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 elasticity of trade with respect to income per capita and population 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 estimate the model using data on the bilateral trade flows of 162 countries and compare its quantitative implications to those of a special case in which the model delivers the gravity equation. 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, doubling a country's GDP decreases its trade share by 3% according to the data, 6% according to the general model and by 23% according to 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. In contrast, the restricted model implies that a technology shock in one country increases the welfare of all countries.

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1 Introduction

It is well known that poor countries trade much less than rich countries, both with each other and with the rest of the world. In 2000, for example, transactions to and from the twelve Western European countries alone accounted for 45% of international merchandize trade, 36% of which was intra Western European. The fifty-seven African economies, in contrast, accounted for only 4.2% of world trade, and intra African trade, a meager 0.2%. Intra Western European trade accounts for 14% of Western European GDP, while intra African trade accounts for only 2.7% of African GDP. Doubling a country's income per capita increases trade (average between imports and exports) as a share of GDP by 1.7% on average, while doubling a country's population decreases its trade share by 2.0%. Despite these differences, standard models of international trade, which typically yield a gravity relationship, predict that trade increases in proportion with both importer and exporter total income, and ignore how total income is divided into income per capita and population.

Protectionist policies and high transport costs are the usual explanations for the small volume of trade in poor countries. But even after controlling for tariffs and direct measures of trade costs, income per capita continues to have a significant, increasing effect on trade–e.g., Coe and Hoffmaister (1998), Limão and Venables (2001), Rodrik (1998). Further, this explanation does not take incentives into account–the low quality of infrastructure in poor countries, for example, may simply be a result of poor countries' lack of incentives to trade.

This paper takes an alternative, probably concomitant, view. I purposely abstract away from differences in trade costs across countries and focus instead on two assumptions of gravity type models that are inconsistent with micro-level evidence. The first assumption is homothetic preferences. There is exhaustive evidence that the income elasticity of demand varies across goods, and that this variation is economically significant–e.g., Bils and Klenow (1998), Deaton (1975), Grigg (1994), Hunter (1991). Food, for example, has a low income elasticity. Expenditures on it ranged in the early 1980s from 64% in Tanzania to less than 15% in Australia and North America (Grigg (1994)). The second assumption is homothetic supply. Typically in gravity models, production in poor and rich countries differs only in quantitative, not qualitative, aspects. This assumption is at odds with the theory of product cycle and with empirical evidence on technology diffusion–e.g, Comin and Hobjin (2006), Nabseth and Ray (1974), Romer (1990), Vernon (1966). When a good is first invented, the argument goes, the technology to produce it differs greatly across countries (most of which do not know how to make it). At this stage, the good is generally produced in the, typically high income, country where it was invented. Methods to produce it become standardized as the product matures and they can then be applied similarly to any country, including those where labor is cheap. In a cross-section, one should thus expect poor countries to produce disproportionately more goods whose technologies have already diffused and are therefore similar across countries.

I propose an analytically tractable Ricardian model of trade that, in line with the evidence above, relaxes the assumptions of homotheticity on the demand and supply sides of the economy. Goods in the model are subdivided into types, which may differ in two respects: demand and technology. Poor households concentrate their 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 others. Analogous to the product cycle theory above, in general equilibrium, countries where overall productivity is low have low wages and consequently specialize in less differentiated goods. Technologically advanced countries, in contrast, have high wages and a comparative advantage in goods whose production technologies are more variable across countries.

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.

I estimate the model, with one type (EK model) and with two types of goods, using data on bilateral merchandize trade flows of 162 countries in the year 2000. The EK model fails to reconcile the large volumes of trade observed among rich countries to the paucity of trade in poor regions. Two types of goods suffice for the new model to explain these patterns of 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, rich 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 rich countries large incentives to trade. Poor countries, in contrast, produce and consume more goods whose production technologies are similar across countries. As a result, they trade little.

The model with this configuration is able to capture some key moments in the data that contradict the EK model. According to the data, trade share increases with a country's income per capita. For example, the 30 richest countries in the sample trade on average 37% of their income, while the 30 poorest countries trade 24%, or 13% *less*. Similarly, the new model predicts that trade share in the poorest countries is 18% *less* than in the richest countries, while the EK model predicts that it is 4% *more*. The relationship between trade share and total income, in turn, is small and statistically insignificant in the data. In contrast, the EK model predicts a sharp decreasing relationship. The elasticity of trade share with respect to GDP is -0.043 according to the data, -0.096 according to the new model and -0.368 according to the EK model.

The new model also predicts well the volume of trade among countries of similar income levels. Trade among the 30 richest countries in the sample accounts on average for 28% of these countries' income according to the data. Similarly, the new model predicts this trade to be 17% of richest countries' income, while the EK model predicts that it is only 2%. Trade among the 30 poorest countries, in turn, is less than 2% of these countries' income according to the data, the new model and the EK model.

The new model differs from EK not only in its predictions regarding trade flows, but also in its welfare implications. If the rate of growth that 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 the new model, I simulate counterfactual situations numerically using the parameter estimates. A technology shock in China decreases the price of goods that China and other poor countries produce. A shock that quadruples Chinese wages increases wages in the 50 richest countries in the sample by 0.3% relative to the rest of the world. The shock accordingly benefits rich countries, and hurts middle income countries. Poor countries, in turn, are generally left indifferent. Although their wages decrease relative to rich countries', they do not consume enough goods produced in rich countries to be significantly affected by the change.

A technology shock in the United States 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 25% increase in American wages decreases wages in the 30 richest countries in the sample by 1.3% relative to the rest of the world. While some poor and rich countries are made worse off with the shock, all middle income countries benefit.

I also experiment with a move to frictionless trade and to autarky. Eliminating trade costs benefits all countries in the world, especially small, poor countries. Real wage increases range from more than 100% in some small, poor countries to 15% in the United States. A move to autarky, in turn, hurts all countries in the world, especially small, rich countries. Real wage decreases range from -0.1% in India to -17% in Luxembourg.

This paper contributes to two other strands of literature. First, previous models of trade with non-homothetic preferences–e.g, Flam and Helpmann (1987), Markusen (1986), Matsuyama (2000), and Stokey (1991)–are typically highly stylized and often rely on the assumption of a two-country or a two-good world. By admitting a continuum of goods and an arbitrary number of countries, the new model allows one to simultaneously analyze all directions of trade–North-North, North-South and South-South–and to analyze data.

Second, I introduce a new estimation methodology for the EK model and thus contribute to previous papers that estimate the EK model–e.g., Alvarez and Lucas (2007), Eaton and Kortum (2002), Waugh (2008). The regression approach typically used in gravity models is not applicable to the new model because the introduction of non-homotheticity modifies the gravity-type framework in a non-linear fashion. The alternative methodology that I suggest makes full use of the general equilibrium feature of the model, and it does not incur the same endogeneity problems of regression analyses (see section 3). Its application also extends the work of EK to a larger data set–EK estimate their model using a data set containing only manufactures trade among nineteen OECD countries (because their paper had different objectives).

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 and conclude in section 5. 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 sections 2.1 and 2.2, I present a new 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 the new model in section 2.5.

2.1 The Environment

There are N countries, and goods are subdivided into S types, each with a continuum of goods. Goods of type $\tau \in \{1, 2, ..., S\}$ are denoted by $j_\tau \in [0, 1]$. All consumers in the world choose the quantities of goods j_τ, $\{x(j_\tau)\}_{j_\tau \in [0,1]}$, 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 type τ on preferences, $\sum_{\tau=1}^{S} \alpha_\tau = 1$, and $\sigma_\tau > 1$ for all $\tau = 1, ..., S$.

Parameter σ_τ is typically associated with its role as the elasticity of substitution. Here, however, it also governs the income elasticity of demand of goods of type τ. To see this, consider any two types of goods, $\tau = 1, 2$, and denote by $p(j_\tau)$ the price of good j_τ. Then, from the first order conditions, the total expenditures in goods of types 1 and 2, x_1 and x_2, satisfy

$$\frac{x_1}{x_2} = \lambda^{\sigma_2 - \sigma_1} \left[\frac{(\alpha_1)^{\sigma_1}}{(\alpha_2)^{\sigma_2}} \frac{\int_0^1 p(j_1)^{1-\sigma_1} dj_1}{\int_0^1 p(j_2)^{1-\sigma_2} dj_2} \right], \tag{2}$$

where λ is the Lagrangean multiplier associated with 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_1/x_2. A greater α_1 or a smaller set of prices $\{p(j_1)\}_{j1 \in [0,1]}$ increases expenditures in type 1 goods relative to type 2. The term $(\lambda^{\sigma_2 - \sigma_1})$ governs the rate at which x_1/x_2 changes with consumer income. If $\sigma_1 > \sigma_2$, the ratio x_1/x_2 is decreasing in λ and consequently increasing in consumer wealth. Therefore, the utility function in equation (1) captures the notion that consumers with different income levels concentrate their spending in different types of goods in a simple manner: $\sigma_1 > \sigma_2$ implies that goods of type 1 are more income elastic, and hence rich countries demand relatively more of these goods than poor countries do.[1]

2.2 Technologies

Labor is the unique factor of production; it is perfectly mobile across types and immobile across countries.[2] Countries have different access to technologies, so that labor efficiency varies 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 $\frac{w_i}{z_i(j_\tau)}$.

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

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

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

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

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

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

This property of the Fréchet distribution gives a dual role to parameters θ_τ in the model. First, the variability of technologies across *goods* governs comparative advantage *within* types.

A greater dispersion in labor efficiencies (a smaller θ_τ) generates a greater price dispersion, and consequently a greater volume of trade. Trade is more intense in types where θ_τ is small.

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

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

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

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

2.3 Equilibrium

All countries have a continuum of individuals, who supply inelastically the one unit of labor with which they are endowed. Denote by L_i the measure of country i's population.

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

$$x_{n\tau} = (\lambda_n)^{-\sigma_\tau} \left[(\Phi_{n\tau})^{(\sigma_\tau - 1)/\theta_\tau} \xi_\tau \right], \tag{5}$$

where
$$\Phi_{n\tau} = \sum_{i=1}^{N} T_i \left(d_{ni} w_i\right)^{-\theta_\tau},$$
$$\xi_\tau = (\alpha_\tau)^{\sigma_\tau} \Gamma\left(\frac{\theta_\tau + 1 - \sigma_\tau}{\theta_\tau}\right),$$

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.

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

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

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:

[3] 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).

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

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 and preference parameters α_τ and σ_τ, and a matrix of trade barriers $\{d_{ni}\}_{n,i \leq N}$. Given wages, w, the matrix of trade flows $\{X_{ni}\}_{n,i \leq N}$ is given by equations (5) through (7). An equilibrium is a set of wages $w \in \Delta(N-1)$ that satisfies the labor market clearing condition (8) for all countries $i \in \{1, ..., N\}$.

2.4 Income per Capita and Trade Patterns

Having solved the model, we now analyze how the parameters of the model govern the role income per capita on trade. I consider, for simplicity, only the case where there are two types of goods, A and B. This is the special case of the model used in the empirical analysis of section 3 below. Its restriction does not impair our understanding of the model since estimating the model with more than two types does not change its predictions regarding trade flows.

