International trade theory is a general-equilibrium discipline, yet most of the standard portfolio of research focuses on the production side of general equilibrium. In addition, we do not have 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 relationship between skilled-labor intensity in production and income elasticity of demand for several types of preferences, with and without accounting for trade costs and differences in prices. Counter-factual simulations yield a number of results. We can explain at least a third of “missing trade”, and show an important role for per-capita income in understanding trade/GDP ratios, the choice of trading partners, and the composition of trade. Furthermore, an equal rise in productivity in all sectors in all countries leads to a rising skill premium in all countries, with particularly large increases in developing countries.

Keywords: Non-homothetic preferences, gravity, income, missing trade, skill premium.
JEL Classification: F10, O10, F16, J31.
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 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 explore 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. If such a relationship does exist, this can contribute to understanding a number of empirical puzzles in trade as suggested by Markusen (2010). These puzzles 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 equations for the share of total expenditures 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 the presentation of our benchmark model. We carefully account for supply-side effects, which could potentially bias estimates of income elasticities. If rich countries tend to have a comparative advantage in particular industries, consumption in these industries might be larger (goods available at lower prices) and estimates of income elasticities in these industries might be upward-biased if we do not control for such patterns of comparative advantage. 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 data is from the GTAP7 data set. It comprises 94 countries with a wide range of income levels, 56 broad sectors including manufacturing and services, and 5 factors of production: skilled labor, unskilled labor, capital, land, and other natural resources. This is an excellent harmonized data set for our purposes, since it includes production, expenditure and trade data, and input-output tables. However, the broad categories of goods and services make it not very suitable for discussing issues related to product quality and within-industry heterogeneity.

Our results show that the income elasticity of demand varies largely across industries. Moreover, income elasticities of demand are significantly related in both economic and statistical terms to the skill intensity of a sector, with a correlation well over 60%. Accounting for trade costs and supply-side characteristics reduces this estimated 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 relationship to natural-resource intensity is negative.

The results of the estimation are then used to assess the role of non-homotheticity in explaining empirical trade puzzles mentioned above and examine counter-factuals on simulations of the estimated general-equilibrium system of equations and inequalities. In addition to the income-elasticity / factor-intensity relationship, results include the following.

First, we can explain at least one third of the “missing trade” puzzle in the Heckscher-Ohlin-Vanek framework. A systematic relationship between income elasticity of demand and skill intensity in production generates a strong correlation between consumption patterns and specialization in production. The correlation between supply and demand is 86% in the data. While trade costs can explain about a fourth of this correlation, non-homotheticity is even more important quantitatively. In terms of factor content, similar results show that non-homothetic preferences can explain a large fraction of “missing trade” in factor services. By allowing for non-homotheticity in preferences, the variance of predicted factor content of trade is reduced by more than a third compared to the standard Heckscher-Ohlin-Vanek prediction.

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-capita income contributes to understanding the composition of consumption across industries.

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¹As a robustness check, we use actual prices 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).
which itself has large effects on trade. On aggregate, this implies an important role for per-capita income in understanding observed trade-to-GDP ratios.

Finally, we conduct general-equilibrium simulations in which we raise the productivity of all countries by 1%, 10% or actual growth rates between 1995 and 2005. As speculated on in Markusen (2011), this shifts demand toward higher income-elasticity goods, which are on average skilled-labor intensive. In each scenario the counter-factual generates a rising skill premium (wage inequality) in all countries, but particularly in developing countries.

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

Closest to our paper is Fieler (2011). She estimates demand- and supply-side characteristics

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3Our GAMS program simulates bilateral trade, consumption and factor reward in general equilibrium for all countries and sectors available in our estimation sample. We also provide an analytical approximation of the skill-premium-to-productivity elasticity expressed as a simple function of income elasticities and skill intensities.

4Among 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.
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 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-theta goods). On the contrary, our estimation strategy allows and controls for any pattern of comparative advantage. We emphasize the role for 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 also certainly some 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 would 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 taking into account and use data on different deciles and quintiles of within-country income distributions.

2 Theoretical framework

2.1 Model set-up

Demand

There are several industries, indexed by $k$. Each industry 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 \( \sigma_k \) 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 \( \frac{\sigma_i}{\sigma_j} \) and is constant.

The CES price index of goods from industry \( k \) in country \( n \) is:

\[ P_{nk} = \left( \int_{j_k=0}^{1} p_{nk}(j_k)^{1-\eta_k} dj_k \right)^{\frac{1}{1-\eta_k}} \]

Given this price index, individual expenditures \( (P_{nk}Q_{nk}) \) in country \( n \) for goods in industry \( k \) equal:

\[ x_{nk} = \lambda_n^{-\sigma_k} \alpha_{2,k}(P_{nk})^{1-\sigma_k} \tag{1} \]

where \( \lambda_n \) 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 \( \lambda_n \) is determined by the budget constraint: total expenses must equal total income. In general there is no analytical expression for \( \lambda_n \).

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

\[ \varepsilon_{nk} = \sigma_k \cdot \frac{\sum_{k'} x_{nk'}^{k'}}{\sum_{k'} \sigma_{k'} x_{nk'}^{k'}} \tag{2} \]

In particular, 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-\( \sigma_k \) industries, Hence, the consumption-weighted average of \( \sigma_k \) 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 $\beta_{fk}$ 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:

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

where $z_{ik}$ is a productivity shifter reflecting average TFP of country $i$ in sector $k$. As in Eaton and Kortum (2002), $\theta_k$ 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 $\theta_k$ 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

A list of notations and variables is available in the appendix.

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:

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

where $\lambda_n$ is the lagrangian associated with the budget constraint. To determine $\lambda_n$, we thus need to take the budget constraint into account:

$$L_ne_n = \sum_k D_{nk}$$

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) notations, with the addition of industry subscripts. By denoting $X_{nik}$ the value of trade from country $i$ to country $n$, we obtain:

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

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 $\zeta_{ik}$, factor prices and factor intensities:

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

The parameter $\theta_k$ 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 $\theta_k$. In turn, we define $\Phi_{nk}$ as the sum of exporter fixed effects deflated by trade costs. $\Phi_{nk}$ plays the same role as the “inward multilateral trade resistance index” as in Anderson and van Wincoop (2003):

$$\Phi_{nk} = \sum_i S_{ik}(d_{nik})^{-\theta_k}$$
This $\Phi_{nk}$ is actually closely related to the price index, as in Eaton and Kortum (2002):

$$P_{nk} = \alpha_{3,k}(\Phi_{nk})^{-\frac{1}{\sigma_k}}$$  \hspace{1cm} (8)

with $\alpha_{3,k} = \left[ \Gamma \left( \frac{\theta_k + 1 - \eta_k}{\theta_k} \right) \right]^{1/\eta_k - 1}$ where $\Gamma$ 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 $\beta_{fk}$. With factor supply $V_{fi}$ and factor price $w_{fi}$ for factor $f$ in country $i$, factor market clearing implies:

$$V_{fi}w_{fi} = \sum_{n,k} \beta_{fk} X_{nik}$$  \hspace{1cm} (9)

In turn, per-capita income is determined by:

$$L_i e_i = \sum_{f} V_{fi} w_{fi}$$  \hspace{1cm} (10)

In the baseline case, we assume homogenous 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 $\beta_{fk}$) and income elasticity (proportional to $\sigma_k$).

