Innovation, Diffusion and Trade: Theory and Measurement*

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Abstract

In the last decade, some countries such as China, India, and Ireland grew much faster than average, and experienced a significant increase in the variety of goods that they import. At the same time, their investment in R&D is low: 80% of the innovative activity in the world is concentrated in a few rich countries. This evidence suggests that non-innovative economies benefit from foreign technology through imports.

I propose a model of innovation and international diffusion to analyse the connections between trade in varieties and economic growth. International diffusion takes the form of adopting new goods that have been developed elsewhere. In this context, trade arises as the natural vehicle of diffusion. The model is able to capture the main features of the data: countries innovate, adopt new technologies, and grow at different rates.

The model is fitted to five regions: Asia, Eastern Europe, Western Europe, Japan and the US. Using disaggregated trade data, and data on the fraction of workers allocated to R&D, and output growth, I estimate the parameters of innovation and diffusion with Bayesian techniques. I then decompose the sources of productivity growth in each region. The results show that 90% of growth in Asia is explained by imports from the US and Japan. These two regions are also the main sources of foreign technology for other regions in the model.

Finally, counterfactuals examine the connections between trade and growth by changing various exogenous parameters. A 10% permanent decrease in the barriers to technology adoption in Asia increases world growth rates by 0.4%. In the transition, Asia imports and grow faster than the rest of the world. A 10% permanent increase in the innovation productivity in Asia increases world growth rates by 0.7%. The higher productivity in Asia increases the demand of imports by this region by 6%. Thus, either change leads simultaneously to both higher growth and more trade.

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1 Introduction

Advances in technology drive the growth of nations, while barriers to technology diffusion create persistent income differences across countries.[1] In this context, what are the mechanisms connecting the creation of new varieties, technology diffusion, and growth? Can we quantify these connections? I address these questions in this paper.

In the last decade, some countries such as China, India, and Ireland, grew much faster than average, and experienced a significant increase in the number of varieties that they imported.[2] At the same time, their investment in R&D is low: 80% of the innovative activity in the world is concentrated in a few rich countries. This evidence suggests that non-innovative economies benefit from foreign technology through diffusion. The positive correlation between economic growth and growth in imported varieties among non-innovative countries suggests that international diffusion can take the form of adopting new goods that have been developed elsewhere. In this context, trade arises as the channel through which countries benefit from foreign innovations. I propose a model of innovation and international diffusion, taking proliferation of varieties as the measure of diffusion, to explain the connections between trade and growth.

Models of growth based of innovation and technology transfer face the problem that there are not good measures of diffusion. The trade literature has filled this gap, using imports as an indirect measure.[3] However, studies that quantify the impact of imports in growth are based on regression analysis that face endogeneity problems, and miss the fact that these two variables are both equilibrium outcomes.[4] A recent attempt to give a more structural approach is the paper by Broda, Greenfield, and Weinstein (2008), who analyse the impact of trade in new and improved varieties on TFP growth for a large sample of countries. Although they provide a good measure for trade in varieties, their model is too stylized to make precise statements about the channels of growth. My paper constitutes an attempt to structurally analyse and quantify the mechanisms behind the connections between trade an growth, in which both are endogenous variables.

A variety is defined, following Feenstra (1994), as a 6-digit category product from a particular country, reflecting the Armington assumption that products differ according to their source. It is important to note that the Armington assumption implies that each country produces a different

[1] See Parente and Prescott (1994) and Eaton and Kortum (2007).

[2] Santacreu (2006) obtains that more than 60% of the economic growth in Ireland in the last decade can be explained by an increase in the variety of goods that it imports from very innovative countries in the OECD.

[3] See Keller (2004) for a survey of models that use imports to measure diffusion.

[4] Coe, Helpman, and Hoffmaister (1997) and Keller (1998) are good examples.

variety. Therefore, a country that imports a good can never learn how to produce, exactly, that good itself. This differs from the product cycle literature in which countries eventually export the goods that they import. Nevertheless, in my specification, a country's research productivity, is enhanced by having access to a wider range of products, including imports. Having imported a good may then help a country to create its own variety of it.

To measure growth in imported varieties, I follow the methodology developed by Feenstra (1994) and adapted by Broda and Weinstein (2006) and Broda, Greenfield, and Weinstein (2008). They argue that measuring growth in varieties using count data can lead to quality bias. To correct for this bias, they compute the share of new and disappearing varieties in expenditure. If new varieties represent a small share of total expenditure in a good, then a count of varieties overestimates the true impact of new varieties.

I develop and estimate a multicountry growth model in which technology is embodied in new intermediate goods that arrive through domestic innovation. Countries can benefit from foreign innovations by adopting goods that embody the new technology. Innovation and adoption are endogenous processes in this framework. In particular, adoption is a slow process that depends on profit maximizing decisions of economic agents, as in Parente and Prescott (1994): firms in a country need to make a costly investment to be able to import a foreign good. There are four activities in the economy. First, a final sector produces a non-traded good, using as inputs traded intermediate products. Second, the intermediate sector is composed of monopolistic competitive firms that use labor according to a constant returns to scale technology. Taking as given the demand by the final producers, they choose a price that is a constant mark-up over the marginal cost. New technologies arrive by investing resources in the innovation sector, which is the third activity in this economy. Innovators then sell the right to produce the technology to the intermediate firm for a specific transfer price. Finally, an adoption sector invests resources to make the good usable by final producers in foreign markets. With a certain probability they will be able to adopt the good. Diffusion is a slow and costly process. The labor market clearing condition closes the model. Labor is used for manufacturing of intermediate goods, innovation and adoption. There is a trade-off between allocating resources in doing innovation or in doing adoption, which depends on the level of development of the specific country.

The model predicts that, in steady state, all countries grow at the same rate and differ in relative productivity. The model is tractable enough to analyse out of steady state dynamics. Differences in growth rates arise in the transition and are driven by differences in the incentives to innovate or to adopt new goods. This allows me to account for the experience of countries such as China or India, which are growing faster than average but are likely to share the same world growth rates in the long-run.

The model is fitted to thirty seven countries that are grouped, for tractability, into five regions: Asia, Eastern Europe, Western Europe, Japan, and the US. Each region is treated as a different country. I estimate the parameters that govern innovation and diffusion with Bayesian techniques. I use disaggregated trade data, and data on a measure of the fraction of workers allocated to R&D, and output growth. The estimates are used to decompose the sources of productivity growth in each region. The results show that almost 90% of productivity growth in Asia can be explained by imports from the US and Japan. These two regions are also the main sources of foreign technology for other regions of the model.

Finally, counterfactuals examine the connections between trade and growth by changing various exogenous parameters. On the one hand, a 10% permanent decrease in the barriers to technology adoption in Asia increases world growth rates by 0.4%; in the transition to the new steady state, trade rises, while Asia grows faster than the rest of the world. On the other hand, a 10% permanent increase in the innovation productivity in Asia increases world growth rates by 0.7%. The higher productivity in Asia increases the demand of imports in this region by 6%. Both changes induce a positive correlation between trade and growth.

The rest of the paper is organized as follows. Section 2 presents the related literature. Section 3 takes a look at the data. In section 4, I present the model. Section 5 solves for the steady state. The model is estimated in section 6 and I present a decomposition of the growth rate of each country into the contribution of own and foreign innovation in section 7. In section 8, I compute the speed of convergence predicted by the model. I perform counterfactuals in sections 9 and 10, to analyse the implications of the model for the two directions in the connections between trade and growth. Section 11 concludes.

2 Related Literature

The paper builds on several literatures. First, the literature on endogenous growth in which technology is embodied in the creation of new goods (Romer 1987). Technological progress is driven by the invention of new types of intermediate goods, which are the result of decisions made by profit maximizing agents.

Second, the model relates to the literature of technology diffusion. Keller (2004) surveys the empirics of the effects of international diffusion on productivity. The theoretical framework is based on the papers by Eaton and Kortum (1996) and Eaton and Kortum (1999). They present a quality-ladder model in which patents are the indicator of diffusion, for a sample of OECD countries. In my framework, the expansion in the number of varieties through trade, rather than the improvement in existing varieties, is the main driving force of diffusion, especially in developing countries.

The lack of direct measures that can exploit the bilateral nature of adoption have lead some economists to use indirect measures, such as trade in intermediate goods (Rivera-Batiz and Romer (1991), Eaton and Kortum (2001), and Eaton and Kortum (2002)).[5] Countries benefit from ideas developed elsewhere by importing their newly developed products. Coe, Helpman, and Hoffmaister (1997) find that total factor productivity in a panel of seventy-one developing countries is significantly related to the stock of R&D carried out by trading partners. They find evidence that trade, particularly the imports of machinery and equipment, facilitates the diffusion of knowledge. My model complements this literature by explicitly modeling the mechanisms that explain how trade and growth are connected.

Different from previous studies in the literature,[6] in my model, technology diffusion is an endogenous process; firms need to undertake a costly investment to be able to import a good. The incentives to the importer differ across markets and depend on the value of adoption of a new technology. I follow the approach introduced by Comin and Gertler (2006) and used in Comin, Gertler, and Santacreu (2008). They present a closed economy business cycle model in which there is endogenous adoption; countries invest resources in adapting a new product. Endogenous adoption arises as one of the main propagation mechanism for the shocks in the economy. This paper applies their approach to a long-run analysis of open economies. Empirical evidence that shows that innovations cannot be transferred to other locations at a negligible cost can be found in Griliches (1957) and Teece (1977).

Finally, the paper also relates to the literature of trade to identify varieties. In a recent paper, Broda, Greenfield, and Weinstein (2008) estimate the effects of trade in productivity growth. They find that trade in imported varieties accounts for 20% of TFP growth in the typical developing country and only 5% in the typical developed country. My paper follows Broda, Greenfield, and Weinstein (2008) to measure growth in varieties but, different from their paper, I model explicitly the incentives of the different agents in the economy to undertake either re-

[5] Comin and Hobijn (2004) provide direct measures of adoption for a large sample of countries and a large sample period; they do not distinguish, however, which technologies are created in the country and which technologies come from abroad.

[6] See Eaton and Kortum (1999).

search or adoption. This helps me to understand why different countries choose to specialize in one activity or the other, which provides the mechanisms to explain differences in growth rates across economies.

3 A Look at the Data

In the last decade, some countries in Asia and Eastern Europe have experienced a significant increase in the number of goods that they import from the rest of the world. Figure 1 shows that there is a positive correlation between the average growth rate of income per capita and growth in imported varieties.[7] The squares in red represent countries with a relatively low investment in R&D in Asia and Eastern Europe. The circles in blue represent rich countries in the European Union, Japan, and the US. Countries that grow and import faster are the ones with a lower GDP per capita. There is a catch-up effect by which less advanced countries grew faster than richer ones. Figure 2 plots the average growth rate for the period 1994-2003 against the initial level of GDP per capita. There is a clear negative relationship between these two variables.

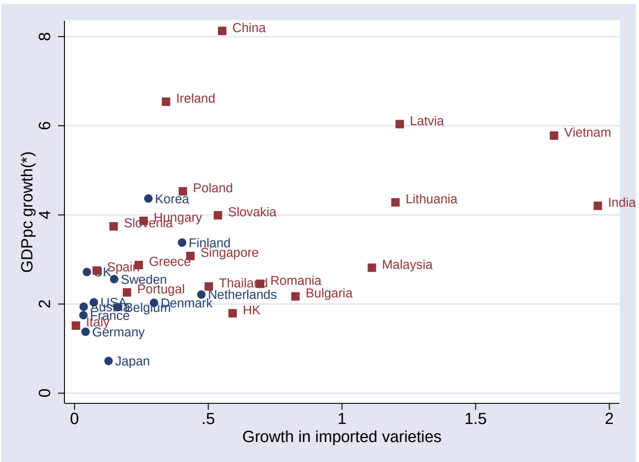

Figure 1: Relation between GDPpc growth and variety growth: (*) PPP adjusted; Average over 1994-2003

When we look at levels, rather than growth rates, we see that richer countries import a higher variety of goods than less advanced economies. Figure 3 plots the level of imports against the level of income per capita. The graph suggests that both variables are positively correlated.

[7] The average is taken over the period 1994-2003 for a sample of thirty seven countries in Asia, the European Union, the United States, and Japan.

