TRADE AND SECTORAL PRODUCTIVITY*

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Cross-country differences in sectoral total factor productivity (TFP) are at the heart of Ricardian trade theory and of many models of growth and development. Our knowledge of the magnitude and the characteristics of cross-country differences in sectoral TFP is limited. This study fills the gap by showing how sectoral TFP differences can be backed out from bilateral trade data using a hybrid Ricardo–Heckscher-Ohlin model. This allows us to overcome the data problems that constrained previous studies and to provide a comparable set of sectoral productivities for 24 manufacturing sectors in more than 60 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 labour and R&D intensive sectors.

The traditional approach to measuring cross-country differentials in industry total factor productivity (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 industrialised 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. This allows us to provide a comparable and, as we will argue, reliable set of industry TFPs for 24 manufacturing sectors in more than 60 countries at all stages of development.

Our point of departure is a model that combines Heckscher-Ohlin trade with the Krugman (1979) model of trade because of increasing returns and consumers' love for variety and also allows for trade costs (Romalis, 2004). We extend this model to differences in industry TFP and to many asymmetric countries. This allows us 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.

The idea behind our method of estimating sectoral productivities is to exploit variation in bilateral sectoral export values compared with those for a benchmark country, appropriately adjusted for differences in total production volume and input costs, across export markets. As an example, consider how we infer Italy's TFP relative to the US in the textile sector. We first measure the fraction of Italy's textile production relative to US textile production that is exported to each market. If Italy

exports more to an average market than the US, once we have adjusted for relative input costs and relative bilateral trade costs, this indicates a higher level of sectoral TFP.

A key virtue of our procedure is that we do not need output price data. The standard production function approach requires such data to make sure that TFP differences do not reflect differences in market structure. Our approach infers sectoral TFPs using exports of different countries to the same destination country and therefore the same competitive environment. To put it differently, our approach exploits that differences in sectoral exports to the same market must reflect differences in TFP rather than output prices once we have taken into account differences in input prices and trade costs.

We show that TFP differences between rich and poor countries are systematically larger in skilled labour 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. Moreover, we find that cross-country TFP differences in manufacturing sectors average about the same substantial orders of magnitude as development accounting literature has found in cross-country variation at the aggregate economy level (Hall and Jones, 1999; Caselli, 2005). We also find that Ricardian TFP differences are quantitatively important to explain trade flows. When restricting TFP differences to be country-specific, the fit of our estimation equations drops by roughly 14 percentage points in terms of adjusted R-squared. To explore the sensitivity of our results to the underlying trade model, we also back out sectoral TFPs in models with firm heterogeneity in productivity (Eaton and Kortum, 2002; Melitz, 2003) and in a model with endogenous markups. The estimation equations implied by these alternative models are similar to the ones of our main approach and the sectoral TFP findings are also similar. We also verify that our estimates for aggregate manufacturing TFP correlate strongly with the productivity esti-mates 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.

We conclude by using our sectoral productivity estimates to test various development theories. Our results show 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 article is organised as follows. The next Section briefly discusses the related literature. Section 2 introduces the theoretical model. Section 3 develops a methodo-logy for computing industry productivity indices. Section 4 presents our empirical findings regarding sectoral productivity profiles. Section 5 covers robustness checks. Section 6 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.

1. Related Literature

Several studies have attempted to compare sectoral productivity indices across countries by specifying sectoral production possibility frontiers, and by using data on sectoral inputs and outputs. Typical of such works are Dollar and Wolff (1988), Bernard and Jones (1996), Acemoglu and Zilibotti (2001) or Griffith *et al.* (2004), which use aggregate Purchasing Power Parity (PPP) indices to deflate sectoral output measures and deal only with a limited number of economies. Only a small number of studies – which are even more limited in terms of country coverage – have constructed sectoral price indices to perform cross-country industry-level productivity comparisons.[1] A notable early example is Jorgenson *et al.* (1987), who compare sectoral TFP between Japan and the US. They obtain industry deflators using price and expenditure information from consumer surveys and direct retail price surveys. Using an alternative approach, van Ark and Pilat (1993) construct sectoral prices with information on unit values and physical quantities to compare sectoral TFP levels between Germany, Japan and the US. The most important attempt to tackle the price data issue is the International Comparison Project (ICOP), located at the University of Groningen. One of ICOPs latest projects, EU KLEMS, is a high-quality growth-accounting database for the countries of the European Community. As 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. Thus – like for primal TFP comparisons – the main obstacle to applying this method at the sector level for developing countries is again the shortage of industry price data.

In the trade literature, there are also several contributions that construct sectoral productivity indices at various levels of aggregation. Notably, Harrigan (1997) computes industry TFP levels for eight sectors in 10 OECD countries to test the fit of a generalised 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) carefully constructs sectoral price indices for six manufacturing sectors in eight OECD countries and shows that even across this restricted set of economies sectoral prices vary substantially.

Other related works are the following: 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 (2010) extends their model to Heckscher-Ohlin trade and differences in sectoral characteristics, such as financial dependence and volatility. Taking a track parallel to ours, Finicelli *et al.* (2008) apply the baseline Eaton–Kortum model to calibrate aggregate manufacturing TFPs for 18 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

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[1] See van Biesebroeck (2009) for a discussion of most of these studies.

for a sample that includes a large number of developing countries. In fact, their main contribution is to develop 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 this article. Finally, Morrow (2010) also augments the Romalis (2004) model for Ricardian TFP differences to test the hybrid Ricardian–Heckscher-Ohlin model. He estimates the model by employing sectoral TFPs constructed from production data instead of backing out TFPs from the model.