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 $n$): $X_{nik} / D_{nk} = S_{ik} / \sum_{j} S_{jk}$. Summing over all industries, total import penetration by country $i$ in country $n$ is:

$$\frac{X_{ni}}{X_n} = \sum_{k} \left( \frac{S_{ik}}{\sum_{j} S_{jk}} \right) \left( \frac{\alpha_{4,k} \lambda_n^{-\sigma_k}}{\sum_{k'} \alpha_{4,k'} \lambda_n^{-\sigma_{k'}}} \right)$$  \hspace{1cm} (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 $\sigma_k$ varies across industries, exporters with a comparative advantage in high-$\sigma$ industries have a relatively larger penetration in rich countries (low $\lambda_n$), while exporters with a comparative advantage in low-$\sigma$ industries have a relatively larger penetration in poor countries (high $\lambda_n$). We will show empirically that rich countries have a comparative advantage in high-$\sigma$ industries which can quantitatively explain large differences in trade volumes across country pairs depending on each partner’s per-capita income.\(^5\)

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:

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

(12)

where $\Phi_{nk} = \sum_j S_{jk} \theta_{njk}$ by definition (equation 7) and $\alpha_{5,k} = \alpha_{2,k} \alpha_{3,k}^{-1}$ is an industry constant. In the empirical section, we thus need to carefully examine the distinct contribution of trade 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.\(^6\) 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

\(^5\)Formally, 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 $\sigma_k$ increases with $k$, then $X_{ni}$ is log-supermodular, which means that $\frac{X_{ni}}{X_n} > \frac{X_{ni'}}{X_n'}$, 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.

\(^6\)Formally, this can arise when $\lambda_n^{-\sigma_k} \Phi_{nk}^{\sigma_k^{-1}}$ is not log-supermodular, even if $\lambda_n^{-\sigma_k}$ is log-supermodular.
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. Factor content of trade $F_{fn}$ as the value of factor $f$ required to produce exports minus imports. It equals $F_{fn} = \sum_k \beta_{fk} \left( \sum_{i\neq n} X_{nik} - \sum_{i\neq n} X_{ink} \right)$ when production coefficients $\beta_{kf}$ are common across countries.\(^7\)

After simple reformulations, we can decompose $F_{fn}$ in two terms:

\[
F_{fn} = s_n \sum_k \bar{Y}_k \beta_{fk} \left[ \frac{Y_{nk}}{s_n \bar{Y}_k} - 1 \right] - s_n \sum_k \bar{Y}_k \beta_{fk} \left[ \frac{D_{nk}}{s_n \bar{Y}_k} - 1 \right] = F_{fn}^{HOV} - F_{fn}^{CB}
\]

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 (number of workers or machines).\(^8\)

\(^7\)The empirical section and the appendix derive additional results to account for traded intermediate inputs and production coefficients that differ across countries.

\(^8\)Standard 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 or 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.
In the brackets, the ratio $\frac{D_nk_s}{s_nY_k}$ equals the share of consumption of $k$ in country $n$ relative to the share of consumption of $k$ in the world. The ratio $\frac{Y_{nk}}{s_nY_k}$ 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: $\frac{D_nk_s}{s_nY_k} - 1 = 0$. Hence, with homothetic preferences and free trade, the expression above can be simplified into:

$$F_{fn} = F_{fn}^{HOV} = w_{fn}V_{fn} - s_n \sum_i w_{fi}V_{fi}$$

(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 $\frac{D_nk_s}{s_nY_k} - 1$ 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 $\frac{D_nk_s}{s_nY_k}$ is positively correlated with production $\frac{Y_{nk}}{s_nY_k}$, 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 $\frac{D_nk_s}{s_nY_k}$ and $\frac{Y_{nk}}{s_nY_k}$ 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 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 when we account for more complex vertical linkages.

### 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, as we show, are more intensive in skilled labor. 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 $d \log z_n$:

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

where $\varepsilon_{nk}$ 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 to the share of unskilled workers in sector $k$), and $\xi_n$ is defined in the appendix.

We can see that this term is positive if income elasticity $\varepsilon_{nk}$ 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 $\xi_n$ 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:

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

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 to increases in the skill premium from general equilibrium simulations.

In this expression, we see that the effect of TFP growth on the skill premium is larger 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, which can be seen by taking the second derivative of expression (17) w.r.t to productivity:

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

Assuming that the evolution of income is not driven by an accumulation of skills, which can of course mitigate the increase in the skill premium.
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 $s_{nk}^H - s_{nk}^L$ (“between” effect). The between effect is negative if there is more
scope for reallocation of skilled workers than unskilled workers across sectors.\(^{10}\)

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:

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

(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 $\lambda_n$. The larger is per-capita
income, the smaller is $\lambda_n$.

If there is no trade cost ($d_{nk} = 1$), 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 $\sigma_k$.

When trade is not free ($d_{nk} > 1$), 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. As the elasticity of substitution be-
tween 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.

\(^{10}\)Formally, 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:

$$\sum_k s_{nk}^H (\varepsilon_{nk} - \sum_{k'} s_{nk'}^H \varepsilon_{nk'})^2 > \sum_k s_{nk}^L (\varepsilon_{nk} - \sum_{k'} s_{nk'}^L \varepsilon_{nk'})^2$$
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 $\Phi_{nk}$), 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 $\log \Phi_{nk}$ (Section 5).

**Step 1: Gravity equation estimation and identification of $\Phi_{nk}$**

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

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

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:

$$\log d_{nik} = \delta_{Dist,k} \log Dist_{ni} - \delta_{Contig,k} Contiguity_{ni} - \delta_{Lang,k} CommonLang_{ni}$$

$$- \delta_{Colony,k} ColonialLink_{ni} - \delta_{HomeBias,k} I_{n=i}$$

Parameters $\delta_{var,k}$ capture the elasticity of trade costs w.r.t. each trade cost variable $var$.\(^{11}\) It is indexed by sector $k$: we allow the effect of distance, contiguity, common language, etc. to differ across industries.

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

$$\log X_{nik} = FX_{ik} + FM_{nk} - \beta_{Dist,k} \log Dist_{ni} + \beta_{Contig,k} Contiguity_{ni}$$

$$+ \beta_{Lang,k} CommonLang_{ni} + \beta_{Colony,k} ColonialLink_{ni} + \beta_{HomeBias,k} I_{n=i}$$

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.

