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Abstract

Even though differences in sectoral total factor productivity are at the heart of Ricardian trade theory and many models of growth and development, very little is known about their size and their form. In this paper we try to fill this gap by using a Hybrid-Ricardo-Heckscher-Ohlin trade model and bilateral sectoral trade data to overcome the data problem that has limited previous studies, which have used input and output data to back out productivities, to a small number of OECD economies. We provide a comparable set of sectoral productivities for 24 manufacturing sectors and more than sixty countries at all stages of development. Our results show that TFP differences in manufacturing sectors between rich and poor countries are substantial and far more pronounced in skill and R&D intensive sectors. We also apply our productivity estimates to test theories on development that have implications for the patterns of sectoral productivities across countries.

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1 Introduction

Differences in sectoral total factor productivity (TFP) across countries are at the heart of trade theory and of many theories on growth and development. The Ricardian approach to international trade emphasizes those productivity differences as the main reason for cross country flows of goods, while the growth literature analyzes factors such as adequate technologies (Acemoglu and Zilibotti (2001)), human capital and technology adoption (Ciccone and Papaioannou (2007)), external financial dependence (Rajan and Zingales (1998)), or the interplay between contracting institutions and technology adoption (Acemoglu et al. (2007)) that have clear predictions on the form of sectoral differences in total factor productivity. Moreover, information on sectoral productivity differences across countries is of interest not only to theorists but also to policy makers since it is important for the design of industrial and trade policy. Nevertheless, due to data limitations, very little is known about the form and the size of sectoral productivity differentials across countries outside the industrialized world.

In this paper we try to overcome the data problem faced by the traditional approach to TFP measurement, which requires comparable information on outputs and inputs at the sectoral level. We introduce and apply a new method for estimating sectoral TFP levels that relies on information contained in bilateral trade. To our knowledge we are the first to provide a comparable and - as we will argue - reliable set of sectoral TFPs for twenty four manufacturing sectors in more than sixty countries at all stages of development.

Our approach extends the Romalis (2004) model - that combines Heckscher-Ohlin trade with trade due to increasing returns and love for variety and trade costs - to sectoral differences in total factor productivity and many asymmetric countries. In this way, we are able to back out sectoral productivity differences as observed trade that cannot be explained by differences in factor intensities and factor prices or by differences in trade barriers across countries.

Our results provide evidence that cross country TFP differences in manufacturing sectors are large - in general even larger than the substantial variation across countries at the aggregate economy level that has been found in the development accounting literature (see, for example, Hall and Jones (1999), Caselli (2005)). In addition, we show that productivity differences between rich and poor countries are systematically larger in skill intensive sectors and sectors that are more intensive in R&D. Productivity gaps are far more pronounced in sectors such as Scientific Instruments, Electrical- and Non-electrical Machinery and Printing and Publishing, than in sectors such as Apparel, Textiles or Furniture.

We perform a series of robustness checks and show that our productivity estimates are neither sensitive to the specific assumptions of our model nor to the estimation method. Aggregate manufacturing TFPs correlate strongly with the productivity estimates found in the development accounting literature, while sectoral TFPs correlate with the productivities constructed as Solow residuals for the few countries and sectors where this method can be applied.

In the final section of the paper we discuss some applications of our productivity estimates in testing specific theories of development that have implications for the cross section of productivities within countries.

2 Related Literature

There is a long line of papers that study sectoral productivity differences across countries by specifying a production possibility frontier and using data on sectoral inputs and outputs to calculate sectoral productivity indices. Some of the earlier contributions that use sectoral value value added as an output measure are Dollar and Wolff (1993) and Maskus (1991). Those studies are limited to a number of OECD-economies and do not disentangle sectoral price indices, which are usually unavailable, from output quantities. As a consequence, variation in product prices across countries may wrongly be attributed to differences in TFP. Another line of research that tries to tackle this issue is the work within the International Comparison Project (ICOP) at the University of Groningen. Researchers working in this project have constructed comparable sectoral price indices for several countries and years. They have computed sectoral productivity indices for up to 30 countries. However, also these studies include mainly OECD-members and compare mostly labor productivities.

Acemoglu and Zilibotti (2001) calculate productivity indices for 27 3-digit manufacturing sectors in 22 developed and developing countries, using data from the United Nations. They realize that their indices are a mixture of output prices and TFP differences, but do not try to separate the two parts.

In the trade literature there is also a large number of contributions that construct productivity indices at various levels of aggregation. Harrigan (1997) and Harrigan (1999) computes sectoral TFP indices for 8 (6) sectors, 2 (9) years, in 10 (8) OECD countries to test the fit of a generalized neoclassical trade model that allows for both Ricardian and Heckscher-Ohlin trade. He finds support for the existence of Rybzcynski effects.

Golub and Hsieh (2000) construct labor productivities to test a Ricardian model of trade using data for OECD countries, while Eaton and Kortum (2002) develop a multi-country Ricardian model with a probabilistic technology specification that they calibrate to fit trade between OECD countries. Chor (2006) extends their model to differences in factor proportions and differences in other sectoral characteristics like financial dependence, volatility, and other variables. This class of models provides an alternative approach to construct sectoral productivity indices from trade data.[1]

Trefler (1993), Trefler (1995) and Davis and Weinstein (2001) have shown convincingly that differences in total factor productivity at the country- or factor- and country- level can help to substantially improve the fit of the Heckscher-Ohlin-Vanek prediction on cross country trade in factors but those studies do not investigate sector specific productivity differences.

Finally, Antweiler and Trefler (2002) provide some evidence for the importance of increasing returns to scale at the sectoral level using again the Heckscher-Ohlin-Vanek framework.

One advantage of our approach is that we do not require information on inputs at the sectoral level to compute productivities but just on aggregate factor prices. Another point is that our model generates predictions on differences in sectoral prices so that we can dispense of information on sectoral price indices. Finally, we *estimate* sectoral productivities, which allows us to evaluate their reliability.

The next section introduces the theoretical model and provides some intuition for the economic forces at work. Section three develops a methodology for computing sectoral productivity indices. In section four we present our empirical results on productivities. We dedicate section five to robustness checks, while the following section discusses several applications of the productivity estimates in growth theory. The final section concludes.

[1] In our robustness checks we show that the productivity estimates obtained from the extended Eaton-Kortum model are very similar to the ones estimated with our methodology.

3 A Simple Model

In order to use trade data to back out sectoral TFP differences we need a model in which bilateral trade is determined. A convenient way to get this is to follow Krugman (1979) in assuming that consumers have love for variety and that production is monopolistic because of increasing returns.[2] We add three more ingredients to be able to talk about sectoral productivity differences. First, we assume that firms in different sectors use different factor proportions when faced with the same input prices, which gives rise to Heckscher-Ohlin stile trade between countries. Second, we add bilateral transport costs. As Romalis (2004) points out in an important paper, this makes locally abundant factors relatively cheap and strengthens the link between factor abundance and trade. While without transport costs trade is undetermined in the Helpman-Krugman-Heckscher-Ohlin model Helpman and Krugman (1985) as long as the number of factors is smaller than the number of goods and countries are not specialized, in this model there is a cost advantage to produce more in those sectors that use the abundant factors intensively. This creates the prediction that countries export more in those sectors. Finally, we add sectoral differences in total factor productivity, which introduces a motive for Ricardian style trade. Countries that have a high productivity in a sector have a cost advantage relative to their foreign competitors and charge lower prices. Because the elasticity of substitution between varieties is larger than one, demand shifts towards the varieties of that country and leads to a larger world market share in that sector. Having explained the main features of the model, let us now develop the details.

[2] An alternative specification has been developed by Eaton and Kortum (2002). In their Ricardian style model there is perfect competition and every good is sourced from the lowest cost supplier that may differ across countries because of transport costs. We will briefly turn to this model in the section dedicated to robustness checks.

3.1 Demand

Out model generalizes the setup of Romalis (2004). We assume that all consumers in a given country have identical, homothetic preferences. These are described by a two tiered utility function. The first level is assumed to be a Cobb-Douglas aggregator over K sectoral sub-utility functions. This implies that consumers spend a constant fraction of their income, σ_{ik}, which we allow to differ across countries, on each sector.[3]

$$U_i = \prod_{k=0}^{K} u_{ik}^{\sigma_{ik}} \tag{1}$$

Sectoral sub-utility is a symmetric CES function over sectoral varieties, which means that consumers value each of the available varieties in a sector in the same way.

$$u_{ik} = \left[\sum_{b \in B_{ik}} x_b^{\frac{\epsilon_k - 1}{\epsilon_k}} \right]^{\frac{\epsilon_k}{\epsilon_k - 1}} \tag{2}$$

Note also that utility is strictly increasing in the number of sectoral varieties available in a country. $\epsilon_k > 1$ denotes the sector specific elasticity of substitution between varieties and B_{ik} is the set of varieties in sector k available to consumers in country i.

Goods can be traded across countries at a cost that is specific to the sector and country pair. In order for one unit of good that has been produced by sector k of country j to arrive in destination i, τ_{ijk} units need to be shipped.

The form of the utility function implies that the demand function of country i consumers for a sector k variety produced in country j has a constant price elasticity, ϵ_k, and is given by the

[3]For our baseline specification preferences can be generalized to two-tiered CES.

following expression.

$$x_{ijk} = \frac{\hat{p}_{ijk}^{-\epsilon_k} \sigma_{ik} Y_i}{P_{ik}^{1-\epsilon_k}}, \tag{3}$$

where $\hat{p}_{ijk} = \tau_{ijk} p_{jk}$ is the market price of a sector k good produced by country j in the importing country i[4] and P_{ik} is the optimal sector k price index in country i, defined as

$$P_{ik} = \left[\sum_{b \in B_{ik}} \hat{p}_b^{1-\epsilon_k} \right]^{\frac{1}{1-\epsilon_k}}. \tag{4}$$

3.2 Supply

In each country, firms may be active in one of $k = 0, ..., K$ different sectors. Production technology differs across sectors due differences in factor intensities and differences in sectoral total factor productivity. In each sector firms can freely invent varieties and have to pay a fixed cost to operate. Because of the demand structure and the existence of increasing returns production is monopolistic, since it is always more profitable to invent a new variety than to compete in prices with another firm that produces the same variety.

Firms in country j combine physical capital, $K_j(n)$, with price r_j[5], unskilled labor, $U_j(n)$, with price w_{uj} and skilled labor $S_j(n)$ with price w_{sj} to produce.[6] In addition, there is a country and sector specific total factor productivity term, A_{jk}. Firms' production possibilities in sector k of country j are described by the following total cost function

[4] This implies that exporting firms charge the same factory gate price in all markets, so there is no pricing to the market behavior. We discuss the effects of relaxing this assumption in the section on robustness.

[5] For notational ease, we denote r_j alternatively as w_{capj} in the cost function.

[6] The fact that within every country every factor has a single price reflects the assumption that factors can freely move across sectors within a country. For the empirical model we need not make any assumptions on factor mobility across countries.

$$TC(q_{jk}) = (f_{jk} + q_{jk})\frac{1}{A_{jk}} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}}, \tag{5}$$

where $F = \{u, s, cap\}$. The form of the cost function implies that the underlying sectoral production function of each firm is Cobb-Douglas with sectoral factor intensities $(\alpha_{uk}, \alpha_{sk}, \alpha_{capk})$. To produce, firms need to pay a sector and country specific fixed cost, f_{jk} that uses the same combination of capital, skilled and unskilled labor as the constant variable cost.

Monopolistic producers maximize profits given (3) and (5). Their optimal decision is to set prices as a fixed mark up over their marginal costs,

$$p_k = \frac{\epsilon_k}{\epsilon_k - 1}\frac{1}{A_{jk}} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}}. \tag{6}$$

The combination of sectors with different factor intensities, and country-sector specific TFP differences gives the model Heckscher-Ohlin as well as Ricardian features. Since the elasticity of substitution across varieties, ϵ_k, is larger than one, consumers spend more on cheaper varieties. This together with the pricing structure implies that lower production costs translate into larger market shares. Low production costs may be either due to the fact that a sector is intensive in locally cheap factors, or due to high productivity in this sector. In the appendix we develop a general equilibrium version of the model and discuss in more detail how comparative advantage is determined.

4 Towards Estimating Sectoral Productivities

In this section we derive a method to estimate sectoral productivity levels across countries based on our model of international trade. To make progress, we write the sectoral volume of bilateral trade (measured at destination prices), which is defined as imports of country i from country j in sector k, as

$$M_{ijk} = \hat{p}_{ijk} x_{ijk} N_{jk} = p_{jk} \tau_{ijk} x_{ijk} N_{jk}. \tag{7}$$

The measured CIF value of bilateral sectoral trade is the factory gate price charged by country j exporters in sector k multiplied by the transport cost, the quantity demanded for each variety by country i consumers and by the number of varieties produced in sector k in the exporting country.

Substituting the demand function $x_{ijk}(\hat{p}_{ijk})$ from (3), we obtain

$$M_{ijk} = \frac{(p_{jk}\tau_{ijk})^{1-\epsilon_k} \sigma_{ik} Y_i}{P_{ik}^{1-\epsilon_k}} N_{jk}. \tag{8}$$

Finally, using the fact that exporting firms choose a factory gate price which is a constant markup over their marginal cost and substituting the marginal cost function (5), we can write bilateral sectoral trade volume as

$$M_{ijk} = \left[\frac{\frac{\epsilon_k}{\epsilon_k - 1} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}}}{A_{jk} P_{ik}} \right]^{1-\epsilon_k} \sigma_{ik} Y_i N_{jk}. \tag{9}$$

Equation (9) makes clear that bilateral trade in sector k measured in dollars depends positively on importing countries' consumers' expenditure share on sector k goods, σ_{ik}, and their total income,

Y_i. On the other hand, because the elasticity of substitution between varieties is larger than one, the value of trade is falling in the price charged by exporting firms, p_{jk}. This and the pricing rule (6) implies that trade is decreasing in the production cost of the exporters. If a factor is relatively cheap in a country, this leads to a cost advantage for exporting firms in sectors where this factor is used intensively. The same holds true for sectoral productivities A_{jk}. If a country has a high productivity in a sector relative to other exporters, it can charge lower prices and has a larger value of exports.

All of the previous statements hold conditional on the number of firms in sector k in the exporting country. Since we do not consider data on the number of firms active in the exporting countries as very reliable but we observe the value of sectoral production, we can use the model to solve for the number of firms given total production. The monetary value of total production of sector k in country j, $\tilde{Q}_{jk}$, equals the monetary value of production of each firm times the number of firms.

$$p_{jk}q_{jk}N_{jk} = \tilde{Q}_{jk} \tag{10}$$

Assuming that new firms can enter freely, in equilibrium firms make zero profits and price at their average cost. Combining this with (6), it is easy to solve for equilibrium firm size, which depends positively on the fixed cost and the elasticity of substitution.

$$q_{jk} = f_{jk}(\epsilon_k - 1) \tag{11}$$

Using this result and plugging it into the definition of sectoral output, we get[7]

$$N_{jk} = \frac{\tilde{Q}_{jk}}{p_{jk}(\epsilon_k - 1) f_{jk}}. \tag{12}$$

Substituting for N_{jk} in the import equation, we obtain

$$M_{ijk} = \left[\frac{\frac{\epsilon_k}{\epsilon_k - 1} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}}}{A_{jk}} \right]^{-\epsilon_k} \left[\frac{\tau_{ijk}}{P_{ik}} \right]^{1-\epsilon_k} \sigma_{ik} Y_i \frac{\tilde{Q}_{jk}}{(\epsilon_k - 1) f_{jk}}. \tag{13}$$

This equation can be rearranged to solve for the sector productivity A_{jk}. Because a productivity index needs to be defined relative to some benchmark, we measure productivity relative to a reference country. We choose the US as a benchmark because they export to the greatest number of destinations in most sectors.[8] Another advantage of choosing a reference country is that all the terms that are not indexed to the exporting country j (i.e. σ_{ik}, Y_i, P_{ik}) drop from the equation. For each importer i we can express the "raw" productivity of country j in sector k relative to the US measured using imports of country i.

$$\begin{aligned} \frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}} &\equiv \frac{A_{jk}}{A_{USk}} \left(\frac{f_{jk}}{f_{USk}} \right)^{-1/\epsilon_k} \left(\frac{\tau_{ijk}}{\tau_{iUSk}} \right)^{\frac{1-\epsilon_k}{\epsilon_k}} = \\ &= \left(\frac{M_{ijk}}{M_{iUSk}} \frac{\tilde{Q}_{USk}}{\tilde{Q}_{jk}} \right)^{1/\epsilon_k} \prod_{f \in F} \left(\frac{w_{fUS}}{w_{fj}} \right)^{\alpha_{fk}} \end{aligned} \tag{14}$$

Our "raw" productivity measure, $\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}}$, is a combination of relative productivities, relative

[7] Here we assume, consistently with our model, that firms do not use intermediate goods to produce. We discuss the effect of dropping this assumption in the section on robustness.

[8] We have also tried other benchmark countries like Germany or Japan and our results are robust to these alternative specifications.

fixed costs and relative transport costs. Intuitively, country j is measured to be more productive than the US in sector k if, controlling for the relative cost of factors, j exports a greater fraction of its production in sector k to country i than the US. Note that we can compute this measure vis a vis every importing country using only data on relative imports and on exporters' relative production and factor prices.

This "raw" measure of relative productivities contains also relative sectoral transport costs and fixed costs of production. While relative transport costs vary by importing country, exporters' relative productivities and fixed costs are invariant to the importing country. Consequently, it is easy to separate the two parts by using regression techniques.

Taking logarithms, and assuming for the moment that sectoral fixed costs are equal across countries, i.e. $f_{jk} = f_k$, [9], we get

$$\log\left(\frac{\tilde{A}_{ijk}}{\tilde{A}_{i,US,k}}\right) = \log\left(\frac{A_{jk}}{A_{US,k}}\right) + \frac{1-\epsilon_k}{\epsilon_k}\log\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right). \tag{15}$$

We assume that bilateral transport costs, τ_{ijk}, are a log-linear function of a vector of bilateral variables (i.e. distance, common language, common border, tariffs, etc.) plus a random error term. Hence, $\tau_{ijk}^{\frac{1-\epsilon_k}{\epsilon_k}} = X_{ijk}^{\beta_k} e^{u_{ijk}}$, where X_{ijk} is a vector of bilateral variables and u_{ijk} is noise. Consequently, we obtain a three dimensional panel with observations that vary by industry, exporter and importer.

[9] Later we will relax this assumption. An alternative interpretation is to consider productivity as a measure that also contains the fixed cost of production. After all, why should only the variable cost of production be taken into account?

$$\log\left(\frac{\tilde{A}_{ijk}}{\tilde{A}_{ikUS}}\right) = \log\left(\frac{A_{jk}}{A_{USk}}\right) + \beta_{1k}(\log Dist_{ij} - \log Dist_{iUS}) + \tag{16}$$
$$+\beta_{2k}(\log Tariff_{ijk} - \log Tariff_{iUSk}) +$$
$$+\beta_{3k}CommonLang_{ij} + \beta_{4k}CommonLang_{iUS} + ... + u_{ijk} - u_{iUSk}$$

Relative TFP of country j in sector k is captured by a country-sector dummy. The coefficients β_k measure the impact of the log difference in bilateral variables on the sectoral trade cost multiplied by the negative sector specific factor $\frac{1-\epsilon_k}{\epsilon_k}$.

