Trade and Sectoral Productivity

Harald Fadinger and Pablo Fleiss*

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*Fadinger: University of Vienna. Fleiss: Inter-American Development Bank. We are grateful to our advisors Antonio Ciccone and Jaume Ventura for their guidance. We would also like to thank two anonymous referees as well as Paula Bustos, Paola Conconi, Gino Gancia, Jonathan Eaton, Jozef Konings, Miklos Koren, Dalia Marin, Elias Papaioannou, Stephen Parente, Diego Puga, Esteban Rossi-Hansberg, André Sapir, Philip Sauré, Massimo Sbracia, Marcel Vaillant, Hylke Vandenbussche, Maurizio Zanardi, and seminar participants at Universitat Pompeu Fabra, Université Libre de Bruxelles, KU Leuven, University of Munich, University of Vienna, Inter-American Development Bank, Institute for Advanced Studies, the 2007 GTAP Annual Conference, the fifth ELSNIT Annual Conference, the XXXII Simposio de Análisis Económico, the 2008 RES Annual Conference, the CRENOS Workshop on Trade and Productivity and the 2008 CEPR-MNB Conference for helpful comments and suggestions. Correspondence Address: Department of Economics, University of Vienna, Hohenstaufeng. 9, A-1010 Vienna, Austria. E-mail: harald.fadinger@univie.ac.at, pfleiss@iadb.org

Abstract

This paper clarifies a little known subject: the magnitudes and patterns of cross-country differences in sectoral total factor productivity (TFP). The topic is important because those differences are at the heart of Ricardian trade theory and of many models of growth and development. This study fills in this gap by using a hybrid Ricardo-Heckscher-Ohlin trade model and bilateral sectoral trade data. Our approach overcomes the data problem that has constrained previous studies, which had to focus on a small number of OECD economies, because they relied on input and output data. We provide a comparable set of industry productivities for twenty-four manufacturing sectors in more than sixty countries at all stages of development. Our results imply that TFP differences in manufacturing sectors between rich and poor countries are substantial and far more pronounced in skilled labor and R&D intensive sectors than in others. We also apply our productivity estimates to test development theories that have implications for cross-country industry-level productivity patterns.

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1 Introduction

The present study suggests a fresh approach to a major problem. Cross-country differences in sectoral total factor productivity (TFP) are at the heart of trade theory and of many theories of growth and development. Traditionally, literature on growth has been preoccupied with explaining cross-country differentials in aggregate efficiency. Unfortunately, empirical challenges (reverse causality, omitted variables, collinerarity, etc.) make theories that only have implications for aggregate productivity very hard to test. Largely for this reason, recent work on the field has emphasized cross-country differences in industry productivity. Indeed, having measures of sector productivity also permits fruitful study of specific microeconomic channels that affect aggregate productivity.[1] In international trade, the Ricardian model emphasizes these productivity differences as the source of comparative advantage and the reason for cross-country flows of goods. Yet, there are very few empirical tests of this model due to the lack of data on industry productivity. In this paper, we attempt to further such analyses in two ways. First, we estimate sector productivity profiles from trade data. Second, we meanwhile provide evidence that cross-country differences in sector productivity are quantitatively important to explaining trade flows. The results should interest not only theorists but also policy makers. For, information on sectoral productivity differences across countries is vital to effective design of industrial and trade policy.

The traditional approach to measuring cross-country differentials in industry TFP requires comparable information on output, and inputs, at the sector level. Because of large gaps in these data for virtually all developing countries, very little is known about the magnitudes and the patterns of those differences outside the industrialized world. Thus, it is important to consider alternatives. We introduce and apply a new method for estimating sectoral TFP levels that relies on information contained in bilateral trade. In this way, to our knowledge, we are the first to provide a comparable and, as we will argue, reliable set of industry TFPs for twenty-four manufacturing sectors in more than sixty countries at all stages of development.

Our point of departure is a model that combines Heckscher-Ohlin trade with Krugman [1979] model of trade due to increasing returns and consumers' love for variety and also allows for trade costs (see Romalis [2004]). We extend this model to differences in industry TFP and to 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 in factor prices or by differences in trade barriers across countries.

In the model, monopolistic firms produce differentiated varieties of an aggregate consumption bundle in each industry. Since varieties of each bundle are gross substitutes, it follows that less expensive ones

[1] A good example is the seminal contribution by Rajan and Zingales [1998], who study the effect of financial development on growth. "*... financial markets and institutions help a firm overcome problems of moral hazard and adverse selection, thus reducing the firm's cost of raising money from outsiders. So financial development should disproportionately help firms (or industries) typically dependent on external finance for their growth.*"

will attract higher expenditure. Therefore, countries that can produce more cheaply in a given sector must have larger sectoral export values for it. The market price of each variety in a given destination depends on factor prices and productivity in the country of origin and on trade costs. The idea behind our method of estimating industry productivities is to exploit variation in bilateral sectoral export values compared to those for a benchmark country (appropriately adjusted for total production and for input costs) across export markets. As an example, consider how we infer Italy's productivity (relative to that of the US) in the Textiles sector. We measure which fraction of its sectoral production value Italy exports to each market compared to the US, controlling for sectoral factor input costs and trade costs. If Italy exports more of its textile production to an average market than does the US, once we have adjusted export values for relative input costs and relative bilateral sectoral trade costs, this indicates a higher level of industry TFP.

A key virtue of our procedure is that we do not need output price data. They are, of course, vital for computing comparable productivity profiles with the standard production function method for the following reason. If market structure or trade costs in a given industry differ across countries, price variation due to differentials in the level of competition or of trade costs leads to differences in industry value added. This will wrongly be measured as differences in productivity. Avoiding this problem, our approach exploits the fact that exporters from any given country face the same competitive environment as those from the benchmark country in any given market. Let us say, for example, that export values for a specific country are higher than those for the benchmark country vis-*à*-vis an average destination once we control for differences in trade costs. That result can only occur because producers from that country are more competitive than producers from the benchmark country. Holding constant differences in factor input costs, this happens if and only if productivity is higher than in the benchmark country.[2]

Our results provide evidence that cross-country TFP differences in manufacturing sectors are large. They average about the same substantial orders of magnitude as development accounting literature has found in cross-country variation at the aggregate economy level (for example, Hall and Jones [1999], and Caselli [2005]). In addition, we show that productivity differences between rich and poor countries are systematically larger in skilled labor- and R&D-intensive sectors. Specifically, 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 sensitive neither to the specific assumptions of our model nor to the estimation method. As alternatives we consider a model with endogenous markups, allow for firm heterogeneity in productivity (Melitz [2003]) and study the Ricardian model by Eaton and Kortum [2002]. We demonstrate that, with regard to industry productivity, all of these

[2]Even if firms charge different prices in different export markets because of differences in market structure, we do not need this information. In the robustness checks, we consider a model with endogenous markups and show that a similar logic applies.

models lead to similar structural expressions and estimates. We also verify that our estimates for aggregate manufacturing TFP correlate strongly with the productivity estimates found in the development accounting literature and that estimated industry TFPs correlate with the productivities constructed as Solow residuals for the few countries and industries where the information needed to apply that method is available.

Finally, we apply our sectoral productivity estimates to testing a number of development theories that have implications for cross-country industry productivity differentials. We provide evidence that technology spillovers are important in explaining cross-country sectoral TFP differences; that larger endowments of human capital lead to faster technology adoption in human capital intensive industries; and that financial development impacts on growth by leading to a more efficient allocation of credit within a given sector.

This paper is organized as follows. The next section briefly discusses the related literature. Section 3 introduces the theoretical model. Section 4 develops a methodology for computing industry productivity indices. Section 5 presents our empirical findings regarding sectoral productivity profiles. Section 6 covers robustness checks. Section 7 discusses a number of applications of our productivity estimates with regard to testing specific development theories that have implications for cross-industry patterns in productivity. The final section presents our conclusions.

2 Related Literature

Many studies attempt to compute industry productivity indices by specifying sectoral production possibility frontiers, and by using data on sectoral inputs and outputs. Typical of earlier such works are Dollar and Wolff [1993] and Maskus [1991], which employ industry value added as an output measure. Commonly, literature of this sort deals only with a limited number of OECD economies and does not disentangle sectoral price indices -which for that matter are usually unavailable- from output quantities.

Another notable line of research has developed within the International Comparison Project (ICOP), located at the University of Groningen. Here again, there is an attempt to tackle the price data issue. Seeking that goal, one of ICOP's latest projects, EU KLEMS, is a high-quality growth-accounting database for the countries of the European Community.

Since we use cost functions to measure input costs, our approach is also related to dual growth accounting, a method originally developed by Jorgenson and Griliches [1967] and applied by Aiyar and Dalgaard [2004] to aggregate TFP accounting, in levels, for a cross section of OECD economies. This procedure assumes constant returns to scale and perfect competition in goods and factor markets and requires information on input and output prices, as well as on factor income shares. The main obstacle to applying this method at the sector level is again the shortage of industry price index data.

In the trade literature there are also many contributions that construct productivity indices at various levels of aggregation. Notably, Harrigan [1997] computes industry TFP indices for eight sectors in ten 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. In another paper, Harrigan [1999] arefully constructs sector-level price indices for six manufacturing sectors in eight OECD countries and shows that even across this restricted set of economies sectoral prices vary substantially.

Finally, the following works are very related to our approach. 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 [2008] extends their model to Heckscher-Ohlin trade and differences in sectoral characteristics such as financial dependence and volatility. Taking a tack parallel to ours, Finicelli, Pagano and Sbracia [2008] apply the baseline Eaton-Kortum model to calibrating aggregate manufacturing TFPs for eighteen OECD economies. Their model, however, does not include Heckscher-Ohlin rationales for trade. Also, the authors compute only aggregate manufacturing productivity indices, whereas we estimate productivity differences at the industry level and for a sample that includes a large number of developing countries. In fact, their main contribution is to have developed a method for evaluating the impact of trade openness on aggregate TFP, which occurs through reallocation of resources towards more efficient firms, a channel that we disregard in the present paper.

3 A Simple Model

We use trade data to estimate sectoral TFP differences. This requires a model in which bilateral trade is determined. We follow Krugman [1979] in assuming that consumers love variety and that production is monopolistic due to increasing returns. To address sectoral productivity differences, we add three more ingredients. 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 style trade between countries. Second, we add bilateral transport costs.In order to use trade data to estimate sectoral TFP differences we need a model in which bilateral trade is determined. As Romalis [2004] points out, this makes locally abundant factors relatively cheap and strengthens the link between factor abundance and trade.[3] Thus, there is a cost advantage to producing more in those sectors that use the abundant factors intensively. We can therefore predict that countries will export more in those sectors. Finally, we add sectoral differences in TFP, which introduces a rationale for Ricardian-style trade. Countries having high productivity in a sector enjoy a cost

[3]In the Helpman-Krugman-Heckscher-Ohlin model (Helpman and Krugman [1985]), which itself does not feature transport costs, trade in goods is undetermined as long as the number of factors is smaller than the number of goods and insofar as countries are not specialized.

advantage relative to their foreign competitors and charge lower prices. Because the elasticity of substitution between varieties is larger than one, demand shifts towards such a country's varieties and leads to a larger world market share in the sector.