\(^{11}\)Note 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.
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 $\Phi_{nk}$ would be to use importer fixed effects. However, since we use $\Phi_{nk}$ as a means to capture supply-side characteristics, it is arguably better to use supply-side variables to estimate $\Phi_{nk}$.

We follow a strategy developed by Redding and Venables (2004). Following Equation (7) defining $\Phi_{nk}$, 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 $\Phi_{nk}$:

$$\hat{\Phi}_{nk} = \sum_i \exp \left( FX_{ik} - \hat{\beta}_{Dist,k} \log Dist_{ni} + \hat{\beta}_{Contig,k} \cdot Contiguity_{ni} 
+ \hat{\beta}_{Lang,k} \cdot CommonLang_{ni} + \hat{\beta}_{Colony,k} \cdot ColonialLink_{ni} + \hat{\beta}_{HomeBias,k} \cdot I_{I=n} \right)$$

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.

**Step 2: Demand system estimation and identification of $\sigma_k$**

The first step estimation gives us an estimate of $\Phi_{nk}$, but the price index is proportional to $(\Phi_{nk})^{\frac{1}{\theta_k}}$, not $\Phi_{nk}$, and $\theta_k$ is more difficult to estimate. $\theta_k$ 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 $\theta_k$ and $\delta_{Dist,k}$.

We make four different assumptions relative to $\theta_k$: 1) we calibrate $\theta_k$ using aggregate esti-

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

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

14 Some authors have used the coefficient on import tariffs in gravity equations to identify $\theta_k$. In our dataset however, these coefficients are often statistically insignificant and we do not feel comfortable with using them.
mates from the literature; 2) we do not impose any restriction on \( \theta_k \); 3) we assume that \( \theta_k = \theta \) is constant across sectors and estimate \( \theta \); 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 \( \lambda_n \). 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 \( \theta_k \) 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 parameter \( \hat{\theta} \), the final demand system to be estimated is:

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

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

**D2)** In an other 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:

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

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

**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 \( \theta \). Given \( \hat{\Phi}_{nk} \), the final demand system to be estimated is:

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

where \( \alpha_{5,k} \) is an sector fixed effect.
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:

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

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

In all cases, given the inclusion of industry fixed effects, \( \lambda_n \) can be identified only up to a constant. To see this, we can multiply \( \lambda_k \) by a common multiplier \( \lambda' \) and multiply the industry fixed effect \( \alpha_k \) by \( (\lambda')^{\alpha_k} \). Using \( \lambda_k \lambda' \) instead of \( \lambda_k \) and \( \alpha_k (\lambda')^{\alpha_k} \) instead of \( \alpha_k \) 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 \( \sigma_k \) in specifications D2 and D4. In these cases, \( \sigma_k \) can be estimated only up to a common multiplier. By multiplying \( \sigma_k \) by a common multiplier \( \sigma' \) and replacing \( \lambda_n \) by \( \lambda_n \sigma' \), 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 \( \sigma_k \) 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 \( \sigma ' s \) 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.\(^{15}\) Bootstrapped standard errors for the estimates of \( \sigma_k \), 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

\(^{15}\)We 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.
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 (20) 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, ferous 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. 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). 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.

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.

We now focus on the final demand estimation (step 2). Parameters to be estimated are $\lambda_n$, $\sigma_k$ and the industry fixed effects $\alpha_k$. Summary statistics are reported in Table 1.

With an R2 equal to 0.57, the specification with no trade costs (D4) already fits the data

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

17 See: https://www.gtap.agecon.purdue.edu/resources/download/4183.pdf

18 See: http://www.cepii.fr/anglaisgraph/bdd/distances.htm
Table 1: NLLS estimation of demand: regression statistics

<table>
<thead>
<tr>
<th>Specification:</th>
<th>(D1)</th>
<th>(D4)</th>
<th>(D2)</th>
<th>(D3)</th>
<th>(D1')</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta = 4$ No trade</td>
<td>Unconstraint</td>
<td>$\theta_k$</td>
<td>Common $\theta$</td>
<td>$\theta = 8$</td>
<td></td>
</tr>
<tr>
<td>Correlation $\sigma_k$ with D1 specification ($\theta = 4$)</td>
<td>1</td>
<td>0.881</td>
<td>0.838</td>
<td>0.978</td>
<td>0.924</td>
</tr>
<tr>
<td>Weighted av. of $\sigma_k$</td>
<td>2.76</td>
<td>/</td>
<td>/</td>
<td>1.49</td>
<td>4.47</td>
</tr>
<tr>
<td>F-stat: $\sigma_k = \sigma$</td>
<td>4.62</td>
<td>19.60</td>
<td>8.63</td>
<td>5.05</td>
<td>4.07</td>
</tr>
<tr>
<td>Correlation log $\lambda_n$ with log per capita income</td>
<td>-0.985</td>
<td>-0.999</td>
<td>-0.986</td>
<td>-0.986</td>
<td>-0.986</td>
</tr>
<tr>
<td>$\theta$ (calibrated or estimated)</td>
<td>4</td>
<td>/</td>
<td>/</td>
<td>1.17</td>
<td>8</td>
</tr>
<tr>
<td>Average coeff for $\Phi_{nk}$</td>
<td>0.507</td>
<td>/</td>
<td>0.532</td>
<td>0.518</td>
<td>0.486</td>
</tr>
<tr>
<td>R2</td>
<td>0.731</td>
<td>0.568</td>
<td>0.607</td>
<td>0.596</td>
<td>0.609</td>
</tr>
<tr>
<td>weighted R2</td>
<td>0.914</td>
<td>0.903</td>
<td>0.918</td>
<td>0.915</td>
<td>0.914</td>
</tr>
<tr>
<td>Observations</td>
<td>4700</td>
<td>4700</td>
<td>4700</td>
<td>4700</td>
<td>4700</td>
</tr>
</tbody>
</table>

Notes: NLLS regressions: step 2 of the estimation procedure described in the text. Weighted by industry size (world’s expenditure by industry). Bootstrapped standard errors and F-test (100 draws).

well. The weighted R2\(^{19}\) equals 0.90. The inclusion of trade costs in specifications (D1)-(D3) significantly improves the fit, as the coefficients associated with $\Phi_{nk}$ are jointly significant. In the unconstrained-$\theta_k$ specification (D2), we can simply test whether coefficients associated with $\Phi_{nk}$ are jointly null which yields a F-stat of 16.07 and clearly rejects this hypothesis.

Imposing homotheticity (i.e. common $\sigma_k = \sigma$ across industries) yields a R2 = 0.52 (and a weighted-R2 = 0.882).\(^{20}\) This is significantly lower. The F-stat associated with imposing common $\sigma_k$ across industries shows that homotheticity is clearly rejected in all specifications D1 to D4 (third row of Table 1).

