Non-Homotheticity and Bilateral Trade: Evidence and a Quantitative Explanation*

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Abstract

Gravity models predict that trade flows increase with importer and exporter total income, but ignore how income is divided into income per capita and population. Bilateral trade data, however, show that trade grows strongly with income per capita but is largely unresponsive to population.

I develop a general equilibrium, Ricardian model of trade that allows for the elasticity of trade with respect to income per capita and population to diverge. Goods are subdivided into types, which differ in the income elasticity of demand and the extent of heterogeneity in production technologies. I estimate the model using bilateral trade data of 162 countries and compare it to a special case that delivers the gravity equation. The general model improves the restricted model's predictions regarding variations in trade due to size and income. I experiment with counterfactuals. A technology shock in China makes poor and rich countries better off, and middle income countries worse off.

Keywords: international trade, income per capita, gravity equation, non-homotheticity.

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1 Introduction

It is well known that poor countries trade much less than rich countries, both with each other and with the rest of the world. In 2000, for example, transactions to and from the twelve Western European countries alone accounted for 45% of international merchandize trade, and intra Western European trade, for 16%. The fifty-seven African economies, in contrast, accounted for only 4.2% of world trade, and intra African trade, a meager 0.2%. Doubling a country's income per capita *increases* trade (average between imports and exports) as a share of GDP by 1.7% on average, while doubling a country's population *decreases* its trade share by 2.0%. Despite these differences, standard models of international trade, which typically yield a gravity relationship, predict that trade increases in proportion to both importer and exporter total income, and ignore how total income is divided into income per capita and population.

Protectionist policies and high transport costs are the usual explanations for the small volume of trade in poor countries. But even after controlling for tariffs and direct measures of trade costs, income per capita continues to have a significant, increasing effect on trade.[1] Further, this explanation does not take incentives into account–the low quality of infrastructure in poor countries, for example, may simply be a result of these countries' lack of incentives to trade.

This paper takes an alternative, probably concomitant, view. I purposely abstract away from differences in trade costs across countries and focus instead on two assumptions of gravity type models that are inconsistent with micro-level evidence. The first assumption is homothetic preferences. There is exhaustive evidence that the income elasticity of demand varies across goods and that this variation is economically significant.[2] Food, for instance, has a low income elasticity. Spending on it ranged in the early 1980s from 64% in Tanzania to less than 15% in Australia and North America (Grigg (1994)). The second assumption is homothetic supply. Typically in gravity models, production in poor and rich countries differs only in quantitative, not qualitative, aspects. This assumption is at odds with the theory of product cycle and with

[1] See, for example, Coe and Hoffmaister (1998), Limão and Venables (2001), Rodrik (1998).

[2] See Bils and Klenow (1998), Deaton (1975), Grigg (1994), Hunter (1991).

empirical evidence on technology diffusion.[3] When a good is first invented, the argument goes, the technology to produce it differs greatly across countries, most of which do not know how to make it. At this stage, the good is generally produced in the, typically high income, country where it was invented. As the product matures, methods to produce it become standardized, and they can then be applied similarly to any country, including those where labor is cheap. In a cross-section, one should thus expect poor countries to produce disproportionately more goods whose technologies have already diffused and are therefore similar across countries.

I propose an analytically tractable Ricardian model of trade that, in line with the evidence above, relaxes the assumptions of homotheticity on the demand and supply sides of the economy. Goods in the model are subdivided into types, which may differ in two respects: Demand and technology. Poor households concentrate their spending on types with low income elasticity, and rich ones, on types with high income elasticity. The supply side set up is Ricardian. All goods are homogeneous, markets are perfectly competitive, and comparative advantage arises from differences in technologies across goods and countries. Labor is the unique factor of production, and the distribution of its efficiency may be more variable for some types of goods than for others. Analogous to the product cycle theory above, in general equilibrium, countries where overall productivity is low have low wages and consequently specialize in less differentiated goods. Technologically advanced countries, in contrast, have high wages and a comparative advantage in types of goods whose production technologies are more variable across countries.

If there is only one type of good, the model reduces to Eaton and Kortum (2002, EK henceforth) and delivers the gravity equation. This special case thus makes the same predictions for trade flows as other gravity type models.[4] None of these models allow for non-homotheticity in demand or supply, and they all imply the same elasticity of trade with respect to income per capita and to population.

I estimate the model, with one type (EK model) and with two types of goods, using data on bilateral merchandize trade flows of the year 2000. I use two data sets–one containing 162

[3]See Comin and Hobjin (2006), Nabseth and Ray (1974), Romer (1990), Vernon (1966).
[4]For example, Anderson and van Wincoop (2003), Redding and Venables (2004).

countries, and the other, a subset of 19 OECD countries. In both data sets, I observe the total value of trade for each importer-exporter country pair. The EK model explains trade among OECD countries very well, but not trade in the full sample, among countries of different size and income levels. The new model, in turn, explains trade among OECD countries as well as the EK model, and significantly improves upon EK in explaining the full sample. The estimated parameters of the model are such that the type of good that is more elastic coincides with the type whose production technologies are more variable across countries. Hence, rich countries consume and produce these goods more intensively. And the variability in their production technologies generates large price dispersions, which in turn give rich countries large incentives to trade. Poor countries, in contrast, produce and consume more goods whose production technologies are similar across countries. As a result, they trade little.

So with this configuration, the new model simultaneously explains the large volume of trade among rich countries and the small volume among poor countries, patterns which cannot be reconciled with the EK model. For example, trade among the 20 richest countries in the sample accounts on average for 27% of these countries' income. Similarly, the new model predicts this trade to be 19% of the richest countries' income, while the EK model, when estimated with the full sample of countries, predicts that it is only 5%. Trade among the 20 poorest countries, in turn, is less than 2% of these countries' income according to the data, the new and the EK model.

One implication of the parameters of the model is that, as a country's income grows, its demand for the type of good with high elasticity increases before its supply does. Middle income countries are rich enough to consume these goods intensively, but not to produce them. They are thus the largest net importers of high elasticity goods, while high income countries are the largest net exporters.

I use counterfactual simulations to show that this implication has welfare consequences. If the rate of growth that China has experienced since the early 1980s persists, China's income will roughly quadruple every 15 years. In the model, a technology shock in China decreases the price of the low income elastic goods produced by China and other poor countries. A shock that quadruples Chinese wages increases wages in the 50 richest countries in the sample by

0.7% relative to the 50 poorest countries. The shock benefits both poor and rich countries, and it hurts middle income countries. Poor countries are the largest consumers of the low income elastic goods, whose prices decrease; rich countries are their largest net importers, and middle income countries, their largest net exporters. A shock to the technology of the United States, a rich country, has the opposite effect as the shock in China.

I also experiment with a move to frictionless trade and to autarky. Eliminating trade frictions benefits all countries in the world, especially the least populous ones. Real wage increases range from 140% in some small countries to 15% in the United States. A move to autarky, in contrast, hurts all countries in the world, especially small, rich countries. Real wage decreases range from -1.1% in India to -19% in Luxembourg. As others have found, changes in welfare are much larger when the world moves to frictionless trade than to autarky (Waugh (2008)).

This paper contributes to two other strands of literature. First, previous models of trade with non-homothetic preferences are typically highly stylized and often rely on the assumption of a two-country or a two-good world.[5] By admitting a continuum of goods and an arbitrary number of countries, the new model allows one to simultaneously analyze all directions of trade–North-North, North-South and South-South–and to analyze data.

Second, I introduce a new estimation methodology for the EK model, thereby contributing to previous papers that estimate it.[6] The regression approach typically used in gravity models is not applicable to the new model because the introduction of non-homotheticity modifies the gravity-type framework in a non-linear fashion. The alternative methodology that I suggest makes full use of the general equilibrium feature of the model, and it does not incur the same endogeneity problems of regression analysis (see section 3). Its application also extends the work of EK to a larger data set–EK estimate their model using a data set containing only manufactures trade among nineteen OECD countries.

The paper is organized as follows. In section 2, I present the theory. In section 3, I present the empirical analysis. I exploit counterfactuals in section 4 and conclude in section 5. The

[5] See, for example, Flam and Helpmann (1987), Markusen (1986), Matsuyama (2000), and Stokey (1991).

[6] See Alvarez and Lucas (2007), Eaton and Kortum (2002), Waugh (2008).

appendix discusses alternative set ups for the model, explains details of the data and of the empirical methodology, and presents robustness checks.

2 Theory

This section is organized as follows. In sections 2.1 and 2.2, I present the theory. I solve the model in section 2.3 and explain its workings in section 2.4. I conclude by showing that the EK model is a special case of the new model in section 2.5.

2.1 The Environment

There are N countries, and goods are subdivided into S types, each with a continuum of goods. Goods of type $\tau \in \{1, 2, ..., S\}$ are denoted by $j_\tau \in [0, 1]$. All consumers in the world choose the quantities of goods j_τ, $\{q(j_\tau)\}_{j_\tau \in [0,1]}$, to maximize the same utility function:

$$\sum_{\tau=1}^{S} \left\{ (\alpha_\tau)^{1/\sigma_\tau} \left(\frac{\sigma_\tau}{\sigma_\tau - 1} \right) \int_0^1 \left[q(j_\tau)^{(\sigma_\tau - 1)/\sigma_\tau} \right] dj_\tau \right\} \tag{1}$$

where $\alpha_\tau \in [0, 1]$ is the weight of type τ on preferences and $\sigma_\tau > 1$ for all $\tau = 1, ..., S$. I normalize $\sum_{\tau=1}^{S} (\alpha_\tau)^{1/\sigma_\tau} = 1$.

Parameter σ_τ is typically associated with its role as the elasticity of substitution, but here it also governs the income elasticity of demand of goods of type τ. To see this, consider any two types of goods, $\tau = 1, 2$. Denote by $p(j_\tau)$ the price of good j_τ, and by x_τ the total spending on goods of type τ. Then, from the first order conditions, spending on goods of type 1 relative to type 2 satisfies

$$\frac{x_1}{x_2} = \lambda^{\sigma_2 - \sigma_1} \left(\frac{\alpha_1 P_1^{1-\sigma_1}}{\alpha_2 P_2^{1-\sigma_2}} \right), \tag{2}$$

where P_τ is the CES price index of goods of type $\tau = 1, 2$, and λ is the Lagrange multiplier associated with the consumer's problem. This multiplier, it can be easily shown, is strictly decreasing in the consumer's total income.

In equation (2), the term in parenthesis governs the level of the ratio x_1/x_2. It increases with α_1 and decreases with P_1. The term $(\lambda^{\sigma_2-\sigma_1})$ governs the rate at which x_1/x_2 changes with consumer income. If $\sigma_1 > \sigma_2$, the ratio x_1/x_2 is decreasing in λ and consequently increasing in consumer wealth. Therefore, the utility function in equation (1) captures the notion that consumers with different income levels concentrate their spending on different types of goods in a simple manner: $\sigma_1 > \sigma_2$ implies that goods of type 1 are more income elastic, and hence rich countries demand relatively more of these goods than poor countries do.[7]

2.2 Technologies

Labor is the unique factor of production. It is perfectly mobile across types and immobile across countries.[8] Countries have different access to technologies, so that labor efficiency varies across countries and goods. Let $z_i(j_\tau)$ be the efficiency of labor to produce good j_τ of type τ in country i. Assuming constant returns to scale and denoting country i's wage by w_i, the unit cost of producing each unit of good j_τ in country i is $\frac{w_i}{z_i(j_\tau)}$.

Geographic barriers take the form of Samuelson's "iceberg costs": Delivering one unit of a good from country i to country n requires the production of d_{ni} units. Transportation costs are positive if $d_{ni} > 1$. Let $d_{ii} = 1$ for all i, and assume that trade barriers obey the triangle inequality, $d_{ni} \leq d_{nk}d_{ki}$ for all i, k and n. Taking these barriers into account, the total cost of delivering one unit of good j_τ from country i to country n becomes

$$p_{ni}(j_\tau) = \frac{d_{ni}w_i}{z_i(j_\tau)}.$$

Assuming perfect competition, the price of good j_τ faced by consumers in country n is

$$p_n(j_\tau) = \min\{p_{ni}(j_\tau) : i = 1, ..., N\}.$$

[7] Appendix 6.1 presents a more general utility function in which one parameter controls the elasticity of substitution across goods within a type and another parameter controls the income elasticity of demand. I show there that the more general functional form predicts the same trade flows as the function in equation (1). Therefore, nothing in my results relies on the assumption that the type of good with the greater elasticity of substitution has a greater income elasticity of demand.

[8] Labor can be interpreted more generally in the theoretical model as an input bundle, including capital. I maintain the term labor throughout, however, because that is the interpretation used in the empirical analysis of section 3 below.

Following EK, in order to obtain the distribution of prices in the economy, I employ a probabilistic representation of technologies. I also use the same functional form they do. For any $z \geq 0$, the measure of the set of goods $j_\tau \in [0, 1]$ such that $z_i(j_\tau) \leq z$ is equal to the cumulative distribution function of a Fréchet random variable:

$$F_{i\tau}(z) = \exp\left(-T_i z^{-\theta_\tau}\right), \tag{3}$$

where $T_i > 0$ for all countries $i = 1, ..., N$, and $\theta_\tau > 1$ for all types $\tau = 1, ..., S$. These distributions are treated as independent across countries and types.

Figure 1 illustrates four examples of densities of the Fréchet distribution. Given θ_τ, the country-specific parameter T_i determines the level of the distribution–a larger T_i increases the measure of goods with large, efficient technologies $z_i(j_\tau)$. Thus, the assumption that T_i does not depend on the type of good τ, made just for parsimony, implies that a country that is generally good at making goods of one type will also be good at making goods of other types.