The sector-country dummies are computed as

$$\frac{A_{jk}}{A_{US,k}} = exp\left[\log\left(\frac{\bar{\tilde{A}}_{ijk}}{A_{i,US,k}}\right) - \beta^{k}_{FE}\bar{X}_{ijk}\right] \tag{17}$$

where the bars indicate means across importing countries i and $\hat{\beta}_{kFE}$ is the fixed effect panel estimator for the vector β_k. Consequently, the estimated productivity of country j in sector k relative to the US is the mean of $\left(\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}}\right)$ across importing countries controlling for the average effect of relative sectoral transport costs. This is a consistent estimator for relative productivities as long as there are no omitted variables with a nonzero mean across importers.

Our measure of relative TFP is transitive. This implies that productivities are comparable across countries *within* sectors in the sense that $\frac{A_{jk}}{A_{j'k}} = \frac{A_{jk}}{A_{USk}}\left(\frac{A_{j'k}}{A_{USk}}\right)^{-1}$. However, one cannot compare TFP in any country *between* sectors k and k' because this would mean to compare productivities across different goods.

Our productivity indices could alternatively be interpreted as differences in sectoral product quality across countries. In this case there would not exist any cost differences arising from TFP differentials across countries but consumers would be willing to spend more on goods of higher quality. Differences in M_{ijk} across countries would not arise because of differences in quantities shipped due to cost differentials but because of differences in quality. Since we look only at the value of trade, the two interpretations are equivalent.[10]

Before describing the results of our estimations, we briefly describe all the inputs needed to construct our measures of sectoral productivity. A more detailed description of the data can be found in the appendix. We compute sectoral productivities for 24 (ISIC Rev. 2) manufacturing sectors in 64 countries at all stages of development for three time periods, the mid-eighties, the mid-nineties and the beginning of the 21st century. In order to do so, we require data on bilateral trade at the sector level, information on sectoral production, factor prices, sectoral factor intensities, elasticities of substitution and sectoral bilateral trade barriers. We take information on bilateral trade at the sectoral level and on sectoral gross output from the World Bank's trade, production and protection database Nicita and Olarreaga (2007). We construct factor prices for skilled and unskilled labor and capital following methods proposed by Caselli (2005) and Caselli and Feyrer (2006) . Sectoral factor income shares are computed from US data, while information on sectoral elasticities of substitution comes from Broda and Weinstein (2006). Data on distance and other

[10] An isomorphic model to the one presented in the main text is the following one. Replace sectoral subutility with the expression $u_{ik} = \left[\sum_{b \in B_{ik}} (\lambda_b x_b)^{\frac{\epsilon_k - 1}{\epsilon_k}}\right]^{\frac{\epsilon_k}{\epsilon_k - 1}}$, where $\lambda_b > 0$ is a utility shifter that measures product quality and let the cost functions be identical across countries for a given sector, such that $TC(q_{jk}) = (f_k + q_{jk}) \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}}$. Assuming that all firms within a sector of the exporting country produce varieties of the same quality, demand of country i consumers for sector k varieties produced in j is $x_{ijk} = \frac{\hat{p}_{ijk}^{-\epsilon_k} \lambda_{jk}^{\epsilon_k - 1} \sigma_{ik} Y_i}{\tilde{P}_{ik}^{1-\epsilon_k}}$, where $\tilde{P}_{ik} = \left[\sum_{b \in B_{ik}} (\frac{\hat{p}_b}{\lambda_b})^{1-\epsilon_k}\right]^{\frac{1}{1-\epsilon_k}}$ is the optimal quality adjusted price index. In this case the value of bilateral trade is $M_{ijk} = \frac{(p_{jk}\tau_{ijk})^{1-\epsilon_k} \lambda_{jk}^{\epsilon_k - 1} \sigma_{ik} Y_i}{\tilde{P}_{ik}^{1-\epsilon_k}} N_{jk}$. Comparing this expression with the one in the main text, (8), it becomes clear that productivity differences are indistinguishable from differences in product quality, because the value of bilateral trade is identical in both cases.

bilateral variables such as information on a common border between exporter and importer and between the US and the importing country, and whether a trading partner has been a colony of the exporter or importer are taken from Mayer and Zignago (2005) and Rose (2004). Finally, we use information on bilateral sectoral tariffs from the UNCTAD TRAINS database.

Table 1provides some descriptive industry statistics. Skill intensity, measured as the share of non-production workers in sectoral employment, varies from 0.15 (Footwear) to 0.49 (Beverages) with a mean of 0.27 , while capital intensity, measured as one minus labor compensation in value added, varies from 0.56 (Fabricated Metals) to 0.85 (Beverages) with a mean of 0.66. Finally, the elasticity of substitution varies between 1.81 (Plastic Products) and 12.68 (Non-Ferrous Metals) with an average of 4.28.

5 Results

In this section we report the results of computing productivities using our baseline specification (16). We use a simple stepwise linear panel estimation[11] with sector-country specific fixed effects. We limit the sample to exporter-sector pairs for which we observe exports to at least five destinations but ignore zeros in bilateral trade flows and issues of sample selection at this stage of our analysis.

Table 2 shows the regression results for our baseline model using data for the mid-nineties. The overall fit is very good with an R-square of 0.85 and a within R-square of 0.52. This implies that for a given sector productivity A_{jk}, the transport costs due to the gravity type variables in our regression account for more than half of the variation in $\tilde{A}_{ijk}$ across importers. In addition ρ - the

[11]The stepwise procedure starts with the full model that includes all right hand side variables and one by one discards variables that are not significant at the 10 percent level of significance using robust standard errors, while taking care of the fact that a discarded variable might become significant once another one has been dropped.

fraction of the variance of the error term that is due to A_{jk} - is 80%. Both facts corroborate our interpretation of A_{jk} as an exporter-sector specific productivity measure.

Recall that the sign of the coefficients reflects the impact of the relevant variable on transport costs multiplied by the negative term $\frac{1-\epsilon_k}{\epsilon_k}$, so that a negative coefficient implies that a given variable increases relative transport costs.

Differences in distance have a large and very significant negative effect on our relative raw productivity measure in all sectors. Differences in bilateral sectoral tariffs between country j and the US are also negative and significant for all sectors except Other Chemicals (352). Indicators for common language between the importer and the exporter have a significant positive effect on raw productivity in all sectors but Iron and Steel (371) and Non-ferrous Metals (372). Having English as a common language with the exporter US or the fact that one of the exporters has a common border with the importer has a significantly positive effect on raw productivity only for some sectors. The same holds true for the common colony dummy.

Having run regression (16), we use (17) to construct sectoral productivities. We compute almost 1500 sectoral TFPs for each period (24 by country for 64 countries[12]). Table 4 summarizes some information about these productivities in the mid-nineties. We present the country mean of TFP across industries[13], the standard deviation and the sectors with maximum and minimum TFP for each country in our sample.

[12]For some countries we cannot compute TFP for all sectors either because of missing production data or because the country does not export to enough countries in a sector, so that we drop the sector from (16). Ivory Coast is the country with the smallest number of sectors for which we obtain productivity measures, 16 and only in 14 (out of 64) countries we construct productivities for less than 20 sectors. The complete set of productivity estimates is available upon request and will soon be online under http://www.pablofleiss.com.

[13]These means of sector productivities cannot be interpreted as aggregate manufacturing productivity indices in terms of economic theory, since we would need to take into account agents' preferences for a proper aggregation. Nevertheless, they give some sense of the magnitude of average sectoral productivity differences across countries

First we observe that there is a strong correlation between a country's income per worker and average relative TFP in manufacturing. Poor countries tend to have far lower sectoral productivities than rich ones, but within countries relative productivities vary a lot across sectors. Taking for example Pakistan, a typical developing country, we measure an average relative manufacturing TFP of 0.22 of the US level. This hides a large amount of heterogeneity across sectors: A productivity of 0.72 of the US level in Apparel (322) and one of only of 0.08 in the sector Transport Equipment (384). In general, Plastics (356), Metals (381) and Transport Equipment (384) are the sectors in which many of the poor countries tend to be least productive relative to the US, while Footwear (324) and Furniture (332) are the sectors in which rich countries seem to have their smallest productivities relative to the US, although these patterns are not as clear as for poor nations. Many poor countries have their highest relative productivities in the sectors Food (311) and Apparel (322) while again, there is no clear pattern in which sectors rich countries are the most productive relative to the US.

The panels of figures 1 and 2 show scatter plots of estimated sectoral productivities against log GDP per worker in the mid-nineties for 8 out of the 24 sectors (the first sector of each 2 digit classification, i.e. 311, 321....)[14]. Again, there is a high correlation between sectoral productivity and log GDP per worker in all sectors. While this is true for all sectors, the magnitude of productivity differences varies a lot across sectors. For example, the relation between log income per worker and productivity is much more pronounced in the sector Metal Products (381) than in Food (311). We also note that in general, the richest European countries tend to be more productive than the US in most manufacturing sectors.

At this point it seems interesting to compare our mean sectoral productivities for manufacturing

[14]We present these 8 scatters to exemplify our results. They extend to the sectors within the same 2 digit classification.

with the aggregate productivities found in the Development Accounting literature. To this end we compute weighted averages (by value added) of our sectoral TFPs and correlate them with aggregate productivities constructed from production and endowment data.[15] Figure 3 shows a scatter plot of our aggregate manufacturing productivity against aggregate economy productivity indices computed as Solow residuals. We note that there is a very strong correlation between the two sets of productivity estimates. The correlation coefficient is 0.7 and the Spearman rank correlation is 0.72. Productivity differences in manufacturing tend to be even larger than aggregate ones. This is driven by the fact that European countries seem to be more productive in manufacturing than at the aggregate economy level and that a number of poor countries, like Tunisia, Egypt, Guatemala and Venezuela that are close to the US productivity level according to the Hall and Jones method are estimated to far less productive than the US in manufacturing when using our methodology.

To get an even better feeling for the productivity differences between rich and poor countries we split the countries in two samples: Developing countries (with income per worker below 8000 US Dollars in 1995) and developed countries. Figure 4 shows a histogram of sector productivities for the mid-nineties for both subsamples, where each observation is given by a sector-country pair. We observe that the productivity distribution of developing countries is left skewed, so that most sectoral productivities are far below the US level, with a long tail on the right, meaning that there are a few developing countries that are more productive than the US in certain sectors. Developed countries' have a relatively symmetric productivity distribution with a mean sectoral productivity that is slightly below one, and a significant variation to both sides, ranging from around 0.2 to 1.5 of the US level.

[15] We use data on income, capital stocks and human capital per worker for 1996 from Caselli (2005) and follow Hall and Jones (1999) in calculating TFP using the formula $y_c = A_c \left(\frac{K_c}{Y_c}\right)^{\alpha/(1-\alpha)} h_c$.

Figure 5 shows the evolution of developing countries' relative productivities over time. The black line is the histogram of developing countries' productivities in the mid-eighties, the red line is the histogram for the mid-nineties and the blue line the one for the beginning of the 21st century. We see that the distribution is shifting to the right over time, meaning that over this twenty year period poor countries are slowly catching up in sectoral TFP relative to the US. [16] This is an interesting finding that we do not investigate further here, and its causes are left for future research.

Our productivity estimates also allow us to construct "Ricardian" style curves of comparative advantage due to productivity differences for any country pair. The panels of figure 6 depict productivities arranged in a decreasing order according to the magnitude of relative productivity differences with the US for four representative countries: Germany, Spain, Uruguay and Zimbabwe. Here, for example, we see that Spain's comparative advantage relative to the US is greatest in the sectors Other Non Metallic Mineral Products (369), Iron and Steel (371) and Rubber Products (355), while its sectors with the greatest comparative disadvantage are Printing and Publishing (342) and Plastic Products (356). The comparative advantage of Zimbabwe, on the other hand, is largest in the sectors Apparel (322, with a productivity of less than 25% of the US level) and Non Ferrous Metals (372), and smallest in the sectors Plastic Products (356) and Footwear (324).

6 Robustness

In this section we perform several robustness checks on our productivity estimations. We try alternative econometric specifications and we discuss the effects of changing particular assumptions of our model. Moreover, we compare our productivities with those computed as Solow residuals.

[16] This finding is different from what is found with the Solow residual approach, according to which aggregate productivity differences have become larger in the last two decades. See, for example, (Acemoglu (2007)).

6.1 Hausman Taylor

One potential weakness of our productivity estimates is that we have not estimated the effect of differences in factor prices and factor proportions but calibrated it. If trade is not systematically related to these factors, our productivity estimates could be biased. In order to avoid such concerns, we show that our results are robust to directly estimating the effect of factor intensities and elasticities.

An alternative specification rearranges (14) such that we can write trade relative to production as a function of TFP, factor cost and bilateral variables.

$$(\frac{M_{ijk}}{M_{iUSk}}\frac{\tilde{Q}_{USk}}{\tilde{Q}_{jk}}) = \left(\frac{A_{jk}}{A_{iUSk}}\right)^{\epsilon_k}\left[\prod_{f\in F}\left(\frac{w_{fj}}{w_{fUS}}\right)^{\alpha_{fk}}\right]^{-\epsilon_k}\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right)^{1-\epsilon_k} \tag{18}$$

Then, using the fact that $\alpha_{capk} = 1 - \alpha_{sk} - \alpha_{uk}$, we can write

$$log(\frac{M_{ijk}}{\tilde{Q}_{jk}}) - log(\frac{M_{iUSk}}{\tilde{Q}_{USk}}) = \epsilon_k log\left(\frac{A_{jk}}{A_{USk}}\right) - \epsilon_k\left[\log\left(\frac{r_j}{r_{US}}\right) + \sum_{f\neq cap}\alpha_{fk}log\left(\frac{w_{fj}}{r_j}\right) - \alpha_{fk}log\left(\frac{w_{fUS}}{r_{US}}\right)\right] + \tag{19}$$
$$+(1-\epsilon_k)log\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right).$$

Under the assumption that productivities are not correlated with relative factor prices within a country, which is true if productivity is Hicks-neutral, a consistent estimator for $\left(\frac{A_{jk}}{A_{iUSk}}\right)$ can be obtained from the following two step procedure.

In the first stage, we regress our dependent variable on sector-country dummies and bilateral variables.

$$log(\frac{M_{ijk}}{\tilde{Q}_{jk}}) - log(\frac{M_{iUSk}}{\tilde{Q}_{USk}}) = D_{jk} + \beta_k log\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right) + u_{ijk} \tag{20}$$

Having obtained the first stage estimates, we regress the sector-country dummy on factor prices weighted by factor intensities,

$$\hat{D}_{jk} = D_j + D_k + \sum_{f \neq cap} \beta_{fk} \left[\alpha_{fk} log \left(\frac{w_{fj}}{r_j} \right) - \alpha_{fk} log \left(\frac{w_{fUS}}{r_{US}} \right) \right] + \nu_{jk}, \quad (21)$$

for $h \in \{s, u\}$ in order to obtain a measure of sectoral TFP, which is computed using the relation

$$\left(\frac{A_{jk}}{A_{iUSk}} \right) = exp[1/\epsilon_k (D_j + D_k + \nu_{jk}) + log \left(\frac{r_j}{r_{US}} \right)]. \quad (22)$$

This procedure is similar to the Hausman-Taylor GMM estimator, which allows some of the right hand side variables to be correlated with the fixed effects and at the same time to estimate the coefficients of the variables that do not vary by importing country. However, the Hausman Taylor procedure requires instrumenting all variables that are potentially correlated with the fixed effects, which is not feasible. The two step procedure provides (under our assumptions) consistent estimates of sectoral TFPs without requiring us to make too specific assumptions about which set of variables is correlated with the error term.

Table 4 reports the results of this regression. Differences in tariffs and in distance have a very significant negative impact on relative normalized trade in all sectors and the other bilateral variables have the expected sign and are mostly significant. The fit of the first stage has an R-square of 0.64. In the second stage, the interactions between factor intensities and the relative price of skilled labor have the expected sign in all but three sectors (Textiles, Printing and Publishing and Rubber) and are strongly significant. The magnitude of the coefficients, which theoretically should be an estimate of the elasticity of substitution is too large, however. In the case of unskilled labor, the coefficients have the expected sign in all sectors except Iron and Steel and are again very significant and of plausible magnitude. The R-square of the second stage is 0.55, implying that country and sector dummies and the Heckscher-Ohlin components explain around half of the country-sector specific variation.

The productivities obtained with this procedure are again very similar to our our baseline set of productivities. The first columns of table 5 show correlations and rank correlations between these two sets of productivities by sector. For most sectors correlations are around 0.99 with an overall correlation of 0.95. Still, we prefer the mixed calibration and estimation approach of the baseline model because it does not require any assumptions on the correlations between the independent variables and the country-sector fixed effect and because not all of the coefficients in this specification have the correct magnitudes.

This approach to estimating sectoral productivities also allows to assess the importance of Ricardian productivity differences for explaining bilateral trade. To do so, we compare the fit of the first stage (20) with the one of a model with country specific productivities and a Heckscher-Ohlin component that ignores Ricardian productivities.[17]

$$log(\frac{M_{ijk}}{\tilde{Q}_{jk}})-log(\frac{M_{iUSk}}{\tilde{Q}_{USk}}) = D_j+D_k+\sum_{f\neq cap}\beta_{fk}\left[\alpha_{fk}log\left(\frac{w_{fj}}{r_j}\right)-\alpha_{fk}log\left(\frac{w_{fUS}}{r_{US}}\right)\right]+\beta_k log\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right)+u_{ijk} \tag{23}$$

The adjusted R-square of this model is 0.5 compare with 0.63 for the one with Ricardian productivities, so there is a 13% gain in fit by introducing Ricardian productivity differences.[18]

[17]This model is very popular in the literature. See, for example, Trefler (1995), Davis and Weinstein (2001).

[18]We obtain very similar results regarding the importance of Ricardian productivity differences when comparing (16) with a restricted version that allows only for country specific TFP differences.

Also the Akaike information criterion tells us that the Ricardian model does much better.[19]

6.2 Heterogeneous Firms and Zeros in Bilateral Trade

Up till now we have assumed that firms are homogeneous, so that either all firms in a sector of country j export to country i, or none does. In reality, only a fraction of firms exports and very few firms export to many destinations. In addition, we have ignored zeros in bilateral trade flows, which are quite prevalent in the data[20], hence our estimates are conditioned on observing positive trade flows. In a recent paper Helpman et al. (2007) argue that one needs to take these facts into account when trying to explain the volume of bilateral trade with gravity type regressions in order to obtain unbiased estimates of the impact of distance and other bilateral variables on trade flows. The reason why heterogeneous firms matter is that one has to correct for the extensive margin of trade, i.e. the number of firms engaged in bilateral trade, otherwise one confuses the impact of trade barriers on the number of firms with the effect on exports per firm. Zeros in bilateral trade matter since the sample selection of observing positive trade flows is not random, because many of the variables that determine bilateral fixed costs to trade also affect the variable cost to trade, so that countries with large observed barriers that trade a lot are likely to have low unobserved trade barriers. In this section we check if our productivity estimates are robust to controlling for these factors. We follow the approach suggested by Helpman et al. (2007), which forces us to use a somewhat different specification for our productivity estimates and obliges us to use information on the number of firms active in the exporting country, which we consider less reliable than data on aggregate production. Nevertheless, our results on productivities remain suprisingly similar.