XXX COMMENTS ON AKAIKE OR SCHWARZ CRITERION

XXX ADD RESULTS IN TABLE

The estimated $\sigma_k$ can be used to compute income elasticity estimates according to equation 2, using fitted median-income-country expenditure shares as weights.\(^{21}\) In our preferred 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

\(^{19}\)with variance and average weighted by world production by industry

\(^{20}\)Allowing for trade costs with homothetic preferences increases the R2 to 0.58, which is still lower than the R2 for non-homothetic preferences without trade costs (D4).

\(^{21}\)With CRIE preferences, the ratio of income elasticities between two sectors does not depend on the choice of the reference country.
### Table 2: Estimated income elasticity by sectors

<table>
<thead>
<tr>
<th>GTAP code</th>
<th>Sector name</th>
<th>Income elast.</th>
<th>Std error</th>
<th>Skill intensity</th>
</tr>
</thead>
<tbody>
<tr>
<td>gro</td>
<td>Cereal grains nec</td>
<td>0.362*</td>
<td>0.040</td>
<td>0.135</td>
</tr>
<tr>
<td>pdr</td>
<td>Paddy rice</td>
<td>0.490*</td>
<td>0.150</td>
<td>0.061</td>
</tr>
<tr>
<td>oap</td>
<td>Animal products nec</td>
<td>0.498*</td>
<td>0.067</td>
<td>0.132</td>
</tr>
<tr>
<td>osd</td>
<td>Oil seeds</td>
<td>0.588*</td>
<td>0.158</td>
<td>0.119</td>
</tr>
<tr>
<td>frs</td>
<td>Forestry</td>
<td>0.596*</td>
<td>0.115</td>
<td>0.118</td>
</tr>
<tr>
<td>v.f</td>
<td>Vegetables, fruit, nuts</td>
<td>0.601*</td>
<td>0.102</td>
<td>0.095</td>
</tr>
<tr>
<td>ctl</td>
<td>Bovine cattle, sheep and goats, horses</td>
<td>0.621*</td>
<td>0.078</td>
<td>0.164</td>
</tr>
<tr>
<td>pcr</td>
<td>Processed rice</td>
<td>0.654*</td>
<td>0.126</td>
<td>0.130</td>
</tr>
<tr>
<td>vol</td>
<td>Vegetable oils and fats</td>
<td>0.696*</td>
<td>0.066</td>
<td>0.217</td>
</tr>
<tr>
<td>fsh</td>
<td>Fishing</td>
<td>0.712*</td>
<td>0.092</td>
<td>0.124</td>
</tr>
<tr>
<td>p.c</td>
<td>Petroleum, coal products</td>
<td>0.740*</td>
<td>0.047</td>
<td>0.313</td>
</tr>
<tr>
<td>c.b</td>
<td>Sugar cane, sugar beet</td>
<td>0.777</td>
<td>0.206</td>
<td>0.091</td>
</tr>
<tr>
<td>sgr</td>
<td>Sugar</td>
<td>0.800*</td>
<td>0.142</td>
<td>0.221</td>
</tr>
<tr>
<td>b.t</td>
<td>Beverages and tobacco products</td>
<td>0.802*</td>
<td>0.031</td>
<td>0.297</td>
</tr>
<tr>
<td>tex</td>
<td>Textiles</td>
<td>0.847*</td>
<td>0.055</td>
<td>0.231</td>
</tr>
<tr>
<td>wht</td>
<td>Wheat</td>
<td>0.854</td>
<td>0.139</td>
<td>0.117</td>
</tr>
<tr>
<td>e1y</td>
<td>Electricity</td>
<td>0.923*</td>
<td>0.036</td>
<td>0.372</td>
</tr>
<tr>
<td>ofd</td>
<td>Food products nec</td>
<td>0.944*</td>
<td>0.036</td>
<td>0.268</td>
</tr>
<tr>
<td>nmm</td>
<td>Mineral products nec</td>
<td>0.944</td>
<td>0.072</td>
<td>0.281</td>
</tr>
<tr>
<td>cns</td>
<td>Construction</td>
<td>0.963*</td>
<td>0.023</td>
<td>0.294</td>
</tr>
<tr>
<td>wtp</td>
<td>Water transport</td>
<td>0.963</td>
<td>0.087</td>
<td>0.299</td>
</tr>
<tr>
<td>cmt</td>
<td>Bovine meat products</td>
<td>0.972</td>
<td>0.068</td>
<td>0.238</td>
</tr>
<tr>
<td>ocr</td>
<td>Crops nec</td>
<td>0.974</td>
<td>0.108</td>
<td>0.115</td>
</tr>
<tr>
<td>mil</td>
<td>Dairy products</td>
<td>0.990</td>
<td>0.046</td>
<td>0.248</td>
</tr>
<tr>
<td>lum</td>
<td>Wood products</td>
<td>1.001</td>
<td>0.085</td>
<td>0.248</td>
</tr>
<tr>
<td>atp</td>
<td>Air transport</td>
<td>1.028</td>
<td>0.047</td>
<td>0.313</td>
</tr>
<tr>
<td>crp</td>
<td>Chemical, rubber, plastic products</td>
<td>1.039</td>
<td>0.051</td>
<td>0.356</td>
</tr>
<tr>
<td>otp</td>
<td>Transport nec</td>
<td>1.046</td>
<td>0.052</td>
<td>0.296</td>
</tr>
<tr>
<td>omt</td>
<td>Meat products nec</td>
<td>1.051</td>
<td>0.075</td>
<td>0.233</td>
</tr>
<tr>
<td>fmp</td>
<td>Metal products</td>
<td>1.065</td>
<td>0.053</td>
<td>0.297</td>
</tr>
<tr>
<td>otn</td>
<td>Transport equipment nec</td>
<td>1.107</td>
<td>0.057</td>
<td>0.343</td>
</tr>
<tr>
<td>ome</td>
<td>Machinery and equipment nec</td>
<td>1.111</td>
<td>0.030</td>
<td>0.372</td>
</tr>
<tr>
<td>osg</td>
<td>Public Administration and Services</td>
<td>1.112*</td>
<td>0.019</td>
<td>0.503</td>
</tr>
<tr>
<td>ppp</td>
<td>Paper products, publishing</td>
<td>1.115</td>
<td>0.039</td>
<td>0.340</td>
</tr>
<tr>
<td>trd</td>
<td>Trade</td>
<td>1.119</td>
<td>0.036</td>
<td>0.308</td>
</tr>
<tr>
<td>wrtr</td>
<td>Water</td>
<td>1.123</td>
<td>0.048</td>
<td>0.378</td>
</tr>
<tr>
<td>lea</td>
<td>Leather products</td>
<td>1.126</td>
<td>0.041</td>
<td>0.212</td>
</tr>
<tr>
<td>mnh</td>
<td>Motor vehicles and parts</td>
<td>1.135</td>
<td>0.030</td>
<td>0.341</td>
</tr>
<tr>
<td>wap</td>
<td>Wearing apparel</td>
<td>1.138</td>
<td>0.050</td>
<td>0.247</td>
</tr>
<tr>
<td>cmm</td>
<td>Communication</td>
<td>1.161*</td>
<td>0.049</td>
<td>0.485</td>
</tr>
<tr>
<td>ros</td>
<td>Recreational and other services</td>
<td>1.164*</td>
<td>0.042</td>
<td>0.475</td>
</tr>
<tr>
<td>omf</td>
<td>Manufactures nec</td>
<td>1.210*</td>
<td>0.037</td>
<td>0.279</td>
</tr>
<tr>
<td>ele</td>
<td>Electronic equipment</td>
<td>1.280*</td>
<td>0.050</td>
<td>0.358</td>
</tr>
<tr>
<td>ofi</td>
<td>Financial services nec</td>
<td>1.292*</td>
<td>0.054</td>
<td>0.546</td>
</tr>
<tr>
<td>obs</td>
<td>Business services nec</td>
<td>1.327*</td>
<td>0.039</td>
<td>0.504</td>
</tr>
<tr>
<td>pfb</td>
<td>Plant-based fibers</td>
<td>1.363</td>
<td>0.171</td>
<td>0.167</td>
</tr>
<tr>
<td>rmk</td>
<td>Raw milk</td>
<td>1.367*</td>
<td>0.077</td>
<td>0.152</td>
</tr>
<tr>
<td>isr</td>
<td>Insurance</td>
<td>1.378*</td>
<td>0.046</td>
<td>0.533</td>
</tr>
<tr>
<td>wol</td>
<td>Wool, silk-worm cocoons</td>
<td>1.543*</td>
<td>0.167</td>
<td>0.089</td>
</tr>
<tr>
<td>gdt</td>
<td>Gas manufacture, distribution</td>
<td>2.209*</td>
<td>0.160</td>
<td>0.362</td>
</tr>
</tbody>
</table>