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

$$\frac{X_{nA}}{X_{nB}} = (\lambda_n)^{\sigma_B - \sigma_A} \left[\frac{(\Phi_{nA})^{-(1-\sigma_A)/\theta_A} \, \xi_A}{(\Phi_{nB})^{-(1-\sigma_B)/\theta_B} \, \xi_B} \right]. \tag{9}$$

Equation (9) is the same as equation (2), except that the price terms are solved for according to the market structure and technology set up–i.e., $\int_0^1 p(j_\tau)^{1-\sigma_\tau} dj_\tau =$
$\Gamma\left(\frac{\theta_\tau + 1 - \sigma_\tau}{\theta}\right)(\Phi_{n\tau})^{-(1-\sigma_\tau)/\theta_\tau}$ for $\tau = A, B$. Assume $\sigma_A > \sigma_B$. Then, the ratio $\frac{X_{nA}}{X_{nB}}$ is decreasing in λ_n and increasing in wealth. Rich households spend a larger fraction of their incomes in goods of type A than poor households do.

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

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

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

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

This scenario is reversed if country n is rich and $\frac{X_{ni}}{X_{nn}} \approx \frac{X_{niA}}{X_{nnA}}$. Since θ_A is small, the term $\left(\frac{d_{ni}w_i}{w_n}\right)^{-\theta_A}$ will be relatively close to 1 irrespective of whether $\left(\frac{d_{ni}w_i}{w_n}\right)$ is smaller or greater than 1. Thus, $\frac{X_{niA}}{X_{nnA}}$ 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 $\frac{X_{niB}}{X_{nnB}}$ was. This result has two implications. First, rich countries will 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 trade more with other rich countries, whose technology parameters T_i are large. So in accordance with the empirical evidence mentioned in the introduction, the model predicts trade to be more intense among rich countries whenever $\sigma_A > \sigma_B$ and $\theta_A < \theta_B$.

2.5 A Special Case: The Eaton-Kortum Gravity Model

I show two special cases of the new model under which its solution reduces to the EK model. The most straightforward case is to suppose there exists only one type of good, $\alpha_\tau = 1$ for some

τ. Production efficiencies are then distributed as per EK (equation (3)), and the utility function becomes

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

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 $X_n = w_n L_n$ is country n's total income. This is the solution to the EK model.[4] Trade flows do not depend on income per capita, only on total income.

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

The converse, however, is not true. One way to make preferences homothetic, while preserving the multi-type technology distribution, is to assume $\sigma_\tau = \sigma$ for $\tau = 1, ..., S$. Although I do not present the results, I did estimate the new model with this restriction. The explanatory power of this restricted model (formally defined in section 3 below) is about two-thirds of the way between the EK and the unrestricted, new model. (Section 3.2.2 below, on parameter identification, explains for the role of each individual parameter in modifying trade flows.)

3 Empirical Analysis

The objective of this section is to evaluate quantitatively the ability of the new model to explain bilateral trade flows. Throughout, I use the EK model as a benchmark because Eaton and

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

Kortum (2002) show that their model provides a theoretical foundation for the gravity equation. Hence, it predicts the same general patterns of trade as other gravity-type models, such as Anderson and van Wincoop (2003) and Redding and Venables (2004).

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 the new model. The non-homotheticity introduced here modifies the gravity equation in a non-linear form. I propose an alternative methodology that takes advantage of the general equilibrium set up in both models. In the case of the new model, I focus exclusively in the special case with only two types, denoted by A and B.[5]

In section 3.1, I present the data. The empirical methodology is presented in section 3.2, and the results, in section 3.3.

3.1 Data

I use data on bilateral merchandize trade flows for the year 2000 from the UN Comtrade (United Nations (2008)), and data on population and income from the World Bank (2008). The details of the compilation of the data are in appendix 6.2. The data comprise 162 countries and account for 96% of the total trade flow reported to the UN for the year 2000. Table 1 lists all the countries in the sample and shows, for each country, the percentage of its imports originating in countries within the sample.

Of the 162 countries in the sample, 145 countries directly report trade to the UN. The data contain bilateral trade flows of these 145 reporting countries to and from all other countries in the sample. The remaining 17 countries are marked with a cross on table 1. Trade flows between them are missing from the data. Hence, of all possible importer-exporter country pairs, 25,810 ($= 162^2 - 17^2 - 145$) are observed and 272 ($= 17^2 - 17$) are missing. In addition to these data, I also use data specific to country pairs–distance between their most populated cities, common official language, and border–from the Centre d'Etudes Prospectives et d'Informations Internationales (2005) webpage.

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

These are the data used in the estimation. When I present the results, I analyze some moments of the data that involve the total trade flow for each country. Since the data above contain total trade for only 145 countries, I complement them with data from the World Bank (2008) on the total value of merchandize trade flows for 16 of the 17 non-reporting countries (there are no data on Taiwan). Figure 2 shows the similarity of the data on trade shares from the two sources. It plots trade share in UN Comtrade as a function of trade share in the World Bank (2008) for the 145 reporting countries. Most countries lie close to the 45º line.

3.2 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)):

$$
\begin{aligned}
X_{ni} &= L_n \left(x_{niA} + x_{niB} \right) \qquad \text{where, for } \tau = A, B, \\
x_{ni\tau} &= \frac{T_i (d_{ni} w_i)^{-\theta_\tau}}{\Phi_{n\tau}} x_{n\tau}, \\
x_{n\tau} &= (\lambda_n)^{-\sigma_\tau} \left[(\Phi_{n\tau})^{(\sigma_\tau - 1)/\theta_\tau} \, \xi_\tau \right], \\
\Phi_{n\tau} &= \sum_{i=1}^{N} T_i \left(d_{ni} w_i \right)^{-\theta_\tau}, \\
\xi_\tau &= (\alpha_\tau)^{\sigma_\tau} \Gamma \left(\frac{\theta_\tau + 1 - \sigma_\tau}{\theta_\tau} \right),
\end{aligned}
\tag{12}
$$

$\alpha_B = 1 - \alpha_A$, and the Lagrangean multiplier λ_n is implicitly defined through the budget constraint of a typical consumer in country n, $x_{nA} + x_{nB} = w_n$.

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

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

$$d_{ni} = 1 + \left\{(\gamma_1 + \gamma_2 D_{ni} + \gamma_3 D_{ni}^2) * \gamma_{\text{border}} * \gamma_{\text{language}} * \gamma_{\text{trade agreement}}\right\}, \tag{13}$$

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, say, 0.8, sharing a border reduces trade costs by 20%, but has no impact on production costs; if $\gamma_{\text{border}} > 1$, sharing a border increases trade barriers. Similarly, parameters γ_{language} and $\gamma_{\text{trade agreement}}$ refer, respectively, to whether countries n and i share a common language, and whether they are both members of the same trade agreement.[6]

Henceforth, I refer to the set of iceberg cost parameters as
$\Upsilon = \{\gamma_1, \gamma_2, \gamma_3, \gamma_{\text{border}}, \gamma_{\text{language}}, \gamma_{\text{trade agreement}}\}$.

Technology parameters T_i. The equilibrium conditions in equation (8) pin down a one-to-one relation between the set of technology parameters $\{T_i\}_{i=1}^N$ and the market clearing wages $\{w_i\}_{i=1}^N$. That is, given a set of parameters $\{\Upsilon, \alpha_A, \sigma_A, \sigma_B, \theta_A, \theta_B\}$, data on population L, geographic characteristics and trade agreements, one could either use the technology parameters T to find the market clearing wages w, or conversely, use the wages to find the technology parameters. I use the latter approach. I take income per capita from the data as a proxy for wages.[7] Then, for each guess of parameters $\{\Upsilon, \alpha_A, \sigma_A, \sigma_B, \theta_A, \theta_B\}$, I simulate the whole economy generating all trade flows X_{ni} until I find the technology parameters T that satisfy the

[6] I use only the trade agreements that the WTO lists as the best known: ASEAN, COMESA, EFTA, European Union, Mercosur, and NAFTA.
Usually, an exponential functional form is assumed for iceberg costs, *e.g.*, $d_{ni} = \exp\left(\gamma_1 + \gamma_2 D_{ni} + \gamma_3 D_{ni}^2 + \gamma_{\text{border}} + \gamma_{\text{language}} + \gamma_{\text{trade agreement}}\right)$, which facilitates log-linearizing regression models. In my estimation procedure this convenience is useless, and the choice between these two functional forms make no difference in the empirical results. I chose equation (13) because, unlike the exponential function, its parameters are easily interpretable.

[7] 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.

system of equations (8): $\sum_{n=1}^{N} X_{ni} = w_i L_i$ for $i = 1, ..., N$.[8]

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

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

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

Parameters σ_A and σ_B are not separately identifiable either. These parameters, together, govern how the allocation of expenditures across goods of type A and B varies with a country's income per capita, but they play no role individually. Just as with θ_A, I need to assume a specific value for σ_A (or σ_B) in order to estimate and interpret the remaining parameters of the model. 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.[9]

In appendix 6.4, I experiment with alternative values for θ_A and σ_A. Although estimates for the remaining parameters $(\Upsilon, \alpha_A, \theta_B, \sigma_B)$ vary, predictions on trade flows do not change. (If

[8] Alvarez and Lucas (2007) prove existence and uniqueness of equilibrium in the EK model. The new model satisfies standard conditions for existence (Mas-Colell et al. (1995), chapter 17), but I do not prove uniqueness. Still, I did not encounter any cases where the relation between w and T in the market clearing conditions was many-to-one or one-to-many. The United States's technology parameter T_i is normalized to 1. All Fortran programs are available upon request to the author.

[9] 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 I estimate the model with only two types (or two "industries"). Hence, presumably, goods within each type should be very different, and their elasticity of substitution should be small.

it were not so, parameters θ_A and σ_A would be identifiable.) For all values of θ_A and σ_A in the appendix, the interpretation of the parameter estimates and of the results presented below remain absolutely unchanged for both the EK and the new model.

Objective function. Having fixed the values of θ_A and σ_A, nine parameters–Υ, α_A, σ_B and θ_B–are sufficient to estimate the set of technology parameters $\{T_i\}_{i=1}^N$ and thereby the matrix of trade flows $\{\hat{X}_{ni}(\Upsilon, \alpha_A, \sigma_B, \theta_B)\}_{n,i \leq N}$. I choose $\{\Upsilon, \alpha_A, \sigma_B, \theta_B\}$ to minimize the 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 importer-exporter country pairs in the data and $\hat{X}_{ni}(\Upsilon, \alpha_A, \sigma_B, \theta_B)$ is the equivalent vector for the flows predicted by the model. Each of these vectors thus contain $25,810$ observations (see section 3.1).

