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

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Abstract

Standard empirical models of international trade (i.e., gravity type models) predict that trade flows increase with both importer and exporter total income, but ignore how total 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 international trade that allows for the elasticities of trade with respect to these two variables to diverge. Goods in the model are subdivided into types, which may differ in two respects: income elasticity of demand and the extend of heterogeneity in production technologies. In equilibrium, low income countries consume relatively more goods of the low income elasticity types, and they have a comparative advantage in producing goods with low levels of heterogeneity in production technologies. Conversely, high income countries consume relatively more income-elastic goods and have a comparative advantage in producing goods with high levels of heterogeneity in production technologies.

I calibrate the model, with two types of goods, to data on the bilateral trade flows of 144 countries and compare its quantitative implications to those of a special case in which the model delivers the gravity equation (i.e., with no distinction between income per capita and population). The general model improves the restricted model's predictions regarding variations in trade due to a country's size and income per capita. For example, the effect from doubling a country's income per capita on the share of trade in that country's GDP is a 2.1% increase according to the data, a 2.1% increase according to the general model, and a 5.7% *decrease* according to the restricted model.

I use the model to analyze counterfactuals. A technology shock in China increases the welfare of rich countries, decreases that of middle income countries, and leaves poor countries indifferent. A shock that quadruples China's income increases wages in the 50 richest countries by 0.5% relative to the rest of the world. In contrast, the restricted model implies that a technology shock in one country increases the welfare of all countries, and preserves their relative wages (except with respect to the country experiencing the shock).

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1 Introduction

So great are the differences between rich and poor countries in their trading practices that in 1999 transactions to and from the twelve Western European countries alone accounted for 49% of international merchandize trade, 38% of which was intra Western European. The fifty-seven African economies, in contrast, accounted for only 3.8% of world trade, and intra African trade, a meager 0.1%.[1] These intra Western European trade flows account for 13% of Western European GDP, while intra African trade accounts for only 1.4% of African GDP. Doubling a country's income per capita increases trade (average between imports and exports) as a share in that same country's GDP by 2.1% on average, while doubling a country's population decreases trade as share of its GDP by 2.4%. In spite of these clear relationships, standard models of international trade, which typically yield a gravity relationship, predict that trade increases in proportion with both importer and exporter total income, and ignore how total income is divided into income per capita and population.

This paper proposes a Ricardian model of trade that allows for the elasticity of trade with respect to income per capita and population to diverge. Other trade models with non-homothetic preferences–*e.g.,* Flam and Helpmann (1987), Markusen (1986), Matsuyama (2000), and Stokey (1991)–also allow for this distinction between income per capita and population, but these models are highly stylized and often rely heavily on the assumption of a two-country or a two-good world. My model relaxes these assumptions, and by admitting a continuum of goods and an arbitrary number of countries, it is amenable to analyzing data.

Goods in my model are subdivided into types, which may differ in two respects: demand and technology. Poor households concentrate their expenditures in types with low income elasticity, and rich ones, in 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

[1] Belgium and Luxembourg report trade jointly so that trade between these two countries is excluded from the data set. Likewise, trade between the five members of the South African Customs Union–South Africa, Botswana, Lesotho, Swaziland and Namibia–is not reported. Only their trade with other countries is included in the database.

others. 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 goods whose production technologies are more variable across countries.

Although the purpose of the model is to explain macro-level trade data (i.e., total trade flow for each importer-exporter country pair), the set up above may be interpreted through micro-level evidence. The demand specification accords with previous empirical papers which, rejecting the hypothesis of homothetic preferences, find large variations in the income elasticity of demand across goods. The example of food is the most stark: Deaton (1975), Grigg (1994), Hunter (1991), and Hunter and Markusen (1988) all find that spending on food as a fraction of total expenditures decreases systematically with countries' income per capita. According to Grigg (1994), this fraction ranged in the early 1980s from 64% in Tanzania to less than 15% in Australia and North America. On the supply side, while the model is static, the configuration could be seen as driven by a product cycle. When a good is first invented, the technology to produce it differs greatly across countries (most of which do not even 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 can then be applied similarly to any country, including those where labor is cheap. Evidence of this cross-country process of technology diffusion is found, for example, in Nabseth and Ray (1974), and Comin and Hobijn (2006).

If there is only one type of good, the model delivers the gravity equation, or more specifically, it reduces to Eaton and Kortum (2002, EK henceforth). This special case thus makes the same predictions for trade flows as other gravity type models–e.g., Anderson and van Wincoop (2003), Redding and Venables (2004). None of these models allow for non-homotheticity in demand or supply, and they all imply an elasticity of trade with respect to income per capita and to population of one. My empirical analysis allows me to compare the quantitative implications of the restricted to the general model, and thereby quantify the importance of non-homotheticity (as modelled here) in explaining features of the data on bilateral trade flows.

Among theoretical models of international trade that deliver the gravity equation, EK is the only one with a truly Ricardian framework, in which all countries can potentially produce all goods but differences in comparative advantages prevent them from doing so. (Other models generally assume that goods are differentiated by country.) Since comparative advantage plays a crucial role in my argument, I use the modelling techniques developed by EK to construct my model. And since the EK model is nested in mine, comparing the two models' empirical implications is straightforward. But the purpose of doing so, I emphasize, is not to criticize the EK model exclusively. Rather, it is to underscore some limitations of gravity type models in replicating patterns of trade in the data, and to show that non-homotheticity in demand and supply, both supported by micro-level evidence, can mend these limitations.

I estimate the model, with one type (EK model) and with two types of goods, using the 1999 data on bilateral merchandize trade flows of 144 countries. The regression approach typically used in gravity models is not applicable to my model because the introduction of non-homotheticity modifies the gravity-type framework in a non-linear fashion. I suggest an alternative methodology that makes full use of the general equilibrium feature of the model (see section 3). This methodology contributes to previous papers that also estimate the EK model–e.g., Eaton and Kortum (2002), and Alvarez and Lucas (2007), and its application 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 (because their paper had different objectives).

The EK special case explains well trade among large and wealthy countries, but not among countries of different sizes and income levels. To substantiate this point, I estimate each model twice–once with the full 144-country sample and once with a sub-sample containing only the OECD countries used by EK. The EK special case explains trade among the large and wealthy OECD countries just as well as the general model–the explanatory power (formally defined in section 3) of both cases is 84%. Under the full sample, in contrast, the EK special case explains only 30% of the data, while the general model explains 49%.

One important limitation of the EK model in explaining the full sample is its failure to reconcile the large volumes of trade observed among wealthy countries to the paucity of trade in poor regions. Two types of goods suffice for my model to simultaneously account for these moments in the data. The estimated parameters are such that the type of good that is more elastic coincides with the type whose production technologies are more variable across countries. Hence, wealthy countries tend to consume and produce these goods more intensively. In addition, the variability in their production technologies generates large price dispersions, which in turn give wealthy countries large incentives to trade. Poor countries, by contrast, produce and consume more goods whose production technologies are similar across countries. As a result, they trade little.

The model with this configuration recovers some moments in the data that contradict the predictions of the EK special case. For example, the share of trade in a country's income increases with its income per capita, but not with its total income. The data show that doubling a country's income per capita increases its trade share by 2.1%. My model, similarly, predicts a 2.1% increase while the EK model predicts a 5.7% *decrease*. Doubling a country's total income, in turn, has a statistically insignificant and economically minor effect on trade share in the data (it causes a 0.3% decrease). My model, again similarly, predicts a small 0.7% decrease while the EK model predicts a 7.4% decrease. Another key moment is the number of trade flows too small to be recorded in the data. (The data do not record trade flows under US$100,000.) Of all possible importer-exporter country pairs, 10,816 (52%) have no registered trade in the data. While my model predicts 6,254 trade flows with values under US$100,000, the EK model predicts only 24.

My model differs from EK not only in its predictions regarding trade flows, but also in its welfare implications. If the rate of growth China has experienced since the early 1980s persists, China's income will roughly quadruple every 15 years. The EK model's predictions on welfare due to these changes in China are simple: A technology shock in one country benefits all other countries. To analyze this type of question with my model, I simulate counterfactual situations numerically using the parameter estimates. I experiment with a technology shock in China that causes its total income to quadruple. The shock decreases the price of goods that China and other poor countries produce. As a result, wages in the 50 richest countries in the sample increase by 0.5% relative to the rest of the world. The shock accordingly benefits rich countries, and hurts the welfare of low-middle income countries. Poor countries, in turn, are left nearly indifferent. Although their wages decrease relative to rich countries', they do not consume enough of the high elasticity goods produced in rich countries to be significantly affected by the change.

A technology shock in the USA has the opposite effects as the shock in China. It decreases the price of goods rich countries produce, and consequently decreases these countries' relative wages. A shock that causes a 30% increase in American wages, decreases wages in the 30 richest countries in the world by 1.6% relative to the rest of the world. Most of these rich countries are made worse off with the shock while the rest of the world benefits.

I also experiment with a move to autarky and to frictionless trade by letting transportation costs tend to infinity in the first case and zero in the second. A move to autarky has a relatively small impact in the price indices of low and high income countries because industries in these regions have comparative advantages in the goods their consumers demand most intensively. Middle income countries are therefore the ones to suffer the largest welfare losses when moving to autarky. Likewise, they are also the ones to experience the largest price decreases, and consequently welfare improvements when trade barriers are eliminated.

The paper is organized as follows. In section 2, I present the theoretical model. The empirical analysis of both models is done in section 3. I exploit counterfactuals in section 4. The appendix discusses alternative set ups for the model, and presents robustness checks.

2 A New Model: Theory

This section is organized as follows. In subsections 2.1 and 2.2, I present the theoretical model. I solve the model in section 2.3, and explain its workings in section 2.4. I conclude by showing that the EK model, a gravity-type model, is a special case of mine in subsection 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 $j^\tau \in [0, 1]$. I use throughout the terms sector and type interchangeably. All consumers in the world choose the quantities of goods j^τ, $\{x(j^\tau)\}_{j^\tau \in [0,1]}$ of all types τ to maximize the same utility function:

$$\sum_{\tau=1}^{S}\left\{\alpha^{\tau}\left(\frac{\sigma^{\tau}}{\sigma^{\tau}-1}\right)\int_{0}^{1}\left[x(j^{\tau})^{\sigma^{\tau}-1/\sigma^{\tau}}\right]dj^{\tau}\right\} \tag{1}$$

where $\alpha^{\tau} \in [0,1]$ is the weight of sector τ on preferences, with $\sum_{\tau=1}^{S}\alpha^{\tau}=1$, and $\sigma^{\tau}>1$ for all $\tau=1,...,S$.

Parameter σ^{τ} is typically associated with its role as the elasticity of substitution across goods within type τ. Here, however, it also governs the income elasticities of goods of type τ. To see this, let $\{p(j^{\tau})\}_{j^{\tau}\in[0,1]}$ and $\{p(j^{\tau'})\}_{j^{\tau'}\in[0,1]}$ be the set of prices of goods in any two sectors τ and τ', respectively. Then, from the first order conditions, the total expenditures in goods of type τ, x^{τ}, and in goods of type τ', $x^{\tau'}$, satisfy

$$\frac{x^{\tau}}{x^{\tau'}}=\lambda^{\sigma^{\tau'}-\sigma^{\tau}}\left[\frac{(\alpha^{\tau})^{\sigma^{\tau}}}{(\alpha^{\tau'})^{\sigma^{\tau'}}}\frac{\int_{0}^{1}p(j^{\tau})^{1-\sigma^{\tau}}dj^{\tau}}{\int_{0}^{1}p(j^{\tau'})^{1-\sigma^{\tau'}}dj^{\tau'}}\right], \tag{2}$$

where λ the Lagrangean multiplier associated to the consumer's problem. This multiplier, it can be easily shown, is strictly decreasing in the consumer's total expenditure.

In equation (2), the term in square brackets governs the level of the ratio $x^{\tau}/x^{\tau'}$. A greater α^{τ} or a smaller set of prices $\{p(j^{\tau})\}_{j^{\tau}\in[0,1]}$ increases expenditures in sector τ relative to those in sector τ'. The term $(\lambda^{\sigma^{\tau'}-\sigma^{\tau}})$ governs the rate at which $x^{\tau}/x^{\tau'}$ changes with consumer income. If $\sigma^{\tau}>\sigma^{\tau'}$, the ratio $x^{\tau}/x^{\tau'}$ 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 in different types of goods in a simple manner: $\sigma^{\tau}>\sigma^{\tau'}$ implies that goods of type τ are more income elastic, and consequently rich countries demand relatively more of these goods than poor countries do.[2]

2.2 Technologies

Labor is the unique factor of production; it is perfectly mobile across sectors and immobile across countries.[3] Countries have different access to technologies, so that labor efficiency varies

[2]Appendix 6.1 further justifies the choice of the utility function in equation 1 by showing that it is isomorphic in its predictions to a more general functional form.

[3]Labor can be interpreted more generally in the theoretical model as an input bundle, if capital is assumed to be perfectly mobile across countries. I maintain the term labor throughout, however, because

across countries and across 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 $w_i/z_i(j^\tau)$.

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 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

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

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 the parameter $T_i > 0$ for all countries $i = 1, ..., N$, and $\theta^\tau > 1$ for all sectors $\tau = 1, ..., S$. These distributions are treated as independent across countries and sectors.