*Notes:* Income elasticities evaluated using median country expenditure shares; NLLS estimations (imposing $\theta = 4$); bootstrapped standard errors; * denotes 5% significance (difference from unity); total skill intensities.
Table 2.

The distribution of estimated income elasticities is quite similar across specifications. In particular, the choice of $\theta$ does not affect estimates of $\sigma_k$ and income elasticities. As shown in Table 1 (first row), the correlation between estimated $\sigma_k$ in other specifications and estimated $\sigma_k$ in specification D1 ($\theta = 4$) is always above 80%. This is also the correlation between income elasticities among specifications since income elasticities are proportional to $\sigma_k$. Sectors where income elasticities vary the most across specifications are the smallest ones in terms of final demand (see Figure 1).

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.22

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.23 As shown in section 5, our results are robust to different measures of factor intensities. Our results are also robust to different demand specifications. Table 3 reports estimations with CRIE preferences, while alternative demand systems are examined in section 5.

Table 3: Correlation between income elasticity and skill intensity

<table>
<thead>
<tr>
<th>Specification</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skill intensity</td>
<td>0.526</td>
<td>0.508</td>
<td>0.692</td>
<td>0.673</td>
<td>0.555</td>
<td>0.617</td>
</tr>
<tr>
<td></td>
<td>[0.123]**</td>
<td>[0.115]**</td>
<td>[0.103]**</td>
<td>[0.100]**</td>
<td>[0.113]**</td>
<td>[0.098]**</td>
</tr>
<tr>
<td>Capital intensity</td>
<td>0.002</td>
<td>0.024</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.153]</td>
<td>[0.126]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Natural resources int.</td>
<td>-0.152</td>
<td>-0.139</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.102]</td>
<td>[0.076]*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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%.

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 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.

22Table 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.

23Total factor usage is computed using a Leontiev inversion of country-specific input-output tables as provided by GTAP
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 correlations 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 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 (eliminating countries with extreme quartiles in skill endowment), the correlation between estimated income elasticities and skill intensity 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 systematically varies 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:

$$\frac{\sum_k \beta_{f_k} D_{nk}}{\sum_k D_{nk}}$$

We can define the latter by using either actual consumption or fitted consumption with different assumptions. With homothetic preferences and no trade costs, expression (20) should be the same for all countries. Trade costs may already explain part of the variations in the factor content of consumption: rich countries tend to spend more in skilled-labor intensive industries, even if preferences are homothetic, because goods are relatively cheaper in these industries. We can see however in Figure 3 that an even better fit is obtained with both trade costs and non-homothetic preferences.

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. Since rich countries tend to specialize in skill-intensive sectors, this generates correlation between relative specializations in consumption and production. In the first row of Table 4, we examine the correlation between $Y_{nk}/s_n Y_k$ and $D_{nk}/s_n Y_k$. 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 $\hat{X}_{nk}$ from our second-stage estimations and in column (5) we use actual consumption $D_{nk}$. In column (1), we impose homothetic preferences (i.e. common $\sigma$ across industries) and assume that there is no trade cost, as in standard Heckscher-Ohlin models. In this case, the correlation is obviously zero as consumption patterns are the same across all countries ($D_{nk}/s_n Y_k = 1$). In column (2), we allow for trade costs. Trade costs 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).

Allowing for non-homotheticity significantly increases this correlation between supply and demand, 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 $\theta_k = 4$). 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 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 $\beta_{kf}$ across countries, we impute $F_{nf}^{HOV}$ using production data and $F_{nf}^{CB}$ using either fitted demand (columns 1 to 4) or actual consumption (column 5). The second row of Table 4 shows that trade costs can already explain a large correlation between consumption and supply factor content even if preferences are assumed to be homothetic (column 2). This correlation is 78% across countries and factors (against 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

$^{24}$Similar and even larger correlations are found for alternative specifications for the estimation of preferences.