To make our approach manageable we need to assume Cobb-Douglas cost functions in each sector. In our model, because of fixed costs there are increasing returns to scale at the firm level. Despite that, our setup, which presupposes a constant price elasticity demand function, implies de facto constant returns at the industry level. This is because firm size is fixed and any change in sectoral output occurs through entry and exit within the industry. Therefore, an increase in industry output does not change firms' average costs. Any internal (or external) increasing returns to scale that might exist in the real world will show up as larger sectoral productivities in the model. It should be noted, however, that the literature on aggregate-level cross-country TFP comparisons usually assumes a constant returns to scale Cobb-Douglas production function (see, for example, Hall and Jones [1999], and Caselli [2005]).

Having explained the main features of the model, let us now develop the details.

3.1 Demand

Our model generalizes the setup of Romalis [2004]. We assume that all consumers in a given country i have identical and homothetic preferences. These are described by a two-tiered utility function. The first level is a Cobb-Douglas aggregator over K sectoral sub-utility functions. This implies that consumers spend a constant fraction of their income, σ_{ik}, which potentially differs across countries, on goods produced in each sector.[4]

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

Sectoral sub-utility is a symmetric CES function over sectoral varieties, which means that consumers value each of the available varieties in a given 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 that utility is strictly increasing in the number of sectoral varieties available in a country. Sector-specific elasticity of substitution between varieties is denoted by ϵ_k, and in this model we assume it to be

[4]For our baseline specification preferences can be generalized to any country-specific, strictly concave, homothetic and weakly separable utility function $U_i(u_{1i}, ..., u_{Ki})$, where the u_{ik}'s are CES indices as defined in (2). This would lead to demand functions of the form $x_{ijk} = \frac{\hat{p}_{ijk}^{-\epsilon_k}}{P_{ik}^{1-\epsilon_k}} E_{ik}(P_{1i}, ..., P_{iK})Y_i$, where $E_{ik}(P_{1i}, ..., P_{Ki})Y_i$ is expenditure on sector k goods in country i, and the P_{ik}'s are CES price indices as defined in (4).

higher than one, while 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-country pair. In order for one unit of a good produced by sector k of country j to arrive at 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 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, 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 to differences in factor intensities as well as differences in industry TFP. In each sector, firms can freely create new varieties and must pay a fixed cost to operate. Because of the demand structure and the existence of increasing returns, production is monopolistic. For it is always more profitable to create a new variety than to compete in prices with another firm that produces the same variety.

Firms in country j produce by combining 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}.[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 total cost function:

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

where $F = \{u, s, cap\}$, and $\sum_{f\in F}\alpha_{fk} = 1$. The form of the cost function implies that the underlying sectoral production function of each firm is Cobb-Douglas with sectoral factor income shares $(\alpha_{uk}, \alpha_{sk}, \alpha_{capk})$. To produce, firms need to pay a sector- and country-specific fixed cost, f_{jk}, which uses the same combination of capital, and skilled and unskilled labor as the constant variable cost.

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

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

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 results in a model Heckscher-Ohlin with Ricardian features. Since the elasticity of substitution across varieties, ϵ_k,is larger than Unity, 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 occur either because a sector is intensive in locally cheap factors and/or blessed with high productivity. [7]

4 Towards Estimating Sectoral Productivities

In this section, we use our trade model to develop a method for estimating cross-country sectoral productivity levels. To this end, we specify the sectoral volume of bilateral trade (measured at destination prices), which is defined as the value 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, by 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 mark-up over their marginal cost, and substituting the marginal cost function (5), we can rewrite bilateral sectoral trade volume as:

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

Equation (9) makes clear that bilateral trade in sector k measured in dollars depends positively on the

[7] In the supplementary Appendix to this paper we present a general equilibrium version of the model and discuss in more detail how comparative advantage is determined.

importing country 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 Unity, the value of trade is falling in the price charged by exporting firms, p_{jk}. This and the pricing rule (6) imply that trade is decreasing in the exporters' production costs. 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 industry productivity, A_{jk}. If a country has 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. Regrettably, the available data on the number of firms active in the exporting countries is not very reliable. On the other hand, we observe the value of industry production. Thus, by using the model itself, it is possible to solve for the number of firms given total sectoral production.[8] 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, firms in equilibrium make zero profits and price at their average cost. Combining this fact with (6), it is easy to solve for equilibrium firm size, which depends positively on fixed costs and on 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:

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

Substituting for N_{jk} in equation (9), 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 sector productivity A_{jk}. Inasmuch as a productivity index needs to be defined relative to some benchmark, we measure productivity relative to a reference country. We have chosen the US as a benchmark because it exports to the greatest number of destinations in most

[8]Using sectoral gross output instead of the number of firms mitigates mismeasurement problems, because these occur mainly for small firms that have a negligible effect on sectoral gross output.

sectors.[9] Another advantage of choosing a reference country is that all the terms that are not indexed to the exporting country j (i.e., $\sigma_{ik}, Y_i, or P_{ik}$) drop from the equation. For each importer i we can express the "raw" productivity of country j in sector k relative to the US.

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

Our "raw" productivity measure, $\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}}$, is a combination of relative industry productivity, fixed costs, and transport costs.

Intuitively, country j is measured to be more productive than the US in sector k if, after controlling for the relative cost of factors, j exports a greater fraction of its production to country i than does the US. Note that we can compute this measure vis-$\grave{a}$-vis every importing country by using only data on relative imports and on exporters' relative production and factor prices. This "raw" measure of relative productivities also embraces 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 vis-$\grave{a}$-vis the importing country. Consequently, it is easy to separate the two parts by using regression techniques. Relative productivity is to be defined as the product of the relative productivity of variable production and weighted relative fixed cost: $\left(\frac{\breve{A}_{jk}}{A_{USk}}\right) = \left(\frac{A_{jk}}{A_{USk}}\right)\left(\frac{f_{jk}}{f_{USk}}\right)^{-1/\epsilon_k}$.

Taking logarithms, we get:

$$\log\left(\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}}\right) = \log\left(\frac{\breve{A}_{jk}}{A_{USk}}\right) + \frac{1-\epsilon_k}{\epsilon_k}\log\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right) \tag{15}$$

We assume that bilateral transport costs, τ_{ijk}, are a log-linear function of a vector of bilateral variables (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] We have also tried other benchmark countries such as Germany and Japan, and our results are robust to these alternative specifications.

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

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:

$$\frac{\breve{A}_{jk}}{A_{USk}} = exp\left[\log\left(\frac{\bar{\tilde{A}}_{jk}}{A_{USk}}\right) - \beta_k^{FE}\bar{X}_{jk}\right] \tag{17}$$

Here, the bars indicate means across importing countries i, and $\hat{\beta}_k^{FE}$ 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 trade costs. This is a consistent estimator for relative industry productivity as long as there are no omitted variables with a non-zero mean across importers.

Let us discuss at this point why relative fixed costs enter into our expression for relative productivity $\left(\frac{\breve{A}_{jk}}{A_{USk}}\right) = \left(\frac{A_{jk}}{A_{USk}}\right)\left(\frac{f_{jk}}{f_{USk}}\right)^{-1/\epsilon_k}$. Note that $\left(\frac{\breve{A}_{jk}}{A_{USk}}\right) < \left(\frac{A_{jk}}{A_{USk}}\right)$ whenever relative fixed costs are larger than Unity. In that case, we assign relatively too few firms to country j. The reason is that we have replaced the number of firms by (12), which depends on sectoral production and fixed costs. Higher relative fixed costs imply larger relative firm size (see (11)) and consequently a lower relative number of varieties produced given relative sectoral production. Relative bilateral trade given relative sectoral production increases in the relative number of producers because of love for variety. Hence, relatively higher fixed costs require a relatively higher productivity in variable production for a given ratio of exports relative to production. Also, the elasticity of substitution ϵ_k determines how sensitive the volume of relative bilateral sectoral trade is with respect to relative price differences. Indeed, a lower elasticity implies less sensitivity to price differences. Hence, observed differences in export volumes relative to sectoral production must be due to larger differences in variable productivity. Simultaneously, the adjustment needed to control for this effect (inverse weighting by elasticities) increases the role played by relative fixed costs in lowering relative productivity compared to relative productivity of variable production.[10]

[10]There are several possibles empirical approaches to investigating fixed costs' effects on industry productivity. One way is

Our measure of relative TFP is transitive. This implies that productivity profiles 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', as this would mean comparing productivities across different goods.

The productivity indices could alternatively be interpreted as differences in sectoral product quality across countries. Under this interpretation 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 rather because of differences in quality. Since we look only at the value of trade, for our purposes the two interpretations are equivalent.[11]

Before presenting 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 twenty-four (ISIC Rev. 2) manufacturing sectors in sixty-four countries at all stages of development, for three periods: the mid-eighties, the mid-nineties, and the beginning of this century. To this end, we use data on the following: bilateral trade at sector level; sectoral production; factor prices; sectoral factor income shares; elasticities of substitution; and sectoral bilateral trade barriers. We obtain information on sectoral bilateral trade and 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 for capital following the methodology proposed by Caselli [2005] and Caselli and Feyrer [2007] . Sectoral factor income shares are computed from US data, while information on sectoral elasticities of substitution come from Broda and Weinstein [2006][12]. Mayer and Zignago [2005] and Rose [2004] afford

to specify fixed costs as multiplicatively separable between a country- and a sector-specific component, $f_{jk} = f_j f_k$. In this case we obtain $\left(\frac{\breve{A}_{jk}}{A_{USk}}\right) = \left(\frac{A_{jk}}{A_{USk}}\right)\left(\frac{f_j}{f_{US}}\right)^{-1/\epsilon_k}$ indicating that fixed costs should matter more for relative productivity in more differentiated sectors. To investigate whether this is indeed the case, we have experimented with regressing estimated productivities on the interaction of sectoral elasticities of substitution and different country-specific measures of entry cost (e.g., entry cost relative to GDP per capita; entry costs in dollars; number of procedures to register a business; time to register a business), and average rank scores of these variables. While coefficients mostly exhibit the correct sign, they are not significant once we control for sector and country fixed effects, presumably because there is not enough variation in sectoral elasticities of substitution. Since there is no robust evidence for the differential impact of fixed costs across sectors, we therefore stick to a simpler specification and assume $f_{jk} = f_k$. In this case fixed costs drop from our specification and productivity levels can be interpreted as corresponding to variable production.

[11] The following model is isomorphic to the one presented in the main text. Replace sectoral sub-utility 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 in an exporting country all firms within a sector 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 $M_{ijk} = \frac{(p_{jk}\tau_{ijk})^{1-\epsilon_k}\lambda_{jk}^{\epsilon_k - 1}\sigma_{ik}Y_i}{\tilde{P}_{ik}^{1-\epsilon_k}} N_{jk}$. It becomes clear, comparing this expression with the one in the main text (8), that productivity differences are indistinguishable from differences in product quality, because the value of bilateral trade is identical in both cases.