Figure 1 illustrates four examples of the densities of Fréchet distributions with different sets of parameters. Given θ^τ, the country-specific parameter T_i determines the level of the distribution in equation (3)–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 in one sector will also be good at

that is the interpretation used in the empirical analysis of section 3 below.

making goods in other sectors.

Parameters θ^τ are common to all countries, but may differ across sectors. These parameters govern the spread of the distribution–the larger the θ^τ, the smaller the variability in labor efficiencies across *goods* and *countries*. A 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 the parameters θ^τ in the model. First, the variability of technologies across *goods* governs comparative advantages *within* sectors. A greater dispersion in labor efficiencies (smaller θ^τ) generate greater price dispersions, and thus a greater volume of trade. Hence, trade will be more intense in sectors where θ^τ is small.

Second, the variability of labor efficiencies across *countries* governs countries' comparative advantages *across* sectors. 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 $\left(\frac{T_i}{T_n}\right)$. Parameter θ^τ controls the relative importance of these two factors. As θ^τ increases, the exponent $-1/\theta^\tau$ gets closer to zero, and wages become more important than technology parameters in determining costs. So poor countries tend to specialize in sectors where θ^τ is large because they have low wages. Rich countries, in turn, specialize in sectors where θ^τ is small because, in general equilibrium, these countries coincide with those with high labor efficiencies–*i.e.*, high 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 (i.e., less variable across countries), and production tends to shift to countries with low labor costs. In the limit, as θ^τ tends to infinity, the Fréchet distribution collapses to 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. Denote by L_i the measure of country i's population and labor supply.

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.[4] The expenditures of a typical consumer in country n on goods of type τ is

$$x_n^\tau = (\lambda_n)^{-\sigma^\tau} \left[(\Phi_n^\tau)^{(\sigma^\tau - 1)/\theta^\tau} \xi^\tau \right], \tag{5}$$

$$\text{where} \qquad \Phi_n^\tau = \sum_{i=1}^{N} T_i \left(d_{ni} w_i\right)^{-\theta^\tau},$$

$$\xi^\tau = (\alpha^\tau)^{\sigma^\tau} \Gamma \left(\frac{\theta^\tau + 1 - \sigma^\tau}{\theta^\tau} \right),$$

Γ is the gamma function, and λ_n is the Lagrangean multiplier associated with the consumer's problem. This multiplier, $\lambda_n > 0$, is implicitly defined through the budget constraint ($\sum_{\tau=1}^{T} x_n^\tau = w_n$) as a continuous and strictly decreasing function of income w_n.

[4] I do not provide a detailed, step by step, derivation of the solution because the procedure is extremely close to that in Eaton and Kortum (2002).

Within sector τ, the expenditures of this consumer in country n in goods from country i is

$$x_{ni}^{\tau} = \frac{T_i(d_{ni}w_i)^{-\theta^{\tau}}}{\Phi_n^{\tau}} x_n^{\tau}. \tag{6}$$

Finally, 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 solution to 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}, weight on preferences α^{τ} and elasticity of substitution σ^{τ}, and a matrix of trade barriers $\{d_{ni}\}_{n,i \leq N}$. Given wages, w, the matrix of trade flows $\{X_{ni}\}_{n,i \leq N}$ can be obtained with equations (5) through (7). An equilibrium is a set of wages $w \in \Delta(N-1)$ such that the labor market clearing condition (8) is satisfied for all countries $i \in \{1, ..., N\}$.

2.4 Income per Capita and Trade Patterns

Having solved the model, we can now analyze how the parameters of the model affect the role income per capita on trade. I consider, for simplicity, only the case analyzed empirically in section 3 below, where there are only two types of goods, A and B. (Estimating the model with more than two types of goods yield the same predictions regarding trade flows as the case with two types. So restricting ourselves to two types does not hamper our analysis of the workings of the model.)

If consumers' preferences were homothetic, they would distribute their resources across goods independently of their income levels. But by equation (5), country n's spending in sector A relative to sector B satisfies

$$\frac{X_n^A}{X_n^B} = (\lambda_n)^{\sigma^B - \sigma^A} \left[\frac{\left(\Phi_n^A\right)^{-(1-\sigma^A)/\theta^A} \xi^A}{\left(\Phi_n^B\right)^{-(1-\sigma^B)/\theta^B} \xi^B} \right]. \tag{9}$$

Equation (9) is the same as equation (2), except that now the price terms $\int_0^1 p(j^\tau)^{1-\sigma^\tau} dj^\tau$ are solved for according to the market structure and technology set up–*i.e.*, $\int_0^1 p(j^\tau)^{1-\sigma^\tau} dj^\tau = \Gamma\left(\frac{\theta^\tau+1-\sigma^\tau}{\theta}\right)\left(\Phi_n^\tau\right)^{-(1-\sigma^\tau)/\theta^\tau}$ for $\tau = A, B$. Assuming $\sigma^A > \sigma^B$, rich households spend a larger fraction of their incomes in type A goods than poor households do. The ratio $\frac{X_n^A}{X_n^B}$ is decreasing in λ_n, and hence increasing in wealth.

Ultimately, however, we are interested on how this ratio affects trade, how it affects the consumer's allocation of income across potential exporters. Let X_{ni}^τ be country n's spending on goods of type $\tau \in \{A, B\}$ 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 $\frac{X_{ni}^A}{X_{nn}^A}$ if country n is rich, and by $\frac{X_{ni}^B}{X_{nn}^B}$ if it is poor. From equation (6), these ratios equal

$$\frac{X_{ni}^A}{X_{nn}^A} = \frac{T_i}{T_n}\left(\frac{d_{ni}w_i}{w_n}\right)^{-\theta^A} \qquad \text{and} \qquad \frac{X_{ni}^B}{X_{nn}^B} = \frac{T_i}{T_n}\left(\frac{d_{ni}w_i}{w_n}\right)^{-\theta^B}. \tag{10}$$

These are the same expressions as the RHS of equation (4), except that they are raised to the power $(-\theta^A)$ and $(-\theta^B)$, respectively. Hence, the conclusions drawn there follow: A higher θ^τ implies a lower variability in production technologies, and therefore a larger emphasis by consumers on the effective cost of labor $\left(\frac{d_{ni}w_i}{w_n}\right)$ than on the technology parameters $\left(\frac{T_i}{T_n}\right)$.

To make this point clearer, consider the case, consistent with the empirical results of section 3 below, where $\theta^A < \theta^B$. Suppose further that country n is poor. Then, $\left(\frac{d_{ni}w_i}{w_n}\right) > 1$ in general, because w_n is low and $d_{ni} > 1$. A large negative exponent will then make $\left(\frac{d_{ni}w_i}{w_n}\right)^{-\theta^B}$ close to zero, and therefore country n's expenditures abroad, $\frac{X_{ni}}{X_{nn}} \approx \frac{X_{ni}^B}{X_{nn}^B}$, small. In words, the low heterogeneity in production technologies of goods of type B, typically consumed by poor countries, dampen the incentives for these countries to trade: If products are not sufficiently differentiated, consumers in poor countries will prefer their domestic version, avoiding transport costs.

This scenario is reversed if country n's income per capita is high and $\frac{X_{ni}}{X_{nn}} \approx \frac{X_{ni}^A}{X_{nn}^A}$. Since

θ^A is small, the term $\left(\frac{d_{ni}w_i}{w_n}\right)^{-\theta^A}$ will be relatively close to 1 irrespective of whether $\left(\frac{d_{ni}w_i}{w_n}\right)$ is smaller than or greater than 1. Therefore, $\frac{X_{ni}^A}{X_{nn}^A}$ will be largely determined by the technology parameters $\frac{T_i}{T_n}$, instead of $\left(\frac{d_{ni}w_i}{w_n}\right)$ as $\frac{X_{ni}^B}{X_{nn}^B}$ was. The effect of this result is twofold. First, rich countries will tend to trade more than their poor counterparts because their consumers place a smaller emphasis on trade barriers and wages ($d_{ni}w_i$). Second, they will tend to trade more with other high income countries, whose technology parameters T_i are large. So in accordance to the empirical evidence mentioned in the introduction, depending on the values of the parameters, the model predicts trade to be more intense among high income countries.

2.5 A Special Case: The Gravity Model

Eaton and Kortum (2002) show that their model delivers the gravity equation. That is, that the flow of goods from country i to country n in their model take the form $X_{ni} = \delta_{ni}X_nX_i$, where X_n and X_i are the total incomes of country's i and n, respectively, and δ_{ni} is a measure of the trade costs between countries n and i, which depends both on geographic barriers d_{ni} and on the importing country's price index.[5]

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

$$\frac{\sigma^\tau}{\sigma^\tau - 1}\int_0^1 \left[x(j^\tau)^{\sigma^\tau - 1/\sigma^\tau}\right] dj^\tau,$$

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 $X_n = w_nL_n$ is country n's total income. This is the solution to the EK model. Aside

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

from iceberg costs, it does not depend on countries' income per capita.

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

The converse, however, is not true. One way to make preferences homothetic, while preserving the two-sector technology distribution is to assume $\sigma^{\tau} = \sigma$ for all $\tau = 1, ..., T$. Trade flows as predicted under this restriction differ from the EK model (see equations (5) and (6)). And although I do not present the results, I did estimate the proposed model with this restriction. The explanatory power of this restricted model (formally defined in section 3 below) is closer to the full model than to the gravity special case. Hence, technologies play a larger role in the empirical results presented in section 3 below than preferences do. Notwithstanding, the model with $\sigma^{\tau} = \sigma$ does not explain any of the stylized facts I discussed above. So I continue to use the interaction between non-homotheticity of preferences and variability in production technologies to explain the workings of the model in replicating the data.[6]

3 Empirical Analysis

I use data on 1999 trade flows from the NBER-UN data set compiled by Feenstra et al. (2005). Data on population and income are from the World Bank (2006). I downloaded from the Centre d'Etudes Prospectives et d'Informations Internationales (2005) webpage data specific to country pairs–distance between their most populated cities, common official language, and border. The

[6]It is not immediately apparent from equations (5) and (6) how trade flows depend on countries' income per capita when preferences are homothetic ($\sigma^{\tau} = \sigma$) and the variability in production technologies differ across types of goods (θ^{τ} varies by type). Poor countries specialize in sectors where production technologies are less variable across countries. In general equilibrium, for markets to clear, the prices of goods in these sectors must be similar across these poor countries. Thus, these countries face tight exporting markets. And again because of general equilibrium, if poor countries export little, they must also import little, even if their consumers would like to purchase more goods of other types. This restricted model, therefore, partially explains why poor countries tend to trade less than rich ones–the main empirical finding I discuss in section 3 below.

data, containing 144 countries, are summarized in table 1. The rest of the world is treated as non-existent throughout this paper, which leads me to neglect 10.6% of world trade. Table 1 shows, for each country, the percentage of its imports coming from countries within the sample. This number is somewhat lower for Asian countries because Taiwan is not in the sample, and it is significantly lower for South Africa's neighbors due to its absence from the sample.

My objective in the empirical analysis is to match the bilateral trade flows observed in the data to those predicted by the model. Eaton and Kortum (2002) show that their model provides a theoretical foundation for the gravity equation, the most widely used empirical model of trade. The general predictions of their model therefore coincide with those of other gravity-type models such as Anderson and van Wincoop (2003) and Redding and Venables (2004). This makes the EK model a convenient benchmark for mine. In order to make the two models comparable, however, I cannot employ the usual regression approach to estimate the EK model, because it is not applicable to my model–the non-homotheticity of preferences introduced here modifies the prediction of trade flows in the gravity equation in a non-linear form. I propose, alternatively, a methodology that takes advantage of the general equilibrium set up in both models. In the case of the proposed model, I focus exclusively in the special case with only two types, denoted A and B.[7]

In subsection 3.1 below, I present the methodology, and in subsection 3.2, I present the results.

3.1 Empirical Analysis: Methodology

The theoretical model presented in section 2 above implies that country n's imports from country i satisfy (equations (5), (6), and (7)):

[7] As a robustness check, I also estimated the model with more than two types, but the predictions of the model regarding trade flows remained unchanged and the type specific parameters α^{τ} and θ^{τ} were not identified.

$$
\begin{aligned}
X_{ni} &= L_n \left(x_{ni}^A + x_{ni}^B \right) \qquad \text{where, for } \tau = A, B, \\
x_{ni}^\tau &= \frac{T_i (d_{ni} w_i)^{-\theta^\tau}}{\Phi_n^\tau} x_n^\tau, \\
x_n^\tau &= (\lambda_n)^{-\sigma^\tau} \left[(\Phi_n^\tau)^{(\sigma^\tau - 1)/\theta^\tau} \, \xi^\tau \right], \\
\Phi_n^\tau &= \sum_{i=1}^{N} T_i \left(d_{ni} w_i \right)^{-\theta^\tau}, \\
\xi^\tau &= (\alpha^\tau)^{\sigma^\tau} \Gamma \left(\frac{\theta^\tau + 1 - \sigma^\tau}{\theta} \right),
\end{aligned}
\tag{12}
$$

$\alpha^B = 1 - \alpha^A$, and the Lagrangean multiplier λ_n is implicitly defined through the budget constraint of a typical consumer in country n, $x_n^A + x_n^B = w_n$.