Parameters θ_τ are common to all countries, but may differ across types. These parameters govern the spread of the distribution–the larger the θ_τ, the smaller the variability in labor efficiencies across *goods* and *countries*. In figure 1, the decrease in θ from 20 to 5 increases the dispersion of the distribution of technologies across goods for a fixed T. But importantly, it also increases the dispersion of technologies across countries–it shifts the density with $T = 100$ away from the one with $T = 10$.

This property of the Fréchet distribution gives a dual role to parameters θ_τ in the model. First, the variability of technologies across *goods* governs comparative advantage *within* types. A greater dispersion in labor efficiencies (a smaller θ_τ) generates a greater price dispersion, and consequently a greater volume of trade. Trade is more intense in types where θ_τ is small.

Second, the variability of labor efficiencies across *countries* governs comparative advantage *across* types. The mean of the Fréchet distribution helps illustrate this point. The cost of delivering one unit of good j_τ from country i to country n relative to the cost of producing it domestically is $\frac{p_{ni}(j_\tau)}{p_{nn}(j_\tau)} = \frac{z_n(j_\tau)}{z_i(j_\tau)} \frac{d_{ni} w_i}{w_n}$. Taking the expectance over j_τ, we get

$$\frac{E(p_{ni}(j_\tau))}{E(p_{nn}(j_\tau))} = \left(\frac{T_i}{T_n}\right)^{-1/\theta_\tau} \frac{d_{ni}w_i}{w_n}. \tag{4}$$

Two factors control the cost of producing goods in country i relative to producing them in country n: The ratio of their effective wages $\left(\frac{d_{ni}w_i}{w_n}\right)$ and the ratio of technology parameters $\left(\frac{T_i}{T_n}\right)$. The parameter θ_τ controls the relative importance of these two factors. As θ_τ increases, the term $\left(\frac{T_i}{T_n}\right)^{-1/\theta_\tau}$ approaches one, and effective wages swamp technology in determining costs. So poor countries tend to specialize in types where θ_τ is large because they have low wages. Rich countries, in turn, specialize in types where θ_τ is small because, in general equilibrium, these are the countries with large labor efficiencies–i.e., large T_i's.

Although the model is static, this production set up can be seen as arising from a product cycle if parameter θ_τ is interpreted as the age of goods of type τ. When a good is first invented, θ_τ is small, methods to produce it vary greatly across countries. Goods at this stage are produced in the, typically high income, country where it was invented. As θ_τ increases, methods to produce goods of type τ become standardized (less variable across countries), and production tends to shift to countries with low labor costs. As θ_τ tends to infinity, the Fréchet distribution approaches a discrete random variable with all its mass at 1, irrespective of the country-specific parameter T_i. This is the end of the learning process: All countries' technology parameters $z_i(j_\tau)$ get arbitrarily close to 1, costs are exclusively determined by wages, and production occurs in the country with the lowest effective cost of labor, $d_{ni}w_i$.

2.3 Equilibrium

All countries have a continuum of individuals, who supply inelastically the one unit of labor with which they are endowed. Let L_i be the population of country i. I denote the spending of individuals with small x and of countries with capital X, and where needed, I use subscripts to specify type (τ), importer (n), and exporter (i).

Assume that $(\theta_\tau + 1) > \sigma_\tau$ for all $\tau = 1, ..., S$, the well-known necessary condition for a finite solution (see Eaton and Kortum (2002)). Given a set of wages w_i, technology parameters T_i, and iceberg costs d_{ni}, we can derive the distribution of prices faced by consumers in any country $n = 1, ..., N$ from the distribution of technologies (equation (3)). These prices, together with the utility function, allow us to calculate the demand function.

The spending of a typical consumer in country n on goods of type τ is

$$x_{n\tau} = \lambda_n^{-\sigma_\tau} \alpha_\tau P_\tau^{1-\sigma_\tau} \tag{5}$$

where λ_n is the Lagrange multiplier associated with the consumer's problem, and the CES price index is the same as in EK, $P_\tau = \left[\Gamma\left(\frac{\theta_\tau+1-\sigma_\tau}{\theta_\tau}\right)\right]^{1/(1-\sigma_t au)} (\Phi_{n\tau})^{-\frac{1}{\theta_\tau}}$ where Γ is the gamma function and $\Phi_{n\tau} = \sum_{i=1}^{N} T_i (d_{ni}w_i)^{-\theta_\tau}$. The multiplier, $\lambda_n > 0$, is implicitly defined through the budget constraint, $\sum_{\tau=1}^{S} x_{n\tau} = w_n$, as a continuous and strictly decreasing function of income w_n.

The spending of a consumer in country n on goods of type τ from country i is

$$x_{ni\tau} = \frac{T_i(d_{ni}w_i)^{-\theta_\tau}}{\Phi_{n\tau}} x_{n\tau}. \tag{6}$$

Country n's imports from country i total

$$X_{ni} = L_n \left(\sum_{\tau=1}^{S} x_{ni\tau}\right). \tag{7}$$

By equating supply to demand, we obtain country i's labor market clearing conditions:

$$\sum_{n=1}^{N} X_{ni} = L_i w_i. \tag{8}$$

This completes the statement of the model. To summarize, an economy is defined by a set of N countries, each with its population L_i and technology parameter T_i; a set of types $\{1, ..., S\}$, each with its technology parameter θ_τ and preference parameters α_τ and σ_τ, and a matrix of trade barriers $\{d_{ni}\}_{n,i \leq N}$. Given wages w, the matrix of trade flows $\{X_{ni}\}_{n,i \leq N}$ is given by equations (5) through (7). An equilibrium is a set of wages $w \in \Delta(N-1)$ that satisfies the labor market clearing condition (8) for all countries $i \in \{1, ..., N\}$.

2.4 Income per Capita and Trade Patterns

Having presented the model, I now analyze how its parameters govern the role income per capita on trade. I consider, for simplicity, the case with two types of goods, A and B, as in the empirical analysis of section 3 below.

If preferences were homothetic, the distribution of income across goods would be independent of income levels. But by equation (5), country n's spending on goods of type A relative to type B satisfies

$$\frac{X_{nA}}{X_{nB}} = (\lambda_n)^{\sigma_B - \sigma_A} \left(\frac{\alpha_A P_A^{1-\sigma_A}}{\alpha_B P_B^{1-\sigma_B}} \right). \tag{9}$$

Equation (9) is the same as equation (2). Assuming $\sigma_A > \sigma_B$, the ratio $\frac{X_{nA}}{X_{nB}}$ is decreasing in λ_n and increasing in wealth. Rich households spend a larger fraction of their incomes in goods of type A than poor households do.

Ultimately, however, we are interested on how this ratio affects the consumer's allocation of income across potential exporters. Let $X_{ni\tau}$ be country n's spending on goods of type τ from country i. Since $\sigma_A > \sigma_B$, country n's imports from country i relative to its domestic consumption, $\frac{X_{ni}}{X_{nn}}$, is mostly determined by $\frac{X_{niA}}{X_{nnA}}$ if country n is rich, and by $\frac{X_{niB}}{X_{nnB}}$ if it is poor. By equation (6), these ratios equal

$$\frac{X_{niA}}{X_{nnA}} = \frac{T_i}{T_n} \left(\frac{d_{ni} w_i}{w_n} \right)^{-\theta_A} \quad \text{and} \quad \frac{X_{niB}}{X_{nnB}} = \frac{T_i}{T_n} \left(\frac{d_{ni} w_i}{w_n} \right)^{-\theta_B}. \tag{10}$$

These are the same expressions as the RHS of equation (4), except that they are raised to the power $(-\theta_\tau)$. So the conclusions drawn there follow: If θ_τ is large, the variability in production technologies across goods and countries is small, and consequently consumers place a larger emphasis on the effective cost of labor $\left(\frac{d_{ni} w_i}{w_n}\right)$ than on technology parameters $\left(\frac{T_i}{T_n}\right)$.

To make this point clearer, suppose that $\theta_A < \theta_B$, as in the empirical results of section 3 below. Suppose further that country n is poor. Then, $\left(\frac{d_{ni} w_i}{w_n}\right) > 1$ in general because w_n is small and $d_{ni} > 1$. And hence $\left(\frac{d_{ni} w_i}{w_n}\right)^{-\theta_B}$ is close to zero because θ_B is large. Country n's imports are then small, $\frac{X_{ni}}{X_{nn}} \approx \frac{X_{niB}}{X_{nnB}} = \frac{T_i}{T_n} \left(\frac{d_{ni} w_i}{w_n}\right)^{-\theta_B} \approx 0$. In words, the low heterogeneity in the production technologies of the goods typically consumed by poor countries, type B goods, dampen the incentives for these countries to trade. If products are not sufficiently differentiated, consumers in poor countries prefer the domestic version, made with cheap labor and free from transport costs.

This scenario is reversed if country n is rich and $\frac{X_{ni}}{X_{nn}} \approx \frac{X_{niA}}{X_{nnA}}$. Since θ_A is small, the term $\left(\frac{d_{ni}w_i}{w_n}\right)^{-\theta_A}$ is relatively close to 1 irrespective of whether $\left(\frac{d_{ni}w_i}{w_n}\right)$ is smaller or greater than 1. Thus, $\frac{X_{niA}}{X_{nnA}}$ is largely determined by the ratio $\frac{T_i}{T_n}$, instead of $\left(\frac{d_{ni}w_i}{w_n}\right)$ as $\frac{X_{niB}}{X_{nnB}}$ is. This result has two implications. First, rich countries trade more than their poor counterparts because their consumers place a smaller emphasis on trade barriers and wages ($d_{ni}w_i$). Second, they trade more with other rich countries, whose technology parameters T_i are large. So in accordance with the empirical evidence mentioned in the introduction, the model predicts trade to be more intense among rich countries whenever $\sigma_A > \sigma_B$ and $\theta_A < \theta_B$.

2.5 A Special Case: The Eaton-Kortum Gravity Model

I show two special cases of the new model under which its solution reduces to the EK model. The most straightforward case is to suppose there exists only one type of good, $\alpha_\tau = 1$ for some τ. Production efficiencies are then distributed as per EK (equation (3)), and the utility function becomes

$$\frac{\sigma_\tau}{\sigma_\tau - 1} \int_0^1 \left[q(j_\tau)^{(\sigma_\tau - 1)/\sigma_\tau} \right] dj_\tau,$$

which represents standard homothetic, CES preferences. The flow of trade from country i to country n is then given by

$$X_{ni} = X_{ni\tau} = \frac{T_i \left(d_{ni}w_i\right)^{-\theta_\tau}}{\Phi_{n\tau}} X_n, \tag{11}$$

where $X_n = w_n L_n$ is country n's total income. This is the solution to the EK model.[9] Trade flows do not depend on income per capita, only on total income.

[9]Eaton and Kortum (2002) consider only trade in manufacturing products. So, instead of country n's total income, X_n, they have its manufacturing absorption.

An alternative way to recover the EK model is to modify the supply side of the economy. If $\theta_\tau = \theta$ for all $\tau = 1, ..., S$, then country i exports to country n, X_{ni}, is again given by equation (11). This example shows that non-homothetic preferences alone are not sufficient to modify trade patterns. If the distribution of technologies were equal across types, then consumers of different income levels would demand goods from exactly the same sources–only the names (or types) of goods would change.

The converse, however, is not true. One way to make preferences homothetic, while preserving the multi-type technology distribution, is to assume $\sigma_\tau = \sigma$ for all $\tau = 1, ..., S$. Although I do not present the results, I did estimate the new model with this restriction. The explanatory power of this restricted model (formally defined in section 3 below) is about 50% closer to the new model than to the EK model. (This result will be clearer after I explain the role of each individual parameter in modifying trade flows in section 3.1.1 below.)

3 Empirical Analysis

The objective of this section is to evaluate qualitatively and quantitatively the ability of the model to explain bilateral trade flows. The regression approach often used to estimate the EK model is not applicable to the new model, and so I propose an alternative methodology that takes advantage of its general equilibrium set up. I focus exclusively in the special case with only two types of goods, denoted by A and B.[10]

I use data on bilateral merchandize trade flows of the year 2000 from the UN Comtrade (United Nations (2008)), and data on population and income from the World Bank (2008). The details of the data and their compilation are in appendix 6.2. The data comprise 162 countries and account for 95% of world trade in the year 2000. There are 25,810 observations, each containing the total value of trade for an importer-exporter country pair. Table 1 lists all the countries in the sample and shows, for each country, the percentage of its imports originating in countries within the sample. In addition to these data, I use data specific to country pairs–

[10] As a robustness check, I also estimate the model with three and with four types. In both cases, the trade flows predicted by the model do not change with respect to the two-type case, and the type specific parameters α_τ and θ_τ are not identified.

distance between their most populated cities, common official language, and border–from the Centre d'Etudes Prospectives et d'Informations Internationales (2005) webpage.

I present the empirical methodology in section 3.1, the results in section 3.2 and robustness checks in section 3.3.

3.1 Empirical Analysis: Methodology

Equations (5), (6), and (7) above imply that country n's imports from country i satisfy:

$$\begin{aligned}
X_{ni} &= L_n \left(x_{niA} + x_{niB} \right) \qquad \text{where, for } \tau = A, B, \\
x_{ni\tau} &= \frac{T_i (d_{ni} w_i)^{-\theta_\tau}}{\Phi_{n\tau}} x_{n\tau}, \\
x_{n\tau} &= \left(\lambda_n \right)^{-\sigma_\tau} \alpha_\tau P_\tau^{1-\sigma_\tau}, \\
\Phi_{n\tau} &= \sum_{i=1}^{N} T_i \left(d_{ni} w_i \right)^{-\theta_\tau}, \\
P_\tau &= \left[\Gamma \left(\frac{\theta_\tau + 1 - \sigma_\tau}{\theta_\tau} \right) \right]^{1/(1-\sigma_\tau)} \left(\Phi_{n\tau} \right)^{-\frac{1}{\theta_\tau}},
\end{aligned}$$

$(\alpha_A)^{1/\sigma_A} + (\alpha_B)^{1/\sigma_B} = 1$, and the Lagrange multiplier λ_n is implicitly defined through the budget constraint of a typical consumer in country n, $x_{nA} + x_{nB} = w_n$.