2. A Hybrid Ricardo–Heckscher-Ohlin 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 with increasing returns at the firm level. We add three ingredients to the Krugman model. 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. As Romalis (2004) points out, this makes locally abundant factors relatively cheap and strengthens the link between factor abundance and trade.[2] 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 advantage relative to their foreign competitors and charge lower prices. As 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. We now turn to a formal description of the model, discussing first demand and then production technology and firms' pricing decisions.

2.1. Demand

Our model generalises 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.[3]

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

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[2] 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 specialised.

[3] For our baseline specification, preferences can be generalised to any country-specific, strictly concave, homothetic and weakly separable utility function $U_i(u_{i1}, \ldots, u_{iK})$, where the u_{ik}s are CES indices as defined in (2). This would lead to demand functions of the form $x_{ijk} = (\hat{p}_{ijk}^{-\varepsilon_k})/(P_{ik}^{1-\varepsilon_k})E_{ik}(P_{i1}, \ldots, P_{ik})Y_i$, where $E_{ik}(P_{i1}, \ldots, P_{iK})Y_i$ is expenditure on sector k goods in country i, and the P_{ik}'s are CES price indices as defined in (4).

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

$$u_{ik} = \left(\sum_{b \in B_{ik}} x_b^{\frac{\varepsilon_k - 1}{\varepsilon_k}} \right)^{\frac{\varepsilon_k}{\varepsilon_k - 1}}. \tag{2}$$

Note that utility is strictly increasing in the number of sectoral varieties available in a country. The sector-specific elasticity of substitution between varieties is denoted by ε_k, and in this model, we assume it to be 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:

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

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:

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

2.2. Supply

In each country, firms may be active in one of $k = 0, \ldots, K$ different sectors. Production technology differs across sectors because of 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,[4] unskilled labour, $U_j(n)$, with price w_{uj}, and skilled labour $S_j(n)$, with price w_{sj}.[5] In addition, there is a country and sector-specific TFP term, A_{jk}. Firms' production possibilities in sector k of country j are described by the total cost function:

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

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

where $F = \{u, s, \text{cap}\}$ 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 ($\alpha_{uk}, \alpha_{sk}, \alpha_{\text{cap}k}$). 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 labour as the constant variable cost.

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

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

The combination of sectors with different factor intensities and country–sector-specific TFP differences results in a Heckscher-Ohlin model with Ricardian features. As 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 has high productivity.[6]

3. Towards Estimating Sectoral Productivities

We now 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's imports 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 cost, insurance and freight (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:

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

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:

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

Equation (9) makes clear that bilateral trade in sector k measured in dollars depends positively on the importing country consumers' expenditure share on sector k goods,

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[6] In the online Technical Appendix to this article we present a general equilibrium version of the model and discuss in more detail how comparative advantage is determined.

σ_{ik}, and their total income, Y_i. In contrast, 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 sectoral data on the number of firms active in the exporting countries is scarce and not always comparable across countries. However, 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.[7] 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.

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

Using this result and substituting it into the definition of sectoral output, we get:

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

Substituting for N_{jk} in (9), we obtain:

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

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 sectors.[8] Another advantage of choosing a reference country is that all the terms that are not indexed to the exporting country j (i.e. σ_{ik}, Y_i or P_{ik}) drop from the equation. For each

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[7] Moreover, 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.
[8] We have also tried other benchmark countries, such as Germany and Japan, and our results are robust to these alternative specifications.

importer i, we can express the 'raw' productivity of country j in sector k relative to the US

$$\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}} \equiv \frac{A_{jk}}{A_{USk}} \left(\frac{f_{jk}}{f_{USk}}\right)^{-1/\varepsilon_k} \left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right)^{\frac{1-\varepsilon_k}{\varepsilon_k}}$$

$$= \left(\frac{M_{ijk}}{M_{iUSk}} \frac{\tilde{Q}_{USk}}{\tilde{Q}_{jk}}\right)^{1/\varepsilon_k} \prod_{f \in F} \left(\frac{w_{fj}}{w_{fUS}}\right)^{\alpha_{fk}}. \qquad (14)$$

Our 'raw' productivity measure, $(\tilde{A}_{ijk}/\tilde{A}_{iUSk})$, 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-à-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. Although relative transport costs vary by importing country, exporters' relative productivities and fixed costs are invariant vis-à-vis the importing country. Consequently, it is easy to separate the two parts by using regression techniques. Relative productivity is defined as the product of the relative productivity of variable production and weighted relative fixed cost, $(\breve{A}_{jk}/\breve{A}_{USk}) = (A_{jk}/A_{USk})(f_{jk}/f_{USk})^{-1/\varepsilon_k}$. Taking logarithms, we get:

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

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

$$\log\left(\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}}\right) = \log\left(\frac{\breve{A}_{jk}}{\breve{A}_{USk}}\right) + \beta_{1k}(\log \mathrm{Dist}_{ij} - \log \mathrm{Dist}_{iUS})$$

$$+ \beta_{2k}(\log \mathrm{Tariff}_{ijk} - \log \mathrm{Tariff}_{iUSk})$$

$$+ \beta_{3k}\mathrm{CommonLang}_{ij} + \beta_{4k}\mathrm{CommonLang}_{iUS} + \cdots + u_{ijk} - u_{iUSk}. \qquad (16)$$