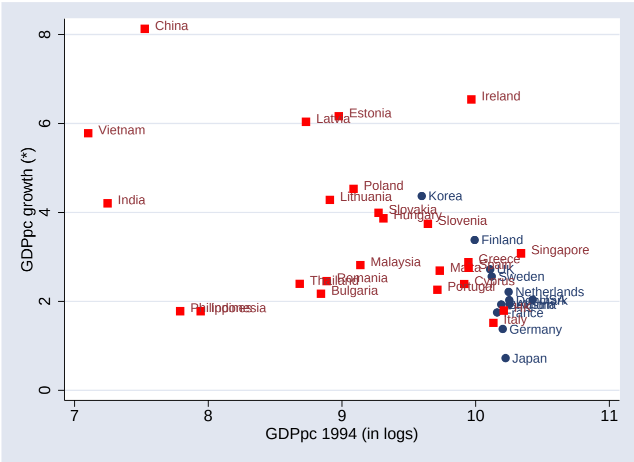

Figure 2: Relation between GDPpc growth and initial level of GDPpc: (*) PPP adjusted; Average over 1994-2003

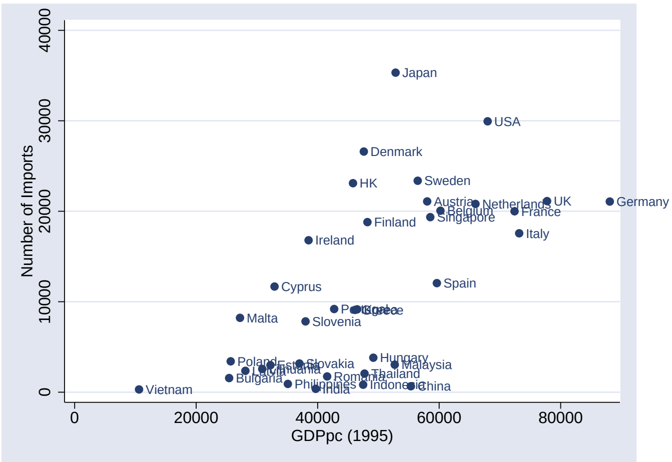

Figure 3: Relation between GDPpc and number of imported variety: (*) PPP adjusted; Average over 1994-2003

Figures 1 to 3 show that rich countries import a larger number of varieties, while their growth rates are relatively low. Less advanced countries are taking advantage of their backward position and getting closer to the frontier by importing new varieties.

Fast growing countries do not tipically invest a significant amount of resources in R&D. Figure 4 shows a negative correlation between R&D investment and growth in trade of varieties. While innovations are concentrated in a few rich countries (especially in Japan, the US, and Sweden), less innovative economies also grow, sometimes, at a higher rate than their innovative counterparts (it is the case of Vietnam, India, or China). If technology is embodied in new intermediate goods, this evidence suggests that countries benefit form innovations done elsewhere, and trade arises as the natural measure of international diffusion.

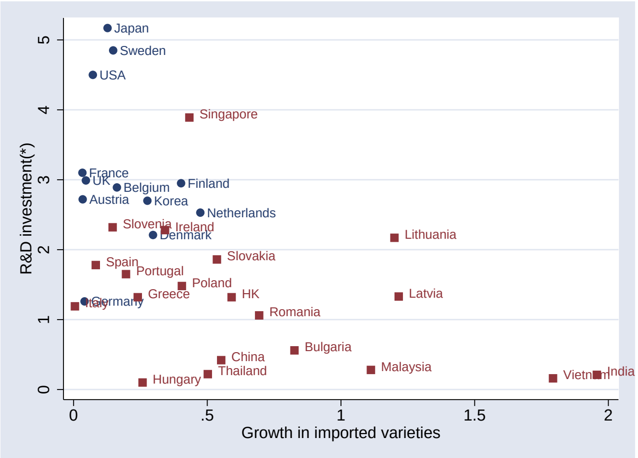

Figure 4: Relation between R&D investment and variety growth: (*) PPP adjusted; Average over 1994-2003

Diffusion across countries is a slow process, and takes time on average. In table 1, I report the hazard of adoption over the period 1994-2003, for a sample of 37 countries that are grouped in five regions.[8] The inverse of the hazard rate represents the average time that it takes, for each importer, to adopt goods from each exporter.[9] The table shows that the average diffusion lag

[8]For a sample of the countries that are included in each regions, see the Appendix.

[9]I use the tools of survival analysis (or duration dnalysis) with censored data. I estimate a non-parametric survival function (using the Meier Kaplan estimator with right-censored data). Ideally, we would need to know the time at which each good is invented by the exporter and the time at which is first imported by each destination. There are several limitations in the data. First, I do not observe the time of invention. I assume that this is given by the first time a source starts exporting a good to any country. There are left and right censoring in the data.

is between three and ten years.

Exporter	Importer	Hazard
EU+	Asia	0.31
EU-	Asia	0.19
Japan	Asia	0.35
US	Asia	0.34
Asia	EU+	0.28
EU-	EU+	0.33
Japan	EU+	0.29
US	EU+	0.28
Asia	EU-	0.24
EU+	EU-	0.33
Japan	EU-	0.31
US	EU-	0.34
Asia	Japan	0.35
EU+	Japan	0.28
EU-	Japan	0.20
US	Japan	0.25
Asia	US	0.35
EU+	US	0.29
EU-	US	0.32
Japan	US	0.28

Table 1: Hazard rates

EU+ (Western Europe); EU- (Eastern europe); Japan (includes Korea)

On the one hand, there is left-censoring because, for those products that are exported in 1994, we do not know if they were invented in that year or earlier. On the other hand, there is right-censoring becausesome importers have not adopted, before 2003, all the goods that are exported. It is easy to fix the right-censoring problem, but dealing with left censoring data is more problematic. It is straighforward to handle if we assume that the hazard rate does not vary with survival time. The standard way of handling left-censoring is to drop the spells that started before the window of observation.

4 The Model

In this section, I construct an endogenous growth model of trade in varieties that captures the key features of the data. I consider a world economy composed of M countries that interact with each other through imports. Technology is embodied in new goods that are used for final production, as in Romer (1987). There are four activities in this economy: final production, intermediate production, innovation, and adoption. Technological change is driven either by innovation or technology diffusion. Diffusion is indirectly measured through trade in intermediate goods. The model predicts that, in steady state, all the countries grow at the same rate and differ in relative productivity, which depend on their ability to innovate and import goods. Differences in growth rates arise in the transition.

Throughout the paper, whenever a variable has both a subscript and a superscript, the superscript indexes the destination of imports and the subscript indexes the source of exports. The goods are indexed by j and the time is indexed by t.

4.1 Final production sector

Each country i produces, at time t, a non-traded final good Y_{it} using traded intermediate goods, j, according to the Ethier (1982) CES function

$$Y_{it} = e^{a_{it}} \left(\sum_{j=1}^{T_{it}} (b_{nj}^{i})^{\frac{1}{\sigma}} (x_{njt}^{i})^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where $\sigma > 1$ is the elasticity of substitution among differentiated intermediate goods;[10] x_{ijt}^{n} is the amount of input j that is used in the production of final output; b_{nj}^{i} is a preference parameter that represents expenditure shares; and T_{it} is the total number of varieties available for final production in country i at time t.[11] It is a measure of embodied technology and it includes both domestic and foreign adopted intermediate goods. Finally, a_{it} is a country-specific productivity in manufacturing, which is assumed to be common across sectors. It follows the AR(1) process $a_{it} = \rho a_{i,t-1} + u_{i,t}$, with $u_{it} \sim N(0, \sigma^2)$.

The CES production function was first proposed by Ethier (1982) and it has implications for the analysis of growth. First, it implies that the level of productivity in a country is determined

[10] When $\sigma \to \infty$, goods are perfect substitutes.

[11] b_{nj}^{i} is assumed to be unknown ex-ante and it is only realized once innovation of a new variety has taken place.

by the number of varieties available in the country. In fact, the data show that rich countries, with higher levels of GDP per capita, also import a higher variety of goods. Second, the growth rate of a country's productivity growth is given by an expansion in the variety of goods in the final sector. Countries that have experienced faster than average growth rates, have also been importing goods at a faster rate. As in Romer (1987), creation and adoption of new intermediate products are the source of embodied productivity growth.

4.2 Intermediate production sector

The intermediate goods sector is composed of monopolistic competitive firms. There is a continuum of intermediate producers with market power who each sell a different variety to the competitive final good producer. Intermediate goods are produced according to the same CRS production function: one unit of intermediate good is produced using one unit of labor,[12]

$$x_{ijt} = l_{ijt} \tag{2}$$

with $\sum_j l_{ijt} = L_{it}$.

These assumptions have implications for pricing, firm profits and the value of having an innovation adopted in a country. Under monopolistic competition each good is produced by a separate monopolist. Markets are segmented so that producers can set a different price in each market. Producers in each country endogenously choose to produce a different set of goods.[13]

Each intermediate good firm chooses a price to be a constant mark-up over the marginal cost, taking as given the demand by the final producers (the final good producer chooses optimal demand for each variety, and this yields a downward sloping demand curve.). The value of goods that domestic final producers demand from n is

$$x^i_{nt} = (a_{it})^{\sigma} b^i_n X_{it} \left(\frac{p^i_{nt}}{P_{it}}\right)^{(-\sigma)} \tag{3}$$

[12] Labor is the only factor of production in the economy. It is assumed to be immobile across countries and perfectly mobile across sectors within a country. Labor is used for manufacturing of intermediate goods, innovation, and adoption.

[13] As I explained in the introduction, my analysis does not explain specialization of production across countries (the Armington assumption of goods differentiated per source of exports implies that countries exogenously specialize in a different set of goods) or within a country (the monopolistic competition setting implies that firms produce differentiated goods).

where $b_n^i = \int_j b_{nj}^i dj$ is the aggregate preference parameter, $X_{it} = \omega_{it} L_{it}$ is total spending by country i, and P_{it} is the price index

$$P_{it} = \left(\sum_{n=i}^{M} A_{nt}^i \left(p_{nt}^i \right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

Trade is assumed to be costly: there is an iceberg transport cost for the products shipped from country n to i equal to $d_n^i > 1$, with $d_i^i = 1$. Intermediate firms prices differ in the domestic and the foreign market by the transport cost d_n^i.[14] That is, they set a price

$$p_{i,t}^i = \bar{m} \omega_{it} \tag{4}$$

in the domestic market and

$$p_{i,t}^n = \bar{m}(\omega_{it} d_i^n) \tag{5}$$

in each foreign market, with $\bar{m} = \frac{\sigma - 1}{\sigma}$ as the constant mark-up.

Instantaneous profits by intermediate firms are given by the following expression

$$\pi_{nt}^i = \left(\frac{1}{\sigma} \right) e^{a_{it}} \left(\frac{p_{nt}^i}{P_{it}} \right)^{-(\sigma-1)} \omega_{it} L_i$$

They depend on the expenditure in each intermediate good, which at the same time depend on the size of the country. Larger countries are a bigger source of profits.

4.3 Innovation and adoption

The relevant processes to analyse the connections between trade in varieties and growth are innovation and adoption. This section explains the mechanisms by which new goods arrive to the economy and diffuse to other countries. Both processes are endogenous and depend on profit maximization decisions by the economic agents.

In a given country, new goods arrive endogenously by investing resources in R&D. A competitive set of entrepreneurs bid for the right to produce the good. They need to pay the market price for an innovation, which is given by the discounted present value of profits that the entrepreneur who gets the production right will obtain by selling the good. There are positive profits because

[14] The iceberg cost affects how much of the intermediate good is shipped across countries but it does not affect whether a new product is imported. This is determined by barriers to technology adoption, as I explain in section 4.3.2.

the producers of the intermediate goods are monopolistic competitors, who set prices taking as given the demand by final producers in each potential market. This is a fixed cost to start producing the good, given by the investment needed to acquire the 'design' from the research sector. Note that in this framework, the research department is treated as a separate sector from the intermediate producers and technologies embodied in intermediate goods are transferred to the firm for a specific transfer price.

