

SKILL PREMIUM AND TRADE PUZZLES: A SOLUTION LINKING PRODUCTION AND PREFERENCES

Justin Caron, Thibault Fally and James R. Markusen*

September 2012

Abstract

The international trade literature, despite its reliance on general-equilibrium analysis, focuses on the supply side and does not provide a good understanding of the relationship between characteristics of goods in production and characteristics of preferences. This paper conducts an empirical investigation into the relationship between a good's factor intensity in production and its income elasticity of demand in consumption. In particular, we find a strong and significant positive correlation between skilled-labor intensity and income elasticity for several types of preferences, with and without accounting for trade costs and cross-country price differences. Our general-equilibrium framework allows us to quantify the implications of this correlation. We show that it can explain about one third of "missing trade", and that per-capita income plays an important role in determining trade/GDP ratios and the choice of trading partners. It implies, furthermore, that uniform productivity growth shifts consumption towards skilled-labor intensive goods, generating a novel demand-driven explanation for the observed increase in the skill premium. Counterfactual simulations in general-equilibrium find this effect to be large, particularly in developing countries.

Keywords: Non-homothetic preferences, gravity, income, missing trade, skill premium.

JEL Classification: F10, O10, F16, J31.

*Justin Caron: MIT Joint Program on the Science and Policy of Global Change and ETH Zurich; Thibault Fally and James Markusen: University of Colorado-Boulder. We thank Donald Davis, Peter Egger, Lionel Fontanie, Juan Carlos Hallak, Gordon Hanson, Wolfgang Keller, Keith Maskus, Tobias Seidel, David Weinstein, conference and seminar participants at the NBER Summer Institute (ITI), Society of Economic Dynamics, ERWITT CEPR conference, Midwest Trade Meetings, UC San Diego, Paris School of Economics, ETH Zurich and the University of Colorado-Boulder for helpful comments. Contact: Thibault Fally, Department of Economics, University of Colorado-Boulder, 256 UCB Boulder, Colorado 80309-0256, USA. fally@colorado.edu.

1 Introduction

International trade theory is a general-equilibrium discipline. Yet it is probably fair to suggest that most of the standard portfolio of research focuses on the production side of general equilibrium. Price elasticities of demand do play a role in oligopoly models and, of course, a preference for diversity is important in all models, not just monopolistic competition. Income elasticities of demand are, however, generally assumed to be either one (homothetic preferences) or zero (so-called quasi-homothetic preferences used in oligopoly models). The emphasis on non-homothetic preferences and the role of non-unitary income elasticities of demand that were so crucial in the work of Linder (1961) for example, largely disappeared from trade theory over the last few decades.

Beyond a lack of focus on the demand side of general equilibrium, we have a sharply limited set of theoretical and empirical results on possible relationships between the demand and supply sides of general equilibrium; that is, not much is understood about whether certain characteristics of goods in production are correlated with other characteristics of preferences and demand. The purpose and focus of our paper is to investigate such a relationship empirically. In particular, we explore a systematic relationship between factor intensities of goods in production and their corresponding income elasticities of demand in consumption. The existence of such a relationship can contribute to a number of empirical puzzles in trade as suggested by Markusen (2010). These include: i) the mystery of the missing trade, ii) a home bias in consumption, iii) larger trade volumes among rich countries, and iv) a growing skill premium with rising per-capita income.

We provide a discussion of alternative representations of non-homothetic preferences and expressions for expenditure shares across goods: (1) the linear expenditure system, derived from Stone-Geary preferences, (2) Deaton and Muellbauer’s almost ideal demand system (AIDS) (Deaton and Muellbauer, 1980), and (3) what we will term “constant relative income elasticity” (CRIE) preferences, recently used in Fieler (2011). While we present estimated income elasticities for all three, we focus on the latter in our benchmark model. We carefully account for supply-side effects. If rich countries tend to have a comparative advantage in particular industries, consumption in these industries might be larger (goods available at lower prices). Not controlling for such patterns of comparative advantage could bias income elasticity estimates upwards. We provide a two-step estimation strategy by first estimating gravity equations in each industry and then using the estimated parameters to structurally control for supply-side effects in a second step. While the estimation of models with non-homothetic preferences has been considered as challenging in the past, our method is actually quite simple to implement as

it does not rely on actual price data.¹ Our two-step empirical strategy is inspired from Redding and Venables (2004) and would be suitable for alternative standard frameworks.²

Our estimations rely on the GTAP7 data set, which comprises 94 countries with a wide range of income levels, 56 broad sectors including manufacturing and services, and 5 factors of production including the disaggregation of skilled and unskilled labor. This is an excellent harmonized data set for our purposes, since it includes production, input-output, expenditure and trade data. However, the broad categories of goods and services make it unsuitable for the discussion of issues related to product quality and within-industry heterogeneity.

Results show that the income elasticity of demand varies considerably across industries. Moreover, it is significantly related both in economic and statistical terms to the skill intensity of a sector, with a correlation well over 60%. As expected, accounting for trade costs and supply-side characteristics reduces this correlation, but it remains larger than 40% and highly statistically significant. The relationship to capital intensity is positive but much weaker in economic terms and not statistically significant, consistent with Reimer and Hertel (2010), while the correlation with natural-resource intensity is negative.

The estimated parameters are then used to assess the role of non-homotheticity in explaining the empirical trade puzzles mentioned above. In addition to the income-elasticity / factor-intensity relationship, results include the following.

First, our model can explain a smaller factor content of trade, which is famously overpredicted in the Heckscher-Ohlin-Vanek framework. A systematic relationship between income elasticity and skill intensity at the sector level generates a strong correlation between specialization in consumption and specialization in production at the country level. This correlation is 86% in the data. While about a fourth can be explained by trade costs, we find non-homotheticity to be even more important quantitatively. Similar results show that non-homothetic preferences can explain a large fraction of the “missing trade” in factor services. The variance of the predicted factor content of trade is reduced by 30% compared to the standard Heckscher-Ohlin-Vanek framework. In a model with trade costs, this reduction is 41%. Moreover, these results are robust to the use of the “actual” factor content of trade, which we estimate by taking into account the factors embodied in both domestic and imported intermediate goods.

Second, per-capita income helps us understand the choice of trading partners, in particular the higher share of rich countries’ trade with rich-country partners. In our framework, per-

¹As a robustness check, we use actual price data from the International Comparison Program (ICP).

²Our model is based on Costinot, Donaldson and Komunjer (forthcoming) combined with non-homothetic preferences such as in Fieler (2011). Our empirical strategy would also be consistent with alternative frameworks based on Dixit-Stiglitz-Krugman model, as in Redding and Venables (2004), or Chaney (2008).

capita income contributes to understanding the composition of consumption across industries which, through its correlation with production specialization, has large effects on trade. On aggregate, this also implies an important role for per-capita income in understanding observed trade-to-GDP ratios.

Finally, we propose a novel demand-driven explanation for the observed rise in the skill premium (wage inequality). The supply and demand parameters from the two-step estimation procedure allow the counter-factual simulation, in general equilibrium, of factor-neutral productivity growth.³ As speculated in Markusen (2010), this shifts demand towards higher income-elasticity goods and, since these are on average skilled-labor intensive, raise the relative wage of skilled workers. We simulate both a uniform growth across countries and actual growth rates between 1995 and 2005.⁴ In each scenario, the models predicts a rising skill premium in all countries, with particularly large increases in the developing world.

Literature

Early papers exploring the factor-intensity / income-elasticity relationship are Markusen (1986), Hunter and Markusen (1988), Hunter (1991), and Bergstrand (1990). A particular focus of this literature is on the volume of trade in aggregate and among sets of countries, and its relationship to a world of identical and homothetic preferences as generally assumed in traditional trade theory. A general conclusion of this research was that non-homotheticity reduces trade volumes among countries with different endowments and per-capita income levels, though trade among high-income countries can increase. Matsuyama (2000) uses a competitive Ricardian model to arrive at a similar prediction.

There has been a renewed interest in the role of preferences in explaining trade volumes recently, including Reimer and Hertel (2010), Fieler (2011), Bernasconi (2011), Martinez-Zarzoso and Vollmer (2011), Simonovska (2010), and Cassing and Nishioka (2009).

Previous papers have emphasized the role of consumption patterns in explaining part of the “missing trade” puzzle but our results present several contributions. In a recent paper, Cassing and Nishioka (2009) show that allowing for richer consumption patterns play a more important role than allowing for heterogeneous production techniques. They do not however specifically estimate non-homothetic preferences to examine how much of the missing trade can actually be attributed to non-homotheticity. Both Cassing and Nishioka (2009) and Reimer and Hertel (2010) put an emphasis on capital intensity, which is positively but not strongly correlated

³Our tight model formulation allows us to numerically solve a large non-linear system of simultaneous equations and inequalities, including the determination of factor rewards, bilateral trade flows, consumption and production (with or without intermediate goods) for all countries and sectors in our sample.

⁴We also provide an analytical approximation of the skill-premium-to-productivity elasticity expressed as a simple function of income elasticities and skill intensities.

with income elasticity of demand, but they do not differentiate skilled vs. unskilled labor and thus underestimate the role of non-homothetic preferences in explaining missing factor content trade.⁵

Closest to our paper is Fieler (2011). She estimates demand- and supply-side characteristics by combining a similar preference structure and gravity equations. While Fieler (2011) uses data on aggregate trade flows, we rather examine sector-level data and factor usage. Moreover, the specific structure of the Fieler (2011) model implies by construction that countries with higher average productivity have a comparative advantage in the production of goods where the elasticity of trade flows to trade costs is higher (low- θ goods). On the contrary, our estimation strategy allows and controls for any pattern of comparative advantage. We emphasize the role of non-homothetic preferences compared to homothetic preferences while keeping the same structure of comparative advantage and trade-cost elasticities on the supply side.

To our knowledge, our paper is the first to investigate a demand-side explanation for the rising skill-premium. Previous research has emphasized the role of skill-biased technological change (Autor et al., 1998), outsourcing and competition from low-wage countries (Feenstra and Hanson, 1999). We find that, quantitatively, productivity growth combined with non-homothetic preferences has a comparable if not larger impact on the relative demand for skilled labor.

There are other topic areas where per-capita income plays a key role. One is a large and growing literature on product quality where per-capita income clearly matters: if a consumer is to buy one unit of a good, consumers with higher incomes buy higher quality goods. In line with Linder (1961), the role of quality differentiation has been underscored by Hallak (2010). In addition, the distribution of income within a country matters, and a fairly general result is that higher inequality leads to a higher aggregate demand for high-quality products. We view this literature as important and most welcome. Note that within-industry reallocations only reinforce the mechanisms described in our model. If high-quality goods are associated with both higher income elasticities and stronger skill intensity, the same mechanisms would apply for within-industry reallocations as for the between-industry reallocations described in our paper. Concerning within-country inequalities, we find very similar results – if not stronger – when using within-country income distribution data by decile.

⁵Among other papers, most of the attention has been put on the home bias or the border effect (e.g. Trefler (1995)). Here, we directly estimate the border effect, or equivalently a home bias in consumption, in the first-step gravity equation for each industry and control for it to compare homothetic and non-homothetic preferences.

2 Theoretical framework

2.1 Model set-up

Demand

Each industry k corresponds to a continuum of product varieties indexed by $j_k \in [0, 1]$. Preferences take the form:

$$U = \sum_k \alpha_{1,k} Q_k^{\frac{\sigma_k - 1}{\sigma_k}}$$

where $\alpha_{1,k}$ is a constant (for each industry k) and Q_k is a CES aggregate:

$$Q_k = \left(\int_{j_k=0}^1 q(j_k)^{\frac{\eta_k - 1}{\eta_k}} dj_k \right)^{\frac{\eta_k}{\eta_k - 1}}$$

Preferences are identical across countries, but non-homothetic if σ_k varies across industries. If $\sigma_k = \sigma$, we are back to traditional homothetic CES preferences. These preferences are used in Fieler (2011), with early analyses and applications found in Hanoch (1975) and Chao and Manne (1982). To the best of our knowledge, there is no common name attached to these preferences, so we will refer to them as constant relative income elasticity (CRIE) tastes: As shown in Fieler (2011) and below, the ratio of income elasticities of demand between goods i and j is given by σ_i/σ_j and is constant.

The CES price index of goods from industry k in country n is $P_{nk} = \left(\int_0^1 p_{nk}(j_k)^{1-\eta_k} dj_k \right)^{\frac{1}{1-\eta_k}}$. Given this price index, individual expenditures ($P_{nk}Q_{nk}$) in country n for goods in industry k equal:

$$x_{nk} = \lambda_n^{-\sigma_k} \alpha_{2,k} (P_{nk})^{1-\sigma_k} \quad (1)$$

where λ_n is the Lagrangian associated with the budget constraint of individuals in country n , and $\alpha_{2,k} = (\alpha_{1,k} \frac{\sigma_k - 1}{\sigma_k})^{\sigma_k}$. The Lagrangian λ_n is determined by the budget constraint: total expenditures must equal total income. In general there is no analytical expression for λ_n .

The income elasticity of demand for goods industry k in country n equals:

$$\varepsilon_{nk} = \sigma_k \cdot \frac{\sum_{k'} x_{nk'}}{\sum_{k'} \sigma_{k'} x_{nk'}} \quad (2)$$

Income elasticity for good 1 relative to income elasticity for good 2 equals the ratio $\frac{\sigma_1}{\sigma_2}$ and is constant across countries. Note that CRIE preferences precludes any inferior good: the income elasticity of demand is always positive for any good.

Another important feature of income elasticities is that they decrease with income. A larger

income induces a larger fraction of expenditures in high- σ_k industries. Hence, the consumption-weighted average of σ_k is larger (denominator in expression 2 above) which yields lower income elasticities.

Production

We assume that factors of production are perfectly mobile across sectors but immobile across countries. We denote by w_{fn} the price of factor f in country n .

We assume a Cobb-Douglas production function for each sector with constant returns to scale. Factor intensities are denoted by β_{fk} and vary across industries but are assumed to be common across countries. Total factor productivity $z_{ik}(j_k)$ varies by country, industry and variety.

As common in the trade literature, we assume iceberg transport costs $d_{nik} \geq 1$ from country i to country n in sector k . The unit cost of supplying variety j_k to country n from country i equals:

$$p_{nik}(j_k) = \frac{d_{nik}}{z_{ik}(j_k)} \prod_f (w_{fi})^{\beta_{fk}}$$

There is perfect competition for the supply of each variety j_k . Hence, the price of variety j_k in country n in industry k equals:

$$p_{nk}(j_k) = \min_i \{p_{nik}(j_k)\}$$

We follow Eaton and Kortum (2002) and related papers and assume that productivity is a random variable with a Frechet distribution. This setting generates gravity within each sector. Productivity is independently drawn in each country i and industry k , with a cumulative distribution:

$$F_{ik}(z) = \exp \left[-(z/z_{ik})^{-\theta_k} \right]$$

where z_{ik} is a productivity shifter reflecting average TFP of country i in sector k . As in Eaton and Kortum (2002), θ_k is related to the inverse of productivity dispersion across varieties within each sector k . Note that we also assume $\theta_k > \eta_k - 1$ to insure a well-defined CES price index within each industry (Eaton and Kortum, 2002).

We allow the dispersion parameter θ_k to vary across industries. In keeping with Costinot, Donaldson and Komunjer (2010), we also allow the shift parameter z_{ik} to vary across exporters and industries, keeping a flexible structure on the supply side and controlling for any pattern of Ricardian comparative advantage forces at the sector level.

Endowments

Each country is populated by a number L_i of individuals. The total supply of factor f is fixed in each country and denoted by V_{if} .

As a first approximation, each person is endowed by V_{if}/L_i units of factor V_{fi} . This implies that there is no within-country income inequality. We relax this assumption in section (5.4) and examine how within-country income inequalities affect our estimates.

2.2 Equilibrium

Equilibrium is defined by the following equations. On the demand side, total expenditures D_{nk} of country n for sector k simply equals population L_n times individual expenditures as shown in (1). This gives:

$$D_{nk} = L_n (\lambda_n)^{-\sigma_k} \alpha_{2,k} (P_{nk})^{1-\sigma_k} \quad (3)$$

where λ_n is the Lagrangian associated with the budget constraint. To determine λ_n , we thus need to take the budget constraint into account:

$$L_n e_n = \sum_k D_{nk} \quad (4)$$

On the supply side, each industry mimics an Eaton and Kortum (2002) economy. In particular, given the Frechet distribution, we obtain a gravity equation for each industry. We follow Eaton and Kortum (2002) notation, with the addition of industry subscripts. By denoting X_{nik} the value of trade *from* country i to country n , we obtain:

$$X_{nik} = \frac{S_{ik} (d_{nik})^{-\theta_k}}{\Phi_{nk}} D_{nk} \quad (5)$$

Here, S_{ik} , which we call the ‘‘supplier fixed effect’’ is inversely related to the cost of production in country i and industry k . It depends on the total factor productivity parameter z_{ik} , factor prices and factor intensities:

$$S_{ik} = z_{ik}^{\theta_k} \left(\prod_f (w_{fi})^{\beta_{fk}} \right)^{-\theta_k} \quad (6)$$

The parameter θ_k is inversely related to the dispersion of productivity within sectors, which means that differences in productivity and factor prices across countries have a stronger impact on trade flows in sectors with higher θ_k . In turn, we define Φ_{nk} as the sum of exporter fixed effects deflated by trade costs. Φ_{nk} plays the same role as the ‘‘inward multilateral trade

resistance index” as in Anderson and van Wincoop (2003):

$$\Phi_{nk} = \sum_i S_{ik} (d_{nik})^{-\theta_k} \quad (7)$$

This Φ_{nk} is actually closely related to the price index, as in Eaton and Kortum (2002):

$$P_{nk} = \alpha_{3,k} (\Phi_{nk})^{-\frac{1}{\theta_k}} \quad (8)$$

with $\alpha_{3,k} = \left[\Gamma \left(\frac{\theta_k + 1 - \eta_k}{\theta_k} \right) \right]^{\frac{1}{\eta_k - 1}}$ where Γ denotes the gamma function.

