173	0.103
Y_2^r	0.128	0.173	0.128
Y_3^r	0.171	0.173	0.171
g_y	0.089	0.149	0.089
g_z	0.030	0.050	0.030
ε_{12}	0.319	0.323	0.329
ε_{13}	0.311	0.323	0.323
ε_{21}	0.310	0.331	0.313
ε_{23}	0.320	0.331	0.323
ε_{31}	0.316	0.334	0.318
ε_{32}	0.332	0.335	0.333

Note: 1 refers to emerging markets; 2 to OED −; and 3 to OECD+

If all countries converged to the research productivity of the rich OECD countries while maintaining the same barriers to adoption, their research intensity would increase by 50% in emerging economies and by 30% in less innovative OECD countries. More innovative countries would also benefit because they would then have access to a larger pool of innovations from other countries (although their research productivity would increase only by 1%). The probability of adoption around the world would increase on average by 2%; this suggests that, the more innovative a country, the greater its ability to adopt foreign technologies. Finally, the growth rate of the world would double from 2% to 4%, which indicates that policies to improve innovation can help increase the world's rate of economic growth. At the same time, developing countries would close the gap (with respect to developed countries) not only in growth rates but also in levels of income per capita.

If instead all countries became equally good at adopting but without improving their research productivity, then the world economic gains would be lower (albeit non negligible). All countries would increase their research intensity by about 0.4%, and the world's economic growth rate would increase by 1%.

8 Conclusion

In this paper, I decompose the sources of embodied growth around the world into domestic innovation and adoption of foreign innovations through trade. I develop a dynamic general equilibrium model in which imports and growth are endogenous variables connected by technological innovations and their international diffusion through trade. The engine of growth is 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 allow income differences to persist. Countries grow at different rates during the transition from developing to developed status. 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, which are closer to the technological frontier, grow instead by developing new technologies through R&D. Counterfactual exercises show that if all countries reached the same research productivity then the world's economic growth rate would double, mainly through an increase in research intensity. Countries also converge in levels of income per capita.

The analysis has abstracted from several of interesting issues. The introduction of physical and human capital would enrich the structure of the model and allow for the use of TFP as a measure of productivity. We would be able to disentangle the effect of additional channels in explaining differences in growth rates around the world. Right now, these channels are embedded in the exogenous disembodied source of growth, which is a black box in the model. Opening this black box is left for future research.

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Appendix A: Data and Statistics

Table A.1: Country Statistics

Country	R&D Intens.	GDP pc (log)	EM (count)	EM (Humm-Klen)
Argentina	0.43	12.81	4.33	0.41
Australia	1.74	13.34	2.30	0.44
Austria	2.04	12.42	2.67	0.76
Brazil	1.17	14.09	4.66	0.47
Canada	1.91	13.81	4.13	0.64
China	0.97	15.39	4.46	0.95
Hong Kong	0.73	12.34	3.14	0.61
Denmark	2.29	12.01	3.25	0.71
Finland	3.19	11.88	2.66	0.60
France	2.17	14.32	1.79	0.34
Germany	2.42	14.69	1.49	0.19
Greece	0.71	12.31	3.32	0.32
India	0.72	14.54	5.48	0.73
Indonesia	1.19	13.42	3.50	0.44
Ireland	1.20	11.79	3.77	0.76
Italy	1.06	14.29	1.85	0.27
Japan	3.07	15.14	2.01	0.12
Malaysia	0.64	12.30	1.89	0.38
Netherlands	1.93	13.14	1.82	0.38
New Zealand	1.11	11.43	3.64	0.78
Norway	1.57	12.19	2.80	0.56
Philippines	0.76	12.48	5.12	0.59
Portugal	0.72	12.16	3.59	0.53
South Korea	2.51	13.75	3.39	0.63
Singapore	1.90	11.70	2.01	0.42
Spain	0.96	13.77	2.73	0.75
Sweden	3.33	12.49	2.24	0.35
Switzerland	2.18	12.48	2.67	0.52
United States	2.62	16.23	1.62	0.27
United Kingdom	1.77	14.34	1.24	0.25
Average	**1.63**	**13.23**	**2.99**	**0.51**
S.D.	**0.83**	**1.24**	**1.12**	**0.20**

Table A.2: Product classification

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

Note: 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).