[19] AIC drops from 171455 for the restricted model to 157827 for the Ricardian model.

[20] 8907 out of 51029 possible trade flows are zero in our sample.

To start out, we introduce heterogeneity in firms' marginal costs.

$$MC(a) = \frac{a}{A_{jk}} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}}, \tag{24}$$

where a is an inverse measure of random firm productivity with sector specific cumulative distribution function $G_k(a)$ and support $[a_{Lk}, a_{Hk}]$ that is identical across countries. Aggregate sectoral productivity differences are measured by the term A_{jk}.[21]. In this way we are able to measure which fraction of firms is engaged in bilateral trade, once we filter out average sectoral productivity differences across countries.

Profits from exporting to country i for producers in sector k of country j with productivity $\frac{A_{jk}}{a}$ can be written as

$$\Pi_{ijk}(a) = \frac{1}{\epsilon_k} \left[\frac{\epsilon_k a \tau_{ijk} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}}}{(\epsilon_k - 1) A_{jk} P_{ik}} \right]^{1-\epsilon_k} \sigma_{ik} Y_i - f_{ijk} \tag{25}$$

Firms export from j to i in sector k only if they can recoup the bilateral fixed cost to export. This defines a cutoff productivity level a_{ijk} such that $\Pi_{ijk}(a_{ijk}) = 0$. Hence, only a fraction $G(a_{ijk})$ (potentially zero) of country j's N_{jk} firms export to country i. Define $V_{ijk} = \int_{a_{Lk}}^{a_{ijk}} a^{1-\epsilon_k} dG(a)$ if $a_{ijk} \geq a_{Lk}$ and zero otherwise. We assume that $G(a)$ is such that V_{ijk} is a monotonic function of $G(a_{ijk})$, the proportion of firms of country j exporting to country i in sector k.[22] Then the volume of bilateral trade can be written as

[21]Hence, $G_{jk}(a) = 1/A_{jk}G_k(a)$

[22]This is true if 1/a is Pareto, for example.

$$M_{ijk} = \left[\frac{\frac{\epsilon_k}{\epsilon_k - 1} \tau_{ijk} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}}}{A_{jk} P_{ik}} \right]^{1-\epsilon_k} \sigma_{ik} Y_i N_{jk} V_{ijk}. \tag{26}$$

Let $\tilde{A}_{ijk} \equiv \left(\frac{M_{ijk}}{N_{jk}} \right)^{\frac{1}{\epsilon_k - 1}} \prod_{f \in F} \left(\frac{w_{fk}}{\alpha_{fk}} \right)^{\alpha_{fk}}$ be our measure of "raw" productivity. Taking logs and rearranging, we obtain again a gravity type relation.

$$\log(\tilde{A}_{ijk}) = \log(A_{jk}) + \frac{1}{\epsilon_k - 1} \log(\sigma_{ik} Y_i) + \log(P_{ik}) + \log\left(\frac{\epsilon_k - 1}{\epsilon_k} \right) + \log(\tau_{ijk}) + \frac{1}{\epsilon_k - 1} \log(V_{ijk}) \tag{27}$$

From this equation we can see a potential source for bias in the productivity estimates. $log(V_{ijk})$, a variable related to the fraction of exporting firms, appears in the equation. Since this variable is correlated with the right hand side variables (see below), all the estimates are biased when omitting this variable. To be more specific, distance affects negatively the profits to export and reduces the number of firms engaged in bilateral trade. As the same variable also affects our "raw" productivities, the coefficient for distance is biased (upward).

Define the variable Z_{ijk} as the ratio of variable profits to bilateral fixed costs to export for the most productive exporter,

$$Z_{ijk} = \frac{\frac{1}{\epsilon_k} \left[\frac{\epsilon_k a_{Lk} \tau_{ijk} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}}}{(\epsilon_k - 1) A_{jk} P_{ik}} \right]^{1-\epsilon_k} \sigma_{ik} Y_i}{f_{ijk}}. \tag{28}$$

Hence, we observe postive trade flows from j to i in sector k if and only if $Z_{ijk} \geq 1$.

Using (25) and (28) one can show that $Z_{ijk} = \left(\frac{a_{ijk}}{a_L} \right)^{\epsilon_k - 1}$ and that consequently V_{ijk} a monotonic function of Z_{ijk} if $V_{ijk} > 0$. Next, specifying z_{ijk} as the log of Z_{ijk}, we obtain:

$$z_{ijk} = -log(\epsilon_k) + (1-\epsilon_k) log(\frac{\epsilon_k}{\epsilon_k - 1}) + (\epsilon_k - 1) log(P_{ik}) + log(\sigma_{ik} Y_i) + (1-\epsilon_k) log(p_{jk}) + (1-\epsilon_k) log(\tau_{ijk}) - log(f_{ijk}). \tag{29}$$

We assume that bilateral sectoral variable transport costs can be written as a function of bilateral variables, X_{ijk}, an exporter specific term ϕ_j, an importer specific term ϕ_i and a sector specific term ϕ_k as well as an idiosyncratic normally distributed error term $u_{ijk} \sim N(0, \sigma_u^2)$, so that $\tau_{ijk} = exp(\phi_j + \phi_i + \phi_k + \kappa_k X_{ijk} - u_{ijk})$. For f_{ijk} we make a similar assumption , such that $f_{ijk} = exp(\varphi_j + \varphi_i + \varphi_k + \delta_k X_{ijk} - \nu_{ijk})$, where φ_j, φ_i and φ_k are exporter, importer and sector specific and $\nu_{ijk} \sim N(0, \sigma_\nu^2)$.

Consequently, we can write the latent variable z_{ijk} as

$$z_{ijk} = \xi_k + \xi_i + \xi_j - \gamma_k X_{ijk} + \eta_{ijk}, \tag{30}$$

where ξ_{jk} and ξ_{ik} are exporter, importer and sector specific effects[23] and $\eta_{ijk} = u_{ijk} + \nu_{ijk} \sim N(0, \sigma_u^2 + \sigma_\nu^2)$ is i.i.d (but correlated with the error term in the equation of trade flows). Hence $z_{ijk} > 0$ if $M_{ijk} > 0$ and zero else. As a next step define the latent variable T_{ijk}, which equals one if $z_{ijk} > 0$ and zero otherwise.

Specify the Probit equation

$$\rho_{ijk} = Pr(T_{ijk} = 1 | X_{ijk}) = \Phi(\xi_k^* + \xi_i^* + \xi_j^* - \gamma_k^* X_{ijk}), \tag{31}$$

[23]We cannot control for importer-sector and exporter-sector effects because then many outcomes would be perfectly predicted, as a lot of countries export to all importers in a specific sector.

where starred coefficients are divided by the standard deviation of the error term, which cannot be estimated separately. Finally, let $\hat{\rho}_{ijk}$ be the predicted probability of exports from j to i in sector k and let $\hat{z}^*_{ijk}$ be the predicted value of the latent variable z^*_{ijk}.

We want to obtain an estimate of "raw" productivity,

$$E[\log(\tilde{A}_{ijk})|X_{ijk}, T_{ijk} = 1] = \log(A_{jk}) + D_{ik} + \beta_k X_{ijk} + E[\frac{1}{\epsilon_k - 1}\log(V_{ijk})|T_{ijk} = 1] + E[e_{ijk}|T_{ijk} = 1] \tag{32}$$

Then a consistent estimation of the log-linear equation requires estimates of $E[\log(V_{ijk})|T_{ijk} = 1]$ and $E[e_{ijk}|T_{ijk} = 1]$. A consistent estimator for $E[e_{ijk}|T_{ijk} = 1] = Cov(\eta, e)/\sigma^2_\eta E(\eta_{ijk}|T_{ijk} = 1)$ is $\beta_{\eta,e,k}\phi(z^*_{ijk})/\Phi(z^*_{ijk}$, the inverse Mill's ratio, and a consistent estimator for $E[\log(V_{ijk}|T_{ijk} = 1]$ can be obtained by approximating the unknown function $\log(V_{ijk}(\hat{z}^*_{ijk}))$ with a polynomial in $\hat{z}^*_{ijk}$

$$\log(\tilde{A}_{ijk}) = \log(A_{jk}) + D_{ik} + \beta_k X_{ijk} + \beta_{\eta,e,k}\frac{\phi(\hat{z}^*_{ijk})}{\Phi(\hat{z}^*_{ijk})} + \sum_{l=1}^{L} \gamma_{kl}(\hat{z}^*_{ijk})^l + \nu_{ijk} \tag{33}$$

Table 5 shows the results of our productivity estimates with different specifications. The first one ignores the issues of sample selection and heterogeneous firms to check how much results are affected by using the number of firms instead of aggregate production (columns labeled 'number of firms'). We can see that the results are very similar with an overall correlation with our baseline productivity estimates of 0.89. In the next columns we control for sample selection by including the inverse Mill's ratio (columns labeles 'Heckman'). This term is positive and significant in all sectors, so that there is indeed sample selection towards countries with low unpbserved trade barriers. However, results for productivities change very little compared to the specification that only uses the number of firms. Finally, we simultaneously control for sample selection and the extensive margin of trade (via a 3rd order polynomial approximation) of $E[log(V_{ijk})|T_{ijk}] = 1$ (columns labeled. 'heterogeneous firms'). Even though these terms are all significant (results not reported), correlations and Spearman rank correlations for our productivities remain around 0.9.

6.3 Pricing to the Market and Endogenous Markups

Markups charged by exporting firms may depend on the level of competition in the destination market (Melitz and Ottaviano (2005), Sauré (2007)) . In this section we study how our productivity estimates are affected by the presence of pricing to the market. Following Sauré (2007) we slightly modify agents' utility function to make marginal utility bounded, so that consumers' demand drops to zero whenever a veriety is too expensive.

$$u_{ik} = \left[\sum_{b \in B_{ik}} \ln(x_{bk} + 1) \right] \tag{34}$$

Then demand for a sector k variety produced in country j by consumers in country i is given by

$$x_{ijk} = \max\{\frac{1}{\mu_{ik}\tau_{ijk}p_{ijk}} - 1, 0\}, \tag{35}$$

where μ_{ik} is the shadow price of the sector k budget sub-constraint for country i consumers. Solving country j producers' profit maximization problem, one finds that exporters price discriminate across markets and set prices in destination i equal to a markup over their marginal cost that depends inversely on the toughness of competition in the export market, so that $p_{ijk} = \left(\frac{\frac{1}{A_{jk}} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}}}{\mu_{ik}\tau_{ijk}} \right)^{1/2}$. Substituting into the definition of bilateral trade and simplifying we obtain

$$M_{ijk} = \mu_{ik}^{-1} \left\{ 1 - \left[\mu_{ik}\tau_{ijk} \frac{1}{A_{jk}} \prod_{f\in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}} \right]^{1/2} \right\} N_{jk}, \tag{36}$$

whenever bilateral trade is positive.[24] Dividing by M_{iUSk} and taking logs we get

$$log(\frac{M_{ijk}}{M_{iUSk}}) \approx \left(\frac{A_{jk}}{A_{USk}} \prod_{f\in F} \left(\frac{w_{fUS}}{w_{jk}} \right)^{\alpha_{fk}} \frac{\tau_{iUSk}}{\tau_{ijk}} \right)^{1/2} + \log \left(\frac{N_{jk}}{N_{USk}} \right) \tag{37}$$

We see that the shadow price μ_{ik}, which is related to markups and the level of competition in the export market, drops from the equation but the relationship is no longer linear in logs. Moreover, N_{jk} can no longer be replaced with aggregate production, since the production level of individual firms q_{jk} depends on the trade weighted level of competition in the destination markets and prices charged in those markets, $N_{jk} \sum_{i\in I_{jk}} p_{ijk}q_{ijk}\tau_{ijk} = Q_{jk}$. Hence, our productivity estimation procedure remains valid as long as we use the number of firms in the exporting country instead of aggregate production.

6.4 Comparing with Solow Residual

To assess the validity of our method for computing sectoral TFPs we compare our productivity estimates with TFPs constructed from the OECD STAN database for the few countries and sectors where this is feasible. We assume sectoral production functions to be Cobb-Douglas with sectoral factor income shares equal to the ones of the US. For reasons of data availability, we are limited to 11 countries[25] , two factors - capital and efficient labor - and eight sectors[26].

[24]Endogenous markups are an alternative explanation to fixed cost to exporting for observing zeros in bilateral trade.

[25]Austria, Belgium, Canada, Finland, France, Italy, Netherlands, Norway, Spain, United Kingdom, United States.

[26]Those sectors are 31,32,...,38. Data are limited by the availability of information on gross fixed capital formation.

We compute the Cobb-Douglas TFP index as

$$\frac{A_{jk}}{A_{USk}}\frac{p_{jk}}{p_{USk}} = \left(\frac{VA_{jk}}{VA_{USk}}\right)\left(\frac{K_{USk}}{K_{jk}}\right)^{\alpha_k}\left(\frac{H_{USk}}{H_{jk}}\right)^{1-\alpha_k} \tag{38}$$

Note that we do not have information on sectoral price indices, so that our TFP measures are contaminated by relative prices, which may potentially severely bias these productivity indices. [27] To make our baseline productivities comparable with the ones computed from STAN, we aggregate trade data to fit the STAN definitions and construct wages for workers with no education.

Table 5 presents correlations and Spearman rank correlations between TFPs computed with our baseline specification and TFPs computed from STAN. The overall correlation between the two measures is 0.34 and the rank correlation is 0.3. These aggregate numbers hide a large variation in fit by sector. Rank correlation are quite high for sectors 37 (0.7) and 31 (0.5) but very low sectors 32 (0.13) and 33 (0.11).[28] Interestingly, the sectors with poor fit are those with high transport costs for which relative prices tend to vary much more across countries. Overall, the correlations are not overwhelming, but there clearly is a positive relation between the results of the two methods. One has to take into account that we have not only used a different approaches but also completely different datasets to compute the two sets of TFPs and that variation in relative prices may be severely distorting their comparability. In the end, the relative success of this robustness check together with the high correlation of our aggregate TFPs with the more reliable aggregate measures obtained using Hall and Jones' method makes us confident that we are indeed

[27] Harrigan (1999) constructs internationally comparable sectoral price indices for some manufacturing sectors and finds large differences in sectoral prices even across a small number of OECD economies.

[28] Productitivities in sector 35 are not directly comparable, because we have removed some subsectors where exports depend mostly on the availability of oil resources from our dataset.

capturing productivity differences with our TFP measures constructed from trade data.

6.5 Eaton and Kortum's (2002) Model

An alternative model to compute sectoral productivities is the Eaton and Kortum (2002) model of trade. This is a Ricardian model that can easily be extended to Heckscher-Ohlin style trade. Chor (2006) uses a version of this model to divide comparative advantage into different components, but is not specifically interested in measuring sectoral TFPs. The model assumes a fixed measure of varieties $n \in [0, 1]$ in each sector and perfect competition so that firms price at their (constant) marginal cost and countries source a given variety only from the lowest cost supplier. The price of variety n of sector k produced in country j as perceived by country i consumers is

$$\hat{p}_{ijk}(n) = \frac{1}{A_{jk}(n)} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}} \tau_{ijk}. \tag{39}$$

Here, $A_{jk}(n)$ is stochastic and parameterized such that $log(A_{jk}(n)) = \lambda_{jk} + \beta_k \epsilon_{ik}(n)$, where $\epsilon_{ik}(n)$ follows a Type I extreme value distribution with spread parameter β_k. This distribution has a mode of λ_{jk} and $E[log(A_{jk})] = \lambda_{jk} + \beta_k * \gamma$, where γ is a constant.

Using the assumption of perfect competition and the properties of the extreme value distribution it can be shown that exports of country j to country i in sector k as a fraction of $i's$ sectoral absorption are given by Π_{ijk}, the probability that country j is the lowest cost supplier for a variety

n in sector k to country i.[29]

$$\frac{M_{ijk}}{\sum_{j\in J} M_{ijk}} = \Pi_{ijk} = \frac{\left[\prod_{f\in F}\left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}}\tau_{ijk}\right]^{-1/\beta_k} exp(1/\beta_k\lambda_{jk})}{\sum_{j\in J}\left[\prod_{f\in F}\left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}}\tau_{ijk}\right]^{-1/\beta_k} exp(1/\beta_k\lambda_{jk})} \tag{40}$$

Consequently, normalizing with imports from the US,

$$\frac{M_{ijk}}{M_{iUSk}} = \frac{\Pi_{ijk}}{\Pi_{iUSk}} = \frac{\left[\prod_{f\in F}\left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}}\tau_{ijk}\right]^{-1/\beta_k} exp(1/\beta_k\lambda_{jk})}{\left[\prod_{f\in F}\left(\frac{w_{fUS}}{\alpha_{fk}}\right)^{\alpha_{fk}}\tau_{iUSk}\right]^{-1/\beta_k} exp(1/\beta_k\lambda_{USk})}. \tag{41}$$

Taking logs, we obtain

$$log(\frac{M_{ijk}}{M_{iUSk}}) = 1/\beta_k(\lambda_{jk} - \lambda_{USk}) - 1/\beta_k \sum_{f\in F}\alpha_{fk} log(\frac{w_{fj}}{w_{fUS}}) - 1/\beta_k log(\frac{\tau_{ijk}}{\tau_{iUSk}}). \tag{42}$$

Then we have $E(\frac{log(A_{jk})}{log(A_{USk})}) = \lambda_{jk} - \lambda_{USk}$. [30]

The main difference between this specification and our model is that it requires no information on exporters' production. Relative exports depend exclusively on the relative probabilities of offering varieties in the importing market at the lowest cost, which depends only on bilateral variables, factor prices and productivity.

To obtain productivity estimates from this model, we can either calibrate it by using information on the spread parameter β_k from other studies, or estimate it using our two step procedure.

When trying to estimate the equations with a two stage procedure analogous to (20), (21), many of the coefficients of relative factor prices have the wrong sign, so this specification seems to

[29] For the derivations, see Eaton and Kortum (2002) or Chor (2006).

[30] Note that this is an estimate of the underlying technology parameter and not directly of realized TFP, which is the average productivity of active firms only.

be performing poorly. Alternatively, we can do our hybrid calibration and estimation exercise of first constructing raw productivities and then regressing these on bilateral variables. In order to do so, we require estimates of β_k. Chor reports an aggregate value of β of around 12.41^{-1}, Eaton and Kortum estimate β to lie between 2.44^{-1} and 12.86^{-1}. While the relative order of countries is meaningful for any β, the absolute size of productivity differences is very sensitive to the choice of β. Choosing a β of 12.41^{-1} (Chor's estimate) gives productivity estimates, that are very similar to the ones obtained with our model[31], while when setting β equal to 2.44^{-1}, productivity differences explode.

Hence, the Eaton-Kortum model seems to be a good alternative for estimating sectoral productivities. Its main advantage is that it does not require information on production, the drawback is that one has to estimate a sectoral spread parameter that is hard to pin down.