Finally, two other market clearing conditions are required to pin down factor prices and income in general equilibrium. Given the Cobb-Douglas production function, total income from a particular factor equals the sum of total production weighted by the factor intensity coefficient β_{fk} . With factor supply V_{fi} and factor price w_{fi} for factor f in country i , factor market clearing implies:

$$V_{fi} w_{fi} = \sum_{n,k} \beta_{fk} X_{nik} \quad (9)$$

In turn, per-capita income is determined by:

$$L_i e_i = \sum_f V_{fi} w_{fi} \quad (10)$$

In the baseline case, we assume homogeneous income within countries (the role of within-country inequalities is examined in section 5.4).

By Walras’ Law, trade is balanced at equilibrium.

2.3 Implications: the role of non-homothetic preferences

2.3.1 Trade patterns

With non-homothetic preferences, differences in income per capita across countries can result in large differences in consumption patterns, even though preferences are identical. In this section, we illustrate how non-homotheticity affects trade patterns when there is a systematic relationship between preference parameters and characteristics of the supply side, e.g. factor intensities. This is supported by our empirical analysis which finds, in particular, a positive correlation across sectors between skill labor intensity (parameter β_{fk}) and income elasticity (proportional to σ_k).

Let’s first consider the case in which trade costs are assumed away ($d_{nik} = 1$). In this case, prices are the same in all countries and the share of consumption corresponding to imports

from i in industry k is the same for all importers (country n): $\frac{X_{nik}}{D_{nk}} = \frac{S_{ik}}{\sum_j S_{jk}}$. Summing over all industries, total import penetration by country i in country n is:

$$\frac{X_{ni}}{X_n} = \sum_k \left(\frac{S_{ik}}{\sum_j S_{jk}} \right) \left(\frac{\alpha_{4,k} \lambda_n^{-\sigma_k}}{\sum_{k'} \alpha_{4,k'} \lambda_n^{-\sigma_{k'}}} \right) \quad (11)$$

where $X_n = L_n e_n$ is total expenditures in country n , $X_{ni} = \sum_k X_{nik}$ is total bilateral trade from country i to n , and $\alpha_{4,k}$ is an industry constant incorporating common prices. The first term in parentheses is the share of imports from i in consumption of k – in other words this term reflects the comparative advantage of country i in sector k . The second is the share of industry k in final consumption of country n .

Aggregate import penetration by country i in country n obviously depends on the sectoral composition of both supply and demand, but the latter has generally been neglected by previous work. If preferences are homothetic, $\sigma_k = \sigma$ is common across industries and import penetration is the same across all importers n (for a given exporter i). When preferences are non-homothetic and σ_k varies across industries, exporters with a comparative advantage in high- σ industries have a relatively larger penetration in rich countries (low λ_n), while exporters with a comparative advantage in low- σ industries have a relatively larger penetration in poor countries (high λ_n). We will show empirically that rich countries have a comparative advantage in high- σ industries which can quantitatively explain large differences in trade volumes across country pairs depending on each partner's per-capita income.⁶

Trade costs provide an alternative explanation as to why import penetration varies across markets. On the supply side, proximity reduces unit costs. On the demand side, consumption might be biased towards goods produced locally if their price is lower (e.g. Saudi Arabia consuming more petroleum). The latter argument requires that the elasticity of substitution be larger than one. These effects of trade costs can reinforce the patterns described above. In our framework, a general expression for the import penetration of exporter i in market n yields:

$$\frac{X_{ni}}{X_n} = \sum_k \left(\frac{S_{ik} d_{nik}^{-\theta_k}}{\Phi_{nk}} \right) \left(\frac{\alpha_{5,k} \lambda_n^{-\sigma_k} \Phi_{nk}^{\frac{\sigma_k-1}{\theta_k}}}{\sum_{k'} \alpha_{5,k'} \lambda_n^{-\sigma_{k'}} \Phi_{nk'}^{\frac{\sigma_{k'}-1}{\theta_{k'}}}} \right) \quad (12)$$

where $\Phi_{nk} = \sum_j S_{jk} d_{nj}^{-\theta_k}$ by definition (equation 7) and $\alpha_{5,k} = \alpha_{2,k} \alpha_{3,k}^{1-\sigma_k}$ is an industry constant. In the empirical section, we thus need to carefully examine the distinct contribution of trade

⁶Formally, if per capita income e_n increases with n , if S_{ik} is log-supermodular (i.e. countries with higher index i have a comparative advantage in sectors with higher index k as in Costinot (2009)), and if σ_k increases with k , then X_{ni} is log-supermodular, which means that $\frac{X_{ni}}{X_{n'i'}} > \frac{X_{n'i}}{X_{n'i'}}$ for any countries $n > n'$ and $i > i'$. The proof follows from Athey (2002) since both S_{ik} and $\lambda_n^{-\sigma_k}$ are log-supermodular.

costs and non-homotheticity. In addition, we should note that import penetration by exporter i in rich countries might not increase with exporter i 's per capita income if competition effects dominate demand effects.⁷ For instance, a car producer may find it difficult to export cars to Germany because of trade costs and competition with local producers, even if Germany has a relatively large consumption of cars. Our empirical results however indicate that demand effects dominate.

2.3.2 Missing factor content of trade

One reason why comparative advantage may be related to consumption patterns is that the income elasticity of demand is correlated with the intensity in skilled labor. Such a correlation can also shed light on the “missing trade” puzzle, as we describe now.

Standard Heckscher-Ohlin models assume homothetic preferences. This assumption implies that, under free trade, consumption shares over different industries are the same across all countries. Accounting for non-homothetic preferences can yield very different predictions in terms of factor content of trade. In particular, it can potentially explain why poor countries trade so little with rich countries (in factor content) even if their endowments differ largely. The intuition is simple. When the income elasticity of demand is correlated with skill intensity, consumption in rich countries is biased towards skill-intensive industries, which also means that they are more likely to import from skill-abundant countries, i.e. rich countries. The same intuition would apply to capital if the income elasticity of demand would be correlated with capital intensity and if richer countries were relatively more endowed in capital.

These intuitions can be simply illustrated in our framework. We define the factor content of trade F_{fn} as the *value* of factor f required to produce exports minus imports. It equals $F_{fn} = \sum_k \beta_{fk} (\sum_{i \neq n} X_{nik} - \sum_{i \neq n} X_{ink})$ when production coefficients β_{kf} are common across countries.⁸ After simple reformulations, we can decompose F_{fn} in two terms:

$$F_{fn} = \underbrace{s_n \sum_k \bar{Y}_k \beta_{fk} \left[\frac{Y_{nk}}{s_n \bar{Y}_k} - 1 \right]}_{F_{fn}^{HOV}} - \underbrace{s_n \sum_k \bar{Y}_k \beta_{fk} \left[\frac{D_{nk}}{s_n \bar{Y}_k} - 1 \right]}_{F_{fn}^{CB}} \quad (13)$$

$$= \underbrace{s_n \sum_k \bar{Y}_k \beta_{fk} \left[\frac{Y_{nk}}{s_n \bar{Y}_k} - 1 \right]}_{F_{fn}^{HOV}} - \underbrace{s_n \sum_k \bar{Y}_k \beta_{fk} \left[\frac{D_{nk}}{s_n \bar{Y}_k} - 1 \right]}_{F_{fn}^{CB}} \quad (14)$$

where $Y_{nk} = \sum_i X_{ink}$ denotes the value of production of country n in sector k , $\bar{Y}_k = \sum_n Y_{nk}$ denotes the value of world's production in sector k , and s_n denotes the share of country n in world's GDP. Note that we define factor content in terms of factor reward instead of quantities

⁷Formally, this can arise when $\lambda_n^{-\sigma_k} \Phi_{nk}^{\frac{\sigma_k-1}{\theta_k}-1}$ is not log-supermodular, even if $\lambda_n^{-\sigma_k}$ is log-supermodular.

⁸The empirical section and the appendix derive additional results to account for traded intermediate inputs and production coefficients that differ across countries.

(number of workers or machines).⁹

In the brackets, the ratio $\frac{D_{nk}}{s_n Y_k}$ equals the share of consumption of k in country n relative to the share of consumption of k in the world. The ratio $\frac{Y_{nk}}{s_n Y_k}$ equals the share of production in sector k in country n relative to the share of production in sector k in the world. Homothetic preferences and free trade would imply that the second term in brackets is null: $\frac{D_{nk}}{s_n Y_k} - 1 = 0$. Hence, with homothetic preferences and free trade, the expression above can be simplified into:

$$F_{fn} = F_{fn}^{HOV} = w_{fn} V_{fn} - s_n \sum_i w_{fi} V_{fi} \quad (15)$$

Under factor price equalization, w_{fn} is the same across countries, and the above expression corresponds to the standard prediction of factor content trade in the Heckscher-Ohlin-Vanek model. This equation states that the content of factor f in exports of a country n should equal the total value of the supply of factor f in this country minus the value of the world's supply of this factor adjusted by the share s_n of country n in world GDP.

Equation (15) is violated when preferences are not homothetic and $\frac{D_{nk}}{s_n Y_k} - 1$ differs from zero. It thus needs to be corrected by a consumption term F_{fn}^{CB} (where ‘‘CB’’ stands for consumption bias). In particular, if relative consumption $\frac{D_{nk}}{s_n Y_k}$ is positively correlated with production $\frac{Y_{nk}}{s_n Y_k}$, then F_{fn}^{CB} is correlated with F_{fn}^{HOV} and predicted factor trade is smaller. It can explain why the factor content of trade is smaller than predicted by models with homothetic preferences. In the empirical section, we verify that $\frac{D_{nk}}{s_n Y_k}$ and $\frac{Y_{nk}}{s_n Y_k}$ are indeed strongly correlated across countries and industries and that F_{fn}^{CB} is correlated with F_{fn}^{HOV} across countries and factors.

Again, trade costs can also explain positive correlations between supply and demand across industries and in terms of factor content. In the empirical section, we disentangle the effect of each (trade costs vs. fitted non-homothetic demand) and show that non-homotheticity plays an important role. Also, differences in factor usage across countries and trade in intermediate goods may also partially explain the missing trade puzzle. In the empirical section, we follow the methodology developed by Trefler and Zhu (2010) to illustrate the role of non-homotheticity accounting for more complex vertical linkages.

⁹Standard HOV estimation assumes factor price equalization. Under this assumption, both approaches are equivalent. When FPE is violated, for instance when factor productivity differ across countries, predicted factor content has to be adjusted for such differences if written in terms of factor units (e.g. number of workers of machines). No adjustment is necessary if we focus on values, i.e. factor supply times factor prices. This approach greatly simplifies the exposition of the main intuitions and better illustrate the contribution of non-homothetic preferences compared to homothetic preferences without providing too much details on factor prices.

2.3.3 Skill premium

The correlation between skill intensity and income elasticity not only affects trade patterns and trade volumes, but also has important implications for the skill premium (the wage of skilled workers divided by the wage of unskilled workers). In particular, it can generate a positive effect of total factor productivity (TFP) growth on the skill premium. The intuition, again, is simple. As productivity increases, people become richer, they consume more goods from income-elastic industries which are, as we show, more intensive in skilled labor.¹⁰ This increases the demand for skilled labor relative to unskilled labor and thus increases the relative wage of skilled workers.

On the contrary, with homothetic preferences, uniform productivity growth across countries is neutral in terms of skill premium. Also note that this effect holds in a closed economy and that international trade is not key. For a closed economy, with only skilled and unskilled labor, we can derive the elasticity of the skill premium sp_n to an increase in TFP $d \log z_n$:

$$\frac{d \log sp_n}{d \log z_n} = \frac{1}{1 + \xi_n} \sum_k (sh_{nk}^H - sh_{nk}^L) \varepsilon_{nk} \quad (16)$$

where ε_{nk} is the income elasticity in sector k , country n , and $sh_{nk}^H \equiv \frac{\beta_{Hk} Y_{nk}}{\sum_{k'} \beta_{Hk'} Y_{nk'}}$ is the share of sector k in the total skill labor employment in country n (and sh_{nk}^L refers to the share of unskilled workers in sector k), and ξ_n is defined in the appendix.

We can see that this term is positive if income elasticity ε_{nk} is correlated with the demand for skilled labor vs. unskilled labor (the term in $sh_{nk}^H - sh_{nk}^L$). In that case, growth in TFP generates an increase in the skill premium.

The term ξ_n reflects the feedback effect of the skill premium increase on the composition of consumption. When the skill premium increases, the relative price of skill-intensive goods increases, the relative demand for skill intensive goods tends to decrease and thus the relative demand for skilled workers tends to decrease. We can expect this feedback to be small compared to the direct effect and: $\xi_n \approx 0$. An approximation for the elasticity of skill premium to TFP growth would then be:

$$\frac{d \log sp_n}{d \log z_n} \approx \sum_k (sh_{nk}^H - sh_{nk}^L) \varepsilon_{nk} \quad (17)$$

This equation provides a good approximation of the skill premium increase even if skilled and unskilled labor are not the only factors of production. We show later on how this approximation compares estimates of skill premium increases from general equilibrium simulations.

In this expression, we see that the effect of TFP growth on the skill premium is larger

¹⁰Assuming that the evolution of income is not driven by an accumulation of skills, which can of course mitigate the increase in the skill premium.

for larger income elasticities (*ceteris paribus*). As income elasticities decrease with income (or productivity), we might expect smaller skill premium increases in rich countries.

This is not necessarily the case, as can be seen by taking the second derivative of expression (17) w.r.t to productivity :

$$\frac{d^2 \log sp_n}{d \log z_n^2} \approx -\frac{\sum_k x_{nk}(\varepsilon_{nk}-1)^2}{\sum_k x_{nk}} + \frac{\sum_k (sh_{nk}^H - sh_{nk}^L)\varepsilon_{nk}^2}{\sum_k (sh_{nk}^H - sh_{nk}^L)\varepsilon_{nk}} - \sum_k (sh_{nk}^H + sh_{nk}^L)\varepsilon_{nk} \quad (18)$$

The first term corresponds to the decrease in income elasticity with income (which is referred to as the “within” effect in Section 4.3), whereas the other two terms corresponds to changes in the weights $sh_{nk}^H - sh_{nk}^L$ (“between” effect). The between effect is negative if there is more scope for reallocation of skilled workers than unskilled workers across sectors.¹¹

3 Estimation

The objective of this section is two-fold. We first estimate income elasticities of demand and then test for positive correlation between income elasticity and factor intensity.

3.1 Estimation of income elasticities: identification

Demand by industry (in value) is determined as in Equation (3) or equivalently Equation (1) for individual expenditures $x_{nk} = \frac{D_{nk}}{L_n}$. In log, this gives:

$$\log x_{nk} = -\sigma_k \cdot \log \lambda_n + \log \alpha_{2,k} + (1 - \sigma_k) \cdot \log P_{nk} \quad (19)$$

where $\alpha_{2,k}$ is a preference parameter to be considered as an industry fixed effect. In addition, demand should satisfy the budget constraint, which pins down λ_n . The larger is per-capita income, the smaller is λ_n .

If there is no trade cost ($d_{nik} = 1$), the price index P_{nk} is the same across countries and cannot be distinguished from an industry fixed effect. If richer countries’ consumption is larger in a particular sector relative to other sectors, this sector can be associated with a larger elasticity σ_k .

¹¹Formally, the between effect is negative if and only if the variance of income elasticity weighted by skilled labor is larger than the variance of income elasticity weighted by unskilled labor:

$$\sum_k sh_{nk}^H (\varepsilon_{nk} - \sum_{k'} sh_{nk'}^H \varepsilon_{nk'})^2 > \sum_k sh_{nk}^L (\varepsilon_{nk} - \sum_{k'} sh_{nk'}^L \varepsilon_{nk'})^2$$

When trade is not free ($d_{nik} > 1$), the price index P_{nk} plays a key role in controlling for supply-side characteristics. As richer countries have a comparative advantage in skill intensive industries, the price index is relatively lower in these industries. Conversely, poor countries have a comparative advantage in unskilled labor intensive industries and thus have a lower price index in these industries relative to other industries. When the elasticity of substitution between industries is larger than one, these differences in price indices in turn affect consumption patterns. If we do not control for P_{nk} , we might conclude by mistake that skill intensive sectors have larger income elasticities.

Hence we put a particular care into correcting for supply-side effects through P_{nk} . We proceed in two steps. The main goal of the first step is to obtain a proxy for $\log P_{nk}$. According to the equilibrium condition (8) on the price index, $\log P_{nk}$ depends linearly on $\log \Phi_{nk}$ which can be identified using gravity equations. Then, using the estimated price indices (or equivalently $\hat{\Phi}_{nk}$), we can estimate the demand equation (19).

As a robustness check, we estimate the demand equation using actual price data instead or in addition to using $\log \hat{\Phi}_{nk}$ (Section 5).