Trade flows are therefore a function of the set of N countries, each with its population L_i, wages 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; the elasticities of substitution σ^A and σ^B, and the weight of type A goods in the utility function α. From the data, I will take the set of $N = 144$ countries, the population of each country L_i and their wages w_i. In order to calculate bilateral trade flows, I need to estimate the set of iceberg costs d_{ni}, utility parameters α, σ^A and σ^B, and technology parameters T_i, θ^A and θ^B. (I do not consider the Lagrangean multipliers as additional parameters because, given all other variables, one can compute the unique set of multipliers $\{\lambda_n\}_{n=1}^N$ that satisfies the budget constraints.)

Iceberg costs. Assume the following functional form for the iceberg costs:

$$
d_{ni} = 1 + \left\{ (\gamma_0 + \gamma_1 D_{ni} + \gamma_2 D_{ni}^2) * \gamma_{\text{border}} * \gamma_{\text{language}} * \gamma_{\text{EU}} * \gamma_{\text{NAFTA}} \right\}, \tag{13}
$$

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 impact of distance in trade costs. Parameter γ_{border} equals 1 if countries n and i do not share a border, and it is a parameter to be calibrated otherwise. If γ_{border} is, for example, 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}, γ_{EU} and γ_{NAFTA} refer, respectively, to whether countries n and i share a common language, or if they are both members of the European Union (EU) or the North American Free Trade Agreement (NAFTA).[8]

Empirical work on trade often uses other variables, such as colonial links and other trade agreements, in its specification of iceberg costs. I refrained from using these here because preliminary analyses indicated that they were not altering my results, and by keeping the number of parameters to a minimum, I gained computational time in estimating the model.

Henceforth, I refer to the set of iceberg cost parameters as
$\Upsilon = \{\gamma_0, \gamma_1, \gamma_2, \gamma_{\text{border}}, \gamma_{\text{language}}, \gamma_{\text{EU}}, \gamma_{\text{NAFTA}}\}$.

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 $\{L_i\}_{i=1}^N$, geographic characteristics and trade agreements, one could either use the technology parameters $\{T_i\}_{i=1}^N$ to find the market clearing wages $\{w_i\}_{i=1}^N$, 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.[9] 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 $\{T_i\}_{i=1}^N$ that satisfy the system of equations (8): $\sum_{n=1}^N X_{ni} = w_i L_i$ for $i = 1, ..., N$.[10]

This procedure reduces the number of parameters in the model from $(N + 12)$ to 12: The

[8] Usually, an exponential functional form is assumed for iceberg costs, *e.g.*, $d_{ni} = \exp\left(\gamma_0 + \gamma_1 D_{ni} + \gamma_2 D_{ni}^2 + \gamma_{\text{border}} + \gamma_{\text{language}} + \gamma_{\text{EU}} + \gamma_{\text{NAFTA}}\right)$, 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 my empirical results. I chose equation (13) because, unlike the exponential function, its parameters are easily interpretable.

[9] I use income per capita as a proxy for wages. As presented in section 2, the model does not distinguish between population and labor force, or income per capita and wages. 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.

[10] Alvarez and Lucas (2007) prove uniqueness of equilibrium in the EK model, but their proof is not applicable to my model. Although I do not prove uniqueness of equilibrium, I did not encounter any cases where the relation between w_i and T_i in the market clearing conditions was many-to-one or one-to-many. The United States's technology parameter T_i is normalized to 100. All Fortran programs are available upon request to the author.

seven parameters in Υ, and α^A, σ^A, σ^B, θ^A and θ^B. These, together with the data, are sufficient to estimate the whole matrix of trade flows X_{ni}.

Identification. In their paper, EK are not able to identify parameters θ^A and σ^A from the 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 equally be attained by decreasing the iceberg cost parameters. So, data on bilateral trade flows do not distinguish between these two changes–*i.e.*, a decrease in θ^A or in iceberg costs d_{ni}. Moreover, in order to obtain values for and to interpret the remaining parameters of the model, 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 Eaton and Kortum (2002).

Parameters σ^A and σ^B are not separately identifiable either. These parameters, together, govern how the allocation of expenditures across goods of type A and B varies with a country's per capita income, 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. Broda and Weinstein (2006) estimate the elasticity of substitution across goods within each industry, where an industry is defined by the set of products with the same three-digit Standard International Trade Classification (SITC) code. I fix $\sigma^A = 4.0$, the mean of their estimates.[11]

In appendix 6.2, I experiment with other values of θ^A and σ^A. Although estimates for the remaining parameters $(\Upsilon, \alpha^A, \theta^B, \sigma^B)$ vary, predictions on trade flows barely change. (If it were not so, parameters θ^A and σ^A would be identifiable.) For all values of θ^A and σ^A tried in the appendix, the interpretation of the parameter estimates and of the results presented below–for both EK and my model–remain absolutely unaltered.

[11] Broda and Weinstein (2006) estimate the elasticity of substitution across goods within industries, when industries are defined at ten-, five-, and three-digit classification codes. I chose the broadest definition of an industry, because my model contemplates only two sectors (or two "industries"). Hence, presumably, goods within each one of these sectors should be very different, and their elasticity of substitution consequently be low.

Having fixed the values of θ^A and σ^A, ten parameters–the seven elements in 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 $\{\hat{X}_{ni}(\Upsilon)\}_{n,i\leq N}$. I choose $\{\Upsilon, \alpha^A, \sigma^B, \theta^B\}$ to minimize the distance between the actual trade flows in the data and the estimated ones:

$$\Psi(\Upsilon, \alpha^A, \sigma^B, \theta^B) = (X_{ni} - \hat{X}_{ni}(\Upsilon, \alpha^A, \sigma^B, \theta^B))' W (X_{ni} - \hat{X}_{ni}(\Upsilon, \alpha^A, \sigma^B, \theta^B)) \tag{14}$$

where W is a weighting matrix (specified below), X_{ni} here is a vector containing trade flows for all possible importer-exporter country pairs–*i.e.*, all n and i with $n \neq i$ and $n, i \in \{1, ..., N\}$–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 contain $(N^2 - N) = 20,592$ observations.

I normalize the objective function in equation (14) by dividing it by $X'_{ni} W X_{ni}$, and refer to

$$1 - \left(\frac{\Psi(\Upsilon, \alpha^A, \sigma^B, \theta^B)}{X'_{ni} W X_{ni}} \right) \tag{15}$$

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%, and 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.

Since I cannot observe the variance of the observations X_{ni}, I assume a functional form for the weighting matrix W. I assume it is a diagonal matrix, and that the entry corresponding to country n's imports from country i, X_{ni}, equals $(X_n X_i)^{-\kappa}$, where X_n and X_i are the total incomes of countries n and i, respectively, and κ is a constant. Depending on κ, trade among large countries receives a greater or smaller weight in the objective function with respect to trade among small countries. Appendix 6.4 experiments with different values for $\kappa \in [0, 2]$. From the results there, when $\kappa = 0$ and W is the identity matrix, the optimization algorithm disregards trade among small countries, and focuses almost exclusively on the large values of trade flows in X_{ni}, which occurs among large, rich countries. On the other extreme, when $\kappa = 2$, the algorithm captures only observations corresponding to trade among small countries because $(X_n X_i)^{-2}$ is very small whenever countries n and i are large.

The thrust of the present paper is that the gravity model fails to reconcile the large volumes of trade among rich countries with the small volumes observed among small, poor countries. Non-homotheticity in demand and supply, I argue, can simultaneously account for these two moments. So, in order to make this point, it is convenient to pick an intermediary value for κ, where neither poor nor rich countries are over represented in the objective function. I choose $\kappa = 1.0$ and summarize in appendix 6.4 the results for $\kappa \in [0, 2]$. My model outperforms EK's in explaining the data for all values of $\kappa \in [0, 2]$, and the direction of the changes between the two models is the same as the one presented in this section.[12] [13]

3.1.1 EK Model: Estimation Methodology

According to the EK model, trade flows from country i to country n are given by equation (11):

$$X_{ni} = \frac{T_i \left(d_{ni} w_i\right)^{-\theta^A}}{\Phi_n^A} L_n w_n. \tag{16}$$

They are a function of the same variables as those in the general model except for parameters α^A, σ^A, σ^B and θ^B, which either do not exist or do not affect trade flows in this special case.

The estimation methodology described above can thus be seamlessly applied to the EK model: I use data on population and income per capita as proxies for L_i and w_i, respectively; assume the functional form in equation (13) for iceberg costs d_{ni}; recover the country-specific technologies T_i through the set of N market clearing conditions, and fix $\theta^A = 8.28$. This procedure reduces the parameters of the model to the seven elements of Υ. I choose these parameters to minimize function (14), the distance between trade flows in the data X_{ni} and those estimated by the model $\hat{X}_{ni}(\Upsilon)$. I again focus on the case where the weighting matrix

[12] The case where $\kappa = 2$ is interesting because the gravity model provides a theoretical justification for it. The gravity equation postulates that trade flows from country i to country n equals $X_{ni} = \delta_{ni} X_n X_i$, where δ_{ni} is a measure of trade barriers between countries n and i–typically a function of geographic and economic barriers and the price indices of the two countries. So, if $\kappa = 2$, we can write the objective function as $(\delta_{ni} - \hat{\delta}_{ni}(\Upsilon))'(\delta_{ni} - \hat{\delta}_{ni}(\Upsilon))$, where $\hat{\delta}_{ni}(\Upsilon) = \frac{X_{ni}(\Upsilon)}{X_n X_i}$ is the model's theoretical measure of the barrier between countries n and i, and δ_{ni} is the real one. From an applied viewpoint imposing this as a limiting case makes sense because the EK model predicts such small values for trade when $\kappa = 2$ that its explanatory power is only 1%.

[13] Santos Silva and Tenreyro (2006) discuss extensively the problem of weighting observations in the gravity model in trade. It is neither desirable, they argue, to give excessive weight to trade among poor countries, whose data are of lower quality, nor to large countries, whose observations present larger variances. As I do here, they also propose the use of the size of the importer and of the exporter to weight observations.

parameter κ equals 1.0 and relegate to the appendix the results for other values $\kappa \in [0, 2]$. I also continue to refer to expression (15) as the model's explanatory power.

All supplementary empirical results are in the appendix. In appendix 6.2, I re-estimate both models using different values for parameters θ^A and σ^A. I derive confidence intervals for the parameter estimates in appendix 6.3, and I present a synthesis of the results for all values of the weighting matrix parameter κ in $\{0, 0.1, 0.2, ..., 1.9, 2.0\}$ in appendix 6.4.

3.2 Results

I estimate both the EK and the new model using two different samples–the first includes only the nineteen OECD countries used by EK (marked with an asterisk on table 1) and the second includes all 144 countries in the data set. Table 2 displays the estimated parameters. Both models explain trade among OECD countries equally well–their explanatory power is 84%. Under the full sample, in contrast, the new model significantly improves the explanatory power of EK from 30% to 49%. This makes clear the contribution of the new model. It lies not in explaining trade among countries with similar characteristics (as in the OECD sample), but rather in reconciling some features of the data observed across countries of different sizes and income levels.

Table 3 summarizes the distribution of residuals of the full sample estimation. It displays the contribution of each importing country n in the objective function (14). The values are divided by $X_{ni}' W X_{ni}$ so that the sum of residuals across importers equals 70% ($= 100\% - 30\%$) for the EK model, and 51% for the new model. A significant fraction of the residuals in both models correspond to Hong Kong and Singapore, the countries in the sample that trade the largest fraction of their incomes. But even if these countries are removed from the sample, all results remain qualitatively unchanged.[14]

[14]If Hong Kong and China, and Malaysia and Singapore are merged into a single country, the explanatory power of the EK model increases to 41%, and that of the new model decreases to 47%. The estimates of the parameters that distinguish the new model from EK's become $(\alpha^A, \sigma^B, \theta^B) = (0.85, 1.23, 11.1)$. They thus satisfy the inequalities required for my explanation linking income per capita to trade to follow through: $\alpha^A \in (0, 1)$, $\sigma^A > \sigma^B$, and $\theta^A < \theta^B$. The patterns depicted in figures 3 and 2 discussed below likewise hold.

EK model. The data present large volumes of trade among large, rich countries and small volumes among small, poor countries. Unable to reconcile these facts, the EK model simply underestimates trade among rich countries and overestimates that of poor countries. Evidence of the first part of this assertion is found in the comparison between the EK estimates under the OECD and the full sample. As $(\gamma_1, \gamma_2, \gamma_3)$ changes from $(1.49, 0.34, -0.06)$ in the OECD to $(1.72, 0.28, -0.02)$ in the full sample, trade among all OECD importer-exporter country pairs decrease. Thus trade among these large and rich countries is underestimated when the full sample is used. Further evidence is found in the EU and NAFTA parameters. In the estimation with the full sample, these parameters are used as proxies for wealth since members of the EU and NAFTA have on average higher income per capita than the remaining countries in the sample. By decreasing $(\hat{\gamma}_{\text{EU}}, \hat{\gamma}_{\text{NAFTA}})$ from $(0.90, 0.64)$ in the OECD to $(0.75, 0.52)$ in the full sample, the optimization algorithm increases trade among the participants of these agreements without significantly affecting trade in the rest of the world. A $\hat{\gamma}_{\text{EU}} = 0.75$ and $\hat{\gamma}_{\text{NAFTA}} = 0.52$ in the full sample implies implausibly that participating in the EU and the NAFTA decreases trade barriers by 25% and 48%, respectively.