Table A.3: Countries grouped by level of development

Country	**Group**
Argentina	Emerging
Brazil	Emerging
China	Emerging
Hong Kong	Emerging
India	Emerging
Indonesia	Emerging
Malaysia	Emerging
Philippines	Emerging
Australia	OECD+
Austria	OECD+
Canada	OECD+
Denmark	OECD+
Finland	OECD+
France	OECD+
Germany	OECD+
Japan	OECD+
Netherlands	OECD+
New Zealand	OECD+
Norway	OECD+
South Korea	OECD+
Singapore	OECD+
Sweden	OECD+
Switzerland	OECD+
United States	OECD+
United Kingdom	OECD+
Greece	OECD−
Ireland	OECD−
Italy	OECD−
Portugal	OECD−
Spain	OECD−

Appendix B: Gravity Equation Results

Table B.1: Bilateral trade equation

Variable	Estimate	S.E.
Distance $[0, 375)$	-5.115***	(0.291)
Distance $[375, 750)$	-4.797***	(0.207)
Distance $[750, 1500)$	-5.051***	(0.162)
Distance $[1500, 3000)$	-5.169***	(0.149)
Distance $[3000, 6000)$	-5.754***	(0.084)
Distance $[6000, \text{maximum})$	-6.215***	(0.030)
Shared Border	0.435***	(0.131)
Shared Language	0.551***	(0.082)
Regional Trade Agreement	0.922***	(0.173)

		Source country			Destination country	
Country		Estimate	S.E.		Estimate	S.E.
ARG	S_1	-1.196***	(0.116)	M_1	-0.031	(0.116)
AUS	S_2	-0.011	(0.117)	M_2	1.613***	(0.117)
AUT	S_3	-0.977***	(0.117)	M_3	-0.627***	(0.117)
BRA	S_4	-0.044	(0.116)	M_4	-0.112	(0.116)
CAN	S_5	0.199*	(0.118)	M_5	-0.182	(0.118)
CHE	S_6	-0.046	(0.117)	M_6	0.202*	(0.117)
CHN	S_7	1.711***	(0.118)	M_7	-0.418***	(0.118)
DEU	S_8	1.744***	(0.117)	M_8	-0.510***	(0.117)
DNK	S_9	-0.843***	(0.118)	M_9	-0.028	(0.118)
ESP	S_{10}	-0.145	(0.117)	M_{10}	-0.433***	(0.117)
FIN	S_{11}	-0.568***	(0.117)	M_{11}	-0.511***	(0.117)
FRA	S_{12}	0.979***	(0.117)	M_{12}	-0.712***	(0.117)
GBR	S_{13}	1.035***	(0.118)	M_{13}	-0.141	(0.118)
GRC	S_{14}	-2.855***	(0.118)	M_{14}	0.370***	(0.118)
HKG	S_{15}	-0.000	(0.122)	M_{15}	2.461***	(0.122)
IDN	S_{16}	0.014	(0.118)	M_{16}	0.142	(0.116)
IND	S_{17}	-0.377***	(0.123)	M_{17}	-0.603***	(0.123)
IRL	S_{18}	-0.730***	(0.117)	M_{18}	-0.507***	(0.117)
ITA	S_{19}	0.859***	(0.117)	M_{19}	-0.791***	(0.117)
JPN	S_{20}	2.431***	(0.118)	M_{20}	-0.797***	(0.118)
KOR	S_{21}	1.175***	(0.118)	M_{21}	-0.133	(0.118)
MYS	S_{22}	0.364***	(0.116)	M_{22}	0.525***	(0.116)
NLD	S_{23}	0.407***	(0.118)	M_{23}	0.424***	(0.118)
NOR	S_{24}	-1.315***	(0.117)	M_{24}	-0.116	(0.117)
NZL	S_{25}	-1.630***	(0.117)	M_{25}	0.675***	(0.117)
PHL	S_{26}	-1.135***	(0.118)	M_{26}	0.283**	(0.118)
PRT	S_{27}	-2.008***	(0.118)	M_{27}	-0.440***	(0.118)
SGP	S_{28}	0.083	(0.118)	M_{28}	1.071***	(0.120)
SWE	S_{29}	0.068	(0.117)	M_{29}	-0.478***	(0.117)
USA	S_{30}	2.813***	(0.118)	M_{30}	-0.198*	(0.118)