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 $[(1-\varepsilon_k)/\varepsilon_k]$. The sector–country dummies are computed as:

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

Here, the bars indicate means across importing countries i, and $\boldsymbol{\beta}_k^{\mathrm{FE}}$ is the fixed effect panel estimator for the vector $\boldsymbol{\beta}_k$. Consequently, the estimated productivity of country j in sector k relative to the US is the mean of $(\tilde{A}_{ijk}/\tilde{A}_{iUSk})$ 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 $(\breve{A}_{jk}/\breve{A}_{USk}) = (A_{jk}/A_{USk})(f_{jk}/f_{USk})^{-1/\varepsilon_k}$. Note that $(\breve{A}_{jk}/\breve{A}_{USk}) < (A_{jk}/A_{USk})$ 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 owing 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.[9]

Our measure of relative TFP is transitive. This implies that productivity profiles are comparable across countries *within* sectors in the sense that $(A_{jk}/A_{j'k} = A_{jk}/A_{USk}(A_{j'k}/A_{USk})^{-1}$. 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 because of cost

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[9] There are several possible empirical approaches to investigate fixed costs' effects on industry productivity. One way is 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 $(\breve{A}_{jk}/\breve{A}_{USk}) = (A_{jk}/A_{USk})(f_j/f_{US})^{-1/\varepsilon_k}$ 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.

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.[10]

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 24 (ISIC Rev. 2) manufacturing sectors in 64 countries at all stages of development, for three periods: the mid-1980s, the mid-1990s 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 labour 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).[11] Mayer and Zignago (2005) and Rose (2004) afford 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 generalised 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 labour 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.

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[10] The following model is isomorphic to the one presented in the main text. Replace sectoral sub-utility with the expression $u_{ik} = \left\{ \sum_{b \in B_{ik}} (\lambda_b x_b)^{[(\varepsilon_k-1)/\varepsilon_k]} \right\}^{[\varepsilon_k/(\varepsilon_k-1)]}$, 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 $TC(q_{jk}) = (f_k + q_{jk}) \prod_{f \in F} (w_{fj}/\alpha_{fjk})^{\alpha_{fk}}$. 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:

$$x_{ijk} = \frac{\hat{p}_{ijk}^{-\varepsilon_k} \lambda_{jk}^{\varepsilon_k-1} \sigma_{ik} Y_i}{\tilde{P}_{ik}^{1-\varepsilon_k}},$$

where $\tilde{P}_{ik} = \left[\sum_{b \in B_{ik}} (\hat{p}_b/\lambda_b)^{1-\varepsilon_k} \right]^{[1/(1-\varepsilon_k)]}$ is the optimal quality adjusted price index. In this case, the value of bilateral trade is

$$M_{ijk} = \frac{(p_{jk}\tau_{ijk})^{1-\varepsilon_k} \lambda_{jk}^{\varepsilon_k-1} \sigma_{ik} Y_i}{\tilde{P}_{ik}^{1-\varepsilon_k}} N_{jk}.$$

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.

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

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 and 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.

4. Results

We first report the results of computing productivities using our baseline specification equation (16). We use a stepwise linear panel estimation[12] 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 information contained in zeros in bilateral trade flows and issues of sample selection. This leaves us with a sample of around 42,000 observations for a given period.

Table 2 shows the regression results for our baseline model using data for the mid-1990s. The overall fit is very good, with an R-squared of 0.80 and a *within* R-squared 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 $(\tilde{A}_{ijk}/\tilde{A}_{iUSk})$ across importers. In addition ρ – the fraction of the variance of the error term that is due to

[12] 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.