6.6 Trade in Intermediates

In this section we study how our results are affected by the existence of trade in intermediate goods. Ethier (1982), Rivera-Batiz and Romer (1991) and others formalize the idea that having access to more varieties of differentiated intermediate goods through trade may boost sectoral productivity. This feature can easily be incorporated into our framework. We modify the production function in a way such that firms use not only capital and different labor types but also varieties of differentiated intermediates produced by other firms (and potentially in other countries) as inputs. The cost

[31] The correlation is 0.89. See table 5 for correlations and rank correlations by sector.

function now becomes

$$TC(q_{ik}) = (f_{ik} + q_{ik})\frac{1}{A_{ik}}\left[\prod_{f\in F}\left(\frac{w_{fi}}{\alpha_{fk}}\right)^{\alpha_{fk}}\right]^{1-\beta_k}\left[\prod_{k'=1}^{K}\left(\sum_{b\in B_{ik'}}\hat{p}_{bk'}^{1-\epsilon_{k'}}\right)^{\frac{\sigma_{k'}}{1-\epsilon_{k'}}}\right]^{\beta_k}, \tag{43}$$

where $\sum_{k'=1}^{K}\sigma_{k'} = 1$ and $\epsilon_{k'} > 1$. Firms in sector k are assumed to spend a fraction $\sigma_{k'}\beta_k$ of their revenues on a CES aggregate of differentiated intermediate inputs produced by sector k' with elasticity of substitution $\epsilon_{k'}$.

Demand for intermediates by firms from sector k in country i for sector k' intermediates produced in country j can be found applying Shepard's Lemma to (43),

$$x_{ijkk'} = \frac{\hat{p}_{ijk'}^{-\epsilon_{k'}}\sigma_{k'}\beta_k N_{ik} TC(q_{ik})}{P_{ik}^{1-\epsilon_{k'}}}. \tag{44}$$

These demand functions can be easily aggregated over sectors k and combined with consumers' demand for varieties to get total bilateral demand for sector k' varieties. Hence, trade in intermediates does not change the value of imports from country j relative to those from the US, nor does it affect the functional form of our raw productivity measure relative to the US, (14).

Since we do not explicitly take into account that firms use intermediates our measured productivity is $\breve{A}_{jk} \equiv A_{jk}\left[\prod_{k'}\left(\sum_{b\in B_{jk}}\hat{p}_b^{1-\epsilon_{k'}}\right)^{\frac{\sigma_{k'}}{1-\epsilon_{k'}}}\right]^{\beta_k}$. This implies that in countries and sectors where more varieties of intermediates are available and intermediates are cheaper on average, measured productivity is higher.

6.7 Varying Factor Income Shares

In our modelling procedure we have assumed that sectoral factor income shares do not vary across countries in order to be able to use the values of the US for these parameters. In this section we investigate the effects of violating this assumption. For concreteness, let us focus on skilled labor shares. Suppose $\alpha_{kjs} = \alpha_{kUSs} + \nu_{jk}$. Then with some manipulations productivities can be written as[32]

$$E\left[log(\frac{A_{ijk}}{A_{iUSk}}|actual)\right] \approx E\left[log(\frac{A_{ijk}}{A_{iUSk}}|measured)\right] + E(\nu_{jk})log(\frac{w_{sj}}{w_{uj}}) + \quad (45)$$

$$E(\nu_{jk})(1 - \alpha_{kUSs} - \alpha_{kUScap}) + E[\nu_{jk}(\nu_{jk} - \alpha_{kUSs} - \alpha_{kUScap})].$$

Consequently, if the intensity differences are random, i.e. ν_{jk} is i.i.d. with $E(\nu_{jk}) = 0$ and $Var(\nu_{jk}) = \sigma_{jk}$, we get $E\left[log(\frac{A_{ijk}}{A_{iUSk}}|actual)\right] = E\left[log(\frac{A_{ijk}}{A_{iUSk}}|measured)\right] + \sigma_{jk}$. Hence, on average we tend to overestimate productivities in those sectors and countries that have very - but not systematically - different factor input ratios than the US. Since this kind of measurement error is more likely to occur in poor countries, it may lead to overestimation of poor countries' productivities in specific sectors.

If poor countries have a systematically larger wage bill for skilled labor than the US in more skill intensive sectors, we tend to predict systematically lower productivities of poor countries in skill intensive sectors. To see this, assume $E(\nu_{jk}) = \overset{(+)}{f}(\alpha_{sUS})$ Then the bias is negative, provided that the only negative term $-(\alpha_{kUSs} + \alpha_{kUScap})E(\nu_{jk})$ does not dominate the other terms, which

[32] To derive this, substitute the definition of skilled labor shares in (13), divide by the value of the US, take logs, simplify and use $log(1 + x) \approx x$.

are all positive. This case seems unlikely to occur in reality. If there is skill biased technological change, such that the gap in the wage share of skilled labor between rich and poor countries is larger in more skill intensive sectors, it should be the other way round - namely that we tend to overestimate the productivity of poor countries in skill intensive sectors. The intuition is that in this case we overestimate the cost of skilled labor inputs in poor countries, which have on average higher skill premia than rich ones.

7 Productivity Differences and Theories of Development

In this section we apply our productivity estimates to test a number of development theories that have implications for sectoral productivity differences across countries. At a deeper level differences in sector productivities reflect differences in institutions, (in)adequate technology or decisions of technology adoption, which affect the efficiency with which production is undertaken differentially across sectors.

A first application is to relate our productivity estimates to spending on research and development (R&D). In the presence of knowledge externalities relative productivity levels are related to expenditure on R&D (see, for example Klenow and Rodriguez-Clare (2005)). If the US is on the world's technology frontier and knowledge is sector specific, sectoral R&D expenditure in the US indicates how fast new knowledge is created in a sector. When a country spends less on R&D than the US and sectoral spending is proportional to aggregate spending, technology gaps should be larger in those sectors where more R&D is performed in the US. We measure sectoral R&D intensity with information on total private sectoral R&D expenditure in the US in 1995 (from the National Science Foundation) as a fraction of sectoral value added (from our dataset). We use the

Lederman and Saenz (2005) database for information on R&D expenditure per capita. Column one of table 6 shows the result of regressing relative sectoral productivities on the interaction of R&D intensity and R&D expenditure per capita relative to the US.[33] controlling for sector and country fixed effects. The variable has a large positive effect on relative productivity and is significant at the one percent level.[34]

Next, we relate our sectoral productivities to factors that affect the efficiency of the organization of production differentially across sectors. One such factor is the quality of a country's contracting environment that has a different effect on sector productivity depending on how relationship specific investments are (see Acemoglu et al. (2007), Nunn (2007)). If the contracting environment is poor and inputs a taylored to a specific firm, this gives rise to a hold up problem and consequently leads to too little investment in the project by suppliers of intermediates, which increases the costs for specific inputs and lowers sectoral productivity. Hence, relative productivities should be lower in sectors that rely a lot on differentiated intermediate inputs if enforcing contracts is difficult in a country. Nunn (2007) uses a trade model to show empirically that the interaction between contract enforcement and relationship specificity affects countries' comparative advantage. We follow Nunn in using 'rule of law' from Kaufmann et al. (2003) as a measure for contract enforcement and we use data that measure what fraction of intermediate inputs is relationship specific from Nunn. He constructs this measure by using information whether a product is sold on an organized exchange, or reference priced in trade publications. We test whether our sectoral productivity differences reflect differentials in the contracting environment by regressing them on the interaction of 'rule of law' and relationship specificity. Column two of table 6 provides the results of this regression, controlling

[33]Results are robust to using relative R&D expenditure as a fraction of GDP instead.

[34]Since the dependent variable is estimated, we bootstrap all standard errors in this section.

for sector and country effects. Indeed, relative productivities in relationship intensive sectors are significantly (at the one percent level) larger in countries that have good contract enforcement.

A further application is to relate our sectoral productivities to financial development. In a seminal article Rajan and Zingales (1998) show that industries, which are more dependent on external finance, grow faster in more financially developed countries, while Beck (2003) relates financial development to comparative advantage. Here, we test whether relative productivities in sectors that rely a lot on external financing are lower in those countries that have less developed financial sectors because firms are credit constrained. To proxy for the tightness of credit constraints, we use the fraction of investment that cannot be financed from internal cash flow from Rajan and Zingales and interact it with financial development of the country measured as private credit as a fraction of GDP in 1995 from Beck et al. (2000). We use this as an regressor for our sectoral productivities, again controlling for sector and country fixed effects. Looking at column three of table 6, we find that financial development has a significantly (at the one percent level) positive effect on relative productivities in sectors that depend more on outside finance.

At this point we relax the assumption that the fixed costs are the same across countries. Instead, we assume that $f_{jk} = f_j f_k$. Let us have a look at the definition of raw productivity given this new assumption on fixed costs.

$$\log\left(\frac{\tilde{A}_{ijk}}{\tilde{A}_{i,US,k}}\right) = \log\left(\frac{A_{jk}}{A_{US,k}}\right) - 1/\epsilon_k \log\left(\frac{f_j}{f_{US}}\right) + \frac{1-\epsilon_k}{\epsilon_k}\log\left(\frac{\tau^i_{jk}}{\tau^i_{US,k}}\right). \tag{46}$$

We see that the smaller ϵ_k, the more a higher country specific fixed cost to produce should lower our raw productivity measure. The reason for this is the following: if relative fixed costs differ across countries, this will influence the number of firms that enter in a given sector. In particular, a higher fixed cost implies less entry. Consequently, for countries with higher fixed costs we overestimate the number of firms and thus underestimate true productivity. Hence raw productivity, which also includes relative fixed costs is too large because the true productivity is raw productivity plus the adjustment for the difference in fixed costs. In addition, the smaller ϵ_k, the more consumers value variety in that sector and the larger is the mistake in the number of firms if we do not consider differences in fixed costs. To proxy for differences in fixed costs across countries we use the Djankov et al. (2002) measure of firm setup costs as a fraction of per capita income relative to the US[35] and interact it with $1/\epsilon_k$, expecting a negative sign in a regression of this variable on sectoral productivities. Column four of table 6 shows the result of this regression, controlling for sector and country effects. Higher entry costs have a larger negative effect on relative productivities in sectors in which variety is valued more. However, this variable just fails to be significant at the 10% level.

Finally, in column five of table 6 we test all the previous theories jointly. We note that our measures of contractual dependence, financial dependence and R&D dependence, while dropping somewhat in magnitude, remain positive and significant at the 1 (10%) level. The business setup cost variable, on the other hand, has the wrong sign and becomes completely insignificant.

Another potential application is adequateness of technology. Acemoglu and Zilibotti (2001) develop a model in which there is a mismatch between the skill requirements of frontier technologies and poor countries' endowments of skilled and unskilled labor. Their model predicts that - since technology is developed to optimally complement the skill endowments of the industrialized coun-

[35]Results are robust to using setup cost measured as business days required to start a business.

tries - productivity gaps between rich and poor countries are largest in sectors with intermediate skill intensities. The idea is that in those sectors rich countries employ skilled workers using a skill complementary technology, while poor countries use unskilled workers and labor intensive technologies. The authors are not able to test this prediction of their model since they lack a measure of sectoral TFP which is not contaminated by differences in sectoral prices across countries.[36]

In a first attempt to scrutinize their prediction that productivity differentials between rich and poor countries should be largest in sectors with intermediate skill intensity, we divide our sample in two parts: developing countries (with a per capita GDP below 8000 International Dollars in 1995[37]) and industrialized countries. Figure 7 plots the average sector productivity for rich relative to poor countries against sectoral skill intensity, α_{ks}. We see that in general productivity gaps tend to be larger in skill intensive sectors than in unskill intensive ones and that the relationship seems to be nonlinear. The productivity differences in the most skill intensive sectors are slightly smaller than in sectors with intermediate skill intensity.

To more formally address this issue, we regress $\log(\frac{A_{jk}}{A_{USk}})$ on skill intensity, the square of the same variable, to allow for a nonlinear relationship, capital intensity and its square, controlling for country specific effects. We run this regression separately for developing and developed countries. For the sample of developing countries there is indeed a very significant nonlinear relationship that gives us a mostly negative relation between the relative sectoral TFP of developing countries and the sectoral skill intensity. Moving from the 10th to the 90th percentile of skill intensity reduces sectoral productivity of developing countries relative to the US by roughly 8.5%.

[36]They compute a TFP measure that uses value added as an output measure. Their model predicts that for this measure, which includes differences in prices, "TFP" differences should be larger in *un*skill intensive sectors, because labor intensive goods are relatively cheaper in developing countries. They provide some evidence for this prediction.

[37]Results are robust to choosing other income values to split the sample.

Note that also for capital intensities productivity differences seem to be somewhat smaller in more capital intensive sectors. Repeating the same regression for the sample of developed countries, we find no systematic relationship between productivity differences and skill or capital intensity at all. As a next step we use the whole sample and include an interaction term between per capita income and skill intensity as well as capital intensity. This term is expected to be positive, since skill intensity should matter only for poor countries. Indeed, we find that the interaction term between income per capita and skill intensity is strongly positive and significant, while the interaction between income per capita and capital intensity is insignificant. Hence, we conclude that relative sectoral productivities are systematically lower in skill intensive sectors in developing countries but not in industrialized ones, while productivity differences in capital intensive sectors relative to the US tend to be lower for both poor and rich countries. Overall, the patterns of productivity differences do not provide much support for the Acemoglu and Zilibotti (2001) version of the adequate technology hypothesis which predicts that the technology skill mismatch should cause the largest productivity differences in sectors with intermediate skill intensity.

An alternative theory on human capital intensity and sectoral productivity differences related to technology adoption that is in line with the patterns in our data is due to Ciccone and Papaioannou (2007). They develop a model in which an initially higher level of human capital helps to adopt technology faster in skill intensive sectors and leads to faster growth of productivity and output in those sectors because new technologies are skill biased. To test for this we use their dataset and regress sectoral TFP growth (relative to the US) between the mid-eighties and the mid-nineties on the interaction of the initial level of human capital and sectoral human capital intensity, controlling for the initial relative level of productivity, an interaction of the initial physical capital level and physical capital intensity, an interaction of contract intensity and the quality of the contracting institutions and an interaction of financial dependence and financial development, as well as sector and country fixed effects.[38] We find that initially higher levels of human capital indeed lead to higher subsequent TFP growth in human capital intensive sectors and in addition initially higher levels of physical capital lead to higher TFP growth in physical capital intensive sectors. Both effects are significant at the 1% level. [39]

8 Conclusion

In this paper we have estimated sectoral manufacturing total factor productivities (TFP) for more than sixty countries at all stages of development by using information contained in bilateral sectoral trade data. To this end we have derived structural estimation equations from a Hybrid-Ricardo-Heckscher-Ohlin model with transport costs. Differences in sectoral TFP have been estimated as observed trade that cannot be explained by differences in factor intensities and factor prices or by differences in trade barriers across countries. The main advantage of our methodology is that it allows us to overcome severe data limitations which render the application of traditional methods for TFP computations which rely on information on sectoral inputs and outputs in physical units unfeasible for virtually all developing countries. To compute sectoral productivities, we only need data on bilateral trade, aggregate factor prices and (depending on the model) sectoral production values.

Our results show that productivity differences in manufacturing sectors are large and system-

[38] For a detailed description of the data see their dataset.

[39] While Ciccone and Papaioannou (2007) obtain similar results using output growth and employment growth as dependent variables, they are not able to test whether their channel really works through TFP growth, which we confirm here. In their regressions the physical capital interaction is mostly insignificant.

atically related to income per capita. In addition, productivity variation between rich and poor countries is more pronounced in skill and R&D intensive sectors. Some poor countries have higher productivities than the US in a small set of sectors. Moreover, our methodology permits to compute bilateral rankings of comparative advantage that are due to productivity for any country pairs.

We perform a series of robustness checks and show that productivity estimates are neither very sensitive to the specific estimation method, nor to the particular trade model we used in deriving our structural estimation equations.

Finally, we relate our productivity estimates to a number of theories on productivity differences, like adequate technology, financial development or contract enforcement that have predictions for the variation of sectoral productivities across countries and show that there is a strong correlation between variation in sectoral TFP and proxies for the above factors. Moreover, we show that allowing for Ricardian productivity differences is important to explain bilateral trade data.

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Appendix

A Data Description

Bilateral sectoral trade data, M_{ijk}, and sectoral production, $Output_{jk}$, are obtained from the from the World Bank's Trade, Production and Protection database. This dataset merges trade flows and production data from different sources into a common classification: the International Standard Industrial Classification (ISIC), Revision 2. The database potentially covers 100 developing and developed countries over the period 1976-2004. We use trade and production data for the periods 1984-1986, 1994-1996 and 2002-2004, considering 36 importing countries and 64 exporting countries. The 36 importers represent more than $\frac{2}{3}$ of world imports[40]. To mitigate problems of data availability and to smooth the business cycle, we average the data over three years. We exclude, tobacco (314), petroleum refineries (353), miscellaneous petroleum and coal products (354) and other manufactured products not classified elsewhere (390) from the 28 sectors in the ISIC classification because trade data do not properly reflect productivity in those sectors.

For the monetary value of production, $Output_{jk}$, we use information on Gross Output from the Trade, Production and Protection database [41]. The original source of this variable is the United Nations Industrial Development Organization's (UNIDO) Industrial Statistics. For the years 1994-1996 some data have been updated by Mayer and Zignago (2005) [42]. The production data published by UNIDO is by no means complete, and that is the main limitation in computing productivities

[40] We have to exclude US as an importer country because we use them as our benchmark country. The countries represent more than 80% of the remaining imports.

[41] Gross Output represents the value of goods produced in a year, whether sold or stocked. It is reported in current dollars. Our results are robust to using Value Added instead.

[42] They have updated a previous version of the Trade and Production Database. As in the latest version of the Trade, Production and Protection Database, data from years 94-96 remain the same, the Mayer & Zignago database of 2005 is more complete than the Nicita & Olarreaga database of 2006.

[43]. UNIDO also collects data on establishments that we could have used directly, instead using Gross Output data. However, these data are less reliable than production data because different countries use different threshold firm sizes when reporting data to the UNIDO[44].

Sectoral elasticities of substitution, ϵ_k, are obtained from Broda and Weinstein (2006). They construct elasticities of substitution across imported goods for the United States at the Standard International Trade Classification (SITC) 5 digit level of disaggregation for the period 1990-2001. We transform those elasticities to our 3 digit ISIC rev. 2 level of disaggregation by weighting elasticities by US import shares.

Factor intensities, $(\alpha_{ku}, \alpha_{ks}, \alpha_{kcap})$, are assumed to be fixed across countries. This assumption allows us to use factor income share data for just one country, namely the US. To proxy for skill intensity, we follow Romalis (2004), in using the ratio of non-production workers to total employment, obtained from the NBER-CES Manufacturing Industry Database constructed by Bartelsman et al. (2000) and converting USSIC 87 categories to ISIC rev 2. Capital intensity is computed as one less the share of total compensation in value added, using the same source. In our three factor model intensities are re-scaled such that $\sum_i \alpha_{k,i} = 1; \qquad i = u, s, cap$[45].