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%. 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 observations X_{ni}, I assume a functional form for the weighting matrix W. I assume that 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. A large κ increases the weight on the objective function of trade flows among small countries relative to flows among large countries.[10]

[10] 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

The new model, unlike gravity-type models, reconciles differences in trade patterns across countries of different income levels. So to clearly distinguish the new model from EK, the objective function must place enough weight on small, poor countries–i.e., κ must be sufficiently large. In section 3.3 below, I present only the results for $\kappa = 2$ and in appendix 6.5, a summary of the results for other values of $\kappa \in [0, 2]$. The appendix shows that the new model outperforms EK in explaining the data for all values of $\kappa \in [0, 2]$, and that the direction of the changes between the two models is the same as the one presented in section 3.3. But when κ is close to zero the difference between the two models is small since the optimization algorithm focuses almost exclusively on trade flows among large, rich countries.

Aside from the practical issues above, the trade literature provides a theoretical foundation for the choice of $\kappa = 2$. According to the gravity equation, trade flows from country i to country n equal $X_{ni} = \delta_{ni} X_n X_i$, where δ_{ni} is a measure of trade barriers between countries n and i–typically a function of geographic and economic barriers, and of the price indices of the two countries. So when $\kappa = 2$, we can rewrite the objective function as $(\delta_{ni} - \hat{\delta}_{ni}(\Upsilon, \alpha_A, \sigma_B, \theta_B))'(\delta_{ni} - \hat{\delta}_{ni}(\Upsilon, \alpha_A, \sigma_B, \theta_B))$, where $\hat{\delta}_{ni}(\Upsilon, \alpha_A, \sigma_B, \theta_B) = \frac{X_{ni}(\Upsilon, \alpha_A, \sigma_B, \theta_B)}{X_n X_i}$ is the model's theoretical measure of the barrier between countries n and i, and δ_{ni} is the real one.

I close this subsection with notes on income inequality (3.2.1), on parameter identification (3.2.2), and on the methodology to estimate the EK model (3.2.3).

3.2.1 Income Inequality. I have thus far ignored income inequalities within countries. But in principle, these inequalities affect demand patterns and thereby, trade. For 121 countries in the sample, the World Bank (2008) presents data on the share of income held by each quintile in the population, from the poorest to the richest. To assess the effect of inequality on trade, I use these data to re-estimate the model for this subset of countries. Instead of calculating demand for a single representative consumer in each country, I calculate it for five consumers, each representing one income quintile. A country's total demand is the sum of these representative consumers weighted by 20% of the population.[11]

weight observations.

[11]More formally, the representative consumer of quintile $q \in \{1, ..., 5\}$ in country n has his own Lagrangean multiplier, λ_n^q, which satisfies his budget constraint $\sum_{\tau=1}^{S} x_{n\tau}^q = w_n^q$ where w_n^q is the income held by a typical consumer in quintile q in country n, and $x_{n\tau}^q$ is the expenditures of this consumer

Note that the estimation with income inequalities does not add any new parameters to the model. Yet, it modestly increases the model's explanatory power by 1%. This result, however, should be viewed with care since inequality data are available only for 121 countries, and they are spread across different years.[12] Precisely because of the paucity of data, I choose to present below only the results with no income inequality within countries.

3.2.2 Data and Parameter Identification. The formal methodology for estimating the model is the one presented above. But before presenting the results, I briefly note on the features of the data that allow me to identify the parameters to be estimated, Υ, α_A, σ_B and θ_B.

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

The volume of trade between rich and poor countries, in turn, provides information on parameter σ_B, since σ_A is set to 4.0. If the income elasticity of demand is equal across types, $\sigma_B = \sigma_A$, the model predicts large volumes of trade between rich and poor countries because these countries specialize in producing different types of goods. If instead $\sigma_B < \sigma_A$, as the results below indicate, demand patterns suppress trade among countries of different income levels. Rich countries demand relatively more type A goods, generally produced in rich countries, while poor countries demand more type B goods. Finally, parameter α_A, the weight of type A goods in preferences, govern the size of sector A relative to sector B, thereby controlling the size of the "rich" and "poor" country groups above. This completes the identification Υ, α_A, σ_B and θ_B.

---

in goods of type τ, given by equation (5). The total demand of goods from country i by country n is $\left[\frac{L_i}{5}\sum_{q=1}^{5}\sum_{\tau=1}^{S} x_{ni\tau}^q\right]$, where $x_{ni\tau}^q = \frac{T_i(w_i d_{ni})^{-\theta_\tau}}{\Phi_{n\tau}} x_{n\tau}^q$ as in equation (7).

[12] Countries typically only report their distribution of income sporadically. In order to collect data for the 121 countries above, I used reports from 1990 to 2007, giving priority to the information available in the year closest to 2000, the year of the trade data.

3.2.3. EK Model: Estimation Methodology. The procedure to estimate the EK model is exactly the same as the one for the new model, above. The only difference is that, after normalizing parameter θ_A and backing out the technology parameters T_i, trade flows are exclusively a function of iceberg cost parameters Υ. Parameters α_A, σ_A, σ_B and θ_B do not exist or do not affect trade flows in the EK model (see equation (11)).

3.3 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 162 countries in the data. Table 2 displays the estimated parameters. Both models explain trade among OECD countries equally well–their explanatory power is 74%. Under the full sample, in contrast, the new model improves the explanatory power of EK from 34% to 42%. Thus, the new model does not help explaining trade among countries with similar characteristics (as in the OECD sample), but reconciling some features of the data observed across countries of different sizes and income levels.

Table 3 summarizes the distribution of residuals in the full sample estimation. It displays the contribution of each importing country in the objective function (14). The values are divided by $X'_{ni}WX_{ni}$ so that the sum of residuals across importers equals 66% ($= 100\% - 34\%$) for the EK model and 58% for the new model. Since the objective function places a large weight on the observations of small countries ($\kappa = 2$), these countries account for a significant fraction of the residuals in both models. But even if small countries such as Dominica, Tajikistan and Tonga are removed from the sample, all results remain practically unchanged.[13]

While the difference in explanatory power between the new and the EK model is significant, it is not large. The starker difference between the models is in predicting some qualitative features of the data, discussed next. As per section 3.1, whenever needed, I combine two data sets to obtain the total trade flows for each country in the sample: the UN Comtrade bilateral trade data used to estimate the model (145 countries) and total trade shares from the World

[13]Depending on the set of countries in the sample, the gap in explanatory power between the two models may increase or decrease, but the estimated parameters barely change. Consequently, the stylized facts discussed below do not change either.

Bank (16 countries). So a small part of the discussion below involves an out-of-sample check on the two models.

EK model: OECD and full sample. The data with the full sample present large volumes of trade among large, rich countries and small volumes among small, poor countries. Unable to reconcile these differences, the EK model severely underestimates trade among large, rich countries. For example, as $(\hat{\gamma}_1, \hat{\gamma}_2, \hat{\gamma}_3)$ changes from $(1.24, 0.84, -0.21)$ in the OECD sample to $(1.96, 0.26, 0.0)$ in the full sample, iceberg costs increase for all OECD country pairs, and they increase by 80% on average.

Full sample: New versus EK model. Four parameters distinguish the new model from EK: $\alpha_A, \sigma_B, \theta_B$ (estimated) and σ_A (normalized). Parameters $\alpha_A = 0.81$, $\sigma_A = 4.00$ and $\sigma_B = 1.18$ define the utility function. Types A and B coexist in the economy, $\alpha_A \in (0, 1)$, and rich consumers allocate a larger fraction of their incomes in goods of type A than poor consumers do, $\sigma_A > \sigma_B$. More specifically, spending in type A ranges from 85% of Japan's GDP to only 3×10^{-5} of the Democratic Republic of Congo's. Type A also presents a greater heterogeneity in production technologies, $\theta_A < \theta_B$ ($\theta_A = 8.28$ and $\theta_B = 14.19$). Hence, rich countries have a comparative advantage in producing them. Type A goods constitute 99% of Luxembourg's production and only 3×10^{-13} of the Democratic Republic of Congo's. In sum, rich countries produce and consume more goods of type A, the type whose production technologies are more heterogeneous across countries. As a result, rich countries trade a lot, while poor countries trade little (recall section 2.4).

Figures 3, 4 and 5 use moments of the data to compare the predictions of the two models. All graphs in figure 3 plot countries' trade share (i.e., $\frac{\text{imports + exports}}{2{*}\text{GDP}}$) as a function of the logarithm of their GDP per capita. Graph 3(a) refers to the data, graph 3(b) to the EK model and graph 3(c) to the new model. Recall from the estimation methodology that there is no difference between countries' real and predicted incomes. So the position of countries along 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 clearly underestimates trade shares as it attempts to match the small volumes of trade of poor countries. While the *average* trade share in the data is 33%, the EK model predicts that the *largest* trade share is only 25%. The maximum trade share according to the new model is 78% and its average is 18%.

The new model correctly predicts that trade share increases with income per capita. The slope of the regression lines in figures 3(a) and 3(c) is positive and statistically significant at a 1% level. Its value is also economically significant, although it is overestimated in the new model. Take, for example, the richest and poorest countries in the sample–Luxembourg and the Democratic Republic of Congo (DRC). The ratio of their income per capita equals 538. Hence, the slopes in figures 3(a) and 3(c) imply that Luxembourg's trade share is expected to be 16% larger than that of the DRC according to the data ($0.16 = 0.025 \log(538)$) and 33% larger according to the new model. The EK model, in turn, contradicts the data by predicting a small negative relationship between trade share and income per capita (figure 3(b)).

Figure 4 is analogous to figure 3, except that the logarithm of GDP per capita on the x-axes is replaced with the logarithm of total GDP. Trade shares still appear on the y-axes, and graphs 4(a), 4(b) and 4(c) refer to the data, the EK model and the new model, respectively.

The regression lines in figures 4(a), 4(b) and 4(c) have similar slopes, but the graphs are qualitatively different. The EK model predicts a clear, decreasing relationship between trade share and total income, a relationship which is at best weak in the data and in the new model. This prediction of the EK model is robust to all choices of weighting matrices in the appendix ($\kappa \in [0, 2]$) and stems from a tendency of large countries to trade less in general equilibrium models. In a two-country world, for example, the smaller country necessarily trades a larger share of its income than the large country does, simply because trade flows must be the same in the two countries. The new model counterpoises this general equilibrium tendency of large countries to trade less with the tendency of rich (often large) countries to trade more. As a result, the new model correctly predicts that a country's total income contains little information on its trade share. The R^2 of the regression line in figure 4 equals 0.01 according to the data (4(a)), 0.32 according to the EK model (4(b)) and 0.03 according to the new model (4(c)).

Figures 4(a) and 4(c) both present large variances among observations corresponding to medium-sized countries. This pattern emerges in the data and in the new model because medium-sized countries with high income per capita and small population have large trade shares (e.g., Singapore and Hong Kong), while countries with low income per capita and large population have small trade shares (e.g., Pakistan and Bangladesh).