[12] Working with elasticities of substitution from Hummels [1999] does not affect results significantly.

us data on distance and other bilateral variables (e.g., existence of a common border between exporter and importer; whether a trading partner was formerly a colony of the exporter or importer; whether the partners share a common language, are members of the same regional trade agreement, are members of a generalized system of preferences, or share in a common currency union). Finally, we use information on bilateral sectoral tariffs from the UNCTAD TRAINS database.

Table 1 provides some descriptive industry statistics. Skill intensity, measured as the share of non-production workers in sectoral employment, varies from 0.15 (Textiles and Footwear) to 0.49 (Beverages) with a mean value of 0.27. Capital intensity, measured as Unity minus labor compensation in value added, varies from 0.56 (Fabricated Metals) to 0.85 (Beverages) with a mean value of 0.66. Finally, the elasticity of substitution varies between 1.90 (Pottery) and 12.68 (Non-Ferrous Metals) with a mean value of 4.36.

5 Results

In this section we report the results of computing productivities using our baseline specification (16). We use a stepwise linear panel estimation[13] with sector-country specific fixed effects. We limit the sample to exporter-sector pairs for which we observe exports to at least five destinations. At this stage of our analysis, however, we ignore zeros in bilateral trade flows and issues of sample selection. This leaves us with a sample of around 42000 observations for a given year.

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 0.80 and a *within* R-square of 0.47. This implies that in our regression, trade costs due to the gravity type variables account for approximately half of the variation in $\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}}$ across importers. In addition ρ -the fraction of the variance of the error term that is due to $\frac{A_{jk}}{A_{USk}}$- is 74%. Both of these facts corroborate our interpretation of the sector-country fixed effect as an exporter-sector specific productivity measure.

Recall that the sign of the coefficients reflects the relevant variable's impact on transport costs multiplied by the negative term $\frac{1-\epsilon_k}{\epsilon_k}$. Thus, a negative coefficient implies that an increase in the dependent variable will increase relative transport costs.

In all sectors, differences in distance have a large and very significant negative effect on our relative raw productivity measure (i.e., increase trade costs). Differences in bilateral sectoral tariffs between country j and the US are also negative and significant for all sectors except Other Chemicals (sector 352). The indicators for common language between the importer and the exporter have a significant positive effect on

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

raw productivity (i.e., reduce the transport costs) in all sectors but two. 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 last variable we include, having a common colonial past between exporter and importer has a positive impact on our raw productivity in all sectors but two.[14]

Having run regression (16), we use (17) to construct sectoral productivities. We compute almost 1500 sectoral TFPs for each period. Table 3 summarizes some information about these productivities in the mid-nineties. For each country in our sample, we present the country mean of TFP across industries,[15] the standard deviation, and the sectors with maximum and minimum TFP.

First, we observe that there is a strong correlation between a country's income per worker and average relative TFP in manufacturing. Lower-income countries tend to have markedly lower sectoral productivities than do rich ones. Within countries, however, relative productivities vary greatly from sector to sector. Taking for example Pakistan (PAK), we measure an average relative manufacturing TFP equivalent to 0.20 of the US level. This figure masks considerable heterogeneity across sectors: from a productivity of 0.63 with respect to the US level in Furniture (322) to one of only 0.07 in Printing (341). In general, Plastics (356), Fabricated Metals (381), and Transport Equipment (384) are sectors in which many of the lower-income countries tend to be least productive relative to the US. Meanwhile 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 reach their highest relative productivity figures in the sectors Food (311) and Apparel (322), while again, there is no clear pattern regarding in which sectors rich countries are the most productive relative to the US.

In order to exemplify our results, the panels of Figure 1 show scatter plots of estimated sectoral productivities against the log GDP per worker in the mid-nineties for four out of the twenty-four sectors. There is a high correlation between sectoral productivity and log GDP per worker in all sectors. However, the magnitude of productivity differences varies greatly across sectors. For example, the relationship between log income per worker and productivity is much more pronounced in 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

[14] Overall, of all estimated significant coefficients, only one has a wrong sign: Common English Language in the sector Footwear. Note also that of all the other bilateral variables that were in principle included in the regression (common regional trade agreement, common membership in a currency union, common membership in a generalized system of preferences), none have any robust effect on relative raw productivities once we control for relative tariffs and distance. Consequently, those variables do not appear in the final specification.

[15] These means of sector productivity cannot be interpreted as aggregate manufacturing productivity indices in terms of economic theory. For, to do so, we would need to take agents' preferences into account for a proper aggregation. Nevertheless, they give some sense of the magnitude of average sectoral productivity differences across countries. 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. In such cases, we drop the sector from (16). Ivory Coast is the country with the smallest number of sectors for which we obtain productivity measures, specifically fifteen of them. Only in nine (out of sixty-four) countries we construct productivities for less than twenty sectors. The complete set of productivity estimates is online at http://www.pablofleiss.com.

in most manufacturing sectors.

At this point it seems interesting to compare our mean sectoral productivities in manufacturing with the aggregate productivities found in Development Accounting literature. To this end we compute weighted averages (by value added) for our sectoral TFPs and correlate the results with aggregate productivities constructed from production and endowment data.[16] Figure 2 shows a scatter plot of our aggregate manufacturing productivity set against aggregate productivity indices computed as Solow residuals. We note that there is a very strong correlation between these two sets of productivity estimates. The correlation coefficient between the two is 0.68. Productivity differences in manufacturing tend to be even larger than aggregate ones. This pattern is determined by the fact that European countries seem to be relatively more productive in manufacturing than at the aggregate level. It is nevertheless notable that, in manufacturing, our methodology estimates as far less productive than the US a number of lower-income countries countries (e.g., Tunisia, Egypt, Guatemala, and Venezuela), which the Solow residual method places close to the US productivity.

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 US$8000 in 1995) and developed countries. Figure 3 (left) 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 more productive than the US in certain sectors. Developed countries', on the other hand, have a relatively symmetric productivity distribution with a mean sectoral productivity that is slightly below Unity, and a significant variation to both sides, from around 0.2 to 1.5 of the US level.

Figure 3 also shows (in the right panel) the evolution of the relative productivities of developing countries over time. The dashed line is the histogram of developing countries' productivities in the mid-eighties, the solid line is the histogram for the mid-nineties and the dotted line the one for the beginning of this century for the sample of twenty-two developing countries for which we have data for all three periods. We see that the distribution is shifting to the right over time, meaning that over this twenty-year period lower income countries are slowly catching up in sectoral TFP relative to the US.[17]

[16] 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 $y_c = A_c \left(\frac{K_c}{Y_c}\right)^{\alpha/(1-\alpha)} h_c$.

[17] The countries in our sample that have on average experienced the fastest convergence in TFP towards the US level over these two decades (annualized growth rates in parenthesis) are China (5.1%), Uruguay (4.67%), Argentina (4.3%), Egypt (4.1%), and Poland (4%). The countries with the greatest divergence are Jordan (-3.6%), Panama (-2%), Kenya (-1.2%), and Ecuador (-0.3%). The sectors in which developing countries have on average experienced the fastest speed of catch up are Pottery (4.9%), Printing and Publishing (3.7%), Electrical Machinery (3.4%), and Other Chemicals (3.3%), while the ones with the lowest speed of convergence are Beverages (-0.8%), Transport Equipment (-0.7%), Food (-0.6%), and Industrial Chemicals (0.7%).

Our estimates also allow us to construct "Ricardian"-style curves of comparative advantage due to productivity differences for any given sector-country pair. The panels of Figure 4 depict productivities arranged in decreasing order, according to the magnitude of relative productivity differences with the US, for four representative countries: Germany, Spain, Uruguay, and Zimbabwe.

As a further application, we look to see whether productivity differences between developing and industrialized countries are systematically related to sector characteristics. Table 4 shows the results of a weighted regression[18] (with the inverse of the standard deviation of log(TFP)) of log(TFP) relative to the US in the mid-nineties on sectoral human capital intensity and the interaction of human capital intensity and log income per worker controlling for country fixed effects.[19] In lower-income countries, productivity differences relative to the US are systematically larger in human capital intensive sectors, but in richer countries this effect disappears. Repeating the same exercise with sectoral physical capital intensity we do not find much evidence for a relation between productivity, capital intensity, and income per worker. Finally, we relate relative productivities to R&D intensity measured by sectoral investment in R&D in the US as a fraction of sectoral value added. Again, lower-income countries have systematically larger productivity gaps in R&D intensive sectors, an effect that is mitigated as countries become richer.

6 Robustness

In order to make sure that our productivity estimates are not sensitive to the specific assumptions of our model and to our econometric strategies, we have performed a series of robustness checks. For brevity's sake only the most important ideas and results are discussed in the main text. The detailed results and derivations are relegated to a supplementary Appendix.

One potential weakness of our productivity estimates is that we have calibrated rather than estimated the effect of differences in factor prices and in factor proportions. 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 with regard to estimating directly the effect of factor intensities and elasticities alike.

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

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

[18] Results also go through without weighting observations.

[19] We prefer not to overemphasize this result because it may be partially affected -even though this is unlikely- by mismeasurement of sectoral factor income shares. See the supplementary Appendix for an analysis of measurement errors in factor income shares.

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

$$\log\left(\frac{M_{ijk}}{\tilde{Q}_{jk}}\right) - \log\left(\frac{M_{iUSk}}{\tilde{Q}_{USk}}\right) = \tag{19}$$

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

Provided that productivities are not correlated with relative factor prices within a country -as for the moment, we assume-, a consistent estimator for $\left(\frac{A_{jk}}{A_{iUSk}}\right)$ can be obtained from the following two-step procedure.

First, we regress our dependent variable on sector-country dummies and bilateral variables

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

Having obtained the first stage estimates, next we regress the sector-country dummy on factor prices weighted by factor intensities as well as on country and sector dummies.

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

for $f \in \{s, u\}$. In order to obtain a measure of sectoral TFP, we use the relation:

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

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 makes it possible to estimate the coefficients of those variables that do not vary by importing country.

Table 5 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. 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 and unskilled labor are highly significant. The R-square of the second stage is 0.55. This implies that country and sector dummies and the Heckscher-Ohlin components explain around half of the country-sector specific variation.

The productivity estimates obtained through this procedure are very similar to our baseline set of productivities. The first rows of Table 6 show the aggregate correlation and the Spearman rank correlation between these two sets of productivities. For most sectors the correlations exceed 0.90, with an overall correlation of 0.98. Still, we prefer the main specification's mix of calibration and estimation. This is because that approach does not require any assumptions regarding the correlations between the independent variables and the country-sector fixed effect, and also because not all of the coefficients in this specification exhibit the correct magnitudes.

This way of estimating sectoral productivities also allows us to assess the importance of Ricardian productivity differences for explaining bilateral trade. To do so, we compare the fit of the first step (20) with the one of a model having country-specific productivities combined with a Heckscher-Ohlin component that ignores Ricardian productivity differences.