Step 1: Gravity equation estimation and identification of Φ_{nk}

By taking the log of trade flows in Equation (5), we get:

$$\log X_{nik} = \log S_{ik} - \theta_k \log d_{nik} + \log D_{nk} - \log \Phi_{nk} \quad (20)$$

We estimate this equation by including importer and exporter fixed effects. As we do not have data on transport costs by industry and country pairs, we assume d_{nik} to depend on physical distance, common language, colonial link, contiguity and a border effect dummy, as usual in the gravity equation literature:

$$\begin{aligned} \log d_{nik} = & \delta_{Dist,k} \log Dist_{ni} - \delta_{Contig,k} \cdot Contiguity_{ni} - \delta_{Lang,k} \cdot CommonLang_{ni} \\ & - \delta_{Colony,k} \cdot ColonialLink_{ni} - \delta_{HomeBias,k} \cdot I_{n=i} \end{aligned}$$

Parameters $\delta_{var,k}$ capture the elasticity of trade costs w.r.t. each trade cost variable var .¹² It is indexed by sector k : we allow the effect of distance, contiguity, common language, etc. to differ across industries.

¹²Note that d_{nik} also captures a potential home bias in preferences. A home bias would be equivalent to multiplying d_{nik} by a scalar larger than one whenever trade occurs between two different countries, which is equivalent to the border effect in this framework.

Incorporating the expression for trade costs into trade flows, we obtain:

$$\begin{aligned} \log X_{nik} = & FX_{ik} + FM_{nk} - \beta_{Dist,k} \log Dist_{ni} + \beta_{Contig,k} \cdot Contiguity_{ni} \\ & + \beta_{Lang,k} \cdot CommonLang_{ni} + \beta_{Colony,k} \cdot ColonialLink_{ni} + \beta_{HomeBias,k} \cdot I_{n=i} + \varepsilon_{nik} \end{aligned}$$

where FM_{nk} refers to importer fixed effects and FX_{ik} to exporter fixed effects, and $\beta_{var,k} = \theta_k \delta_{var,k}$ for each trade cost variable var . Note that i refers to the exporter and n to the importer (following Eaton and Kortum 2002 notations). Since all coefficients to be estimated are sector specific, we estimate this gravity equation separately for each sector.

According to the model, importer and exporter fixed effects contain valuable information and correspond to $FM_{nk} = \log D_{nk} - \log \Phi_{nk}$ and $FX_{ik} = \log S_{ik}$. A first way to estimate Φ_{nk} would be to use importer fixed effects. However, since we use Φ_{nk} as a means to capture supply-side characteristics, it is arguably better to use supply-side variables to estimate Φ_{nk} .¹³ We follow a strategy developed by Redding and Venables (2004)¹⁴. Following Equation (7) defining Φ_{nk} , we use the estimate of S_{ik} and $\theta_k \log d_{nik}$ (using all transport cost proxies and their coefficients) to construct a structural estimate of Φ_{nk} :

$$\begin{aligned} \hat{\Phi}_{nk} = & \sum_i \exp \left(\widehat{FX}_{ik} - \hat{\beta}_{Dist,k} \log Dist_{ni} + \hat{\beta}_{Contig,k} \cdot Contiguity_{ni} \right. \\ & \left. + \hat{\beta}_{Lang,k} \cdot CommonLang_{ni} + \hat{\beta}_{Colony,k} \cdot ColonialLink_{ni} + \hat{\beta}_{HomeBias,k} \cdot I_{n=i} \right) \end{aligned}$$

This constructed $\hat{\Phi}_{nk}$ varies across industries and countries in an intuitive way. It is the sum of all potential exporters' fixed effect (reflecting unit costs of production) deflated by distance and other trade cost variables. When country n is close to an exporter that has a comparative advantage in industry k , i.e. an exporter associated with a large exporter fixed effect FX_{ik} (large S_{ik}), our constructed $\hat{\Phi}_{nk}$ is relatively larger for this country n reflecting a lower price index of goods from industry k in country n . Note that $\hat{\Phi}_{nk}$ also accounts for domestic supply in each industry k (when $i = n$).

Such a method would fit various structural frameworks. If our model were based on Dixit-Stiglitz-Krugman framework instead of Eaton-Kortum, price indices by importer and industry could be obtained in the same way. This would also account for the range of available varieties when it is endogenous and would also fit a model such as Chaney (2008) that yield a gravity equation in trade flows by industry.

¹³An alternative method uses importer fixed effects and observed demand. The two methods are actually equivalent when gravity is estimated with Poisson PML, see Fally (2012b).

¹⁴See also Fally et al. (2010), Head and Mayer (2006).

Step 2: Demand system estimation and identification of σ_k

The first step estimation gives us an estimate of Φ_{nk} , but the price index is proportional to $(\Phi_{nk})^{\frac{1}{\theta_k}}$, not Φ_{nk} , and θ_k is more difficult to estimate. θ_k corresponds to the elasticity of trade flows to trade costs and thus appears in the gravity equation. However it cannot be directly identified from $\delta_{var,k}$. For instance, the coefficient in the gravity equation associated with distance is the product of θ_k and $\delta_{Dist,k}$.¹⁵

We make four different assumptions relative to θ_k : 1) we calibrate θ_k using aggregate estimates from the literature; 2) we do not impose any restriction on θ_k ; 3) we assume that $\theta_k = \theta$ is constant across sectors and estimate θ ; 4) in order to better illustrate the role of trade costs, we also estimate demand elasticities by assuming that there are no trade costs.

In all cases the estimated equation is subject to the budget constraint, which identifies λ_n . For any country n , we impose:

$$\sum_k \hat{x}_{nk} = e_n$$

where e_n is observed expenditure per capita.

D1) In a first specification, we take a strong stand on θ_k and assume that it equals 4. This imposes a strong link between income elasticities of demand and price elasticities. Alternatively, we take a value of 8 (specification D1'). The first choice is close to Simonovska and Waugh (2010) estimates of 4.12 and 4.03. Donaldson (2008), Eaton et al. (2011), Costinot et al. (forthcoming) provide alternative estimates that range between 3.6 and 5.2. The second choice ($\theta = 8$) is in line with Eaton and Kortum (2002) estimate of 8.28. Given our estimate of $\hat{\Phi}_{nk}$ and the calibrated parameter $\hat{\theta}$, the final demand system to be estimated is:

$$\log x_{nk} = -\sigma_k \cdot \log \lambda_n + \log \alpha_{5,k} + (\sigma_k - 1) \cdot \frac{\log \hat{\Phi}_{nk}}{\hat{\theta}} + \varepsilon_{nk}$$

where $\alpha_{5,k}$ is an sector fixed effect.

D2) In another specification, we take an opposite approach and do not impose any constraint on the price elasticity of demand. Given our estimate of $\hat{\Phi}_{nk}$, the final demand system to be estimated is:

$$\log x_{nk} = -\sigma_k \cdot \log \lambda_n + \log \alpha_{5,k} + \mu_k \cdot \log \hat{\Phi}_{nk} + \varepsilon_{nk}$$

¹⁵Some authors have used the coefficient on import tariffs in gravity equations to identify θ_k . In our dataset however, these coefficients are often statistically insignificant and we do not feel comfortable with using them.

where $\alpha_{5,k}$ is an sector fixed effect, and μ_k is a sector specific coefficient (to be estimated) capturing a combination of σ_k and θ_k . μ_k is identified given how expenditure depends on price levels proxied by Φ .

D3) As an alternative approach, we assume that $\theta_k = \theta$ is constant across countries (as in the first specification) but we do not impose any value. Instead, we use this restriction to identify θ . Given $\widehat{\Phi}_{nk}$, the final demand system to be estimated is:

$$\log x_{nk} = -\sigma_k \cdot \log \lambda_n + \log \alpha_{5,k} + \frac{(\sigma_k - 1)}{\theta} \cdot \log \widehat{\Phi}_{nk} + \varepsilon_{nk}$$

where $\alpha_{5,k}$ is an sector fixed effect.

D4) As a benchmark, we also estimate a demand system assuming that there is no trade cost and prices are the same across all countries. The final demand system to be estimated is then:

$$\log x_{nk} = -\sigma_k \cdot \log \lambda_n + \log \alpha_{4,k} + \varepsilon_{nk}$$

where $\alpha_{4,k}$ is an sector fixed effect capturing prices indices.

In all cases, given the inclusion of industry fixed effects, λ_n can be identified only up to a constant. To see this, we can multiply λ_k by a common multiplier λ' and multiply the industry fixed effect α_k by $(\lambda')^{\sigma_k}$. Using $\lambda_k \lambda'$ instead of λ_k and $\alpha_k (\lambda')^{\sigma_k}$ instead of α_k in the demand system generates the same demand and the same expenditures by industry. We thus normalize $\lambda_{USA} = 1$ for the US.

A similar issue arises for the identification of σ_k in specifications D2 and D4. In these cases, σ_k can be estimated only up to a common multiplier. By multiplying σ_k by a common multiplier σ' and replacing λ_n by $\lambda_n^{\frac{1}{\sigma'}}$, we obtain the same demand by industry and the same total expenditures (maintaining the normalization of the Lagrangian to unity for the US).

This is not an issue if we focus on the income elasticity of demand which equals the ratio of σ_k to the weighted average of $\sigma_{k'}$ across sectors (weighted by consumption). For instance, in the no-trade-cost specification (D4), we can verify that relative σ 's can be pinned down by the formula:

$$\frac{\sigma_k}{\sigma'_k} = \frac{\log x_{nk} - \log x_{n'k}}{\log x_{nk'} - \log x_{n'k'}}$$

for any pair of countries (n, n') and any pair of industries (k, k') . Ratios $\frac{\sigma_k}{\sigma'_k}$ and fitted consumption shares are then sufficient to derive income elasticities of demand in line with Equation (2).

The above demand systems are estimated using constrained non-linear least squares.¹⁶ Bootstrapped standard errors for the estimates of σ_k , income elasticities and other variables are obtained by resampling the set of regions.

3.2 Data

Our empirical analysis is almost entirely based on the Global Trade Analysis Project (GTAP) version 7 dataset (Narayanan and Walmsley, 2008). GTAP contains consistent and reconciled production, consumption, endowment and trade data for 57 sectors of the economy, 5 production factors, and 94 countries in 2004. The set of sectors covers both manufacturing and services and the set of countries covers a wide range of per-capita income levels. The list of countries can be found in the appendix.

To estimate gravity equations (21) by industry, we use gross bilateral trade flows from GTAP measured including import tariffs, export subsidies and transport cost (c.i.f.). Demand systems are estimated over all 94 available countries using final demand values based on the aggregation of private and public expenditures. Some sectors in GTAP are used primarily as intermediates and correspond to extremely low consumption shares of final demand. 6 sectors for which less than 5% of output goes to final demand (coal, oil, gas, ferrous metals, metals n.e.c. and minerals n.e.c.) are assumed to be used exclusively as intermediates and are dropped from the demand estimations. We also drop “dwellings” from our analysis.¹⁷ We are left with 50 sectors (see Table 2 for the list of sectors).

Factor usage data, by sector, are directly available in GTAP and cover capital, skilled and unskilled labor, land and other natural resources. There are, however, some limitations concerning the skill decomposition of labor: while the GTAP dataset provides skilled vs. unskilled labor usage for all countries, part of this information is extrapolated from a subset of European countries and 6 non-European countries (US, Canada, Australia, Japan, Taiwan and South Korea).¹⁸ Also, skilled labor is defined on an occupational basis for some of these countries (e.g. US). In most of our analysis, we measure factor intensities by the weighted average factor intensities across all countries, but our results carry on if we simply based our factor intensity measures on the subset of countries mentioned above, as shown in section 5.3.

Finally, bilateral variables on physical distance, common language, colonial link and contiguity are obtained from CEPII (www.cepii.fr).

¹⁶We minimize the sum of squared errors on log consumption, weighted by world consumption by industry in order to avoid putting too much weight on a few small sectors. Very close results are obtained by minimizing unweighted sums of error squares in logs or alternatively in consumption shares (see robustness section 5). The optimization procedure is implemented in GAMS and solved using the Conopt3 NLP solver.

¹⁷This sector is associated with large measurement errors in consumption and factor intensities.

¹⁸See: <https://www.gtap.agecon.purdue.edu/resources/download/4183.pdf>

3.3 Demand system estimation results

Results from the gravity equation (step 1) are very standard and more detailed results are presented in the appendix section. In brief, there is significant variation in distance and border effect coefficients across industries. As usually found in the gravity equation literature, the coefficient for distance is on average close to -1, while the border effect is large. Coefficients for other trade cost proxies are significant for most industries.

Table 1: NLLS estimation of demand: regression statistics

Specification:	(D1) $\theta = 4$	(D4) No trade cost	(D2) Unconstrained θ_k	(D3) Common θ	(D1') $\theta = 8$
Correlation $\hat{\sigma}_k$ with D1 specification ($\theta = 4$)	1	0.881	0.838	0.978	0.924
$\hat{\theta}$ (calibrated or estimated)	4	/	/	1.17	8
Weighted av. coeff on Φ_{nk}	0.507	/	0.532	0.518	0.486
Correlation $\log \lambda_n$ with log per capita income	-0.985	-0.999	-0.986	-0.986	-0.986
F-stat: $\sigma_k = \sigma$	4.62	19.60	8.63	5.05	4.07
Weighted R2	0.959	0.954	0.961	0.959	0.959
Partial R2	0.276	0.179	0.306	0.280	0.272
Schwarz criterion	6.168	6.294	6.214	6.171	6.174
Parameters	194	194	244	195	194
Observations	4700	4700	4700	4700	4700

Notes: Constrained NLLS regressions: step 2 of the estimation procedure described in the text; weighted by industry size (world expenditure by industry); “Partial R2” computed as $1 - \frac{SSE}{SSE^{homoth}}$; Schwarz criterion computed as $\ln(\frac{SSE}{n}) + \frac{k \ln(n)}{n}$, where n is the number of observations and k is the number of parameters.

We now focus on the final demand estimation (step 2). Parameters to be estimated are λ_n , σ_k , the industry fixed effects α_k and in specification (D3), θ . Summary statistics are reported in Table 1. A large part of the variability in the dependent variable is captured by industry fixed effects, which leads to very high measures of fit (weighted R2). In order to better illustrate the contributions of non-homotheticity and price differences in explaining demand patterns, we also propose an alternative metric (Partial R2) which measures the increase in fit relative to a model with homothetic preferences and no trade costs. The partial R2 from the specification with no trade costs (D4) shows that non-homotheticity alone captures 18% of the variability left unexplained by homothetic preferences. The overall R2 equals 0.954. The contribution of non-homotheticity is significant: The F-stats associated with imposing common σ_k across industries (fifth row of Table 1) show that homotheticity is clearly rejected in all specifications (all P-values < 0.001).

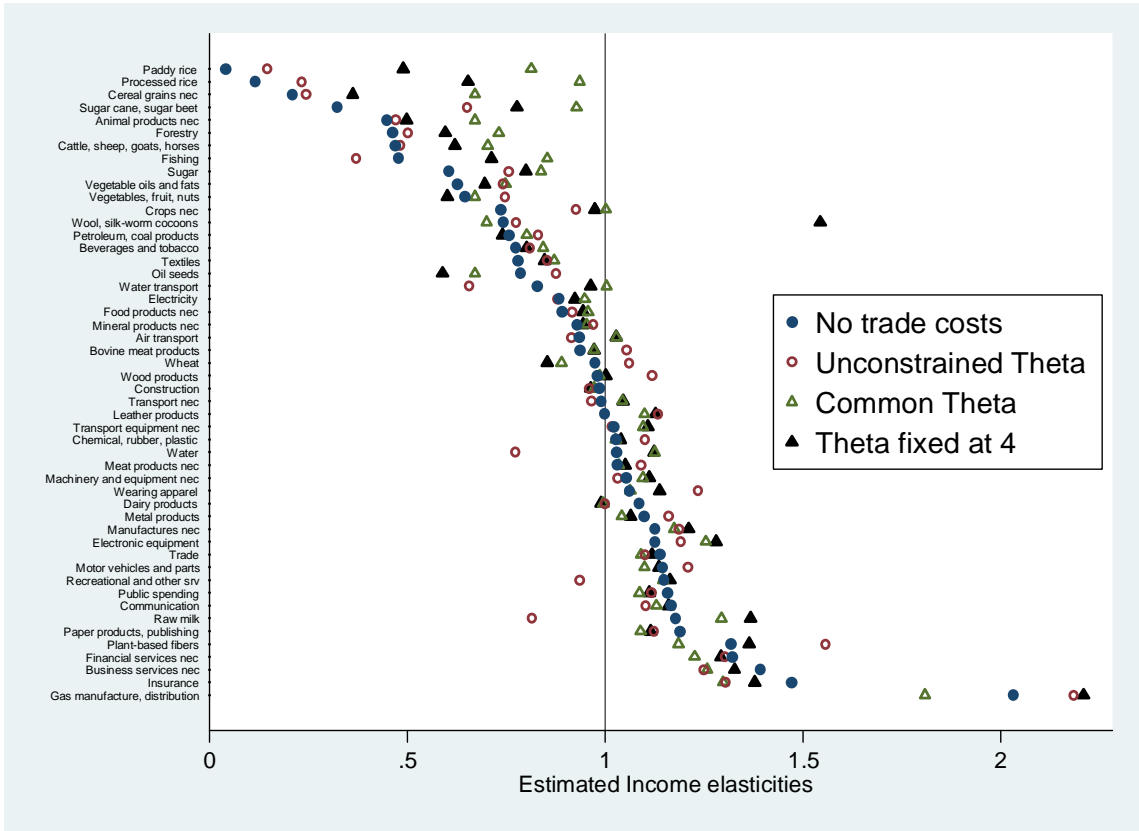


Figure 1: Income elasticity estimates across specifications

The inclusion of prices indexes in specifications (D1)-(D3) significantly improves this fit, as the coefficients associated with $\hat{\Phi}_{nk}$ are jointly significant. In the unconstrained- θ_k specification (D2), we can simply test whether they are jointly null which yields a F-stat of 16.07 (P-value < 0.001) and clearly rejects this hypothesis. The partial R2 increases to 0.306 and the R2 to 0.961. We find the contribution of prices differences in explaining demand patterns to be slightly higher than that of non-homotheticity, as the R2 in an homothetic specification with trade costs is 0.239 – higher than the 0.179 corresponding to non-homothetic preferences without trade costs.