Table 2

Regression Coefficients

ISIC Rev. 2	Sector name	Difference distance	Difference tariff	Common language	Common English	Common border	Common colony
311	Food	−0.272	−0.003	0.098	−0.1		0.23
		(0.015)	(0.001)	(0.03)	(0.014)		(0.042)
313	Beverages	−0.274	−0.003	0.217	−0.074	0.191	0.149
		(0.022)	(0.002)	(0.056)	(0.029)	(0.094)	(0.066)
321	Textiles	−0.348	−0.017	0.139	−0.093		0.217
		(0.015)	(0.002)	(0.042)	(0.025)		(0.046)
322	Apparel	−0.372	−0.026	0.142			0.342
		(0.043)	(0.004)	(0.054)			(0.057)
323	Leather	−0.515	−0.055	0.31	−0.096		0.441
		(0.042)	(0.006)	(0.083)	(0.05)		(0.089)
324	Footwear	−0.244	−0.01	0.164	0.073	0.288	
		(0.033)	(0.003)	(0.046)	(0.032)	(0.085)	
331	Wood	−0.138	−0.017	0.086	0.108	0.053	
		(0.011)	(0.003)	(0.016)		(0.031)	(0.02)
332	Furniture	−0.597	−0.104	0.252		0.26	0.456
		(0.051)	(0.011)	(0.066)		(0.122)	(0.09)
341	Paper	−0.304	−0.014	0.085			
		(0.016)	(0.003)	(0.031)			
342	Printing	−0.438	−0.058	0.55	−0.465	0.275	0.538
		(0.029)	(0.01)	(0.097)	(0.054)	(0.09)	(0.091)
351	Chemicals	−0.24	−0.004	0.048	−0.084	0.063	0.098
		(0.009)	(0.002)	(0.04)	(0.02)	(0.041)	(0.038)
352	Other Chemicals	−0.275		0.202	−0.064		0.142
		(0.013)		(0.048)	(0.017)		(0.047)
355	Rubber	−0.311	−0.06	0.157	−0.046	0.148	0.105
		(0.024)	(0.005)	(0.05)	(0.027)	(0.075)	(0.059)
356	Plastic	−0.646	−0.052	0.369	−0.089		0.25
		(0.047)	(0.006)	(0.084)	(0.048)		(0.098)
361	Pottery	−0.511	−0.063	0.465			0.279
		(0.058)	(0.007)	(0.081)			(0.119)
362	Glass	−0.393	−0.027	0.198		0.187	0.11
		(0.017)	(0.004)	(0.05)		(0.086)	(0.064)
369	Other Non-Metallic	−0.288	−0.019	0.081		0.139	0.096
		(0.017)	(0.004)	(0.036)		(0.047)	(0.046)
371	Iron and Steel	−0.211	−0.018				0.102
		(0.009)	(0.005)				(0.028)
372	Non-Ferrous Metals	−0.138	−0.012		−0.04		0.078
		(0.006)	(0.003)		(0.009)		(0.017)
381	Fabricated Metals	−0.437	−0.045	0.234	−0.1	0.113	0.315
		(0.027)	(0.005)	(0.054)	(0.028)	(0.066)	(0.066)
382	Machinery	−0.276	−0.022	0.225	−0.121		0.217
		(0.015)	(0.004)	(0.044)	(0.018)		(0.049)
383	Electrical Machinery	−0.329	−0.046	0.278	−0.059		0.254
		(0.021)	(0.004)	(0.062)	(0.027)		(0.063)
384	Transport	−0.248	−0.031	0.105		0.148	0.194
		(0.016)	(0.004)	(0.052)		(0.069)	(0.063)
385	Scientific	−0.398	−0.036	0.395	−0.221		0.419
		(0.025)	(0.005)	(0.093)	(0.038)		(0.101)
Observations		42,217					
R^2		0.805					
R^2-within		0.469					
ρ		0.742					

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

$(A_{jk}/A_{\mathrm{US}k})$ – 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 $[(1 - \varepsilon_k)/\varepsilon_k]$. Thus, a negative coefficient implies that an increase in the 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 raw productivity (i.e. reduce 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.[13]

Having run regression (16), we use (17) to construct sectoral productivities. We compute almost 1,500 sectoral TFPs for each period. Table 3 summarises some information about these productivities in the mid-1990s. For each country in our sample, we present the country mean of TFP across industries,[14] 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. However, many poor countries reach their highest relative productivity figures in the sectors Food (311) and Apparel (322).

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-1990s for four of

[13] 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 generalised 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.

[14] 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 15 of them. Only in nine (out of 64) countries we construct productivities for less than 20 sectors. The complete set of productivity estimates is available online at http://www.pablofleiss.com.

Table 3

Descriptive Statistics – Middle of the 1990s

Exporter	Mean	SD	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

Table 3

(Continued)

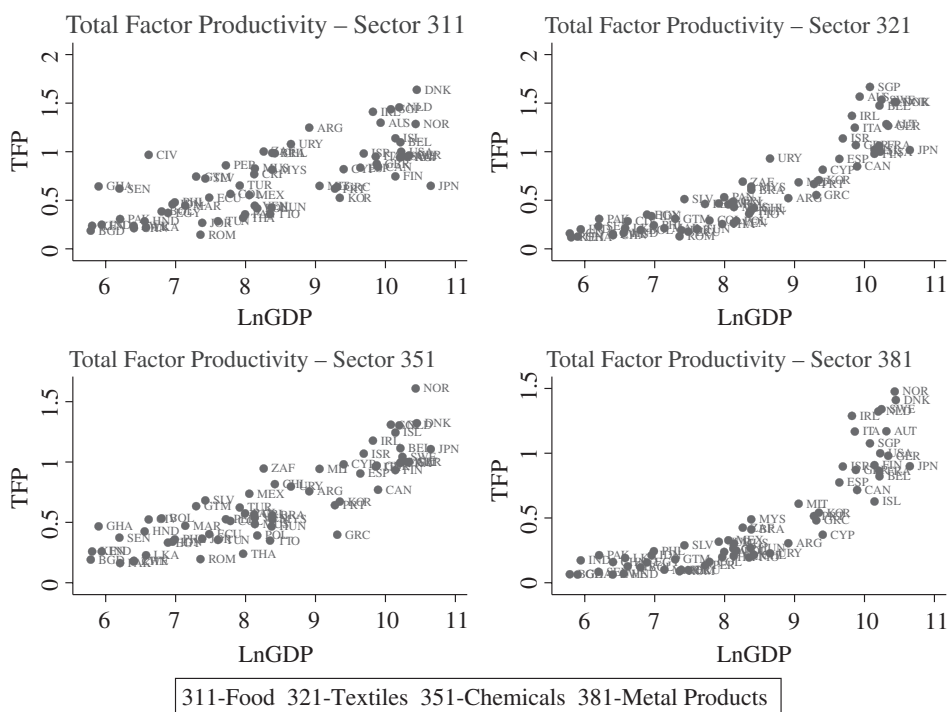| Exporter	Mean	SD	Lowest TFP		Highest TFP	
TTO	0.28	0.11	Electrical Machinery	0.12	Beverages	0.47
TUN	0.22	0.08	Leather	0.08	Chemicals	0.35
TUR	0.39	0.15	Pottery	0.13	Food	0.65
URY	0.61	0.27	Plastic	0.21	Apparel	1.16
USA	1.00	0	Food	1.00	Food	1.00
VEN	0.27	0.14	Furniture	0.07	Non-Ferrous Metal	0.57
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

Fig. 1. *Relative TFP – Selected Sectors*

the 24 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).