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

The adjusted R-square of this model is 0.5 compared to the 0.63 obtained by allowing for Ricardian productivity differences. Thus, there is a 13% gain in fit by introducing Ricardian productivity differences. Also the Akaike information criterion tells us that the Ricardian model does much better in terms of fit.[20]

Again, for brevity's sake, the other robustness checks are only sketched in the main text. Results on aggregate correlations and rank correlations between the baseline productivities and the alternative estimates are reported in Table 6.

A further extension introduces heterogeneity in firms' marginal costs and fixed costs to exporting, so as both to explain zeros in bilateral trade flows and to decompose bilateral trade flows into an extensive (number of exporters) and an intensive (exports per firm) margin. When estimating this more general model with a two-step procedure as suggested by Helpman, Melitz and Rubinstein [2008] we continue to obtain quite similar results for our sectoral productivity estimates (columns labeled "Heckman" & "Heterogeneous Firms").

We also demonstrate that, when augmented by a Heckscher-Ohlin component, Eaton and Kortum's Ricardian trade model leads to a structural estimation equation that is very similar to our baseline specification and so also produces comparable productivity estimates (column "Eaton-Kortum")

Next, we generalize our specification to allow for endogenous markups that depend on toughness of competition in each market. We show that our baseline estimation equation remains approximately valid. The main idea is that we always compare exporters from a given country and the US with respect to a

[20] AIC drops from 171455 for the restricted model to 157827 for the Ricardian model. When comparing (16) with a restricted version that allows only for country specific TFP differences, we get very similar results regarding the importance of Ricardian productivity differences.

specific market, where firms of both origins face the same environment.

Moreover, we explain how (traded) intermediate goods can easily be incorporated into our model. Under some mild assumption, this leaves the estimation equations unaffected but introduces room for sectoral productivities to be influenced by cross-country and cross-industry differences in the availability and prices of intermediates. Lower productivities are predicted for countries where fewer varieties are available and where intermediates are more expensive. Whether this is indeed the case in the data is an interesting question for further research.

Another check investigates whether the fact that we have used US factor income shares as proxies for sectoral factor intensities is likely to cause systematic biases in productivity patterns. We find that for most plausible assumptions regarding differences in sectoral factor income shares, this is not the case.

Finally, we use the OECD STAN database to show that our sectoral productivity estimates correlate with those calibrated from production data for the few industrialized countries where such calculations are feasible.

7 Productivity Differences and Theories of Development

In this section, we apply our sectoral productivity estimates to testing a number of development theories which have implications for cross-country sectoral productivity differences. Here, we focus on three examples that, in our view, show particularly well the advantages of having estimates of industry productivities for a large set of countries: R&D spillovers, the role of human capital for technology adoption and the impact of financial development on TFP.

International technology spillovers are a prominent explanation both for the persistent differences in cross country productivity levels and for the stability of the world income distribution (Parente and Prescott [1994], Howitt [2000], Klenow and Rodriguez-Clare [2005]). Cross-country knowledge spillovers guarantee a stable world income distribution even in the presence of persistent international differences in R&D investment rates. In those models, there is a certain advantage to backwardness in the sense that countries that are further away from the technology frontier experience faster technology improvements. For a given distance to the frontier higher R&D investment rates lead to faster rates of technology adoption.

Here, it os relevant that, when applied at the sector level, Klenow and Rodriguez-Clare [2005]'s model has several predictions which can be usefully assessed by use of our sector productivities. First, the effect of a higher R&D investment rate on the steady state TFP level relative to the frontier is larger in those sectors where the world technology frontier grows faster. Second, since there is an advantage to backwardness, TFP growth will be higher the further from the cutting edge a sector is. Third, the impact of a higher R&D

investment rate on the TFP growth rate relative to the frontier is larger precisely in those sectors where the relevant technology advances grows faster.[21]

To examine the effect of R&D investment on technology adoption, we perform the following exercises. To check the first prediction, we regress the level of log TFP relative to the US in the mid-90's[22] on the interaction of countries' R&D investment rates, R_j/Y_j, and the sectoral R&D investment rate in the US, R_{USk}/Y_{USk} -which we take as a proxy for the growth rate of the sectoral technology frontier-, controlling for sector- and country-specific effects.

$$\log\left(\frac{A_{jk}}{A_{USk}}\right) = \beta_1 X_{jk} + D_k + D_j + \epsilon_{jk} \tag{24}$$

where $X_{jk} = (R_j/Y_j) * (R_{USk}/Y_{USk})$, D_j and D_k are country and sector fixed effects and ϵ_{jk} is an i.i.d. error term. Data on countries' R&D investment rates come from the Lederman and Saenz [2005] database and US R&D investment rates by industry, defined as R&D expenditure as a fraction of sectoral value added, are constructed using data from the National Science Foundation.

To investigate the second and third prediction, we regress the growth rate of sectoral TFP relative to the US between the mid-80's and the mid-90's on the initial level of sectoral TFP and the interaction of countries' R&D investment rates with industry R&D investment rates in the US.

$$\Delta\log\left(\frac{A_{jk}}{A_{USk}}\right) = \beta_1 X_{jk} + \beta_2 \log\left(\frac{A_{jk0}}{A_{USk0}}\right) + D_k + D_j + \epsilon_{jk} \tag{25}$$

where X_{jk} is again the R&D interaction term and $\log\left(\frac{A_{jk0}}{A_{USk0}}\right)$ is the initial level of TFP relative to the US. We expect the coefficient on the initial level of sectoral TFP to be negative and the coefficient of the interaction term to be positive.

The first two columns of Table 7 report the results of the previous specifications. The R&D interaction has a significant positive effect on relative TFP levels both in the level and in the growth rate specification. There is also clear evidence for a convergence effect - the coefficient for the initial TFP level enters with a highly significant negative sign into the growth rate specification.

Another category of models emphasizes the role of human capital in the adoption of new technologies (e.g., Nelson and Phelps [1966], Caselli and Coleman [2006]). In a classic paper, Nelson and Phelps [1966] explore a one-sector model where higher levels of human capital help to adopt new technologies from a world

[21] Empirical evidence for these mechanisms is relatively limited. At the aggregate level Coe and Helpman [1995] and Eaton and Kortum [1999] provide evidence for R&D spillovers. Meanwhile Griffith, Redding and Reenen [2004] who use sectoral TFP growth rates for manufacturing in 12 OECD countries for the period 1974-90, find support for the hypothesis that R&D investment facilitates technology adoption.

[22] All regressions in this section are weighted by the inverse of the standard deviation of TFP. Our results also hold true without weighting observations and for the other periods for which we have computed TFPs.

technology frontier that grows at an exogenous rate.

Ciccone and Papaioannou [2009] build a multi-sector version of the Nelson-Phelps model and assume that technological progress is skill-biased in the sense that the world technology frontier grows faster in skill intensive sectors. They show that if the rate of technology adoption depends on a country's total endowments of human capital, productivity levels as well as productivity growth rates relative to the frontier are higher in skill intensive sectors if a country has a higher level of human capital. They empirically implement their model by regressing sectoral growth rates of value added and employment in manufacturing on the interaction between sectoral skill intensity, α_{sk}, and countries' initial human capital endowments, H_j, as measured by the average years of schooling in the population in 1980 for a large sample of countries. Their work lends support to the hypothesis that countries with higher initial levels of human capital grow faster in human capital-intensive sectors.

Having measures of industry TFP relative to the US allows us to test if the level of industry TFP is significantly higher in skill intensive sectors for those countries that have larger endowments of human capital. Second, this information enables us to see if sectoral productivity growth rates are indeed higher in skill intensive sectors whenever countries have larger endowments of human capital. In this regard, we have an advantage over Ciccone and Papaioannou [2009] because the latter cannot control for accumulation of certain factor inputs at the industry level (e.g., physical or human capital) which may affect sectoral value added or employment growth.

To evaluate the predictions of the multi-sector Nelson-Phelps model, we regress both the level and the growth rate of sectoral TFP relative to the US, whose productivity we take as the one of the frontier, on the human capital interaction, $\alpha_{sk} * H_j$. For the regression in levels we consider the mid-nineties, while for the second specification we take the growth rate of sectoral TFP relative to the US between the mid-80's and the mid 90's. The econometric specification is again analogous to (24) and (25). Once more, we control for sector- and country fixed effects in all regressions.

Looking at columns 3 and 4 of Table 7 we see that the coefficient of the human capital interaction term is positive and significant at the 1% level both in the level and in the growth rate specification. This implies that, in more skill intensive sectors, more human capital abundant countries have relatively higher productivity levels and productivity growth rates alike.[23]

A further application relates our sectoral productivity profiles to financial development. In a seminal article Rajan and Zingales [1998] show that industries that are more dependent on external finance grow

[23]The the results for TFP levels should be interpreted cautiously, as they may reflect a mismeasurement of the Heckscher-Ohlin effect in the construction of our productivity estimates. Notwithstanding, we are more confident about the validity of our results for TFP growth rates, where no such critique applies. To avoid any risk of measuring any Rybczynski effects, moreover, we have experimented with including an interaction between human capital intensity and the change in human capital endowments, which was never significant and did not affect the significance of the human capital interaction term in levels.

faster in financially developed countries, thereby providing evidence for a causal relationship between finance and growth. The main advantage of our sectoral productivity estimates is that we can address the specific channel through which financial development affects growth.

The empirical finance-growth literature has difficulties in assessing whether financial development leads to growth by: a) easing financial constraints and increasing the amount of investment firms are able to undertake; or b) more efficient allocation of credit within sectors.[24] This is because, for most countries, reliable sectoral investment series are not available. We provide evidence for the second explanation by showing that financial development leads to significantly higher relative productivity levels, and enhanced growth rates in sectors that depend more on external finance.

Here, our empirical strategy closely follows Rajan and Zingales. External financial dependence, $EXTFIN_k$, is measured by the fraction of sectoral investment that US firms cannot finance with internal cash flows and comes from Rajan and Zingales [1998]. To proxy for the tightness of credit constraints, we use sectoral financial dependence and interact it with country-level financial development, $PRIV_j$, as measured by private credit as a fraction of GDP in 1995 from Beck [2000]. Thus, first, we regress (log) sectoral productivity in the mid-90's on the $EXTFIN_k * PRIV_j$ interaction using specification (24) and controlling for sector and country fixed effects. Column 5 of Table 7 shows that financial development has a significantly (at the one percent level) larger positive effect on relative productivities in sectors that depend more on outside finance. Next, we regress the growth rate of sectoral TFP on the same interaction using specification (25), and controlling for sector and country fixed effects. Again, we find a significant (at the one percent level) positive coefficient of the financial interaction variable. This likewise corroborates the idea that financial development affects the efficiency of investment.