The Schwarz model-selection criterion favors specification (D1), which, along with (D1'), incorporates price differences without increasing the number of parameters to be estimated. Thus, the higher fit achieved by (D2), which does not impose any constraint on θ_k , does not appear to justify the use of additional degrees of freedom. The Schwarz criterion thus justifies the use of (D1) as our preferred specification.

The estimated σ_k can be used to compute income elasticity estimates according to equation

Table 2: Estimated income elasticity by sectors

GTAP code	Sector name	Income elast.	Std error	Skill intensity
gro	Cereal grains nec	0.362*	0.040	0.135
pdr	Paddy rice	0.490*	0.150	0.061
oap	Animal products nec	0.498*	0.067	0.132
osd	Oil seeds	0.588*	0.158	0.119
frs	Forestry	0.596*	0.115	0.118
v_f	Vegetables, fruit, nuts	0.601*	0.102	0.095
ctl	Bovine cattle, sheep and goats, horses	0.621*	0.078	0.164
pcr	Processed rice	0.654*	0.126	0.130
vol	Vegetable oils and fats	0.696*	0.066	0.217
fsh	Fishing	0.712*	0.092	0.124
p_c	Petroleum, coal products	0.740*	0.047	0.313
c_b	Sugar cane, sugar beet	0.777	0.206	0.091
sgf	Sugar	0.800*	0.142	0.221
b_t	Beverages and tobacco products	0.802*	0.031	0.297
tex	Textiles	0.847*	0.055	0.231
wht	Wheat	0.854	0.139	0.117
ely	Electricity	0.923*	0.036	0.372
ofd	Food products nec	0.944*	0.036	0.268
nmm	Mineral products nec	0.944	0.072	0.281
cns	Construction	0.963*	0.023	0.294
wtp	Water transport	0.963	0.087	0.299
cmt	Bovine meat products	0.972	0.068	0.238
ocr	Crops nec	0.974	0.108	0.115
mil	Dairy products	0.990	0.046	0.248
lum	Wood products	1.001	0.085	0.248
atp	Air transport	1.028	0.047	0.313
crp	Chemical, rubber, plastic products	1.039	0.051	0.356
otp	Transport nec	1.046	0.052	0.296
omt	Meat products nec	1.051	0.075	0.233
fmp	Metal products	1.065	0.053	0.297
otn	Transport equipment nec	1.107	0.057	0.343
ome	Machinery and equipment nec	1.111	0.030	0.372
osg	Public Administration and Services	1.112*	0.019	0.503
ppp	Paper products, publishing	1.115	0.039	0.340
trd	Trade	1.119	0.036	0.308
wtr	Water	1.123	0.048	0.378
lea	Leather products	1.126	0.041	0.212
mvh	Motor vehicles and parts	1.135	0.030	0.341
wap	Wearing apparel	1.138	0.050	0.247
cmn	Communication	1.161*	0.049	0.485
ros	Recreational and other services	1.164*	0.042	0.475
omf	Manufactures nec	1.210*	0.037	0.279
ele	Electronic equipment	1.280*	0.050	0.358
ofi	Financial services nec	1.292*	0.054	0.546
obs	Business services nec	1.327*	0.039	0.504
pfb	Plant-based fibers	1.363	0.171	0.167
rmk	Raw milk	1.367*	0.077	0.152
isr	Insurance	1.378*	0.046	0.533
wol	Wool, silk-worm cocoons	1.543*	0.167	0.089
gdt	Gas manufacture, distribution	2.209*	0.160	0.362

Notes: Income elasticities evaluated using median country expenditure shares; NLLS estimations (imposing $\theta = 4$); bootstrapped standard errors (100 draws); * denotes 5% significance (difference from unity); total skill intensities.

2, using fitted median-income-country expenditure shares as weights.¹⁹ In specification (D1), estimates range from 0.36 for Cereal grains to 2.21 for gas manufacture and distribution with a clear dominance of agricultural sectors at the low end and service sectors at the high end. 30 out of 50 estimates are significantly different than 1 (at 95 %) as shown in Table 2.

The distribution of estimated income elasticities is quite similar across specifications (see Figure 1). In particular, the choice of θ does not affect estimates of σ_k substantially. As shown in Table 1, the correlation between the estimated σ_k in other specifications and those of specification D1 ($\theta = 4$) is always above 80%. This is also the correlation between income elasticities among specifications since income elasticities are proportional to σ_k . Sectors where income elasticities vary the most across specifications are actually the smallest ones, and weighing this correlation by final demand yields larger correlation estimates in all cases.

For robustness, these are compared with estimates based on more standard demand systems in section 5 and are found to be well correlated.

3.4 Correlation with factor intensities

We now investigate the relationship between income elasticities and factor intensities across sectors. Although the implications of such a relationship will be best illustrated in section 4, we first demonstrate its significance through simple correlations. Table 3 reports correlation coefficients between factor intensities and income elasticities (or, equivalently, the σ 's) estimated under different assumptions about trade costs.²⁰

Our measures of factor intensity correspond to the ratio of skilled labor, capital or natural resource (including land) to total labor input. They are computed including the factor usage embedded in the intermediate sectors used in each sector's production.²¹ As shown in section 5, our results are robust to different measures of factor intensities and to different demand specifications. Table 3 reports estimations with CRIE preferences, while alternative demand systems are examined in section 5.

We find that skill intensity is positively and significantly correlated with income elasticity, natural resources intensity is negatively correlated, and capital intensity exhibits a small weakly

¹⁹With CRIE preferences, the ratio of income elasticities between two sectors does not depend on the choice of the reference country.

²⁰Table 3 displays heteroskedasticity-robust standard errors. As the dependent variable, income elasticity, is itself estimated, we alternatively use a feasible generalized least squares (FGLS) regression in which the bootstrapped standard errors from the NLLS estimations of income elasticities are used to construct weights (see Lewis and Linzer (2005)). The resulting standard errors are slightly smaller: for example, the estimate in column 1 is 0.116 instead of 0.123. The similarity between estimates suggests that the bias caused by the use of an estimated dependent variable is small.

²¹Total factor usage is computed using a Leontiev inversion of country-specific input-output tables as provided by GTAP

Table 3: Correlation between income elasticity and skill intensity

Dependent variable:	Income elasticity					
	(1)	(2)	(3)	(4)	(5)	(6)
Specification	$\theta = 4$	$\theta = 4$	No trade cost	No trade cost	Unconstrained Theta	Common Theta
Skill intensity	0.526 [0.123]**	0.508 [0.115]**	0.692 [0.103]**	0.673 [0.100]**	0.555 [0.113]**	0.617 [0.098]**
Capital intensity		0.002 [0.153]		0.024 [0.126]		
Natural resources int.		-0.152 [0.102]		-0.139 [0.076]*		
Observations (sectors)	50	50	50	50	50	50

Notes: Dependent variable: income elasticity by sector evaluated at median-country income; beta coefficients; robust standard errors in brackets; * significant at 10%; ** significant at 1%.

positive correlation. As expected, the correlation with skill intensity diminishes if we account for trade costs and control for differences in price indexes. This is illustrated in Figure 2 and also seen by comparing column (1) versus (3) in Table 3. This correlation remains however particularly large and above 50% in most specifications.

Part of this large correlation can be explained by the composition of consumption into services vs. manufacturing industries, with the former being generally associated with a larger income elasticity. However, even after excluding service industries, the correlation is above 40% in all specifications.

It is interesting to see that capital intensity would otherwise be positively correlated with income elasticity, as found by Reimer and Hertel (2010), but this correlation is not as large as for skill intensity (less than 10% in most specifications) and not robust to controlling for skill intensity as shown in columns (2) and (4) of Table 3.

These results show a large correlation between per capita income and consumption patterns depending on skill intensity. We emphasize the demand side. One may be worried, however, that these results are driven by differences in skill endowment across countries rather than differences in per capita income. In the GTAP data, the fraction of skilled labor is indeed correlated at 88% with per capita income. In order to check the robustness of our results with respect to differences in education, we re-estimated income elasticities for subsets of countries with smaller variations in skilled labor endowment (and still large variations in per capita income). If we restrict the set of countries to those within the inter-quartile range in skilled-labor endowments, the correlation between estimated income elasticities and skill intensity

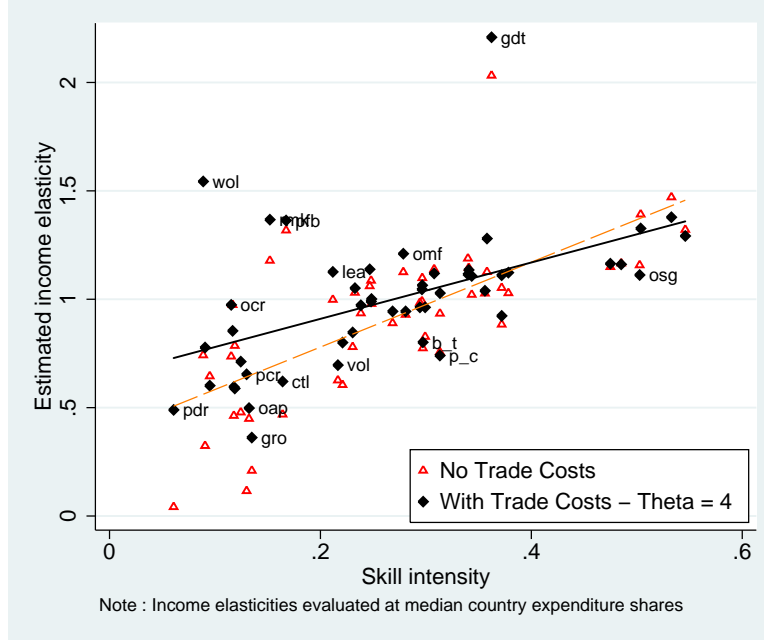


Figure 2: Income elasticity and skill intensity correlation.

remains very high for the main specifications (above 40%) while the correlation between per capita income and education is sensibly lower (60% instead of 88%). A more extreme exercise is to select specific groups of countries where the correlation between income and education becomes zero by construction. In these cases we find again very large correlations between skill intensity and (re-estimated) income elasticity, showing that our main results are not driven by differences in education across countries.

4 Implications for trade, skill premium and welfare

4.1 Consumption patterns and missing trade

The correlation between skill intensity and income elasticity in consumption implies that the factor content of consumption varies systematically with income. In Figure 3, we plot a measure of skilled-labor content of consumption against per capita income (in log) where the former is defined as:

$$\frac{\sum_k \beta_{fk} \widehat{D}_{nk}}{\sum_k \widehat{D}_{nk}} \quad (21)$$

and where β_{fk} is defined as the total skilled-labor intensity of production (average of all regions weighted by production). We define demand by using either actual consumption or fitted consumption \widehat{D}_{nk} with different assumptions. With homothetic preferences and no trade costs,

expression (21) should be the same for all countries. Trade costs already explain part of the variations in the factor content of consumption: rich countries tend to spend more on skilled-labor intensive industries, even if preferences are homothetic, because goods are relatively cheaper in these industries. However, we can see in Figure 3 that an even better fit is obtained when non-homothetic preferences are allowed on top of trade costs.

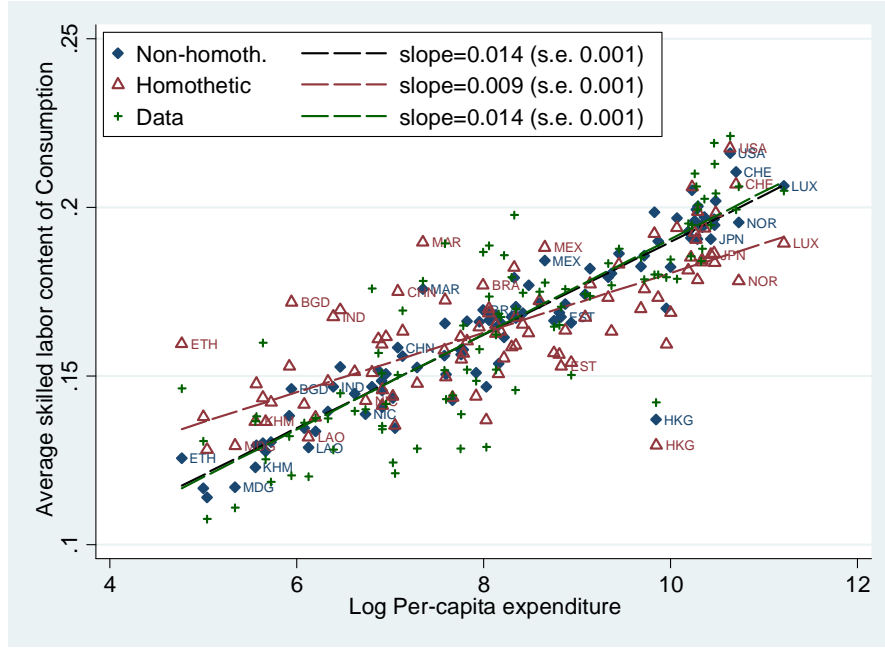


Figure 3: Skilled-labor content of consumption and per capita income

This systematic relationship between income and the factor content of consumption has important implications for trade patterns. Since rich countries tend to specialize in skill-intensive sectors, this generates a correlation between relative specializations in consumption and production. In the first row of Table 4, we examine the correlation between $\frac{Y_{nk}}{s_n Y_k}$ and $\frac{D_{nk}}{s_n Y_k}$. The first term reflects actual production relative to world's production of goods k multiplied by country n 's share of world expenditures. In columns (1) to (4), we use fitted demand \widehat{D}_{nk} from our second-stage estimations and in column (5) we use actual consumption D_{nk} . In column (1), we impose homothetic preferences (i.e. σ common across industries) and assume that there are no trade costs, as in standard Heckscher-Ohlin models. In this case, the correlation is obviously zero as consumption patterns are the same across all countries ($\frac{D_{nk}}{s_n Y_k} = 1$). In column (2), we allow for trade costs. These generate a positive correlation between consumption and production. The estimated correlation is 19% (across countries and industries) and significantly positive at 1%, although it is much lower than the 86% correlation observed in the data (column 5).

Table 4: Patterns of supply, demand and factor content trade

	(1)	(2)	(3)	(4)	(5)	Dimension
Preferences:	Homothetic		Non-homothetic		data	
Correcting for trade costs:	No	Yes	No	Yes		
1- Correlation between supply $\frac{Y_{nk}}{s_n Y_k}$ and demand $\frac{D_{nk}}{s_n Y_k}$	0	0.19	0.33	0.49	0.86	n x k
2- Correlation between F_{nf}^{HOV} and Consumption bias F_{nf}^{CB}	0	0.78	0.59	0.92	0.99	n x f
3- Normalized by country size	0	0.79	0.86	0.90	0.93	n x f
Corrected HOV slope test:						
4- Assuming common β_{kf}	0.46	0.38	0.60	0.64	1	n x f
5 - With fitted \hat{A}_{kfn}^D	0.19	0.35	0.23	0.58	1	n x f
6 - With observed A_{kfn}^D	0.37	0.35	0.47	0.58	1	n x f
Variance test: $\frac{Var(F_{fn}^{meas})}{Var(F_{fn}^{pred})}$						
7- Assuming common β_{kf}	0.37	0.40	0.53	0.68	1	n x f
8- With fitted \hat{A}_{kfn}^D	0.10	0.40	0.13	0.70	1	n x f
9- With observed A_{kfn}^D	0.27	0.40	0.46	0.69	1	n x f

Allowing for non-homotheticity significantly increases the correlation between consumption and production, even if we assume no trade cost and common prices across countries, and even though preferences are still assumed to be identical across countries. As shown in column (3), by using fitted demand from the no-trade-cost specification (D4) we obtain a correlation of 33%. In column (4), we further account for trade costs and differences in price indices across countries and we find a correlation of 49% (specification D1 imposing $\theta_k = 4$).²² This is closer to the 86% correlation observed in the data.