Notes: The number of observation is 869
Standard errors in parentheses
***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.2: Countries ordered by source of competitive advantage

S_n	Z_n	$\log \omega_n$
United States	United States	Norway
Japan	Japan	Switzerland
China	Germany	Ireland
Germany	Switzerland	Denmark
South Korea	United Kingdom	United States
United Kingdom	France	Netherlands
France	Netherlands	Sweden
Italy	Norway	Austria
Malaysia	Italy	Japan
Netherlands	Ireland	United Kingdom
Australia	Sweden	Finland
Brazil	Canada	Germany
Canada	Denmark	Canada
Indonesia	Australia	France
Singapore	Finland	Australia
Sweden	Austria	Italy
Switzerland	Singapore	New Zealand
Spain	Spain	Singapore
Hong Kong	South Korea	Spain
India	Hong Kong	Hong Kong
Finland	New Zealand	Greece
Ireland	Portugal	Portugal
Denmark	Greece	South Korea
Austria	Malaysia	Malaysia
Argentina	Brazil	Brazil
Philippines	Argentina	Argentina
Norway	China	China
New Zealand	Indonesia	Indonesia
Portugal	Philippines	Philippines
Greece	India	India

Appendix C: Estimation Results

Table C.1: Calibrated parameters

Parameter	Description	Value
θ	Elast. Subst.	4
g	S.S. growth	2%
γ_a	Elast. adopt.	0.8
γ_r	Elast. innov.	0.6
d_n^i	Distance	[1.2,1.5]
β	Discount factor	0.99
α_1^r	R&D productivity	0.189
α_2^r	R&D productivity	0.238
α_3^r	R&D productivity	0.331
α_1^a	Barriers adoption	5.17
α_2^a	Barriers adoption	5.17
α_3^a	Barriers adoption	5.24

Note: 1 refers to emerging markets; 2 to OECD $-$; and 3 to OECD+

Table C.2: Estimated Parameters

Parameter	Prior	Mean	5%	95%
ρ_1	Beta(0.75,015)	0.36	0.21	0.54
ρ_2	Beta(0.75,015)	0.86	0.82	0.89
ρ_3	Beta(0.75,015)	0.65	0.59	0.72
σ_1^y	IGamma(0.1,∞)	0.053	0.029	0.077
σ_2^y	IGamma(0.1,∞)	0.047	0.033	0.059
σ_3^y	IGamma(0.1,∞)	0.065	0.044	0.082
σ_1^r	IGamma(1.0,∞)	0.312	0.230	0.408
σ_2^r	IGamma(1.0,∞)	0.250	0.171	0.327
σ_3^r	IGamma(1.0,∞)	0.274	0.189	0.351
σ_{12}	IGamma(0.1,∞)	1.072	0.771	1.445
σ_{13}	IGamma(0.1,∞)	0.563	0.361	0.779
σ_{21}	IGamma(0.1,∞)	0.345	0.251	0.436
σ_{23}	IGamma(0.1,∞)	0.113	0.060	0.171
σ_{31}	IGamma(0.1,∞)	0.282	0.195	0.361
σ_{32}	IGamma(0.1,∞)	0.406	0.296	0.514