But more obvious is EK model's overestimation of trade among small countries, illustrated in figure 2. Each of the graphs in the figure plot countries' trade share ($i.e.$, $\frac{\text{imports + exports}}{2*\text{GDP}}$) as a function of the logarithm of their total GDP. Graph 2(a) refers to the data and 2(b) to the EK model. Recall from the estimation methodology used here that there is no difference between countries' real and predicted incomes. So, the position of countries on the x-axes is the same in all graphs. The graphs diverge only because of differences between the real and the estimated trade shares, plotted on the y-axes. The EK model predicts a clear, strong negative correlation between countries' total income and trade share (figure 2(b)), which does not exist in the data. It estimates, for example, that the ten smallest countries in the sample trade on average 90% of their incomes, while the ten largest countries trade only 14%. These same numbers are 37% and 18%, respectively, according to the data. The pattern in figure 2(b) ensues from a tendency in general equilibrium models for large countries to trade less. In a two-country world, for example, because imports and exports must be the same in the two countries, the smaller one necessarily trades a larger fraction of its income.[15]

Figure 3 is analogous to figure 2, except that the logarithm of total income on the x-axes is substituted for the logarithm of income per capita. Trade shares still appear on the y-axes, and graphs 3(a) and 3(b) refer to the data and the EK model, respectively. While the data show that trade share increases with income per capita, the EK model predicts that it decreases. (This prediction of the EK model stems from the decreasing effect size has on trade share in the model and the positive correlation between countries' size and income per capita.)

New model. Through the mechanisms described in section 2.4, the new model amends the shortcomings of the EK model described above. Three parameters distinguish the new model from EK: $\alpha^A, \sigma^B, \theta^B$. Parameters $\alpha^A = 0.63$, $\sigma^A = 4.00$ and $\sigma^B = 2.43$ define the consumers' utility function. Sectors A and B coexist in the economy ($\alpha^A \in (0,1)$), and since $\sigma^A > \sigma^B$, rich consumers allocate a larger fraction of their incomes in goods of type A than poor consumers do. To be specific, the non-homotheticity in demand is so acute that spending in sector A ranges from 87% of Japan's GDP to only 5% of the Democratic Republic of Congo's. Sector A also presents a greater heterogeneity in production technologies since $\theta^A < \theta^B$ ($\theta^A = 8.28$ and $\theta^B = 14.28$). Hence, rich countries have a comparative advantage in producing goods of type A. These goods constitute 96% of Switzerland's production, and only 5×10^{-13} of the Democratic Republic of Congo's. Rich countries thus produce and consume more goods in sector A, the sector whose production technologies are more heterogeneous across countries. As a result, international trade is most intense among wealthy countries; poor countries trade little (recall the explanation in section 2.4).

Figures 2(c) and 3(c) revisit the plots of trade share on size, and trade share on income per capita using the predictions of the new model. They are analogous to figures 2(b) and 3(b) for the EK model. Recall from figure 2(b) that the EK model predicts a decreasing effect of size on trade share because of its general equilibrium set up. The new model counterpoises this

[15] An alternative way to look at this correlation in the EK model is through the gravity equation. According to gravity models, the flow of trade from country i to country n equals $X_{ni} = \delta_{ni} X_n X_i$, where δ_{ni} is a measure of trade barriers between countries n and i. Rearranging, we get that country n's trade share is equal to $\frac{X_{ni}}{X_n} = \sum_{i \neq n} \delta_{ni} X_i$. It is decreasing in the size of country n, the country excluded from the sum.

effect with a tendency for rich (often large) countries to trade less. As a result, its predictions are much closer to the data than those of the EK model: The regression lines in figure 2 imply that doubling a country's total income decreases its trade share by 0.3% according to the data, 0.8% according to the new model, and 7.4% according to the EK model. Figures 2(a) and 2(c) present large variances among observations corresponding to medium-sized countries. This pattern emerges in the data and the new model because medium-sized countries with small populations and high income per capita have the largest trade shares, and those with large populations and low income trade little.

The new model also correctly predicts that trade share increases with income per capita. The slopes of the regression lines in all three graphs of figure 3 are not only statistically significant at 1%, but also economically significant. Take, for example, the richest and poorest countries in the sample–Switzerland and the Democratic Republic of Congo (DRC). The ratio of their incomes per capita equals 380. Thus, the slopes in figure 3 imply that Switzerland's trade share is expected to be *18% larger* than that of the DRC according to both the data and the new model ($0.18 = 0.031 \log(380)$), and *49% smaller* according to the EK model!

Another key moment of the data is the number of bilateral trade flows whose values are too small to be recorded. The data are classified into approximately 1,400 commodity categories. In each of these categories, whenever the trade flow between two countries is less than US$100,000, it is excluded from the data set. As a result, the data entail 10,816 (52%) country pairs with no registered trade. The new model, similarly, predicts 6,254 bilateral trade flows of less than US$100,000 while the EK model predicts only 24, clearly overestimating trade among small, poor countries.[16] [17]

[16]This comparison is, in some sense, unfair to the EK model. A country pair may trade several commodity categories, but as long as the value of trade in each category is less than US$100,000, the data record zero trade flows for that particular country pair. Thus, the total value of trade between two countries may exceed US$100,000 and still appear as zero in the data. Notwithstanding, the difference between the model and the data is so stark, that the model would fail even more lenient comparison criteria.

[17]This last result is important in its contribution to a recent paper by Helpman, Melitz and Rubinstein (2005) which addresses the question of zero bilateral flows observed in trade data. The paper introduces two modifications to a monopolistic competition model of the gravity type: bounded technology spaces, and fixed entry costs. A zero trade flow is generated if the most productive firm of a potential exporting country does not find it profitable to incur in the fixed cost necessary to enter a particular importing market–a possible scenario given that the technology space is bounded.
Although the rational is clear, my results indicate that Helpman et al. (2005) probably overestimate the

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 understanding of the model itself.

The methodology used here is as follows. From the data, we have the population of each country, and from the calibration in section 3, we have the estimates of countries' technology parameters $\{T_i\}_{i=1}^{N}$, of parameters α^A, θ^A, θ^B and of the matrix of iceberg costs $\{d_{ni}\}_{n,i\leq N}$ through the estimate of Γ. So we have all the elements defining an economy. Initially, the wages w that clear the market coincide with the real 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.

In section 4.1, I experiment with changes in trade costs, d_{ni}, and in section 4.2, I experiment with changes in technology parameters, T_i.

4.1 Trade Barriers

to be completed

4.2 Technology Shocks

I experiment in this subsection with a technology shock in one country, i.e., a unilateral increase in its parameter T_i. Looking at this change at a theoretical level first will help us understand the counterfactual results.

Technology Shocks: Theory. The effects of a technology shock depend on both the supply and the demand sides of the economy. To separate the two, I consider three cases: (i) $\sigma^A > \sigma^B$

magnitude of entry costs. By using a gravity type model, they neglect the diminished incentives that small, typically poor, countries have for consuming goods abroad. The comparison between the number of bilateral trade flows of less than US$100,000 estimated by the new model–6,254–to that estimated by the EK model–24–makes this point evident.

and $\theta^A = \theta^B$, (ii) $\sigma^A = \sigma^B$ and $\theta^A < \theta^B$, and (iii) $\sigma^A > \sigma^B$ and $\theta^A < \theta^B$. I suppose there are no transportation costs (i.e., $d_{ni} = 1$).

In case (i), preferences are non-homothetic, but supply is not. The model then reduces to EK (see section 2.5): A technology shock in one country must benefit all other countries in the world, and preserve their relative wages. (Before and after the shock, expenditures of all countries n in goods from country j relative to those from country j' must equal $\frac{X_{nj}}{X_{nj'}} = \frac{T_j}{T_{j'}} \left(\frac{w_j}{w_{j'}}\right)^{-\theta}$.) If, on the other hand, preferences are homothetic, but supply is not (case (ii)), a technology shock may hurt some countries. To study this case and case (iii), I use simulations in a fictitious economy with 100 countries, population vector $L = 1$ and technology parameters $T = 1, 2^{-1}, ..., 2^{-99}$.

Figure 4 summarizes the welfare results from a technology shock in the world's poorest country. The left graph refers to case (ii), and the right, to case (iii). On the x-axis is the logarithm of initial wages. On the y-axis, the dots are the share of type A goods in supply (S), and the triangles are the share of type A goods demand (D). In both graphs, poor countries supply mostly type B goods, and rich ones, type A. In case (ii), the demand curve is horizontal because preferences are homothetic, and in case (iii), it is upward sloping–rich countries consume relatively more type A goods. The net supply of type A goods ($S - D$) is plotted in diamonds and crosses. The diamonds are the countries which are made better off with the shock, and the crosses those that are made worse off.

The economy's poorest country produces practically only type B goods. Hence, its technology shock decreases the price of these goods relative to those of type A, and consequently, it also decreases wages in poor countries–type B producers–relative to rich ones. The result of case (ii) thus follows: Poor countries are made worse off with the shock, and rich ones better off. In case (iii), these same price and wage changes occur. But now the poorest countries in the economy are made better off with the shock. The decrease in the price of type B goods hurts these countries are hurt as producers, but benefit them as consumers. They are hardly affected by the decrease in their wages relative to rich countries' because they consume few goods produced in rich countries. Only middle income countries, the major net importers of type A goods, are hurt with the shock.

Technology Shocks: Counterfactuals. Now return to the economy estimated in section 3. To define it, take from the data the set of $N = 144$ countries and their population, and from the estimation procedure, the parameters $\{T_i\}_{i=1}^N$, Υ, α^A, σ^A, σ^B, θ^A, θ^B. Initially, the wages that clear the market are equal to those in the data. I experiment here with unilateral increases in China's and in the U.S.A.'s technology parameters T_{China} and T_{USA}. I then recalculate equilibrium wages and utility levels.

Between 1984 and 1999 (the year of the data), China grew nearly four times relative to the rest of the world. To view the model's predictions of a continued growth in China, I experiment with a technology shock in China that increases its wages by 300% relative to the rest of the world. Figure 5 summarizes the results. The figure follows the same pattern as figure 4 explained above: The logarithm of initial wages are on the x-axis, and on the y-axis, the dots are share of type A goods in production, the triangles are the share of type A goods in demand, and the diamonds and crosses are the net supply of type A goods. The shock in China makes the 36 richest countries in the world better off (diamonds), and the vast majority of the remaining countries, worse off (crosses). As in the theoretical cases above, a technology shock in China decreases the relative price of type B goods, and consequently decreases wages in poor countries relative to rich ones. More specifically, wages in the world's 50 richest countries increase by 0.5% relative to the rest of the world. The largest wages increases are experienced by China's rich neighbors–Macao (6.7%), Hong Kong (5.8%), Singapore (1.9%)–and the largest wage decreases are experienced by some of its poor neighbors–Mongolia (-4.0%), Tajikistan (-1.9%), Kyrgyztan (-1.5%). Yet, for the same rationale of case (iii) above, welfare in the last three countries improves with the shock. The biggest utility losses are experienced by middle income countries–e.g., Malaysia, the Philippines, Thailand–the largest net importers of type A goods.

The effects of a technology shock in the U.S.A. have the opposite direction of those of the shock in China. As figure 6 shows, the shock makes most rich countries worse off, and all poor countries better off. (Figure 6 is analogous to figure 5.) A shock in the U.S.A. decreases the price of type A goods, and consequently decreases wages in rich countries relative to wages poor countries. A shock that increases American wages by 30% relative to the rest of the world decreases wages in the 30 richest countries in the sample by 1.6% relative to the rest of the world. The largest net exporters of type A goods are generally rich countries with neighbors poorer than themselves–e.g., Singapore, Japan, and Switzerland. These countries experience the largest utility losses with the shock in the U.S.A.

5 Conclusion

An integrated trade model, one that provides a single framework for trade among rich countries as well as trade among countries of differing 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 comparative advantage in technology or factor endowments. The model I have proposed delivers both these N-N and N-S patterns. Trade among rich countries occurs primarily within a sector whose goods are highly differentiated, while trade of rich with poor occurs across sectors.

A comparison of the quantitative trade flows of this integrated model to those of a gravity type model show the benefits of the integrated approach. Theoretical foundations of the gravity relationship are typically based on intra-industry trade of differentiated goods. So the EK gravity model does a good job of explaining trade among the rich OECD countries but not trade among countries at very different income levels. My integrated model, in turn, explains the N-N trade of OECD countries just as well as EK, and explains the N-N and N-S trade in the full sample much better than EK. My model, for example, correctly predicts that trade share increases with income per capita, and is largely unresponsive to total income. It also correctly predicts small volumes of trade among small, poor countries, and large volumes among rich countries.

Although I focused on macro-level trade data, my model has implications at the micro-level. Specifically, the parameter estimates imply that goods with high income elasticity of demand coincide with goods of high production heterogeneity. As a result, the model predicts that rich countries have a comparative advantage in producing the same goods that their consumers demand more intensely and that these goods are different from those produced and consumed more intensely in poor countries. I use micro-level trade data to verify this prediction in Fieler

(2007).