Please note that our results concerning the significantly larger positive impact of financial development on TFP in financially dependent sectors represented a marked contrast to the insignificant effect of the same variable that other studies have found using growth in industry value added per worker as a measure of productivity (see, for example Barone and Cingano [2008]). One possible explanation is that better financial development induces faster employment growth than growth in industry capital stocks in more financially dependent sectors, so that industry capital-labor ratios decrease in those countries and sectors. In line with this interpretation, Rajan and Zingales [1998] provide some evidence that the effect of better external finance works through differentials in the growth rate of the number of firms rather than in value added per firm. Hence, if higher financial development disproportionately benefits new, small firms, which operate at a lower capital intensity than large, established ones, industry capital labor ratios might well be lower in financially dependent sectors in countries with better financial systems. This mechanism would explain why financial

[24] An exception is Jayaratne and Strahan [1996]. Using data for several banking liberalization episodes in different US states, they show that bank branch deregulation has increased the efficiency but not the overall amount of bank credit in the US.

development has no significant effect on value added per worker but a positive impact on TFP.[25]

Finally, we include all the previous dependent variables simultaneously in the level and in the growth rate specification. In both specifications all dependent variables have the expected sign and remain significant, except for the R&D interaction, which becomes insignificant.

8 Conclusions

In this paper, we have estimated total factor productivity (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 in 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 that vitiate the application of traditional methods of TFP computations. For, the basic problem is that those techniques rely on information on sectoral inputs and outputs in physical units that is not available for virtually all of the developing countries. To compute sectoral productivities by our method, however, one only needs data on bilateral trade, aggregate factor prices, and sectoral production values.

Our results show that productivity differences in manufacturing sectors are large and systematically related to income per capita. In addition, productivity variation between rich and poor countries is more pronounced in skilled labor and R&D intensive sectors. We have also provided evidence that Ricardian productivity differences are very important in explaining bilateral sectoral trade patterns. Moreover, our methodology permits us to compute bilateral rankings of productivity-based comparative advantage for any pair of countries.

We have also performed a series of robustness checks and have shown that our productivity estimates are not sensitive to either the specific estimation methods, or the particular trade model, which we used in deriving our structural estimation equations.

Finally, we have related our productivity estimates to a number of theories on productivity differences (technology spillovers; the role of human capital for technology adoption; financial development). These theories have been selected because they have predictions for the variation of sectoral productivities across countries. We have demonstrated that there is a strong correlation between variation in sectoral TFP and proxies for the above factors.

[25] Indeed, Beck, Demirguc-Kunt, Laeven and Levine [2008] find that financial development has a differential impact on the growth rate of small firms. Industries that for exogenous technological reasons have smaller firms grow faster in countries with higher financial development. Guiso, Sapienza and Zingales [2004] provide similar evidence for Italy.

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Appendix

A Data Description

Bilateral sectoral trade data, M_{ijk}, and sectoral production, $Output_{jk}$, are obtained 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, covering 36 importing countries and 64 exporting countries. The 36 importers represent more than $\frac{2}{3}$ of world imports. Recall we exclude the US as an importer country because we use it as our benchmark.To mitigate problems of data availability and to smooth the business cycle, we average the data over three years. Of the 28 sectors in the ISIC classification we exclude Tobacco (314), Petroleum Refineries (353), Miscellaneous Petroleum and Coal Products (354), and Other Manufactured Products Not Classified Elsewhere (390). This we do because the trade data do not properly reflect productivity in those sectors.

For the monetary value of production, $\tilde{Q_{jk}}$, we use information on Gross Output from the Trade, Production and Protection database. Gross Output represents the value in current dollars of goods produced in a year, whether sold or stocked.[26]. The original source of this variable is the United Nations Industrial Development Organization's (UNIDO) Industrial Statistics. For the years 1994-1996 some of these data have been updated by Mayer and Zignago [2005]. The production data published by UNIDO are by no means complete, and that is the main limitation in computing productivities. UNIDO also collects data on the number of establishments which we could have used directly, in place of Gross Output data. However, these alternative data are less reliable than production data because different countries use different threshold firm sizes when reporting data to UNIDO.

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 these elasticities to our 3 digit ISIC rev. 2 level of disaggregation by weighting elasticities by US import shares. [27]

[26]Our results are robust even using Value Added instead.

[27]We have also worked with elasticities obtained from Hummels [1999] at the SITC 2 digit level and from Broda and Weinstein [2006] at the SITC 3 digit level. While computed elasticities are different depending on the source, final estimates of TFP are highly correlated. We prefer the SITC 5 digit level of disaggregation. For, on the one hand, there is a unique correspondence between SITC 5 digits and ISIC 3 digits -i.e., the SITC code 01111 maps only to ISIC code 31-, and on the other, there is no unique mapping between ISIC 3 digits and SITC 2 or 3 digits. For example, the SITC code 53 could correspond to ISIC codes 351 or 352. Thus, in the latter case choosing one specific ISIC code could lead to measurement bias, as we are defining more or less arbitrarily which code to choose (note that one reasonable option is to choose the ISIC code which has more correspondences at the SITC 5 digit level). Moreover, in some cases we still have to aggregate using import shares. For example, ISIC sector 311 corresponds to SITC sectors 01-09, 21 and 22. In that case (and others), we again have to weight somehow. So even working

Sectoral factor income shares, $(\alpha_{ku}, \alpha_{ks}, \alpha_{kcap})$, 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] and use the ratio of non-production workers to total employment, obtaining data from the NBER-CES Manufacturing Industry Database constructed by Bartelsman, Becker and Gray [2000] and converting US-SIC 87 categories to ISIC rev 2. The capital income share is computed as one less the share of total compensation in value added, using the same source. In our three factor model intensities are rescaled in such a way that $\sum_i \alpha_{k,i} = 1; \qquad i = u, s, cap$. As in Romalis [2004], $\alpha_{k,cap} = cap.intensity$; $\alpha_{ks} = skill\ intensity * (1 - \alpha_{kcap})$ and $\alpha_{ku} = 1 - \alpha_{ks} - \alpha_{kcap}$.

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 [2007]. 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. Firms set the marginal value product equal to the rental rate, $p_{jk}MPK_{jk} = P_{Kj}(interest_j + \delta)$, where P_{Kj} is 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 by 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 as to whether to invest an additional dollar in the firm itself or to put the same amount in an alternative investment opportunity that has a return $interest_j$, when the above-mentioned relationship holds true. Because capital is mobile across sectors within a country the marginal value product must likewise be equalized across sectors. Total payments to capital in country j are $\sum_k p_{jk}MPK_{jk}K_{jk} = p_jMPK_j \sum_k K_{jk} = r_jK_j$ where K_j is the country $j's$ capital stock in physical units and the first equality follows from capital mobility across sectors. Since $\alpha_{j,cap} = \frac{r_jK_j}{P_YY}$, 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). 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 of non-corporate employees.

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

with SITC at a higher level of aggregation does not eliminate completely a potential measurement bias problem.

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

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 workers with complete secondary education.[28] 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

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

Data for educational attainment of workers over 25 years at each 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 UNESCO. 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. 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 $e^{\beta*(prim.dur.+lowsec.dur.)}$. By our calculations, wages of both skilled and unskilled workers are much higher in rich countries, but the wage premium is negatively related to 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 [2007] once the latter correct for price differences and natural capital. Although in our three factor model we do not adjust for the fraction of income that goes to natural capital, we do 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. CEPII has developed a distance database that uses city-level data in the calculation of the distance matrix in order to assess the geographic distribution of population inside each nation. The basic idea is to calculate the distance between two countries on the basis of bilateral distances between cities, weighting by each city's share of the country's overall population. Also, CEPII provides us a bilateral sectoral tariff database. Tariffs are measured at the bilateral level and for each

[28]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 Caselli's papers referenced here.

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 world imports as weights for HS6 products. Using Rose [2004] as a source, other bilateral variables which we employ are the following indicators for any country pair sharing: a common border; a common language; membership in the same regional trade agreement; membership in the same currency union; membership in the same general system of preferences. Finally, we an indicator variable that equals one if one of the countries is a former colony of the other.

For TFP computed as Solow residuals from the OECD STAN database we proceed as follows. Capital stocks are computed by the perpetual inventory method using sectoral gross fixed capital formation from the STAN database. 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, as reported by Caselli [2005]. Our output measure is sectoral value added (from STAN).

Table 1: Industry Statistics

Isic Rev. 2	Sector Name	Skill Intensity	Capital Intensity	Elasticity of Substitution
311	Food	0.24	0.77	5.34
313	Beverages	0.49	0.85	3.94
321	Textiles	0.15	0.59	3.88
322	Apparel	0.16	0.6	3.3
323	Leather	0.17	0.63	2.24
324	Footwear	0.15	0.6	4.13
331	Wood	0.17	0.59	9.04
332	Furniture	0.19	0.55	2.07
341	Paper	0.23	0.72	5.72
342	Printing	0.47	0.64	2.58
351	Chemicals	0.41	0.82	5.62
352	Other Chemicals	0.45	0.82	4.73
355	Rubber	0.22	0.62	3.68
356	Plastic	0.23	0.68	2.11
361	Pottery	0.18	0.57	1.9
362	Glass	0.18	0.66	3.5
369	Other Non-Metallic	0.25	0.65	4.72
371	Iron and Steel	0.21	0.63	6.98
372	Non-Ferrous Metal	0.22	0.66	12.68
381	Fabricated Metal	0.25	0.56	2.91
382	Machinery	0.35	0.62	3.81
383	Electrical Machinery	0.35	0.7	3.04
384	Transport	0.32	0.62	4.6
385	Scientific	0.47	0.67	2.07
	Mean	0.27	0.66	4.36

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 one minus the share of total compensation in value added

Table 2: Regression Coefficients

Isic Rev. 2	Sector Name	Difference Distance	Difference Tariff	Common Language	Common English	Common Border	Common Colony
311	Food	-.272	-.003	.098	-.1		.23
		(.015)	(.001)	(.03)	(.014)		(.042)
313	Beverages	-.274	-.003	.217	-.074	.191	.149
		(.022)	(.002)	(.056)	(.029)	(.094)	(.066)
321	Textiles	-.348	-.017	.139	-.093		.217
		(.015)	(.002)	(.042)	(.025)		(.046)
322	Apparel	-.372	-.026	.142			.342
		(.043)	(.004)	(.054)			(.057)
323	Leather	-.515	-.055	.31	-.096		.441
		(.042)	(.006)	(.083)	(.05)		(.089)
324	Footwear	-.244	-.01	.164	.073	.288	
		(.033)	(.003)	(.046)	(.032)	(.085)	
331	Wood	-.138	-.017	.086		.108	.053
		(.011)	(.003)	(.016)		(.031)	(.02)
332	Furniture	-.597	-.104	.252		.26	.456
		(.051)	(.011)	(.066)		(.122)	(.09)
341	Paper	-.304	-.014	.085			
		(.016)	(.003)	(.031)			
342	Printing	-.438	-.058	.55	-.465	.275	.538
		(.029)	(.01)	(.097)	(.054)	(.09)	(.091)
351	Chemicals	-.24	-.004	.048	-.084	.063	.098
		(.009)	(.002)	(.04)	(.02)	(.041)	(.038)
352	OtherChemicals	-.275		.202	-.064		.142
		(.013)		(.048)	(.017)		(.047)
355	Rubber	-.311	-.06	.157	-.046	.148	.105
		(.024)	(.005)	(.05)	(.027)	(.075)	(.059)
356	Plastic	-.646	-.052	.369	-.089		.25
		(.047)	(.006)	(.084)	(.048)		(.098)
361	Pottery	-.511	-.063	.465			.279
		(.058)	(.007)	(.081)			(.119)
362	Glass	-.393	-.027	.198		.187	.11
		(.017)	(.004)	(.05)		(.086)	(.064)
369	OtherNonMetallic	-.288	-.019	.081		.139	.096
		(.017)	(.004)	(.036)		(.047)	(.046)
371	IronAndSteel	-.211	-.018				.102
		(.009)	(.005)				(.028)
372	NonFerrousMetals	-.138	-.012		-.04		.078
		(.006)	(.003)		(.009)		(.017)
381	FabricatedMetals	-.437	-.045	.234	-.1	.113	.315
		(.027)	(.005)	(.054)	(.028)	(.066)	(.066)
382	Machinery	-.276	-.022	.225	-.121		.217
		(.015)	(.004)	(.044)	(.018)		(.049)
383	ElectricalMachinery	-.329	-.046	.278	-.059		.254
		(.021)	(.004)	(.062)	(.027)		(.063)
384	Transport	-.248	-.031	.105		.148	.194
		(.016)	(.004)	(.052)		(.069)	(.063)
385	Scientific	-.398	-.036	.395	-.221		.419
		(.025)	(.005)	(.093)	(.038)		(.101)
	Observations	42217					
	R-Square	.805					
	R-Square Within	.469					
	rho	.742					

Fixed country-industry effects. Robust standard deviation clustered by exporter in parenthesis.