Wages and rental rates at the country level are computed using the methodology exposed in Caselli (2005), Caselli and Coleman (2006) and Caselli and Feyrer (2006). The definition of the rental rate is consistent with a dynamic version of our model in which firms solve an inter-temporal maximization problem and capital markets are competitive[46]. Total payments to capital in country

[43] Besides this, we require exporting countries to export at least to 5 importing countries in any given sector during the relevant period.

[44] While the fact that some countries do not consider micro-firms, whereas others do does not change aggregate output numbers much, the number of establishments is indeed severely affected by this inconsistency. For a description of UNIDO's data issues see Yamada (2005).

[45] As in Romalis (2004), $\alpha_{k,cap} = cap.intensity$; $\alpha_{ks} = skill\ intensity * (1 - \alpha_{kcap})$ and $\alpha_{ku} = 1 - \alpha_{ks} - \alpha_{kcap}$

[46] Firms set the marginal value product equal to the rental rate, $p_{jk}MPK_{jk} = P_{Kj}(interest_j + \delta)$, where P_{Kj} is

j are $\sum_k p_{jk} MPK_{jk} K_k = p_j MPK_j \sum_k K_k = r_j K_j$ where K_j is the country $j's$ capital stock in physical units and the first equality follows from capital mobility across sectors. Since $\alpha_{j,cap} = \frac{r_j K_j}{P_Y Y}$, where Y is GDP in Purchasing Power Parities, the following holds.

$$r_j = \alpha_{j,cap} \frac{GDP_j}{K_j} \tag{A-1}$$

Capital stocks in physical units are computed with the permanent inventory method using investment data from the Penn World Table (PWT).[47]. GDP_j is also obtained from the PWT and is expressed in current dollars. $\alpha_{j,cap}$ is country j's aggregate capital income share. We compute the capital share as one minus the labor share in GDP, which we take from Bernanke and Gürkaynak (2002) and Gollin (2002). In turn, the labor share is employee compensation in the corporate sector from the National Accounts plus a number of adjustments to include the labor income of the self-employed and non-corporate employees.

Similarly, to compute the skilled and unskilled wages we use the the following result for the labor share:

$$(1 - \alpha_{j,cap}) = \frac{w_u U + w_u \frac{w_s}{w_u} S}{GDP_j} \tag{A-2}$$

The total labor share is equal to payments to both skilled and unskilled workers relative to GDP. Skilled and unskilled workers are expressed in efficiency units of non-educated workers and

the price of capital goods in country j, $interest_j$ is the net interest rate in country j and δ is the depreciation rate. This can be seen considering the decision of firms in sector k in country j to buy an additional unit of capital. The return from such an action is $\frac{p_{jk}(t) MPK_{jk}(t) + P_{Kj}(t+1)(1-\delta)}{P_{Kj}(t)}$. Abstracting from capital gains, firms will be indifferent between investing an additional dollar in the firm or in an alternative investment opportunity that has a return $interest_j$, when the above relationship holds. Because capital is mobile across sectors within a country the marginal value product must be equalized across sectors.

[47] For details see Caselli (2005)

workers with complete secondary education.[48]. Thus,

$$U = L_{noeduc} + e^{\beta * \frac{prim.dur.}{2}} L_{prim.incomp.} + e^{\beta * prim.dur.} L_{prim} + e^{\beta * lowsec.dur.} L_{lowsec.} \tag{A-3}$$

and

$$S = L_{secondary} + e^{2\beta} L_{ter.incomp.} + e^{4\beta} L_{tertiary} \tag{A-4}$$

Educational attainment of workers over 25 years at each educational level are taken from Barro and Lee (2001) and Cohen and Soto (2001). Information on the duration of each level of schooling in years by country is provided by the UNESCO[49]. Skill premia β by country are obtained from Bils and Klenow (2000) and Banerjee and Duflo (2005). The wage premium $\frac{w_{skill}}{w_u}$ equals $e^{\beta*(prim.dur.+lowsec.dur.)}$. The panels of figure 8 plot the computed skilled and unskilled wages, the wage premium, the capital stock per worker and the rental rate for the countries against log income per worker for the mid-nineties. We observe that although wages of both skilled and unskilled workers are much higher in rich countries, the wage premium is negatively related with income per worker, which gives rich countries a relative advantage in skilled labor intensive sectors. The relation between the rental rate and income per worker is slightly positive. The absence of a strong relationship between the marginal product of capital and income per worker is similar to Caselli and Feyrer (2006) once they correct for price differences and natural capital. Although we do not adjust for the fraction of income that goes to natural capital in our three factor model, we do

[48] Changing the base of skilled workers from completed secondary to completed primary, incomplete secondary or incomplete tertiary education does not alter the results significantly. Further details about the construction of the wages and rental rates can be found in the referenced papers of Caselli.

[49] Notice that for non-complete levels, we assume that workers have half completed half of the last level (except when we have data of lower secondary duration). For tertiary education we consider a duration of 4 years given lack of data for most of the countries

correct for the price level of GDP.

To compute the productivity measures, we also require a number of bilateral variables commonly used in gravity-type regressions. We take them from two sources: Rose (2004) and Mayer and Zignago (2005). We include bilateral distance from the latter, who have developed a distance database which uses city-level data in the calculation of the distance matrix to assess the geographic distribution of population inside each nation. The basic idea is to calculate the distance between two countries based on bilateral distances between cities weighted by the share of each city in the overall country's population. CEPII also provides a bilateral sectoral tariff database. Tariffs are measured at the bilateral level and for each product of the HS6 nomenclature in the TRAINS database from UNCTAD. Those tariffs are aggregated from TRAINS data in order to match the ISIC Rev.2 industry classification using the world imports as weights for HS6 products.

For the TFP computed as Solow residuals from the OECD STAN database we proceed as follows. Capital stocks are computed with the perpetual inventory method using sectoral gross fixed capital formation from the STAN database[50]. Investment is transformed into international dollars using exchange rates and price indices for investment from the Penn World Table. Finally, we transform investment into constant dollars using a deflator for US fixed nonresidential investment from the BEA National Income and Product Accounts. Labor inputs are constructed from STAN sectoral employment data which we transform to efficient labor by using information on human capital per worker from Caselli (2005). Our output measure is sectoral value added (from STAN).

[50] For consistency reasons we use a depreciation rate of 6%.

B A Two Country General Equilibrium Model

In this section we present a two country general equilibrium version of the model we estimate in the paper which is based on Romalis (2004). Several features of the model in this section are more restrictive than the model estimated in the main text. These assumptions are just made to simplify the exposition and do not affect the basic results of the model.

There are two countries, Home and Foreign ($*$). Transport costs are allowed to be sector specific and asymmetric and are denoted by τ_k and τ_k^*. We assume in this section that there are only two factors of production, capital, K and labor, L The total number of varieties in each sector at the world level is $N_k = n_k + n_k^*$.

It follows from (4) that the Home price index in sector k is defined as

$$P_k = \left[n_k p_k^{1-\epsilon_k} + n_k^* (p_k^* \tau^*)^{1-\epsilon_k}\right]^{\frac{1}{1-\epsilon_k}}. \tag{A-5}$$

A similar expression holds for the Foreign price index.

The revenue of a Home firm is given by the sum of domestic and Foreign revenue and using the expressions for Home and Foreign demand (3), we get

$$p_k q_{jk} = \sigma_k Y \left(\frac{p_k}{P_k}\right)^{1-\epsilon_k} + \sigma_k^* Y^* \left(\frac{p_k \tau_k}{P_k^*}\right)^{1-\epsilon_k}. \tag{A-6}$$

An analogous expression applies to Foreign Firms.

Given the demand structure firms optimally set prices as a fixed mark up over their marginal cost.

$$p_k = \frac{\epsilon_k}{\epsilon_k - 1} \frac{1}{A_{jk}} \left(\frac{w_j}{1-\alpha_k} \right)^{1-\alpha_k} \left(\frac{r_j}{\alpha_k} \right)^{\alpha_k} \tag{A-7}$$

Since firms can enter freely, in equilibrium they make zero profits and price at their average cost. Combining this with (A-7), it is easy to solve for equilibrium firm size, which depends positively on the fixed cost and the elasticity of substitution.

$$q_{jk} = q_k = f_k(\epsilon_k - 1) \tag{A-8}$$

Let us now solve for partial equilibrium in a single sector. For convenience, define the relative price of Home varieties in sector k, to be $\tilde{p}_k \equiv \frac{p_k}{p_k^*}$ and the relative fixed cost in sector k as $\tilde{f}_k \equiv \frac{f_k}{f_k^*}$.

Dividing the Home market clearing condition by its Foreign counter part, one can derive an expression for $\frac{n_k}{n_k^*}$, the relative number of home varieties in sector k.

A sector is not necessarily always located in both countries. In fact, if Home varieties are too expensive relative to Foreign ones, Home producers may not be able to recoup the fixed cost of production and do not enter this sector at Home.

Consequently, if $\tilde{p} \geq \underline{p}_k$, we have that $n_k = 0$ and $n_k^* = \frac{\sigma_k(Y+Y^*)}{f_k^*(\epsilon_k - 1)}$, while if $\tilde{p} \leq \underline{p}_k$, the whole sector is located in Home, $n_k = \frac{\sigma_k(Y+Y^*)}{f_k(\epsilon_k-1)}$ and $n_k^* = 0$.

For intermediate relative prices of Home varieties sectoral production is split across both countries, and the relative number of home varieties is given by the following expression

$$\frac{n_k}{n_k^*} = \frac{[\sigma_k Y(\tilde{p}_k \tilde{f}_k - \tilde{p}_k^{1-\epsilon_k}(\tau_k^*)^{\epsilon_k - 1}) + \sigma_k^* Y^*(\tilde{p}_k \tilde{f}_k - \tilde{p}_k^{1-\epsilon_k}\tau_k^{1-\epsilon_k})]}{[\sigma_k^* Y^* \tilde{p}_k^{1-\epsilon_k}(\tau_k^*)^{\epsilon_k - 1}(\tilde{p}_k \tau_k^{1-\epsilon_k} - \tilde{p}_k \tilde{f}_k) - \sigma_k Y \tilde{p}_k^{1-\epsilon_k} \tau_k^{1-\epsilon_k}(\tilde{p}_k \tilde{f}_k - \tilde{p}_k^{1-\epsilon_k}(\tau_k^*)^{\epsilon_k - 1})]} \tag{A-9}$$

for $\tilde{p}_k \in (\underline{p}_k, \bar{p}_k)$, where

$$\underline{p}_k = \left[\frac{(\sigma_k^* Y^* + \sigma_k Y)(\tau_k^*)^{\epsilon_k - 1} \tau_k^{1-\epsilon_k}}{\sigma_k Y \tau_k^{1-\epsilon_k} \tilde{f}_k + \sigma_k^* Y^* (\tau_k^*)^{\epsilon_k - 1} \tilde{f}_k} \right]^{1/\epsilon_k} \tag{A-10}$$

and

$$\bar{p}_k = \left[\frac{\sigma_k^* Y^* \tau^{1-\epsilon_k} + \sigma_k Y (\tau_k^*)^{\epsilon_k - 1}}{\tilde{f}_k \sigma_k^* Y^* + \tilde{f}_k \sigma_k Y} \right]^{1/\epsilon_k}. \tag{A-11}$$

Defining the Home revenue share in industry k as $v_k \equiv \frac{n_k p_k x_k^s}{n_k p_k x_k^s + n_k^* p_k^* x_k^{s*}}$ we can derive that $v_k = 0$ if $\tilde{p}_k \geq \bar{p}_k$. On the other hand, v_k is given by $\frac{1}{1+(\frac{n}{n^*})^{-1}\tilde{p}^{-1}\tilde{f}^{-1}}$if $\tilde{p}_k \in (\underline{p}_k, \bar{p}_k)$ and finally $v_k = 1$ if $\tilde{p}_k \leq \underline{p}_k$.

The model is closed by substituting the pricing condition (6) into $\tilde{p}$ and the expressions for v_k in the factor market clearing conditions for Home and Foreign.

$$\sum_{k=1}^{K} (1 - \alpha_k) v_k \sigma_k (Y + Y^*) + (1 - \alpha_{NT}) \sigma_{NT} Y = wL \tag{A-12}$$

$$\sum_{k=1}^{K} \alpha_k v(k) \sigma_k (Y + Y^*) + \alpha_{NT} \sigma_{NT} Y = rK \tag{A-13}$$

$$\sum_{k=1}^{K} (1 - \alpha_k)(1 - v_k) \sigma_k (Y + Y^*) + (1 - \alpha_{NT}) \sigma_{NT} Y^* = w^* L^* \tag{A-14}$$

$$\sum_{k=1}^{K} \alpha_k (1 - v_k) \sigma_k (Y + Y^*) + \alpha_{NT} \sigma_{NT} Y^* = r^* K^* \tag{A-15}$$

Here σ_{NT} is the share of expenditure spent on non-tradable goods. Normalizing one relative factor price, we can use 3 factor market clearing conditions to solve for the remaining factor prices.

One can show that the home revenue share in sector k, v_k, is decreasing in the relative price of home varieties $\tilde{p}_k$. This implies that countries have larger revenue shares in sectors in which they can produce relatively cheaply. Cost advantages may arise both because a sector uses the relatively cheap factor intensively and because of high relative sectoral productivity.

B.1 Romalis' Model

In the special case in which sectoral productivity differences are absent, $\frac{A_k}{A_k^*} = 1$ for all $k \in K$, relative fixed costs of production are equal to one, $\tilde{f}_k = 1 \, \forall \, k \in K$, sectoral elasticities of substitution are the same in all sectors, $\epsilon_k = \epsilon$, trade costs are symmetric and identical across sectors $\tau_k = \tau_k^* = \tau$ and preferences are identical, $\sigma_k = \sigma_k^*$, the model reduces to Romalis (2004) model.

In his framework, the relative price of home varieties, $\tilde{p}_k = \frac{\left(\frac{w}{1-\alpha_k}\right)^{1-\alpha_k}\left(\frac{r}{\alpha_k}\right)^{\alpha_k}}{\left(\frac{w^*}{1-\alpha_k}\right)^{1-\alpha_k}\left(\frac{r^*}{\alpha_k}\right)^{\alpha_k}}$, is decreasing in the capital intensity, α_k, if and only if Home is relatively abundant in capital, i.e. $\frac{K}{L} > \frac{K^*}{L^*}$.

Factor prices are not equalized across countries because of transport costs, which gives Home a cost advantage in the sectors that use its abundant factor intensively. This in turn leads to a larger market share of the Home country in those sectors as consumers shift their expenditure towards the relatively cheap home varieties. This is the intuition for the Quasi-Heckscher-Ohlin prediction that countries are net exporters of those goods which use their relatively abundant factor intensively. The main advantage of this model is that it solves the production indeterminacy present in the standard Heckscher-Ohlin model with more goods than factors whenever countries are not fully specialized and that it provides a direct link between factor abundance and sectoral trade patterns. This makes it ideal for empirical applications.

B.2 A Ricardian Model

If we make the alternative assumption that all sectors use labor as the only input, i.e. $\alpha_k = 0$ for all $k \in K$ and we order sectors according to home comparative advantage, such that $\frac{A_k}{A_k^*}$ is increasing in k, we obtain a Ricardian model. The advantage of this model is that because of love for variety, consumers are willing to buy both Home and Foreign varieties in a sector even when they do not have the same price. The setup implies that $\tilde{p}_k = \frac{w}{w^*}\frac{A_k^*}{A_k}$ is decreasing in k, so that Home offers lower relative prices in sectors with higher k. Consequently, Home captures larger market shares in sectors with larger comparative advantage since v_k is decreasing in $\tilde{p}_k$ and $\tilde{p}_k$ is decreasing in $\frac{A_k}{A_k^*}$.

B.3 The Hybrid Ricardo-Heckscher-Ohlin Model

In the more general case comparative advantage is both due to differences in factor endowments and due to differences in sectoral productivities. Note that $\tilde{p}_k$ is given by the following expression:

$$\tilde{p}_k = \frac{\frac{1}{A_k}\left(\frac{w}{1-\alpha_k}\right)^{1-\alpha_k}\left(\frac{r}{\alpha_k}\right)^{\alpha_k}}{\frac{1}{A_k^*}\left(\frac{w^*}{1-\alpha_k}\right)^{1-\alpha_k}\left(\frac{r^*}{\alpha_k}\right)^{\alpha_k}} \tag{A-16}$$

Assume again that Home is relatively capital abundant, $\frac{K}{L} > \frac{K^*}{L^*}$. Then, conditional on $\frac{w}{r}, \frac{w^*}{r^*}$, Home has lower prices and a larger market share in sectors where $\frac{A_k}{A_k^*}$ is larger. In addition, factor prices depend negatively on endowments unless the productivity advantages are systematically much larger in sectors that use the abundant factor intensively. A very high relative productivity in the capital intensive sectors can increase demand for capital so much that $\frac{w}{r} < \frac{w^*}{r^*}$ even though $\frac{K}{L} > \frac{K^*}{L^*}$. As long as this is not the case, locally abundant factors are relatively cheap and - holding constant productivity differences - this increases market shares in sectors that use the abundant factor intensively.

The model is illustrated in figure 9. In this example, $\epsilon_k = 4$, Home is relatively capital abundant, $\frac{K/L}{K^*/L^*} = 4$, and transport costs are high, $\tau_k = \tau_k^* = 2$. The panels of figure 9 plot Homes' relative productivity, Homes' sectoral revenue share, Homes' relative prices, as well as Homes' net exports, Homes' exports relative to production and Homes' imports relative to production against the capital intensity of the sectors, which is ordered on the zero-one interval. In the first case (solid lines) there are no productivity differences between Home and Foreign. Because Home is capital abundant it has lower rentals and higher wages which leads to lower prices and larger revenue shares in capital intensive sectors. In addition, Home is a net importer in labor intensive sectors and a net exporter in capital intensive ones and its exports relative to production are larger in capital intensive sectors, while its imports relative to production are much larger in labor intensive sectors. This illustrates neatly the Quasi-Heckscher-Ohlin prediction of the model.

In the second case (dashed lines) - besides being more capital abundant - Home also has systematically higher productivities in more capital intensive sectors. This increases home comparative advantage in capital intensive sectors even further. The consequence of higher productivity is an increased demand for both factors that increases home factor prices and makes home even less competitive in labor abundant sectors, while the relative price in capital abundant sectors is lower than without productivity differences. The result is a higher revenue share in capital intensive sectors and more extreme import and export patterns than without productivity differences.

Figure 10 is an example of the Quasi-Rybczynski effect. Initially both Home and Foreign have the same endowments, $\frac{K/L}{K^*/L^*} = 1$, and Home has a systematically higher productivity than Foreign in capital intensive sectors (solid lines), which explains Homes' larger market share in those sectors.

In the case with the dashed lines Home has doubled its capital stock, so that now $\frac{K/L}{K^*/L^*} = 2$. This leads to an expansion of production and revenue shares in the capital intensive sectors and a decline of production in the labor intensive sectors. The additional capital is absorbed both through more capital intensive production and an expansion of production in capital intensive sectors. The increased demand for labor in those sectors drives up wages and makes Home less competitive in labor intensive sectors.