Adding dynamics is the most natural extension of my model. Throughout this paper, I have emphasized the connection between product cycles and the variability in production technologies in my model. A dynamic version of my model should be useful in studying the effects of non-homothetic preferences on technology diffusion, the evolution of trade, and growth.

6 Appendix

6.1 An Alternative Form for the Utility Function

The purpose of this appendix is to discuss the chosen form for 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 food, while rich ones spend more on luxuries. The main text explains how equation (1) captures this phenomenon (see equation (2) and its explanation). Despite its simplicity, the reader may feel uncomfortable with the role of σ^τ in demand having little to do with its original interpretation as the elasticity of substitution across goods. One way to solve this issue is to assume a more general form:

$$\sum_{\tau=1}^{S} \left\{ \alpha^\tau \frac{\sigma^\tau}{\gamma^\tau(\sigma^\tau - 1)} \left[\int_0^1 x(j^\tau)^{\sigma^\tau - 1/\sigma^\tau} dj^\tau \right]^{\gamma^\tau} \right\}.$$

Denote by $p(j^\tau)$ be the price of good $j^\tau \in [0,1]$ 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. Assuming first order conditions hold with equality, the Lagrangean multiplier corresponding to the consumer's problem satisfies

$$\lambda = \alpha^\tau \left[\int_0^1 p(j^\tau)^{1-\sigma^\tau} dj^\tau \right]^{1/(1-\sigma^\tau)}$$

for all τ. Since these conditions cannot hold simultaneously for arbitrary prices, the consumer will only demand products from the sector with lowest price index. More importantly, the Lagrangean multiplier and hence *consumer demand do not depend on income.* This leads us back to the homotheticity assumption: whenever consumers are faced with the same price, their demand for all goods are proportional to their income.

Case 2: $\gamma^\tau \neq \sigma^\tau/(\sigma^\tau - 1)$ for all τ. The ratio of expenditures in any two types of goods, τ and τ', equals

$$\frac{x^\tau}{x^{\tau'}} = \lambda^{\xi_1^\tau - \xi_1^{\tau'}} \left[\frac{(\alpha^\tau)^{\xi_1^\tau} \left(\int_0^1 p(j^\tau)^{1-\sigma^\tau} dj \right)^{\xi_2^\tau}}{(\alpha^{\tau'})^{\xi_1^{\tau'}} \left(\int_0^1 p(j^{\tau'})^{1-\sigma^{\tau'}} dj^{\tau'} \right)^{\xi_2^{\tau'}}} \right],$$

where λ is the consumer's Lagrangean multiplier, $\xi_1^\tau = -\sigma^\tau + \frac{\sigma^\tau(1-\sigma^\tau)(\gamma^\tau-1)}{\sigma^\tau+\gamma^\tau-\sigma^\tau\gamma^\tau}$ and $\xi_2^\tau = \frac{\gamma^\tau}{\sigma^\tau+\gamma^\tau-\sigma^\tau\gamma^\tau}$. As in the main text (equation (2)), the term in brackets determines the level of $x_\tau/x_{\tau'}$, and $(\lambda^{\xi_1^\tau - \xi_1^{\tau'}})$ 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 considered in the empirical analysis where sectors A and B are the only two sectors, γ^A and γ^B are not separately identifiable from σ^A, σ^B and α. For any set of prices p and parameters $(\sigma^A, \sigma^B, \gamma^A, \gamma^B)$, the parameter α can be judiciously chosen to match any desirable level of the ratio x^A/x^B. The rate of change of x^A/x^B, in turn, is ultimately determined by the the exponent of the Lagrangean multiplier, $(\xi_1^A - \xi_1^B)$. Parameters $(\sigma^A, \sigma^B, \gamma^A, \gamma^B)$, therefore, all play the same role and thus only one of them is sufficient to determine the value of $(\xi_1^A - \xi_1^B)$ – the rest can be normalized. In our chosen functional form, equation (1), γ^A and γ^B are set to 1.[18]

6.2 Normalization of parameters θ^A and σ^A

In section 3, I estimated the EK model by fixing the value of θ^A to 8.28. Table 4 shows the parameter estimates for $\theta^A = 3.60$, 8.28 and 12.86, the three estimates found by Eaton and Kortum (2002). An increase in θ^A decreases the variance of the distribution of technologies in equation 3, which decreases trade across all country pairs. So, in order to compensate for this change, parameters γ_1 and γ_2, capturing the effect of distance on transportation costs, must decrease as θ^A increases from 3.60 to 12.86. Apart from this change, the observations made in section 3 persist: The explanatory power of the model is the same for all values of θ^A, and the estimates for the EU and the NAFTA parameters are all implausibly low–they range from 0.47 to 0.70 implying that these agreements decrease trade barriers by some factor between 53% to 30%. The latter result is important because, as previously explained, it is indicative of the EK model's inability to reconcile the large volumes of trade among rich nations to the small volumes observed for poor economies.

Table 5 shows the results of the new model, when the values of θ^A and σ^A change. The

[18] The fact that the term $\left[\int_0^1 p(j^\tau)^{1-\sigma^\tau}\right]$ has an exponent in case 2 but not in the original text does not change the analysis either. In the same way that γ^A and γ^B are confounded with other parameters of the utility function, the exponent ξ_2^A is not be separately identifiable from the parameters in the production side of the economy.

newly chosen values for σ^A, 2.20 and 6.60, were both taken from Broda and Weinstein's (2006) estimates for the elasticity of substitution across goods. (Their estimates vary depending on the level of aggregation of products and on whether the mean or the median is picked.) And the conclusions drawn in section 3.2 again persist. The explanatory power of the new model changes only slightly as θ^A and σ^A vary. For all values of θ^A and σ^A, the parameter estimates satisfy $\alpha \in (0,1)$, $\sigma^A > \sigma^B$ and $\theta^A < \theta^B$, thus indicating that the previously given explanation for the effects of non-homotheticity of preferences on trade patterns remains the same.

One way to pin down the values of θ^A or σ^A in both models is to compare the iceberg costs implied in the parameter estimates to direct measures of transportation costs. Anderson and Wincoop (2004), for example, estimate that trade costs in OECD countries are equivalent to an ad-valorem tax of approximately 74%. Of all the values of θ^A or σ^A shown on tables 4 and 5, the selected ones, $\theta^A = 8.28$ and $\sigma^A = 4.00$, are the ones that best approximate Anderson and Wincoop's figure in both models. In the EK model, transportation costs $(d_{ni} - 1)$ between U.S. and Germany are estimated to 110% and those between the U.S. and Canada, to 49%; in the new model, estimates for these same costs are 133% and 49%, respectively. The other parameter estimates on tables 4 and 5 generate either much higher or much lower iceberg costs. The conclusions from this exercise, however, should not be stretched because measurement errors in transportation costs are extremely large, and estimates vary tremendously across goods and countries.

6.3 Confidence intervals

to be completed

6.4 Estimates with different weighting matrices, W

In estimating the EK and the new model, I chose the parameters that minimized $(X_{ni} - \hat{X}_{ni})'W(X_{ni} - \hat{X}_{ni})$ on equation (14), where W was parameterized to be a diagonal matrix with the element corresponding to country n's imports from country i equal to $(X_n X_i)^{-\kappa}$. In the main text, I focused exclusively on the case where $\kappa = 1.0$. In this appendix, I present a summary of the results from estimating both the EK and the new model for several values of $\kappa \in [0.2]$. Or more specifically, for all $\kappa \in \{0, 0.1, 0.2, ..., 1.9, 2.0\}$.

The most straightforward comparison between the performance of my model and EK's is through the objective function. Using the same normalization of section 3, I refer to

$$1 - \left\{ \frac{(X_{ni} - \hat{X}_{ni})' W (X_{ni} - \hat{X}_{ni})}{X'_{ni} W X_{ni}} \right\}$$

as the model's explanatory power. Figure 7 plots the explanatory power of the new model and of the EK model as a function of κ. The new model explains the data better than the EK model for all values of $\kappa \in [0, 2]$. An additional comparison of interest in figure 7 is that between the EK model with the full sample to the one with the reduced sample, containing only OECD countries. This comparison confirms that the EK model predicts well trade among wealthy countries, but performs poorly when a lot of small, poor economies are added to the sample–the curve of the EK model with the full sample lies everywhere well below the one for the reduced sample. Note also that when $\kappa = 0$ all three curves lie close together. By definition, the weight in the objective function of trade among large economies with respect to trade among small ones is decreasing in κ. When $\kappa = 0$, the observations that receive the greatest weight in the objective function are precisely the ones where both the importer and the exporters are the large, OECD countries. So, the finding that the explanatory power of the proposed model (83%) is only marginally greater than that of the EK model (82%) shows that the true contribution of the proposed model occurs only when the sample contains a combination of small and poor, with large and wealthy countries.

On the other extreme, when $\kappa = 2$, the objective function places a lot of weight on the zero trade flows observed among small countries. As a result, both models grossly underestimate trade–the explanatory power of the EK is only 1% and that of the new model, 9%.

Figure 2 discussed in section 3 depicts the relation between trade share (*i.e.*, $\frac{\text{imports + exports}}{2{*}\text{GDP}}$) and income, comparing the data to the predictions of the two models. Figure 8 summarizes the equivalent figure for all values of $\kappa \in [0, 2]$ by plotting κ against the coefficient on GDP per capita in the regression of trade share on a constant and on the logarithm of GDP (*i.e.*, the slope of the regression line illustrated in figure 2). Analogously, figure 9 plots the slope of the regression line illustrated in figure 3, obtained from regressing trade share on a constant and on the logarithm of total GDP. In both figures 8 and 9, the horizontal line represents the slope as observed in the data; the curve marked by diamonds refer to the proposed model, and that marked by asterisks refer to the EK model.

Unquestionably, the curves corresponding to the proposed model are persistently closer to the line of the data than the curves of the EK model are. According to the data, the correlation between a country's trade share and its total income is approximately zero, while the correlation between trade share and income per capita is positive and statistically significant–the slopes in figures 2(a) and 3(a) equal 0.004 and 0.030, respectively, and their standard errors are 0.007 and 0.009. The new model captures the first of these trends for all values of $\kappa \geq 1.1$ (figure 8) and the second for all $\kappa \geq 0.8$ (figure 9). When $\kappa \leq 0.7$, both models fail to reproduce these two trends in the data, predicting instead large, negative and statistically significant correlations between trade share and income, and trade share and income per capita. For these low values of κ, the contribution of trade to and from small poor countries in the objective function is very small, and consequently these countries are largely ignored in the estimation of both models, especially of the EK model.[19]

In section 3, I discussed how, contradicting the evidence in the data, the EK model predicts a negative or near zero correlation between income per capita and trade share, and a strong negative correlation between total income and trade share. While this assertion clearly holds for all values of $\kappa \leq 1.3$, figures 8 and 9 can give the misleading impression that the EK model is able to capture the trends in the data for $\kappa \geq 1.4$. It is not so. The slopes plotted in these figures are distorted because of the EU and NAFTA parameters. For $\kappa \in [1.4, 2]$, the EU parameter in the EK model ranges from 0.46 to 0.31, and the NAFTA parameter ranges from 0.29 to 0.21, which implies implausibly that these trade agreements decrease iceberg costs across its participants by at least 54% and up to 79%. The model, in this fashion, estimates large trade shares for the participants of the the EU and the NAFTA, a prediction which increases the values of the

[19] To give a concrete example, when $\kappa = 0$, the trade share of the 43 smallest economies in the sample are all greater than 95% according to the EK model, and they average 79% in my model. By contrast, the data show that the trade share of these economies never exceeds 73% and is only 27% on average.

slopes plotted in figures 8 and 9, because the participants of these agreements are on average larger and wealthier than most countries in the sample. If, however, EU and NAFTA countries are excluded from the sample in the calculation of the slopes in figures 8 and 9, the conclusions drawn in the main text hold for all values of $\kappa \geq 1.4$: In both the data and the predictions of the new model, there is a positive and statistically significant at a 1% level correlation between a country's trade share and its income per capita, and a small and insignificant correlation between trade share and total income; in the EK model, the relation between a country's trade share and its income per capita is negative or close to zero, while that between trade share and income is strong, negative and statistically significant at a 1% level.

The last point I make in the empirical analysis concerns the amount of trade flows too small to be captured in the data. Trade flows whose values are US$100,000 are not registered, and 10,816 country pairs have no registered trade. Figure 10 compares 10,816 to the number of trade flows predicted in the EK and in the new model, whose values are smaller than US$100,000. As before, the curve marked with diamonds refer to the new model, and that with asterisks to the EK model. As I have insisted throughout the paper, the EK model, in its inability to conciliate the small trade flows observed across small, poor economies with the large flows observed across large, wealthy economies, tends to overestimate trade among small, poor countries. One of the consequences of this overestimation is that, for all $\kappa \leq 1.5$, the EK model predicts less than 1,000 bilateral trade flows valuing less than US$100,000, which is inexpressible compared to the 10,816 zero bilateral flows found in the data (see figure 10). When $\kappa \geq 1.6$, on the other hand, the entry of the weighting matrix $W_{ni} = (X_n X_i)^{-\kappa}$ is so large when both the importing and exporting countries are small that the EK and the new model focus almost exclusively on these country pairs. By trying to predict the small volumes of trade observed across these pairs, the models underestimate trade for virtually all countries. When $\kappa = 2$, for example, the number of countries trading less than 1% of their incomes is 122 according to the EK model and 10 according to the new model; in the data, the smallest trade share in the world is Rwanda's and it is equal to 4%.