Table 3: Descriptive Statistics - Middle of the 90's

exporter	Mean	S.D.	Lowest TFP		Highest TFP	
ARG	0.48	0.27	Pottery	0.08	Food	1.25
AUS	0.91	0.30	Pottery	0.45	Textiles	1.57
AUT	1.04	0.27	Furniture	0.46	Scientific	1.53
BEL	1.12	0.26	Pottery	0.36	Leather	1.61
BGD	0.15	0.08	Electrical Machinery	0.06	Scientific	0.36
BOL	0.27	0.12	Plastic	0.10	Apparel	0.54
BRA	0.47	0.20	Pottery	0.09	Food	0.99
CAN	0.72	0.15	Footwear	0.48	Paper	1.01
CHL	0.44	0.28	Plastic	0.16	Beverages	1.15
CHN	0.16	0.06	Transport	0.09	Plastic	0.31
CIV	0.42	0.21	Fabricated Metal	0.13	Food	0.97
COL	0.27	0.13	Plastic	0.10	Food	0.57
CRI	0.45	0.17	Plastic	0.17	Non-Ferrous Metal	0.81
CYP	0.70	0.26	Fabricated Metal	0.37	Transport	1.35
DNK	1.41	0.22	Pottery	0.91	Rubber	1.69
ECU	0.23	0.11	Plastic	0.08	Food	0.53
EGY	0.25	0.09	Electrical Machinery	0.11	Non-Ferrous Metal	0.42
ESP	0.83	0.14	Leather	0.52	Other Non-Metallic	1.09
FIN	0.81	0.23	Pottery	0.16	Iron and Steel	1.17
FRA	0.97	0.18	Leather	0.67	Beverages	1.54
GBR	0.94	0.17	Furniture	0.64	Beverages	1.42
GER	0.99	0.11	Footwear	0.76	Textiles	1.27
GHA	0.24	0.14	Fabricated Metal	0.06	Food	0.64
GRC	0.44	0.14	Pottery	0.08	Food	0.64
GTM	0.37	0.18	Electrical Machinery	0.15	Food	0.74
HND	0.21	0.12	Leather	0.06	Transport	0.54
HUN	0.38	0.20	Leather	0.09	Apparel	1.09
IDN	0.32	0.15	Transport	0.15	Furniture	0.78
IND	0.18	0.11	Pottery	0.07	Furniture	0.59
IRL	1.10	0.31	Pottery	0.11	Beverages	1.65
ISL	0.92	0.31	Furniture	0.23	Iron and Steel	1.39
ISR	0.93	0.20	Leather	0.52	Machinery	1.30
ITA	1.13	0.20	Electrical Machinery	0.81	Furniture	1.57
JOR	0.22	0.10	Leather	0.06	Beverages	0.40
JPN	0.89	0.28	Leather	0.36	Rubber	1.39
KEN	0.15	0.06	Rubber	0.07	Pottery	0.27
KOR	0.53	0.13	Furniture	0.28	Rubber	0.83
LKA	0.20	0.06	Machinery	0.11	Furniture	0.35
MAR	0.26	0.11	Leather	0.09	Chemicals	0.47
MEX	0.45	0.15	Leather	0.24	Beverages	0.82
MLT	0.63	0.19	Pottery	0.28	Chemicals	0.94
MUS	0.45	0.18	Leather	0.23	Food	0.83
MYS	0.60	0.21	Other Non-Metallic	0.35	Apparel	1.24
NLD	1.32	0.19	Pottery	0.69	Beverages	1.59
NOR	1.24	0.33	Printing	0.59	Paper	1.68
PAK	0.20	0.15	Printing	0.07	Furniture	0.63
PAN	0.37	0.09	Plastic	0.24	Chemicals	0.57
PER	0.30	0.18	Leather	0.12	Food	0.86
PHL	0.31	0.15	Rubber	0.13	Furniture	0.75
POL	0.26	0.11	Pottery	0.08	Iron and Steel	0.45
PRT	0.58	0.14	Furniture	0.29	Beverages	0.91
ROM	0.14	0.04	Leather	0.06	Iron and Steel	0.23
SEN	0.38	0.24	Fabricated Metal	0.08	Scientific	0.92
SGP	1.19	0.33	Pottery	0.41	Textiles	1.67
SLV	0.50	0.16	Printing	0.22	Glass	0.73
SWE	1.15	0.20	Leather	0.76	Textiles	1.53
THA	0.26	0.11	Beverages	0.13	Furniture	0.58
TTO	0.28	0.11	Electrical Machinery	0.12	Beverages	0.47
TUN	0.22	0.08	Leather	0.08	Chemicals	0.35
TUR	0.39	0.15	Pottery	0.13	Food	0.65
URY	0.61	0.27	Plastic	0.21	Apparel	1.16
USA	1.00	0	Food	1.00	Food	1.00
VEN	0.27	0.14	Furniture	0.07	Non-Ferrous Metal	0.57
ZAF	0.56	0.25	Printing	0.22	Food	1.00
ZWE	0.16	0.07	Fabricated Metal	0.06	Iron and Steel	0.26

Table 4: TFP and Sector Characteristics

	log(TFP)	log(TFP)	log(TFP)	log(TFP)
skill	-15.074			-9.679
	(3.205)***			(3.473)**
skill * income	1.510			0.960
	(0.346)***			(0.375)*
capital		1.370		2.852
		(2.025)		(2.030)
capital * income		-0.018		-0.177
		(0.217)		(0.217)
R&D			-13.900	-12.894
			(4.400)**	(4.262)**
R&D * income			1.528	1.364
			(0.474)**	(0.461)**
Country Fixed Effects	Yes	Yes	Yes	Yes
Observations	1450	1450	1450	1450
Countries	64	64	64	64

Fixed effect panel regression weighted by the inverse of the standard deviation of TFP.
Robust standard deviation clustered by exporter in parenthesis. Significant at the 1% (***), 5% (**), and 10% (*) level.

Table 5: Coefficients, Hausman-Taylor Regression

		First Stage						Second Stage	
Isic Rev 2	Sector Name	Difference Distance	Difference Tariff	Common Language	Common English	Common Border	Common Colony	Relatively Skill	Relatively Unskill
311	Food	-1.440	-0.016	0.510	-0.529	0.136	1.227	-14.242	-7.6
		(0.054)***	(0.005)***	(0.141)***	(0.091)***	(0.215)	(0.214)***	(1.988)***	(0.601)***
313	Beverages	-1.079	-0.014	0.856	-0.290	0.751	0.589	-10.493	-5.416
		(0.071)***	(0.007)**	(0.18)***	(0.111)***	(0.292)**	(0.271)**	(2.041)***	(1.796)***
321	Textiles	-1.349	-0.064	0.540	-0.362	-0.004	0.841	-6.215	-3.801
		(0.054)***	(0.008)***	(0.134)***	(0.088)***	(0.203)	(0.182)***	(1.477)***	(0.269)***
322	Apparel	-1.201	-0.090	0.424	0.094	0.234	1.115	-17.248	-3.798
		(0.08)***	(0.01)***	(0.155)***	(0.096)	(0.243)	(0.207)***	(1.758)***	(0.343)***
323	Leather	-1.146	-0.123	0.686	-0.213	0.074	0.985	-6.16	-5.167
		(0.061)***	(0.012)***	(0.157)***	(0.102)**	(0.227)	(0.203)***	(1.615)***	(0.338)***
324	Footwear	-1.005	-0.043	0.706	0.304	1.195	-0.105	-7.504	-4.558
		(0.075)***	(0.009)***	(0.18)***	(0.118)***	(0.286)***	(0.252)	(2.147)***	(0.342)***
331	Wood	-1.239	-0.155	0.817	-0.112	0.951	0.481	-14.735	-3.969
		(0.061)***	(0.021)***	(0.135)***	(0.096)	(0.246)***	(0.174)***	(1.446)***	(0.287)***
332	Furniture	-1.232	-0.213	0.564	-0.119	0.515	0.946	-13.989	-3.296
		(0.069)***	(0.018)***	(0.154)***	(0.101)	(0.26)**	(0.203)***	(1.259)***	(0.308)***
341	Paper	-1.710	-0.080	0.413	-0.076	0.301	0.252	-10.515	-3.237
		(0.057)***	(0.015)***	(0.165)**	(0.103)	(0.217)	(0.215)	(1.84)***	(0.524)***
342	Printing	-1.130	-0.150	1.418	-1.198	0.708	1.388	-1.437	-6.863
		(0.054)***	(0.023)***	(0.151)***	(0.087)***	(0.229)***	(0.212)***	(0.522)***	(0.491)***
351	Chemicals	-1.349	-0.022	0.272	-0.473	0.356	0.552	-8.352	-8.3
		(0.049)***	(0.011)**	(0.161)*	(0.098)***	(0.202)*	(0.22)**	(1.272)***	(0.933)***
352	Other Chemic	-1.270	-0.006	0.931	-0.291	0.272	0.657	-12.864	
		(0.047)***	(0.013)	(0.152)***	(0.089)***	(0.241)	(0.187)***	(1.259)***	
355	Rubber	-1.145	-0.221	0.580	-0.170	0.544	0.386	-1.956	-3.064
		(0.058)***	(0.019)***	(0.16)***	(0.098)*	(0.238)**	(0.208)*	(1.248)	(0.341)***
356	Plastic	-1.327	-0.112	0.738	-0.172	0.380	0.514	-7.392	-4.08
		(0.057)***	(0.009)***	(0.139)***	(0.092)*	(0.274)	(0.198)***	(1.177)***	(0.355)***
361	Pottery	-0.966	-0.121	0.849	0.081	0.056	0.523	-14.707	-3.61
		(0.07)***	(0.011)***	(0.162)***	(0.112)	(0.288)	(0.224)**	(1.718)***	(0.34)***
362	Glass	-1.374	-0.093	0.720	-0.074	0.637	0.390	-15.683	-2.853
		(0.054)***	(0.013)***	(0.177)***	(0.102)	(0.258)**	(0.218)*	(1.542)***	(0.346)***
369	Other Non-Metal	-1.354	-0.089	0.436	-0.138	0.629	0.458	-14.9	-0.796
		(0.056)***	(0.018)***	(0.153)***	(0.106)	(0.233)***	(0.194)**	(1.207)***	(0.376)**
371	Iron and Steel	-1.470	-0.120	-0.137	-0.134	0.104	0.807	-18.398	-0.458
		(0.054)***	(0.021)***	(0.162)	(0.112)	(0.21)	(0.207)***	(1.65)***	(0.397)
372	Non-Ferrous	-1.782	-0.140	0.034	-0.516	-0.322	1.005	-19.678	-2.493
		(0.069)***	(0.037)***	(0.185)	(0.123)***	(0.258)	(0.226)***	(1.613)***	(0.433)***
381	Fabricated Metal	-1.271	-0.131	0.681	-0.292	0.329	0.917	-4.467	-3.099
		(0.048)***	(0.011)***	(0.123)***	(0.079)***	(0.202)	(0.179)***	(0.844)***	(0.289)***
382	Machinery	-1.035	-0.084	0.838	-0.453	0.176	0.820	-6.047	-3.022
		(0.044)***	(0.015)***	(0.12)***	(0.083)***	(0.192)	(0.174)***	(0.613)***	(0.349)***
383	Electrical Machin	-0.968	-0.141	0.807	-0.164	0.364	0.761	-4.113	-4.495
		(0.047)***	(0.011)***	(0.135)***	(0.09)*	(0.237)	(0.185)***	(1.074)***	(0.577)***
384	Transport	-1.140	-0.138	0.537	-0.146	0.651	0.896	-7.412	-2.051
		(0.068)***	(0.016)***	(0.188)***	(0.118)	(0.278)**	(0.293)***	(1.01)***	(0.438)***
385	Scientific	-0.796	-0.077	0.784	-0.445	0.316	0.856		-9.907
		(0.043)***	(0.011)***	(0.127)***	(0.083)***	(0.215)	(0.192)***		(0.509)***
	Observations	42217						42217	
	R-square	0.64						0.55	
	R-square Within	0.46						0.35	
	rho	0.47						0.61	