Summing up, the general prediction of the Hybrid-Ricardo-Heckscher-Ohlin model is that exporting countries capture larger market shares in sectors in which their abundant factors are used intensively (Quasi-Heckscher-Ohlin prediction) and in which they have high productivities relative to the rest of the world (Quasi-Ricardian prediction). In addition, the model has a Quasi-Rybczynski effect. Holding productivities constant, factor accumulation leads to an increase in revenue shares in sectors that use the factor intensively and a decrease in those sectors that use little the factor.

ISIC REV. 2	Sector Name	Skill Intensity	Capital Intensity	Elasticity of Substitution
311	Food Products	0.24	0.77	5.33
313	Beverages	0.49	0.85	3.72
321	Textiles	0.15	0.59	3.27
322	Apparel	0.16	0.60	2.90
323	Leather Products	0.17	0.63	3.80
324	Footwear	0.15	0.60	3.29
331	Wood Products	0.17	0.59	8.38
332	Furniture	0.19	0.55	2.29
341	Paper And Products	0.23	0.72	4.72
342	Printing And Publishing	0.47	0.64	2.73
351	Industrial Chemicals	0.41	0.82	3.77
352	Other Chemicals	0.45	0.82	3.27
355	Rubber Products	0.22	0.62	3.80
356	Plastic Products	0.23	0.68	1.81
361	Pottery	0.18	0.57	3.26
362	Glass And Products	0.18	0.66	3.38
369	Other Non-Metallic	0.25	0.65	4.52
371	Iron And Steel	0.21	0.63	7.58
372	Non-Ferrous Metals	0.22	0.66	12.68
381	Fabricated Metals	0.25	0.56	3.54
382	Machinery, Non Electric.	0.35	0.62	4.19
383	Machinery, Electric.	0.35	0.70	3.39
384	Transport Equipment	0.32	0.62	3.86
385	Professional, Scientific	0.47	0.67	3.17
	MEAN	**0.27**	**0.66**	**4.28**

Table 1: INDUSTRY STATISTICS. Source: Own computations using data of Bartelsman et al (2000) and Broda & Weinstein (2006). Skill Intensity is defined as the ratio of non-production workers over total employment. Capital intensity is defined as 1 minus the share of total compensation in value added.

ISIC REV. 2	Sector	Difference Distance	Difference Tariff	Common Language	Common English	Common Border	Common Colony
311	Food Products	-0.277	-0.003	0.100	-0.104		0.235
		(0.012)	(0.001)	(0.033)	(0.023)		(0.053)
313	Beverages	-0.285	-0.003	0.179	-0.077	0.289	0.263
		(0.015)	(0.002)	(0.04)	(0.027)	(0.059)	(0.059)
321	Textiles	-0.404	-0.020	0.162	-0.101		0.233
		(0.014)	(0.002)	(0.033)	(0.023)		(0.053)
322	Apparel	-0.409	-0.037	0.132			0.417
		(0.014)	(0.002)	(0.033)			(0.054)
323	Leather Products	-0.307	-0.032	0.172			0.257
		(0.013)	(0.003)	(0.034)			(0.054)
324	Footwear	-0.304	-0.013	0.177	0.061	0.352	
		(0.016)	(0.002)	(0.038)	(0.029)	(0.062)	
331	Wood Products	-0.145	-0.020	0.104		0.118	
		(0.014)	(0.005)	(0.031)		(0.056)	
332	Furniture	-0.520	-0.098	0.251	-0.050	0.286	0.388
		(0.016)	(0.004)	(0.039)	(0.027)	(0.061)	(0.058)
341	Paper And Products	-0.366	-0.017	0.107			
		(0.013)	(0.003)	(0.034)			
342	Printing And Publishing	-0.394	-0.067	0.517	-0.441	0.242	0.467
		(0.014)	(0.005)	(0.036)	(0.025)	(0.057)	(0.056)
351	Industrial Chemicals	-0.356	-0.008	0.103	-0.128		0.139
		(0.012)	(0.003)	(0.035)	(0.024)		(0.054)
352	Other Chemicals	-0.387		0.300	-0.086		0.200
		(0.011)		(0.035)	(0.024)		(0.054)
355	Rubber Products	-0.288	-0.059	0.213	-0.066	0.125	
		(0.014)	(0.004)	(0.036)	(0.026)	(0.058)	
356	Plastic Products	-0.692	-0.064	0.474	-0.117	0.152	0.325
		(0.015)	(0.002)	(0.039)	(0.026)	(0.064)	(0.059)
361	Pottery	-0.306	-0.034	0.256			0.181
		(0.013)	(0.002)	(0.037)			(0.057)
362	Glass And Products	-0.404	-0.027	0.219		0.132	0.143
		(0.014)	(0.003)	(0.039)		(0.058)	(0.059)
369	Other Non-Metallic	-0.288	-0.022	0.107		0.133	
		(0.015)	(0.004)	(0.034)		(0.059)	
371	Iron And Steel	-0.193	-0.016				
		(0.013)	(0.005)				
372	Non-Ferrous Metals	-0.137	-0.014				
		(0.014)	(0.008)				
381	Fabricated Metals	-0.354	-0.038	0.183	-0.087		0.277
		(0.013)	(0.003)	(0.034)	(0.024)		(0.055)
382	Machinery, Non Electric	-0.264	-0.023	0.223	-0.113		0.211
		(0.012)	(0.004)	(0.033)	(0.023)		(0.054)
383	Machinery, Electric	-0.280	-0.042	0.250	-0.058	0.104	0.243
		(0.013)	(0.003)	(0.034)	(0.023)	(0.056)	(0.054)
384	Transport Equipment	-0.314	-0.034	0.155	-0.057		0.290
		(0.013)	(0.003)	(0.035)	(0.024)		(0.055)
385	Professional, Scientific	-0.240	-0.024	0.263	-0.143	0.108	0.270
		(0.014)	(0.003)	(0.037)	(0.025)	(0.057)	(0.057)
	Observations	42122					
	R-square	0.85					
	R-square within	0.52					
	ρ	0.8					

Table 2: PRODUCTIVITY Stepwise Regression. Panel with Fixed Country-Industry Effect. Robust Standard Deviation in parenthesis.

Country	Mean TFP	S.D.	Lowest TFP		Highest TFP	
ARG	0.45	0.25	Plastic	0.08	Food	1.21
AUS	0.87	0.29	Footwear	0.51	Textiles	1.61
AUT	1.05	0.24	Furniture	0.54	Apparel	1.55
BEL	1.10	0.27	Pottery	0.46	Other.Chemicals	1.51
BGD	0.14	0.10	Furniture	0.06	Plastic	0.45
BOL	0.29	0.24	Plastic	0.07	Pottery	1.21
BRA	0.51	0.20	Plastic	0.23	Food	1.04
CAN	0.70	0.14	Footwear	0.41	Paper	1.01
CHL	0.43	0.31	Plastic	0.11	Beverages	1.26
CHN	0.17	0.10	Transport	0.10	Plastic	0.55
CIV	0.36	0.19	Metal.Products	0.15	Food	0.90
COL	0.27	0.13	Plastic	0.08	Food	0.60
CRI	0.29	0.10	Plastic	0.09	Metals	0.52
CYP	0.64	0.22	Metal.Products	0.39	Transport	1.30
DNK	1.38	0.20	Glass	1.01	Rubber	1.68
ECU	0.27	0.13	Footwear	0.12	Food	0.61
EGY	0.27	0.10	Plastic	0.13	Metals	0.47
ESP	0.84	0.13	Plastic	0.56	Minerals	1.10
FIN	0.88	0.20	Footwear	0.37	Paper	1.23
FRA	0.95	0.16	Footwear	0.70	Beverages	1.52
GBR	0.92	0.17	Plastic	0.63	Beverages	1.47
GER	1.04	0.12	Footwear	0.72	Textiles	1.33
GHA	0.21	0.13	Metal.Products	0.08	Food	0.62
GRC	0.44	0.13	Other.Chemicals	0.28	Scientific.Equipm	0.71
GTM	0.39	0.18	Plastic	0.15	Apparel	0.81
HND	0.20	0.15	Metal.Products	0.09	Transport	0.71
HUN	0.36	0.08	Plastic	0.18	Apparel	0.50
IDN	0.33	0.20	Transport	0.16	Plastic	0.94
IND	0.17	0.12	Plastic	0.10	Furniture	0.60
IRL	1.17	0.24	Pottery	0.67	Other.Chemicals	1.56
ISL	0.89	0.29	Furniture	0.24	Iron.Steel	1.35
ISR	0.89	0.25	Pottery	0.47	Scientific.Equipm	1.45
ITA	1.18	0.18	Other.Chemicals	0.88	Apparel	1.50
JOR	0.23	0.10	Footwear	0.09	Rubber	0.45
JPN	0.78	0.25	Footwear	0.31	Rubber	1.27
KEN	0.13	0.07	Electrical.Mach	0.06	Food	0.27
KOR	0.54	0.14	Furniture	0.32	Rubber	0.86
LKA	0.21	0.07	Transport	0.11	Furniture	0.40
MAR	0.26	0.10	Metal.Products	0.14	Metals	0.48
MEX	0.42	0.14	Transport	0.24	Beverages	0.77
MUS	0.42	0.16	Furniture	0.21	Food	0.77
MYS	0.60	0.24	Minerals	0.36	Apparel	1.46
NGA	0.25	0.27	Metal.Products	0.08	Ind.Chemichals	1.05
NLD	1.43	0.15	Pottery	0.93	Beverages	1.61
NOR	1.12	0.28	Printing	0.56	Paper	1.50
PAK	0.17	0.17	Electrical.Mach	0.07	Apparel	0.75
PAN	0.32	0.08	Plastic	0.19	Ind.Chemichals	0.52
PER	0.27	0.18	Footwear	0.10	Food	0.83
PHL	0.27	0.13	Rubber	0.12	Furniture	0.72
PRT	0.63	0.14	Furniture	0.35	Beverages	0.97
ROM	0.12	0.04	Scientific.Equipm	0.07	Iron.Steel	0.21
SEN	0.32	0.22	Plastic	0.09	Apparel	0.86
SGP	1.24	0.30	Pottery	0.57	Footwear	1.69
SLV	0.54	0.22	Plastic	0.19	Pottery	1.19
SWE	1.22	0.22	Printing	0.84	Textiles	1.64
THA	0.26	0.12	Beverages	0.14	Furniture	0.67
TTO	0.47	0.19	Printing	0.22	Beverages	0.81
TUN	0.22	0.09	Plastic	0.09	Metals	0.39
TUR	0.31	0.10	Printing	0.13	Food	0.53
URY	0.63	0.29	Plastic	0.12	Apparel	1.28
USA	1.00	-				
VEN	0.27	0.13	Furniture	0.08	Metals	0.59
ZAF	0.52	0.21	Printing	0.24	Food	0.92
ZWE	0.13	0.06	Metal.Products	0.06	Metals	0.23

Table 3: Descriptive Statistics TFP 1990

		Stage 1						Stage 2	
ISIC	**Sector**	**Difference**	**Difference**	**Common**	**Common**	**Common**	**Common**	**Relative**	**Relative**
REV. 2		**Distance**	**Tariff**	**Border**	Colony	Language	English	Skill	Unskill
311	Food Products	-1.44	-0.016	0.136	1.227	0.51	-0.529	-6.56	-4.859
		(0.052)***	(0.005)***	(0.185)	(0.204)***	(0.154)***	(0.095)***	(2.381)***	(0.811)***
313	Beverages	-1.079	-0.014	0.751	0.589	0.856	-0.29	-5.471	
		(0.071)***	(0.008)*	(0.355)**	(0.290)**	(0.204)***	(0.113)**	(2.036)***	
321	Textiles	-1.349	-0.064	-0.004	0.841	0.54	-0.362	0.308	-2.63
		(0.054)***	(0.009)***	(0.227)	(0.183)***	(0.155)***	(0.094)***	(1.5649	(0.369)***
322	Apparel	-1.201	-0.09	0.234	1.115	0.424	0.094	-11.649	-2.569
		(0.064)***	(0.011)***	(0.238)	(0.211)***	(0.173)**	(0.084)	(2.200)***	(0.489)***
323	Leather Products	-1.146	-0.123	0.074	0.985	0.686	-0.213		-4.468
		(0.046)***	(0.010)***	(0.216)	(0.204)***	(0.168)***	(0.096)**		(0.468)***
324	Footwear	-1.005	-0.043	1.195	-0.105	0.706	0.304	-1.049	-3.605
		(0.077)***	(0.010)***	(0.299)***	(0.264)	(0.162)***	(0.104)***	(2.492)	(0.499)***
331	Wood Products	-1.239	-0.155	0.951	0.481	0.817	-0.112	-8.823	-2.643
		(0.064)***	(0.019)***	(0.210)***	(0.164)***	(0.135)***	(0.099)	(1.503)***	(0.394)***
332	Furniture	-1.232	-0.213	0.515	0.946	0.564	-0.119	-9.181	-2.105
		(0.060)***	(0.018)***	(0.239)**	(0.242)***	(0.150)***	(0.103)	(1.309)***	(0.403)***
341	Paper And Products	-1.71	-0.08	0.301	0.252	0.413	-0.076	-3.601	-1.1
		(0.058)***	(0.015)***	(0.2)	(0.19)	(0.180)**	(0.122)	(1.711)**	(0.584)*
342	Printing And Publishing	-1.13	-0.15	0.708	1.388	1.418	-1.198	0.922	-4.596
		(0.053)***	(0.025)***	(0.224)***	(0.215)***	(0.164)***	(0.091)***	(0.655)	(0.733)***
351	Industrial Chemicals	-1.349	-0.022	0.356	0.552	0.272	-0.473	-2.575	-3.649
		(0.053)***	(0.011)**	(0.197)*	(0.235)**	(0.161)*	(0.107)***	(1.230)**	(1.043)***
352	Other Chemicals	-1.27	-0.006	0.272	0.657	0.931	-0.291	-7.834	4.545
		(0.059)***	(0.012)	(0.271)	(0.197)***	(0.158)***	(0.080)***	(1.433)***	(1.535)***
355	Rubber Products	-1.145	-0.221	0.544	0.386	0.58	-0.17	2.802	-1.591
		(0.055)***	(0.016)***	(0.236)**	(0.211)*	(0.191)***	(0.089)*	(1.169)**	(0.421)***
356	Plastic Products	-1.327	-0.112	0.38	0.514	0.738	-0.172	-1.93	-2.291
		(0.054)***	(0.009)***	(0.292)	(0.166)***	(0.133)***	(0.079)**	(1.173)*	(0.483)***
361	Pottery	-0.966	-0.121	0.056	0.523	0.849	0.081	-9.424	-2.422
		(0.066)***	(0.011)***	(0.27)	(0.235)**	(0.173)***	(-0.105)	(1.955)***	(0.493)***
362	Glass And Products	-1.374	-0.093	0.637	0.39	0.72	-0.074	-9.679	-1.333
		(0.054)***	(0.011)***	(0.241)***	(0.261)	(0.194)***	(0.105)	(1.682)***	(0.430)***
369	Other Non-Metallic	-1.336	-0.09	0.61	0.46	0.445	-0.161	-11.668	1.131
		(0.065)***	(0.020)***	(0.209)***	(0.242)*	(0.177)**	(0.116)	(1.377)***	(0.565)**
371	Iron And Steel	-1.47	-0.12	0.104	0.807	-0.137	-0.134	-13.389	0.975
		(0.056)***	(0.019)***	(0.262)	(0.203)***	(0.161)	(0.106)	(1.707)***	(0.558)*
372	Non-Ferrous Metals	-1.782	-0.14	-0.322	1.005	0.034	-0.516	-13.602	-0.857
		(0.066)***	(0.039)***	(0.22)	(0.219)***	(0.204)	(0.143)***	(1.482)***	(0.489)*
381	Fabricated Metals	-1.271	-0.131	0.329	0.917	0.681	-0.292	-0.854	-1.873
		(0.052)***	(0.011)***	(0.218)	(0.190)***	(0.138)***	(0.078)***	(1.046)	(0.427)***
382	Machinery, Non Electric	-1.035	-0.084	0.176	0.82	0.838	-0.453	-3.091	-1.359
		(0.043)***	(0.014)***	(0.215)	(0.142)***	(0.124)***	(0.085)***	(0.679)***	(0.531)**
383	Machinery, Electric	-0.968	-0.141	0.364	0.761	0.807	-0.164	-0.286	-2.325
		(0.053)***	(0.013)***	(0.215)*	(0.220)***	(0.141)***	(0.096)*	(1.181)	(0.791)***
384	Transport Equipment	-1.14	-0.138	0.651	0.896	0.537	-0.146	-4.24	-0.419
		(0.062)***	(0.017)***	(0.247)***	(0.311)***	(0.189)***	(0.107)	(1.088)***	(0.557)
385	Professional, Scientific -0.796	-0.077	0.316	0.856	0.784	-0.445	2.537	-7.407	
		(0.040)***	(0.012)***	(0.187)*	(0.176)***	(0.131)***	(0.086)***	(0.694)***	(0.790)***
	Observations		42122						
	R-square		0.643						0.5467

Table 4: Hausman-Taylor Regression Bootstrapped standard deviations in parenthesis. Significant at the 1% (***), 5% (**) and 10%(*) level.