$^{25}$Note also that all variables are in values (e.g. wages instead of number of workers) which mitigates cross-country differences related to differences in factor prices.
### Table 4: Patterns of supply, demand and factor content trade

<table>
<thead>
<tr>
<th>Preferences:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>Dimension</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correcting for trade costs:</td>
<td>Homothetic</td>
<td>Non-homothetic</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correlation between supply and demand $\frac{Y_{nk}}{s_nY_k}$</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>0.86</td>
<td>n x k</td>
</tr>
<tr>
<td>Correlation between $F_{n}^{HOV}$ and Consumption bias $F_{n}^{CB}$</td>
<td>0</td>
<td>0.78</td>
<td>0.59</td>
<td>0.92</td>
<td>0.99</td>
<td>n x f</td>
</tr>
<tr>
<td>Normalized by country size</td>
<td>0</td>
<td>0.79</td>
<td>0.86</td>
<td>0.90</td>
<td>0.93</td>
<td>n x f</td>
</tr>
</tbody>
</table>

Corrected HOV slope test:

- assuming common $\beta_{kf}$
  - with fitted $\hat{A}_{kfn}^D$ | 0.46 | 0.38 | 0.60 | 0.64 | 1 | n x f |
  - with observed $A_{kfn}^D$ | 0.37 | 0.35 | 0.47 | 0.58 | 1 | n x f |

Variance test: $\frac{\text{Var}(F_{n}^{\text{meas}})}{\text{Var}(F_{n}^{\text{pred}})}$

- assuming common $\beta_{kf}$
  - with fitted $\hat{A}_{kfn}^D$ | 0.37 | 0.40 | 0.53 | 0.68 | 1 | n x f |
  - with observed $A_{kfn}^D$ | 0.10 | 0.40 | 0.13 | 0.70 | 1 | n x f |

The consumption bias. Allowing for both non-homotheticity and the presence of trade costs further increases the correlation to 92%, which is closer to the very large correlation observed in the data (99%!). One may be worried however that these correlations between $F_{n}^{HOV}$ and $F_{n}^{CB}$ 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). Though, after rescaling, 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” as previous results have shown.
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.

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 brings 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.

**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:

$$A_{kfn}^D = \frac{\sum_i A_{kfi}^P X_{nik}}{\sum_i X_{nik}}$$

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

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

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 follow, we construct

---

26For the slope and variance tests, all observations are scaled by $(s_n \sum_i w_{if} V_{if})^{1/2}$ to adjust for heteroskedasticity.
the predicted factor content of trade using fitted demand \( \hat{D}_{nk} \) and fitted factor content of consumption \( \hat{A}_{kfn} \) to illustrate the role of non-homotheticity and trade costs.\(^27\) In particular, when we assume homothetic preferences and no trade cost, 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 \( \hat{D}_{nk} \) and fitted trade flows to construct \( \hat{A}_{kfn}^D \) as described in equation (21). Note that, when trade costs are assumed to be zero (columns 1 and 3), the implied matrix \( \hat{A}_{kfn}^D \) does not vary across countries. In all cases, we find that non-homothetic preferences perform better than homothetic preferences. 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 \( \hat{A}_{kfn}^D \) (which now varies across countries in columns 1 and 3). Interestingly, allowing for non-homotheticity 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 22. 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 there is so small volumes of North-South trade in comparison to North-North trade?\(^28\) 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.

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\(^{27}\)Note that our final demand estimates are robust to incorporating intermediate goods in our framework as described in Section 5.5.

\(^{28}\)see Fieler (2011), Waugh (2010) among others.
of comparative advantage. In particular, if a country has a comparative advantage in high-income-elastic industries (high-\(\sigma_k\)), 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 level of income. To be more precise, we compute import penetration from developing countries in market \(n\):

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

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 \(\sigma_k\)) 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 \(Y_k^{South}/Y_k^{South} + Y_k^{North}\) 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.

In Figure 4, we plot \(X_n^{South}/X_n\) as a function of the importer’s average income per capita (in log). As shown in this 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 capital 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 industries, we can expect poorer countries to have a smaller share of exports towards developed countries.

These results solely reflects changes in consumption patterns and do not account for trade costs. As developed countries are closer to other developed countries and vice versa, trade costs can also contribute to such a correlation between import penetration by developing countries and importers’ income. An interesting question is whether these trade costs are sufficient to
Using estimates from both steps of our estimations, we can construct predicted trade flows \( \hat{X}_{nik} \) (from country \( i \) to country \( n \) in sector \( k \)) using the gravity equation 5:

\[
\hat{X}_{nik} = \frac{\hat{S}_{ik}(d_{nik})^{-\theta_k}}{\hat{\Phi}_{nk}} \hat{X}_{nk}
\]

where \( \hat{S}_{ik}, (d_{nik})^{-\theta_k} \) and \( \hat{\Phi}_{nk} \) are constructed using estimates from the gravity equation (see step 1 of the estimation procedure) and where \( \hat{X}_{nk} \) 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 (import + exports) with rich partners; ii) the ratio of trade over 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. Not surprisingly, however, non-homothetic preferences magnify this correlation. In particular, we can observe substantial differences in predicted shares for the poorest countries.
Since rich countries are also the largest markets in terms of GDP\textsuperscript{29}, 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

\textsuperscript{29}Developed countries account for 80\% of total GDP in our sample of 94 countries.
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 take the same trade cost and supply-side estimates in the homothetic and non-homothetic cases.

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 homogenous 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 consumer 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 is a new demand-driven explanation contrasting with previous studies that have focused on the supply side. In this section, we examine how much skill premium increase our model can quantitatively generate. Several approaches are used. First we simulate a 1% increase in productivity (TFP) in all countries and examine how it affects the skill premium in open or 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 use estimated parameters to simulate and solve the economy in general equilibrium. Both demand-side and supply-side parameters are taken from our estimations (gravity equation and final demand estimation, specification D1). Note that, in our simulated general-equilibrium model, 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%

30The same elasticities are obtained by simulating a 10% increase in TFP.
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)). For South American countries, the elasticity is also above 0.2. 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. For India, our model could explain about half of the skill premium.

---

The Gini coefficient in China has also sharply increased from less than 30 in the early 1990s to 42 in 2005 (World Bank data).

South 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.
increase in the 90’s.\textsuperscript{33} 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.\textsuperscript{34}

While Figure 7 illustrates the elasticity of the skill premium with a homogenous TFP increase in all countries, we find about the same elasticities when we simulate productivity increases that match GDP per capita growth between 1995 and 2005 for each country (simulating the full model with trade flows). The largest deviation, of XXX\%, is found for XXX.\textsuperscript{35}

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.

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 ($\varepsilon_{nk}$) as well as labor shares ($sh^H_{nk}$ and $sh^L_{nk}$) 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 $\xi_n$ (See equation 16 and appendix sec-

\textsuperscript{33}According 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.

\textsuperscript{34}In a conservative estimate, Feenstra and Hanson (1999) show that outsourcing can explain about 15\% of the skill premium increase.