Robust standard deviations in parenthesis. Significant at the 1% (***), 5% (**), and 10% (*) level.

Table 6: Robustness of TFP estimates

Specification	Correlation	Spearman
Hausman-Taylor	0.98	0.96
Heckman	0.90	0.93
Heterogenous Firms	0.89	0.93
Eaton-Kortum	0.89	0.90

Table 7: Productivity and Theories of Development

	Log(TFP)	TFP Growth	Log(TFP)	TFP Growth	Log(TFP)	TFP Growth	Log(TFP)	TFP Growth
R&D Interaction	1.896	1.574					0.643	0.030
	(0.484)***	(0.633)*					(0.501)	(0.692)
HC Interaction			0.516	0.751			0.520	0.739
			(0.152)**	(0.198)***			(0.148)**	(0.271)**
Financial Int.					0.575	0.606	0.480	0.671
					(0.103)***	(0.137)***	(0.131)***	(0.199)**
log TFP 85		-0.602		-0.523		-0.530		-0.664
		(0.169)***		(0.126)***		(0.119)***		(0.185)***
Sector and Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	974	897	1280	1164	1381	1220	888	830
Countries	42	40	56	55	61	58	38	37

Fixed effect panel regression weighted by the inverse of the standard deviation of TFP.

Robust standard deviation clustered by exporter in parenthesis. Significant at the 1% (***), 5% (**), and 10% (*) level.

Table 8: Productivity and Openness

Variable	VA share Whole sample	VA share No Open before 90	VA share Open before 90	VA share No Open before 80	VA share Open before 80	VA share	VA share	VA share	VA share	VA share
Ln(TFP) relative to the US	0.005	-0.006	0.009	-0.005	0.013	0.006	0.005	0.006	0.007	0.006
	(0.003)	(0.004)	(0.004)*	(0.003)	(0.006)*	(0.004)	(0.003)	(0.003)*	(0.003)**	(0.003)*
Ln(TFP)*Open before 90						-0.003				
						(0.005)				
Ln(TFP)*Open before 80							-0.002			
							(0.006)			
Import over VA								-0.000		
								(0.000)		
Ln(TFP)*import over VA								-0.000		
								(0.000)		
Export over VA									-0.001	
									(0.000)**	
Ln(TFP)*export over VA									0.001	
									(0.000)	
Total trade over VA										-0.000
										(0.000)
Ln(TFP)*trade over VA										-0.000
										(0.000)
Observations	1419	656	763	844	575	1419	1419	1418	1418	1418
Countries	63	30	33	38	25	63	63	63	63	63

Fixed effect panel regression non weighted.

Robust standard deviation in parenthesis. Significant at the 1% (***), 5% (**), and 10% (*) level.

Table 8: Productivity and Openness (Weighted regression)

	VA share	VA share	VA share	VA share	VA share	VA share	VA share	VA share	VA share	VA share
Variable	Whole sample	No Open before 90	Open before 90	No Open before 80	Open before 80					
Ln(TFP) relative to the US	-0.002	-0.010	0.002	-0.008	0.005	-0.003	-0.003	-0.002	-0.001	-0.001
	(0.002)	(0.003)***	(0.004)	(0.002)***	(0.007)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Ln(TFP)*Open before 90						0.002				
						(0.005)				
Ln(TFP)*Open before 80							0.003			
							(0.008)			
Import over VA								-0.000		
								(0.000)		
Ln(TFP)*import over VA								0.000		
								(0.000)		
Export over VA									-0.001	
									(0.000)***	
Ln(TFP)*export over VA									0.000	
									(0.000)	
Total trade over VA										-0.000
										(0.000)
Ln(TFP)*trade over VA										0.000
										(0.000)
Observations	1395	632	763	820	575	1395	1395	1395	1395	1395
Countries	62	29	33	37	25	62	62	62	62	62

Fixed effect panel regression weighted by the inverse of the standard deviation of TFP.

Robust standard deviation clustered by exporter in parenthesis. Significant at the 1% (***), 5% (**), and 10% (*) level.