	Hausman Taylor		Number of Firms		Heckman		Heterogenous Firms			Solow Residual		Eaton & Kortum	
isic	corr	Spearman	corr	Spearman	corr	Spearman	corr	Spearman	isic	corr	Spearman	corr	Spearman
311	0.9998	0.9995	0.9534	0.9578	0.9582	0.9641	0.9332	0.9524	31	0.5532	0.4914	0.9217	0.9297
313	0.9959	0.9935	0.9245	0.936	0.9251	0.9439	0.89	0.9294				0.8955	0.8899
321	0.9907	0.9898	0.9416	0.957	0.9517	0.948	0.9434	0.9436	32	0.3076	0.1348	0.9213	0.9526
322	0.9816	0.9814	0.8031	0.8431	0.8307	0.8326	0.8047	0.8077				0.7671	0.8018
323	0.9989	0.9976	0.9239	0.9563	0.9333	0.9481	0.9099	0.9319				0.9	0.9212
324	0.9983	0.9961	0.805	0.912	0.8086	0.909	0.8416	0.9133				0.6987	0.8338
331	0.9083	0.9268	0.9755	0.9731	0.9778	0.9745	0.9736	0.9704	33	0.3954	0.1143	0.9563	0.9624
332	0.9749	0.9525	0.794	0.8387	0.8482	0.8073	0.8485	0.818				0.7697	0.7111
341	0.9581	0.9553	0.9578	0.9818	0.9584	0.9789	0.9574	0.975	34	0.4043	0.383	0.9648	0.9641
342	0.9956	0.9937	0.9195	0.935	0.9465	0.9237	0.939	0.9292				0.8683	0.8989
351	0.9975	0.9953	0.9376	0.9563	0.9362	0.9431	0.9532	0.9606	35	0.1391	0.06	0.9248	0.9345
352	0.9856	0.9884	0.9574	0.9708	0.9604	0.9671	0.9402	0.9662				0.9372	0.943
355	0.9647	0.9643	0.9395	0.9575	0.9536	0.9646	0.9246	0.9552				0.9423	0.9509
356	0.9926	0.9932	0.9095	0.9369	0.9245	0.9381	0.9185	0.9446				0.8129	0.8025
361	0.9944	0.9873	0.749	0.8198	0.7364	0.7827	0.7087	0.7904	36	0.209	0.282	0.8233	0.7775
362	0.9895	0.989	0.9039	0.9337	0.916	0.9287	0.8903	0.9349				0.9644	0.9526
369	0.9665	0.9736	0.9693	0.9682	0.9674	0.9693	0.9513	0.9579				0.9744	0.9736
371	0.8873	0.9128	0.9801	0.9881	0.9734	0.9815	0.9465	0.9785	37	0.7866	0.734	0.9609	0.9701
372	0.8896	0.9039	0.9824	0.9833	0.9821	0.9875	0.8777	0.9344				0.9523	0.9366
381	0.9793	0.9736	0.9387	0.9473	0.9546	0.9436	0.9501	0.9438	38	0.4532	0.368	0.9656	0.9627
382	0.9721	0.9752	0.9363	0.9553	0.94	0.9568	0.9237	0.9546				0.9632	0.9511
383	0.9833	0.9862	0.921	0.95	0.9286	0.9503	0.9128	0.9415				0.965	0.9604
384	0.9626	0.9686	0.8653	0.9206	0.8708	0.911	0.8926	0.9332				0.906	0.9203
385	0.9916	0.9837	0.8371	0.9122	0.8457	0.9239	0.804	0.9074				0.9073	0.9077
Total	0.9531	0.9649	0.8921	0.9337	0.9016	0.9294	0.8907	0.9264		0.343	0.3	0.888	0.9031

Table 5: Robustness of Productivity Estimates

	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP	TFP growth
R&D	1.81				0.659				
Interaction	(0.32)***				(0.34)*				
Rule of Law		0.425			0.352				0.01
Interaction		(0.052)***			(0.076)***				(0.024)
Financial			0.581		0.468				0.005
Interaction			(0.084)***		(0.1)***				(0.002)*
Setup Cost				-0.534	0.214				
Interaction				(0.34)	(0.45)				
Human capital						-16.82	-0.42	-10.55	
Intensity						(3.52)***	(2.52)	(2.14)***	
Physical capital						-10.11	1.69	-3.96	
Intensity						(3.65)***	(2.68)	(2.20)*	
Human capital						66.93	-1.49	33.001	
Intensity^2						(16.99)***	(11.92)	(9.96)***	
Physical capital						7.56	-1.00	3.26	
Intensity^2						(2.57)***	(1.91)	(1.54)**	
Human capital*Income								4.82	
								(1.21)***	
Phys. capital*Income								-0.57	
								(0.4)	
Human capital									0.029
Interaction									(0.008)***
Physical capital									0.098
Interaction									(0.036)***
Initial TFP level									-0.732
									(0.028)***
Sample	All	All	All	All	All	Developing	Developed	All	All
Sector Fixed Effects	Yes	Yes	Yes	Yes	Yes	No	No	No	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1402	1471	1244	995	973	735	736	1471	853
R-squared	0.83	0.83	0.83	0.83	0.84	0.48	0.65	0.78	0.66

Table 6: Sectoral Productivity and Theories of Development. Bootstrapped standard deviations in parenthesis. Significant at the 1% (***), 5% (**) and 10%(*) level.

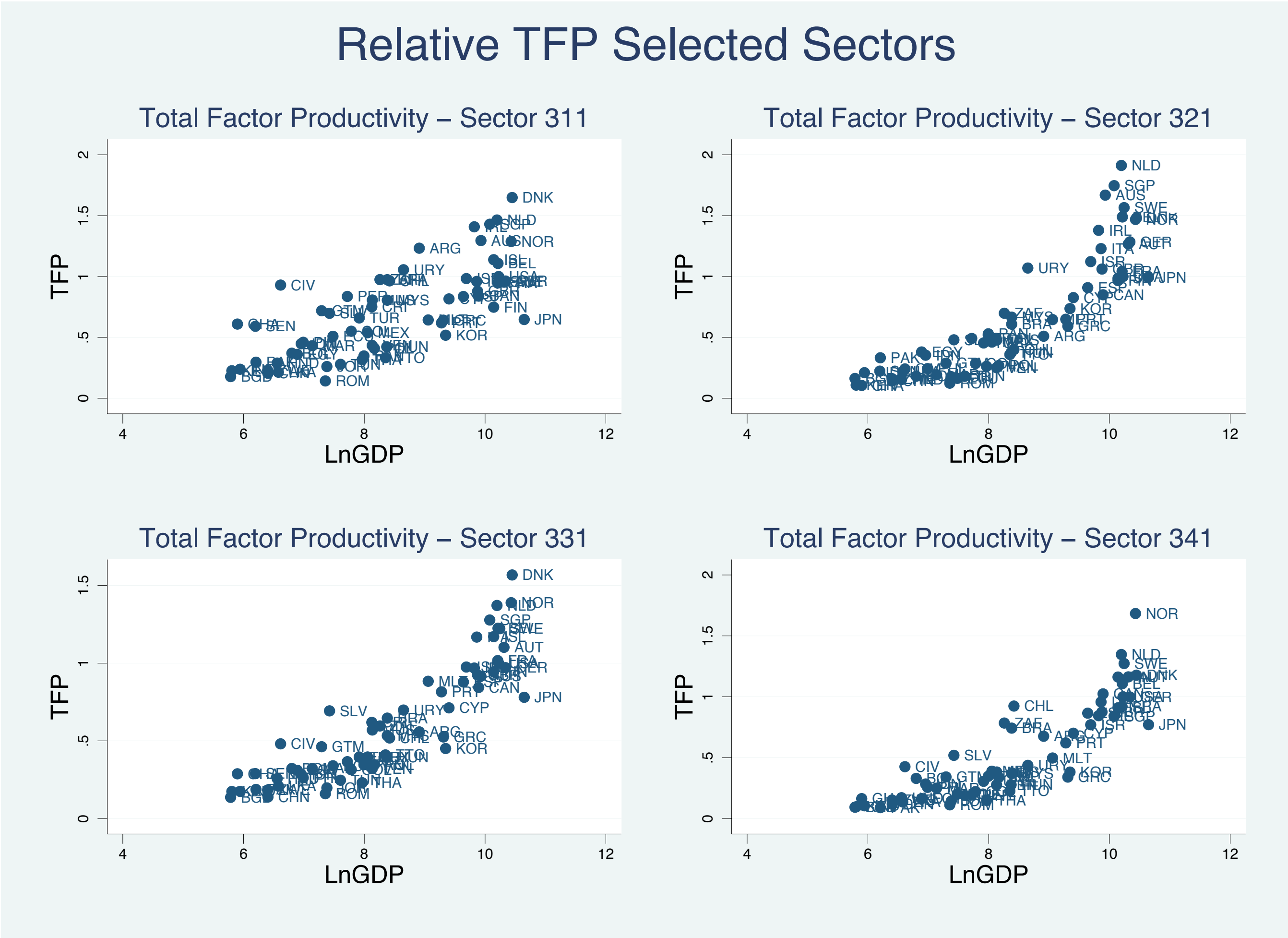

Figure 1: Relative TFP selected sectors

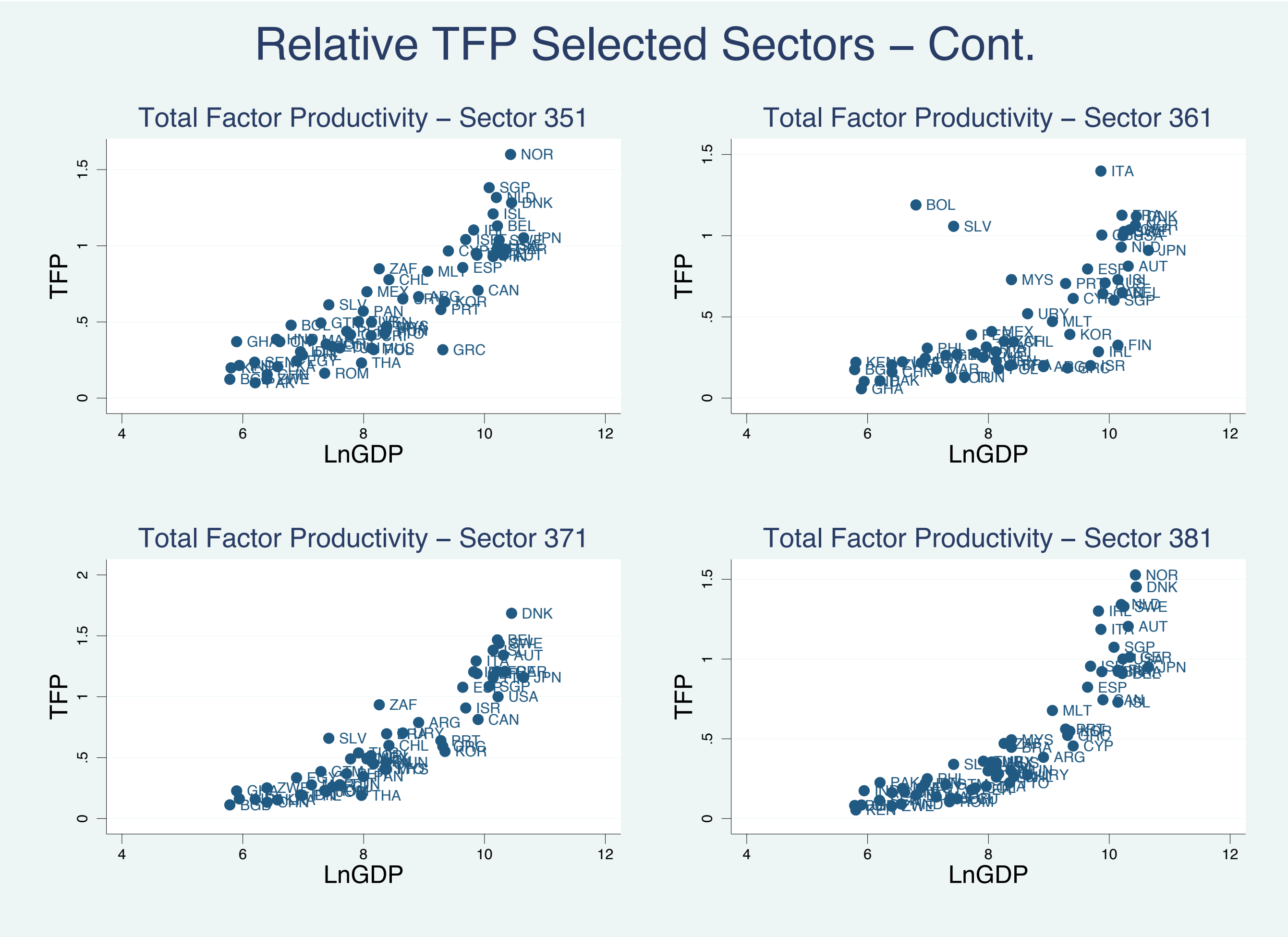

Figure 2: Relative TFP selected sectors (continued)