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Table 1: summary of country data (1/3)

Country	Imports from the sample as a % of total imports	GDP (1999 US$ BI)	GDP per capita (1999 US$)	Institutional infrastructure index
Albania	100	3.4	1,112	-0.6
Algeria	99	48	1,589	-1.1
Angola	90	6.2	511	-1.8
Argentina	98	284	7,789	0.2
Armenia	100	1.85	587	-0.7
Australia*	93	404	21,295	1.6
Austria*	98	210	26,271	1.6
Azerbaijan	100	4.6	574	-0.9
Bahamas	100	4.6	15,275	0.9
Bahrain	100	6.6	10,093	0.2
Bangladesh	100	44	344	-0.5
Barbados	100	2.5	9,277	-
Belarus	100	10.9	1,090	-1.1
Belgium, Luxembourg*	98	271	25,436	1.2
Belize	100	0.73	3,021	0.2
Benin	98	2.4	394	0.0
Bolivia	100	8.3	1,016	-0.2
Brazil	97	529	3,151	0.1
Bulgaria	99	13	1,578	0.0
Burkina Faso	100	2.8	256	-0.4
Burundi	96	0.71	107	-1.4
Cambodia	100	3.5	278	-0.6
Cameroon	99	9.2	621	-0.8
Canada*	98	651	21,352	1.6
Central African Rep.	99	1.05	286	-0.7
Chad	100	1.53	201	-0.7
Chile	97	73	4,864	1.1
China	84	991	791	-0.4
Colombia	98	86	2,075	-0.6
Congo	96	2.4	705	-1.4
Costa Rica	100	16	4,235	0.9
Cote d'Ivorie	99	13	812	-0.8
Croatia	100	20	4,375	0.2
Cyprus	100	9.6	12,752	0.9
Czech Rep.	99	59	5,743	0.6
Dem. Rep. Congo	65	4.7	98	-2.2
Denmark*	98	173	32,548	1.7
Dep. of Reunion	89	0.22	410	-
Djibouti	99	0.54	824	-
Dominican Rep.	100	17	2,114	0.0
Ecuador	98	17	1,364	-0.8
Egypt	100	89	1,419	-0.2
El Salvador	100	12.5	2,038	0.1
Equatorial Guinea	98	0.87	1,954	-
Estonia	100	5.6	4,038	0.9
Finland*	96	128	24,750	1.9
France, Monaco*	97	1,444	24,629	1.2
Gabon	98	4.4	3,540	-0.6

* OECD country

Table 1: List of countries in the sample

Table 1: summary of country data (2/3)

Country	Imports from the sample as a % of total imports	GDP (1999 US$ BI)	GDP per capita (1999 US$)	Institutional infrastructure index
Gambia	99	0.43	341	-0.3
Georgia	100	2.8	586	-0.7
Germany*	98	2,108	25,680	1.5
Ghana	96	7.7	400	-0.1
Greece*	97	120	11,032	0.8
Guatemala	100	18	1,652	-0.5
Guinea	98	3.5	477	-0.8
Guyana	100	0.68	897	-0.1
Haiti	100	4.2	532	-1.2
Honduras	100	5.4	862	-0.3
Hong Kong	92	161	24,313	1.0
Hungary	99	48	4,772	0.8
Iceland	100	8.4	30,362	1.8
India	83	447	447	-0.1
Indonesia	88	140	688	-0.9
Iran	91	93	1,481	-0.7
Ireland	98	95	25,376	1.6
Israel	97	104	16,955	0.7
Italy*	97	1,180	20,478	0.8
Jamaica	100	7.2	2,813	0.1
Japan*	88	4,453	35,160	1.1
Jordan	100	8.1	1,716	0.2
Kazakhstan	99	17	1,103	-0.6
Kenya	89	10.6	359	-0.9
Korea	89	445	9,549	0.5
Kuwait	88	29	13,851	0.3
Kyrgyzstan	100	1.25	257	-0.7
Latvia	100	7.2	3,021	0.4
Lebanon	100	17	3,951	-0.3
Libya	100	30	5,935	-1.3
Lithuania	100	10.8	3,070	0.4
Macau	100	6.1	14,265	-
Macedonia	100	3.7	1,821	-0.4
Madagascar	94	3.7	247	-0.3
Malawi	37	1.78	176	-0.3
Malaysia	93	79	3,485	0.2
Mali	96	2.6	243	-0.2
Malta	100	3.6	9,396	0.7
Mauritania	100	0.96	373	-0.6
Mauritius	87	4.2	3,555	0.8
Mexico	99	481	4,982	-0.1
Mongolia	100	0.91	381	0.3
Morocco	93	35	1,248	0.0
Mozambique	42	4.0	230	-0.4
Nepal	100	5.0	224	-0.6
Netherlands*	96	399	25,216	1.8
New Zealand*	95	57	14,982	1.6
Nicaragua	100	3.7	757	-0.4

* OECD country

Table 1: summary of country data (3/3)

Country	Imports from the sample as a % of total imports	GDP (1999 US$ BI)	GDP per capita (1999 US$)	Institutional infrastructure index
Niger	100	2.0	194	-0.6
Nigeria	96	35	281	-1.0
Norway*	98	158	35,448	1.5
Oman	67	16	6,691	0.6
Pakistan	81	63	467	-0.9
Panama	100	11.5	4,076	0.2
Papua New Guinea	100	3.4	682	-0.6
Paraguay	100	7.7	1,503	-0.9
Peru	99	51	2,009	-0.2
Philippines	90	76	1,017	-0.2
Poland	98	164	4,254	0.6
Portugal*	98	115	11,313	1.2
Qatar	83	12.4	21,930	0.5
Rep. Moldova	99	1.17	273	-0.7
Romania	98	36	1,585	-0.3
Russian Fed.	98	196	1,339	-0.9
Rwanda	95	1.93	258	-0.8
Senegal	99	4.8	512	-0.3
Seychelles	89	0.62	7,747	-
Singapore	91	81	20,592	1.6
Slovakia	98	20	3,783	0.4
Slovenia	99	21	10,689	0.8
Spain*	97	602	14,984	1.3
Sri Lanka	99	16	860	-0.5
Sudan	100	10.7	349	-1.5
Suriname	100	0.89	2,109	-0.2
Sweden*	99	251	28,374	1.7
Switzerland, Liechtenstein	99	265	37,097	1.8
Syria	100	16	1,005	-0.9
Tajikistan	99	1.09	179	-1.3
Tanzania	84	8.6	262	-0.4
Thailand	90	122	2,031	0.2
Togo	99	1.58	360	-0.9
Trindad Tobago	100	6.8	5,310	0.5
Tunisia	98	21	2,200	0.3
Turkey	96	184	2,773	-0.3
Turkmenistan	100	2.5	537	-1.3
U. S. A.*	95	9,216	33,028	1.5
Uganda	89	6.0	264	-0.7
Ukraine	100	32	633	-0.8
United Kingdom*	97	1,462	24,898	1.6
Uruguay	100	21	6,332	0.8
Uzbekistan	100	17	700	-1.2
Venezuela	97	98	4,105	-0.7
Yemen	100	7.5	439	-0.8
Yugoslavia	89	10.2	961	-0.9
Zambia	36	3.1	323	-0.5
Zimbabwe	42	5.5	443	-1.2

* OECD country

	OECD only	Full sample	
	EK = New model	EK model	New model
Explanatory power	**84%**	**30%**	**49%**
Normalized parameters			
σ^A			4.00
θ^A	8.28	8.28	8.28
Estimated parameters			
γ_1	1.49	1.72	1.74
γ_2	0.34	0.28	0.19
γ_3	-0.06	-0.05	-0.02
border	0.92	0.78	0.80
language	0.88	0.90	0.74
EU	0.90	0.75	0.75
NAFTA	0.64	0.52	0.72
α^A			0.63
σ^B			2.43
θ^B			14.28

Table 2: Estimation Results

Table 3: Distribution of residuals by importer (1/3)

Country	EK model	New model	Δ = EK - New model
Albania	0.1	0.0	0.0
Algeria	0.2	0.1	0.1
Angola	0.1	0.0	0.0
Argentina	0.2	0.1	0.1
Armenia	0.0	0.0	0.0
Australia	0.4	0.4	0.0
Austria	0.2	0.8	-0.6
Azerbaijan	0.1	0.0	0.0
Bahamas	0.1	0.1	0.0
Bahrain	0.1	0.1	0.0
Bangladesh	0.1	0.1	0.0
Barbados	0.0	0.0	0.0
Belarus	2.0	2.2	-0.2
Belgium, Luxembourg	1.3	1.3	0.0
Belize	0.0	0.1	0.0
Benin	0.1	0.0	0.1
Bolivia	0.1	0.0	0.0
Brazil	0.1	0.1	0.0
Bulgaria	0.3	0.2	0.0
Burkina Faso	0.1	0.0	0.1
Burundi	0.0	0.0	0.0
Cambodia	0.2	0.2	0.0
Cameroon	0.1	0.1	0.0
Canada	0.2	0.1	0.1
Central African Rep	0.0	0.0	0.0
Chad	0.0	0.0	0.0
Chile	0.1	0.1	0.0
China	0.5	0.9	-0.4
Colombia	0.1	0.1	0.1
Congo	0.1	0.0	0.1
Costa_Rica	0.2	0.1	0.1
Cote d'Ivorie	0.5	0.5	0.0
Croatia	0.3	0.3	0.0
Cyprus	0.1	0.1	0.0
Czech Rep.	0.8	1.1	-0.3
Dem. Rep. Congo	0.1	0.0	0.1
Denmark	0.1	0.4	-0.2
Dep. of Reunion	0.0	0.0	0.0
Djibouti	0.0	0.0	0.0
Dominican Rep	0.1	0.1	0.1
Ecuador	0.1	0.0	0.0
Egypt	0.2	0.2	0.0
El Salvador	0.2	0.0	0.2
Eq_Guinea	0.0	0.0	0.0
Estonia	0.8	0.8	0.0
Finland	0.3	0.6	-0.4
France, Monaco	0.3	0.4	-0.1
Gabon	0.1	0.0	0.1
Gambia	0.0	0.0	0.0
Georgia	0.0	0.0	0.0

Table 3: Distribution of residuals by importing country

Table 3: Distribution of residuals by importer (2/3)

Country	EK model	New model	Δ = EK - New model
Germany	1.1	1.2	-0.1
Ghana	0.2	0.2	0.0
Greece	0.1	0.1	0.0
Guatemala	0.2	0.0	0.2
Guinea	0.1	0.0	0.1
Guyana	0.0	0.0	0.0
Haiti	0.1	0.0	0.1
Honduras	0.2	0.1	0.1
Hong Kong	15.1	8.5	6.6
Hungary	0.5	0.4	0.0
Iceland	0.1	0.0	0.0
India	0.5	0.5	0.0
Indonesia	0.2	0.2	0.1
Iran	0.1	0.2	0.0
Ireland	0.3	0.3	0.0
Israel	0.5	0.7	-0.2
Italy	0.5	0.6	-0.1
Jamaica	0.1	0.0	0.0
Japan	0.6	0.5	0.1
Jordan	0.2	0.1	0.1
Kazakhstan	0.2	0.2	0.0
Kenya	0.1	0.0	0.1
Korea	0.6	0.7	-0.1
Kuwait	0.1	0.1	0.0
Kyrgyzstan	0.0	0.0	0.0
Latvia	0.2	0.2	0.0
Lebanon	0.2	0.1	0.1
Libya	0.1	0.1	0.1
Lithuania	0.2	0.2	0.0
Macau	0.1	0.1	-0.1
Macedonia	0.2	0.3	0.0
Madagascar	0.0	0.0	0.0
Malawi	0.0	0.0	0.0
Malaysia	4.2	1.5	2.7
Mali	0.1	0.0	0.0
Malta	0.2	0.2	0.0
Mauritania	0.0	0.0	0.0
Mauritius	0.0	0.0	0.0
Mexico	0.2	0.1	0.1
Mongolia	0.0	0.0	0.0
Morocco	0.1	0.1	0.1
Mozambique	0.0	0.0	0.0
Nepal	0.0	0.0	0.0
Netherlands	0.5	0.5	0.0
New Zealand	0.2	0.1	0.1
Nicaragua	0.1	0.0	0.1
Niger	0.1	0.0	0.0
Nigeria	0.2	0.1	0.1
Norway	0.2	0.8	-0.6
Oman	0.1	0.1	0.0

Table 3: Distribution of residuals by importer (3/3)