\textsuperscript{35}It 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.
Figure 8: Open-economy vs. closed-economy simulation and approximation

In 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.
allocation across sectors (between effect); iv) and a covariance term:

\[ \sum_k (s_{h_{nk}}^H - s_{h_{nk}}^L) \varepsilon_{nk} = \sum_k (\bar{s}_{L_k} - \bar{s}_{H_k}) \bar{\varepsilon}_k + \sum_k (\bar{s}_{L_k} - \bar{s}_{H_k}) \Delta \varepsilon_{nk} + \sum_k (\Delta s_{h_{nk}}^H - \Delta s_{h_{nk}}^L) \bar{\varepsilon}_k \]

where \( \bar{s}_{H_k} \) denotes the average of \( s_{h_{nk}}^H \) across countries \( n \); \( \bar{\varepsilon}_k \) denotes the average of \( \varepsilon_{nk} \) across countries \( n \); \( \Delta s_{h_{nk}}^H \) denotes the difference between \( s_{h_{nk}}^H \) and its average \( \bar{s}_{H_k} \); \( \Delta \varepsilon_{nk} \) denotes the difference between \( \varepsilon_{nk} \) 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](image)

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

\(^{37} s_{h_{nk}}^H \) is defined as the share of sector \( k \) in skilled labor employment in country \( n \), see Section 2.3.3.
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 $\Phi_{nk}$ (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 $\Phi_{nk}$ would tend to bias our correlation estimates downwards, if anything.
Table 5: Skilled labor to income elasticity correlation - Robustness across specifications

<table>
<thead>
<tr>
<th>Demand system:</th>
<th>CRIE</th>
<th>LES</th>
<th>AIDS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable:</td>
<td>Log expenditure</td>
<td>Expenditure shares</td>
<td>Expenditure shares</td>
</tr>
<tr>
<td>Prices:</td>
<td>Phi (θ = 4)</td>
<td>ICP</td>
<td>Both</td>
</tr>
<tr>
<td>Region(s):</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>All</td>
<td>0.526</td>
<td>0.693</td>
<td>0.552</td>
</tr>
<tr>
<td>With robust data</td>
<td>0.469</td>
<td>0.645</td>
<td>0.487</td>
</tr>
<tr>
<td>USA</td>
<td>0.390</td>
<td>0.497</td>
<td>0.333</td>
</tr>
<tr>
<td>EU</td>
<td>0.529</td>
<td>0.564</td>
<td>0.442</td>
</tr>
<tr>
<td>Japan</td>
<td>0.489</td>
<td>0.642</td>
<td>0.536</td>
</tr>
<tr>
<td>Observations</td>
<td>50</td>
<td>38</td>
<td>38</td>
</tr>
</tbody>
</table>

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 behaviour: 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:

**LES:** \( \sum_k \frac{x_{nk}}{x_{nk}} = \alpha_k + \gamma_k e_n^{-1} \)

**AIDS:** \( \sum_k \frac{x_{nk}}{x_{nk}} = \alpha_k + \gamma_k \log e_n \)

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 CREI preferences by minimizing errors in expenditure shares (whereas our benchmark estimates minimize errors in log expenditures). The resulting estimates of \( \alpha_k \) and \( \gamma_k \) are then used to compute income elasticities \( \varepsilon_{nk} \) with LES and AIDS:

**LES:** \( \varepsilon_{nk} = \alpha_k (\gamma_k + \alpha_k e_n^{-1})^{-1} \)

**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 homogenous 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 Fieler (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 0.238\(^{38}\). 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.

\(^{38}\)comparing estimates generated with the comparable set of 89 countries
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 vs. intermediate goods within the same industry. However, if we assume that goods within the same industry are produced with similar technics (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 $X_{nk}$ now refers to total absorption and not only final demand. 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 ($\Phi_{nk}$ 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 is can be simply formalized as in the input-output literature as a multiplier effect (see Fally (2012)): 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:

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

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

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

with $D_{nk'}$ denoting the final consumption of good $k'$ and $\gamma_{k'k}$ denoting the coefficient of the Leontief inverse matrix. 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.

6 Summary and conclusions

We begin the paper with an 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 the 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

\[39\text{Coefficients of } (I - \bar{B})^{-1} \text{ where } \bar{B} \text{ denotes the matrix of direct input-output coefficients by industry.}\]

\[40\text{Note however that intermediate goods required to produce skill-intensive goods tend to be skill-intensive as well, and therefore these “total” elasticities of demand do not differ greatly from the usual income elasticities. In fact, the correlation between “total” elasticities and skill intensity is even stronger and increases to 70.0%.}\]
particular, we are interested in the relationship between certain systematic characteristics of demand and characteristics of goods and services in production.

The first task is to develop and estimate a model where preferences are assumed to be identical across countries but non-homothetic. It implies that goods (and services) may differ in their income elasticities of demand and that budget expenditure shares are related to per-capita income. We then back out income elasticities of demand. Both economically and statistically, we find large deviations of these elasticities from the unitary values implied by homothetic preferences.

The next step in this analysis is to relate these income elasticities of demand to factor intensities of goods in production. Here we find a high, positive correlation (higher than 40 percent) between a good’s income elasticity of demand and it’s skilled-labor intensity in production. This correlation is robust to the inclusion of trade costs and other factors.

We then illustrate several implications by these differences in income elasticities. Our first results assess the contribution of non-homothetic preferences (and their relationship to factor intensities) to the “missing trade” puzzle. Our finding is that we can explain about one third or more of missing trade. This is driven by the supply-demand correlation within countries which is absent with homothetic preferences. Here, we find countries relatively specialized in consuming the same goods that they are specialized in producing.

A second set of results relate to trade patterns and trading partners. Our estimation demonstrated that high-income countries have a comparative advantage in high-income-elasticity goods and services, because these goods are skilled-labor intensive and because the high-income countries are skilled-labor abundant. This suggests that rich countries are more like to export to other rich countries and we verify that this is the case. In turn, a country’s level of trade/GDP is likely to depend largely on whether such a country has a large penetration into the richest markets. Since rich countries are also the largest markets in terms of GDP, non-homothetic preferences can generate a positive correlation between income and Trade/GDP ratio.

A final set of results shed light on a heated debate from the 1990s: the growing gap between skilled and unskilled wages, where the two main hypotheses both focused on the supply side of the economy. One was a Stolper-Samuelson argument coming from increased import penetration by unskilled-labor-abundant low-income countries into high-income ones, and the other focused on skill-biased technical change. Our 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 in general equilibrium.
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 amount 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 homogenous 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 \( \lambda \). 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:

\[
\dot{\lambda} = \frac{\sum_k (\sigma_k - 1) x_k}{\sum_k \sigma_k x_k} \hat{z}
\]

After incorporating the solution for \( \lambda \) 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:

\[
\hat{h} = \frac{\sum_k \hat{x}_k \beta_k x_k}{\sum_k \beta_k x_k} = \sum_k \hat{x}_k s_h^H
\]  

(23)

In terms of unskilled wages:

\[
\hat{w} = \frac{\sum_k \hat{x}_k (1 - \beta_k) x_k}{\sum_k (1 - \beta_k) x_k} = \sum_k \hat{x}_k s_h^L
\]  

(24)

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

\[
\hat{s} = \hat{z} \sum_k (s_h^H - s_h^L)(\varepsilon - 1) = \hat{z} \sum_k s_h^H \varepsilon_k - \hat{z} \sum_k s_h^L \varepsilon_k = \hat{z} \sum_k (s_h^H - s_h^L) \varepsilon_k
\]