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
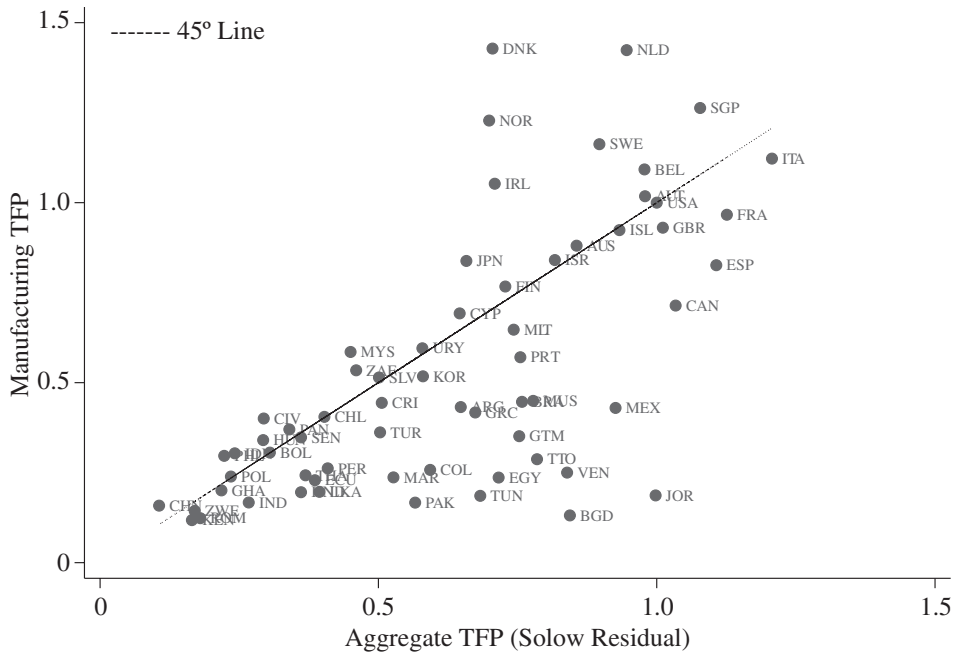
Fig. 2. *Aggregate Manufacturing TFP Versus TFP Solow Residual*

sectoral TFPs and correlate the results with aggregate productivities constructed from production and endowment data.[15] 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 (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 $US8000 in 1995) and developed countries. Figure 3 (left) shows a histogram of sector productivities for the mid-1990s 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, however, have a relatively symmetric productivity distribution with a mean sectoral

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

TFP Developed and Developing Countries   TFP Developing Countries Across Time
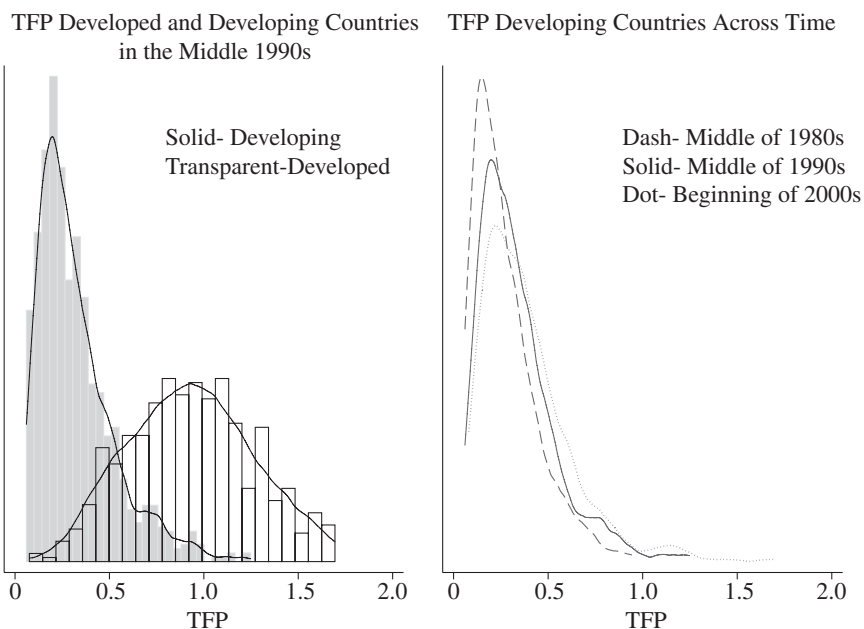   in the Middle 1990s