Note: 1 refers to emerging markets; 2 to OECD $-$; and 3 to OECD+

Table C.3a: Second moments

Variable	**Data**	**Model**
Y_1^r	0.15	0.12
Y_2^r	0.06	0.05
Y_3^r	0.02	0.02
g_1^y	3.12	4.60
g_2^y	1.50	2.20
g_3^y	2.20	3.10
g_{12}^a	1.24	1.23
g_{13}^a	0.55	1.80
g_{21}^a	0.37	0.45
g_{23}^a	0.15	1.90
g_{31}^a	0.24	0.34
g_{32}^a	0.25	0.90

Note: 1 refers to emerging markets; 2 to OECD −; and 3 to OECD+

Table C.3b: Variance decomposition (posterior mean)

Shock/Variable	g_1^y	g_2^y	g_3^y	Y_1^r	Y_2^r	Y_3^r
e_1^y	74.2	0.36	0.32	22.0	0.20	0.20
e_2^y	0.00	25.5	0.00	0.00	7.80	0.00
e_3^y	0.00	0.00	18.5	0.20	0.10	10.0
e_1^r	25.4	0.14	0.13	75.4	0.40	0.30
e_2^r	0.10	73.2	0.25	1.10	90.2	0.70
e_3^r	0.30	0.80	80.8	1.30	1.30	88.8

Note: 1 refers to emerging markets; 2 to OECD −; and 3 to OECD+

Appendix D: 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:

$$g_i = \frac{\Delta T_i}{T_i} = \frac{\Delta Z_i}{T_i} + \sum_{n=1}^{M} \frac{\Delta A_n^i}{T_i} \tag{36}$$

Substituting equations (12) and (18) into equation (36), allows us to express steady-state productivity growth as a function of how much research has been done around the world:

$$g = g_i = \alpha_i r_i^{\gamma_r} + \sum_{n=1}^{M} \varepsilon_n^i \sum_{s=1}^{t} (1-\varepsilon_n^i)^{-(t-s)} \alpha_{ns} r_{ns}^{\gamma_r} \frac{T_{ns}}{T_{it}}, \tag{37}$$

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

Since $T_{ns} = T_{nt}(1+g)^{(t-s)}$ and $r_{ns} = r_n$ for all s in steady state and taking into account that instantaneous diffusion within a country implies that $\varepsilon_{ii} = 1$— equation (36) can be rewritten as

$$g=\sum_{n=1}^{M}\varepsilon_{in}\alpha_n r_n^{\gamma_r}\sum_{s=1}^{M}\left(\frac{1-\varepsilon_n^i}{1+g}\right)^{-(t-s)}=\sum_{n=1}^{M}\varepsilon_n^i\alpha_n r_n^{\gamma_r}\frac{1+g}{g+\varepsilon_n^i}\frac{T_{nt}}{T_{it}}. \tag{38}$$

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

It is important to note that if there were no sources of heterogeneity in the country (i.e., if $\alpha_i^R=\alpha^R$, $\alpha_i^A=\alpha^A$, $L_i=L$ and $d_n^i=d$ for all 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.

Appendix E: Decomposing the Sources of Growth

To obtain the equation, I use the measure for output from the model:

$$Y_{it}=Z_{it}X_{it}^i+\sum_{n\neq i}A_{nt}^iX_{nt}^i.$$

Then, after plugging in the expressions for X_{it}^i and X_{nt}^i and rearranging, we obtain

$$1=e^{a_{it}}Z_{it}(\bar{m}\omega_{it})^{1-\theta}+\sum_{n\neq i}e^{a_{nt}}\frac{A_{nt}^i}{Z_{nt}}Z_{nt}(\bar{m}\omega_{nt}d_n^i/Q_{ni})^{1-\theta}.$$

Since productivity in my model is equivalent to output per capita, and since real output per capita corresponds to real wages ω_{it}, it follows that labor productivity can be expressed as

$$(\omega_{it})^{\theta-1}\bar{m}^{\theta-1}=e^{a_{it}}Z_{it}+\sum_{n\neq i}e^{a_{nt}}A_{nt}^i\left(\frac{\omega_{nt}}{\omega_{it}}\right)^{1-\theta}\left(d_n^i\right)^{1-\theta}Q_{ni}^{\theta-1}.$$