Figure 5 illustrates countries' choice of trading partners. For each country, I calculate the fraction of its trade that flows to or from one of the 20 richest countries in the sample. The graphs in figure 5 plot this share of rich countries in trade against the logarithm of income per capita. Graph 5(a) refers to the data; graph 5(b) depicts both observations of the data (asterisk) and of the EK model (hollow diamonds), and 5(c) does the same for the new model. All three graphs show an increasing relationship between the two variables–high income countries tend to spend a higher fraction of their income in goods from other high income countries. But the new model's predictions are well aligned with the data, while the EK model underestimates the role of rich countries in trade. According to the data, the share of rich countries in trade is on average 39% for poor countries and 59% for rich countries. According to the new model, these same numbers are 22% and 52%, respectively, and according to the EK model, they are 12% and 39%.[14]

Note that figures 3(b) and 5(b), together, imply that the EK model severely underestimates trade among rich countries: It underestimates these countries' trade share (3(b)), and it underestimates the share of their trade that is allocated to other rich countries (5(b)). The same is not necessarily true for poor countries. While the EK model underestimates poor countries' trade share (3(b)), it overestimates the share of their trade that is allocated to other poor countries (5(b)). Reconciling differences in trade patterns across income levels is the main contribution of the new model (see figures 3(c) and 5(c)).

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

[14]The 20 richest countries in the sample are excluded from figure 5 because they mar the analysis since they cannot import goods from themselves. In calculating the last figures above, I refer to the 20 poorest countries in the sample as poor countries, and to the 20 richest countries in the graph (not in the sample) as rich countries.

understanding of the model itself.

The methodology used here is as follows. We define an economy using, from the data, the population of each country, and from section 3, 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. In this economy, 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.

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

4.1 Technology shocks

It is useful to contrast here the predictions of the EK model to those of the new model. In both models, a technology shock in country i consists of a unilateral increase in its technology parameter T_i. In the case of the EK model with no trade costs ($d_{ni} = 1$), it is easy to prove that a technology shock in country i will benefit all countries in the world and preserve the relative wages of countries not undergoing the shock (i.e., $\frac{w_j}{w_{j'}}$ remains unchanged for all $j, j' \neq i$). This theoretical prediction is similar to the one obtained with the EK model using the parameter estimates of section 3, which account for trade costs. Technology shocks in the U.S.A. and in China benefit almost all countries in the world.

A technology shock in the new model, in contrast, may hurt some countries. In general, a technology shock changes the price of type A relative to type B goods. So its welfare impact depends critically on the net exports of different types of goods. Figure 6 plots the production, demand and net exports of type A goods as a fraction of GDP, against the logarithm of income per capita. Each observation corresponds to one of the 162 countries in the sample. The circles represent the share of type A goods in production, and the triangles, the share of type A goods in demand. Both of these curves are upward sloping because countries with higher income per capita produce and consume relatively more type A goods. The crosses represent the net exports in type A goods (production minus demand). They form a V-shaped curve: Net exports of type A are small for low and high income countries, and they are large and negative for middle income countries. Low income countries produce and consume mostly type B goods; high income countries produce and consume mostly type A goods, and middle income countries are rich enough to consume type A goods but not to produce them.

Between 1985 and 2000, the year of the data, China grew nearly four times relative to the rest of the world. To view the effects 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. The shock increases the price of type A relative to type B goods for two reasons. First, as China's income grows with the shock, its consumption of type A goods increases from 1.5% to 21% of GDP. Second, goods of type A represent a small fraction of Chinese production, before and after the shock–they increase from 4e-7 to only 2.6% of GDP. So most productivity gains following the increase in T_{China} accrue to goods of type B.

The increase in the relative price of type A goods benefits primarily the net exporters of these goods. It increases wages in the world's 50 richest countries by 0.3% relative to the rest of the world. While this change in relative wages hurts middle income countries, it barely affects poor countries, which consume only scarcely goods produced in rich countries. Figure 7 plots the real wage changes due to the technology shock in China as a function of the logarithm of income per capita.[15] The V-shaped curve resembles that of the net exports of type A goods shown in figure 6. The shock in China benefits all rich countries, hurts most middle income countries, and it leaves most poor countries close to indifference. The largest real wage increases occur in China's small, rich neighbors–Hong Kong (3.4%), Macao (3.3%), Singapore (0.7%)–and the largest real wage decreases occur in China's middle income neighbors–Malaysia (-0.3%), Thailand (-0.3%).

Contrary to the shock in China, a technology shock in the U.S.A. decreases the price of type A relative to type B goods, and hence it inverts the effects of the Chinese shock. Analogous to figure 7, figure 8 plots the real wage changes due to the shock in the U.S.A. as a function of the logarithm of income per capita. The figure now resembles an inverted V: All middle income countries benefit from the shock, while some low and high income countries are made

[15] I calculate for each country the change in wages that would be necessary to attain the final period's utility level, given the initial period's prices. For visualization purposes, I exclude from figure 7 China, Macao and Hong Kong, whose real wage changes were much larger than other countries'.

worse off. A shock that increases American wages by 25% relative to the rest of the world decreases nominal wages in the 30 richest countries in the sample by 1.3% relative to the rest of the world. The largest real wage increases occur in Mexico (1.7%) and in small, middle income, Central American countries ($\sim$ 3.0%). Japan, Norway and Switzerland, in turn, experiment small welfare losses.

4.2 Trade barriers

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

Removing trade barriers decreases the price of type A and of type B goods relative to local wages in all countries. It thus benefits all countries.[16] But changes in the price of type A and of type B goods differ qualitatively in two aspects. First, decreases in prices are larger and more variable for the more differentiated, type A goods than for type B goods. Price decreases in type A goods range from -74% to -11%, while price decreases in type B goods range from -56% to -13%. Second, changes in the price of type A goods depend primarily on income per capita–the richer the country, the larger its comparative advantage in type A goods and consequently the smaller the price change. Changes in the price of type B goods, in contrast, depend primarily on geography and population–the more populous a country is, the smaller its price changes.

Together, these prices changes imply that small, poor countries are the greatest beneficiaries from a move to frictionless trade. While real wages in numerous small, poor countries rise by more than 100%, they rise by 15% in the United States and by 25% in Japan.

A move to autarky, in contrast, makes all countries worse off because it increases the price of type A and of type B goods relative to wages in all countries. Increases in the price of the more differentiated, type A goods average 479% and range from less than 1% in Japan to more than 2,000% in a few small, poor countries with no comparative advantage in type A goods. Increases

[16] In the discussion below, I consider percentage changes in prices relative to domestic wages: $\Delta P_{i\tau} = 100 * \left(\frac{P_{i\tau}^{\text{counterfactual}}}{w_i^{\text{counterfactual}}} - \frac{P_{i\tau}^{\text{initial}}}{w_i^{\text{initial}}} \right) \div \left(\frac{P_{i\tau}^{\text{initial}}}{w_i^{\text{initial}}} \right)$, where $P_{i\tau} = \left[\int_0^1 p_i(j_\tau)^{(1-\sigma_\tau)} dj \right]^{1/(1-\sigma_\tau)}$ is the usual CES price index for $\tau = A, B$.

in the price of type B goods, in turn, average only 1.3%, range from 1e-6 to 37%, and tend to be larger in small, rich countries, which do not have a comparative advantage in producing type B goods. Despite their magnitude, changes in the price of type B goods generally have a greater impact on welfare than changes in the price of type A goods, because type B goods have a smaller income elasticity of demand. As a result, the largest welfare losses following a the move to autarky are experienced by small, rich countries. While real wages decrease by only 0.1% in India, they decrease by 17% in Luxembourg.

5 Conclusion

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

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

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

Throughout the paper, however, I have ignored two features of the data, both potentially useful in future research. First, the data are available at the product level. Thus, the links between income elasticity of demand, and production and trade patters established by the model are potentially verifiable. Second, data are available for several years. Adding dynamics is the most natural extension of the model. I have emphasized throughout the analogy between product cycles and the variability in production technologies in the model. A dynamic version of the model should thus be fit to study 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

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

$$\sum_{\tau=1}^{S}\left\{\alpha_\tau \frac{\sigma_\tau}{\gamma_\tau(\sigma_\tau-1)}\left[\int_0^1 x(j_\tau)^{\sigma_\tau-1/\sigma_\tau}dj_\tau\right]^{\gamma_\tau}\right\}. \tag{16}$$

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, 1 and 2, equals

$$\frac{x_1}{x_2} = \lambda^{\varphi_1-\varphi_2}\left[\frac{(\alpha_1)^{\varphi_1}\left(\int_0^1 p(j^1)^{1-\sigma_1}dj\right)^{\phi_1}}{(\alpha_2)^{\varphi_2}\left(\int_0^1 p(j_2)^{1-\sigma_2}dj_2\right)^{\phi_2}}\right],$$

where λ is the consumer's Lagrangean multiplier, $\varphi_\tau = -\sigma_\tau + \frac{\sigma_\tau(1-\sigma_\tau)(\gamma_\tau-1)}{\sigma_\tau+\gamma_\tau-\sigma_\tau\gamma_\tau}$ and $\phi_\tau = \frac{\gamma_\tau}{\sigma_\tau+\gamma_\tau-\sigma_\tau\gamma_\tau}$ for $\tau = 1, 2$. As in equation (2), the term in brackets determines the level of x_1/x_2, and $(\lambda^{\varphi_1-\varphi_2})$ determines how it changes with consumer income. Note, however, that this new functional form complicates the algebra without adding anything to the analysis. In the case of the empirical analysis where there are only two types, A and B, γ_A and γ_B are not separately identifiable from σ_A, σ_B and α_A. For any set of prices p and parameters $\{\sigma_A, \sigma_B, \gamma_A, \gamma_B\}$, the parameter α_A can be judiciously chosen to match any level of the ratio x_A/x_B. The rate of change of x_A/x_B, in turn, is determined by the the exponent of the Lagrangean multiplier, $(\varphi_A - \varphi_B)$. Parameters σ_A, σ_B, γ_A and γ_B, therefore, all play the same role and only one of them is sufficient to determine the value of $(\varphi_A - \varphi_B)$–the rest can be normalized. In equation (1), γ_A and γ_B are set to 1.[17]

The utility function in the main text assumes that the type of good with a higher income elasticity of demand also presents a higher elasticity of substitution across goods. Both of these elasticities are controlled by the same parameter σ_τ. Case 2 above shows that this assumption is not necessary for any of the results. Without changing predicted trade flows, a different normalization of the utility function (16) may imply that the type of good with a *higher* income elasticity of demand has a *lower* elasticity of substitution across goods.

6.2 Data

I use bilateral merchandize trade flows from the UN Comtrade database (United Nations (2008)). In compiling the data, I give precedence to trade flows reported by the importing country, whenever available. If the importer report is not available, I use the trade flow reported by the exporter. I keep in the sample only countries with matching data on population and GDP from the World Bank (2008).

I exclude from the sample countries whose total trade flows in the UN Comtrade data are incompatible with the total trade flow reported to the World Bank. In principle, since the UN

[17]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 ϕ_A is not be separately identifiable from the parameters in the production side of the economy.