Once the firm acquires the right to use the technology, it starts producing the intermediate good. This good can be sold immediately to the domestic final producers. In this sense, there is instantaneous diffusion within countries. This is not an unreasonable assumption. Eaton and Kortum (1996) estimate that the probability of diffusion within a sample of five very innovative OECD countries is very high, between 0.8 and 0.9. Diffusion to the foreign market, instead, is slow. To sell the good abroad, the firm needs to make a costly investment to adopt the foreign product.[15] Think of this as an adaptation cost of the product to the specifications of the importer country. Whether the good is ready to be adopted by the destination or not is a random draw with a probability that depends on the amount of resources that are allocated to learn how to use the product, and a spillover effect.[16]

There are two profit maximizing decisions in this setting. On the one hand, innovators choose how much labor they want to employ in R&D by comparing the marginal cost of adding one more worker into research with the marginal benefit, which depends on the market price for an innovation. On the other hand, intermediate producers choose how much labor they want to hire in the potential destination to make their product usable there. They compare the marginal cost of adoption with the marginal benefit, which is given by the difference between the value of a good that has already been adopted and the value of a non-adopted good.

Before explaining in detail the domestic innovation and foreign adoption processes, I introduce some notation. Z_{it} is the stock of new technologies that have been developed in country i. Following Nelson and Phelps (1966), Z_{it} represents the theoretical level of technology, which is the average level of technology that would prevail in a country if diffusion were instantaneous. Technologies need to be adopted to actually affect productivity in a country. A^i_{nt} is the stock of foreign technologies that country i has successfully adopted from country n. Instantaneous diffusion within the country implies that the theoretical and actual number of technologies in country i are the same, that is $A^i_{it} = Z_{it}$. Slow diffusion across countries, instead, implies that

[15]The same results would hold if we think as the intermediate firm that wants to export the good as hiring the services of a third firm in the destination to adapt the products.

[16]The important role of spillovers has been recently analysed by Klenow and Rodriguez-Clare (2005)

the number of adopted goods is a subset of the number of innovations, that is $A^i_{nt} <= Z_{nt}$. The effective level of technology in country i is composed of both domestic and foreign technologies, that is $T_{it} = A^i_{it} + \sum_{n \neq i} A^i_{nt}$.

4.3.1 Innovation process

The creation of new varieties is defined by an endogenous process of innovation in which a firm invests labor into the research activity. The number of new goods depends on the investment in innovation and the productivity of reserach.

As in Phelps (1964) and Eaton and Kortum (1996), I assume that the arrival of new goods at date t in location i, $Z_{i,t+1} - Z_{it}$, is determined by the fraction of workers that are allocated to research, $\frac{R_{it}}{L_{it}}$, where R_{it} is the total number of researchers and L_{it} is the total number of workers. The microfoundations of this function are the following: in country i, workers are ranked according to their productivity at doing research. A worker with productivity j produces ideas at the stochastic rate $\alpha^R_{it} T_{it} \beta_r \left(\frac{j}{L_{it}}\right)^{\beta_{r-1}}$, where $\alpha^R_{it} T_{it}$ represents research productivity, and $\beta_r \in (0, 1)$ is a parameter reflecting the extent of diminishing returns to allocating a larger share of workers into research.[17] If R_{it} workers are doing research in country i at time t, they create new intermediate goods at a rate $\alpha^R_{it} L^{1-\beta_r}_{it} R^{\beta_r}_{it}$ or,

$$Z_{i,t+1} - Z_{it} = \alpha^R_{it} T_{it} \left(\frac{R_{it}}{L_{it}}\right)^{\beta_r} Lit \tag{6}$$

Research productivity, $\alpha^R_{it} T_{it}$, is a linear function of two elements. First, a country-specific factor that is identified by economic policies or institutions promoting innovation in a country, α^R_{it}. This factor is composed of a country-specific parameter, α^R_i, and an i.i.d shock to the productivity of research, ξ_{it}, which is just introduced for estimation purposes. The first element in the productivity of innovation can then be expressed as: $\alpha^R_{it} = e^{\xi_{it}} \alpha^R_i$.[18]

The second element in the productivity of research, T_{it}, is a spillover effect that depends on the total number of intermediate goods available to the country, either domestically or through imports. Countries learn on the basis of the total number of goods that are available for final production. In this respect, there is learning by doing, through domestically produced goods,

[17] This assumption implies that a workers' talent as a researcher is drawn from a Pareto distribution. Workers in a country are equally productive at making intermediates but they differ in their talent for research. They are assumed to be compensated in proportion to their marginal productivities. Thus, those who are more productive at doing research will become researchers.

[18] Reasons for differences in the productivity parameter across countries are a more efficient venture capital market, as in the US, or policies aimed at increasing R&D investments as in Japan.

and learning by using, through imports. This assumption implies that countries with a wider variety of intermediate goods, and therefore enjoy a higher level of GDP per capita, have a lower cost of innovation. Thus, everything else constant, they invest a larger amount of resources into R&D. This is consistent with what we see in the data: richer countries are investing a larger amount of resources in doing R&D.

Another implication of the international spillovers component is the possibility that countries that are expanding their variety of foreign intermediate goods through imports, can speed up the innovation process and therefore increase the number of goods they produce and export. That is, non-innovative countries learn from importing intermediate goods, even if they are not initially very innovative. This reasoning is in line with what Hallward-Driemeier (2000) found. Using data from five Asian countries, she observes that, prior to entry into exports markets, productivity gains are associated with efforts aimed at penetrating the export market, such as more foreign technology and imported goods.

As I mentioned in the introduction, the definition of variety used throughout the paper does not allow countries that import a variety to start exporting the same one, since they are differentiated by source of exports. Nevertheless, a country that imports benefits from the spillover effect, which helps the development and export of its own variety of the good.

4.3.2 Technology Diffusion

Intermediate goods that are invented in a country need to be adopted in order to be used by the final sector. I assume that diffusion within the country is instantaneous and costless, but it takes time and investment across countries. That is, when a new technology is produced in a country, it is immediately ready to be sold to the final sector in that country.[19] On the contrary, when a new good is produced, the exporter needs to make a costly investment to make the product usable in the potential destination. In particular, intermediate producers in the source country hire labor in the destination to adapt the good to the standards of that country. Whether or not adoption is successful is a random draw with positive probability, ε^i_{nt}. The probability or rate of adoption can be expressed in the following way

$$\varepsilon^i_{nt} = \alpha^A_i \left(\frac{H^i_{nt}}{L_i}\right)^{\beta_a} L_i \frac{A^i_{nt}}{Z_{n,t+1}} \tag{7}$$

where H^i_{nt} represents the amount of labor that country n hires in country i to train to use the product; α^A_i is a constant, heterogeneous across countries, that represents barriers to adopt a

[19] As I showed in section 3, the average diffusion lag in the sample of analysis is between 2 and 10 year.

new technology (a higher value of the parameter implies a lower level of barriers to adoption);[20] β_a is the elasticity of adoption with respect to effort, assumed to be common across countries. It is a measure of how an increase in investment in adoption translates into an increase in the probability of importing a foreign good; $\frac{A^i_{nt}}{Z_{n,t+1}}$ represents how far country i is from country n's technology frontier. The motivation for this component of the rate of adoption is the following: consider the case of a country, with a very different culture, language or institutions, to the source of exports. The source country needs to invest resources to adapt its products to the destination economy in order to make them usable there. As the destination starts importing goods and become familiar with the exporter's products, the investment needed by the exporting to start selling the good is lower. Interaction between the countries allows the importer to learn about the source, which is reflected, everything else constant, in an increase in the probability of adoption.[21]

To summarize, the rate of adoption depends on the amount of labor that is allocated into adoption, the cost of technology transfer, and the distance to the frontier.

Finally, I describe the process by which foreign technologies arrive to a country through imports. Following Nelson and Phelps (1966) and Benhabib and Spiegel (1994), the rate at which the potential level of technology in country n is realized in actual technology in country i depends on the probability of adoption, ε^i_{nt}, and the gap between the exporter's level of technology that can be exported and the level of technologies that the importer has already adopted from the exporter, $Z_{n,t+1} - A^i_{nt}$. The technological gap explains the dynamics of imports of new technologies, embodied in intermediate goods.[22]

$$A^i_{n,t+1} - A^i_{nt} = \varepsilon^i_{nt}(Z_{n,t+1} - A^i_{nt}) \tag{8}$$

Expression (8) implies that goods invented in n that have not yet been imported by country i $Z_{n,t+1} - A^i_{nt}$, contribute to an expansion in the variety of exports to country i at a rate ε^i_{nt}.

[20] Examples of economic policis that affect this parameter are an increase in investment in education; an improvement in telecommunication infrastrctures that facilitate communication across countries; trade policies, etc. Eaton and Kortum (1996) and Benhabib and Spiegel (1994) analyse the dependence of the probability of adoption on different factors, such as human capital. They find that human capital has a positive and significant impact on the adoption ability, increasing α^A.

[21] If the speed of diffusion were one, the total number of varieties available for final production would be the same in each region.

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

This is a generalization of Krugman (1979), with the difference that in my model, the rate of adoption is endogenously determined by profit maximizing firms.

By solving equation (8) forward, we can see that the variety of imports is endogenously determined by the research effort done around the world, in the following way

$$A_{nt}^{i}=\sum_{j=1}^{t}\varepsilon_{n,t-j}^{i}\prod_{k=1}^{j}(1-\varepsilon_{n,t-k}^{i})Z_{n,t-j+1} \tag{9}$$

Equation (9) implies that the dynamics of imports are determined by the speed of innovation, through Z.

We can combine the law of motion for new imports, equation (8), and the expression for the probability of adoption, (7), in order to understand better the adoption mechanism

$$A_{n,t+1}^{i}-A_{n,t}^{i}=\alpha_{i}^{A}\left(\frac{H_{nt}^{i}}{L_{i}}\right)^{\beta_{a}}L_{i}\frac{A_{n,t}^{i}}{Z_{n,t+1}}(Z_{n,t+1}-A_{nt}^{i}) \tag{10}$$

and rearranging

$$A_{n,t+1}^{i}-A_{n,t}^{i}=\alpha_{i}^{A}\overbrace{\left(\frac{H_{nt}^{i}}{L_{i}}\right)^{\beta_{a}}}^{\text{Investment in adoption}}L_{i}\quad\overbrace{A_{n,t}^{i}}^{\text{International Spillover}}\quad\overbrace{\left(1-\frac{A_{n,t}^{i}}{Z_{n,t+1}}\right)}^{\text{Relative Backwardness}} \tag{11}$$

The first component in the RHS represents the effect that investment in adoption has in determining an expansion in the number of imports. The second term reflects the impact of foreign sources of technology diffusion. The last term represents the role of relative backwardness. As the country is further away from the exporter's technological frontier, lower $\frac{A_{n,t}^{i}}{Z_{n,t+1}}$, an increase in the number of imports will have a higher impact in growth rates. This is something that we see in the data: countries that are importing fast are relatively backward countries, that are also experiencing growth rates faster than average. This term arises, as in Howitt (2000), from the product of two terms: $\frac{1}{Z_{n,t+1}}\left(Z_{n,t+1}-A_{n,t}^{i}\right)$. The first term implies that as the country n's technology becomes more advanced, country i needs to invest more resources in adoption to be able to use the goods from n; the second term reflects the fact that when a country's imports are low relatively to the technology frontier of the source, every successful technology adoption implies a higher expansion in the number of imports.[23]

[23]Equation (11) can be expressed in terms of growth rates

4.3.3 The value of an idea

There are two profit maximization decisions in the economy (how much labor to invest in R&D and how much labor to invest in adoption). The decisions are based on the value of inventing and adopting a new technology. In this section, I present the value functions that determine the optimal investment in adoption and innovation decisions.

The owner of a technology can earn profits only after the idea has been adopted. Since there is instantaneous diffusion within the country, the value of a new good that is used domestically is given by the present discounted value of future domestic profits.

$$W_{it}^{i} = \pi_{it}^{i} + \beta W_{i,t+1}^{i} \tag{13}$$

where β is the discount factor and π_{it}^{i} represents domestic profits for a firm in country i.

Slow diffusion across countries implies that a technology invented in country n at time t can only be adopted by country i at $t+1$ with probability ε_{nt}^{i}. If successful, country n obtains profits forever. On the other hand, with probability $(1-\varepsilon_{nt}^{i})$, this idea will not be adopted at $t+1$. The value of an idea invented in n at time t that has not been adopted by i yet is

$$J_{nt}^{i} = max_{\mathbf{H}}\{-\mathbf{H}\omega_{nt} + \beta\varepsilon_{nt}^{i}(\mathbf{H})W_{n,t+1}^{i} + \beta(1-\varepsilon_{nt}^{i}(\mathbf{H}))J_{n,t+1}^{i}\}$$

where W_{nt}^{i} is the value of an idea adopted at time t and is given by

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

The market price of an innovation is given by the value of selling the good in the domestic market and the expected value of selling the good in each of the foreign markets, $V_{it} = W_{it}^{i} + \sum_{n=1}^{M} W_{nt}^{i}$.