A positive correlation between supply and demand induces a smaller factor content trade compared to the homothetic case. As described in section 2.3.2, the predicted factor content of trade (PFCT) can be expressed as the difference between standard Heckscher-Ohlin-Vanek PFCT, denoted F_{nf}^{HOV} , and a consumption bias term denoted F_{nf}^{CB} which is null in the special case where preferences are homothetic and trade costs are null (see equation 13). Assuming constant requirements coefficients β_{kf} across countries, we impute F_{nf}^{HOV} using production data

²²Similar and even larger correlations are found for alternative specifications for the estimation of preferences.

and F_{nf}^{CB} using either fitted demand (columns 1 to 4) or actual consumption (column 5).²³ The second row of Table 4 shows that trade costs can already explain a large correlation between consumption and production factor content even if preferences are assumed to be homothetic (column 2). This correlation is 78% across countries and factors (compare to 0% if we assume no trade cost). This is consistent with Davis and Weinstein (2001) who also attribute an important part of the missing trade puzzle to trade costs. In column (3), we find that allowing for non-homotheticity but assuming zero trade cost can generate a 59% correlation between HOV PFCT F_{nf}^{HOV} and the consumption bias. Allowing for both non-homotheticity and the presence of trade costs further increases the correlation to 92%, which is close to the very large correlation observed in the data (99%!). One may be worried however that these correlations between F_{nf}^{HOV} and F_{nf}^{CB} are driven by a few large countries such as the US and China. After rescaling these variables and dividing by country size, the observed correlation in the data is slightly lower (93% as shown in column 5 of the third row) and that our results exhibit an even more important role for non-homotheticity. Allowing for non-homothetic preferences in a zero-trade-cost framework (column 3) yields a larger correlation between supply and demand than allowing for trade costs with homothetic preferences (column 2).

We then examine the “slope test” and the “variance test” usually conducted to test the Heckscher-Ohlin model and amended versions. The slope test is simply the coefficient of a regression of the measured factor content of trade on predicted factor content. The variance test is the ratio of the variance of measured factor content on the variance of predicted factor content of trade. The latter reflects the “missing trade puzzle”: previous results have found a small ratio (Trefler 1995). Both tests should exhibit a coefficient equal to one if predicted and measured factor contents are equal. We construct the predicted factor content of trade in various ways to illustrate the role of trade costs and non-homotheticity.²⁴

We first follow the strategy above by assuming constant factor requirement coefficients across countries (rows 4 and 7). For both tests, allowing for non-homotheticity pushes the coefficient closer to unity. In particular, when we account for trade costs, the slope coefficient increases from 0.38 to 0.64 (comparing columns 2 and 4) and the variance ratio increases from 0.40 to 0.68, corresponding to a 41% decrease in the variance of the predicted factor content of trade.

²³Note also that all variables are in value terms (e.g. wages instead of number of workers) which mitigates cross-country differences related to differences in factor prices.

²⁴For the slope and variance tests, all observations are scaled by $(s_n \sum_i w_{if} V_{if})^{1/2}$ to adjust for heteroskedasticity.

Accounting for traded intermediate goods

We now deviate from our theoretical framework to better account for trade in intermediate goods and differences in factor requirement matrices across countries. In rows 5, 6, 8 and 9 of Table 4, we compute the factor content of trade following the method developed by Trefler and Zhu (2010).

Following Trefler and Zhu (2010), we construct the matrix A_{kfn}^P of direct and indirect factor requirements by taking into account factors embodied in traded intermediate goods. Data on domestic and imported input requirements at the country level are provided in the GTAP database. To further approximate bilateral vertical linkages between any two countries, the construction of the matrix A^P relies on a proportionality assumption (see appendix). The factor content of trade is then constructed as $F_{nf} = A_{kfn}^P Y_{nk} - \sum_i A_{kfi}^P X_{nik}$. We further compute A_{kfn}^D as the matrix of factors embodied in consumption of final goods consumed by country n . Assuming that the share of final goods purchased from source i equals the share of imports from this source (proportionality assumption), we define A^D as:

$$A_{kfn}^D = \frac{\sum_i A_{kfi}^P X_{nik}}{\sum_i X_{nik}} \quad (22)$$

Building on Lemma 1 of Trefler and Zhu (2010), we show in the appendix section that the factor content of trade satisfies:

$$F_{nf} = \left[w_{nf} V_{nf} - s_n \sum_i w_{if} V_{if} \right] - \sum_k \left[A_{kfn}^D D_{nk} - s_n \left(\sum_i A_{kfi}^D D_{ik} \right) \right] \quad (23)$$

This is an accounting equality, which is exactly satisfied by construction when we use observed demand D_{nk} and A_{kfn}^D to construct the right-hand-side term. In what follows, we construct the predicted factor content of trade using fitted demand \widehat{D}_{nk} and fitted factor content of consumption \widehat{A}_{kfn}^D to illustrate the role of non-homotheticity and trade costs.²⁵ In particular, when we assume homothetic preferences and no trade costs, the right-hand side reduces to $w_{nf} V_{nf} - s_n \sum_i w_{if} V_{if}$, even if the factor content coefficients A_{kfn}^P vary across countries. This corresponds to the ‘‘consumption similarity’’ condition emphasized by Trefler and Zhu (2010).

In row 5 of Table 4, we examine the slope test using fitted demand \widehat{D}_{nk} and fitted trade flows to construct \widehat{A}_{kfn}^D as described in equation (22). Note that, when trade costs are assumed to be zero (columns 1 and 3), the implied matrix \widehat{A}_{kfn}^D does not vary across countries. In all cases, we find that non-homothetic preferences perform better than homothetic preferences.

²⁵Note that our final demand estimates are robust to incorporating intermediate goods in our framework as described in Section 5.5.

The difference between homothetic and non-homothetic preferences is small when trade costs are assumed to be zero (comparing columns 1 and 3) and becomes much larger when we allow for trade costs (columns 2 and 4): the coefficient almost doubles.

In row 6, we perform a similar test by using fitted demand D_{nk} and observed factor content of consumption A_{kfn}^D (which now varies across countries in columns 1 and 3). Interestingly, allowing for non-homotheticity when A_{kfn}^D is country-specific largely increases the slope coefficients even in the case where D_{nk} is estimated assuming no trade cost. This suggests that differences in factor requirements across countries further magnifies the role of non-homotheticity.

In rows 7 and 8, we examine the “variance test” by comparing the variance of measured factor content of trade to the variance of predicted factor content of trade based on equation 23. As for the slope test, allowing for non-homotheticity always yields a coefficient closer to unity, especially when trade costs are no longer assumed to be zero or when the factor content of consumption varies across countries.

4.2 Trade patterns

Can non-homothetic preferences explain why the volumes of North-South trade in comparison to North-North trade are so small?²⁶ Results from the previous section shed light on the role of non-homothetic preferences in explaining net trade and its factor content. In particular, our results are related to industry compositions of demand and production. Given that a large fraction of trade is intra-sectoral, it is legitimate to ask whether non-homotheticity can also play a role (quantitatively) in explaining patterns of gross trade volumes.

As argued in section 2.3.1, non-homotheticity can potentially explain differences in import penetration across markets depending on the importer’s income and the exporter’s structure of comparative advantage. In particular, if a country has a comparative advantage in high-income-elastic industries (high- σ_k), such a country is more likely to export to rich importers than developing countries.

This argument can be illustrated using equation 11 on import penetration in the simple case with no trade cost. Using this formula, we can examine how import penetration by poor exporting countries depends on the importer’s per-capita income level. To be more precise, we compute import penetration from developing countries in market n :

$$\frac{X_n^{South}}{X_n} = \sum_k \left(\frac{Y_k^{South}}{Y_k^{South} + Y_k^{North}} \right) \left(\frac{\hat{\alpha}_{4,k} \hat{\lambda}_n^{-\hat{\sigma}_k}}{\sum_{k'} \hat{\alpha}_{4,k'} \hat{\lambda}_n^{-\hat{\sigma}_{k'}}} \right)$$

²⁶see Fieler (2011), Waugh (2010) among others.

where Y_k^{South} refers to total production in industry k by developing countries (annual per capital income less than \$10K), Y_k^{North} to total production by developed countries, and where $\hat{\alpha}_k$, $\hat{\lambda}_n$ and $\hat{\sigma}_k$ are estimated coefficients from the final demand equation (specification D4 assuming no trade cost).

Since income elasticity (or equivalently σ_k) is highly correlated with skill intensity and since developing countries have a comparative advantage in unskilled-labor-intensive tasks (the correlation coefficient between skill intensity and $\frac{Y_k^{South}}{Y_k^{South} + Y_k^{North}}$ is -0.8), we can expect developing countries to have a smaller penetration in richer countries which consume more goods from skill-intensive industries. Note also that import penetration does not depend on the importer's income if preferences are homothetic and trade costs are absent.

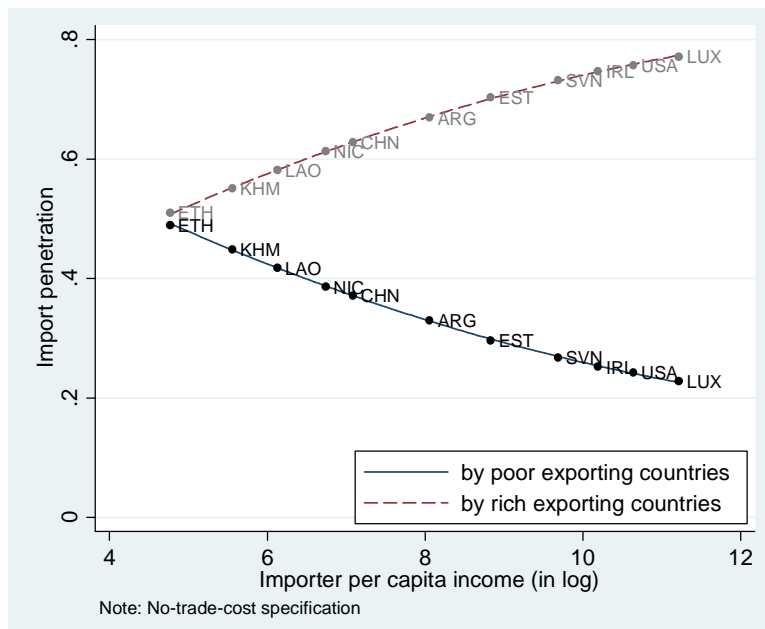


Figure 4: Import penetration by developing countries depending on importer's income

In Figure 4, we plot X_n^{South}/X_n as a function of the importer's average per capita income (in log). As shown in the figure, differences in consumption patterns across industries can generate large differences in import penetration between rich and poor countries. Given our estimated demand parameters, in a situation with no trade cost, import penetration by developing countries can vary from 50% in markets with the lowest per capita income (e.g. Ethiopia) to only 20% in the richest markets (e.g. Luxembourg). Symmetrically, import penetration by developed countries varies from 50% in the poorest markets to 80% in the richest.

Conversely, we can investigate what fraction of exports goes towards rich importers. Since developing countries tend to have a comparative advantage in unskilled-labor-intensive indus-

tries, we can expect poorer countries to have a smaller share of exports towards developed countries.

These results solely reflect differences in consumption patterns and do not account for trade costs. As developed countries tend to be closer to other developed countries and vice versa, trade costs can also generate a correlation between import penetration by developing countries and importers' income. An interesting question is whether these trade costs are sufficient to quantitatively replicate trends in observed patterns.

Using estimates from both steps of our estimations, we can construct predicted trade flows \widehat{X}_{nik} (from country i to country n in sector k) using the gravity equation 5:

$$\widehat{X}_{nik} = \frac{\widehat{S}_{ik}(\widehat{d}_{nik})^{-\theta_k}}{\widehat{\Phi}_{nk}} \widehat{D}_{nk}$$

where \widehat{S}_{ik} , $(\widehat{d}_{nik})^{-\theta_k}$ and $\widehat{\Phi}_{nk}$ are constructed using estimates from the gravity equation (see step 1 of the estimation procedure) and where \widehat{D}_{nk} is fitted demand from the final step of the demand estimation. We can compare fitted demand with non-homothetic preferences with fitted demand imposing homotheticity (i.e. common $\sigma_k = \sigma$ across industries). Accounting for trade costs in both cases we can examine, for each country: i) the share of trade (imports + exports) with rich partners; ii) the ratio of trade to GDP.

Figure 5 plots the share of trade with rich partners (annual per capita income above \$10K) in manufacturing industries against per capita income (in log). As we can see, homothetic preferences with trade costs can already generate a positive correlation since richer countries are more likely to be closer to rich countries and trade with them. As expected, however, non-homothetic preferences further magnify this correlation. In particular, we can observe substantial differences in predicted shares for the poorest countries.

Since rich countries also have the largest GDP²⁷ in absolute terms, a country's level of openness (trade/GDP) is likely to depend largely on whether such a country has a large penetration in the richest markets. Figure 6 plots the ratio of trade over GDP against per capita income (in log). We find indeed that the predicted ratio of Trade/GDP is slightly smaller for developing countries when we allow for non-homotheticity in preferences. Conversely, this ratio is larger for rich countries since they have a larger market penetration in other rich markets.

Note that these results are solely driven by differences in consumption patterns across countries. We use the same trade cost and supply-side estimates in the homothetic and non-homothetic cases.

²⁷Developed countries account for 80% of total GDP in our sample of 94 countries.

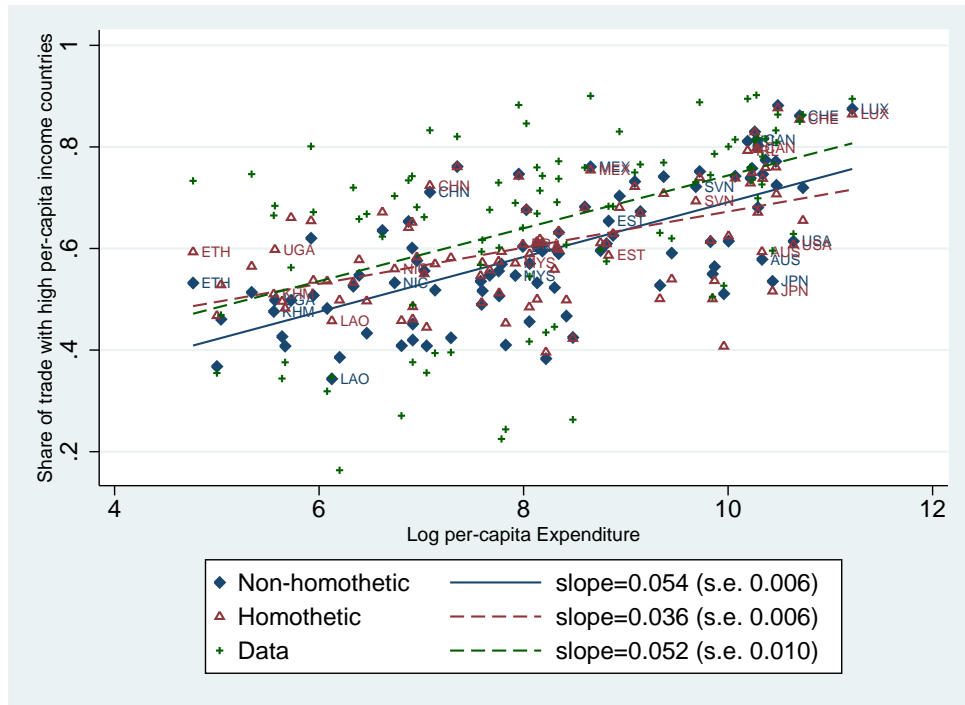


Figure 5: Share of trade with rich partners (imports and exports)

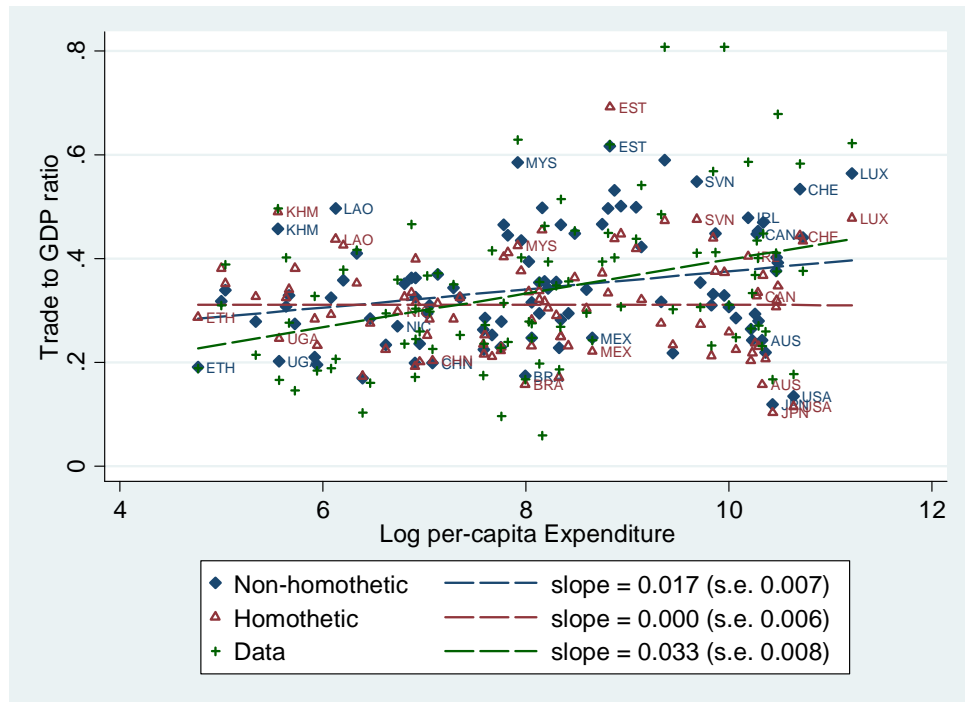


Figure 6: Fitted Trade/GDP ratio across countries

4.3 Productivity growth and the skill premium

As argued in Section 2.3.3, non-homothetic preferences can also shed light on why the skill premium has been increasing for a large number of countries (see Goldberg and Pavcnik (2007), for empirical evidence on the skill premium increase). When preferences are homothetic, an homogeneous increase in productivity in all countries should neither affect the patterns of trade nor the relative demand for skilled labor. However, when preferences are non-homothetic and when the income elasticity of demand is positively correlated with the skill intensity of production, an increase in productivity makes consumers richer which in turn induces a relative increase in consumption in skill-intensive industries (high-income elastic industries) and thus raises the relative demand for skilled labor.