In terms of growth rates, we have:

$(\sigma-1)\left(\omega_{it}\right)^{\theta-1}\bar{m}^{\theta-1}\frac{\Delta\omega_{it}}{\omega_{it}}=$

$e^{a_{it}}Z_{it}\frac{\Delta Z_{it}}{Z_{it}}+e^{a_{nt}}\sum_{n\neq i}A_{nt}^i\left(\frac{\omega_{nt}}{\omega_{it}}\right)^{1-\theta}\left(d_n^i\right)^{1-\theta}Q_{ni}^{\theta-1}\left(\frac{\Delta A_{nt}^i}{A_{nt}^i}+(1-\theta)\left(\frac{\Delta\omega_{nt}}{\omega_{nt}}-\frac{\Delta\omega_{it}}{\omega_{it}}-\frac{\Delta Q_{ni}}{Q_{ni}}\right)\right)$

If the variables are expressed in stationarized terms (to make them consistent with the variables from the code), then

$\frac{\Delta\omega_{it}}{\omega_{it}}=\frac{\bar{m}^{1-\theta}}{\theta-1}\left[e^{a_{it}}\hat{\omega}_{it}^{1-\theta}\frac{\Delta Z_{it}}{Z_{it}}+\sum_{n\neq i}e^{a_{nt}}\frac{A_{nt}^i}{Z_{nt}}\hat{\omega}_{nt}^{1-\theta}\left(d_n^i\right)^{1-\theta}Q_{ni}^{\theta-1}\left(\frac{\Delta A_{nt}^i}{A_{nt}^i}+(1-\theta)\left(\frac{\Delta\omega_{nt}}{\omega_{nt}}-\frac{\Delta\omega_{it}}{\omega_{it}}-\frac{\Delta Q_{ni}}{Q_{ni}}\right)\right)\right]$

Taking $\frac{\Delta\omega_{it}}{\omega_{it}}$ to the LHS of the above expression:

$$(\theta-1)\frac{\Delta\omega_{it}}{\omega_{it}}=e^{a_{it}}\left[\underbrace{\frac{\Delta Z_{it}}{Z_{it}}}+\underbrace{\sum_{n\neq i}e^{a_{nt}-a_{it}}\frac{A_{nt}^i}{Z_{nt}}\hat{\omega}_{nt}^{1-\theta}\left(d_n^i\right)^{1-\theta}Q_{ni}^{\theta-1}\left(\frac{\Delta A_{nt}^i}{A_{nt}^i}+(1-\theta)\left(\frac{\Delta\omega_{nt}}{\omega_{nt}}-\frac{\Delta Q_{ni}}{Q_{ni}}\right)\right)}\right].$$

There are two sources of growth:

- Disembodied growth: $e^{a_{it}}$
- Embodied growth:

$$\left[\underbrace{\frac{\Delta Z_{it}}{Z_{it}}}+\underbrace{\sum_{n\neq i} e^{a_{nt}-a_{it}}\frac{A^i_{nt}}{Z_{nt}}\hat{\omega}_{nt}^{1-\theta}\left(d^i_n\right)^{1-\theta}Q_{ni}^{\theta-1}\left(\frac{\Delta A^i_{nt}}{A^i_{nt}}+(1-\theta)\left(\frac{\Delta\omega_{nt}}{\omega_{nt}}-\frac{\Delta Q_{ni}}{Q_{ni}}\right)\right)}\right].$$

The two sources of embodied growth are:

- Domestic sources (innovation): $\underbrace{\dfrac{\Delta Z_{it}}{Z_{it}}}$
- Foreign sources (international diffusion):

$$\sum_{n\neq i} e^{a_{nt}-a_{it}}\frac{A^i_{nt}}{Z_{nt}}\hat{\omega}_{nt}^{1-\theta}\left(d^i_n\right)^{1-\theta}Q_{ni}^{\theta-1}\left(\frac{\Delta A^i_{nt}}{A^i_{nt}}+(1-\right).$$