Trade flows are therefore a function of the set of N countries, each with its population L_i, wage w_i and technology parameter T_i; the set of iceberg costs d_{ni}; parameters θ_A and θ_B controlling the spread of the distribution of technologies; utility parameters σ_A and σ_B controlling the income elasticity of demand, and the weight of type A goods in the utility function α_A. From the data, I take the set of $N = 162$ countries, the population L_i and wage w_i of each country. In order to calculate bilateral trade flows, I need to estimate $\{d_{ni}\}_{n,i=1}^{N}$, $\{T_i\}_{i=1}^{N}$, θ_A, θ_B, α_A, σ_A, and σ_B.

Iceberg costs d_{ni}. Assume the following functional form for iceberg costs:

$$d_{ni} = 1 + \left\{ (\gamma_1 + \gamma_2 D_{ni} + \gamma_3 D_{ni}^2) * \gamma_{\text{border}} * \gamma_{\text{language}} * \gamma_{\text{trade agreement}} \right\}, \tag{12}$$

for all $n \neq i$, and $d_{nn} = 1$. The expression in brackets is the proxy for geographic barriers, and the number 1 added to it is the production cost. D_{ni} is the distance (in thousands of kilometers) between countries n and i. So the term in parenthesis represents the effect of distance on trade costs. Parameter γ_{border} equals 1 if countries n and i do not share a border, and it is a parameter to be estimated otherwise. If γ_{border} is, say, 0.8, sharing a border reduces trade costs by 20%, but has no impact on production costs; if $\gamma_{\text{border}} > 1$, sharing a border increases trade barriers. Similarly, parameters γ_{language} and $\gamma_{\text{trade agreement}}$ refer, respectively, to whether countries n and i share a common language, and whether they are both members of the same trade agreement.[11]

Henceforth, I refer to the set of iceberg cost parameters as

$\Upsilon = \{\gamma_1, \gamma_2, \gamma_3, \gamma_{\text{border}}, \gamma_{\text{language}}, \gamma_{\text{trade agreement}}\}$.

Technology parameters T_i. The equilibrium conditions in equation (8) pin down a one-to-one relation between the set of technology parameters $\{T_i\}_{i=1}^{N}$ and the market clearing wages $\{w_i\}_{i=1}^{N}$. That is, given a set of parameters $\{\Upsilon, \alpha_A, \sigma_A, \sigma_B, \theta_A, \theta_B\}$, data on population L, geographic characteristics and trade agreements, one could either use the technology parameters T to find the market clearing wages w, or conversely, use the wages to find the technology parameters. I use the latter approach. I take income per capita from the data as a proxy for wages.[12] Then, for each guess of parameters $\{\Upsilon, \alpha_A, \sigma_A, \sigma_B, \theta_A, \theta_B\}$, I simulate the whole economy generating all trade flows X_{ni} until I find the technology parameters T that satisfy the system of equations (8): $\sum_{n=1}^{N} X_{ni} = w_i L_i$ for $i = 1, ..., N$.[13]

[11] I use only the trade agreements that the WTO lists as the best known: ASEAN, COMESA, EFTA, European Union, Mercosur, and NAFTA.
Usually, an exponential functional form is assumed for iceberg costs, *e.g.*, $d_{ni} = \exp\left(\gamma_1 + \gamma_2 D_{ni} + \gamma_3 D_{ni}^2 + \gamma_{\text{border}} + \gamma_{\text{language}} + \gamma_{\text{trade agreement}}\right)$, which facilitates log-linearizing regression models. In my estimation procedure this convenience is useless, and the choice between these two functional forms make no difference in the empirical results. I chose equation (12) because, unlike the exponential function, its parameters are easily interpretable.

[12] As presented in section 2, the model does not distinguish between population and labor force, or income per capita and income per worker. From a theoretical viewpoint, it is easy to introduce this distinction by making the labor endowment of individuals in country i equal to some fraction $\beta_i < 1$, where β_i corresponds to the labor force participation in country i. While this modification complicates the notation, its impact on the empirical results is nil.

[13] Alvarez and Lucas (2007) prove existence and uniqueness of equilibrium in the EK model. The new model satisfies standard conditions for existence (Mas-Colell et al. (1995), chapter 17), but I do not prove uniqueness. Still, I did not encounter any cases where the relation between w and T in the

This procedure reduces the number of parameters in the model from $(N + 11)$ to 11: The six parameters in Υ, and α_A, σ_A, σ_B, θ_A and θ_B. These parameters, together with the data, are sufficient to estimate the whole matrix of trade flows X_{ni}.

Identification of σ and θ. EK are not able to identify parameters θ_A and σ_A from trade data. Here, I face the same problem.

Parameters θ_A and θ_B are not separately identifiable from the iceberg cost parameters Υ. A decrease in θ_A and θ_B increases the variance of the distribution of technologies in equation (3), which in turn increases trade across all country pairs. This effect can be equally attained by decreasing the iceberg cost parameters Υ. So data on bilateral trade flows do not distinguish between these two changes–i.e., a decrease in θ_τ or in iceberg costs d_{ni}. In order to obtain values for and to interpret the remaining parameters of the model, however, I must choose a value for θ_A or, by symmetry, for θ_B. I fix θ_A to 8.28, the median of the values found by EK.

Parameters σ_A and σ_B are not separately identifiable either. These parameters, together, govern how the allocation of income across goods of type A and B varies with a country's income per capita, but they play no role individually. Just as with θ_A, I need to assume a specific value for σ_A (or σ_B) in order to estimate and interpret the remaining parameters of the model. I normalize σ_A to 5 , an arbitrary value satisfying the assumption that $\sigma_A < \theta_A + 1$.

In appendix 6.5, I explore the implications of alternative values for θ_A and σ_A. Predictions on trade flows do not change as these parameters vary. (If it were not so, parameters θ_A and σ_A would be identifiable.) So for all values of θ_A and σ_A in the appendix, the interpretation of the parameter estimates and of the results presented below remain absolutely unchanged. Still, the values of the other parameters $(\Upsilon, \alpha_A, \sigma_B, \theta_B)$ do change with θ_A and σ_A, and they can only be recovered by fixing θ_A and σ_A.

Objective function. Having fixed the values of θ_A and σ_A, nine parameters–Υ, α_A, σ_B and θ_B–are sufficient to estimate the set of technology parameters $\{T_i\}_{i=1}^N$ and thereby the matrix of trade flows $\{\hat{X}_{ni}(\Upsilon, \alpha_A, \sigma_B, \theta_B)\}_{n,i \leq N}$. I choose $\{\Upsilon, \alpha_A, \sigma_B, \theta_B\}$ to minimize the

market clearing conditions was many-to-one or one-to-many. The United States's technology parameter T_i is normalized to 1. All Fortran programs are available upon request to the author.

distance between the actual trade flows in the data and the estimated ones:

$$\Psi(\Upsilon, \alpha_A, \sigma_B, \theta_B) = (X_{ni} - \hat{X}_{ni}(\Upsilon, \alpha_A, \sigma_B, \theta_B))' W (X_{ni} - \hat{X}_{ni}(\Upsilon, \alpha_A, \sigma_B, \theta_B)) \quad (13)$$

where W is a weighting matrix, X_{ni} here is a vector containing trade flows for all importer-exporter country pairs in the data, and $\hat{X}_{ni}(\Upsilon, \alpha_A, \sigma_B, \theta_B)$ is the equivalent vector for the flows predicted by the model. Each of these vectors thus contains $25,810$ observations.

In theory the most efficient weighting matrix W is the inverse of the variance-covariance matrix of the observation vector X_{ni}. In the data, however, I only observe the value of each trade flow, X_{ni}, not its variance. So analogous to an FGLS procedure, I use deviations from the predictions of the model to the data $(X_{ni} - \hat{X}_{ni}(\Upsilon, \alpha_A, \sigma_B, \theta_B))$ to estimate W nonparametrically. Appendix 6.3 presents the details of this procedure, and section 3.3.1 below presents a summary of the results with alternative weighting matrices.

I normalize the objective function in equation (13) by dividing it by $X'_{ni} W X_{ni}$, and refer to

$$1 - \left(\frac{\Psi(\Upsilon, \alpha_A, \sigma_B, \theta_B)}{X'_{ni} W X_{ni}} \right)$$

as the model's explanatory power. If $\hat{X}_{ni}(\Upsilon, \alpha_A, \sigma_B, \theta_B) = X_{ni}$, then the explanatory power is 100%. If $\hat{X}_{ni}(\Upsilon, \alpha_A, \sigma_B, \theta_B) = 0$, which is always feasible to predict by making iceberg costs arbitrarily large, then the explanatory power is 0.

I close this section with 3.1.1 below, where I discuss parameter identification.

3.1.1 Data and Parameter Identification

I explain intuitively the features of the data that allow for the identification of the parameters to be estimated: Υ, α_A, σ_B and θ_B.

Without loss of generality, let $\sigma_A \geq \sigma_B$ so that type A goods are more income elastic and govern patterns of trade among rich countries. Given the heterogeneity in the production technologies of type A goods, $\theta_A = 8.28$, trade flows among rich countries provide information on trade barriers, Υ. And given Υ, the volume of trade among poor countries provide information on θ_B. The larger the θ_B, the smaller the heterogeneity in type B production technologies, and hence the smaller the volume of trade among poor countries.

The volume of trade between rich and poor countries, in turn, provides information on preference parameter σ_B (σ_A is fixed to 5.0). If the income elasticity of demand is equal across types, $\sigma_B = \sigma_A$, the model predicts large volumes of trade between rich and poor countries because these countries specialize in producing different types of goods. If instead $\sigma_B < \sigma_A$, as the results below indicate, demand patterns suppress trade among countries of different income levels. Rich countries demand relatively more type A goods, generally produced in rich countries, while poor countries demand more type B goods. Finally, parameter α_A, the weight of type A goods in preferences, govern the size of sector A relative to sector B, thereby controlling the size of the "rich" and "poor" country groups above.

In appendix 6.4, I conduct Monte Carlo experiments. I simulate data with random parameters, apply the optimization algorithm to simulated data, and find that the algorithm can recover the parameter values with precision.

3.2 Results

I present the results of the new model below and of the EK model in section 3.2.1.

The first column of table 2 presents the estimated parameters, and table 5 presents their confidence intervals (explained in appendix 6.4). The model explains 24% of the data. Table 3 summarizes the distribution of residuals by importing country. The values are divided by $X'_{ni} W X_{ni}$ so that the sum of residuals across importers equals 76% (= 100% − 24%). Residuals are generally well distributed across countries of different size and income levels.

The new model introduces non-homotheticity to demand and supply through four parameters: α_A, σ_B, θ_B (estimated) and σ_A (normalized). Parameters $(\alpha_A)^{1/\sigma_A} = 0.62$, $\sigma_A = 5.00$ and $\sigma_B = 2.99$ define the utility function. Types A and B coexist in the economy, $\alpha_A \in (0, 1)$, and rich consumers allocate a larger fraction of their incomes in goods of type A than poor consumers do, $\sigma_A > \sigma_B$. More specifically, spending on type A ranges from 83% of Japan's GDP to only 3% of the Democratic Republic of Congo's. Type A also presents a greater heterogeneity in production technologies, $\theta_A < \theta_B$ ($\theta_A = 8.28$ and $\theta_B = 12.09$), and thus rich countries have a comparative advantage in producing them. Type A goods constitute 96% of Luxembourg's production and only 1×10^{-8} of the Democratic Republic of Congo's. In sum, rich countries produce and consume more goods of type A, the type whose production technologies are more heterogeneous across countries. Poor countries produce and consume the non-differentiated, type B goods.

The four parameters above, therefore, explain why rich countries trade a lot, while poor countries trade little–a conspicuous pattern in the data. For example, trade among the 20 richest countries in the sample accounts on average for 27% of these countries GDP, while trade among the remaining 142 countries accounts only for 16% of these countries GDP. The new model predicts that these numbers are 19% and 18%, respectively. And as a benchmark, the EK model (discussed below) predicts that these numbers are 5% and 11%, respectively–it underestimates trade in general and reverses the order, predicting less trade among the rich than among the remaining countries.

Figures 2, 3 and 4 illustrate other moments of the data relating trade to income and size, and compares them to predictions of the model. All graphs in figure 2 plot countries' trade share (i.e., $\frac{\text{imports + exports}}{2*\text{GDP}}$) as a function of the logarithm of their GDP per capita. Graph 2(a) refers to the data, and 2(b), to the model. Since the estimation methodology implies that countries' observed and predicted incomes are the same, the position of countries along the x-axes is the same in both graphs. The graphs differ because of differences between observed and estimated trade shares, plotted on the y-axes.

The data show an increasing, statistically and economically significant relationship between trade share and income per capita. The model captures this pattern well, qualitatively and quantitatively. For example, income per capita in Luxembourg, the richest country in the sample, is 538 times that of the Democratic Republic of Congo (DRC), the poorest country. So the slopes in figure 2(a) and 2(b) imply that Luxembourg's trade share is expected to be 16% larger than the DRC according to the data (0.16 = 0.025*ln(538)) and 13% larger according to the model.