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

\[
\frac{\hat{s}}{\hat{z}} = \sum_k (s_h^H - s_h^L) \varepsilon_k
\]

**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:

\[
(\sum_k x_k \beta_k) \hat{h} + (\sum_k x_k (1 - \beta_k)) \hat{w} = 0
\]

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:

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

Denoting $a_k$ the term into bracket above, we obtain $\xi_n$ by weighted $a_k$ by $sh^H_k - sh^L_k$ 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 20). 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>
<thead>
<tr>
<th>Variable:</th>
<th>Mean of estimated coeffs across industries</th>
<th>SD of estimated coeffs across industries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Distance (log)</td>
<td>-0.941</td>
<td>0.504</td>
</tr>
<tr>
<td>Home bias</td>
<td>4.545</td>
<td>1.982</td>
</tr>
<tr>
<td>Contiguity</td>
<td>0.518</td>
<td>0.488</td>
</tr>
<tr>
<td>Common lang.</td>
<td>0.378</td>
<td>0.305</td>
</tr>
<tr>
<td>Colonial link</td>
<td>0.171</td>
<td>0.444</td>
</tr>
<tr>
<td>Exporter FE</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Importer FE</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Nb. of industries</td>
<td>50</td>
<td></td>
</tr>
</tbody>
</table>

*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 $A^P$ 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 $T$ as:

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

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

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

we define the trade matrix $D$ for trade in final goods as:

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

where each $D_{ni}$ 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 $Y$ as the diagonal matrix:

$$
Y = \begin{bmatrix}
Y_1 & 0 & \cdots & 0 \\
0 & Y_2 & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & Y_N
\end{bmatrix}
$$

where each $Y_n$ is the vector of production $Y_{nk}$ of country $n$ in sector $k$.

The input-output matrix is denoted by $B$ 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:

\[
B = \begin{bmatrix}
B_{11} & B_{21} & \cdots & B_{N1} \\
B_{12} & B_{22} & \cdots & B_{N2} \\
\vdots & \vdots & \ddots & \vdots \\
B_{1N} & B_{2N} & \cdots & B_{NN}
\end{bmatrix}
\]

where each individual block \( B_{ni} \) 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 \( B_{nkk'} \), as GTAP only provides information on domestic input uses \( B_{nnkk}' \) and aggregate imported intermediates \( B_{impnkk}' \) 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 \( B_{nkk'} \) as:

\[
B_{nkk'} = B_{nkk}' \frac{X_{nik}}{\sum_{i \neq n} X_{nik}}
\]

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

\[
T = Y - BY - D
\]

which leads to:

\[
Y = (I - B)^{-1}(T + D)
\]  \hspace{1cm} (25)

We now define matrix \( A^P \) as:

\[
A^P = \Xi(I - B)^{-1}
\]

where \( \Xi \) is the matrix of direct factor requirements, i.e. the matrix of coefficients \( \beta_{kfn} \) 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 (25) that \( A^P(T + D) \) equals the matrix of payments to factors (i.e. each \( A^P(T_n + D_n) \) 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: \( F = \Xi(I - B)^{-1}T \) (where each component \( A^P T_n \) is the vector of factor content of trade for country \( n \) for each column-vector of trade \( T_n \)).
Factor content of trade: proof of equation (22)

To prove equation (22), we first show that:

\[ \sum_k A_{kfn}D_{nk} + F_{nf} = w_{nf}V_{nf} \]

and then show that:

\[ \sum_{k,n} A_{kfn}D_{nk} = \sum_n w_{nf}V_{nf} \]

We obtain equation (22) by combining these two equations.

To see the first equality, we can write:

\[ F_{nf} + \sum_k A_{kfn}D_{nk} = F_{nf} + \sum_{k,i} A_{kfi}D_{nik} \]
\[ = \sum_{k,i} A_{kfi}(T_{nik} + D_{nik}) \]

where the first line is obtained from the definition of \( A^P \) and the second line from the definition of the factor content of trade \( F_{nf} \). In matrix form, we know however that \( Y = (I - B)^{-1}(T + D) \) (equation 25) and that the matrix \( A^P \) is defined as \( A^P = \Xi(I - B)^{-1} \) where \( \Xi \) is the matrix with factor requirement coefficient \( \beta_{kfn} \). We thus obtain:

\[ \sum_{k,i} A_{kfi}(T_{nik} + D_{nik}) = \sum k\beta_{kfn}Y_{nk} = w_{fn}V_{fn} \]

We now prove the second equation mentioned earlier, i.e. that \( \sum_{k,n} A_{kfn}D_{nk} = \sum_n w_{nf}V_{nf} \).

Using the definition of \( A^D \), we can write:

\[ \sum_{k,n} A_{kfn}D_{nk} = \sum_{k,n,i} A_{kfi}D_{nik} \]

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

\[ \sum_{k,n} A_{kfn}D_{nk} = \sum_{k,n,i} A_{kfi}(D_{nik} + T_{nik}) \]

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

\[ \sum_{k,n} A_{kfn}D_{nk} = \sum_n w_{nf}V_{nf} \]
Simulation equations

We have in hand data or estimates for the following variables that can be taken as exogenous:\footnote{Concerning 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.}

\[
\begin{align*}
L_n & \quad \text{from GTAP} \\
\sigma_k & \quad \text{estimated in the last stage} \\
\mu_k & \quad \text{estimated in the last stage} \\
\alpha_k & \quad \text{estimated in the last stage} \\
V_{if} & \quad \text{estimated as the value spent on factors in the data } \sum_{n,k} \beta_{k,f} X_{nik} \\
z_{ik} & \quad \text{estimated in the gravity equations as } S_{ik}(\text{taken at the power } 1/\theta) \\
\tau_{nik} & \quad \text{estimated in the gravity equations (taken at the power } 1/\theta) \\
\end{align*}
\]

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

Bilateral pricing (associated with \( X_{nik} \)):
\[
\tau_{nik} z^{-1}_{ik} \prod_f (w_{fi})^{\beta_{fk}} \geq p_{nik}
\]

Trade (associated with \( p_{nik} \)):
\[
X_{nik} = \frac{\sum_{n,k} p_{nk}^{\theta} D_{nk}}{\sum_j p_{njk}^{\theta} D_{nk}} \geq P_{nk}
\]

Price index (associated with \( D_{nk} \)):
\[
\left( \sum_j p_{njk}^{\theta} \right)^{\frac{1}{\theta}} \geq P_{nk}
\]

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 \( \lambda_n \)):
\[
L_n e_n = \sum_k D_{nk}
\]

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


_ and James R. Markusen, Per-Capita Income as a Determinant of Trade*, Cambridge: MIT Press,


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.


XXX Add Trefler and Zhu (2010)!!!