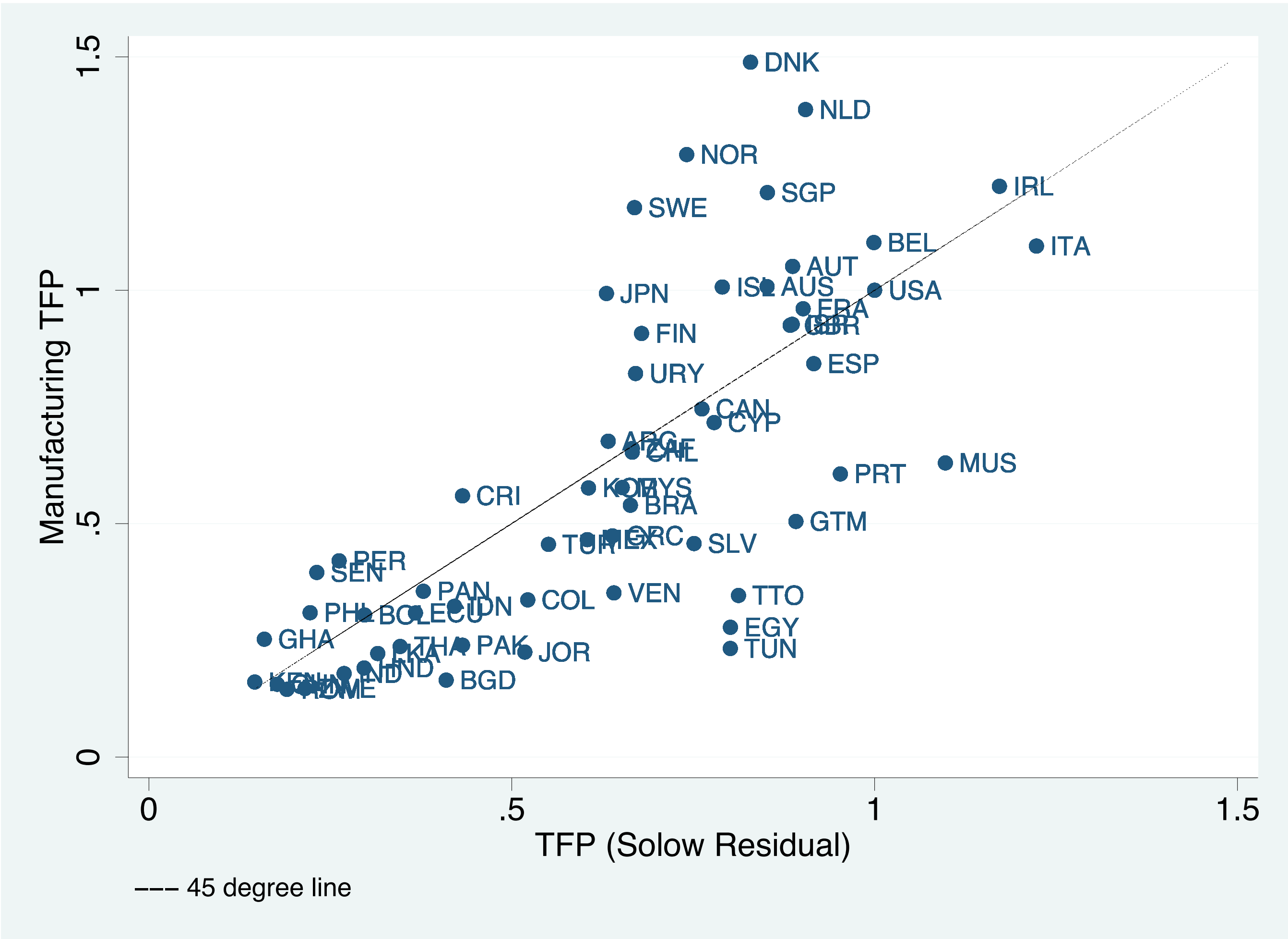

Figure 3: Aggregate Manufacturing TFP vs. TFP Solow Residual

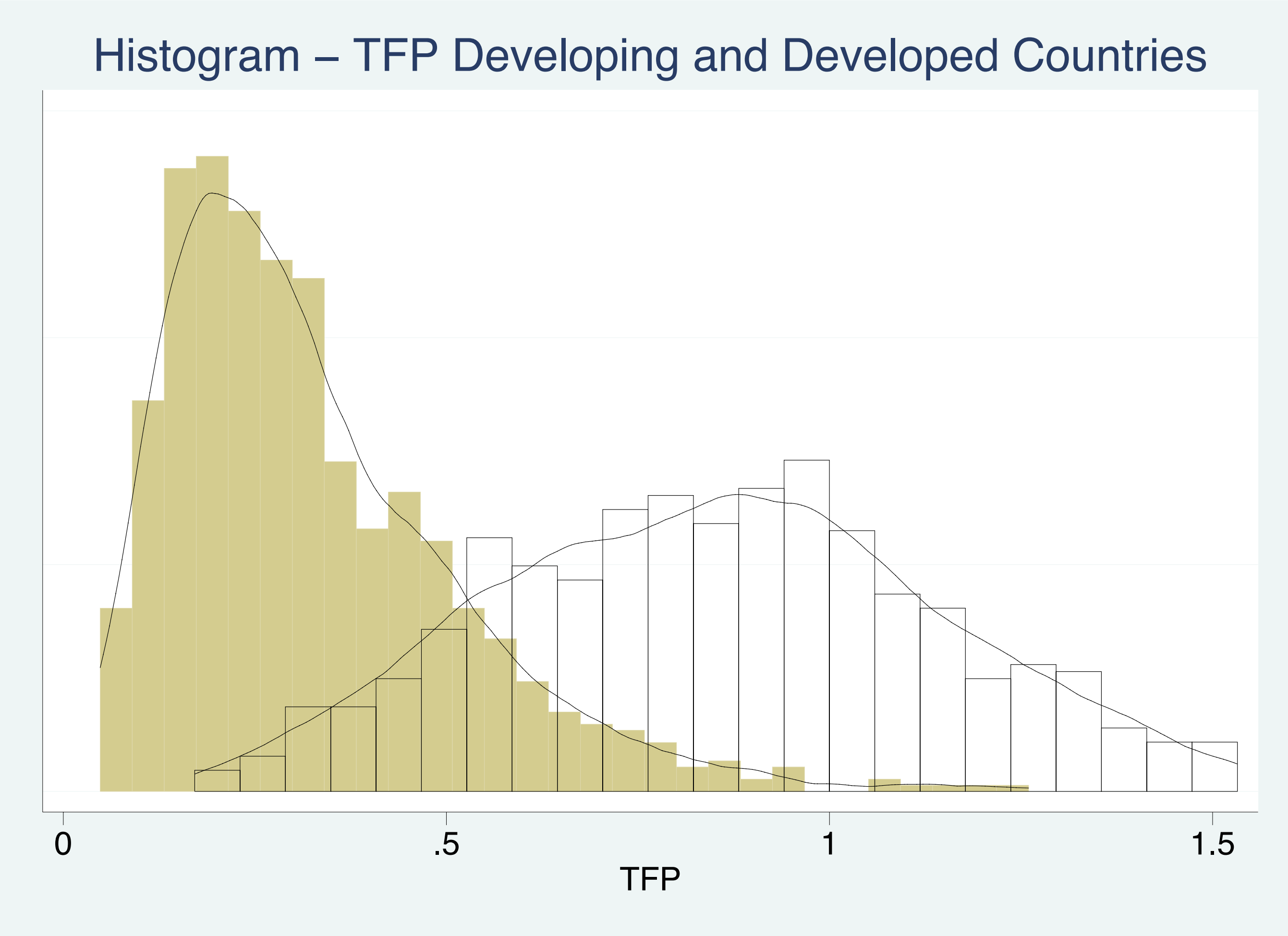

Figure 4: Histogram TFPs rich and poor countries

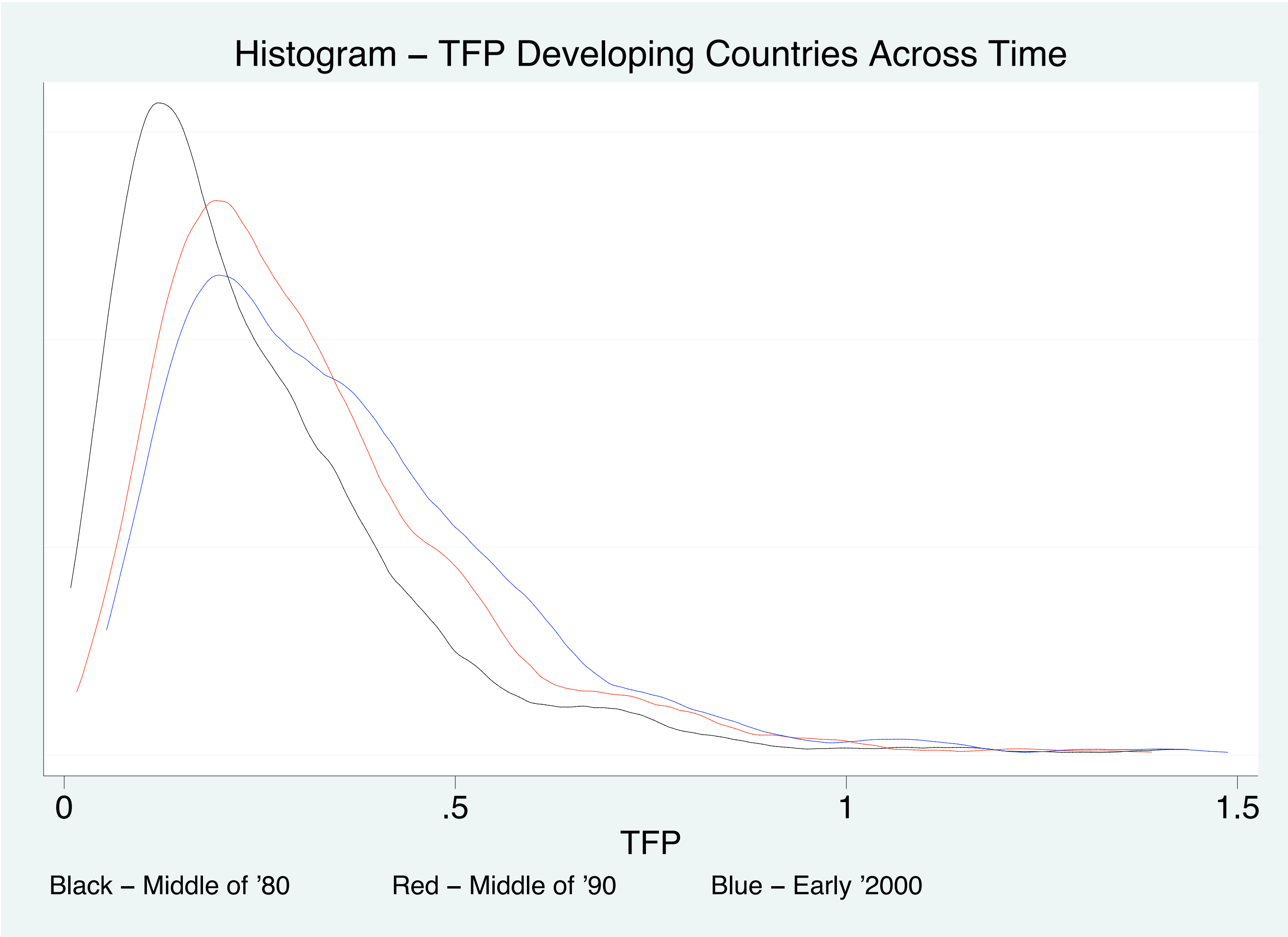

Figure 5: Histogram TFPs rich and poor countries

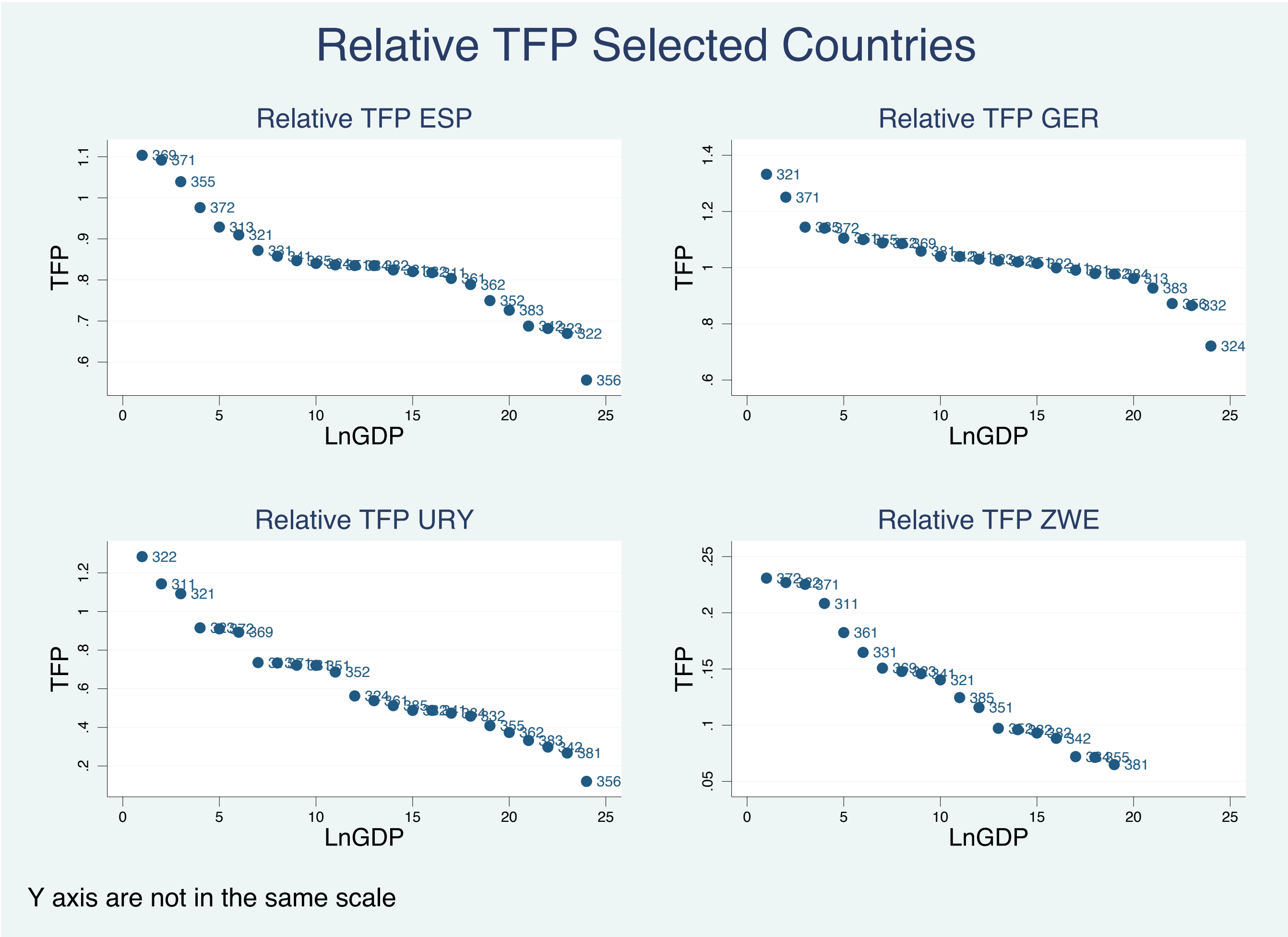

Figure 6: Ricardian Comparative Advantage relative to US

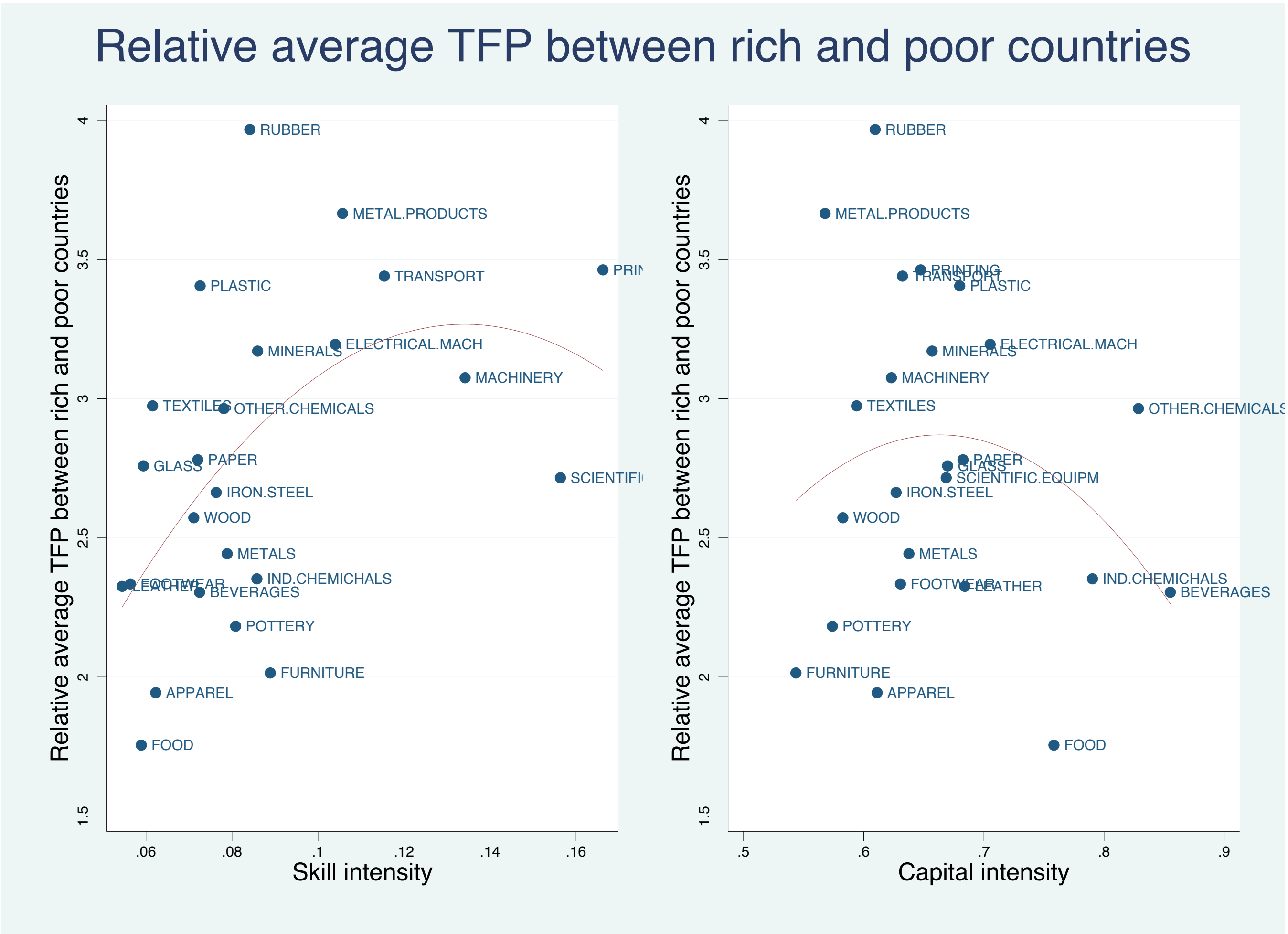

Figure 7: Skill/capital intensity and relative TFP

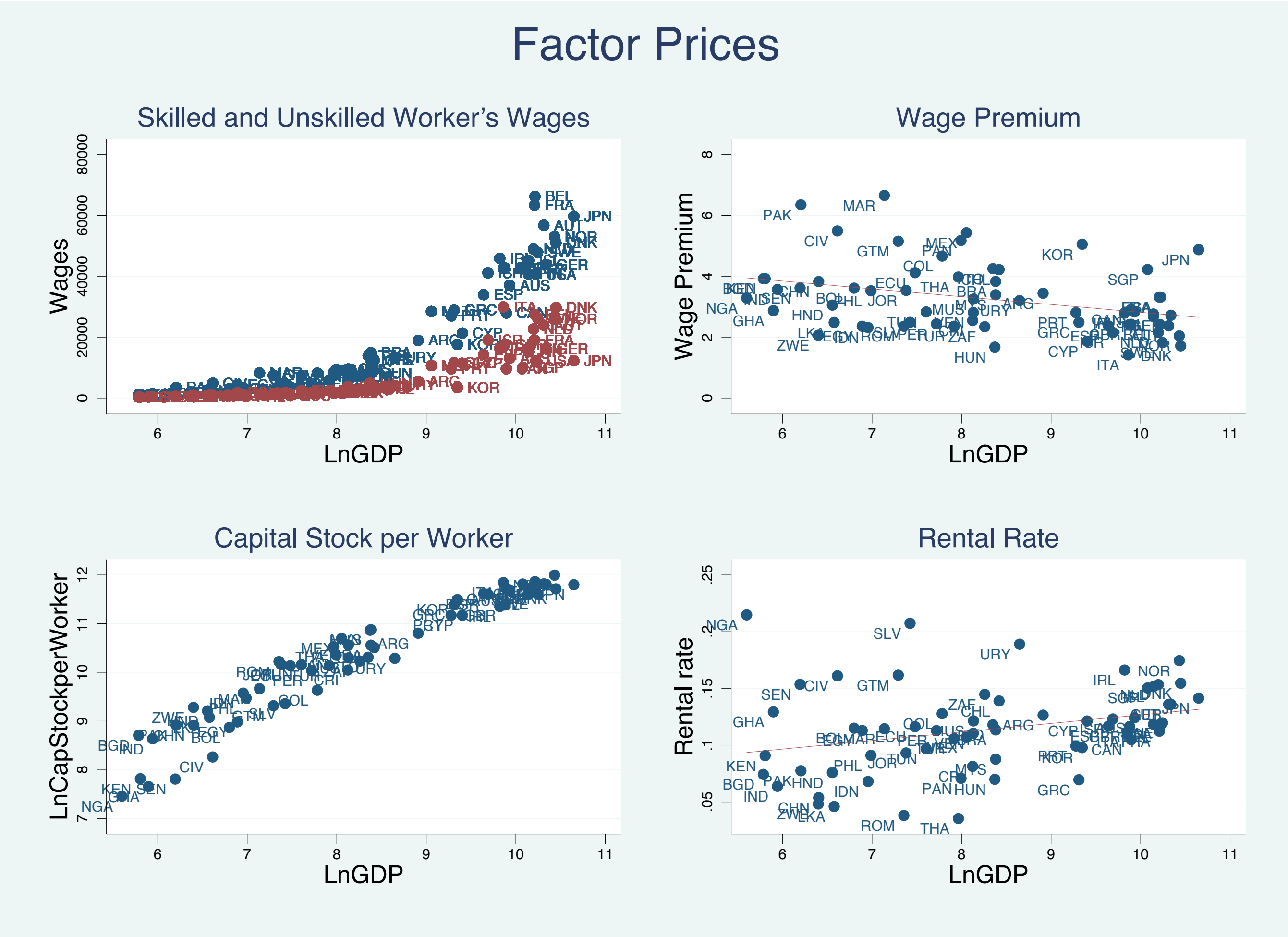

Figure 8: Factor Prices

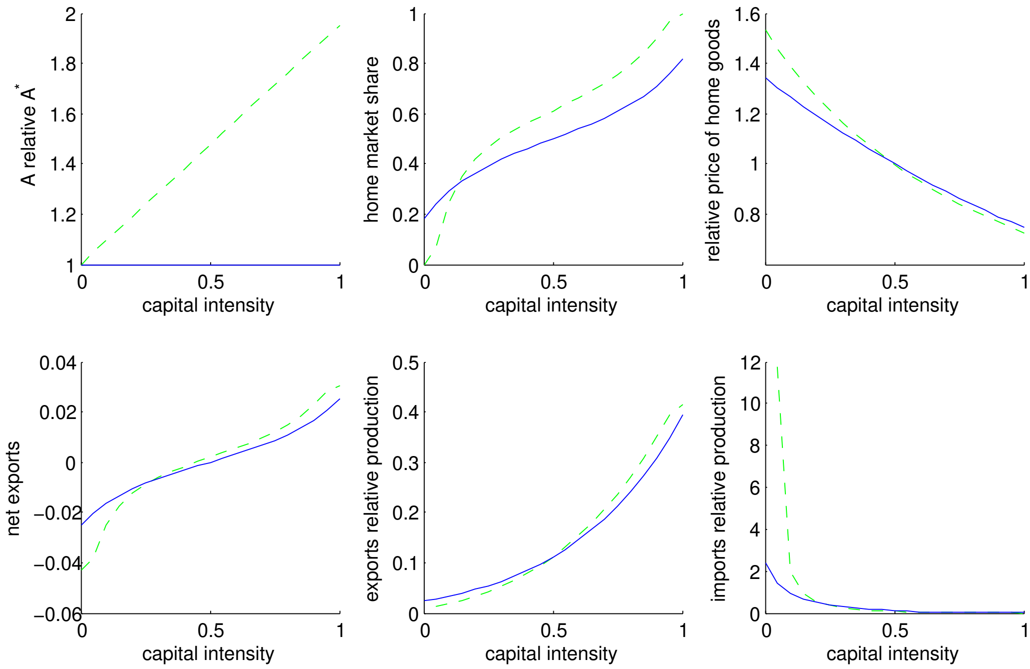

Figure 9: Quasi-Heckscher-Ohlin and Quasi-Ricardo effects

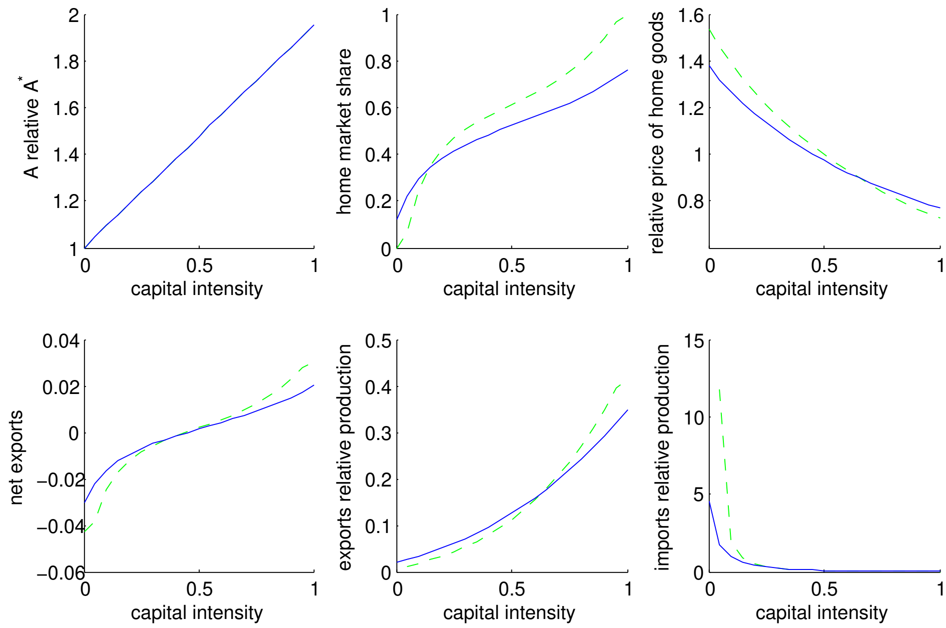

Figure 10: Quasi-Rybczynski effect