Figure 3 is analogous to figure 2, except that income per capita in the x-axis is substituted with total income. The data show that the correlation between these two variables is small and statistically insignificant, while the model predicts a negative correlation. Two opposing forces in the model establish the pattern in figure 3(b). First, large countries tend to trade less in general equilibrium models. In a two country world, for example, trade necessarily represents a smaller fraction of the large country's income than of the small country's. Second, large countries tend to be richer, and hence trade more (as per figure 2(b)). Here, the first effect dominates the second. But in section 3.3.1 below, I show that depending on the weighting matrix W (equation (13)), the second effect may offset the first so that, just like in the data, the model predicts a small, insignificant relationship between total income and trade share.

Figure 4 illustrates countries' choice of trading partners. For each country, I calculate the fraction of its trade that flows to or from one of the 20 richest countries in the sample. The graphs in figure 4 plot this share of rich countries in trade against the logarithm of income per capita. Graph 4(a) refers to the data, and graph 4(b) depicts both observations of the data (asterisks) and of the model (hollow diamonds). Both graphs show an increasing relationship between the two variables–high income countries tend to spend a higher fraction of their income in goods from other high income countries. The model, however, tends to overestimate the role of rich countries in trade, especially for poor countries.

3.2.1 The EK model

The EK model provides a good benchmark for the results above because the new model is built on EK and EK delivers the gravity equation. Using the methodology described in section 3.1 above, I estimate the EK model twice–once with the full sample, and once with a sub-sample containing only the 19 OECD countries used in EK's empirical analysis.[14] Table 2 presents the results, and table 3, the distribution of residuals for the full sample case. EK use their model to study manufacturing trade among OECD countries, while the new model's objective is to study patterns of trade across countries of different sizes and income levels. So, not surprisingly, the EK model predicts very well trade among OECD countries, but not trade

[14] With the EK model, after normalizing parameter θ_A and backing out the technology parameters T_i, trade flows are exclusively a function of iceberg cost parameters Υ. Parameters α_A, σ_A, σ_B and θ_B do not exist or do not affect trade flows in the EK model (see equation (11)). To make the two models comparable, I use for the EK model the weighting matrix W derived in appendix 6.3 for the new model, but estimating W for the EK model separately yields extremely similar results.

with the full sample–its explanatory power decreases from 80% with the OECD sample to 18% with the full sample. Further, the EK and the new model yield similar predictions for the OECD sample, but not for the full sample.

The data with the full sample present large volumes of trade among large, rich countries and small volumes among small, poor countries. Unable to reconcile these differences, the EK model severely underestimates trade among large, rich countries. As $(\hat{\gamma}_1, \hat{\gamma}_2, \hat{\gamma}_3)$ changes from $(1.51, 0.18, -0.02)$ in the OECD sample to $(1.87, 0.33, -0.03)$ in the full sample, iceberg costs increase for all OECD country pairs, and they increase by 36% on average. This underestimation is also evident in figures 2(c) and 4(c), the EK model's analogues to the new model's figures 2(b) and 4(b). The EK model underestimates the share of trade in rich countries' income (2(c)), and it underestimates the share of rich countries trade that is directed to other rich countries (4(c)).

Figure 3, in turn, shows that the EK model predicts a sharp, well-defined decreasing relationship between trade share and total income, a relationship which is nonexistent in the data. As explained above, this pattern arises because, in general equilibrium, large countries tend to trade a smaller fraction of their incomes than small countries do. In the new model, this relationship is attenuated by the tendency of rich countries to trade more combined with the positive correlation between countries' size and income per capita.

3.3 Robustness

I check for robustness with respect to the choice of the weighting matrix in section 3.3.1, and I introduce income inequality within countries in section 3.3.2.

3.3.1 Weighting Matrix

Appendix 6.3 derives the weighting matrix W used in the objective function (13). The procedure allows for the variance of trade flows to vary according to importer and exporter total income. It therefore addresses the concerns of Silva and Tenreyro (2005) that trade flows among large countries may have large variances because they are much larger than flows among small countries. The choice of W is particularly critical here because the purpose of the new model is to explain patterns of trade across countries of different sizes and income levels, and so W should not downplay any income group.

Table 4 presents results from estimating the model with alternative, albeit *ad hoc*, weights. In column I are the original estimates; in II, W is the identity matrix; in III, I use the variance of trade flows across the years 1995 through 2005 to calculate W;[15] in IV, I assume that the standard deviation of trade flows is proportional to the product of importer and exporter total income, and in V, the objective function (13) is substituted with the difference between the logarithm of one plus predicted and observed trade flows. The table presents parameter estimates and some key moments describing figures 2 through 4–namely, the slope and statistical significance of the regression lines in figures 2 and 3, and a subjective judgment on how well aligned predictions of the model are with respect to the data in figure 4.

In all columns, the parameter estimates obey $\sigma_A > \sigma_B$ and $\theta_A < \theta_B$, inequalities which are essential for explaining the workings of the new model (see section 2.4). So in all cases the changes introduced by the new model relative to EK follow the same direction as the original results. Compared with the original W, columns III through V place *larger* weights on observations from small relative to large countries. As a result, they capture better the stylized facts in figures 2, 3 and 4. They predict an increasing relationship between trade share and income per capita (figure 2), and a small, insignificant relationship between trade share and total income (figure 3). They also decrease the estimate of σ_B relative to the original–from 2.99 to 1.6, 1.2 and 2.2–thereby accentuating the non-homotheticity in preferences. Consequently, trade between rich and poor countries decreases, and the fit of figure 4(b) improves.

In contrast, the identity matrix in column II places *smaller* weights on observations from small countries relative to the original W. The resulting parameter estimates are similar to the estimates of the model when the OECD sub-sample is used (not shown). Qualitatively, the predictions of the new model coincides with those of EK under all estimation procedures. That is, contradicting the data, the model predicts that trade share is decreasing in income

[15]I use data on trade flows from the UN Comtrade for years 1995 through 2005. For simplicity, to smoothen out outliers, I divide countries into size quartiles, and I assume that the variance of trade flows is the same within each of the sixteen importer and exporter size bins. I calculate the variance of trade flows for each importer and exporter country pair using the variation across years, and then I use the median of these variances for each bin.

per capita and in total income, and it underestimates the share of rich countries in trade.

In sum, the economic implications of the empirical results are robust to changes in the objective function as long as sufficient weight is placed on observations of small, poor countries. Nonetheless, the parameter estimates in columns II through V are outside the narrow confidence intervals of the original estimates, presented on table 5 (explained in appendix 6.4). So a Hausman test statistically rejects the hypothesis that these estimates are consistent. Since the model uses only 9 parameters to estimate 25,810 observations, it is not surprising that changes in the weights of these observations lead to statistically significant changes in the parameter estimates.

3.3.2 Income Inequality

I have thus far ignored income inequalities within countries. But inequalities affect demand patterns and, thereby, trade. For 121 countries in the sample, the World Bank (2008) provides data on the share of income held by each quintile in the population, from the poorest to the richest. To assess the effect of inequality on trade, I use these data to re-estimate the model for this subset of countries. Instead of calculating demand for a single representative consumer in each country, I calculate it for five consumers, each representing one income quintile. A country's total demand is the sum of these representative consumers weighted by 20% of the population.

The introduction of income inequality improves the model's explanatory power only by 1%. Because of this small difference and of the paucity of data on income distribution, I present in section 3.2 above only the results with no income inequality within countries.[16]

4 Counterfactuals

Having estimated the model, we can now analyze counterfactuals. Since the model is highly stylized, the purpose of this exercise is not to pursue policy recommendations but a better

[16]Data are available only for 121 countries, and even these countries only report their distribution of income sporadically. In order to collect data, I used reports from 1990 to 2007, giving priority to the information available in the year closest to 2000, the year of the trade data.

understanding of the model itself.

The methodology used here is as follows. A world economy is composed of the population of each country, taken from the data, and the estimates from section 3 of countries' technology parameters T, of parameters α_A, σ_A, θ_A, σ_B, θ_B, and of the matrix of iceberg costs d_{ni} through the estimate of Υ. In this economy, the wages w that clear the market coincide with the ones observed from the data. An analysis of counterfactuals consists of changing the parameters defining the economy, solving the system of equations (8) to obtain a new set of market clearing wages and recalculating the utility function of individuals in every country.

I experiment with technology shocks in section 4.1 and with changes in trade costs in section 4.2.

4.1 Technology shocks

In the model, a technology shock in country i consists of a unilateral increase in its technology parameter T_i. It generally changes the price of type A relative to type B goods. So its welfare impact depends critically on the net exports of the different types of goods. Figure 5 plots the production, demand, and net exports of type A goods as a fraction of GDP, against the logarithm of income per capita. Each observation corresponds to one of the 162 countries in the sample. The circles represent the share of type A goods in production, and the triangles, the share of type A goods in demand. Both of these curves are upward sloping because countries with higher income per capita produce and consume relatively more type A goods. The crosses represent the net exports in type A goods (production minus demand). They form a V-shaped curve: Net exports of type A are small for low and high income countries, and they are large and negative for middle income countries. Low income countries produce and consume mostly type B goods; high income countries produce and consume type A goods, and middle income countries are rich enough to consume type A goods but not to produce them.

Between 1985 and 2000, China grew nearly four times relative to the rest of the world. To view the effects of a continued growth in China, I increase China's technology parameter T_{China} until its wages increase by 300% relative to the rest of the world. As China's income grows with the shock, its consumption of type A goods increases from 6% to 16% of GDP, and its production increases from 0.02% to 5%. Two relative price changes ensue. First, the price of type B goods decreases relative to local wages in most countries because the productivity gains following the increase in T_{China} accrue mostly to goods of type B, the type that predominates in Chinese production before and after the shock. This first price change benefits primarily poor countries, the largest consumers of type B goods. Second, the price of type A goods increases relative to type B goods because their demand increases more than their supply. This second price change benefits rich countries, the largest net exporters of type A goods, and hurts middle income countries, the largest net importers of type A goods (as shown in figure 5).

In sum, the shock in China benefits poor and rich countries and makes most middle income countries worse off. It increases wages in the world's 50 richest countries by 0.7% relative to the 50 poorest countries. The largest real wage increases occur in China's small, rich and poor neighbors–e.g., Mongolia (2.1%), Hong Kong (1.1%), Singapore (0.2%)–and the largest real wage decreases occur in China's middle income neighbors–e.g., Malaysia, the Philippines, Thailand.

I also experiment with an increase in the United States' technology parameter T_{US} that increases American wages by 25% relative to the rest of the world. Contrary to the shock in China, a shock in the U.S. decreases the price of type A goods relative to local wages and to type B goods. It thus inverts the welfare effects of the Chinese shock: All middle income countries benefit from the shock; high income countries are made worse off, and poor countries are left close to indifference. The shock decreases nominal wages in the 30 richest countries in the sample by 0.6% relative to the rest of the world. The largest real wage increases occur in Mexico (0.5%) and in small, middle income, Central American countries (approximately 1.1%). Japan, Norway and Switzerland, in turn, experiment small welfare losses.

4.2 Trade barriers

I consider two extreme changes in trade barriers: (i) eliminating trade barriers ($d_{ni} = 1$), and (ii) raising trade barriers to prohibitive, autarky levels ($d_{ni} \to \infty$ for all $n \neq i$).

Eliminating trade barriers decreases the CES price index of type A and of type B goods relative to local wages in all countries. It thus benefits all countries. Decreases in the price of type A goods are larger for small, poor countries, which have no comparative advantage in producing these goods, while decreases in the price of type B goods are larger for small, rich countries. Summing these two price effects, the least populous countries are the greatest beneficiaries from a move to frictionless trade. Real wages increase by 15% in the United States and by more than 140% in some small countries.

A move to autarky, in contrast, makes all countries worse off because it increases the price of type A and of type B goods relative to wages in all countries. In this counterfactual, changes in the price of the more differentiated, type A goods are much larger than those of type B goods. Increases in the prices of type A goods average 180% and range from less than 2% in Japan to more than 700% in some small, poor countries. Increases in the price of type B goods, in contrast, average only 2% and tend to be larger in small, rich countries. But even though the price of type B goods does not increase much, its welfare impact is large because these goods have low elasticity. As a result, the largest welfare losses following a move to autarky are experienced by small, rich countries. While real wages decrease by only 1.1% in India, they decrease by 19% in Luxembourg.

5 Conclusion

An integrated trade model, one that provides a single framework for trade among rich countries as well as trade among countries of different income levels, has concerned economists at least since Markusen (1986). Generally speaking, North-North trade is explained through the differentiation of goods and services, while North-South trade is explained through differences in comparative advantage due to technologies or factor endowments. This paper proposes a model that delivers both these North-North and North-South patterns. Trade among rich countries occurs primarily in highly differentiated goods, while trade of rich with poor countries occurs across sectors.

A quantitative comparison of the predictions on trade flows of this integrated model to those of a gravity type model shows the benefits of the integrated approach. Theoretical foundations of the gravity relationship are typically based on intra-industry trade of differentiated goods. So, not surprisingly, the EK gravity model does a good job of explaining trade among the rich OECD countries but not trade among countries of different income levels. The new model, in turn, explains trade among OECD countries just as well as EK, and it explains trade in the sample with 162 countries much better than EK. For example, the model correctly predicts extensive trade among rich countries and scant trade among poor countries.

I use the parameter estimates of the model to analyze counterfactuals. The model qualitatively predicts some effects from a technology shock in China that are often put forth by the popular press: The shift in Chinese demand and production toward luxury goods; the global decrease in the prices of low-end manufactures such as toys and textiles; the negative wage pressure experienced by textile industries in Malaysia, the Philippines and Thailand, and the benefits accrued by Hong Kong and Singapore for selling high-end products, such as financial services, to China and other fast growing East Asian economies.