Fig. 3. *TFP Rich and Poor Countries and TFP Evolution in Poor Countries*

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-1980s, the solid line is the histogram for the mid-1990s and the dotted line the one for the beginning of this century for the sample of 22 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 20-year period lower income countries are slowly catching up in sectoral TFP relative to the US.[16]

Our estimates also allow us to construct 'Ricardian'-style curves of comparative advantage because of 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 investigate whether productivity differences between developing and industrialised countries are systematically related to sector character-

[16] The countries in our sample that have on average experienced the fastest convergence in TFP towards the US level over these two decades (annualised 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%), whereas the ones with the lowest speed of convergence are Beverages (−0.8%), Transport Equipment (−0.7%), Food (−0.6%), and Industrial Chemicals (0.7%).
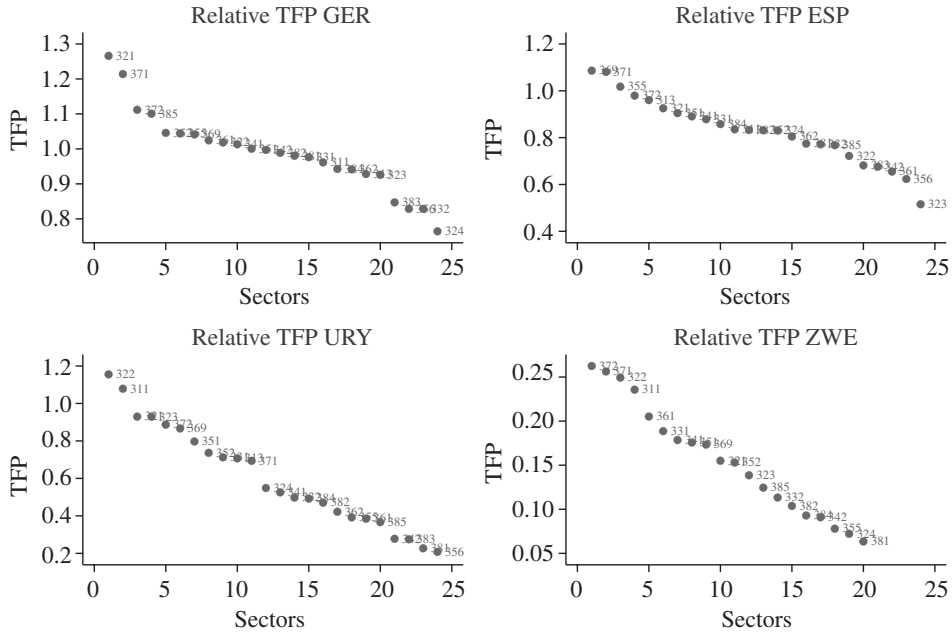
Fig. 4. *Ricardian Comparative Advantage Relative to the US – Selected Countries*
Note. Y-axes are not in the same scale.

istics. Table 4 shows the results of a weighted regression[17] of log(TFP) relative to the US in the mid-1990s on sectoral human capital intensity and the interaction of human capital intensity and log income per worker, controlling for country fixed effects.[18] 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.

5. Robustness

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

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[17] Weighted by the inverse of the standard deviation of log(TFP). Results also go through without weighting observations.

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

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	1,450	1,450	1,450	1,450
Countries	64	64	64	64

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

discussed in the main text. The detailed results and derivations are relegated to the online Technical 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.

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

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

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

Provided that productivities are not correlated with relative factor prices within a country – as for the moment, we assume, – a consistent estimator for (A_{jk}/A_{iUSk}) 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.

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

where $f \in \{s, u\}$. To obtain a measure of sectoral TFP, we use the relation:

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

This procedure is similar to the Hausman–Taylor General Method of Moments (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 normalised 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-squared of 0.64. In the second stage, the interactions between factor intensities and the relative price of skilled and unskilled labour are highly significant. The R-squared 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 our original 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.