This new demand-driven explanation contrasts with previous studies that have focused on the supply side. In this section, we use our general equilibrium model to quantitatively estimate the elasticity of the skill premium to total factor productivity (TFP). Several approaches are used. First we simulate a 1% increase in TFP in all countries²⁸ and examine how it affects the skill premium both in open and in closed economies. This counterfactual pinpoints the role of non-homothetic preferences since the same counterfactual would keep the skill premium unchanged if preferences are homothetic. We also simulate productivity increases corresponding to growth rates of per capita income in each country between 1995 and 2005 (Penn World Table data). Finally, we use the approximation provided in equation (17) to investigate the sources of differences in the skill premium elasticity across countries.

We numerically solve the economy in general equilibrium.²⁹ Both demand-side and supply-side parameters are taken from our estimations (gravity equations and final demand estimation, specification D1). Note that, in our simulated general-equilibrium model, benchmark factor prices and income adjust and slightly differ from observed values, but not by much. Equilibrium conditions are equations (3) to (10) described in section 2.2. Details are provided in the appendix section.

Figure 7 illustrates the elasticity of the skill premium to technology when we simulate a 1% TFP increase in all countries. Our simulations show that this effect is large and stronger for poor countries. For instance, the elasticity of the skill premium to productivity is about 0.25 for China. With an annual productivity growth of about 8%, this yields a large increase of the skill premium of 20% every decade. This figure is close to the 50% increase in the skill premium observed in China between the early 1990s and 2006, in spite of a large increase in skilled labor supply (Zou et al. (2009)).³⁰ For South American countries, the elasticity is also above 0.2.

²⁸The same elasticities are obtained by simulating a 10% increase in TFP.

²⁹The model is formulated in GAMS and solved by the non-linear PATH solver.

³⁰The Gini coefficient in China has also sharply increased from less than 30 in the early 1990s to 42 in 2005



Figure 7: Elasticity of skill premium to TFP

With a 5% growth rate in productivity, this would yield a 10% increase in the skill premium every decade. Such a magnitude is large and could explain a big part of the observed increase in the skill premium.³¹ For India, our model could explain about half of the skill premium increase in the 90's.³² Even for richer countries, the effect on the skill premium is not negligible. For the US, this could explain about 10% of the skill premium increase during the 80's; this magnitude is comparable to the estimated effect of outsourcing on the skill premium in the US in the 80's.³³

While Figure 7 illustrates the elasticity of the skill premium with a homogeneous TFP increase in all countries, we find about the same elasticities when we simulate productivity (World Bank data).

³¹South American countries seem to have experienced large increases in the skill premium: 68% for Mexico between 1987 and 1993 (Cragg and Epelbaum, 1996), 20% in Argentina between 1992 and 1998 (Gasparini, 2004), 16% for Colombia between 1986 and 1998 (Attanasio et al., 2004). Given the growth rates during the corresponding periods, our model could explain increases of nearly 20%, 4% and 16% respectively for Mexico, Argentina and Colombia.

³²According to Kijama (2006), the skill premium increased by 13% between 1987 and 1999, while the growth rate was about 2.2% on average, and our predicted elasticity of skill premium to productivity is larger than 0.25, thus predicting a 6.6% skill premium increase.

³³In a conservative estimate, Feenstra and Hanson (1999) show that outsourcing can explain about 15% of the skill premium increase.

increases that match GDP per capita growth between 1995 and 2005 for each country (simulating the full model with trade flows). The largest deviations are found for the few countries with negative growth rates (Malawi, Madagascar, Paraguay and Zimbabwe), for which our simulation yields a positive increase in the skill premium if we account for trade.³⁴

Actually, the main argument on the role of non-homothetic preferences does not involve trade. It also applies to closed economies. In addition to the open-economy simulations, we also simulate a 1% increase in production for all countries in our sample, assuming infinite trade barriers before and after the productivity increase. Interestingly, our simulated skill-premium elasticities are very close to the results obtained in an open-economy framework. This is illustrated in Figure 8, with the open-economy elasticity on the horizontal axis and the closed-economy elasticity on the vertical axis. Simulated elasticities are all close to the diagonal line, with apparently no systematic deviations.

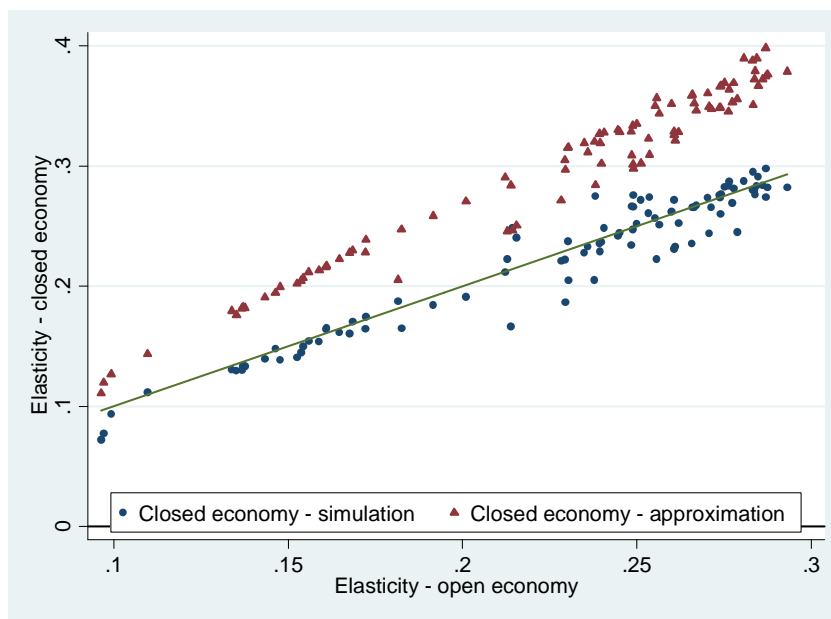


Figure 8: Open-economy vs. closed-economy simulation and approximation

In a closed-economy framework, it is also possible to approximate the skill-premium elasticity to TFP with expression (17). Using our estimates for income elasticities (ε_{nk}) as well

³⁴It would be interesting to directly test our theory by systematically comparing observed skill premium increases and our predicted increases across countries. This requires harmonized panel data on the skill premium over a broad range of countries, which are however not available. Instead we have compared increases in Gini coefficients between the early 1990s and the early 2000s with our predicted skill premium increases for each country, using actual growth rates (controlling for increases in the supply of skilled labor). In our attempts, the beta coefficient is large (about 25%) but not statistically significant. One should however not reject our theory based on these results since increases in the skill premium are very imperfectly reflected in the Gini coefficients.

as labor shares (sh_{nk}^H and sh_{nk}^L) we can obtain an alternative quantitative prediction of the skill-premium elasticity. These values are also plotted on figure 8 (red triangles). As it can be seen, there is a very high correlation between approximated skill-premium elasticity in closed economy with both simulated elasticities in closed and open economy.

By regressing the closed-economy approximations on the closed-economy simulated elasticities, we find a coefficient of 0.741. This coefficient is smaller than one because of general-equilibrium feedback: an increase in the skill premium yields an increase in the relative price of high-income elastic goods which negatively affects relative consumption and the relative income of skilled workers. This feedback effect is embodied in ξ_n (See equation 16 and appendix section): this effect ξ_n is however broadly the same for all countries n . In fact, after multiplying our approximated elasticity by 0.741 as an approximation for $\frac{1}{1+\xi_n}$, we obtain an extremely good approximation of the simulated elasticity in closed economy (R-square of 96.5%).

Our formula from equation (17) also provide a good approximation of the open-economy simulated elasticity. In a regression of the simulated skill premium increase in open economy on the skill premium increase approximation suggested by equation (17), we also obtain a coefficient of 0.74 with an R-square of 87.1%.³⁵ Hence, our approximation is relevant and can be safely used to examine differences in the skill-premium elasticity across countries.

Why is this effect larger for poor countries? As we have shown in section 2.3.3, the effect on the skill premium strongly depends on the income elasticity of demand. These elasticities decrease with income, which could explain why the effect on the skill premium may be smaller for richer countries. While this mechanism plays a role, other effects are also present. To illustrate this, we split the above skill-premium elasticity into i) an average effect; ii) a term reflecting changes in income elasticity (within effect), iii) a term reflecting difference in labor allocation across sectors (between effect); iv) and a covariance term:

$$\begin{aligned} \sum_k (sh_{nk}^H - sh_{nk}^L) \varepsilon_{nk} &= \underbrace{\sum_k (\bar{sh}_k^H - \bar{sh}_k^L) \bar{\varepsilon}_k}_{Average} + \underbrace{\sum_k (\bar{sh}_k^H - \bar{sh}_k^L) \Delta \varepsilon_{nk}}_{Within} + \underbrace{\sum_k (\Delta sh_{nk}^H - \Delta sh_{nk}^L) \bar{\varepsilon}_k}_{Between} \\ &+ \underbrace{\sum_k (\Delta sh_{nk}^H - \Delta sh_{nk}^L) \Delta \varepsilon_{nk}}_{Covariance} \end{aligned}$$

where \bar{sh}_k^H denotes the average of sh_{nk}^H across countries n ;³⁶ $\bar{\varepsilon}_k$ denotes the average of ε_{nk} across countries n ; Δsh_{nk}^H denotes the difference between sh_{nk}^H and its average \bar{sh}_k^H ; $\Delta \varepsilon_{nk}$ denotes the

³⁵In this case, the coefficient is 0.746 with a standard error about 0.02 (open-economy simulation) against 0.01 for the closed-economy simulation. The constant is not significantly different from zero in both cases.

³⁶ sh_{nk}^H is defined as the share of sector k in skilled labor employment in country n , see Section 2.3.3.

difference between ε_{nk} and its average $\bar{\varepsilon}_k$. From this decomposition (Figure 9), both the within and between effects seem equally important in explaining differences across countries. While the within-effect is clearly decreasing with income, as expected, the between effect has an inverted-U shape and is highest for middle-low income countries such as China.

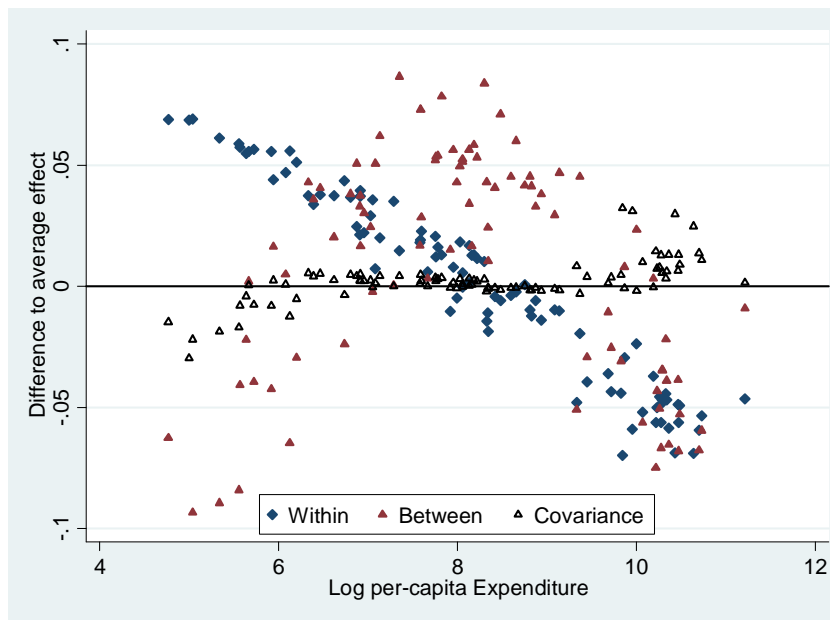


Figure 9: Within and between decomposition of the effect on the skill premium

5 Robustness

We explore the robustness of our results in a variety of dimensions. To save space, all results on the sensitivity of the correlation between skill intensity and income elasticity, our main variable of interest, are summarized in table 5.

5.1 Price data

In section 3, income elasticities are estimated by controlling for supply-side characteristics using a proxy price index P_{nk} which is constructed from the estimated Φ_{nk} (from the gravity equations). Possible mis-estimation of this unobserved variable might raise concerns that our income elasticity estimates are biased. To test for this, we use actual price data from the 2005 International Comparison Program (ICP) (World Bank 2005), an extensive dataset which includes price indices for a wide range of products and countries. Despite mapping issues, we

are able to match ICP price indices to 38 of the 50 sectors and 88 out of 94 countries included in our analysis.

The idea here is not to test whether the estimated P_{nk} perfectly match the actual prices indices, as there are many reasons for them not to. Indeed, a regression of the log of the ICP price index on $\log P_{nk}$ including both country and sector fixed effects reveals a significant but weak correlation (beta correlation coefficient = 0.072, p-value < 0.001).

Rather, we are interested in knowing if the inclusion of ICP price data in demand estimations leads to significantly different income elasticity estimates.

A simple reduced-form log regression of final demand D_{nk} on both price indices (not shown), with both region and sector fixed effects, reveals that the constructed P_{nk} have a stronger explanatory power than the ICP index (beta correlation coefficient of 0.343 versus 0.051, both p-values < 0.01).

Including the ICP price index in the estimation of CRIE demand parameters in a specification similar to (D2) confirms that its predictive power is less than that of the constructed P_{nk} . Indeed, resulting income elasticity estimates are closer to those obtained by ignoring prices entirely (D3). Table 5 displays our correlation of interest when income elasticities are estimated using ICP prices (column 2) and using both indices (column 3). We clearly find that controlling for supply-side characteristics with our proxy price index P_{nk} has a greater impact on demand estimates. Thus, without being a definite test of the validity of our price index proxy, the comparison with external price data suggests that potential mis-estimation of the Φ_{nk} would tend to bias our correlation estimates downwards, if anything.

Table 5: Skilled labor to income elasticity correlation - Robustness across specifications

Demand system:	CRIE			LES	AIDS	
Dependent variable:	Log expenditure		Expenditure shares	Expenditure shares	Expenditure shares	
Prices:	Phi ($\theta = 4$)	ICP	Both	-	-	
Region(s):	(1)	(2)	(3)	(4)	(5)	(6)
All	0.526	0.693	0.552	0.819	0.668	0.858
With robust data	0.469	0.645	0.487	0.766	0.614	0.805
USA	0.390	0.497	0.333	0.629	0.394	0.630
EU	0.529	0.564	0.442	0.703	0.580	0.719
Japan	0.489	0.642	0.536	0.760	0.748	0.829
Observations	50	38	38	50	50	50

Notes : all income elasticities calculated using median country expenditure shares. All correlations are significant at the 1% significance level.

5.2 Alternative demand systems

In order to test how our CRIE income elasticity estimates stack up against other demand systems, we compare them with estimates - generated using the same dataset - from two well-known alternative demand systems which also exhibit non-homothetic behavior: the linear expenditure system (LES) and the "Almost Ideal Demand System" (AIDS). LES is derived from Stone-Geary preferences and is essentially an origin-displaced Cobb-Douglas function. AIDS, first introduced by Deaton and Muellbauer (1980), is not derived from any particular utility function, but has been widely used for its aggregation properties and its simplicity. Under the assumption of identical relative prices across regions, these demand systems can be shown to yield the following relationship between sectoral consumption shares and per-capita expenditures:

$$\text{LES : } \frac{x_{nk}}{\sum_k x_{nk}} = \alpha_k + \gamma_k e_n^{-1} \qquad \text{AIDS : } \frac{x_{nk}}{\sum_k x_{nk}} = \alpha_k + \gamma_k \log e_n$$

Note that the budget constraint imposes $\sum_k \alpha_k = 1$ and $\sum_k \gamma_k = 0$ in both cases. In each case, this relationship is estimated by sector by minimizing errors in expenditure shares (non-linear least squares subject to the budget constraint). For the sake of the comparison, we also reestimate CRIE preferences by minimizing errors in expenditure shares (whereas our benchmark estimates minimize errors in log expenditures). The resulting estimates of α_k and γ_k are then used to compute income elasticities ε_{nk} with LES and AIDS as:

$$\text{LES : } \varepsilon_{nk} = \alpha_k (\gamma_k + \alpha_k e_n^{-1})^{-1} \qquad \text{AIDS : } \varepsilon_{nk} = 1 + \gamma_k (\alpha_k + \gamma_k \log e_n)^{-1}$$

Figure 10 plots the distribution of these income elasticities against the CRIE estimates. All estimates are evaluated at the median country per-capita expenditure level. Clearly, CRIE estimates are in line with both of these alternative demand systems. Spearman coefficients of rank correlation with CRIE estimates are 0.88 for LES and 0.85 for AIDS. Most importantly, columns (5) and (6) of Table 5 confirm that the result of strong correlation between income elasticities and skill intensity is robust across all three demand systems.

Figure 10 also reveals the weakness of the LES demand system : income elasticities are very sensitive to income and converge rapidly to unity as income increases. Thus, even when evaluated at the median country income (as in Figure 10), income elasticities exhibit small deviations to one. AIDS performs better and yields a larger variability which is closer to that generated by CRIE.