Throughout the paper, however, I have ignored two features of the data that are potentially useful in future research. First, the data are available at the product level. Thus, the links between income elasticity of demand, and production and trade patterns established by the model may be verifiable. An alternative is to use data on unit prices within commodity categories. A growing literature infers quality differences from unit prices and quantities, and finds systematic patterns of trade within product categories.[17] In contrast, I infer types of goods from aggregate data. Combining these micro and macro approaches may be fruitful. Second, the data are available for several years. I have emphasized throughout the analogy between product cycles and the variability in production technologies in the model. So a dynamic version of the model should be fit to study the effects of non-homothetic preferences on technology diffusion, the evolution of trade and growth.

[17] See, for example, Hallak (2006), Hallak and Schott (2008), Khandelwal (2005), and Schott (2004).

6 Appendix

6.1 An Alternative Form for the Utility Function

This appendix discusses the form of the utility function in equation (1). The division of goods into types is designed to capture the empirical finding that poor households spend most of their income on basic goods, while rich ones spend it on luxuries. Section 2.1 explains how equation (1) captures this phenomenon. Despite its simplicity, the reader may feel uncomfortable with the assumption that σ_τ simultaneously controls the elasticity of substitution across goods and the income elasticity of demand. One way to solve this issue is to assume a more general form for the utility function:

$$\sum_{\tau=1}^{S}\left\{\alpha_\tau \frac{\sigma_\tau}{\gamma_\tau(\sigma_\tau-1)}\left[\int_0^1 q(j_\tau)^{\sigma_\tau-1/\sigma_\tau}dj_\tau\right]^{\gamma_\tau}\right\}. \tag{14}$$

Denote by λ the consumer's Lagrange multiplier and by P_τ the CES price index for goods of type $\tau = 1, ..., S$. I consider two (not exhaustive, but instructive) cases.

Case 1: $\gamma_\tau = \sigma_\tau/(\sigma_\tau - 1)$ for all τ. The first order conditions imply that, for all τ, $\lambda = \frac{\alpha_\tau}{P_\tau}$ if $q(j_\tau) > 0$ for some j_τ. Since these conditions cannot hold simultaneously with equality for arbitrary prices, the consumer only demands goods of the type with the highest value for $\frac{\alpha_\tau}{P_\tau}$. Importantly, the Lagrange multiplier and hence *consumer demand do not depend on income.* This leads us back to the homotheticity assumption: Whenever faced with the same price, consumers' demand for all goods is proportional to income.

Case 2: $\gamma_\tau \neq \sigma_\tau/(\sigma_\tau - 1)$ for all τ. Spending on any two types of goods, 1 and 2, satisfies

$$\frac{x_1}{x_2} = \lambda^{\varphi_1-\varphi_2}\left[\frac{(\alpha_1)^{\varphi_1}P_1^{\phi_1}}{(\alpha_2)^{\varphi_2}P_2^{\phi_2}}\right],$$

where $\varphi_\tau = -\sigma_\tau + \frac{\sigma_\tau(1-\sigma_\tau)(\gamma_\tau-1)}{\sigma_\tau+\gamma_\tau-\sigma_\tau\gamma_\tau}$ and $\phi_\tau = \frac{(1-\sigma_\tau)\gamma_\tau}{\sigma_\tau+\gamma_\tau-\sigma_\tau\gamma_\tau}$ for $\tau = 1, 2$. As in equation (2), the term in brackets determines the level of x_1/x_2, and $(\lambda^{\varphi_1-\varphi_2})$ determines how it changes with consumer income. Note, however, that this new functional form complicates the algebra without adding anything to the analysis. In the case of the empirical analysis where there are only two types, A and B, γ_A and γ_B are not separately identifiable from σ_A, σ_B and α_A. For any set of prices P_τ and parameters $\{\sigma_A, \sigma_B, \gamma_A, \gamma_B\}$, the parameter α_A can be judiciously chosen to match any level of the ratio x_A/x_B. The rate of change of x_A/x_B, in turn, is determined by the the exponent of the Lagrange multiplier, $(\varphi_A - \varphi_B)$. Parameters σ_A, σ_B, γ_A and γ_B, therefore, all play the same role and only one of them is sufficient to determine the value of $(\varphi_A - \varphi_B)$–the rest can be normalized. In equation (1), γ_A and γ_B are set to 1.

The utility function in the main text assumes that the type of good with a higher income elasticity of demand also presents a higher elasticity of substitution across goods. Both of these elasticities are controlled by the same parameter σ_τ. Case 2 above shows that this assumption is not necessary for any of the results. Without changing predicted trade flows, a different normalization of the utility function (14) may imply that the type of good with a *higher* income elasticity of demand has a *lower* elasticity of substitution across goods.

6.2 Data

I use data on bilateral merchandize trade flows of the year 2000 from the UN Comtrade database (United Nations (2008)). In compiling the data, I give precedence to trade flows reported by the importing country, whenever available. If the importer report is not available, I use the trade flow reported by the exporter. I keep in the sample only countries with matching data on population and GDP from the World Bank (2008).[18] I also exclude countries whose total trade flows in the UN Comtrade data are incompatible with the total trade flow that these countries report to the World Bank. In principle, since the UN Comtrade data do not contain all countries in the world, trade flows in the UN data should be (weakly) smaller than the total trade flow reported to the World Bank. So, I exclude countries whose trade flows in the UN Comtrade data are at least 20% larger than trade flows in the World Bank data. Seventeen countries and 0.3% of world trade are excluded using this criterion.[19]

[18] Neither the United Nations nor the World Bank officially report statistics for Taiwan. But in practice, the UN country classification "Other Asia, not elsewhere specified" (code 490) refers to Taiwan. Hence, the UN Comtrade does contain data on bilateral trade flows to and from Taiwan. Data on Taiwan's population and income, in turn, were taken directly from the Taiwanese government web site, http://eng.stat.gov.tw.

[19] These countries are: Brunei Darussalam, Comoros, Djibouti, Gabon, Georgia, Guinea-Bissau, Guatemala, Honduras, Kiribati, Moldova, Mauritania, Panama, Sierra Leone, Timor-Leste, St. Vincent and Grenadine, Vanatu and Samoa.

The resulting data comprise 162 countries and 95% of world trade in 2000. Of these countries, 145 directly report trade to the UN. Trade flows of reporting countries to and from all other countries in the sample are observed, but trade flows between the remaining 17 countries (marked with a cross on table 1) are missing. Hence, of all possible importer-exporter country pairs, 25,810 ($= 162^2 - 17^2 - 145$) are observed, and 272 ($= 17^2 - 17$) are missing.

These data, used in the estimation, thus contain total trade for 145 countries. To construct figures 2(a), 3(a) and 4(a), I complement them with data from the World Bank (2008) on the total value of merchandize trade flows for 16 of the 17 non-reporting countries (there are no data on Taiwan). Figure 6 shows the similarity of the data from the two sources. It plots trade share in UN Comtrade as a function of trade share in the World Bank (2008) for the 145 reporting countries–most countries lie close to the 45^o line. This use of extraneous data is a small out-of-sample check on the model, and it does not change any of the results in section 3.2.

Data in the UN Comtrade are available up until the year 2005, but I use data for the year 2000 for two reasons. First, there are more and more reliable data for the year 2000. Twenty-four countries that report trade for the year 2000 have not yet reported it for the year 2005, and the inconsistencies between the UN Comtrade and the World Bank data are much larger in the year 2005 than in 2000. Second, matching data for the year 2005 requires a change in the model that is beyond the scope of the paper. Several countries trade close to or more than 100% of their GDP in 2005. The simple versions of the EK and of the new model presented here do not account for trade flows beyond 100% of a country's GDP. One way to incorporate this moment of the data into both models is to introduce intermediate inputs. While this modification is technically feasible–it is shown in Eaton and Kortum (2002)–it complicates the notation without adding anything to the analysis. It is worth noting, however, that all the stylized facts of the data exploited in section 3.2 also hold in the data of the year 2005.

All results are robust to the use of data from 1999 or 2001, instead of 2000. They are also robust to using bilateral trade data from Feenstra et al. (2005) or from the International Monetary Fund (2008), instead of the UN Comtrade.

6.3 Weighting Matrix, W

As commented in the main text, I do not observe the variance-covariance matrix of trade flows needed to construct the ideal weighting matrix W of the objective function (13). So I use a two step estimation procedure analogous to FGLS. I first estimate the model using an arbitrary weighting matrix and then use the residuals to estimate the weighting matrix. The only difference is that I iteratively estimate parameters, calculate residuals and get new weighting matrices until the parameter estimates and the weighting matrix converge.

In estimating the weighting matrix from residuals, I assume that W is a diagonal matrix and use a Gaussian kernel to estimate the variance of trade flows. For each importer-exporter country pair (n, i), the estimated variance of trade flows is a weighted average of the squared residuals $(X_{n'i'} - \hat{X}_{n'i'})^2$ of other dyads (n', i'). The weight attributed to dyad (n', i') is the product of Gaussian densities evaluated at $[\ln(\text{GDP}_i) - \ln(\text{GDP}_{i'})]$ and at $[\ln(\text{GDP}_n) - \ln(\text{GDP}_{n'})]$.[20]

In words, the estimated variance of country n's imports from country i is a weighted average of the squared residuals of observations from country dyads whose sizes (GDP) are similar to those of n and i. The use of importer and exporter sizes as determinants of variance is proposed by Silva and Tenreyro (2005). On the one hand, they argue, trade among large countries is very large and should thus have large variances. On the other hand, trade among small countries may have large measurement errors because these countries are often poor.

6.4 Confidence Intervals and Monte Carlo Simulations

In the main text, there is no explicit source of error generating the difference between the predictions of the model, $X_{ni}(\hat{\Upsilon}, \hat{\alpha_A}, \hat{\sigma_B}, \hat{\theta_B})$, and observed bilateral trade flows, X_{ni}. Here, I assume this difference is due to measurement errors in the data, and I use the following procedure to find confidence intervals for the parameter values of section 3:

[20]For each dyad (n, i) only the 500 observations with largest weights are kept. The bandwidth for the Gaussian densities is set to 2, which implies that the observation with the largest weight receives roughly twice as much weight as the observation with the lowest weight. Sensitivity analysis was performed with respect to both the bandwidth and the number of observations used per country pair (500), and the results were not very sensitive to the choice of these two variables.

1. For each of the 25,810 observed bilateral trade flows, calculate estimates for the residuals $\hat{\varepsilon}_{ni} = (X_{ni} - X_{ni}(\hat{\Upsilon}, \hat{\alpha_A}, \hat{\sigma_B}, \hat{\theta_B}))$, where $(\hat{\Upsilon}, \hat{\alpha_A}, \hat{\sigma_B}, \hat{\theta_B})$ are the parameter estimates from section 3.

2. Normalize residuals by multiplying them by the estimate of their standard errors, i.e., $\hat{\varepsilon}_{ni}^{\text{norm}} = \hat{\varepsilon}_{ni} W_{ni}^{1/2}$ where W_{ni} is the diagonal element of the weighting matrix W corresponding to country n's imports from country i.

3. Using a uniform distribution over the elements of $\hat{\varepsilon}^{\text{norm}}$, randomly draw a new residual $\hat{\varepsilon}_{ni}^{\text{norm}\prime}$ for each importer-exporter country pair (n, i).

4. Construct a new data set using the predicted matrix of trade flows: $X'_{ni} = X_{ni}(\hat{\Upsilon}, \hat{\alpha_A}, \hat{\sigma_B}, \hat{\theta_B}) + \hat{\varepsilon}_{ni}^{\text{norm}\prime} W_{ni}^{-1/2}$. Whenever $X'_{ni} < 0$, substitute it for $X'_{ni} = 0$.

5. Estimate a new set of parameters $(\hat{\Upsilon}', \hat{\alpha_A}', \hat{\sigma_B}', \hat{\theta_B}')$ using simulated data X'_{ni}.

6. Repeat steps 3, 4, and 5, three hundred times and collect the set of parameter estimates, $(\hat{\Upsilon}', \hat{\alpha_A}', \hat{\sigma_B}', \hat{\theta_B}')$.

Table 5 summarizes the results. For each parameter, the table shows the original estimates (from table 2) and the 95% confidence interval of the 300 estimates. There is very little variance in the parameter estimates, and all of the 300 estimates satisfy $\sigma_A > \sigma_B$ and $\theta_A < \theta_B$, inequalities which are indispensable for understanding the model throughout the main text (see section 2.4). As an additional exercise, I use the EK model to estimate the 300 simulated data sets constructed in step 4 above, and I find that the difference between the explanatory power of the two models exceeds 5% in all 300 cases.

To check for the identification of parameters, I conduct Monte Carlo simulations. I first make a random draw for each of the estimated parameters, Υ, α_A, σ_B and θ_B.[21] Given a draw of parameters, I simulate data with the deterministic model of section 2 and then run the optimization algorithm on the simulated data. I repeat this procedure fifty times and compare the obtained parameter estimates with the original parameter draws. The parameters

[21]For each parameter, I randomize over a uniform distribution with support $\gamma_1 \in [0.5, 2]$, $\gamma_2 \in [0.05, 0.5]$, $\gamma_3 \in [-0.1, 0]$, $\gamma_{\text{border}} \in [0.5, 1.2]$, $\gamma_{\text{language}} \in [0.5, 1.2]$, $\gamma_{\text{agreement}} \in [0.5, 1.2]$, $(\alpha_A)^{1/\sigma_A} \in [0.5, 0.9]$, $\sigma_B \in [1.0, 8.]$, $\theta_B \in [5, 20]$.

distinguishing the new model from EK, α_A, σ_B and θ_B, are identified with a high degree of precision–in 98% of the simulations, the estimated parameter is within a 5% distance from its original draw. Identification of the iceberg cost parameters Υ is weaker, but still, in 84% of simulations the estimated parameters are within a 5% distance from the original draw.