4.3.4 Optimal investment in innovation

The creation of new varieties is related to the economic incentive to do research. Innovators choose the amount of labor that maximizes profits. They take as given the market price of an innovation V_{it} and solve the maximization problem

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$$g_{in,t} = \alpha_i^A \left(\frac{H_{nt}^i}{L_i}\right)^{\beta_a} L_i(1-\tau_{nt}^i) \tag{12}$$

with $\tau_{nt}^i = \frac{A_{nt}^i}{Z_{n,t+1}}$.

$max_{R_{it}}\ V_{it}(Z_{i,t+1} - Z_{it}) - \omega_{it} R_{it}$
s.t $Z_{i,t+1} - Z_{it} = \alpha_{it}^R T_{it} \left(\frac{R_{it}}{L_{it}}\right)^{\beta_r} L_{it}$

Country i invests in R&D up to the point where the marginal benefit of research is equal to the marginal cost, given by the wage, ω_{it}.

$$\beta_r \alpha_{it}^R T_{it} V_{it} \left(\frac{R_{it}}{L_{it}}\right)^{\beta_r - 1} = \omega_{it} \tag{14}$$

A higher value of α_i^R means that the country is more productive at doing research, giving more incentive to invest a higher fraction of the labor force into R&D, everything else constant.

4.3.5 Optimal investment in adoption

Intermediate producers in the source country n, hire $H_{in,t}$ units of labor in country i to maximize the profits that they could obtain by selling the good to that country, $J_{n,t}^i$.

They solve the following problem,

$max_{H_{nt}^i}\ J_{nt}^i = -H_{nt}^i \omega_{it} + \beta \varepsilon_{nt}^i W_{n,t+1}^i + \beta(1 - \varepsilon_{nt}^i) J_{n,t+1}^i$
s.t $\varepsilon_{nt}^i = \alpha_i^A \left(\frac{H_{nt}^i}{L_i}\right)^{\beta_a} L_i \frac{A_{nt}^i}{Z_{n,t+1}}$

Intermediate producers in n hire labor in i up to the point where the marginal benefit equals the marginal cost.

$$\beta_a \alpha_i^A \left(\frac{H_{nt}^i}{L_i}\right)^{\beta_a - 1} \frac{A_{nt}^i}{Z_{n,t+1}} (W_{n,t+1}^i - J_{n,t+1}^i) = \beta_a \frac{\varepsilon_{nt}^i}{H_{nt}^i} (W_{n,t+1}^i - J_{n,t+1}^i) = \omega_{it} \tag{15}$$

Note that the marginal benefit depends positively on the difference between what they can earn if adoption is successful, W_{nt}^i and the value of a non adopted intermediate good, $J_{n,t}^i$. Similarily, the higher is the average probability of adoption $\frac{\varepsilon_{nt}^i}{H_{nt}^i}$, the higher is the marginal benefit.

It is important to note that the relevant decision is not whether or not to adopt a new technology, but whether to adopt now or to postpone the decision. The optimal action depends on the expected future profits.

4.4 The Labor Market

Labor is the only factor of production in this economy and it is used for manufacturing, innovation and adoption. The labor market equilibrium implies that

$$L_{it} = L_{it}^M + L_{it}^R + L_{it}^A \tag{16}$$

where L_{it}^M is the amount of labor employed in manufacturing, $L_{it}^R = R_{it}$ is the amount of labor used by the innovators and $L_{it}^A = \sum_{n=1}^M H_{nt}^i$ is the amount of labor demanded by the adopters. In equilibrium these three terms must be equal to the total labor force, L_{it}.

4.5 Labor market clearing condition

Balanced trade implies that we can close the model with the labor market clearing condition, by which the amount of labor used in production must equal labor supply in each period in the production for intermediate goods.

$$\sum_{i=1}^{M} A_{it}^n x_{nt}^i = \bar{m}\omega_{nt} L_{nt}^M \tag{17}$$

The LHS of equation (17) represents total expenditure in manufactures from country i by each country n. The RHS is the value of total supply of labor from country n. L_{nt}^M is the number of workers that are used to produce intermediate goods.

4.6 The equilibrium

A general equilibrium in this economy is defined, $\forall i, n$, as an exogenous stochastic sequence, $\{a_{nt}, \xi_{nt}\}_{t=0}^{\infty}$, an initial vector $\{A_{n0}^i, Z_{n0}\}$, a sequence of parameters common across countries $\{\sigma, \beta_a, \beta_r, \rho\}$, a sequence of parameters that differ across countries, $\{\alpha_i^R, \alpha_i^A, L_i, d_n^i\}$, prices $\{p_{nt}^i, \omega_{nt}\}_{t=0}^{\infty}$, a sequence of endogenous variables $\{Y_{nt}, x_{nt}^i, L_{nt}^M, R_{nt}, H_{nt}^i, \pi_{nt}^i, W_{nt}^i, J_{nt}^i\}_{t=0}^{\infty}$, and laws of motion $\{A_{n,t+1}^i, Z_{n,t+1}\}_{t=0}^{\infty}$ such that

- $\forall t$, given prices and initial conditions, x_{nt}^i solves the final producer's problem (equation (3))
- $\forall t$, given prices and initial conditions, x_{nt}^i, and profits π_{nt}^i, p_{nt}^i and L_{nt}^M solve the intermediate producers problem (equations (4) and (5))
- $\forall t$, given prices and initial conditions, R_{it} solves the innovator's problem (equation (14))

- $\forall t$, given prices and initial conditions $\{H^i_{nt}, \pi^i_{nt}, W^i_{nt}, J^i_{nt}\}$ solve the adopter's problem (equation (15))
- The laws of motion for A^i_{nt} and Z_{nt}, given by equations (6) and (8) are satisfied
- Feasibility is satisfied by equation (1)
- Prices are such that the labor market clears

5 Balanced Growth Equilibrium

The derivation of the steady state for this type of model is explained in detail in Eaton and Kortum (2007)).

Technology diffusion and catch-up assure that all countries eventually grow at the same rate, as in Nelson and Phelps (1966). Countries will differ in the relative levels of technology, depending on parameters of innovation and diffusion, α^R_i and α^A_i.[24] In the transition, the lower a country's initial productivity, the larger is the technology gap from the leader, and the faster the growth.

Population is constant in steady state. Therefore, from equation (16), the allocation of labor in manufacturing, L^M_i, adoption, H^i_n and research, R_n are also constant.

Equation (6) implies that the number of domestically created varieties grows at the same rate as the total number of goods available in the final production sector; similarily, from equations (12) and (7), the number of adopted varieties grows at the same rate as the number of domestically produced varieties, which translates into a constant probability of adoption. A constant rate of adoption, ε^i_n implies that diffusion is exponentially distributed with parameter λ^i_n and $\varepsilon^i_n = \frac{\lambda^i_n}{1+\lambda^i_n}$.[25] Adoption is a stochastic process with mean diffusion lag between county i and country n equal to ${\lambda^i_n}^{-1}$. Instantaneous diffusion within a country implies that $\lambda^i_n \to \infty$ for $n = i$. The lag affects the speed of convergence to the steady state and the dynamics to the long run equilibrium. Assuming $\lambda^i_n > 0$ every good will eventually be available in any country.

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

[24] Jovanovic (Forthcoming) develops a model in which diffusion lags depend on income differences. In my case, differences in the speed of diffusion determine dispersion in income per capita across countries.

[25] See Benhabib and Spiegel (1994).

$$g_i = \frac{\Delta T_i}{T_i} = \frac{\Delta Z_i}{T_i} + \sum_{n=1}^{M} \frac{\Delta A_n^i}{T_i} \tag{18}$$

Substituting equations (6) and (12) into equation (18), productivity growth in steady state can be expressed as a function of the amount of research that has been done around the world:

$$g = g_i = \alpha_i r_i^{\beta_r} + \sum_{n=1}^{M} \varepsilon_n^i \sum_{s=1}^{t} (1 - \varepsilon_n^i)^{-(t-s)} \alpha_{ns} r_{ns}^{\beta_r} \frac{T_{ns}}{T_{it}} \tag{19}$$

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 (18) as

$$g = \sum_{n=1}^{M} \varepsilon_{in} \alpha_n r_n^{\beta_r} \sum_{s=1}^{M} \left(\frac{(1 - \varepsilon_n^i)}{(1 + g)} \right)^{-(t-s)} = \sum_{n=1}^{M} \varepsilon_n^i \alpha_n r_n^{\beta_r} \frac{(1 + g)}{g + \varepsilon_n^i} \frac{T_{nt}}{T_{it}} \tag{20}$$

With positive values for β_r, α_n, ε_{in} and $r_n = \frac{R_n}{L_n}$, the Frobenious Theorem guarantes that we can obtain a value for the growth rate g and relative productivities $\frac{T_i}{T_n}$ (see Eaton and Kortum (2007) for a more complete analysis).

It is important to note that, if there were not any source 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 amount of labor into R&D and adoption, demanding the same amount of intermediate goods, and reaching the same level of income per capita.

6 Empirical strategy

6.1 Bayesian Estimation

I estimate the model using Bayesian techniques, based on maximum likelihood (ML), developed by Schorfheide (1999). Bayesian estimation is a bridge between calibration, through the specification of priors, and maximum likelihood. There are some advantages of this approach. First, Bayesian estimation, based in maximum likelihood, fits the complete model to a vector of time series, while methods like Simulated Method of Moments (SMM) are based on matching particular moments of the data. Second, Bayesian techniques versus classical methods allow the use of priors, that reflect beliefs about the parameters of the model. Finally, Bayesian estimation addresses model misspecification by adding shocks interpreted as observation errors in the structural equations. For an application of Bayesian techniques see Lubik and Schorfheide

(2005). I use Dynare (Juillard 1996) to solve and estimate the model.[26]

6.2 Data and priors

To make the model more tractable, I group the sample of thirty-seven countries into five regions in such a way that countries in the same group share common characteristics (similar innovation intensity and GDP per capita growth): The United States, Japan, Western Europe, Eastern Europe and Asia.[27] Keller (2004) already considered the importance of analysing the interaction between these regions when he said: *'Many economist believe that the increased economic integration [...] has tended to increase the long-run rate of economic growth. If they were asked to make a prediction, they good suggest that prospects for growth would be permanently diminished if a barrier were erected that impeded the flow of all goods, ideas and people between* ***Asia, Europe and North America****'*

6.2.1 Data

I use annual data for the period 1994-2003, since 1993 is the first year that data at a high level of disaggregation became available for a large sample of countries. The observable variables of the model are the annual growth in imported varieties, and data on output growth and the fraction of workers employed in R&D.[28] There are one hundred and thirty-five observations corresponding to nine years, five regions of countries and three observable variables.[29]

I estimate the parameters behind the innovation and adoption processes. It is possible to establish a mapping between the data and the estimated parameters through the equations of the model: These are the laws of motion for Z_{it} and A^i_{nt} (equations (6) and (8)) and the optimall

[26] The code is available upon request. The variables in the code are expressed in stationarized terms, in order to be able to compute the loglinearization around the steady state.

[27] The sample of countries included in each region is reported in the Appendix.

[28] For a more detail in how to compute griwth in varieties, see Broda, Greenfield, and Weinstein (2008). The correspondence between growth in imported varities, computed as in Broda, Greenfield, and Weinstein (2008) and the equations of the model is the following. Define A^i_t as the total number of imported varieties by country i: $A^i_t = \sum_{n=1}^{M} A^i_{nt}$. In the model, the law of motion for the number of goods that country i imports from country n is given by $M \times M - M$ equations (11) $\forall i, n$. If $_{it}$ is the growt rate of the total imported varieties by country i, the correspondence with the variables of the model is given by

$$g_{it} = \frac{\Delta A^i_t}{A^i_t}$$

[29] Note that there is a cross-sectional dimension in the data. DSGE models that are estimated in macroeconomics with Bayesian techniques have a long time series for one or two countries; in my case, I have a short time series sample but I add five countries in the analysis.

allocation of labor into research and adoption (equations (14) and (15)). The data are represented by the variables $\omega_{it}, A^i_{nt}, R_{it}$; the parameters to be estimated are the inverse of costs of technology transfer α_i^A, the diminishing returns to innovation, β_r, and the persistence of the TFP shock, ρ.