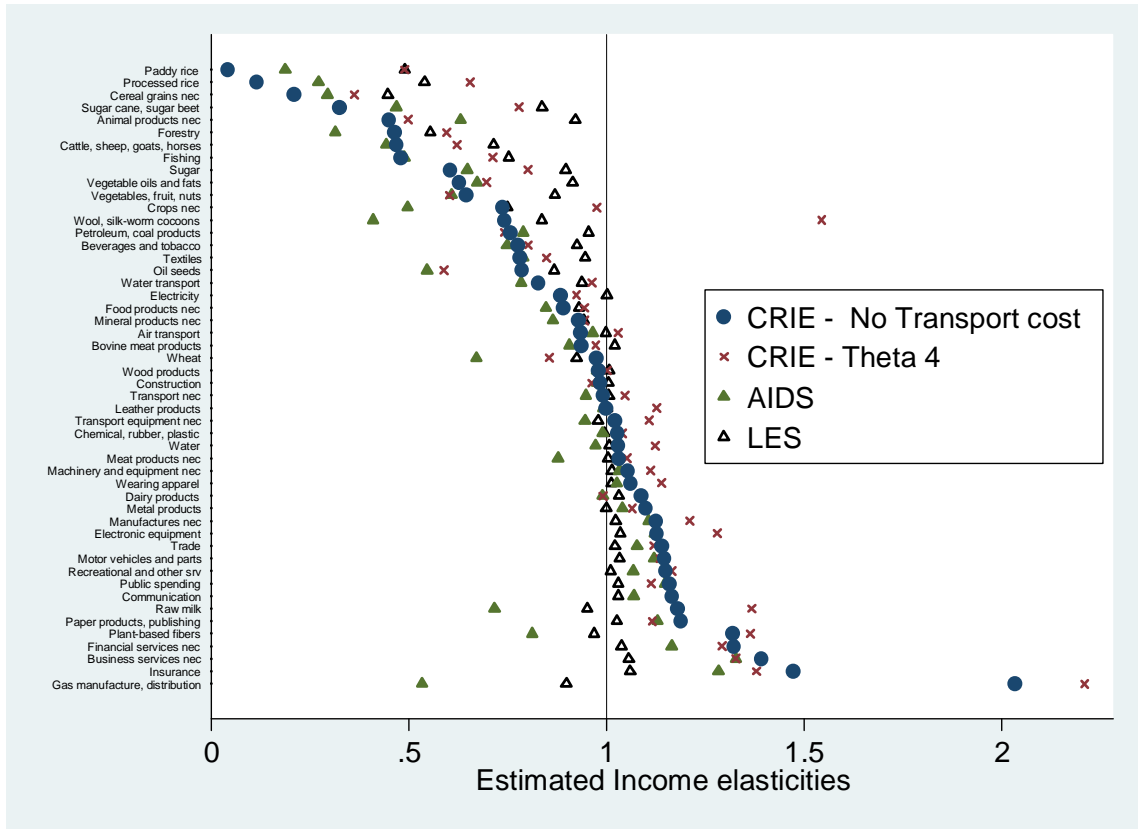


Figure 10: Comparison of distribution of income elasticities across demand systems

5.3 Measurement of skill intensity

All results from the previous sections are estimated using sectoral skill intensity indices which are computed as an average over all countries. We now test whether the main correlations are robust to using skill intensity measured on the subset of countries with the most reliable data (see Section 3.2). Table 5 displays the correlation of income elasticities to skill intensity using different regional subsets of the GTAP data : all GTAP regions, the reliable regions, the US, Europe (EU) and Japan. Although, the correlation seems to generally be smaller for the USA than for the EU and Japan, it remains large and significant for all regions.

5.4 Within-country income distribution

Compared to a hypothetical situation where income is homogeneous within each country, within-country income inequalities can reduce the observed variations in consumption patterns between countries. For instance, income inequalities could explain why it is possible to

find luxurious cars in Africa (as other high-income elastic goods), while this type of goods is clearly not purchased by any individual with the average income of an African country.

Empirically, income inequalities create a downward bias in the dispersion of estimated income elasticities if we fail to take these inequalities into account (i.e. it biases our estimated income elasticities towards unity). Conversely, accounting for within-country inequalities should *reinforce* the differences in estimated income elasticities across sectors: it would be otherwise difficult to explain the large differences in observed consumption patterns across countries.

To confirm this intuition and test the sensitivity of our results to the inclusion of within-country inequalities, we rely as in Fielser (2011) on World Bank data describing the share of total income held by different percentiles of the population. Available data covers 7 income classes (the first two and last two deciles, as well as the 3 middle quintiles) and 89 of the 94 countries in our sample.

The estimation procedure in section 3 is modified to allow for 7 representative consumers in each country (each representing one population quintile or decile). As expected, resulting income elasticity estimates exhibit larger variations across sectors, although the differences are very small : the mean absolute deviations from one increases from 0.225 to 0.238³⁷. The correlation between the two series is 0.995.

Correspondingly, the correlation of these income elasticity estimates with skill intensity increases slightly (from 0.488 to 0.534). Thus, accounting for within-country dispersion in incomes increases the estimated effect of non-homotheticity and makes our results stronger. However, given the small magnitude of the bias, we are comfortable with using the estimates from section 3 for counterfactual analyses.

5.5 Intermediate goods

Estimation with intermediate goods The model above does not explicitly account for intermediate goods. In all the above, we estimate the gravity equation using gross trade flows and we estimate the demand equation using final consumption. This approach is however consistent with a model that does account for intermediate goods under some similarity conditions between final and intermediate goods within each industry.

With intermediate goods, we need to differentiate final demand D_{nk} from total absorption X_{nk} which also includes demand for goods used as intermediates. While the data allows us to separately observe final demand from intermediates goods by industry and destination country, we can only observe trade flows by industry, pooling final goods and intermediate goods together. Hence, it is not possible to separately identify a country's productivity for final goods

³⁷comparing estimates generated with the comparable set of 89 countries

vs. intermediate goods within the same industry. However, if we assume that goods within the same industry are produced with similar techniques (i.e. same average productivity draw and same use of inputs), we obtain a common supply term S_{ik} for both final goods and intermediate goods. If we further assume that trade costs vary by industry but do not depend on the type of goods within an industry, then we obtain again a gravity equation as in equation 5:

$$X_{nik} = \frac{S_{ik}(d_{nik})^{-\theta_k}}{\Phi_{nk}} X_{nk}$$

where $X_{nk} = \sum_i X_{nik}$ refers to total absorption and now differs from final demand D_{nk} . Again, the supplier effect S_{ik} reflects the cost of producing in industry k in country i . This equation can also be estimated as in step 1 of our procedure, with importer and exporter fixed effects to account for S_{ik} and X_{nk} . As in the model without intermediate goods, we can retrieve the price index (Φ_{nk} to be more precise) by using exporter fixed effects and gravity coefficients.

In terms of final demand, x_{nk} satisfies the same equations. These equations can be estimated using the same method, i.e. by following the same steps as in section 3.1. It justifies the use of information on final demand to estimate the final demand equation (2nd step) and the use of total trade flows to estimate gravity equations (1st step).

Counter-factuals with intermediate goods. While our estimation strategy is consistent with a model that incorporates intermediate goods, general equilibrium simulations (as in Section 4.3) need to be amended to account for the use of intermediate goods and inter-industry linkages. With intermediate goods, the effect of productivity growth on the skill premium can be larger or smaller depending on the specification.

First, the effect of productivity shocks on production is magnified in a model with intermediate goods. This can be simply formalized as in the input-output literature as a multiplier effect (see Fally (2012a)): the longer the production chain, the larger is the effect of productivity on output. This effect also mechanically magnifies the effect of productivity growth on the skill premium.

If we assume that the productivity shock only affect the productivity of factors instead of all inputs (factors plus intermediate goods), the multiplier effect is then neutralized. If we further assume that output in each sector is a Cobb-Douglas production function in factors and intermediate goods from other sectors (see appendix section for details), we can generalize equation (17) and show that the elasticity of the skill premium to productivity (in a closed economy) is now:

$$\frac{\partial \log sp_n}{\partial \log z_n} \approx \sum_k (sh_{nk}^H - sh_{nk}^L) \varepsilon_{nk}^{tot}$$

where z_n is an overall productivity shifter and where ε_{nk}^{tot} (which stands for “total” income elasticities) is defined as a weighted average of income elasticity of demand in upstream sectors:

$$\varepsilon_{nk}^{tot} = \frac{\sum_{k'} \gamma_{k'k} D_{nk'} \varepsilon_{nk'}}{\sum_{k'} \gamma_{k'k} D_{nk'}}$$

with $D_{nk'}$ denoting the final consumption of good k' and $\gamma_{k'k}$ denoting the coefficient of the Leontief inverse matrix.³⁸ In other words, the effect of productivity also depends on the skill intensities of other industries required to produce intermediate goods. As the variance of “total” income elasticities across sectors is smaller than for usual income elasticities of demand, the overall effect of productivity on the skill premium should be smaller in this case.³⁹

6 Summary and conclusions

We begin with the assertion that a large proportion of both theoretical and empirical research on international trade focuses on the production side of general equilibrium. The purpose of this paper is then to demonstrate that an examination of the role of demand can contribute to explaining a number of persistent puzzles long debated by trade economists. In particular, we are interested in the systematic relationship between certain characteristics of demand and characteristics of goods and services in production.

Our first task is to develop and estimate a model where preferences are assumed to be identical across countries but non-homothetic. It allows goods to differ in their income elasticity of demand and expenditure shares to be related to per-capita income. Both economically and statistically, we find large deviations of income elasticity estimates from the unitary values implied by homothetic preferences.

The next step is to relate these income elasticities of demand to factor intensities of goods in production. Here we find a strong, positive correlation (higher than 45 percent) between a good’s income elasticity of demand and its skilled-labor intensity in production. The correlation is robust to the inclusion of trade costs and a number of other factors.

We then investigate the implications of non-homothetic preferences and the relationship to factor intensities. Our first results assess their contribution to the “missing trade” puzzle. We find that they can reduce the overpredicted variance in the factor content of trade by 40%. This result is driven by a supply-demand correlation which is absent under homothetic preferences:

³⁸Coefficients of $(I - \bar{B})^{-1}$ where \bar{B} denotes the matrix of direct input-output coefficients by industry.

³⁹Note however that intermediate goods required to produce skill-intensive goods tend to be skill-intensive as well, and therefore these “total” elasticities of demand do not differ greatly from the usual income elasticities. In fact, the correlation between “total” elasticities and skill intensity is even stronger and increases to 70.0%.

countries tend to specialize in the consumption of the same goods that they are specialized in producing.

A second set of results relate to trade patterns and the selection of trading partners. Our findings imply that high-income countries have a comparative advantage in high-income-elasticity goods and services, because these are skilled-labor intensive and because the high-income countries are skilled-labor abundant. This suggests that rich countries should be more likely to export to other rich countries and we verify that this is the case. In turn, a country's level of trade/GDP depends on its penetration into the richest markets. Since rich countries are also the largest markets in terms of GDP, non-homothetic preferences generate a positive correlation between income and the ratio of trade to GDP.

A final set of results shed light on a heated debate from the 1990s: the growing gap between skilled and unskilled wages. The two main hypotheses in this debate focused on the supply side of the economy. One was the Stolper-Samuelson argument that increased import penetration by unskilled-labor-abundant, low-income countries would depress unskilled-labor wages in rich countries. The other focused on skill-biased technical change. Our general equilibrium simulations show that a uniform Hicks-neutral productivity improvement, equal across all sectors and all countries, leads to an increase in the skill premium in *all* countries. The mechanism is straightforward: higher per-capita income shifts demand toward high-income-elasticity goods which are skilled-labor intensive. This drives up the relative wage of skilled labor.

Appendix

Proof of equations (16) and (17)

Equation 17 is an approximation for a closed economy by neglecting feedback effects of the skill premium increase on relative prices. By taking nominal income as the numeraire (thus being constant), this amounts to state that changes in prices are driven by changes in productivity.

As we focus on one economy, we drop country subscripts. We examine the effect of a homogeneous productivity (TFP) increase across all sectors: $\hat{z}_k = \hat{z}$. Hence $\hat{p}_k \approx -\hat{z}$ where $\hat{v} = \frac{dv}{v}$ refers to the relative change for any variable v .

Taking first differences in demand, we obtain:

$$\hat{x}_k = -\sigma_k \hat{\lambda} + (1 - \sigma_k) \hat{p}_k = -\sigma_k \hat{\lambda} + (\sigma_k - 1) \hat{z}$$

We need to solve for the change in the budget constraint Lagrangian λ . We therefore take the first difference of the budget constraint. Normalizing nominal income to a constant, the

following condition must be satisfied:

$$\sum_k \hat{x}_k x_k = 0$$

Inserting demand into the budget constraint, we obtain an expression for the change in Lagrangian:

$$\hat{\lambda} = \frac{\sum_k (\sigma_k - 1) x_k}{\sum_k \sigma_k x_k} \hat{z}$$

After incorporating the solution for λ into the change in demand, we obtain:

$$\hat{x}_k = \hat{z} \left(-\frac{\sigma_k \sum_{k'} (\sigma_{k'} - 1) x_{k'}}{\sum_{k'} \sigma_{k'} x_{k'}} + (\sigma_k - 1) \right) = \hat{z} \left(\frac{\sigma_k \sum_{k'} x_{k'}}{\sum_{k'} \sigma_{k'} x_{k'}} - 1 \right)$$

Using equation (2) for the income elasticity: $\varepsilon_k = \frac{\sigma_k \sum_{k'} x_{k'}}{\sum_{k'} \sigma_{k'} x_{k'}}$, we obtain:

$$\hat{x}_k = \hat{z}(\varepsilon_k - 1)$$

We can see in this expression that an improvement in productivity has a similar effect as an increase in income (keeping prices constant as a first approximation). In particular, demands increases more for income-elastic goods.

Having the change in demand for goods, we can now examine the change in the relative demand for skilled labor. We take the first difference of demand for skilled and unskilled labor. In terms of skilled wages:

$$\hat{h} = \frac{\sum_k \hat{x}_k \beta_k x_k}{\sum_k \beta_k x_k} = \sum_k \hat{x}_k sh_k^H \quad (24)$$

In terms of unskilled wages:

$$\hat{w} = \frac{\sum_k \hat{x}_k (1 - \beta_k) x_k}{\sum_k (1 - \beta_k) x_k} = \sum_k \hat{x}_k sh_k^L \quad (25)$$

Looking for an expression for the increase in skill premium, $\hat{s} = \hat{h} - \hat{w}$, we get:

$$\hat{s} = \hat{z} \sum_k (sh_k^H - sh_k^L) (\varepsilon_k - 1) = \hat{z} \sum_k (sh_k^H - sh_k^L) \varepsilon_k - \hat{z} \sum_k (sh_k^H - sh_k^L) = \hat{z} \sum_k (sh_k^H - sh_k^L) \varepsilon_k$$

Hence the elasticity of the skill premium to the TFP improvement is:

$$\frac{\hat{s}}{\hat{z}} = \sum_k (sh_k^H - sh_k^L) \varepsilon_k$$

General formula

Let's now prove equation (16). We continue taking nominal income as the numeraire. This imposes that average wage increase weighted by the corresponding:

$$\left(\sum_k x_k \beta_k\right) \hat{h} + \left(\sum_k x_k (1 - \beta_k)\right) \hat{w} = 0$$

Turning to prices, we now consider the effect of factor prices on goods prices. Taking first differences, we get:

$$\hat{p}_k = -\hat{z} + \beta_k \hat{h} + (1 - \beta_k) \hat{w}$$

Normalizing per capita income e to unity, we obtain that both \hat{w} and \hat{h} can be expressed as a function of the skill premium change. Taking this normalization into account, we obtain:

$$\hat{p}_k = -\hat{z} + \Delta\beta_k \hat{s}$$

where $\Delta\beta_k = \beta_k - \frac{\sum_{k'} x_{nk'} \beta_{k'}}{\sum_{k'} x_{nk'}}$ and reflects the skill intensity of sector k compared to average skill intensity. As in the proof of equation (17), we combine this expression with demand and the budget constraint. We obtain the Lagrangian:

$$\hat{\lambda} = \left(\frac{\sum_k (\sigma_k - 1) x_k}{\sum_k \sigma_k x_k}\right) \hat{z} - \left(\frac{\sum_k \sigma_k \Delta\beta_k x_k}{\sum_k \sigma_k x_k}\right) \hat{s}$$

Reincorporating the Lagrangian into the demand equation, we obtain:

$$\hat{x}_k = (\varepsilon_{nk} - 1) \hat{z} - \left[(\sigma_k - 1) \Delta\beta_k - \sigma_k \frac{\sum_{k'} \sigma_{k'} \Delta\beta_{k'} x_{k'}}{\sum_{k'} \sigma_{k'} x_{k'}} \right] \hat{s}$$

Denoting a_k the term into bracket above, we obtain ξ_n by weighted a_k by $sh_k^H - sh_k^L$ and rearranging and adding the country subscript:

$$\xi_n = \frac{(\sum_k x_{nk} \beta_k \sigma_k)(\sum_k x_{nk})}{(\sum_k x_{nk} \beta_k)(\sum_k x_{nk} (1 - \beta_k))} \left[\frac{\sum_k x_{nk} \beta_k \Delta\beta_k (\sigma_k - 1)}{\sum_k x_{nk} \beta_k \sigma_k} - \frac{\sum_k x_{nk} \Delta\beta_k (\sigma_k - 1)}{\sum_k x_{nk} \sigma_k} \right]$$

Gravity equation estimates

Table 6 below presents the results of the gravity equation estimations (equation 21). The first column shows the average estimated coefficient across industries while the second column shows the standard deviation of the coefficient estimate across industries. These standard errors reflect the variations of the coefficients across industries but do not reflect measurement errors:

all coefficient estimates are significant at the 1% level for most industries.