6.5 Normalization of parameters θ_A and σ_A

In section 3, I estimate the model by fixing $\theta_A = 8.28$ and $\sigma_A = 5$. Table 6 shows the parameter estimates for θ_A equals 3.60, 8.28 and 12.86, the three estimates found by Eaton and Kortum (2002), and for σ_A equals 2.00, 5.00 and 8.00, arbitrary values satisfying the assumption $1 < \sigma_A < (\theta_A + 1)$. An increase in θ_A decreases the variance of the distribution of technologies in equation (3), which in turn decreases trade across all country pairs. To compensate for this change, parameters γ_1 and γ_2, capturing the effect of distance on trade costs, must decrease as θ_A increases from 3.60 to 12.86. In addition, parameter θ_B increases with θ_A because it is the relative heterogeneity in technologies across types that determines patterns of production, not its level. Similarly, σ_B increases with σ_A because it is the relative value of σ_A to σ_B, not their level, that determines patterns of demand in the model.

Even though parameter estimates change, predicted trade flows do not. So the explanatory power of the model and the stylized facts of section 3.2 are the same for all values of θ_A and σ_A. Table 6 thus confirms the claim, made in section 3.1, that θ_A and σ_A are not identifiable from bilateral trade data.

One way to pin down the value of θ_A is to compare trade costs implied by the parameter estimates to direct measures of trade costs. Anderson and Van Wincoop (2004), for example, estimate that trade costs across OECD countries are equivalent to an ad-valorem tax of approximately 74%. In the model, iceberg costs across OECD countries average 88% when $\theta_A = 8.28$ and 57% when $\theta_A = 12.86$. So θ_A that best approximates Anderson and Van Wincoop's ballpark figure lies between 8.28 and 12.86. But this exercise should not be stretched since measurement errors in trade costs are large, and estimates vary tremendously across goods and countries.

References

[1] Alvarez, F. and Lucas, R. E. (2007), "General Equilibrium Analysis of the Eaton-Kortum Model of International Trade," *Journal of Monetary Economics*, **54(1)**, 1726-1768.

[2] Anderson, J. and Van Wincoop, E. (2003), "Gravity with Gravitas: A Solution to the Border Puzzle," *American Economic Review*, **93(1)**, 170-192.

[3] Anderson, J. and Van Wincoop, E. (2004), "Trade Costs," *Journal of Economic Literature*, **XLII**, 691-751.

[4] Bils, M. and Klenow, P. (1998), "Using Consumer Theory to Test Competing Business Cycle Models," *Journal of Political Economy*, **106(2)**, 233-261.

[5] Centre d'Etudes Prospectives et d'Informations Internationales, CEPII (2005), *The CEPII Databases – Distances*, http://www.cepii.fr/anglaisgraph/bdd/distances.htm

[6] Coe, D. T. and Hoffmaister, A. W. (1999), "North-South Trade: Is Africa Unusual?," *Journal of African Economies*, **8**, 228-256.

[7] Comin, D. and Hobijn, B. (2006), "An Exploration of Technology Diffusion," *NBER Working Paper* No. 12314.

[8] Deaton, A. (1975), "The Measurement of Income and Price Elasticities," *European Economic Review*, **6**, 261-273.

[9] Eaton, J. and Kortum, S. (2002), "Technology, Geography, and Trade," *Econometrica*, **70(5)**, 1741-1779.

[10] Feenstra, R., Lipsey, R. E., Deng, H., Ma, A. C. and Mo, H. (2005), "World Trade Flows: 1962-2000" *NBER Working Paper* No. 11040.

[11] Flam, H. and Helpman, E. (1987), "Vertical Product Differentiation and North-South Trade," *American Economic Review*, **77(5)**, 810-822.

[12] Grig, D. (1994), "Food Expenditure and Economic Development," *GeoJournal*, **33(4)**, 377-382.

[13] Hallak, J. C. (2006), "Product Quality and the Direction of Trade," *Journal of International Economics*, **68(1)**, 238-265.

[14] Hallak, J. C. and Schott, P. (2008), "Estimating Cross-Country Differences in Product Quality," mimeo, Yale University.

[15] Harrigan, J. (2003), "Specialization and the Volume of Trade: Do the Data Obey the Laws?," in E. Kwan Choi and J. Harrigan, ed. *Handbook of International Trade*, (Blackwell Publishing).

[16] Hunter, L. (1991), "The Contribution of Nonhomothetic Preferences to Trade," *Journal of International Economics*, **30**, 345-358.

[17] Hunter, L. and Markusen, J. (1988), "Per Capita Income as a Determinant of Trade," in R. Feenstra, ed. *Empirical Methods for International Economics*, (MIT Press).

[18] Khandelwal, A. (2005), "Product Quality and Competition in International Trade," mimeo, Columbia University.

[19] International Monetary Fund (2008), *Direction of Trade and Statistics CD Rom*.

[20] Limao, N. and Venables, A. J. (2001), "Infrastructure, Geographical Disadvantage, Transport Costs, and Trade," *The World Bank Economic Review*, **15(3)**, 451-479.

[21] Markusen, J. (1986), "Explaining the Volume of Trade: An Eccletic Approach," *The American Economic Review*, **76(5)**, 1002-1011.

[22] Mas-Colell, A., Whinston, M. D. and Green, J. R. (1995), *Microeconomic Theory*, Oxford University Press.

[23] Matsuyama, K. (2000), "A Ricardian Model with a Continum of Goods under Nonhomothetic Preferences: Demand Complementarities, Income Distribution, and North-South Trade," *The Journal of Political Economy*, **108(6)**, 1093-1120.

[24] Nabseth, L. and Ray, G. F., ed. (1974), *The Diffusion of new industrial processes; an international study*, (Cambridge University Press).

[25] Redding, S. J. and Venables, A. J. (2004), "Economic Geography and International Inequality," *Journal of International Economics*, **62)**, 53-82.

[26] Rodrik, D. (1998), "Trade Policy and Economic Performance in Sub-Saharan Africa," *NBER Working Paper* No. W6562.

[27] Romer, P. (1990), "Endogenous Technological Change," *Journal of Political Economy*, **98(5)**, S71-S102.

[28] Schott, P. (2004), "Across-Product versus within Product Specialization in International Trade," *Quarterly Journal of Economics*, **119(2)**, 647-678.

[29] Silva, J. S. and Tenreyro, S. (2005), "The Log of Gravity," *Centre for Economic Policy Research Discussion Papers*, **5311**.

[30] Stokey, N. (1991), "The Volume and Composition of Trade between Rich and Poor Countries," *The Review of Economics Studies*, **58(1)**, 63-80.

[31] United Nations (2008), UN Commodity Trade Statistics Database (UN Comtrade), accessed on June 4, 2008 at http://comtrade.un.org/

[32] Vernon, R. (1966), "International Investment and International Trade in the Product Cycle," *Quarterly Journal of Economics*, **80(2)**, 190-207.

[33] Waugh, M. (2008), "International Trade and Income Differences," *working paper*.

[34] World Bank (2008), *World Development Indicators 2008*, http://web.worldbank.org/data.

Country	Imports from the sample as a % of total imports	GDP (1999 US$ BI)	GDP per capita (1999 US$)
Albania	100	3.7	1,204
Algeria	100	55	1,799
Angola †	100	9.1	660
Antigua and Barbuda	87	0.68	8,871
Argentina	97	284	7,703
Armenia	94	1.9	620
Australia*	98	400	20,867
Austria*	99	194	24,195
Azerbaijan	99	5.3	655
Bahamas, The	96	5.0	16,600
Bahrain	100	8.0	11,861
Bangladesh	98	47	365
Barbados	99	2.5	9,562
Belarus	97	12.7	1,273
Belgium*	100	232	22,623
Belize	86	0.83	3,330
Benin	96	2.3	313
Bhutan †	100	0.45	799
Bolivia	97	8.4	1,010
Bosnia and Herzegovina †	100	5.0	1,312
Botswana	100	6.2	3,522
Brazil	99	644	3,707
Bulgaria	100	12.6	1,563
Burkina Faso	100	2.6	230
Burundi	99	0.71	109
Cambodia	99	3.7	288
Cameroon	95	10.1	678
Canada*	98	714	23,220
Cape Verde	98	0.53	1,179
Central African Republic	87	0.95	252
Chad †	100	1.4	169
Chile	99	75	4,880
China	96	1,198	949

Table 1: List of countries in the sample

Country	Imports from the sample as a % of total imports	GDP (1999 US$ BI)	GDP per capita (1999 US$)
Colombia	96	84	2,010
Congo, Dem. Rep. †	99	4.3	86
Congo, Rep. †	98	3.2	937
Costa Rica	95	16	4,059
Cote d'Ivoire	99	10.4	623
Croatia	98	18	4,093
Cyprus	98	9.1	13,180
Czech Republic	99	57	5,521
Denmark*	97	160	29,993
Dominica	96	0.27	3,802
Dominican Republic	96	20	2,261
Ecuador	96	16	1,295
Egypt, Arab Rep.	95	100	1,484
El Salvador	76	13.1	2,091
Equatorial Guinea †	100	1.3	2,794
Eritrea	99	0.63	178
Estonia	100	5.6	4,106
Ethiopia	99	7.9	123
Fiji	93	1.7	2,039
Finland	97	121	23,292
France*	98	1,328	22,548
French Polynesia	100	3.4	14,601
Gambia, The	99	0.42	320
Germany*	100	1,900	23,114
Ghana	96	5.0	250
Greece*	98	115	10,497
Grenada	97	0.41	4,047
Guinea	98	3.1	379
Guyana	98	0.71	958
Haiti †	97	3.8	485
Hong Kong, China	100	169	25,319
Hungary	100	48	4,697
Iceland	99	8.6	30,705

Country	Imports from the sample as a % of total imports	GDP (1999 US$ BI)	GDP per capita (1999 US$)
India	68	460	453
Indonesia	99	165	800
Iran, Islamic Rep.	99	101	1,591
Ireland	96	96	25,271
Israel	87	115	18,363
Italy*	95	1,097	19,269
Jamaica	95	8.0	3,100
Japan*	99	4,650	36,649
Jordan	93	8.5	1,764
Kazakhstan	97	18	1,229
Kenya	100	12.7	414
Korea, Rep.	99	512	10,884
Kuwait	100	38	17,223
Kyrgyz Republic	100	1.4	279
Lao PDR †	100	1.7	332
Latvia	99	7.8	3,302
Lebanon	99	17	4,459
Lesotho	93	0.85	477
Libya †	100	34	6,501
Lithuania	98	11.4	3,263
Luxembourg	100	20	46,278
Macao, China	100	5.9	13,249
Macedonia, FYR	100	3.6	1,785
Madagascar	91	3.9	239
Malawi	100	1.7	151
Malaysia	99	90	3,927
Maldives	100	0.62	2,151
Mali	98	2.4	208
Malta	100	3.9	9,932
Mauritius	100	4.5	3,766
Mexico	99	581	5,935
Mongolia	100	0.94	393
Morocco	95	33	1,171

Country	Imports from the sample as a % of total imports	GDP (1999 US$ BI)	GDP per capita (1999 US$)
Mozambique	77	3.8	211
Namibia	99	3.4	1,802
Nepal	100	5.5	225
Netherlands*	94	387	24,270
New Caledonia	99	2.7	12,580
New Zealand*	99	53	13,654
Nicaragua	81	3.9	800
Niger	99	1.8	153
Nigeria	98	46	369
Norway*	98	167	37,165
Oman	100	20	8,136
Pakistan	99	73	531
Papua New Guinea	100	3.4	645
Paraguay	100	7.1	1,323
Peru	99	53	2,053
Philippines	100	76	1,002
Poland	98	171	4,455
Portugal*	99	113	11,016
Qatar	100	18	29,290
Romania	96	37	1,651
Russian Federation	98	260	1,775
Rwanda †	100	1.8	226
Saudi Arabia	99	188	9,121
Senegal	100	4.4	423
Serbia and Montenegro	100	8.6	1,057
Seychelles †	100	0.61	7,579
Singapore	99	93	23,077
Slovak Republic	99	20	3,781
Slovenia	100	19	9,709
Solomon Islands †	99	0.30	715
South Africa	99	133	3,020
Spain*	99	581	14,422
Sri Lanka †	100	16	844

Country	Imports from the sample as a % of total imports	GDP (1999 US$ BI)	GDP per capita (1999 US$)
St. Kitts and Nevis	98	0.33	7,434
St. Lucia	97	0.69	4,394
Sudan	100	12.4	376
Suriname	95	0.89	2,056
Swaziland	99	1.4	1,329
Sweden*	100	242	27,287
Switzerland	100	246	34,249
Syrian Arab Republic	100	19	1,149
Taiwan †	100	321	14,519
Tajikistan	100	0.98	159
Tanzania	94	9.1	268
Thailand	96	123	1,998
Togo	94	1.3	248
Tonga	99	0.15	1,471
Trinidad and Tobago	95	8.2	6,347
Tunisia	98	19	2,033
Turkey	96	199	2,956
Turkmenistan	92	2.9	645
Uganda	100	5.9	244
Ukraine	99	31	636
United Arab Emirates	98	71	21,741
United Kingdom*	97	1,443	24,151
United States*	99	9,765	34,599
Uruguay	98	21	6,262
Uzbekistan †	100	14	558
Venezuela, RB	96	117	4,819
Vietnam	99	31	402
Yemen, Rep. †	100	9.4	526
Zambia	100	3.2	303
Zimbabwe	100	7.4	587

* OECD country

† The country does not report trade to the UN.