With the series of data used in the estimation, the diminishing returns parameter β_R, is not separately identified from the productivity of innovation, α_i^R. At the same time, the elasticity of adoption β_A, is not separately identified from the costs of adoption, α_i^A.

The fraction of workers that are allocated into research in equation (6) identifies the parameters of innovation. I do not have data on the number of products that are developed domestically by a country. Broda, Greenfield, and Weinstein (2008) use the number of exports as a proxy for the number of innovations. The problem with this approach is that, at the 6-digit level of disaggregation, large countries like the US start all exporting almost every category so that the increase in new products would underestimate innovation in this region. In my framework, the first order condition for investment, and the law of motion for innovations allow me to identify the parameter β_r.

Growth in varieties in equation (12) and optimal investment in adoption allow me to identify the parameter α^A. Note that there are not data available on the fraction of workers that allocated into adoption.

With data on the share of workers allocated into research, we can identify the elasticity of innovation, β_r, but we need to calibrate theproductivity α_i^R; instead, with data on the growth of imported varieties we can estimate the adoption productivity, α_i^A and need to calibrate the eslaticity of adoption, β^A.

6.2.2 Shocks

In order to have invertibility in the likelihood function, the ML approach requires as many shocks as observable variables. With three series of observable variables, we need to introduce three series of shocks. One of them is given by the neutral technology shock, a_i in final production, for each region. The other one is the i.i.d shock to the innovation productivity, a^{α}_{it}. Finally, I add measurement errors to the growth rates of imported varieties, one for each region. The structural shocks and measurement errors incorporated in the estimation are

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

with $u_{it} \sim N(0, \sigma_i^2)$

$$\xi_{i,t} \sim N(0, \sigma^2)$$

$$g_{it}^{obs} = g_{it} e^{me_{it}}$$

with $me_{it} \sim N(0, \sigma_{me,i}^2)$

where me is the measurement error and $i = 1 \ldots 5$.

6.2.3 Parameters

STRICT PRIORS

A set of the parameters of the model is treated as fixed in the estimation (also called strict priors). These parameters are obtained from other studies or from steady state relations. The strict priors are reported in table 2. The elasticity of substitution across varities, iceberg transport costs and elasticity of adoption, $\{\sigma, d, \beta_a\}$, are obtained from previous studies. The innovation productivity α_i^R, is obtained from steady state relations.

σ is the elasticity of substitution across goods in the final production and is assumed to be 3.4,[30] d is the iceberg transport cost that varies across pairs of countries and it is proportional to distance; the elasticity of adoption with respect to effort β_a, is 0.75. This value is consistent with the papers by Comin and Gertler (2006) and Comin, Gertler, and Santacreu (2008), who find that a reasonable value for β_a in a closed economy model is 0.8. Since there are not 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). Then, they 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 therefore is the measure of embodied adoption. The regression yields a constant of 0.8.

The productivity of the innovation process α_i^R, is set to match the steady state growth rate of output per capita, which for OECD countries is of 2%. Since one of the implications of the model is that, in steady state, all countries share a common growth rate, 2% results in the world

[30] Broda, Greenfield, and Weinstein (2008) estimate that the median elasticity of substitution for a sample of 73 countries is 3.4.

steady state growth rate of income per capita.[31] The results show that Asia and Eastern Europe have the lowest productivity of innovation, while the US and Japan are the most productive regions. The increase in venture capital investments in the US and policies that incentive public R&D in Japan in the last decade, could be explaining a higher value for this parameter. At the same time, note that from the optimal investment in innovation in equation (14), the higher the productivity α_i^R, the higher the fraction of workers that are allocated in R&D, everything else constant. This is consistent with the experiences of the US and Japan in the last decade: they have a higher productivity of research and a higher investment in R&D.

PRIORS

The parameters to be estimated are the extent of diminishing returns in the innovation process, β_r, the cost of adoption, α_i^A, the persistence, ρ_i and the standard deviations, σ_i, of the neutral technology shock and productivity of innovation shocks. The values for the parameters can be found in table 3 and 4.

I assume uninformative priors for the parameters of adoption and diffusion. The prior for the cost of adoption in each region, α_i^A is distributed Uniform with mean 1.75 and standard deviation 0.5. This allows the parameter to take any value within the interval $(0, 3)$. The mean is set to match the hazard rates in table 1, which determine the rate of adoption. α_i^A identifies elements that influence the ability to import new goods, other than the distance to the frontier of the exporter or adoption investment. A higher value implies lower adoption costs. The prior for the diminishing returns in the innovation process, β_r, is set to a Uniform distribution and I allow it to take any value between zero and one. Finally, in the shock processes, an Inverse Gamma distribution is proposed for the standard deviation of the shocks. This guarantees a positive variance.

[31] I apply the Frobenious Theorem recursively to obtain a value for the parameters. Refer to chapter 7 in Eaton and Kortum (2007).

6.3 Estimation results

Tables 3 and 4 report the results from the estimation. The table contains the prior and posterior mean of the estimated parameters as well as 95% confidence intervals.

The posterior mean for the adoption costs reported in table 9, implies that fast growing countries in Asia and Europe, have the lowest costs of adoption, with a value around 2. In the US and Japan, this parameter is 1.4. Note that even with a higher cost of diffusion, the number of imported varieties is higher in the US and Japan, and only the growth rate is lower. The reason is that the ratio $\frac{A}{Z}$ in equation (7) is higher in rich countries, and this translates in a higher probability of adoption, everything else constant. These results can be used to compute the probability of adoption predicted by the model, ε^i_{nt}. The average probability of adoption for the period 1994-2003 is presented in the last column of table 10. The results imply that the average time that it takes for a country to be able to use an intermediate good developed elsewhere, which corresponds to the inverse of the probability of adoption, lies between two and ten years.

The posterior mean for the elasticity of innovation β_r, is 0.7, consistent with the results presented by Griliches (1990). He estimates this parameter using the number of new patents as a proxy for technological change, and obtains estimates between 0.5 and 1.

parameter	value	Description
σ	3.4	Elast. Subst. (BGW(08))
β	0.97	Discount factor
β_a	0.75	Elasticity of adoption (CG(06), CGS(08))
$d(Asia, EU-)$	1.30	Iceberg transport costs
$d(Asia, EU+)$	1.30	Iceberg transport costs
$d(Asia, Japan)$	1.10	Iceberg transport costs
$d(Asia, US)$	1.30	Iceberg transport costs
$d(EU-, EU+)$	1.05	Iceberg transport costs
$d(EU-, Japan)$	1.40	Iceberg transport costs
$d(EU-, US)$	1.30	Iceberg transport costs
$d(EU+, Japan)$	1.40	Iceberg transport costs
$d(EU+, US)$	1.30	Iceberg transport costs
$d(Japan, US)$	1.30	Iceberg transport costs
$\alpha^R(Asia)$	0.0127	Innovation productivity (g*=2%)
$\alpha^R(EU-)$	0.0368	Innovation productivity (g*=2%)
$\alpha^R(EU+)$	0.0379	Innovation productivity (g*=2%)
$\alpha^R(Japan)$	0.0464	Innovation productivity (g*=2%)
$\alpha^R(US)$	0.0578	Innovation productivity (g*=2%)

Table 2: Calibrated parameters

Parameter[32] [33]	Prior[34]	5%	Mean	95%
$\alpha^A(Asia)$	Uniform(0,3)	1.96	1.97	1.98
$\alpha^A(EU-)$	Uniform(0,3)	1.90	1.90	1.91
$\alpha^A(EU+)$	Uniform(0,3)	2.00	2.10	2.20
$\alpha^A(Japan)$	Uniform(0,3)	1.39	1.40	1.41
$\alpha^A(US)$	Uniform(0,3)	1.43	1.44	1.45
β_r	Beta(0.5,0.25)	0.68	0.70	0.72

Table 3: Prior and posterior for the structural parameters For the Beta distribution, the number in parenthesis correspond to the mean and standard deviation

Parameter	Prior	5%	Mean	95%
$\rho(Asia)$	Uniform(0,1)	0.26	0.46	0.72
$\rho(EU-)$	Uniform(0,1)	0.74	0.75	0.76
$\rho(EU+)$	Uniform(0,1)	0.63	0.70	0.75
$\rho(Japan)$	Uniform(0,1)	0.64	0.69	0.73
$\rho(US)$	Uniform(0,1)	0.42	0.55	0.71
$\sigma(Asia)$	IGamma(0.15,∞)	0.04	0.09	0.15
$\sigma(EU-)$	IGamma(0.15,∞)	0.17	0.20	0.24
$\sigma(EU+)$	IGamma(0.15,∞)	0.04	0.05	0.07
$\sigma(Japan)$	IGamma(0.15,∞)	0.05	0.06	0.08
$\sigma(US)$	IGamma(0.15,∞)	0.05	0.06	0.07
$\sigma^r(Asia)$	IGamma(0.15,∞)	5.21	5.88	6.53
$\sigma^r(EU-)$	IGamma(0.15,∞)	2.46	2.98	3.37
$\sigma^r(EU+)$	IGamma(0.15,∞)	1.97	2.70	3.27
$\sigma^r(Japan)$	IGamma(0.15,∞)	0.33	0.39	0.48
$\sigma^r(US)$	IGamma(0.15,∞)	0.17	0.25	0.34
$me(Asia)$	IGamma(0.15,∞)	0.75	0.86	0.97
$me(EU-)$	IGamma(0.15,∞)	0.48	0.65	0.77
$me(EU+)$	IGamma(0.15,∞)	0.77	0.88	1.03
$me(Japan)$	IGamma(0.15,∞)	0.52	0.65	0.80
$me(US)$	IGamma(0.15,∞)	0.67	0.83	1.02

Table 4: Prior and posterior for the shock processes

6.4 MonteCarlo Simulations to check for identification

This section evaluates the identification and performance of the estimation procedure, by running Monte Carlo simulations. The non-linear model is solved and simulated to a first order approximation, for a given set of parameters. The solution has a unique steady state and the Blanchard-Kahn condition is satisfied, that is there are as many eigenvalues larger than one as forward-looking variables. I then simulate the model taking the following steps: first, I generate a set of errors, u_i and measurement errors, me_i for each region. Second, I choose a value for the structural parameters (see table 5) and create a simulated series for the share of researchers allocated to innovation and the growth rate in the number of varieties. Finally, I estimate the parameters behind the innovation and adoption processes, and the persistence and standard deviation of the shocks based on the simulated dataset and compare the estimated parameters to the 'true' values.

The specification for the 'true' parameters can be found in table 5. From this set of values, I estimate the elasticity of innovation β_r, and the adoption costs α_i^A in each region, as well as the parameters governing the shock process (persistence and standard deviation) and the measurement errors. The results are reported in table 6 and table 7. The results show that the estimated parameters are very close to the 'true' value and all of them lie within the 95% interval or are very close , suggesting that identification is successful and the parameters can be recovered with high accuracy.