Table 6: Coefficients from the gravity equation estimations

Variable:	Mean of estimated coeffs across industries	SD of estimated coeffs across industries
Distance (log)	-0.941	0.504
Home bias	4.545	1.982
Contiguity	0.518	0.488
Common lang.	0.378	0.305
Colonial link	0.171	0.444
Exporter FE	Yes	
Importer FE	Yes	
Nb. of industries	50	

Notes: Poisson regressions; dependent variable: trade flows; step 1 of the estimation procedure described in the text. The coefficient above are estimated separately for each industry.

Factor content of trade: measurement

In their definition of the factor content of trade, Trefler and Zhu (2010) construct a matrix \mathbf{A}^P reflecting the factor content in final goods production by taking into account the factor content in traded intermediate goods.

In line with Trefler and Zhu (2010), we define the trade matrix \mathbf{T} as:

$$\mathbf{T} = \begin{bmatrix} (\sum_{n \neq 1} \mathbf{X}_{n1}) & -\mathbf{X}_{21} & \cdots & -\mathbf{X}_{N1} \\ -\mathbf{X}_{12} & (\sum_{n \neq 2} \mathbf{X}_{n2}) & \cdots & -\mathbf{X}_{N2} \\ \vdots & \vdots & \ddots & \vdots \\ -\mathbf{X}_{1N} & -\mathbf{X}_{2N} & \cdots & (\sum_{n \neq N} \mathbf{X}_{nN}) \end{bmatrix}$$

where each \mathbf{X}_{ni} is the vector of trade flows X_{nik} for goods k shipped from i to n :

$$\mathbf{X}_{ni} = \begin{bmatrix} X_{ni1} \\ X_{ni2} \\ \vdots \\ X_{niK} \end{bmatrix}$$

we define the trade matrix \mathbf{D} for trade in final goods as:

$$\mathbf{D} = \begin{bmatrix} \mathbf{D}_{11} & \mathbf{D}_{21} & \cdots & \mathbf{D}_{N1} \\ \mathbf{D}_{12} & \mathbf{D}_{22} & \cdots & \mathbf{D}_{N2} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{D}_{1N} & \mathbf{D}_{2N} & \cdots & \mathbf{D}_{NN} \end{bmatrix}$$

where each \mathbf{D}_{ni} is the vector of trade flows D_{nik} for final goods k shipped from i to n . Given our proportionality assumption, we measure D_{nik} as $\frac{D_{nk}X_{nik}}{\sum_i X_{nik}}$. We also define the production matrix \mathbf{Y} as the diagonal matrix:

$$\mathbf{Y} = \begin{bmatrix} \mathbf{Y}_1 & 0 & \cdots & 0 \\ 0 & \mathbf{Y}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{Y}_N \end{bmatrix}$$

where each \mathbf{Y}_n is the vector of production Y_{nk} of country n in sector k .

The input-output matrix is denoted by \mathbf{B} and reflects the use of inputs k from a particular source i for each downstream industry k' and destination country n . In a matrix form:

$$\mathbf{B} = \begin{bmatrix} \mathbf{B}_{11} & \mathbf{B}_{21} & \cdots & \mathbf{B}_{N1} \\ \mathbf{B}_{12} & \mathbf{B}_{22} & \cdots & \mathbf{B}_{N2} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{B}_{1N} & \mathbf{B}_{2N} & \cdots & \mathbf{B}_{NN} \end{bmatrix}$$

where each individual block \mathbf{B}_{ni} is a K by K matrix where each cell $B_{nikk'}$ reflects the use of intermediate goods k' from country i for the production of one dollar of good k in country n .

We do not have data on each component $B_{nikk'}$, as GTAP only provides information on domestic input uses $B_{nnkk'}$ and aggregate imported intermediates $B_{nkk'}^{imp}$ for each downstream industry k' , upstream industry k in country n . Assuming that import shares from a particular source i do not depend on the downstream industry k' (proportionality assumption), we construct $B_{nikk'}$ as:

$$B_{nikk'} = B_{nkk'}^{imp} \frac{X_{nik}}{\sum_{i \neq n} X_{nik}}$$

As goods are either used as final goods or intermediate goods, we obtain the following accounting equality described in Treffer and Zhu (2010):

$$\mathbf{T} = \mathbf{Y} - \mathbf{B}\mathbf{Y} - \mathbf{D}$$

which leads to:

$$\mathbf{Y} = (\mathbf{I} - \mathbf{B})^{-1}(\mathbf{T} + \mathbf{D}) \quad (26)$$

We now define matrix \mathbf{A}^P as:

$$\mathbf{A}^P = \Xi(\mathbf{I} - \mathbf{B})^{-1}$$

where Ξ is the matrix of direct factor requirements, i.e. the matrix of coefficients β_{kfn} reflecting the value of factor f required in the production of goods k in country n . Since the value of factor k used in production in country n is given by $w_{nf}V_{nf} = \sum_k \beta_{kfn}Y_{nk}$, we obtain from equation (26) that $\mathbf{A}^P(\mathbf{T} + \mathbf{D})$ equals the matrix of payments to factors (i.e. each $\mathbf{A}^P(\mathbf{T}_n + \mathbf{D}_n)$ is the vector of payments to factors used in country n).

Trefler and Zhu (2010) then defines the factor content of trade by taking the trade component of the above equation: $\mathbf{F} = \Xi(\mathbf{I} - \mathbf{B})^{-1}\mathbf{T}$ (where each component $\mathbf{A}^P\mathbf{T}_n$ is the vector of factor content of trade for country n for each column-vector of trade \mathbf{T}_n).

Factor content of trade: proof of equation (23)

To prove equation (23), we first show that:

$$\sum_k A_{kfn}^D D_{nk} + F_{nf} = w_{nf}V_{nf}$$

and then show that:

$$\sum_{k,n} A_{kfn}^D D_{nk} = \sum_n w_{nf}V_{nf}$$

We obtain equation (23) by combining these two equations.

To see the first equality, we can write:

$$\begin{aligned} F_{nf} + \sum_k A_{kfn}^D D_{nk} &= F_{nf} + \sum_{k,i} A_{kfi}^P D_{nik} \\ &= \sum_{k,i} A_{kfi}^P (T_{nik} + D_{nik}) \end{aligned}$$

where the first line is obtained from the definition of A^D and the second line from the definition of the factor content of trade F_{nf} . In matrix form, we know however that $\mathbf{Y} = (\mathbf{I} - \mathbf{B})^{-1}(\mathbf{T} + \mathbf{D})$ (equation 26) and that the matrix \mathbf{A}^P is defined as $\mathbf{A}^P = \Xi(\mathbf{I} - \mathbf{B})^{-1}$ where Ξ is the matrix with factor requirement coefficient β_{kfn} . Hence: $\mathbf{A}^P(\mathbf{T} + \mathbf{D}) = \Xi\mathbf{Y}$ and we thus obtain:

$$\sum_{k,i} A_{kfi}^P (T_{nik} + D_{nik}) = \sum_k \beta_{kfn} Y_{nk} = w_{fn}V_{fn}$$

We now prove the second equation mentioned earlier, i.e. that $\sum_{k,n} A_{kfn}^D D_{nk} = \sum_n w_{nf} V_{nf}$. Using the definition of A^D , we can write:

$$\sum_{k,n} A_{kfn}^D D_{nk} = \sum_{k,n,i} A_{kfi}^P D_{nik}$$

Given that the sum of the coefficients of matrix \mathbf{T} equals zero for each row, we can also write:

$$\sum_{k,n} A_{kfn}^D D_{nk} = \sum_{k,n,i} A_{kfi}^P (D_{nik} + T_{nik})$$

(where the T_{nik} denote the coefficients of matrix \mathbf{T}). As described above, $\sum_{k,i} A_{kfi}^P (D_{nik} + T_{nik})$ equals the payment to factor f in country n . Hence this proves the second equality:

$$\sum_{k,n} A_{kfn}^D D_{nk} = \sum_n w_{nf} V_{nf}$$

Simulation equations

We have in hand data or estimates for the following variables that can be taken as exogenous:⁴⁰

- L_n from GTAP
- σ_k estimated in the last stage
- μ_k estimated in the last stage
- α_k estimated in the last stage
- V_{if} estimated as the value spent on factors in the data $\sum_{n,k} \beta_{k,f} X_{nik}$
- z_{ik} estimated in the gravity equations as S_{ik} (taken at the power $1/\theta$)
- τ_{nik} estimated in the gravity equations (taken at the power $1/\theta$)

Our demand-parameter estimates are obtained from specification D1 assuming $\theta = 4$. All other variables are simulation outcomes. We need to solve for: λ_n , e_n , D_{nk} , X_{nik} , w_{nf} and S_{ik} . Each equation is associated with the corresponding variable for the mixed-complementarity

⁴⁰Concerning factor prices we assume that they equal one in the data, which implicitly rescale endowments; this does not matter anyway because the change in factor prices should correspond to the change in factor demand assuming that factor endowment is exogenous and constant.

solver in GAMS:

Bilateral pricing (associated with X_{nik}) :	$\tau_{nik} z_{ik}^{-1} \prod_f (w_{fi})^{\beta_{fk}} \geq p_{nik}$
Trade (associated with p_{nik}) :	$X_{nik} = \frac{p_{nik}^{-\theta}}{\sum_j p_{nj k}^{-\theta}} D_{nk}$
Price index (associated with D_{nk}) :	$(\sum_j p_{nj k}^{-\theta})^{-\frac{1}{\theta}} \geq P_{nk}$
Total demand by sector (coupled with P_{nk}) :	$D_{nk} = L_n (\lambda_n)^{-\sigma_k} \alpha_{6,k} (P_{nk})^{1-\sigma_k}$
Budget constraint (associated with λ_n) :	$L_n e_n = \sum_k D_{nk}$
Factor market clearing (associated with w_{fi}) :	$V_{fi} w_{fi} = \sum_{n,k} \beta_{fk} X_{nik}$
Per capita income (associated with e_n) :	$L_i e_i = \sum_f V_{fi} w_{fi}$

References

- Anderson, James E. and Eric van Wincoop**, “Gravity with Gravitas: A Solution to the Border Puzzle,” *American Economic Review*, 2003, *93*(1), 170–192.
- Athey, Susan**, “Monotone Comparative Statics Under Uncertainty,” *The Quarterly Journal of Economics*, 2002, *117* (1), 187–223.
- Attanasio, Orazio, Pinelopi Goldberg, and Nina Pavcnik**, “Trade Reforms and Wage Inequality in Colombia,” *Journal of Development Economics*, 2004, *74*, 331–366.
- Autor, David H., Lawrence F. Katz, and Alan B. Krueger**, “Computing Inequality: Have Computers Changed The Labor Market?,” *The Quarterly Journal of Economics*, 1998, *113*(4), 1169–1213.
- Bergstrand, Jeffrey**, “The Heckscher-Ohlin-Samuelson Model, the Linder Hypothesis and the Determinants of Bilateral Intra-industry Trade,” *Economic Journal*, 1990, *100*(403), 1216–29.
- Bernasconi, Claudia**, “Income Similarity and Bilateral Trade Flows,” 2011. University of Zurich working paper.
- Cassing, James and Shuichiro Nishioka**, “Nonhomothetic Tastes and Missing Trade in Factor Services,” 2009. Working paper.
- Chaney, Thomas**, “Distorted Gravity: The Intensive and Extensive Margins of International Trade,” *American Economic Review*, 2008, *98*(4), 1707–21.
- Costinot, Arnaud**, “An Elementary Theory of Comparative Advantage,” *Econometrica*, 2009, *77* (4), 1165–1192.
- , **Dave Donaldson, and Ivana Komunjer**, “What Goods Do Countries Trade? A Quantitative Exploration of Ricardo’s Ideas,” forthcoming.

- Cragg, Michael Ian and Mario Epelbaum**, “Why has wage dispersion grown in Mexico? Is it the incidence of reforms or the growing demand for skills,” *Journal of Development Economics*, 1996, *51*, 99–116.
- Deaton, Angus and John Muellbauer**, “Economics and Consumer Behavior,” *Cambridge University Press*, 1980.
- Donaldson, Dave**, “Railroads of the Raj: Estimating the Impact of Transportation Infrastructure,” 2008. Working paper.
- Eaton, Jonathan and Samuel Kortum**, “Technology, Geography, and Trade,” *Econometrica*, 2002, *79(5)*, 1453–1498.
- , – , and **Francis Kramarz**, “An Anatomy of International Trade: Evidence From French Firms,” *Econometrica*, 2011, *79(5)*, 1453–1498.
- Fally, Thibault**, “Production Staging: Measurement and Facts,” 2012. University of Colorado Mimeo.
- , “Structural Gravity and Fixed Effects,” 2012. University of Colorado Mimeo.
- , **Rodrigo Paillacar**, and **Cristina Terra**, “Economic geography and wages in Brazil: Evidence from micro-data,” *Journal of Development Economics*, 2010, *91(1)*, 155–168.
- Feenstra, Robert C. and Gordon H. Hanson**, “The Impact Of Outsourcing And High-Technology Capital On Wages: Estimates For The United States, 1979-1990,” *The Quarterly Journal of Economics*, 1999, *114(3)*, 907–940.
- Fieler, Ana Cecilia**, “Non-Homotheticity and Bilateral Trade: Evidence and a Quantitative Explanation,” *Econometrica*, 2011, *79(4)*, 1069–1101.
- Gasparini, Leonardo**, “Argentina’s Distributional Failure. The Role of Integration and Public Policies,” 2004. Working Paper.
- Goldberg, Pinelopi Koujianou and Nina Pavcnik**, “Distributional Effects of Globalization in Developing Countries,” *Journal of Economic Literature*, 2007, *45(1)*, 39–82.
- Hallak, Juan Carlos**, “A Product-Quality View of the Linder Hypothesis,” *The Review of Economics and Statistics*, 2010, *92(3)*, 453–466.
- Hanoch, Giora**, “Production and Demand Models with Direct or Indirect Implicit Additivity,” *Econometrica*, 1975, *43(3)*, 395–419.
- Head, Keith and Thierry Mayer**, “Regional wage and employment responses to market potential in the EU,” *Regional Science and Urban Economics*, 2006, *36(5)*, 573–594.
- Hung-po, Sehun Kim Chao and Alan S. Manne**, “Computation of Equilibria for Nonlinear Economies: Two Experimental Model,” *Journal of Policy Modeling*, 1982, *4(1)*, 23–43.

- Hunter, Linda**, “The Contribution of Non-homothetic Preferences to Trade,” *Journal of International Economics*, 1991, 30, 345–358.
- **and James R. Markusen**, *Per-Capita Income as a Determinant of Trade*, Cambridge: MIT Press,
- Kijama, Yoko**, “Why did wage inequality increase? Evidence from urban India 1983-99,” *Journal of Development Economics*, 2006, 81, 97–117.
- Lewis, Jeffrey B. and Drew A. Linzer**, “Estimating Regression Models in which the Dependent Variable is based on Estimates,” *Political Analysis*, 2005, 13(4), 345–364.
- Linder, Staffan B.**, *An Essay on Trade and Transformation*, Stockholm: Almqvist and Wiksell, 1961.
- Markusen, James R.**, “Explaining the Volume of Trade: An Eclectic Approach,” *American Economic Review*, 1986, 76, 1002–1011.
- , “Putting Per-Capita Income Back into Trade Theory,” 2010. NBER Working Paper 15903.
- Martinez-Zarzoso, Inmaculada and Sebastian Vollmer**, “Bilateral Trade Flows and Income-Distribution Similarity,” 2011. BE Working Papers on International Economics and Finance.
- Matsuyama, Kiminori**, “A Ricardian Model with a Continuum of Goods under Non-Homothetic Preferences: Demand Complementarities, Income Distribution, and North-South Trade,” *Journal of Political Economy*, 2000, 108, 1093–2000.
- Narayanan, Badri G. and Terrie L. Walmsley**, “Global Trade, Assistance, and Production: The GTAP 7 Data Base,” 2008. Center for Global Trade Analysis, Purdue University.
- Redding, Stefan James. and Anthony J. Venables**, “Economic geography and international inequality,” *Journal of International Economics*, 2004, 62(1), 53–82.
- Reimer, Jeffery J. and Thomas W. Hertel**, “Nonhomothetic Preferences and International Trade,” *Review of International Economics*, 2010, 18, 408–425.
- Simonovska, Ina**, “Income Differences and Prices of Tradeables,” 2010. NBER Working Paper No. 16233.
- **and Michael Waugh**, “The Elasticity of Trade: Estimates and Evidence,” 2010. UC Davis Working paper No. 11-2.
- Trefler, Daniel**, “The Case of Missing Trade and Other Mysteries,” *American Economic Review*, 1995, 85, 1029–1046.
- **and Susan Zhu**, “The structure of factor content predictions,” *Journal of International Economics*, 2010, 82, 195–207.
- Zou, Wei, Lan Liu, and Ziyin Zhuang**, “Skill Premium, Biased Technological Change and Income Differences,” *China & World Economy*, 2009, 17 (6), 64–87.