	Full sample		OECD only
	New model	EK model	EK $\approx$ New model
Explanatory power	**24%**	**18%**	**80%**
Normalized parameters			
σ_A	5.00		
θ_A	8.28	8.28	8.28
Estimated parameters			
γ_1	1.57	1.87	1.51
γ_2	0.17	0.33	0.18
γ_3	-0.01	-0.03	-0.02
border	0.81	0.84	0.89
language	0.96	0.98	0.80
trade agreement	0.90	0.90	0.96
$(\alpha_A)^{1/\sigma_A}$	0.62		
σ_B	2.99		
θ_B	12.09		

Table 2: Estimation Results

Country	New model	EK model	Δ = EK - New model
Albania	0.1	0.1	0.0
Algeria	0.1	0.1	0.0
Angola	0.3	0.4	0.0
Antigua and Barbuda	0.2	0.2	0.0
Argentina	0.0	0.0	0.0
Armenia	0.1	0.1	0.0
Australia	0.5	0.6	0.0
Austria	0.1	0.1	0.0
Azerbaijan	0.2	0.2	0.0
Bahamas, The	0.3	0.3	0.0
Bahrain	0.9	0.9	0.0
Bangladesh	0.1	0.2	0.1
Barbados	0.6	0.6	0.0
Belarus	1.0	1.1	0.1
Belgium	1.4	1.7	0.4
Belize	0.1	0.0	0.0
Benin	0.4	0.3	-0.1
Bhutan	0.1	0.0	-0.1
Bolivia	0.0	0.1	0.0
Bosnia and Herzegovina	2.0	2.1	0.1
Botswana	0.4	0.5	0.1
Brazil	0.1	0.0	0.0
Bulgaria	0.4	0.5	0.1
Burkina Faso	0.5	0.5	0.0
Burundi	0.2	0.2	0.0
Cambodia	0.2	0.2	0.0
Cameroon	0.2	0.2	0.0
Canada	0.2	0.5	0.3
Cape Verde	0.1	0.2	0.0
Central African Republic	0.1	0.0	0.0
Chad	0.1	0.0	0.0
Chile	0.1	0.1	0.0
China	0.9	1.0	0.1

Table 3: Distribution of residuals by importing country

Country	New model	EK model	Δ = EK - New model
Colombia	0.1	0.1	0.0
Congo, Dem. Rep.	0.4	0.4	0.0
Congo, Rep.	0.1	0.1	0.0
Costa Rica	0.1	0.2	0.0
Cote d'Ivoire	0.8	0.9	0.0
Croatia	1.1	0.9	-0.1
Cyprus	0.2	0.2	0.0
Czech Republic	0.9	0.9	0.0
Denmark	0.1	0.1	-0.1
Dominica	0.3	0.3	0.0
Dominican Republic	0.3	0.6	0.3
Ecuador	0.1	0.1	0.0
Egypt, Arab Rep.	0.1	0.1	0.0
El Salvador	0.3	0.3	-0.1
Equatorial Guinea	0.0	0.1	0.0
Eritrea	0.1	0.1	0.0
Estonia	0.7	0.8	0.1
Ethiopia	0.4	0.4	0.0
Fiji	0.3	0.3	0.0
Finland	0.8	0.9	0.2
France	0.2	0.5	0.3
French Polynesia	0.1	0.2	0.0
Gambia, The	0.1	0.1	0.0
Germany	0.5	1.0	0.6
Ghana	1.5	1.5	0.0
Greece	0.2	0.2	0.0
Grenada	0.3	0.3	0.0
Guinea	0.3	0.3	0.0
Guyana	0.8	0.8	0.0
Haiti	0.1	0.1	0.0
Hong Kong, China	2.0	2.3	0.3
Hungary	0.2	0.3	0.1
Iceland	0.2	0.1	-0.1

Country	New model	EK model	Δ = EK - New model
India	0.1	0.0	0.0
Indonesia	0.1	0.1	0.0
Iran, Islamic Rep.	0.1	0.1	0.0
Ireland	0.2	0.1	0.0
Israel	0.7	0.2	-0.5
Italy	0.3	0.5	0.2
Jamaica	1.8	1.8	0.0
Japan	0.2	0.3	0.0
Jordan	0.1	0.1	0.0
Kazakhstan	0.3	0.3	0.0
Kenya	0.7	0.7	0.1
Korea, Rep.	1.0	1.1	0.1
Kuwait	0.2	0.1	-0.1
Kyrgyz Republic	0.4	0.4	0.0
Lao PDR	0.2	0.2	0.1
Latvia	0.6	0.5	-0.1
Lebanon	0.3	0.3	-0.1
Lesotho	0.3	0.4	0.1
Libya	0.0	0.0	0.0
Lithuania	0.2	0.2	0.0
Luxembourg	0.4	0.2	-0.2
Macao, China	0.1	0.3	0.2
Macedonia, FYR	0.8	0.9	0.0
Madagascar	0.6	0.8	0.1
Malawi	0.1	0.1	0.0
Malaysia	0.4	0.6	0.2
Maldives	0.2	0.3	0.0
Mali	1.5	1.6	0.1
Malta	0.4	0.6	0.2
Mauritius	0.4	0.4	0.0
Mexico	0.2	0.4	0.2
Mongolia	0.1	0.1	0.0
Morocco	0.1	0.1	0.0

Country	New model	EK model	Δ = EK - New model
Mozambique	0.1	0.2	0.0
Namibia	1.0	1.2	0.2
Nepal	0.1	0.3	0.1
Netherlands	0.2	0.3	0.2
New Caledonia	0.2	0.2	0.1
New Zealand	0.2	0.2	0.0
Nicaragua	0.2	0.3	0.1
Niger	0.1	0.1	0.0
Nigeria	0.1	0.3	0.2
Norway	0.3	0.2	-0.1
Oman	0.2	0.3	0.1
Pakistan	0.2	0.3	0.1
Papua New Guinea	0.5	0.5	0.0
Paraguay	0.1	0.1	0.1
Peru	0.1	0.1	0.0
Philippines	0.2	0.2	0.0
Poland	0.1	0.1	0.0
Portugal	0.3	0.3	0.0
Qatar	0.7	0.1	-0.7
Romania	0.1	0.1	0.0
Russian Federation	2.4	2.2	-0.2
Rwanda	0.2	0.2	0.0
Saudi Arabia	0.2	0.0	-0.2
Senegal	1.5	1.9	0.3
Serbia and Montenegro	1.4	1.3	0.0
Seychelles	0.1	0.1	0.0
Singapore	2.4	3.1	0.7
Slovak Republic	1.2	1.2	0.1
Slovenia	0.6	0.6	0.0
Solomon Islands	0.1	0.1	0.0
South Africa	0.1	0.2	0.1
Spain	0.8	0.9	0.1
Sri Lanka	0.1	0.1	0.0

Country	New model	EK model	Δ = EK - New model
St. Kitts and Nevis	0.2	0.2	0.0
St. Lucia	0.4	0.4	0.0
Sudan	0.1	0.1	0.0
Suriname	0.8	0.7	-0.1
Swaziland	1.3	1.5	0.2
Sweden	0.3	0.6	0.3
Switzerland	0.2	0.1	-0.1
Syrian Arab Republic	0.3	0.4	0.1
Taiwan	1.2	1.3	0.1
Tajikistan	3.2	3.2	0.1
Tanzania	0.1	0.1	0.0
Thailand	1.0	1.1	0.0
Togo	0.3	0.2	0.0
Tonga	0.3	0.3	0.0
Trinidad and Tobago	0.5	0.5	0.0
Tunisia	0.1	0.2	0.1
Turkey	0.2	0.2	0.0
Turkmenistan	1.1	1.0	0.0
Uganda	0.4	0.4	0.0
Ukraine	3.7	3.7	0.0
United Arab Emirates	0.4	0.1	-0.3
United Kingdom	0.3	0.6	0.3
United States	0.9	1.4	0.5
Uruguay	0.0	0.0	0.0
Uzbekistan	1.5	1.3	-0.2
Venezuela, RB	0.1	0.2	0.1
Vietnam	1.1	1.1	0.1
Yemen, Rep.	0.2	0.3	0.0
Zambia	0.3	0.3	0.0
Zimbabwe	0.4	0.5	0.1
	76	**82**	**6**

	I (original)	II	III	IV	V
Explanatory power	24%	82%	29%	42%	57%
γ_1	1.57	1.46	1.36	1.37	1.58
γ_2	0.17	0.03	0.18	0.20	0.26
γ_3	-0.01	0.00	-0.01	-0.01	-0.01
border	0.81	0.77	1.04	0.99	0.85
language	0.96	0.90	1.16	0.94	0.85
trade agreement	0.90	0.70	1.02	1.22	1.03
$(\alpha_A)^{1/\sigma_A}$	0.62	0.48	0.70	0.83	0.76
σ_B	2.99	4.64	1.62	1.24	2.18
θ_B	12.1	15.7	13.7	14.5	14.0
Stylized Facts					
Data	I	II	III	IV	V
figure 2–slope of trade share on GDP/capita					
0.03***	0.02***	-0.04***	0.04***	0.06***	0.04***
figure 3–slope of trade share on GDP					
-0.01	-0.04***	-0.09***	-0.01	-0.01**	-0.01*
figure 4–alignment of predictions of the model with the data					
	fair/bad	bad	good	good	fair

In all cases, $\sigma_A = 5.00$ and $\theta_A = 8.28$.

***, ** and * indicate statistical significance at 1%, 5% and 10% level, respectively.

Table 4: Estimates with various weighting matrices

parameter	original	95% confidence interval	
γ_1	1.57	1.55	1.57
γ_2	0.17	0.17	0.18
γ_3	-0.01	-0.02	-0.01
border	0.81	0.81	0.83
language	0.96	0.95	0.96
trade agreement	0.90	0.89	0.91
$(\alpha_A)^{1/\sigma_A}$	0.62	0.61	0.62
σ_B	2.99	2.94	3.04
θ_B	12.1	11.9	12.1

Table 5: Confidence intervals for the new model's parameter

	original				
θ_A	**8.28**	**3.60**	**12.86**	8.28	8.28
σ_A	**5.00**	4.00	5.00	**2.00**	**8.00**
explanatory power	24%	24%	24%	24%	24%
γ_1	1.57	2.19	1.38	1.59	1.48
γ_2	0.17	0.45	0.11	0.18	0.13
γ_3	-0.01	-0.03	-0.01	-0.01	-0.01
border	0.81	0.78	0.83	0.82	0.81
language	0.96	0.96	0.96	0.96	0.97
trade agreement	0.90	0.92	0.90	0.90	0.93
$(\alpha_A)^{1/\sigma_A}$	0.62	0.54	0.62	0.71	0.57
σ_B	2.99	2.55	2.86	1.00	5.10
θ_B	12.1	6.89	16.9	11.7	13.8