Parameter	Description	Value
α^R	Elast. Subst.	0.700
β	Discount factor	0.990
d	Distance	1.100
β_r	Elast. innov.	0.18
$\alpha^R(Asia)$	Productiv. innov.	0.010
$\alpha^R(EU-)$	Productiv. innov.	0.015
$\alpha^R(EU+)$	Productiv. innov.	0.020
$\alpha^R(Japan)$	Productiv. innov.	0.025
$\alpha^R(US)$	Productiv. innov.	0.030
$\alpha^A(Asia)$	Adopt. cost	1.5
$\alpha^A(EU-)$	Adopt. cost	1.5
$\alpha^A(EU+)$	Adopt. cost	1.5
$\alpha^A(Japan)$	Adopt. cost	1.5
$\alpha^A(US)$	Adopt. cost	1.5
β_a	Elast. of adoption	0.250
$\rho(Asia)$	Persistence shock	0.600
$\rho(EU-)$	Persistence shock	0.600
$\rho(EU+)$	Persistence shock	0.500
$\rho(Japan)$	Persistence shock	0.500
$\rho(US)$	Persistence shock	0.500
$\sigma(Asia)$	std. shock	0.240
$\sigma(EU-)$	std. shock	0.240
$\sigma(EU+)$	std. shock	0.240
$\sigma(Japan)$	std. shock	0.240
$\sigma(US)$	std. shock	0.240
$me(Asia)$	std. measurm. error	0.240
$me(EU-)$	std. measurm. error	0.240
$me(EU+)$	std. measurm. error	0.240
$me(Japan)$	std. measurm. error	0.240
$me(US)$	std. measurm. error	0.240

Table 5: Calibrated Parameters

Parameter	True Value	Prior	Posterior mean	5%	95%
β_r	0.18	Beta(0.50,0.10)	0.1788	0.1785	0.1791
$\alpha^A(Asia)$	1.5	Uniform(2.0,0.50)	1.5893	1.5094	1.6722
$\alpha^A(EU-)$	1.5	Uniform(2.0,0.50)	1.4434	1.4044	1.4641
$\alpha^A(EU+)$	1.5	Uniform(2.0,0.50)	1.7778	1.7211	1.8173
$\alpha^A(Japan)$	1.5	Uniform(2.0,0.50)	1.7773	1.7529	1.7944
$\alpha^A(US)$	1.5	Uniform(2.0,0.50)	1.3959	1.3593	1.4325

Table 6: Prior and posterior for the structural parameters: For the Beta distribution, the number in parenthesis correspond to the mean and standard deviation

Parameter	True Value	Prior	Posterior mean	5%	95%
$\rho(Asia)$	0.60	Gamma(0.50,0.10)	0.5805	0.5573	0.5970
$\rho(EU-)$	0.60	Gamma(0.50,0.10)	0.5769	0.5718	0.5819
$\rho(EU+)$	0.50	Gamma(0.50,0.10)	0.5213	0.5139	0.5295
$\rho(Japan)$	0.50	Gamma(0.50,0.10)	0.5056	0.5013	0.5106
$\rho(US)$	0.50	Gamma(0.50,0.10)	0.5480	0.5395	0.5539
$\sigma(Asia)$	0.24	IGamma(0.10,∞)	0.2231	0.2073	0.2411
$\sigma(EU-)$	0.24	IGamma(0.10,∞)	0.2210	0.2174	0.2233
$\sigma(EU+)$	0.24	IGamma(0.10,∞)	0.2422	0.2391	0.2466
$\sigma(Japan)$	0.24	IGamma(0.10,∞)	0.2824	0.2768	0.2872
$\sigma(US)$	0.24	IGamma(0.10,∞)	0.2524	0.2458	0.2591
$me(Asia)$	0.24	IGamma(0.10,∞)	0.2164	0.2141	0.2188
$me(EU-)$	0.24	IGamma(0.10,∞)	0.2295	0.2272	0.2315
$me(EU+)$	0.24	IGamma(0.10,∞)	0.2551	0.2521	0.2583
$me(Japan)$	0.24	IGamma(0.10,∞)	0.2067	0.2044	0.2089
$me(US)$	0.24	IGamma(0.10,∞)	0.2359	0.2327	0.2436

Table 7: Prior (the numbers in parenthesis are the mean and stdev.) and posterior for the shock processes

6.4.1 Robustness

INFORMATIVE PRIORS

To check for robustness, I verify that similar results are obtained when I use a gamma distributions with a fairly loose variance for the parameters of the model. The estimation results are reported in table 8. Similarily to the case of uniform priors, Asia and Eastern European have lower adoption costs. The US and Japan have the highest cost. Although there is some variation across the regions, the differences in adoption costs are not very significant. The elasticity of innovation, β_r is estimated to be 0.77, consistent with the $(0.5, 1)$ interval reported by Griliches (1990).

Parameter	Prior	5%	Posterior mean	95%
$\alpha^A(Asia)$	Gamma(1.5,0.10)	2.21	2.22	2.23
$\alpha^A(EU-)$	Gamma(1.5,0.10)	2.11	2.11	2.12
$\alpha^A(EU+)$	Gamma(1.5,0.10)	1.77	1.78	1.79
$\alpha^A(Japan)$	Gamma(1.5,0.10)	1.63	1.64	1.65
$\alpha^A(US)$	Gamma(1.5,0.10)	1.46	1.47	1.48
β_r	Gamma(0.85,0.10)	0.76	0.77	0.78

Table 8: Prior and posterior for the structural parameters: Loose Priors

INTERMEDIATE GOODS

So far, I have included consumption and intermediate goods to compute growth in varieties. Because varieties enter the production function and they affect GDP in the country, one could argue that it is more correct to introduce only intermediate goods. I repeat the analysis using only intermediate goods in the final production function (1). The classification is presented in the Appendix and obtained from the UN COMTRADE database. The results show that there is not a big difference between including or not consumption goods in the analysis. Qualitatively, the results are the same. Quantitatively, the elasticity of inovtion with respect to effort is lower when only intermediate goods are used in the analysis, but it still lies within the (0.5,1) interval found by (Griliches 1990). In the case of the adoption costs, the US has now a lower value, indicating that the costs of technology transfer are higher. The difference with respect to Asia is higher than when consumption goods were also included in the analysis.

Parameter	Prior	5%	Posterior mean	95%
$\alpha^A(Asia)$	Uniform(0,3)	1.74	1.75	1.77
$\alpha^A(EU-)$	Uniform(0,3)	1.88	1.89	1.90
$\alpha^A(EU+)$	Uniform(0,3)	1.63	1.64	1.65
$\alpha^A(Japan)$	Uniform(0,3)	1.52	1.54	1.56
$\alpha^A(US)$	Uniform(0,3)	1.06	1.15	1.24
β_r	Uniform(0,1)	0.58	0.60	0.60

Table 9: Prior and posterior for the structural parameters: Intermediate Goods

6.5 How well does the model fit the data?

This section checks how well the model fits the data. I match the rate of adoption and the evolution in imported varieties over the period of analysis and per pair of regions.

RATE OF ADOPTION

First, I compare the actual value for the hazard rate or probability of adoption, computed with Survival Analysis techniques, as explained in section 3 to the estimated probability of adoption predicted by the model. The results are reported in table 10.

Exporter	Importer	Hazard	Estimated average
EU+	Asia	0.31	0.22
EU-	Asia	0.19	0.24
Japan	Asia	0.35	0.21
US	Asia	0.34	0.19
Asia	EU+	0.28	0.27
EU-	EU+	0.33	0.26
Japan	EU+	0.29	0.23
US	EU+	0.28	0.20
Asia	EU-	0.24	0.20
EU	EU-	0.33	0.18
Japan	EU-	0.31	0.26
US	EU-	0.34	0.24
Asia	Japan	0.35	0.26
EU+	Japan	0.28	0.23
EU-	Japan	0.20	0.25
US	Japan	0.25	0.21
Asia	US	0.35	0.29
EU+	US	0.29	0.26
EU-	US	0.32	0.28
Japan	US	0.28	0.25

Table 10: Hazard rates and estimated steady state values: MSE=0.01

The model does a good job in capturing the average adoption probability for the five regions considered in the analysis. We can also see the performance of the model in capturing the speed of diffusion in figure 5. The figure reports the actual data and the rates predicted by the model. The two values ate very close for most of the pair of regions.

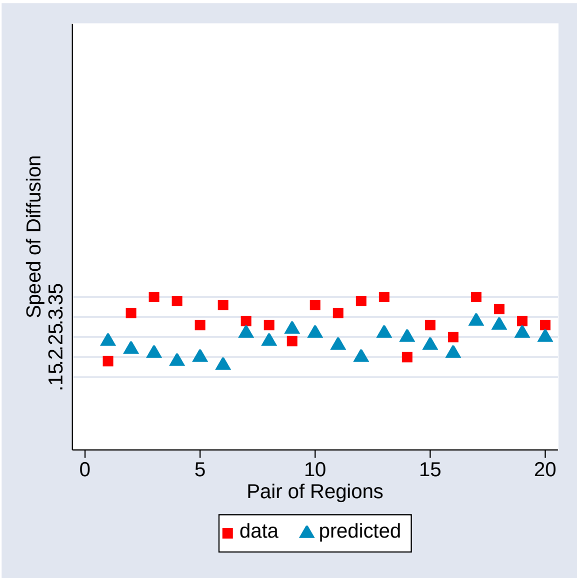
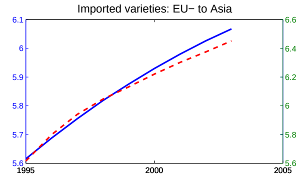
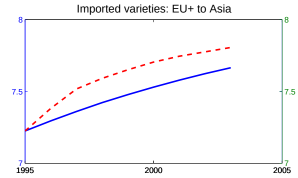


Figure 5: Rate of Adoption

EVOLUTION OF IMPORTED VARIETIES

I also compute the actual and predicted evolution in the number of imported varieties for every pair of regions for the period 1994 to 2003. The results are reported in figure 6.

The model captures fairly well the evolution of the imported varieties at the bilateral level. There has been a steady increase in the number of goods imported by the five regions considered in the analysis, especially by Asia and Eastern Europe from the US and Japan.


Imported varieties: EU− to Asia

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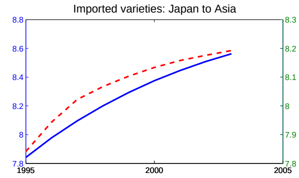
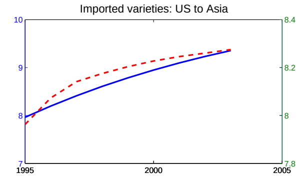
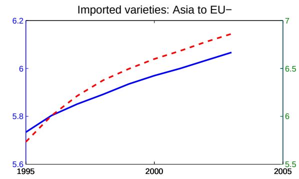

Imported varieties: Japan to Asia

Imported varieties: US to Asia

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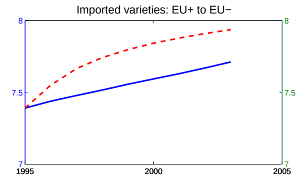
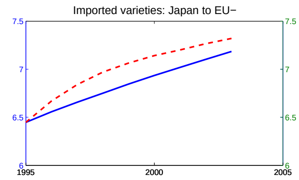

Imported varieties: EU+ to EU−

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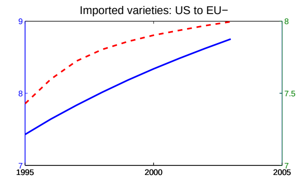
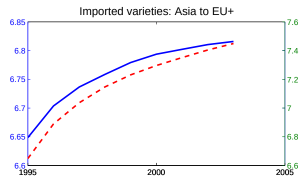

Imported varieties: US to EU−

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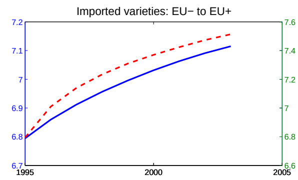
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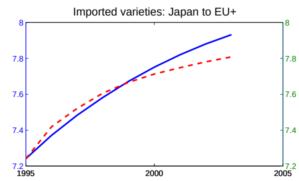
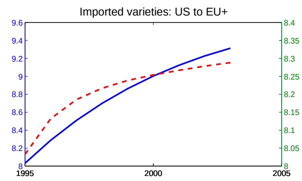
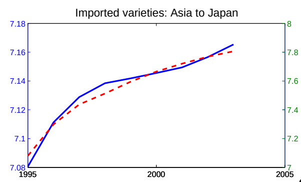
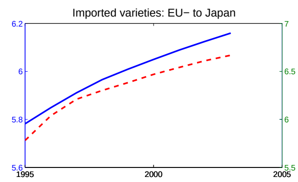
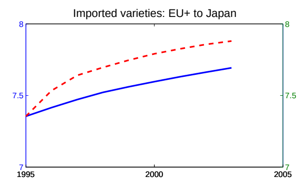

Imported varieties: Japan to EU+

Imported varieties: US to EU+

Imported varieties: Asia to Japan

Imported varieties: EU− to Japan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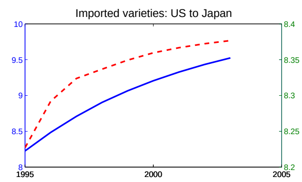
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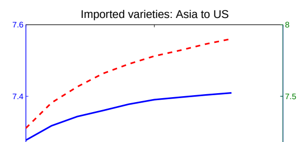
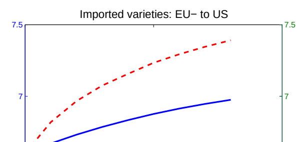

Imported varieties: Asia to US

Imported varieties: EU− to US

7 Contribution of domestic and foreign sources of innovation to embodied productivity growth

This section analyses the sources of productivity growth in each region, in order to asses the quantitative importance of trade in intermediate goods. Using the posterior mean of the estimated parameters, I decompose the growth rate in the total number of varieties into the contribution from domestic innovation (through growth in domestically produced varieties) and foreign sources of innovation (through growth in imported varieties from each exporter).