Comtrade data do not contain all countries in the world, trade flows in the UN data should be (weakly) smaller than the total trade flow as reported to the World Bank (i.e., in figure 2, all countries should lie beneath the 45^o line). I exclude from the sample countries whose trade flows in the UN Comtrade data are at least 20% larger than trade flows in the World Bank data. Seventeen countries and 0.3% of world trade were excluded using this criterion.[18]

Neither the United Nations or the World Bank officially report statistics for Taiwan. But in practice, the UN country classification "Other Asia, not elsewhere specified" (code 490) refers to Taiwan. Hence, the UN Comtrade does contain information on bilateral trade flows to and from Taiwan. Data on Taiwan's population and income, in turn, are taken directly from the Taiwanese government web site, http://eng.stat.gov.tw. Given all the exclusions above, the total value of trade flows in my data is 96% of the trade flows in the UN Comtrade data.

Data in the UN Comtrade are available up until the year 2005, but I use data for the year 2000 for two reasons. First, there are more and more reliable data for the year 2000–twenty-four countries that report trade for the year 2000 have not yet reported it for the year 2005, and the inconsistencies between the UN Comtrade and the World Bank data are much larger in the year 2005 than in 2000. Second, matching data for the year 2005 requires a change in the model that is beyond the scope of the paper. Several countries trade close to or more than 100% of their GDP in 2005. The simple versions of the EK and of the new model presented here do not account for trade flows beyond 100% of a country's GDP. One way to incorporate this feature of the data into both models is to introduce intermediate inputs. While this modification is technically feasible–it is shown in Eaton and Kortum (2002)–it complicates the notation without adding anything to the analysis. It is worth noting, however, that all the stylized facts of the data exploited in section 3.3 also hold in the data of the year 2005.

[18]These countries are: Brunei Darussalam, Comoros, Djibouti, Gabon, Georgia, Guinea-Bissau, Guatemala, Honduras, Kiribati, Moldova, Mauritania, Panama, Sierra Leone, Timor-Leste, St. Vincent and Grenadine, Vanatu and Samoa.
The only additional modification to the data refers to the trade flow from Fiji to Tonga. Instead of using the trade flow reported by the importing country, Tonga, I use the one reported by Fiji. The trade flow reported by Fiji is half of that reported by Tonga and is much closer to the predictions of both models, especially to that of the EK model. Without this modification, the single observation of exports from Fiji to Tonga accounts for 90% of the difference in explanatory power between both models. Still, the chosen value of this observation barely affects the estimated parameters, and therefore it does change the stylized facts discussed in section 3.3.

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

6.3 Confidence Intervals

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

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

2. Normalize error terms by dividing them by the product of the importer and exporter total GDP, $\hat{\varepsilon}_{ni}^{\text{norm}} = \frac{\hat{\varepsilon}_{ni}}{(X_n X_i)}$.

3. For each importer-exporter country pair, randomly draw a new error term $\hat{\varepsilon}_{ni}^{\text{norm}'}$ from the vector $\hat{\varepsilon}^{\text{norm}}$. All elements of $\hat{\varepsilon}^{\text{norm}}$ receive equal probability in this step.

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

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

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

The normalization of the error term in step 3 is consistent with the weighting matrix when $\kappa = 2$. Following the theoretical foundation for $\kappa = 2$ explained in section 3.2, the error term in X_{ni} can be interpreted as arising from a more fundamental error in δ_{ni}. On average, the number of zero trade flows in simulated data (step 4) is 8,188, not far from the 6,872 zero trade flows observed in the original data.

Table 4 summarizes the results. For each parameter in $\{\Upsilon, \alpha_A, \sigma_B, \theta_B\}$, the table shows the median and the 95% confidence interval of the 500 estimates. It also shows the original explanatory power and parameter estimates from table 2 for visualization purposes. There is quite a bit of variance in the model's explanatory power, but very little variance in the parameter estimates. In particular, all of the 500 parameter estimates satisfy the inequalities $\sigma_A > \sigma_B$ and $\theta_A < \theta_B$, inequalities which were indispensable for understanding the new model throughout the main text and for distinguishing it from EK (see section 2.4).

As an additional exercise, I used the misspecified EK model to estimate the 500 simulated data sets constructed in step 4 above. The difference between the explanatory power of the two models exceeds 6% for all 500 data sets, and it averages 8%.

The narrow confidence intervals on table 4 raise doubts about the identification of parameter estimates. That is, if parameters are not identified, estimates will be close to the initial guess, which in the exercise above are equal to the original parameter estimates. To check for identification, I perform Monte Carlo simulations. The procedure is as follows. (1) Make a random draw for each of the estimated parameters, γ_1, γ_2, γ_3, γ_{border}, γ_{language}, $\gamma_{\text{trade agreement}}$, α_A, σ_B and θ_B. The draw is taken from a uniform distribution, whose support ranges from approximately 40% to 300% of the estimates on table 2, depending on the parameter. (2) For each of draw of the parameter estimates, generate data using the deterministic model of section 2. (3) Run the optimization algorithm using the generated data. I repeat steps 1 through 3 one hundred times and compare the obtained parameter estimates with the original parameter draw, from step 1. In 93% of the cases, the parameter estimate is within a 10% distance from the original draw, indicating that the parameters are indeed well identified.

6.4 Normalization of parameters θ_A and σ_A

In section 3, I estimate the EK model by fixing the value of θ_A to 8.28. Table 5 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. 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. But the predicted trade flows do not change, and hence the explanatory power of the model is the same for all values of θ_A and the stylized facts discussed in the main text remain unchanged.

Table 6 shows the results of the new model when the values of θ_A and σ_A change. The 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 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 $\alpha_A \in (0, 1)$, $\sigma_A > \sigma_B$ and $\theta_A < \theta_B$, thus indicating that the previously given explanation for the effects of non-homotheticity on trade patterns remains the same.

One way to pin down the value of θ_A in both models is to compare the iceberg costs implied by 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%. If $\theta_A = 12.86$ in the new model, estimated transportation costs among OECD countries average 73%, close to Anderson and Wincoop's ballpark figure. The EK model, in turn, requires $\theta_A > 12.86$. Estimated transportation costs among OECD countries average 136% when $\theta_A = 12.86$ and they are even larger when $\theta_A < 12.86$. 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.

6.5 Estimates with different weighting matrices, W

In estimating the EK and the new model, I choose the parameters that minimize $(X_{ni} - \hat{X}_{ni})'W(X_{ni} - \hat{X}_{ni})$, equation (14), where W is 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 focus exclusively on the case where $\kappa = 2.0$. In this appendix, I present a summary of the results from estimating both models with all $\kappa \in \{0, 0.1, 0.2, ..., 1.9, 2.0\}$.[19]

The EK model, I argued in the main text, predicts well trade among wealthy countries, but performs poorly when a lot of small, poor countries are added to the sample. Its explanatory power averages 80% when the OECD sample is used and 42% when the full sample is used. The difference between the new and the EK model is apparent only when the full sample is used. Taking an average across the various weights κ, the explanatory power of the new model exceeds that of the EK model by 8% under the full sample and by only 2% under the OECD sample.

Still, the main advantage of the new model over EK, I also argued, is not in the explanatory power but in its ability to capture qualitative features of the data. Table 7 compares some key moments of the data to the results of the models. The moments are chosen to describe figures 3, 4 and 5, the stylized facts discussed in section 3. For each model and each value of κ, I calculate the 12 moments in the table using the matrix of predicted trade flows. I then calculate separately the average of these moments for $\kappa \leq 1.2$ and for $\kappa \geq 1.3$. The cutoff of 1.2 is chosen only because the matrix of predicted trade flows of the EK model changes qualitatively as κ increases from 1.2 to 1.3 (see next paragraph). Rows and columns are labelled for quick reference. A cursory look at the table shows that for all moments and for both weight groups ($\kappa \lesseqqgtr 1.2$), the predictions of the new model are closer to the data than those of the EK model–the only exception appears in bold, in row 12.

Loosely speaking, the EK model is not able to reconcile the large volumes of trade among rich countries with the small volumes among poor countries observed in the data. It either underestimates the former, when $\kappa \geq 1.3$, or it overestimates the latter, when $\kappa \leq 1.2$. When $\kappa \geq 1.3$, the EK model predicts that the average trade share of the 30 richest countries in the sample is only 5% and that 30% of these countries' trade is allocated to other rich countries (column B, rows 4, 11). Together, these two findings imply that the EK model estimates that trade among rich countries represents only 1.5%(= 5% × 30%) of these countries' GDP. In the data, the corresponding value is 22%(= 37% × 59%), and in the new model, it is 14%

[19]An alternative approach to estimating the model would have been a two step estimator. That is, estimate the model with an initial arbitrary κ and then use the deviations $(X_{ni} - \hat{X}_{ni})$ to estimate an efficient $\hat{\kappa}$. This procedure yields a $\hat{\kappa} = 0.7$, which in practice tends to weight excessively observations from large countries.

(= 27% × 52%). Differently, when $\kappa \leq 1.2$, the more obvious shortcoming of the EK model is its overestimation of trade among poor countries. It predicts that the average trade share of the 30 poorest countries in the sample is 87% and that 42% of this trade is allocated to rich countries (column A, rows 5, 12). So roughly, 50% of poor countries' GDP is allocated to trade with other poor countries according to the EK model. In the data, the corresponding value is only 14%, and in the new model, it is 25%.

The new model is able to capture the key moments of the data regarding trade and income whenever $\kappa \geq 1.3$. As illustrated in figure 3, trade share in the data increases with income per capita–the coefficient on income per capita in the regression line is 0.025, and it is statistically significant at a 1% level. The new model correctly predicts a positive and statistically significant coefficient, while the EK model predicts a negative coefficient for all κ. The new model, however, overestimates the coefficient on income per capita to 0.5 (rows 2, 3).

Figure 4 shows that the relationship between trade share and total income in the data is small and statistically insignificant. The regression of trade share on a constant and the logarithm of total GDP yields a coefficient on GDP of -0.01, standard error of 0.007 and R^2 of 0.01 (rows 6, 7, 8). In contrast, the EK model predicts that the single most important determinant of a country's trade share is its total income–the larger a country's income, the smaller its trade share. When $\kappa \leq 1.2$, the R^2 of the regression of trade share on GDP is 0.89. And while in the data, the 30 smallest countries trade only 38% of their income, the EK model predicts that they trade 95% of their income (column A, rows 8, 10). The new model, in turn, correctly predicts the weak relationship between trade share and total income when $\kappa \geq 1.3$. It predicts that regressing trade share on GDP yields a coefficient on GDP of only -0.02 on average and an R^2 of 0.09.

As illustrated in figure 5, the share of rich countries in trade increases with income per capita. On average, the 20 richest countries in the sample account for 59% of rich countries' trade and 41% of poor countries' trade. When $\kappa \geq 1.3$, the corresponding figures for the EK model are 30% and 13%, and for the new model, they are 52% and 27% (rows 11, 12). So while both models capture the increasing pattern in the data, the EK model underestimates the role of rich countries in trade.[20]

[20]To calculate rows 11 and 12, I follow the same procedure as in section 3. Poor countries are the 20 poorest countries in the sample, and rich countries are the 20 richest countries in figure 5, which excludes the 20 richest countries in the sample (see footnote 15).

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

Table 1: List of countries in the sample

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

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

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

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

* OECD country

† The country does not report trade to the UN.