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

Table 5

Coefficients – Hausman–Taylor Regression

Isic Rev 2	Sector name	First stage						Second stage	
		Difference distance	Difference tariff	Common language	Common English	Common border	Common colony	Relatively skill	Relatively unskill
311	Food	−1.440 (0.054)***	−0.016 (0.005)***	0.510 (0.141)***	−0.529 (0.091)***	0.136 (0.215)	1.227 (0.214)***	−14.242 (1.988)***	−7.6 (0.601)***
313	Beverages	−1.079 (0.071)***	−0.014 (0.007)**	0.856 (0.18)***	−0.290 (0.111)***	0.751 (0.292)**	0.589 (0.271)**	−10.493 (2.041)***	−5.416 (1.796)***
321	Textiles	−1.349 (0.054)***	−0.064 (0.008)***	0.540 (0.134)***	−0.362 (0.088)***	−0.004 (0.203)	0.841 (0.182)***	−6.215 (1.477)***	−3.801 (0.269)***
322	Apparel	−1.201 (0.08)***	−0.090 (0.01)***	0.424 (0.155)***	0.094 (0.096)	0.234 (0.243)	1.115 (0.207)***	−17.248 (1.758)***	−3.798 (0.343)***
323	Leather	−1.146 (0.061)***	−0.123 (0.012)***	0.686 (0.157)***	−0.213 (0.102)**	0.074 (0.227)	0.985 (0.203)***	−6.16 (1.615)***	−5.167 (0.338)***
324	Footwear	−1.005 (0.075)***	−0.043 (0.009)***	0.706 (0.18)***	0.304 (0.118)***	1.195 (0.286)***	−0.105 (0.252)	−7.504 (2.147)***	−4.558 (0.342)***
331	Wood	−1.239 (0.061)***	−0.155 (0.021)***	0.817 (0.135)***	−0.112 (0.096)	0.951 (0.246)***	0.481 (0.174)***	−14.735 (1.446)***	−3.969 (0.287)***
332	Furniture	−1.232 (0.069)***	−0.213 (0.018)***	0.564 (0.154)***	−0.119 (0.101)	0.515 (0.26)**	0.946 (0.203)***	−13.989 (1.259)***	−3.296 (0.308)***
341	Paper	−1.710 (0.057)***	−0.080 (0.015)***	0.413 (0.165)**	−0.076 (0.103)	0.301 (0.217)	0.252 (0.215)	−10.515 (1.84)***	−3.237 (0.524)***
342	Printing	−1.130 (0.054)***	−0.150 (0.023)***	1.418 (0.151)***	−1.198 (0.087)***	0.708 (0.229)***	1.388 (0.212)***	−1.437 (0.522)***	−6.863 (0.491)***
351	Chemicals	−1.349 (0.049)***	−0.022 (0.011)**	0.272 (0.161)*	−0.473 (0.098)***	0.356 (0.202)*	0.552 (0.22)**	−8.352 (1.272)***	−8.3 (0.933)***
352	Other Chemic	−1.270 (0.047)***	−0.006 (0.013)	0.931 (0.152)***	−0.291 (0.089)***	0.272 (0.241)	0.657 (0.187)***	−12.864 (1.259)***	
355	Rubber	−1.145 (0.058)***	−0.221 (0.019)***	0.580 (0.16)***	−0.170 (0.098)*	0.544 (0.238)**	0.386 (0.208)*	−1.956 (1.248)	−3.064 (0.341)***
356	Plastic	−1.327 (0.057)***	−0.112 (0.009)***	0.738 (0.139)***	−0.172 (0.092)*	0.380 (0.274)	0.514 (0.198)***	−7.392 (1.177)***	−4.08 (0.355)***
361	Pottery	−0.966 (0.07)***	−0.121 (0.011)***	0.849 (0.162)***	0.081 (0.112)	0.056 (0.288)	0.523 (0.224)**	−14.707 (1.718)***	−3.61 (0.34)***
362	Glass	−1.374 (0.054)***	−0.093 (0.013)***	0.720 (0.177)***	−0.074 (0.102)	0.637 (0.258)**	0.390 (0.218)*	−15.683 (1.542)***	−2.853 (0.346)***

Table 5
(Continued)

Isic Rev 2	Sector name	First stage						Second stage	
		Difference distance	Difference tariff	Common language	Common English	Common border	Common colony	Relatively skill	Relatively unskill
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		42,217						42,217	
R²		0.64						0.55	
R²-within		0.46						0.35	
ρ		0.47						0.61	

Notes. Robust standard deviations in parentheses. 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

The adjusted R-squared of this model is 0.5 compared to 0.64 obtained by allowing for Ricardian productivity differences. Thus, there is a 14 percentage point 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.[19]

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 the Heckman selection model (to take into account the non-random zeros) and with a two-step procedure as suggested by Helpman *et al.*, (2008) (to control also for the extensive margin of trade) we continue to obtain quite similar results for our sectoral productivity estimates (columns labelled 'Heckman' and '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 generalise 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 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 assumptions, 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.

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[19] AIC drops from 171,455 for the restricted model to 157,827 for the Ricardian model. When comparing equation (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.

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 industrialised countries where such calculations are feasible.

6. Productivity Differences and Theories of Development

In this Section, we apply our sectoral productivity estimates to test 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 the advantages of having estimates of industry productivities for a large set of countries particularly well: 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.

When applied at the sector level, Klenow and Rodriguez-Clare's, (2005) 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 faster.[20]

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-1990s[21] 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.

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[20] 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 *et al.* (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.

[21] 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.

$$\log\left(\frac{A_{jk}}{A_{\text{US}k}}\right) = \beta_1 X_{jk} + D_k + D_j + \varepsilon_{jk}, \tag{24}$$

where $X_{jk} = (R_j/Y_j)(R_{\text{US}k}/Y_{\text{US}k})$, 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-1980s and the mid-1990s 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.

$$\Delta\log\left(\frac{A_{jk}}{A_{\text{US}k}}\right) = \beta_1 X_{jk} + \beta_2 \log\left(\frac{A_{jk0}}{A_{\text{US}k0}}\right) + D_k + D_j + \varepsilon_{jk}, \tag{25}$$

where X_{jk} is again the R&D interaction term and $\log(A_{jk0}/A_{\text{US}k0})$ 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 emphasises 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 technology frontier that grows at an exogenous rate.

Table 7

Productivity and Theories of Development

	Log(TFP)	TFP Growth	Log(TFP)	TFP Growth	Log(TFP)	TFP Growth
R&D interaction	1.896 (0.484)***	1.574 (0.633)*				
HC interaction			0.516 (0.152)**	0.751 (0.198)***		
Financial Int.					0.575 (0.103)***	0.606 (0.137)***
log TFP 85		−0.602 (0.169)***		−0.523 (0.126)***		−0.530 (0.119)***
Sector and country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	974	897	1,280	1,164	1,381	1,220
Countries	42	40	56	55	61	58

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

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-1990s, whereas for the second specification we take the growth rate of sectoral TFP relative to the US between the mid-1980s and the mid 1990s. 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.[22]

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 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.