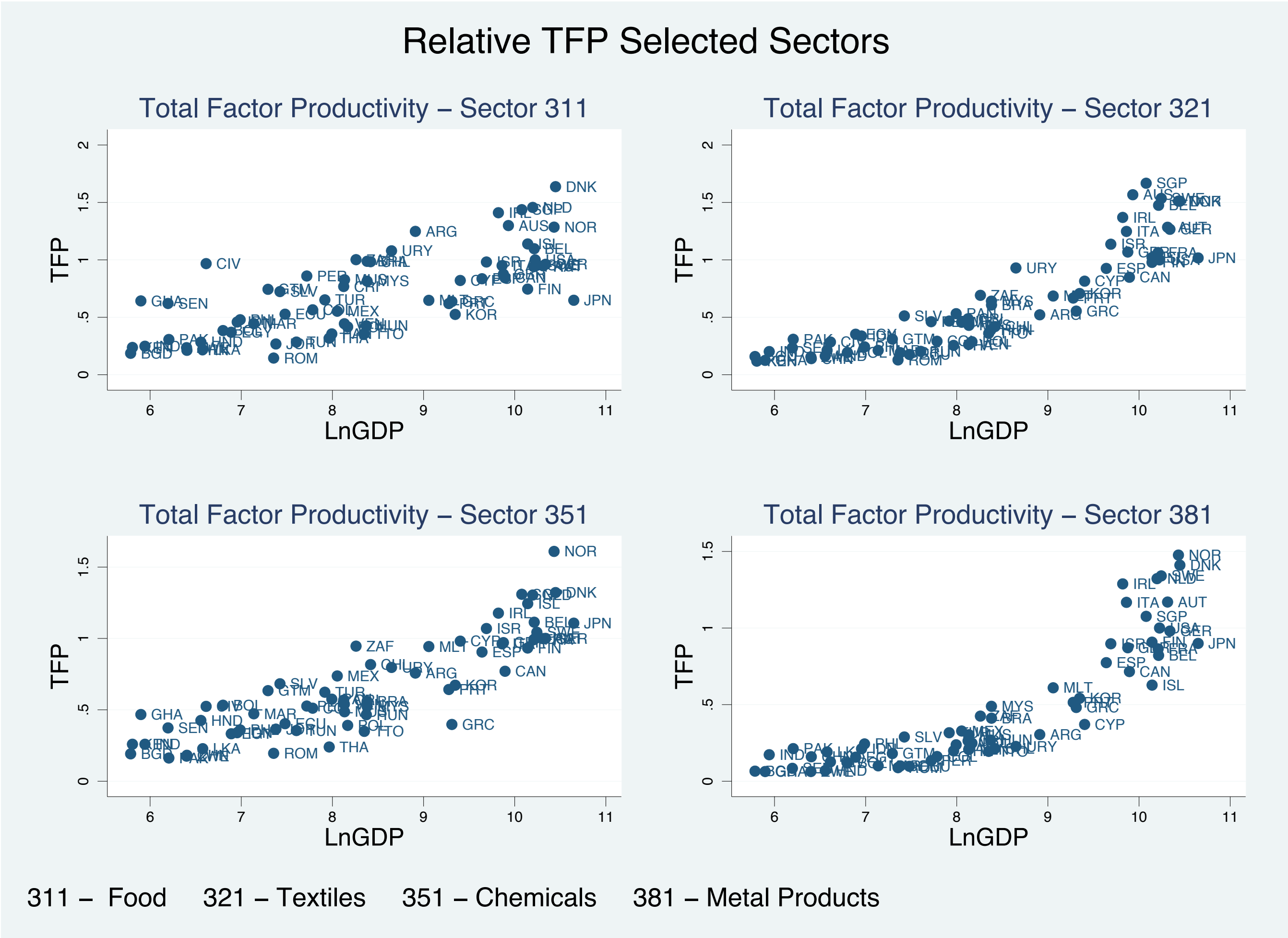

Figure 1: Relative TFP selected sectors

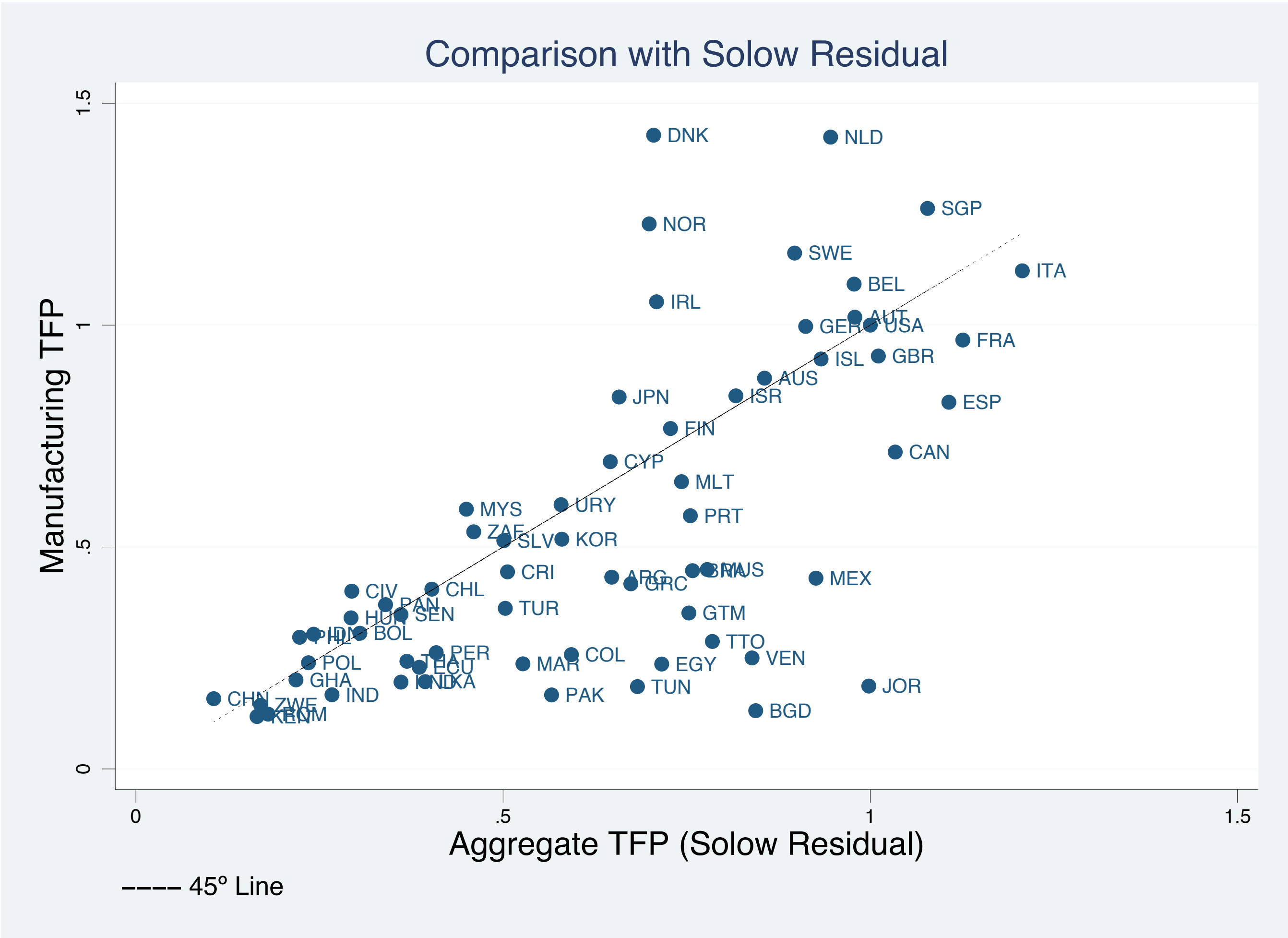

Figure 2: Aggregate Manufacturing TFP vs. TFP Solow Residual

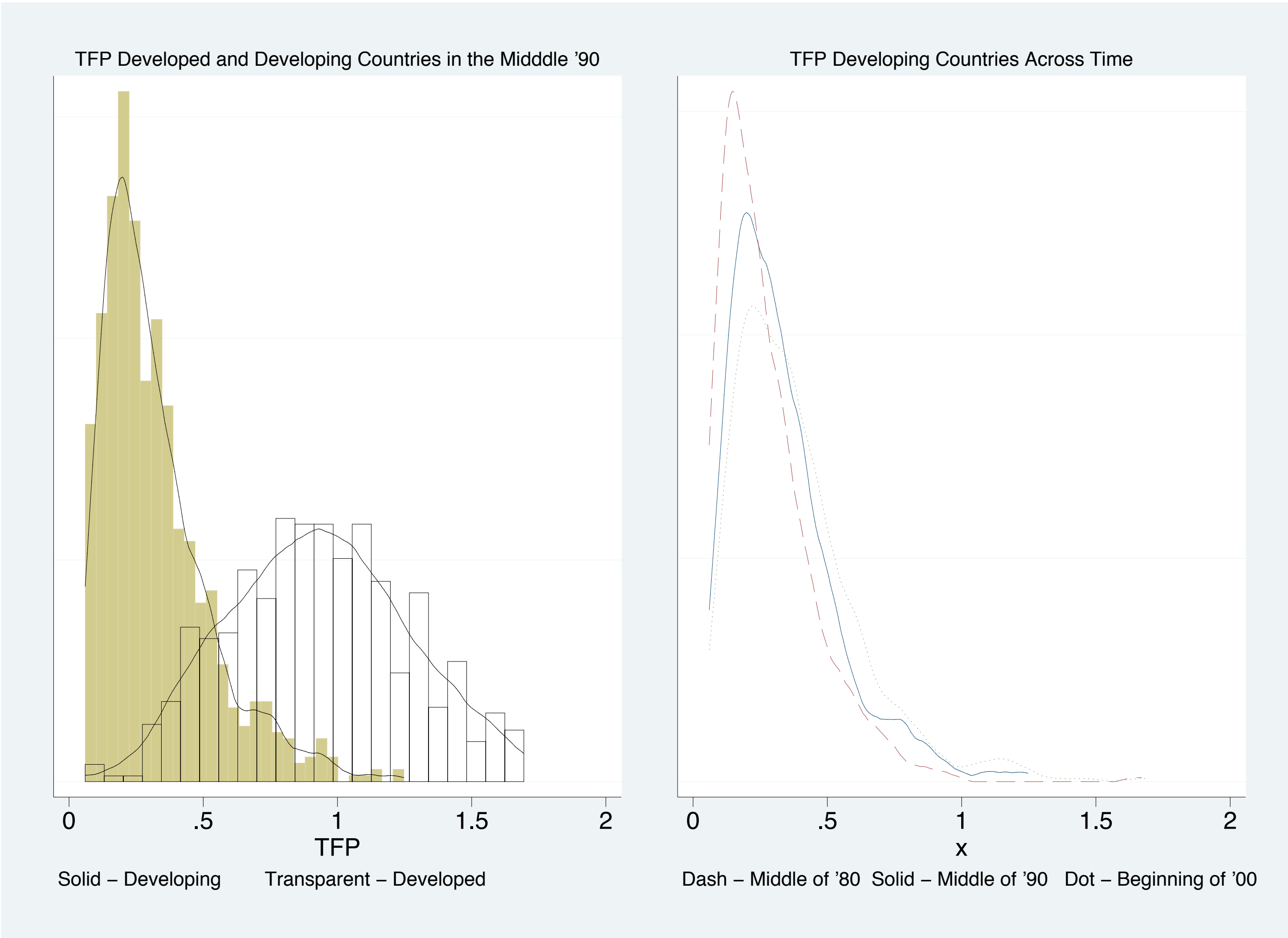

Figure 3: TFPs rich and poor countries and TFPs evolution in poor countries

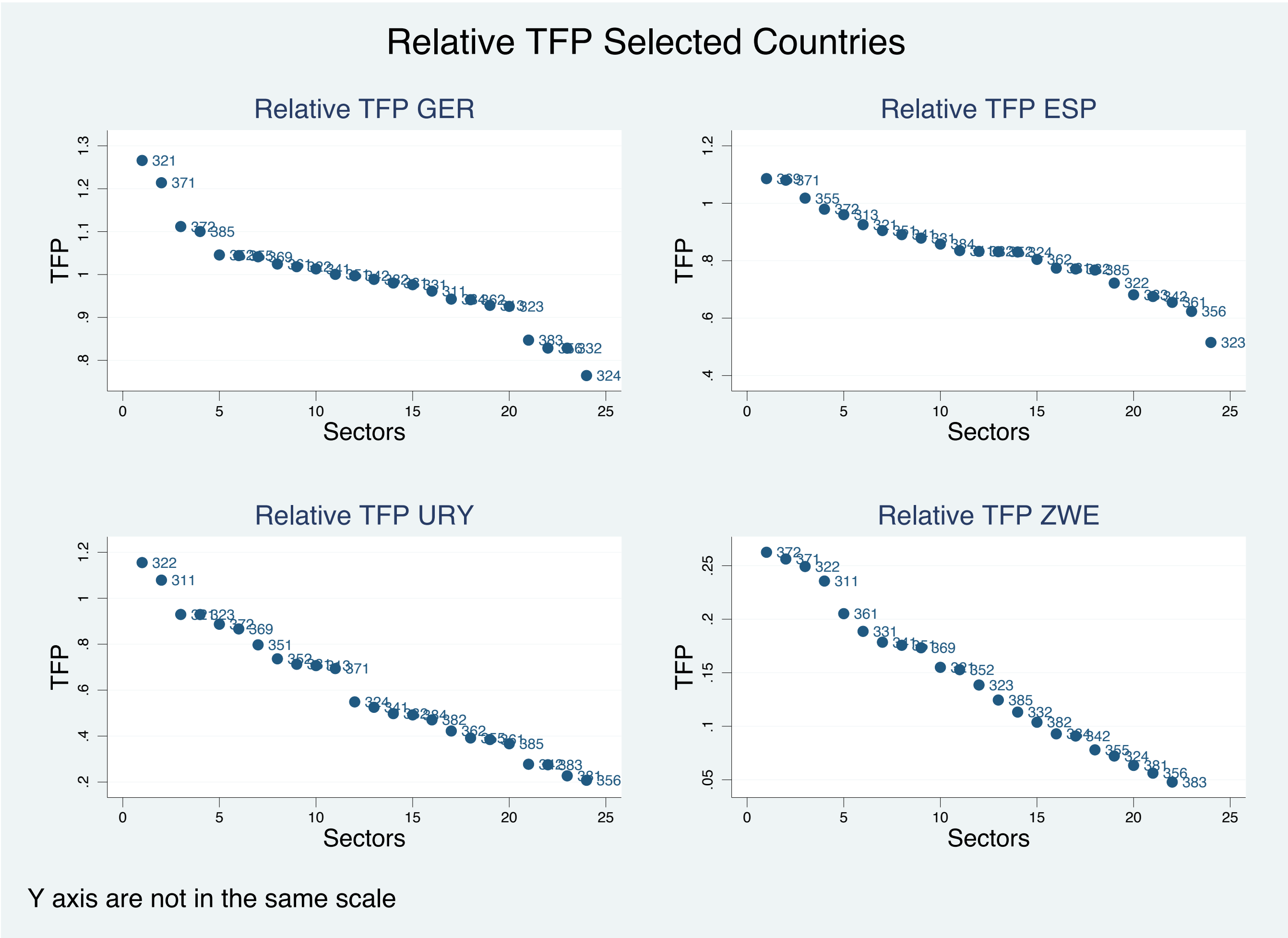

Figure 4: Ricardian Comparative Advantage relative to US