	OECD only	Full sample	
	EK = New model	EK model	New model
Explanatory power	**74%**	**34%**	**42%**
Normalized parameters			
σ_A			4.00
θ_A	8.28	8.28	8.28
Estimated parameters			
γ_1	1.24	1.96	1.38
γ_2	0.84	0.26	0.20
γ_3	-0.21	0.00	-0.01
border	0.98	0.85	0.99
language	1.01	0.92	0.94
trade agreement	0.91	1.27	1.22
α_A			0.81
σ_B			1.18
θ_B			14.19

Table 2: Estimation Results

Country	EK model	New model	Δ = EK - New model
Albania	0.0	0.0	0.0
Algeria	0.0	0.0	0.0
Angola	0.1	0.1	0.0
Antigua and Barbuda	2.6	2.7	-0.1
Argentina	0.0	0.0	0.0
Armenia	0.0	0.0	0.0
Australia	0.0	0.0	0.0
Austria	0.0	0.0	0.0
Azerbaijan	0.1	0.1	0.0
Bahamas, The	0.0	0.1	0.0
Bahrain	0.0	0.2	-0.1
Bangladesh	0.0	0.0	0.0
Barbados	1.7	1.4	0.3
Belarus	0.1	0.1	0.0
Belgium	0.0	0.0	0.0
Belize	0.1	0.2	-0.1
Benin	0.4	0.3	0.0
Bhutan	0.0	0.1	-0.1
Bolivia	0.0	0.0	0.0
Bosnia and Herzegovina	1.1	1.0	0.1
Botswana	0.1	0.1	0.0
Brazil	0.0	0.0	0.0
Bulgaria	0.0	0.0	0.0
Burkina Faso	0.8	0.8	0.0
Burundi	0.4	0.5	-0.1
Cambodia	0.0	0.0	0.0
Cameroon	0.1	0.1	0.0
Canada	0.0	0.0	0.0
Cape Verde	0.3	0.3	0.0
Central African Republic	0.3	0.3	0.0
Chad	0.2	0.2	0.0
Chile	0.0	0.0	0.0
China	0.0	0.0	0.0

Table 3: Distribution of residuals by importing country

Country	EK model	New model	Δ = EK - New model
Colombia	0.0	0.0	0.0
Congo, Dem. Rep.	0.2	0.2	0.0
Congo, Rep.	0.1	0.0	0.1
Costa Rica	0.0	0.0	0.0
Cote d'Ivoire	0.1	0.1	0.0
Croatia	0.1	0.1	0.0
Cyprus	0.0	0.0	0.0
Czech Republic	0.0	0.0	0.0
Denmark	0.0	0.0	0.0
Dominica	4.1	2.1	2.0
Dominican Republic	0.0	0.0	0.0
Ecuador	0.0	0.0	0.0
Egypt, Arab Rep.	0.0	0.0	0.0
El Salvador	0.0	0.0	0.0
Equatorial Guinea	0.2	0.1	0.1
Eritrea	0.1	0.1	0.0
Estonia	0.2	0.2	0.0
Ethiopia	0.2	0.2	0.0
Fiji	0.3	0.1	0.2
Finland	0.0	0.0	0.0
France	0.0	0.0	0.0
French Polynesia	0.0	0.0	0.0
Gambia, The	0.7	1.4	-0.7
Germany	0.0	0.0	0.0
Ghana	0.8	0.8	0.0
Greece	0.0	0.0	0.0
Grenada	4.1	1.7	2.4
Guinea	0.4	0.5	-0.1
Guyana	6.8	6.8	0.0
Haiti	0.1	0.1	0.0
Hong Kong, China	0.0	0.0	0.0
Hungary	0.0	0.0	0.0
Iceland	0.2	0.2	0.0

Country	EK model	New model	Δ = EK - New model
India	0.0	0.0	0.0
Indonesia	0.0	0.0	0.0
Iran, Islamic Rep.	0.0	0.0	0.0
Ireland	0.0	0.0	0.0
Israel	0.0	0.0	0.0
Italy	0.0	0.0	0.0
Jamaica	1.6	1.7	-0.1
Japan	0.0	0.0	0.0
Jordan	0.0	0.0	0.0
Kazakhstan	0.0	0.0	0.0
Kenya	0.0	0.0	0.0
Korea, Rep.	0.0	0.0	0.0
Kuwait	0.0	0.0	0.0
Kyrgyz Republic	0.5	0.5	0.0
Lao PDR	0.1	0.1	0.0
Latvia	0.4	0.3	0.0
Lebanon	0.0	0.0	0.0
Lesotho	0.5	0.6	-0.1
Libya	0.0	0.0	0.0
Lithuania	0.0	0.0	0.0
Luxembourg	0.0	0.0	0.0
Macao, China	0.0	0.0	0.0
Macedonia, FYR	0.7	0.8	0.0
Madagascar	0.3	0.3	0.1
Malawi	0.2	0.2	0.0
Malaysia	0.0	0.0	0.0
Maldives	0.5	0.5	0.0
Mali	2.3	2.3	0.0
Malta	0.1	0.1	0.0
Mauritius	0.1	0.1	0.0
Mexico	0.0	0.0	0.0
Mongolia	0.0	0.0	0.0
Morocco	0.0	0.0	0.0

Country	EK model	New model	Δ = EK - New model
Mozambique	0.1	0.2	-0.1
Namibia	0.2	0.1	0.0
Nepal	0.0	0.1	-0.1
Netherlands	0.0	0.0	0.0
New Caledonia	0.0	0.0	0.0
New Zealand	0.0	0.0	0.0
Nicaragua	0.2	0.1	0.1
Niger	0.4	0.3	0.1
Nigeria	0.0	0.0	0.0
Norway	0.0	0.0	0.0
Oman	0.0	0.0	0.0
Pakistan	0.0	0.0	0.0
Papua New Guinea	0.0	0.0	0.0
Paraguay	0.0	0.0	0.0
Peru	0.0	0.0	0.0
Philippines	0.0	0.0	0.0
Poland	0.0	0.0	0.0
Portugal	0.0	0.0	0.0
Qatar	0.0	0.2	-0.2
Romania	0.0	0.0	0.0
Russian Federation	0.1	0.1	0.0
Rwanda	0.1	0.1	0.0
Saudi Arabia	0.0	0.0	0.0
Senegal	0.6	0.9	-0.3
Serbia and Montenegro	0.5	0.5	0.0
Seychelles	0.4	0.4	0.0
Singapore	0.2	0.1	0.1
Slovak Republic	0.0	0.0	0.0
Slovenia	0.0	0.0	0.0
Solomon Islands	0.2	0.1	0.0
South Africa	0.0	0.0	0.0
Spain	0.0	0.0	0.0
Sri Lanka	0.0	0.0	0.0

Country	EK model	New model	Δ = EK - New model
St. Kitts and Nevis	2.3	2.0	0.2
St. Lucia	2.6	1.5	1.1
Sudan	0.0	0.0	0.0
Suriname	3.9	4.3	-0.4
Swaziland	0.7	1.1	-0.3
Sweden	0.0	0.0	0.0
Switzerland	0.0	0.0	0.0
Syrian Arab Republic	0.0	0.0	0.0
Taiwan	0.0	0.0	0.0
Tajikistan	7.5	7.4	0.1
Tanzania	0.1	0.0	0.0
Thailand	0.0	0.0	0.0
Togo	0.5	0.8	-0.2
Tonga	5.7	1.5	4.3
Trinidad and Tobago	0.7	0.6	0.0
Tunisia	0.0	0.0	0.0
Turkey	0.0	0.0	0.0
Turkmenistan	0.5	0.5	0.0
Uganda	0.3	0.3	0.0
Ukraine	2.0	2.0	0.0
United Arab Emirates	0.0	0.1	-0.1
United Kingdom	0.0	0.0	0.0
United States	0.0	0.0	0.0
Uruguay	0.0	0.0	0.0
Uzbekistan	0.9	0.9	0.0
Venezuela, RB	0.0	0.0	0.0
Vietnam	0.1	0.1	0.0
Yemen, Rep.	0.0	0.0	0.0
Zambia	0.2	0.2	0.0
Zimbabwe	0.3	0.3	0.0
	66	**58**	**8**

	original	median	minimum	maximum
explanatory power	42%	49%	38%	59%
	original	median	95% confidence interval	
γ_1	1.38	1.39	1.37	1.40
γ_2	0.20	0.20	0.19	0.20
γ_3	-0.01	-0.01	-0.01	-0.01
border	0.99	0.99	0.98	1.00
language	0.94	0.94	0.93	0.95
trade agreement	1.22	1.22	1.19	1.23
α_A	0.81	0.81	0.80	0.82
σ_B	1.18	1.19	1.16	1.21
θ_B	14.2	14.1	13.9	14.3

Table 4: Confidence intervals for the new model's parameter

	original		
θ_A	**8.28**	**3.60**	**12.86**
explanatory power	34%	34%	34%
γ_1	1.96	4.60	1.55
γ_2	0.26	1.63	0.13
γ_3	0.00	0.00	0.00
border	0.85	0.80	0.87
language	0.92	0.89	0.93
trade agreement	1.27	1.43	1.24

Table 5: 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	42%	42%	42%	42%	41%
γ_1	1.38	1.61	1.27	1.40	1.37
γ_2	0.20	0.40	0.13	0.20	0.20
γ_3	-0.01	-0.01	-0.01	-0.01	-0.01
border	0.99	1.01	0.98	0.98	0.99
language	0.94	0.91	0.94	0.94	0.93
trade agreement	1.22	1.24	1.21	1.20	1.22
α_A	0.81	0.77	0.80	0.72	0.80
σ_B	1.18	1.22	1.19	1.00	1.61
θ_B	14.2	9.50	19.4	13.8	14.7

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

		Data	EK model $\kappa \leq 1.2$ (A)	EK model $\kappa \geq 1.3$ (B)	New model $\kappa \leq 1.2$ (C)	New model $\kappa \geq 1.3$ (D)
Explanatory power (%)						
	OECD sample		83	75	86	75
	full sample, 162 countries		53	24	61	32
1	average trade share (%)	34	70	9	49	21
Figure 3: Regression of trade share on the logarithm of GDP per capita						
2	coefficient on GDP per capita	0.02	-0.07	-0.01	-0.02	0.05
3	t-value	2.8	-6.9	-2.0	-1.8	6.8
	average trade share (%) of					
4	30 richest countries	37	50	5	44	27
5	30 poorest countries	24	87	10	56	12
Figure 4: Regression of trade share on the logarithm of GDP						
6	coefficient on GDP	-0.01	-0.10	-0.02	-0.07	-0.02
7	t-value	-1.3	-37	-8	-20	-3.7
8	R^2	0.01	0.89	0.29	0.67	0.09
	average trade share (%) of					
9	30 largest countries	29	34	3	28	15
10	30 smallest countries	38	95	14	74	28
Figure 5: Share of trade allocated to the 20 richest countries						
11	average among rich countries (%)	59	46	30	55	52
12	average among poor countries (%)	41	42	13	**55**	27