Country	EK model	New model	Δ = EK - New model
Pakistan	0.3	0.2	0.1
Panama	0.8	0.8	0.0
Papua New Guinea	0.1	0.1	0.0
Paraguay	0.1	0.1	0.0
Peru	0.1	0.1	0.0
Philippines	0.4	0.4	0.1
Poland	0.2	0.3	-0.1
Portugal	0.1	0.2	0.0
Qatar	0.1	0.7	-0.6
Rep. Moldova	0.1	0.1	0.0
Romania	0.1	0.1	0.0
Russian Fed.	2.1	2.9	-0.8
Rwanda	0.1	0.0	0.0
Senegal	0.2	0.1	0.0
Seychelles	0.0	0.0	0.0
Singapore	17.0	5.4	11.6
Slovakia	0.9	1.2	-0.3
Slovenia	0.1	0.2	-0.1
Spain	0.3	0.3	0.0
Sri Lanka	0.1	0.1	0.0
Sudan	0.1	0.0	0.1
Suriname	0.0	0.0	0.0
Sweden	0.3	0.6	-0.3
Switzerland, Liechtenstein	0.2	1.3	-1.0
Syria	0.3	0.1	0.2
Tajikistan	0.1	0.0	0.0
Tanzania	0.1	0.0	0.1
Thailand	1.0	1.0	0.0
Togo	0.1	0.0	0.0
Trindad Tobago	0.1	0.0	0.0
Tunisia	0.1	0.1	0.1
Turkey	0.2	0.4	-0.2
Turkmenistan	0.0	0.0	0.0
Uganda	0.1	0.0	0.1
UK	0.5	0.6	0.0
Ukraine	1.0	1.3	-0.2
Uruguay	0.1	0.0	0.1
USA	1.4	1.6	-0.2
Uzbekistan	0.1	0.0	0.1
Venezuela	0.1	0.1	0.0
Yemen	0.1	0.0	0.0
Yugoslavia	0.2	0.2	0.0
Zambia	0.1	0.0	0.1
Zimbabwe	0.1	0.0	0.1
Σ	**70**	**51**	**19**

	original		
θ^A	**8.28**	**3.60**	**12.86**
explanatory power	30%	30%	30%
γ_1	1.72	3.73	1.42
γ_2	0.28	0.74	0.12
γ_3	−0.05	−0.07	−0.02
border	0.78	0.71	0.81
language	0.90	0.89	0.92
EU	0.75	0.70	0.78
NAFTA	0.52	0.47	0.55

Table 4: Estimates of the EK model with different values for θ^A

	original				
θ^A	**8.28**	**3.60**	**12.86**	8.28	8.28
σ^A	**4.00**	4.00	4.00	**2.20**	**6.60**
explanatory power	49%	47%	49%	50%	47%
γ_1	1.74	3.18	1.46	1.71	1.65
γ_2	0.19	0.22	0.08	0.18	0.10
γ_3	−0.02	−0.01	−0.01	−0.01	−0.01
border	0.80	0.72	0.77	0.77	0.79
language	0.74	0.69	0.82	0.78	0.78
EU	0.75	0.92	0.73	0.72	0.89
NAFTA	0.72	0.77	0.69	0.67	0.78
α^A	0.63	0.60	0.55	0.56	0.57
σ^B	2.43	1.88	2.82	1.41	6.09
θ^B	14.28	10.52	18.29	13.34	19.97

Table 5: Estimates of the new model with different values for θ^A and σ^A

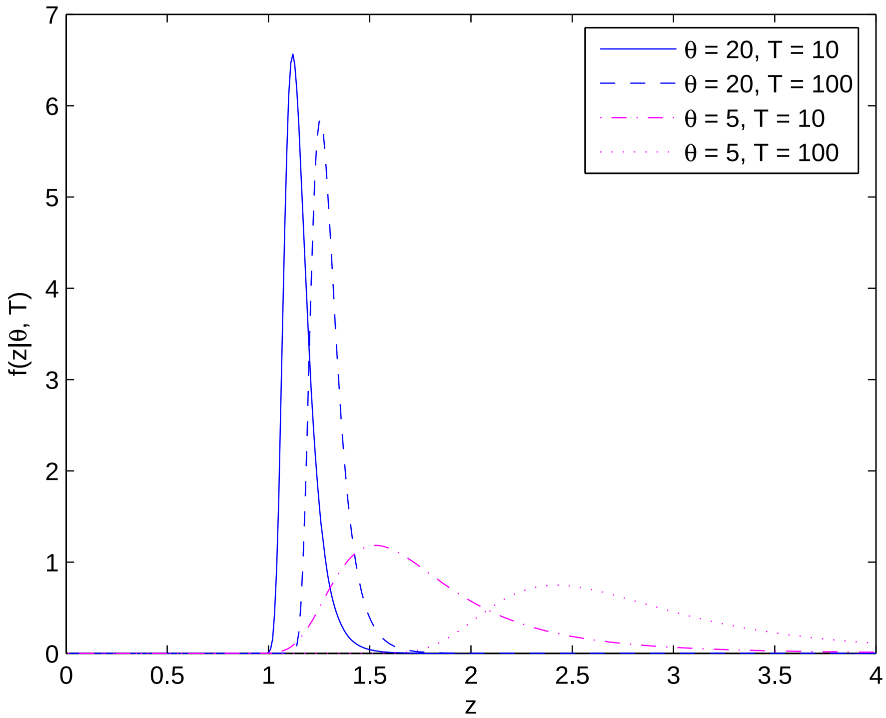
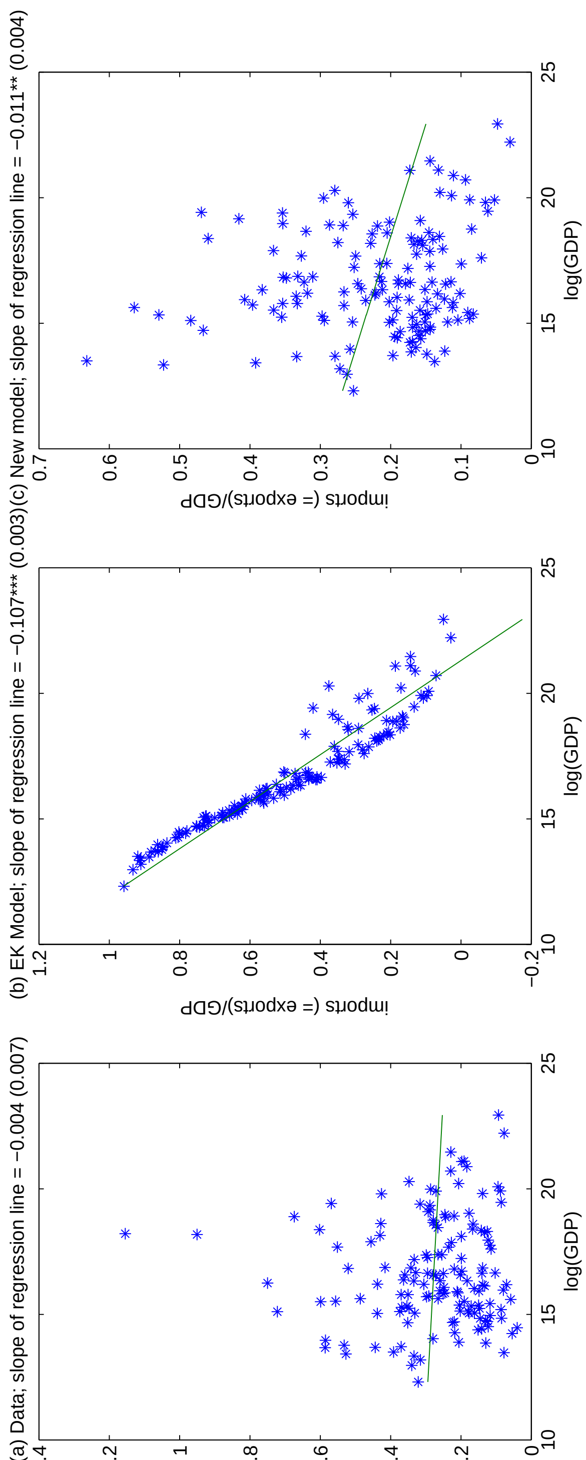