Equation (6) can be used to evaluate the domestic contribution to embodied growth. The relevant parameters are the productivity parameter, α_i^R and the scale effect, β_r. The contribution of foreign sources of innovation is given by expressions (8) and (7). The relevant parameters are the adoption costs, α_i^A and the elasticity of adoption. β_a.

Table 7 reports the growth of productivity growth in each importer (rows) that is explained from technologies developed in each exporter (columns) and diffused through trade, averaged over the period 1994-2003. Each element A_{ij} of the table can be interpreted as the percentage of growth in country i that is explained by innovations done in country j. The diagonal, in bold numbers, measures the contribution of domestic sources innovation for each region.

The results show that nearly 9o% of the productivity growth in Asia can be explained by imports, especially from the US and Japan. The US is, by far, the region for which domestic innovation represents a higher percentage of growth, with 46% of its embodied productivity coming from own innovative effort. Japan, with 23.5 %, and Western Europe, with 23% follow the US. The results are consistent with the empirical evidence: Asia does relatively little research, but it has experienced a fast increase of imported varieties, especially from the US and Japan, which are the most innovative regions.

Around two thirds of the contribution of foreign sources of innovation in Europe and Asia proceed from Japan and the US. Asian and Eastern Europe's innovations only contribute around 10% and 20% to embodied productivity growth in the other regions.

Table 11 reports the contribution of each column-exporter's innovations to each row-importer's technological progress. The US and Japan are the main sources of innovations, while Asia is the country that contributes the least to technological progress in the other regions. These results are consistent with what we see in the data. Table 13 reports the percentage that each column-exporter represents in each row-importer's total imports. In Asia, 4.08% of total imports in varieties comes from less innovative countries in Europe. The US and Japan are the main sources of exports; together, they represent more than 50% of imported varieties in each region. Asia and less innovative EU contribute the least. There is a distance effect, however, that is not present in table 7. More innovative Europe represents a higher percentage than Japan in the imports of less innovative Europe. Asia and more innovative Europe contribute almost the same to Japan's imports, even though Asia only represents 7% of the research intensity in the five regions world. Furthermore, more than 60% of the innovation effort is done in the US and Japan. It is not surprising then that these countries are benefiting, mainly, from domestic sources of innovation.

To—From	Asia	EU-	EU+	Japan	US
Asia	**13.4**	10.6	17.5	22.6	35.9
EU-	9.9	**13.8**	16.5	24.1	35.7
EU+	9.5	9.2	**22.9**	23.5	34.8
Japan	8.5	10.1	16.7	**30.9**	33.7
US	8.6	9.2	15.4	20.9	**45.9**

Table 11: Sources of growth predicted by the model: domestic and foreign innovation (percentage; Columns (exporter); rows (importer))

To—From	Asia	EU-	EU+	Japan	US
Asia		12.2	20.2	26.1	41.4
EU-	11.5		19.1	27.9	41.4
EU+	12.4	11.9		30.5	45.2
Japan	12.4	14.6	24.2		48.8
US	15.9	16.9	28.5	38.6	

Table 12: Foreign Sources of Growth: bilateral contribution predicted by the model (percentage; Columns (exporter); rows (importer))

To—From	Asia	EU-	EU+	Japan	US
Asia		4.1	19.2	36.3	40.4
EU-	9.3		37.1	15.9	37.6
EU+	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 13: Foreign Sources of Growth: bilateral contribution in the data (percentage; Columns (exporter); rows (importer))

8 Speed of convergence: Where will the world be in the long run?

The model predicts that Asia will reach the steady state in 80 years, while the US will reach it in 20. The results are reported in table 13. The US and Japan are relatively close to the steady state, while Asia and Eastern Europe are lagging behind. If we take the US as the baseline country to analyse how far we are from the steady state, we can see in the second column in table 13 that Asia's income per capita in 1995 was 25% the income per capita in the US. Japan was closer, with an income per capita of 80% the one in the US.

The third column of table 13 shows that Asia will improve its position with respect to the US by 40%. That means that in 2075, when Asia reaches the steady state, the income per capita will be 35% that of the US. Japan, that is closer, only improves by 1%. Countries that lag behind (Asia and Eastern Europe) take longer to reach the steady state, their improvement is higher and it decreases as they get closer to the steady state.

Region	Years to convergence	Relative income pc (1995)	Improvement
Asia	80	25%	40%
Eastern europe	70	26%	36%
Western Europe	35	69%	2%
Japan	30	80%	1%
US	20	Baseline	Baseline

Table 14: Speed of Convergence

Figure 8 represents the relative income per capita of the US with respect to Asia predicted by the model. In 1995, the US was four times as rich as Asia, as shown in the second column in table 8. The gap between these two regions decreases over time. In the spirit of the convergence literature, the speed of convergence is faster the farther we are from the steady state, as we can see from the slope of the figure. In 2035 the US will be over three times richer than Asia (table 15), which implies an improvement of 30%. In 2075 (steady state) the US will be less than three times richer, improving 10% with respect to 2035. As we get closer to the steady state, the predicted improvement is lower.

Asia has been closing the gap to the US through an increase in imported varieties, as the data and equation (12) suggest. Another channel by which Asia could close the gap is through domestic innovation. We do not have data on the number of products that have been developed in this region. The direction could go either way, as I show when doing counterfactuals: on the one hand, if the increase in imports by Asia is motivated by a reduction in adoption costs, the higher demand by Asia incentives R&D in the US. The US ends up specializing in doing research, while Asia specializes in adopting goods. US innovations grow faster than Asia's. On the other hand, if Asia demands more imports because there has been an increase in the innovation productivity in this region, it will produce new goods at a faster rate than the US and it will reach a new steady state in which there has been convergence, both in the number of adopted products and in the number of innovations.

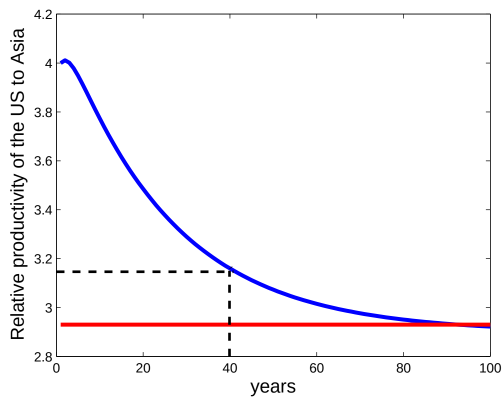


Figure 7: Speed of Convergence

Year	$\frac{Y/L(US)}{Y/L(Asia)}$
1995	4.00
2035	3.15
2075 (s.s)	2.90

Table 15: Evolution of income per capita predicted by the model

9 Counterfactuals

In this section, I perform two experiments to show how changes in the exogenous parameters of the model have something to say about the connections between trade and growth. I analyse both the steady state and the transition dynamics.

- First, I analyse a 10% permanent decrease in the cost of adoption in Asia, that is, an increase in $\alpha^A(Asia)$ in equation (7).
- Second, a 10% permanent increase in the productivity of innovation in Asia, that is, and increase in $\alpha^R(Asia)$ in equation (6).

Finally, I take advantage of the stochastic properties of the model to analyse the impacts of a positive TFP shock in Asia.

I show how the three experiments lead simultaneously to higher trade and faster growth.

9.1 An reduction in adoption costs in Asia

9.1.1 Steady State

A 10% reduction in the cost of adoption in Asia increases world growth rates by 0.4%. The research intensity in Asia is a 0.15% lower, in the new steady state. The reason is that there is a reallocation of workers from research into adoption. In the other regions, research intensity increases by 0.38% in Eastern Europe, 0.40% in Western Europe, 0.54% in Japan and 0.58% in the US. Asia becomes less specialized in research and more specialized in adoption. The higher ability to import goods increases demand from imports, especially from Japan and the US. Remember from previous sections that these two regions are the main exporters in the sample. The higher demand increases the present discounted value of future profits from selling a good abroad, which increases the market price for an innovation and incentives domestic research.

The probability of adoption in Asia increases for three reasons: directly, from the increase in $\alpha^A(Asia)$, then, indirectly, first, from an increase in the investment in adoption, H^i_{nt}, (1%) and, second, for an increase in the ratio $\frac{A^i_{nt}}{Z_{nt}}$ by 0.5%.

Through the increase in imported varieties, Asia closes the gap with respect to its trading partners, as predicted by Nelson and Phelps (1966). The gap is determined by the research efforts of the exporters and the ability of Asia to absorb new technologies. The catch-up effect implies that Asia starts growing faster than average until it reaches the new steady state growth rate, that is constant and common across countries. Relative wages in each region with respect to Asia are around 0.05% lower in the new steady state, reflecting the fact that Asia gets closer. Nevertheless, the income per capita in this region is still lower than in the trading partners. There is convergence in growth rates but not of levels.

The punchline of this analysis is that we do not need to incentive R&D in Asia, in order for this country to grow faster. This region benefits from a higher growth rate by adopting products that have been developed in the US. Given the relative position of Asia, in terms of income per capita, Asia will get closer to the US. However, it will still remain poorer. An improvement in the ability to adopt technologies, and therfore, imports, increases growth rates and income per capita. The predictions of the analysis would be different for countries closer to the frontier. In that case, an innovation policy is appropiate, since these regions are already importing most of the goods invented in the rest of the world.

Variable	% change
$\Delta r(Asia)$	-0.15%
$\Delta r(US)$	0.54%
Δg^*	0.40%
$\Delta \frac{\omega(Asia)}{\omega(US)}$	0.03%
$\Delta \frac{Z(Asia)}{Z(US)}$	-0.20%
$\Delta \frac{A_{US}^{Asia}}{Z_{US}}$	0.30%

Table 16: Reduction in adoption barriers in Asia: Steady State Comparison

9.1.2 Transitional Dynamics

Figure 8 represents the transition path for the main variables in Asia and the US when there is a 10% permanent reduction in barriers of adoption in this region. I choose to focus in the US, as trading partner of Asia, because it is the most innovative region in the sample. Therefore, we can consider it as representative of the technological frontier.

In the first panel of figure 8, we see that the research intensity in Asia (solid line) decreases initially. The increase in $\alpha^A(Asia)$ decreases the cost of adoption, increasing the value to adopt technologies from the US (dashed line in the last panel) and, therefore, investment in adoption (solid line in the last panel). Labor is initially reallocated from innovation into adapting foreign goods. The speed of diffusion and trade increase. This occurs at the intensive and extensive margins (solid and dashed line in the second panel): Asia imports more goods and more of the same goods. Therefore, the research intensity in the US increases and situates in a higher steady state value (dashed line in the first panel).

The increase in imported varieties in Asia decreases the cost of innovation in this country, through the scale effect T_{it} in equation (6). Asia starts reallocating researchers into R&D after the initial drop.

Asia becomes closer to the US through an increase in imported varieties (fifth panel) but lags behind with respect to the number of innovated varieties. Wages, the proxy for income per capita, are still higher in the US but the gap is smaller, suggesting that Asia has been growing faster.
Note that this scenario reproduces, in the transition, the situation we see in the data: rich countries are allocating more resources into R&D, while less advanced countries in Asia are adopting goods through imports of products developed in the US. This translates into faster

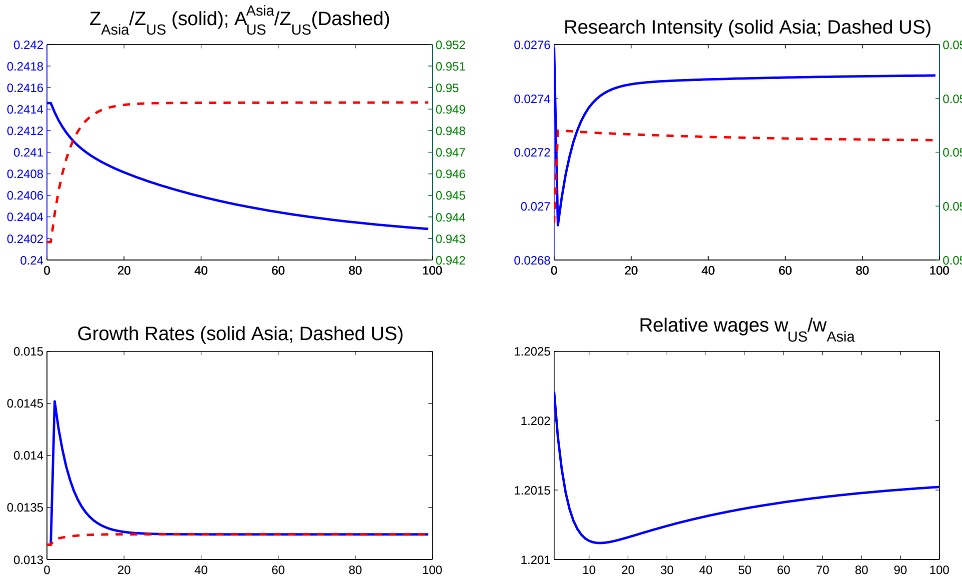


Figure 8: Permanent reduction in barriers to adoption in Asia

growth. Even with higher growth, Asia does not reach the level of income per capita of the US.