Table 7: Summary statistics for estimates with different values of κ

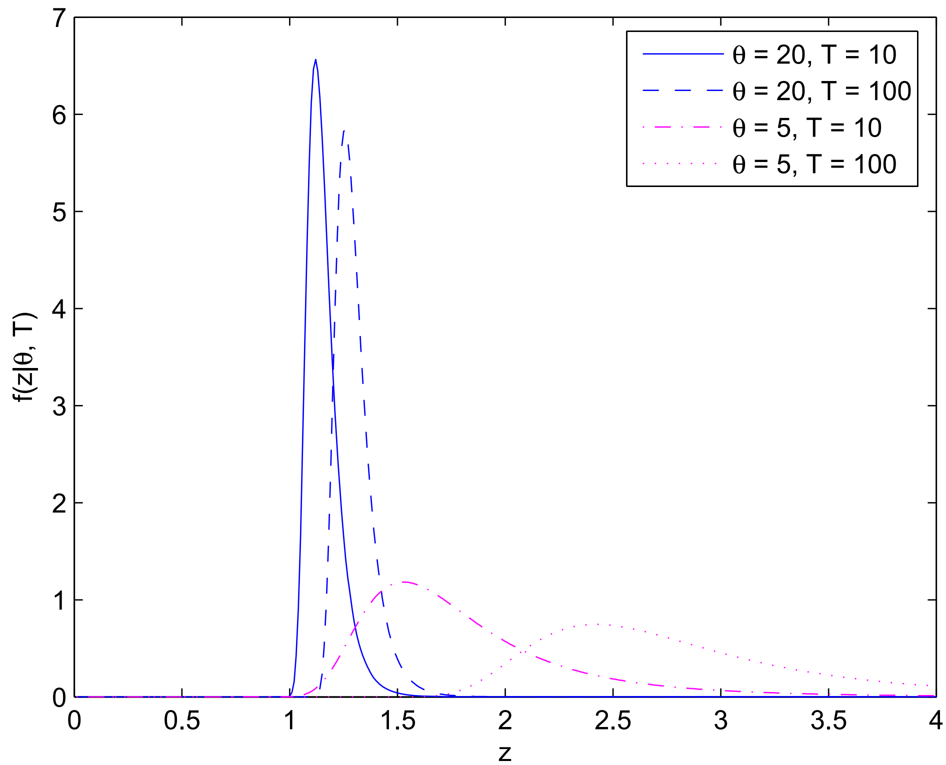

Figure 1: Examples of Fréchet Distributions

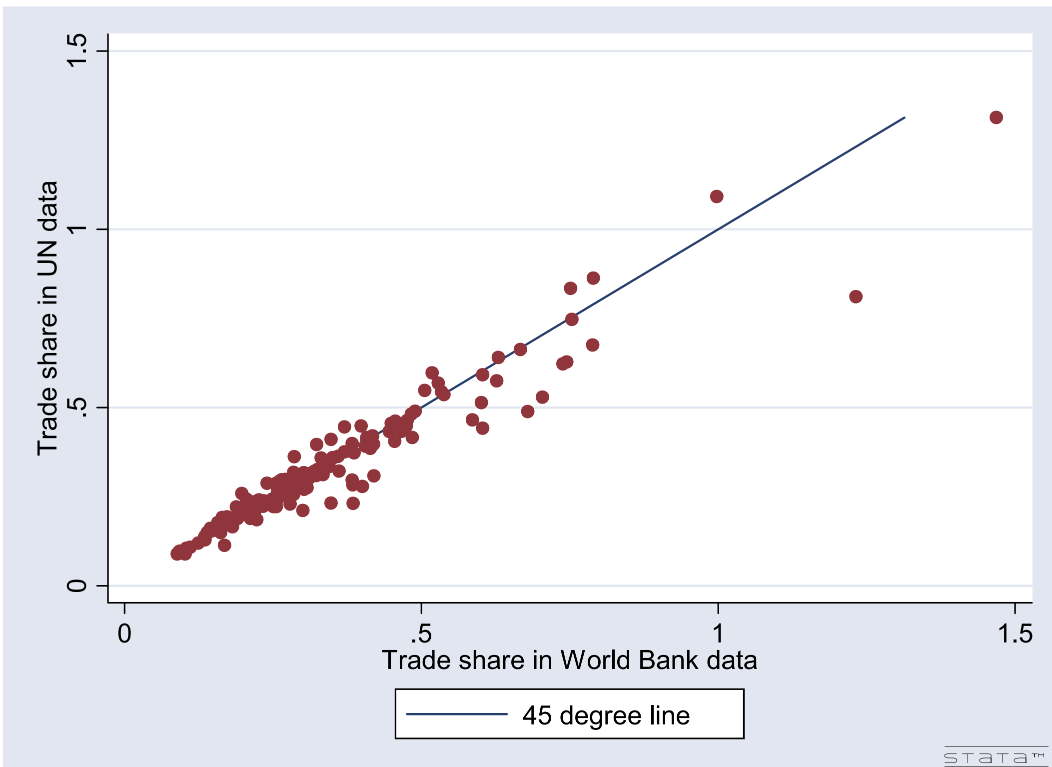

Figure 2: Comparison between trade share in UN (2008) and in the World Bank (2006)