Figure 1: Examples of Fréchet Distributions



51

Figure 2: Total income × trade share

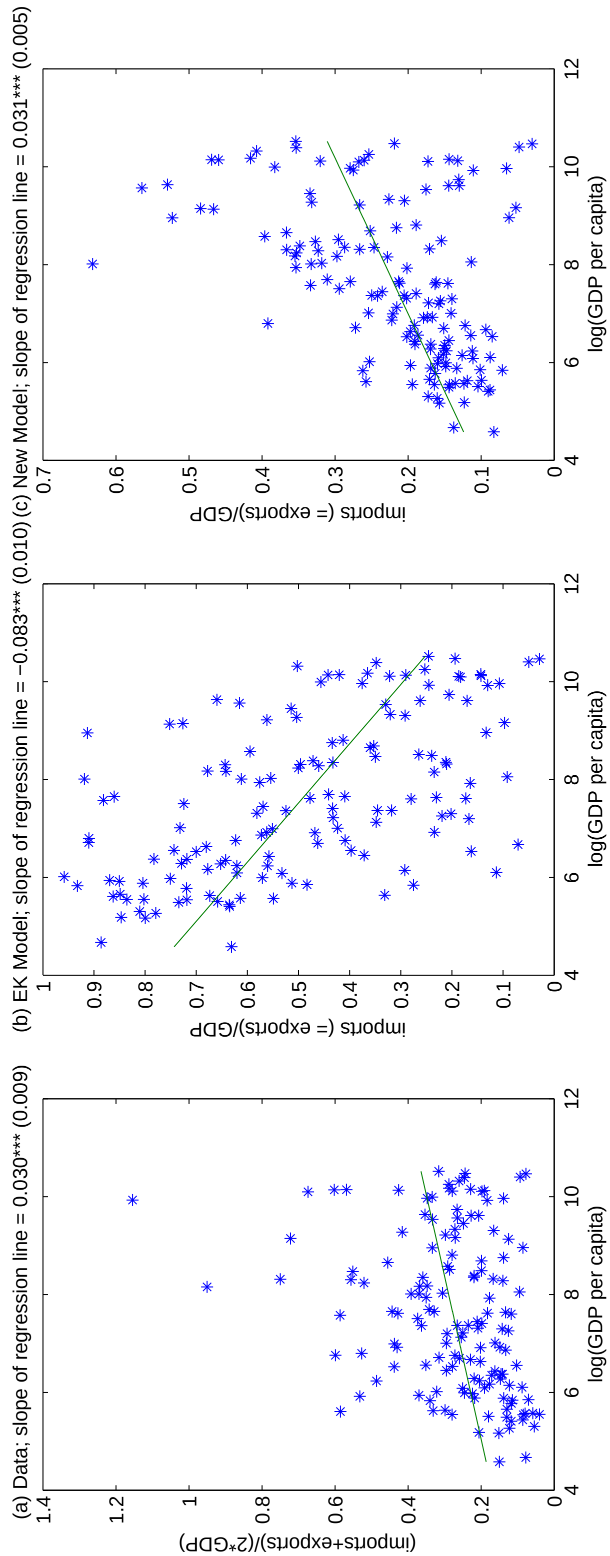


Figure 3: Income per capita × trade share

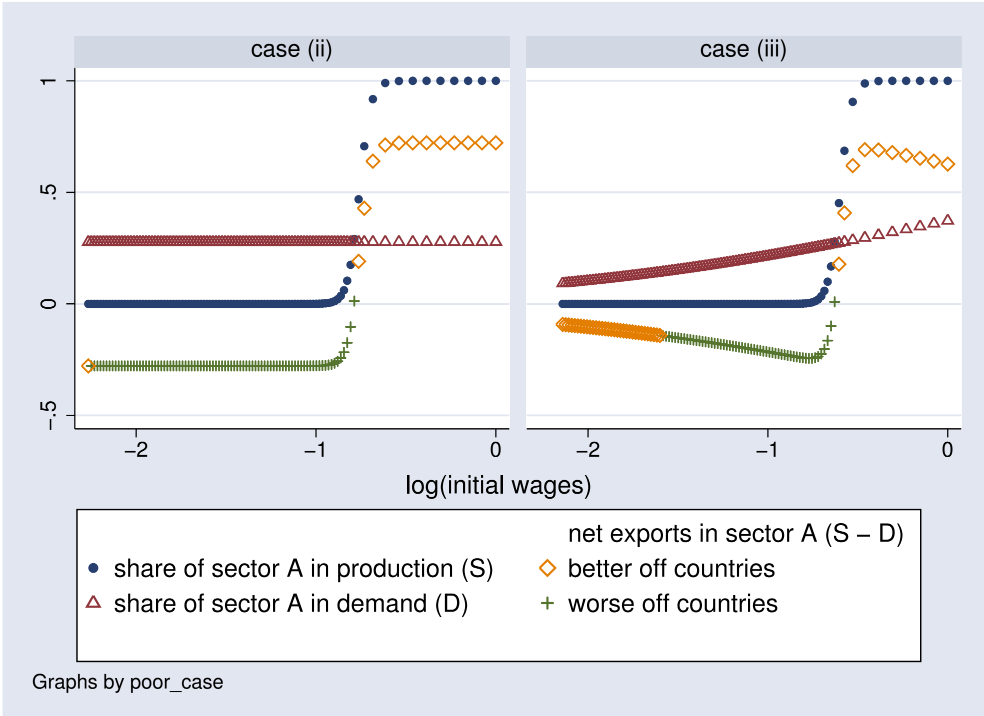


Figure 4: Simulation of a technology shock in the poorest country

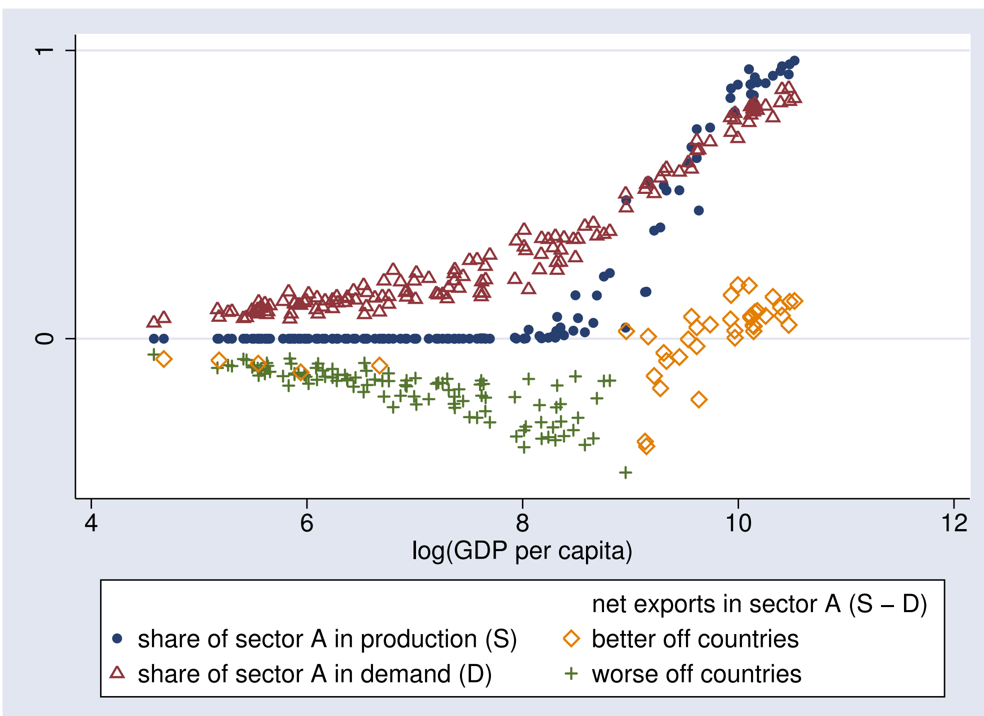


Figure 5: Technology shock in China

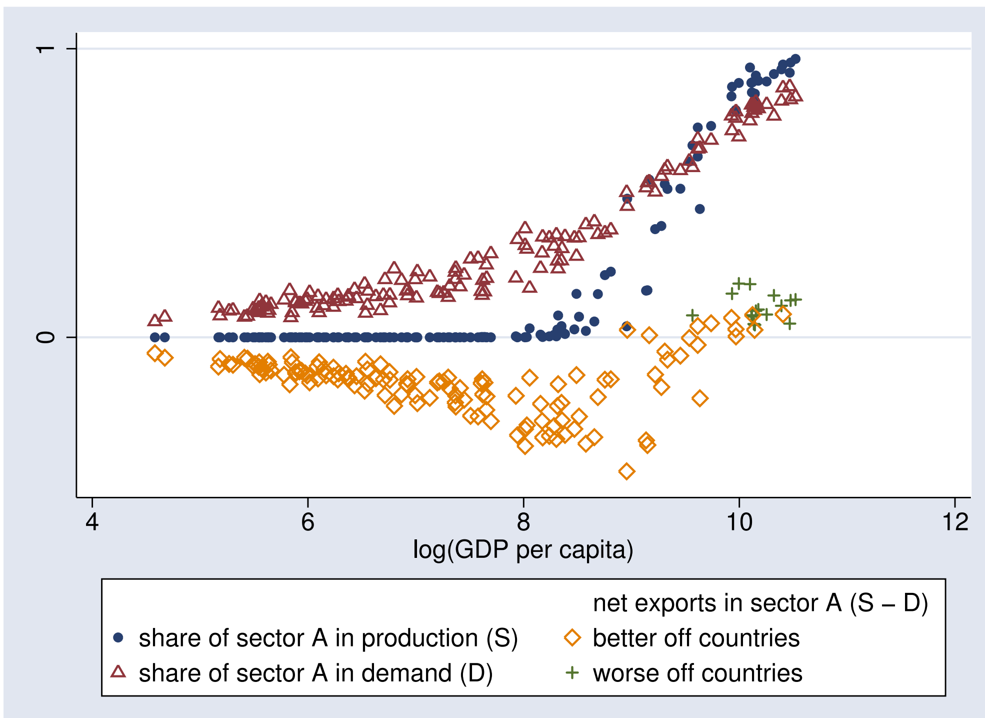


Figure 6: Technology shock in the U.S.A.

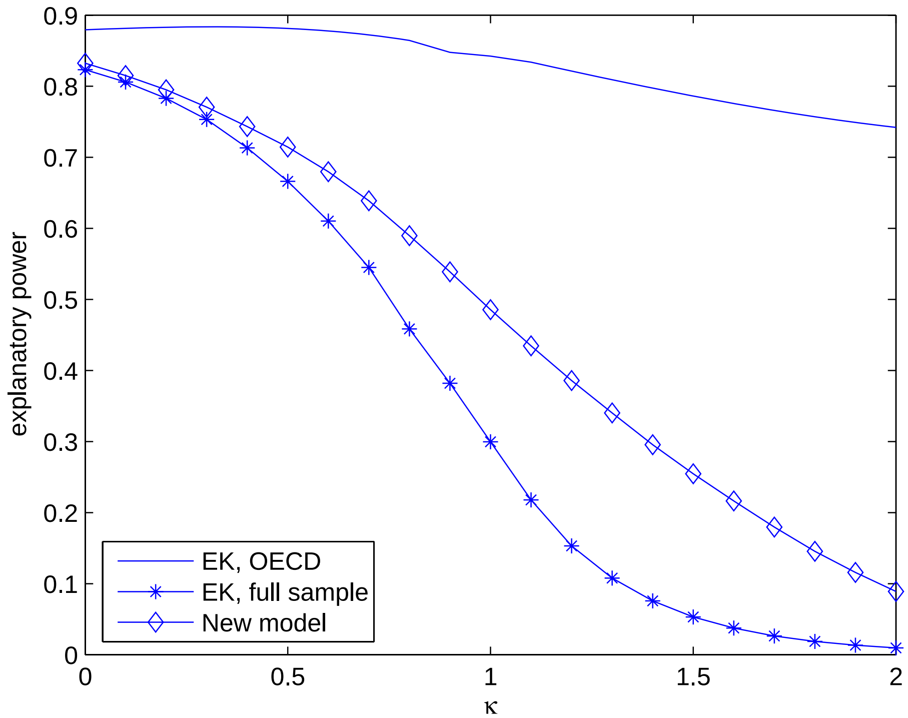


Figure 7: Explanatory Power of the EK and New Model

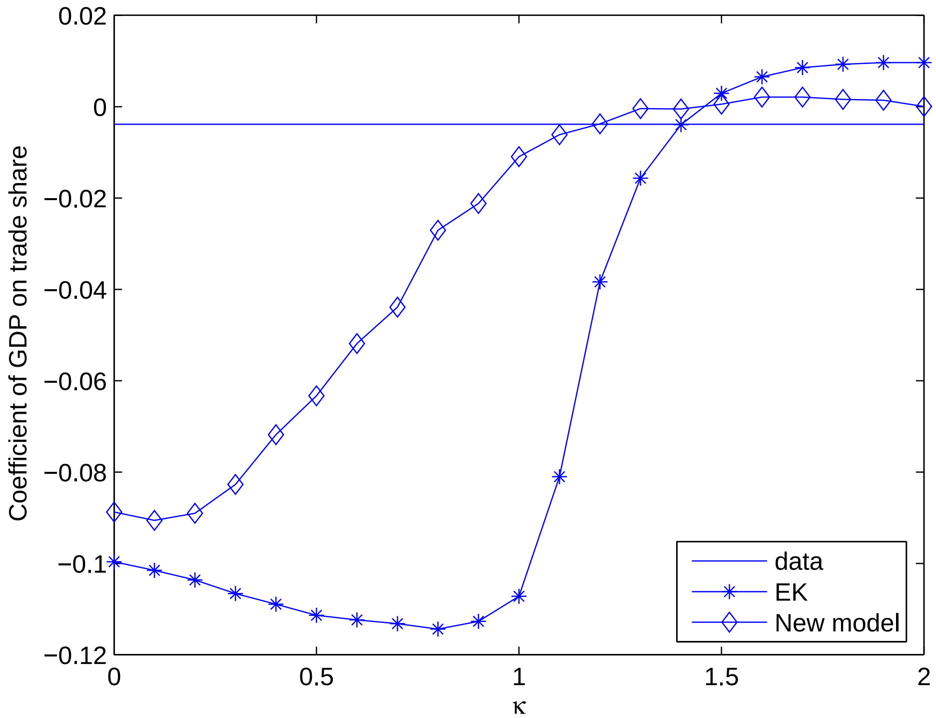


Figure 8: Coefficient of GDP on trade share

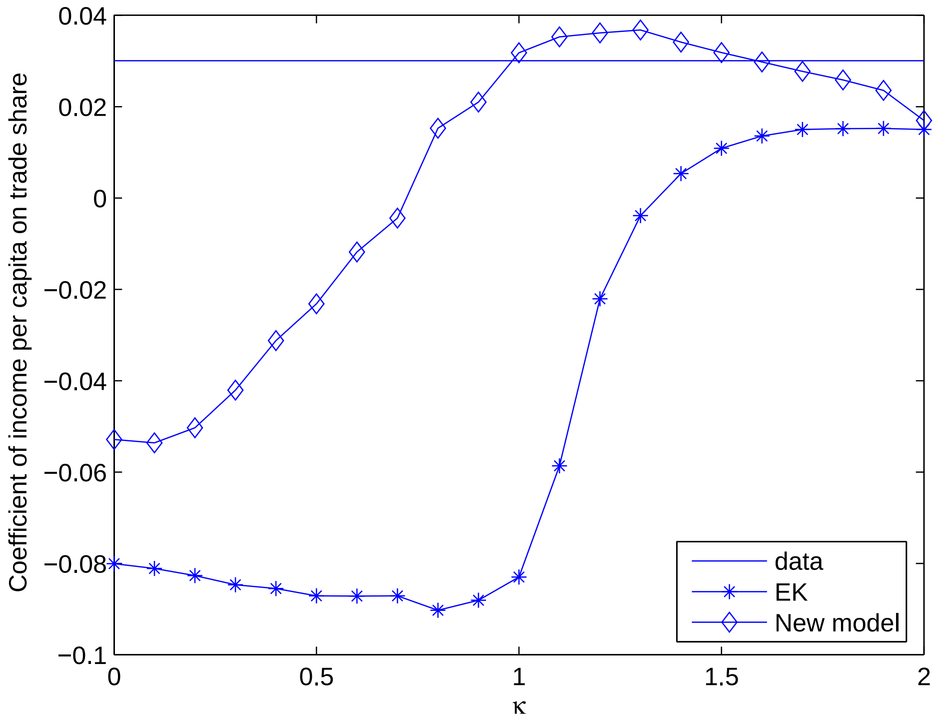


Figure 9: Coefficient of GDP per capita on trade share

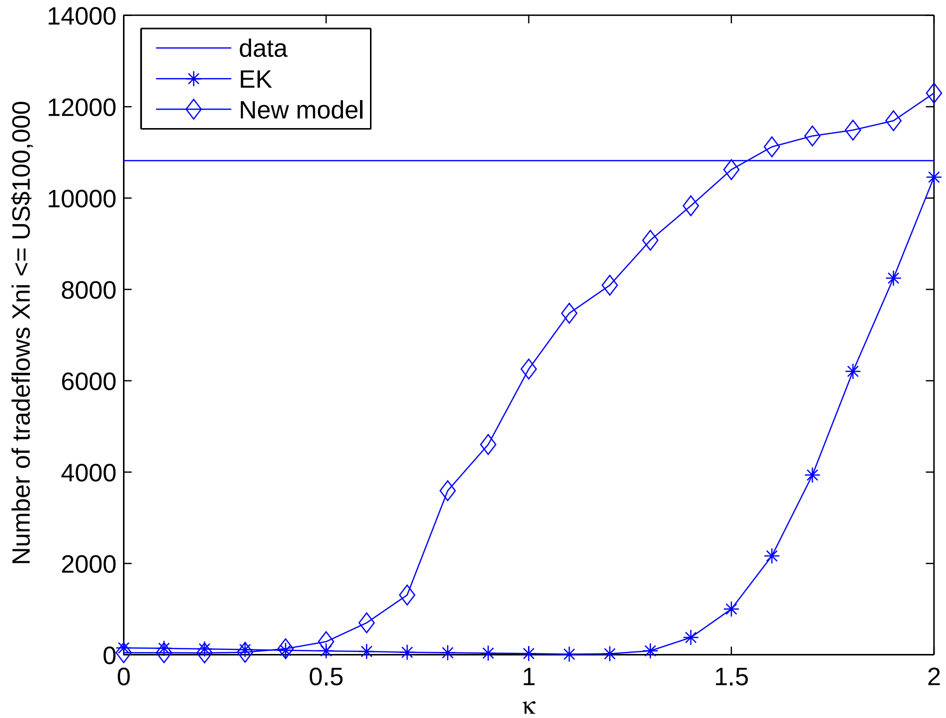


Figure 10: Small Numbers