Variable	% change
$\Delta r(Asia)$	4.50%
$\Delta r(US)$	0.15%
g^*	0.70%
$\frac{\omega(Asia)}{\omega(US)}$	1.02%
$\Delta \frac{Z(Asia)}{Z(US)}$	7.40%
$\Delta \frac{A_{US}^{Asia}}{Z_{US}}$	1.00%

Table 17: Increase in innovation productivity in Asia: Steady State Comparison

9.2 Counterfactual: Increase in productivity of innovation in Asia

9.2.1 Steady State

A 10% permanent increase in the productivity of innovation in Asia increases world growth rates by 0.7%. Research intensity in this region is 4% higher, while research intensity in the US is a 0.4% higher. The increase in productivity promotes growth in Asia, mainly through domestic source. A higher income increases the demand for foreign goods, especially at the intensive margin (relative wages of the US with respect to Asia decrease). Higher profits translate into a higher future value of adopted technologies and therefore the extensive margin. Relative wages in Asia increase by 0.1%. In this experiment, a higher productivity of innovation translates in higher trade as well as faster growth.

9.2.2 Transtional Dynamics

Figure 9 represents the transition path of the positive productivity shock in Asia. In the transition, the research intensity in this region goes up initially (solid line in the first panel). A higher $\alpha^A(Asia)$ decreases the cost of innovation and this incentives a reallocation of labor into research. Note that the higher $\alpha^R(Asia)$ has the same effect on innovation in Asia as the higher $\alpha^A(Asia)$ had on research intensity in the US (dashed line in the first panel of figure 8). Research intensity in the US decreases first and then it starts increasing, mainly because Asia starts demanding products from this country (second panel in 9). After the first increase in reserach, Asia starts reallocating labor into adoption. This region is closing the gap with respect to the leader through an increase in imported varieties (fifth panel) and an increase in innovations (fourth panel). Relative wages of the US decrease, suggesting that Asia has been growing faster in the transition.

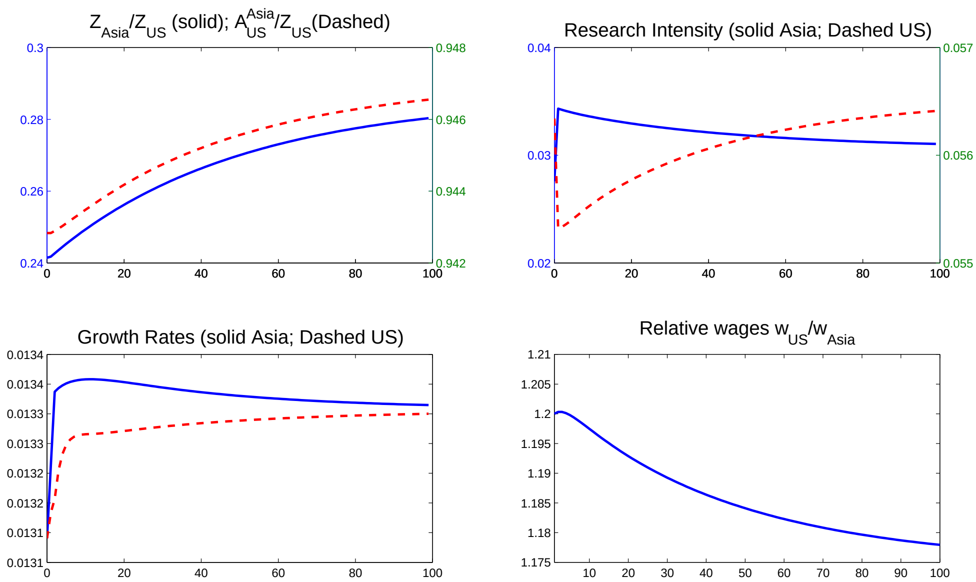


Figure 9: Permanent increase in innovation productivity in Asia

10 Counterfactuals (Stochastic Simulation): A Shock to disembodied technology in Asia

In this section, I take advantage of the stochastic properties of the model to analyse the effects of a positive neutral techological shock in Asia. A neutral technology shock speeds up growth and this translates into an increase in the demand for imports. The experiment explores another direction in the positive correlation between economic growth and growth in imported varieties: economic growth promotes trade, mainly through the intensive margin. The positive productivity shock increases demand for intermediate goods. We can distingush between the extensive and the intensive margin effect: Asia is demanding more products and more of the same products. Relative productivity, measured through wages, decreases everywhere. Asia has been growing faster in the transition.

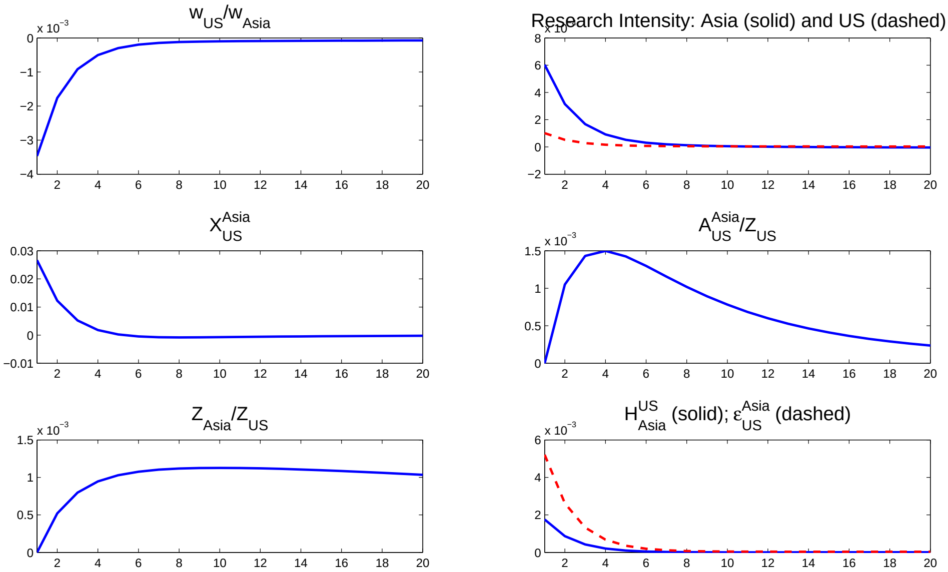


Figure 10: Positive productivity shock in Asia

11 Conclusions

The effects of trade in growth have been studied extensively in economics. However, there are still two gaps in these studies. On the one hand, the mechanisms by which countries benefit from each other's R&D through trade are not fully understood; on the other hand, the magnitudes are unknown. This paper has shown that innovation, through creation of new varieties, and diffusion, through adoption of new varieties through imports, can explain the connections between trade and growth. At the same time, trade in varieties arises as the new way to masure the extent of trade, and therefore diffusion in an economy.

This paper is one step forward in analysing the connections between trade in varieties and growth. First, it does not face the endogeneity problem of regression analysis. Second, the model is tractable enough to analyse the mechanisms outside the steady state. This is important to capture differences in growth rates across countries. Third, Bayesian techniques allow us to incorporate prior knowledge into the analysis and pin down the value of the parameters that govern innovation and adoption.

I have shown that diffusion in the last decade is particularly important in Asia and Eastern

Europe, allowing these countries to benefit form their backward situation and grow faster than average. Innovation, instead, is more important in the US and Japan. The model suggests that, for technologically advanced countries, policies that incentive innovation are more appropiate. For countries that lag behind, their best option is to adopt foreign technologies, through imports. As countries get closer to the frontier, a policy that fosters innovation is appropiate to keep expanding the technological frontier.

In future reserach, I am planning to introduce firm heterogeneity as in Melitz (2003) or Eaton and Kortum (2002), to determine the implications of bilateral trade flows of the model. In the current setting the expenditure of intermediate goods in each country is the same for every variety. By introducing heterogeneity in the firm productivity, we can take into account differences in trade flows. Furthermore, in the framework that I have used in this paper, all the products can potentially be exported, given that all firms have the same productivity. Once again, firm heterogeneity can introduce inter-firm reallocations towards more productive goods.

12 Appendix

12.1 Data

Country	GDPpcgrowth	Varietygrowth	Researchers (10^{-3})	GDPpc(1995)
Austria	1.94	0.03	2.72	28401.87
Belgium	1.93	0.16	2.89	26668.76
Bulgaria	2.17	0.83	0.56	6924.32
China	8.13	0.55	0.42	1853.45
Cyprus	2.39	0.71	4.05	20212.69
Denmark	2.03	0.30	2.21	28323.68
Estonia	6.16	0.85	6.65	7911.48
Finland	3.38	0.40	2.95	21865.56
France	1.75	0.03	3.10	25856.33
Germany	1.38	0.04	1.26	26970.08
Greece	2.88	0.24	1.32	20861.02
HK	1.79	0.59	1.32	27175.87
Hungary	3.87	0.26	0.10	11048.27
India	4.20	1.96	0.21	1403.71
Indonesia	1.78	1.93	2.28	2815.82
Ireland	6.54	0.34	2.28	21328.97
Italy	1.52	0.01	1.19	25151.35
Japan	0.72	0.13	5.17	27551.29
Korea	4.37	0.28	2.70	14716.83
Latvia	6.04	1.22	1.33	6190.58
Lithuania	4.28	1.20	2.17	7402.13
Malaysia	2.81	1.11	0.28	9296.93
Malta	2.69	1.46	0.70	16839.78
Netherlands	2.21	0.47	2.53	28186.20
Philippines	1.78	1.19	0.05	2415.27
Poland	4.53	0.41	1.48	8836.75
Portugal	2.26	0.20	1.65	16543.51
Romania	2.45	0.69	1.06	7223.41
Singapore	3.08	0.43	3.89	30922.08
Slovakia	3.99	0.54	1.86	10651.25
Slovenia	3.74	0.15	2.32	15410.37
Spain	2.75	0.08	1.78	20887.66
Sweden	2.56	0.15	4.85	24843.19
Thailand	2.39	0.50	0.22	5907.27
UK	2.72	0.05	2.99	24555.60
USA	2.04	0.07	4.50	33759.57
Vietnam	5.78	1.79	0.16	1214.14
Asia	3.53	1.12	0.98	9222.73
EU less R&D	3.64	0.57	1.91	13963.97
EU more R&D	2.21	0.18	2.83	26185.70
Japan	2.55	0.20	3.94	21134.06
USA	2.04	0.07	4.50	33759.57

Table 18: Differences across countries: PPP

12.2 Sample of Countries

Asia	EU less R&D	EU more R&D	Japan	North America
China	Bulgaria	Austria	Japan	Canada
Hong Kong, China	Croatia	Belgium	Korea	US
India	Cyprus	Denmark		
Indonesia	Czech Republic	Finland		
Philippines	Estonia	France		
Russian Federation	Greece	Germany		
Singapore	Hungary	Luxembourg		
Thailand	Ireland	Netherlands		
Vietnam	Italy	Sweden		
	Latvia	Switzerland		
	Lithuania	United Kingdom		
	Malta			
	Poland			
	Portugal			
	Romania			
	Slovak Republic			
	Slovenia			
	Spain			
	Turkey			

Table 19: Country Sample

12.3 Intermediate Goods Classification

The codes are under the classification of Broad Economic Categories (BEC). There are three basic classes of goods in SNA in the categories of BEC. These are as follows:

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 spirit) 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, semi-durable 63* Consumer goods not elsewhere specified, non-durable

Table 20: Classification of goods according to BEC

UN Comtrade contains trade data classified by BEC codes. This means that you can design many different kinds of data queries using BEC classes. For instance, you can breakdown Germanys 2005 imports data into Capital, Intermediate and Consumption goods using the above mentioned aggregations; you could even breakdown Germanys imports from Japan into those broad economic classes.

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