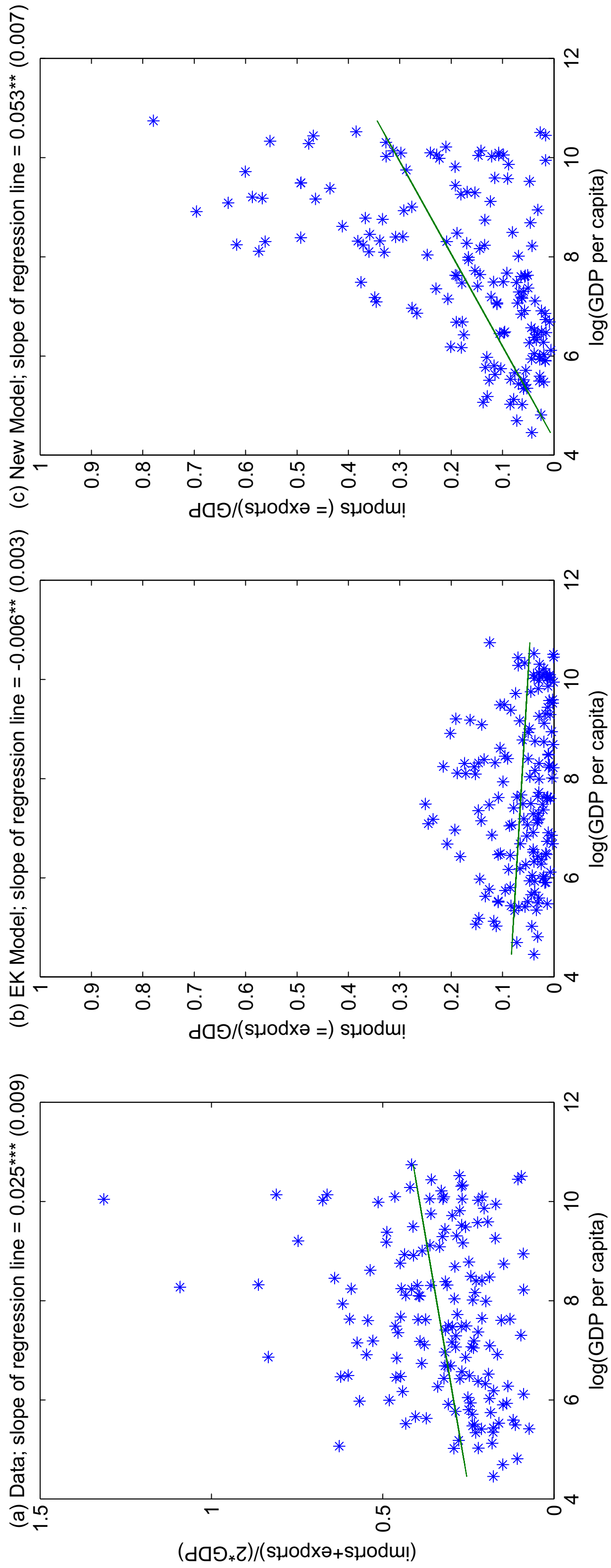

Figure 3: Income per capita × trade share

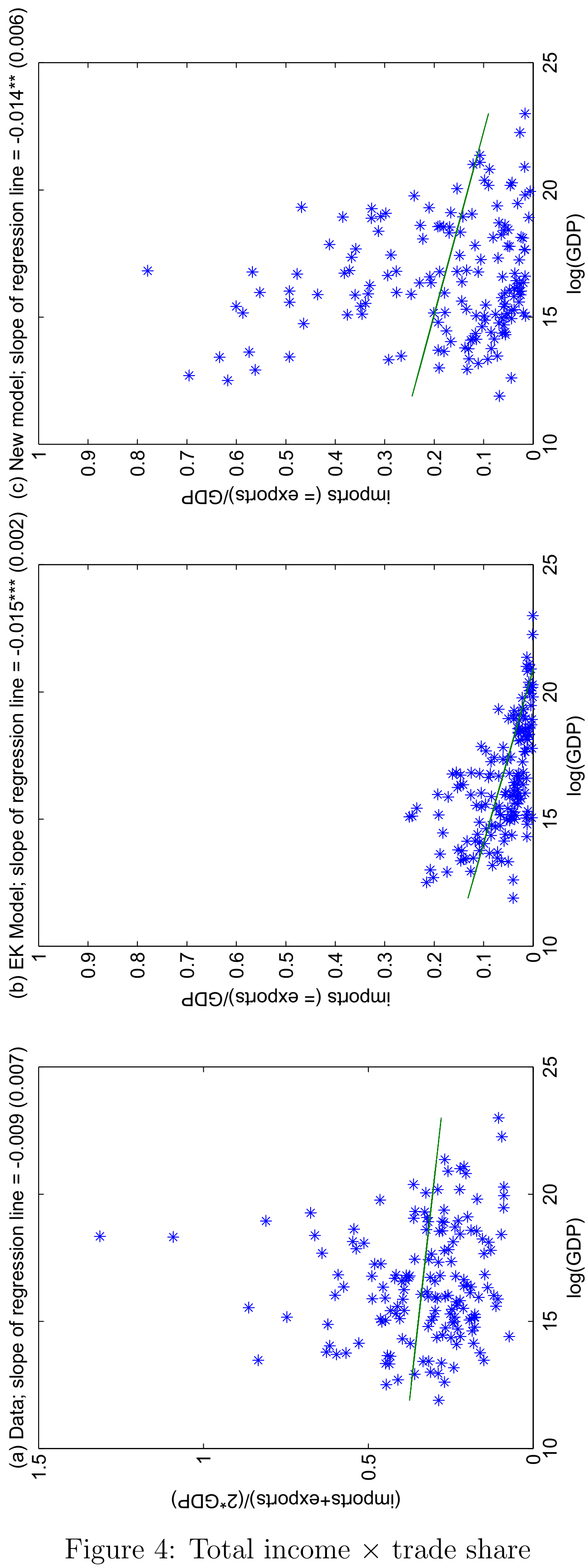

Figure 4: Total income × trade share

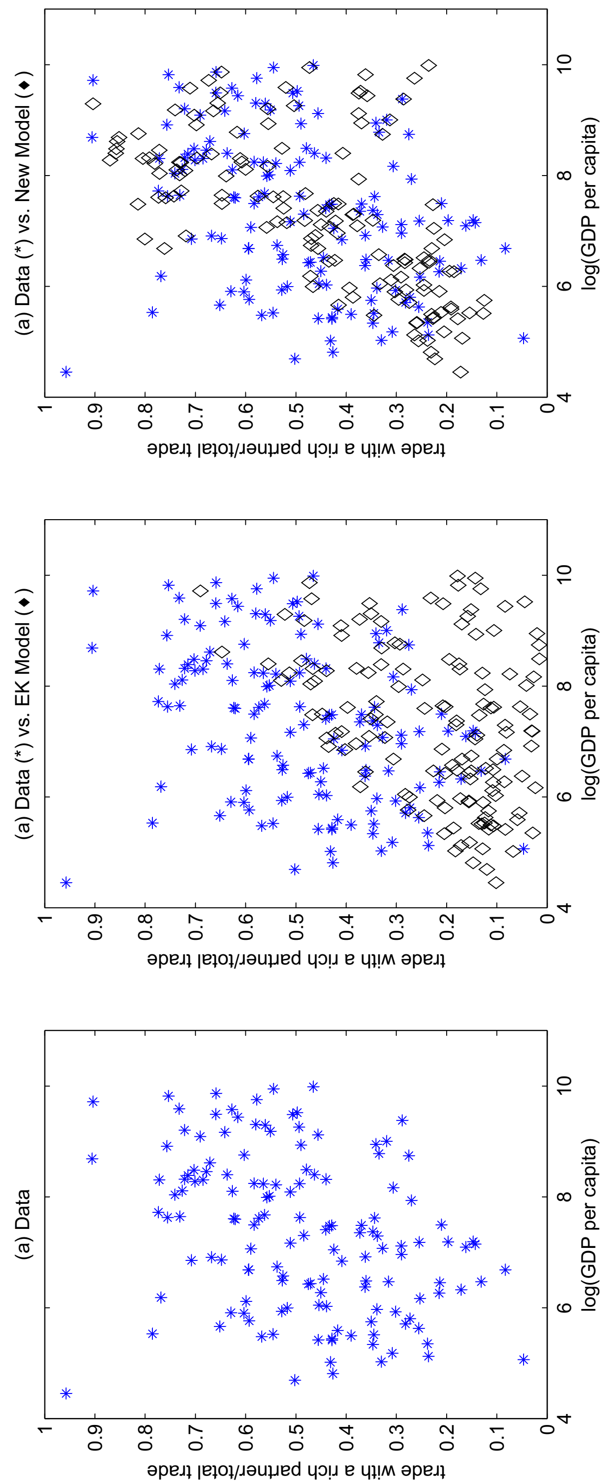

Figure 5: Income per capita × trade with 20 richest countries

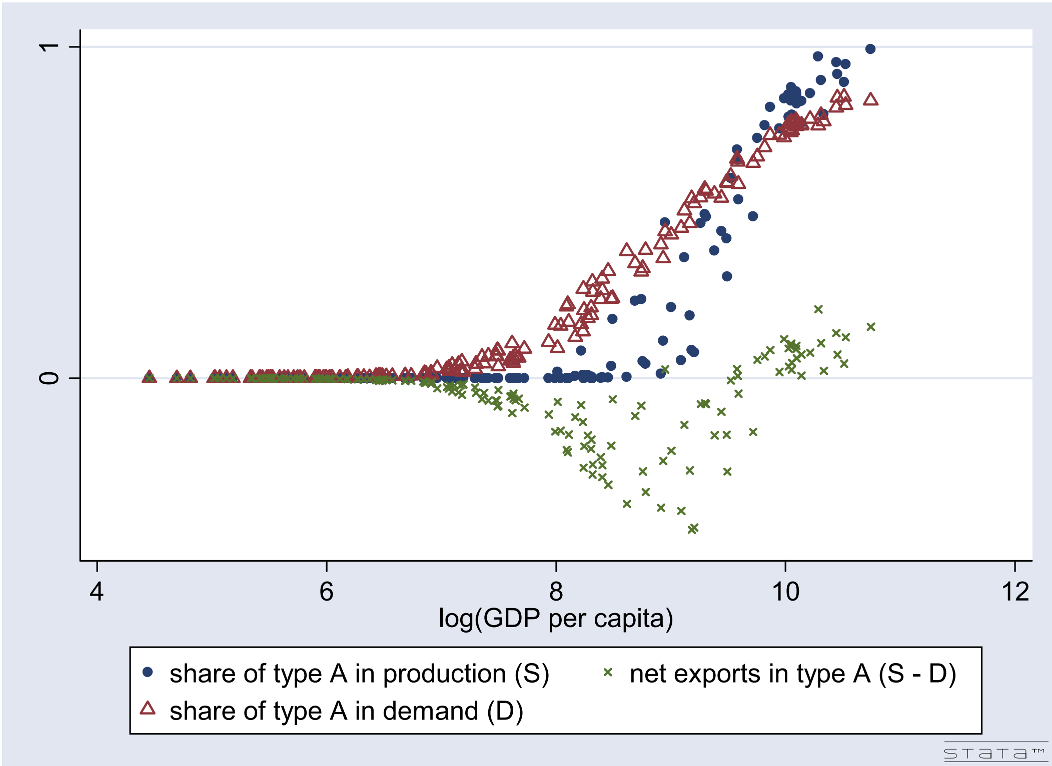

Figure 6: Demand, production and net exports in type A goods

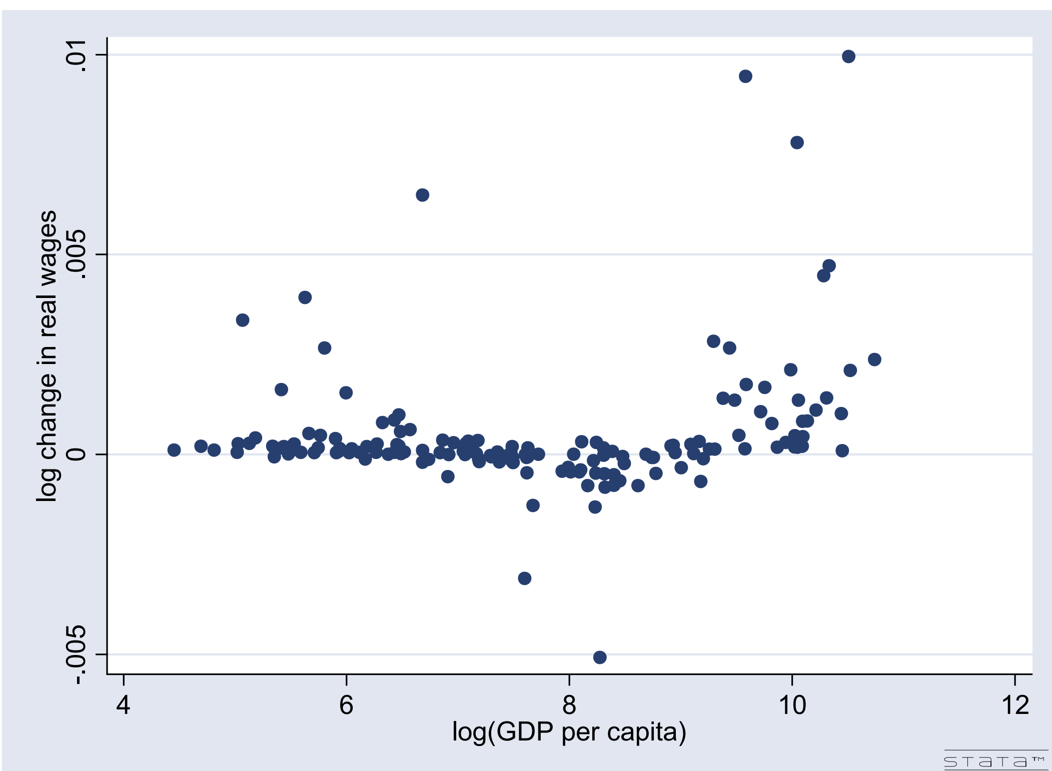

Figure 7: Technology shock in China

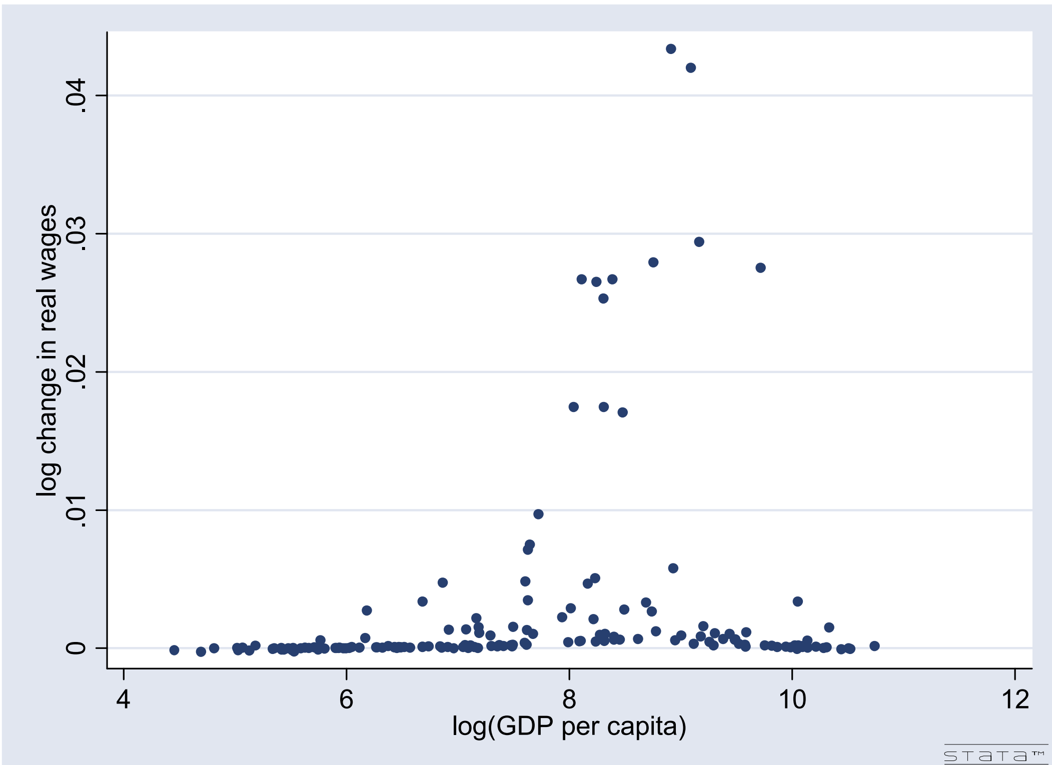

Figure 8: Technology shock in the U.S.A.