Table 6: Estimates of the new model with different values for θ_A and σ_A

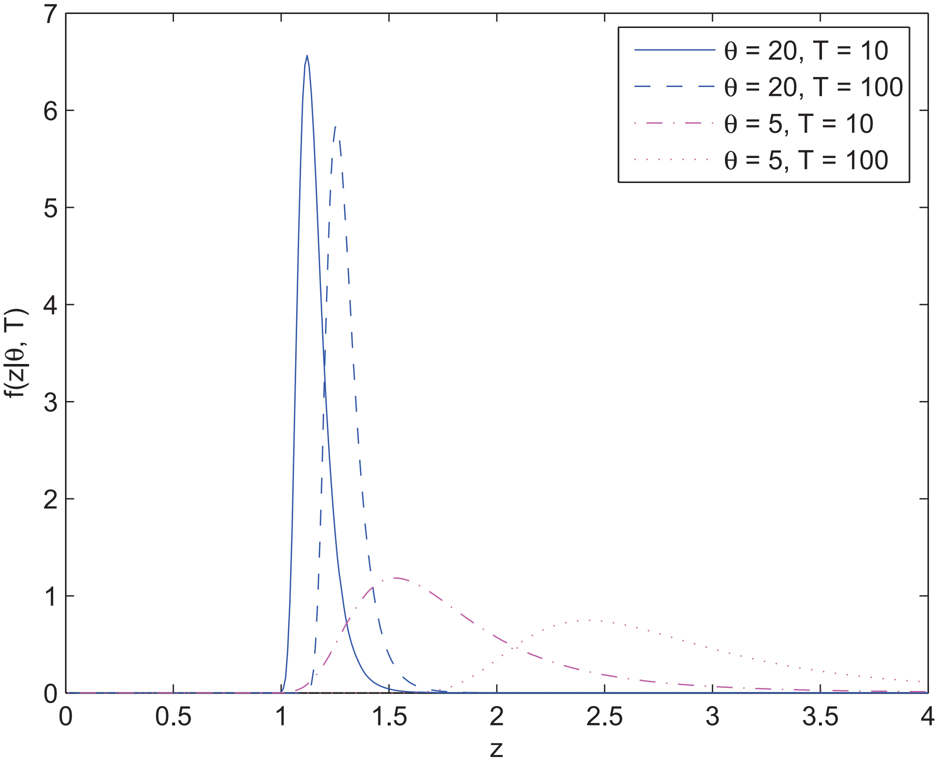

Figure 1: Examples of Fréchet Distributions

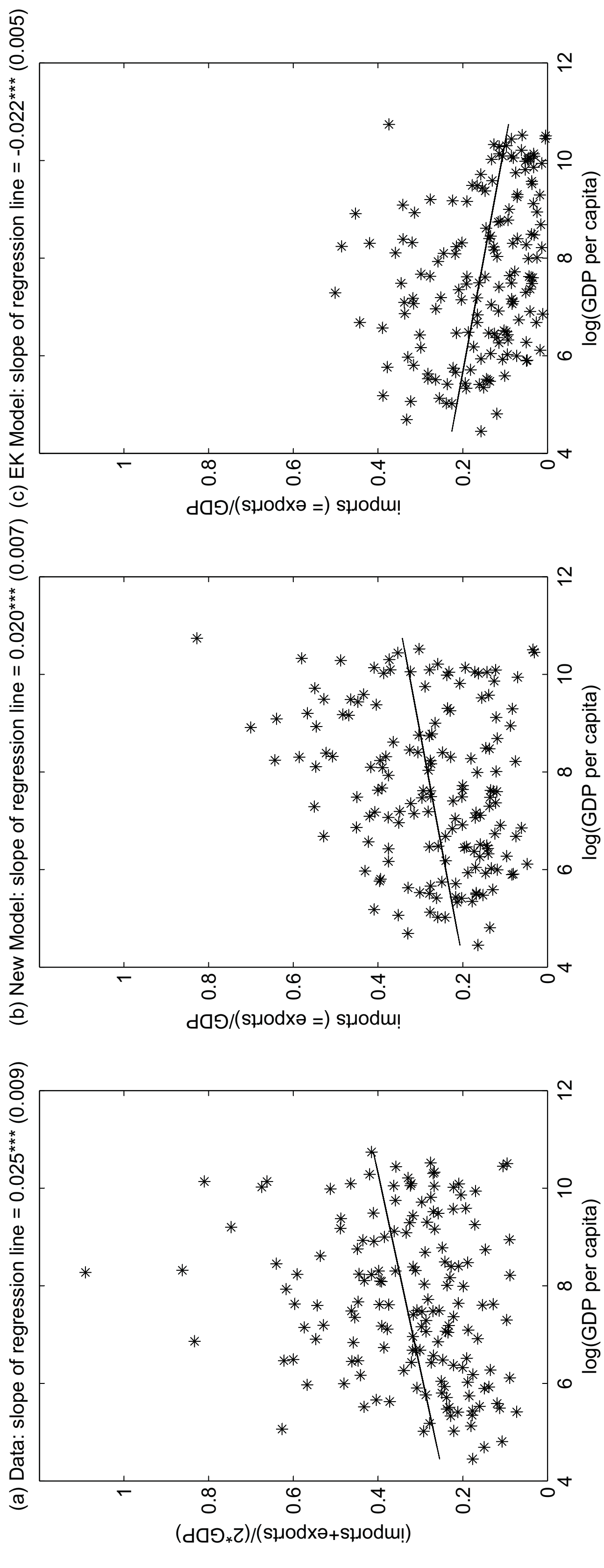

Figure 2: Income per capita × trade share

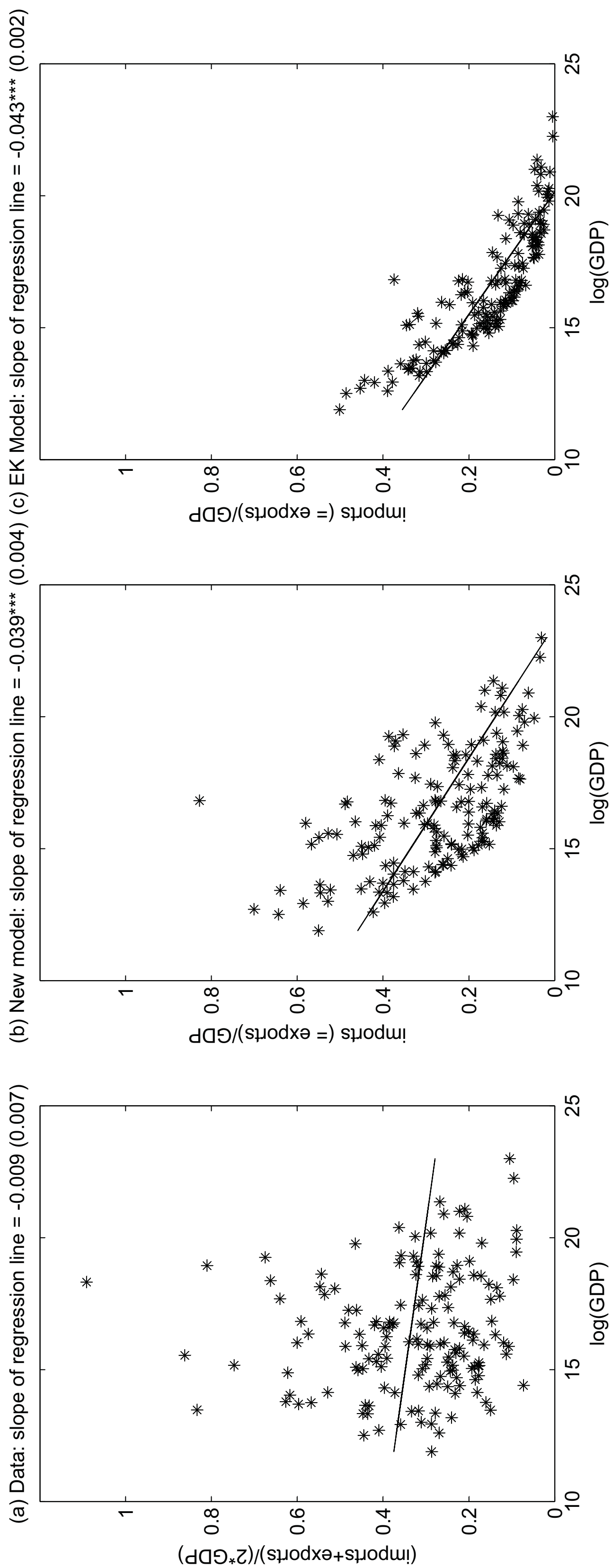

Figure 3: Total income × trade share

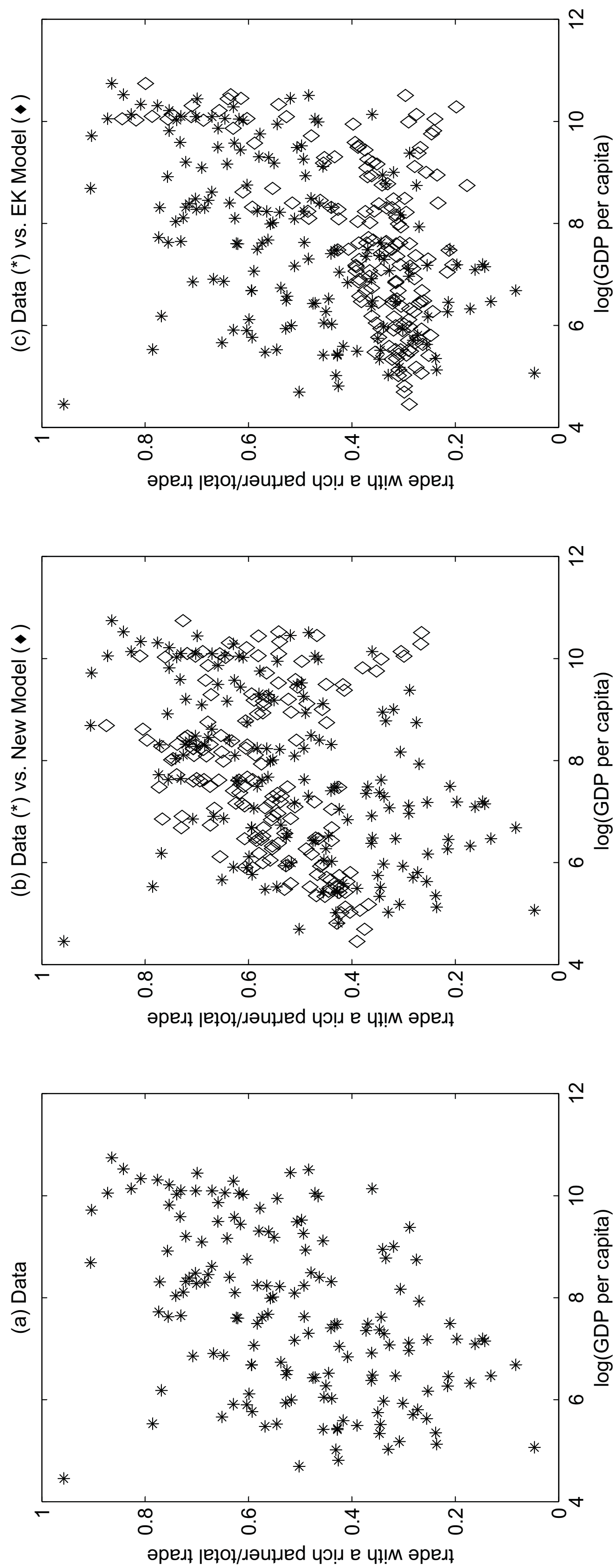

Figure 4: Income per capita × trade with 20 richest countries

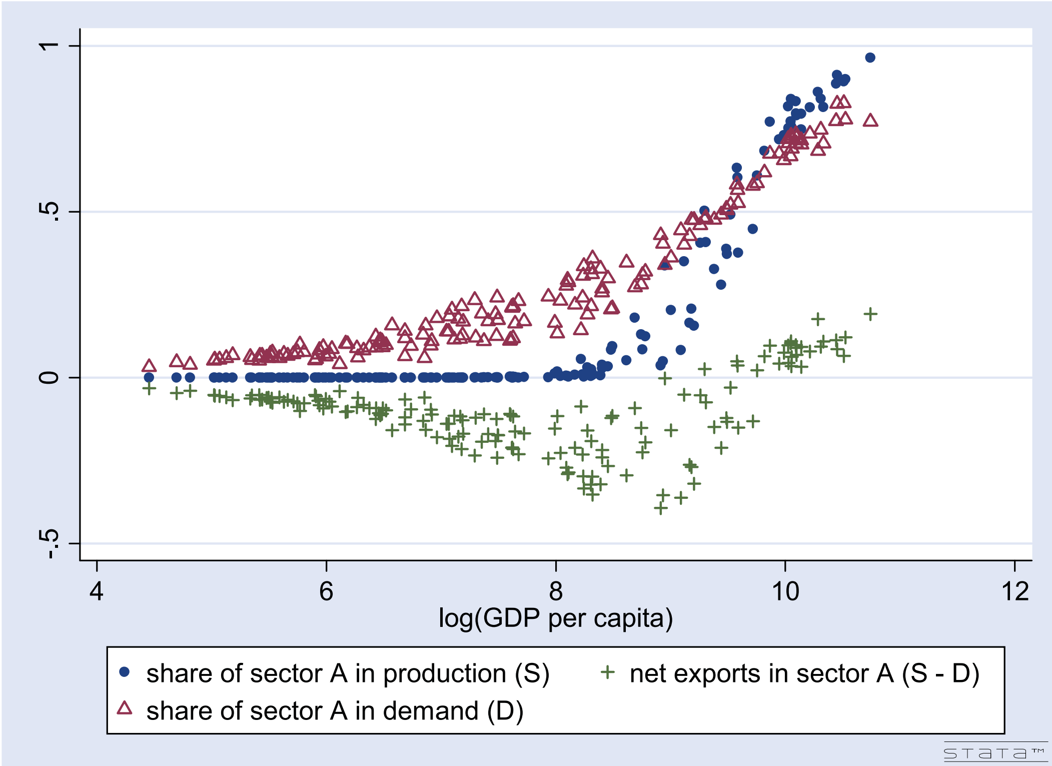

Figure 5: Demand, production and net exports in type A goods

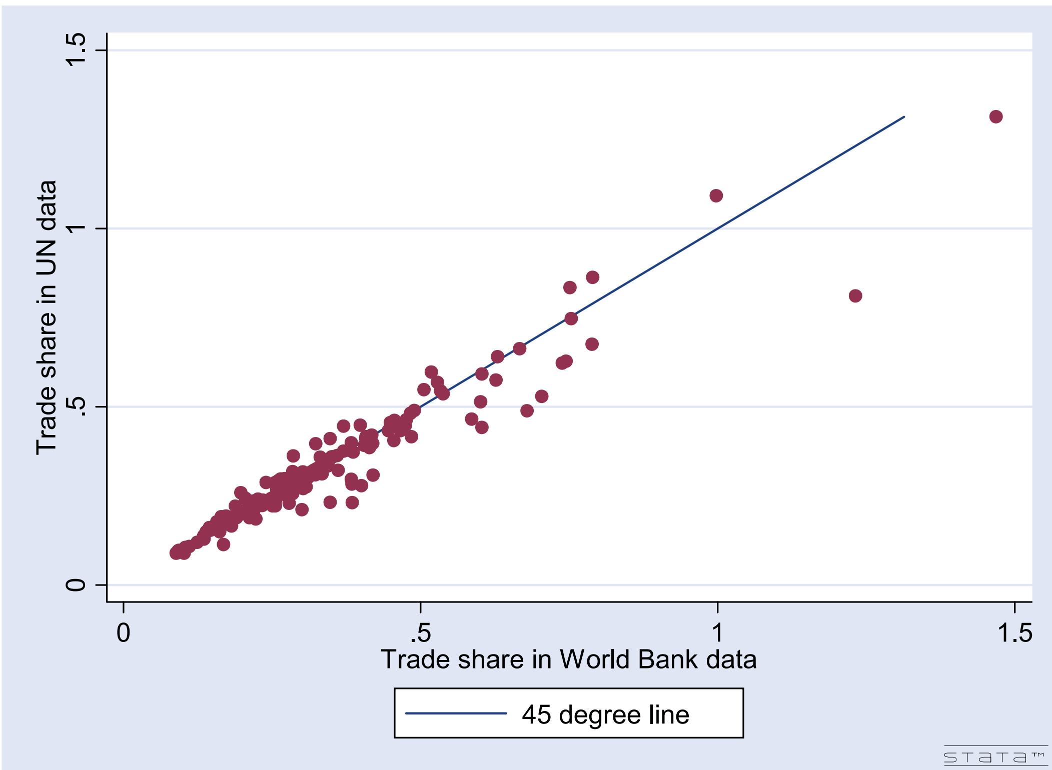

Figure 6: Comparison between trade share in UN (2008) and in the World Bank (2006)