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[22] 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.

The empirical finance-growth literature has difficulties in assessing whether financial development leads to growth by: easing financial constraints and increasing the amount of investment firms are able to undertake; or more efficient allocation of credit within sectors.[23] 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-1990s on the $EXTFIN_k \times PRIV_j$ interaction using specification equation (24) and controlling for sector-and country-fixed effects. Column 5 of Table 7 shows that financial development has a significantly (at the 1% 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 1% level) positive coefficient of the financial interaction variable. This likewise corroborates the idea that financial development affects the efficiency of investment.

Our results concerning the significantly larger positive impact of financial development on TFP in financially dependent sectors represents 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 (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–labour 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 labour ratios might well be lower in financially dependent sectors in countries with better financial systems. This mechanism would explain why financial development has no significant effect on value added per worker but a positive impact on TFP.[24]

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[23] An exception is Jayaratne and Strahan (1996). Using data for several banking liberalisation 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.

[24] Indeed, Beck *et al.* (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 *et al.* (2004) provide similar evidence for Italy.

7. Conclusions

We have estimated sectoral TFP for more than 60 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 constrain the application of traditional methods of TFP computation.

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 labour 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 used our TFP estimates to test a number of development theories that have predictions on cross-country industry-level productivity patterns.

Appendix

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 1984–6, 1994–6 and 2002–4, covering 36 importing countries and 64 exporting countries. The 36 importers represent more than 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.[25] The original source of this variable is the United Nations Industrial Development Organisation's (UNIDO) Industrial Statistics. For the years 1994–6 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.

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

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) five 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.[26]

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 *et al.* (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 $\sum_i \alpha_{k,i} = 1$; $i = u,s$,cap. As in Romalis (2004), $\alpha_{k,\text{cap}} = $ cap. intensity; $\alpha_{ks} = $ skill intensity $\times$ $(1 - \alpha_{kcap})$ 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 intertemporal maximisation problem and capital markets are competitive. Firms set the marginal value product equal to the rental rate, $p_{jk}\text{MPK}_{jk} = P_{Kj}(\text{interest}_j + \delta)$, 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

$$\frac{p_{jk}(t)\text{MPK}_{jk}(t) + P_{Kj}(t+1)(1-\delta)}{P_{Kj}(t)}.$$

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 abovementioned relationship holds true. As capital is mobile across sectors within a country the marginal value product must likewise be equalised across sectors. Total payments to capital in country j are $\sum_k p_{jk}\text{MPK}_{jk}K_{jk} = p_j\text{MPK}_j\sum_k K_{jk} = r_jK_j$, where K_j is the country $j's$ capital stock in physical units and the first equality follows from capital mobility across sectors. Since $\alpha_{j,\text{cap}} = [(r_jK_j)/(P_YY)]$, where Y is GDP in PPP, the following holds

$$r_j = \alpha_{j,\text{cap}}\frac{\text{GDP}_j}{K_j}. \tag{A.1}$$

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. $\alpha_{j,\text{cap}}$ is country j's aggregate capital income share. We compute the capital share as one minus the labour share in GDP, which we take from Bernanke and

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[26] We have also worked with elasticities obtained from Hummels (1999) at the SITC two-digit level and from Broda and Weinstein (2006) at the SITC three-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 five digits and ISIC three digits – i.e., the SITC code 01111 maps only to ISIC code 31 – and on the other, there is no unique mapping between ISIC three digits and SITC two or three 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 five 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 with SITC at a higher level of aggregation does not eliminate completely a potential measurement bias problem.

Gürkaynak (2002) and Gollin (2002). In turn, the labour share is employee compensation in the corporate sector from the National Accounts plus a number of adjustments to include the labour 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 labour share:

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

The total labour 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.[27] Thus,

$$U = L_{\text{noeduc}} + e^{\beta\frac{\text{prim.dur.}}{2}}L_{\text{prim.incomp.}} + e^{\beta\text{prim.dur.}}L_{\text{prim}} + e^{\beta\text{lowsec.dur.}}L_{\text{lowsec}} \qquad \text{(A.3)}$$

and

$$S = L_{\text{secondary}} + e^{2\beta}L_{\text{ter.incomp.}} + e^{4\beta}L_{\text{tertiary}}. \qquad \text{(A.4)}$$

Data for educational attainment of workers over 25 years at each level are taken from Barro and Lee (2001) and Cohen and Soto (2007). 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 completed half of the last level (except when we have data of lower secondary duration). For tertiary education, we consider a duration of four 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 (w_{skill}/w_u) equals $e^{\beta(\text{prim.dur.+lowsec.dur.})}$. 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 labour 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. The Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) has developed a distance database that uses city-level data in the calculation of the distance matrix to assess the geographic distribution of population inside each nation. The basic idea is to calculate the distance between two countries 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 product of the HS6 nomenclature in the TRAINS database from UNCTAD. Those tariffs are aggregated from TRAINS data 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 use an indicator variable that equals one if one of the countries is a former colony of the other.

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[27] 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.

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Additional Supporting information may be found in the online version of this article:

Appendix A. Robustness.
Appendix B. A Two-Country General Equilibrium Model.

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