Essays on Trade, Productivity, and Specialization

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To Giulia, I do it for her

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Abstract

Even though cross-country differences in sectoral total factor productivity (TFP) are at the heart of Ricardian trade theory and many models of growth and development, very little is known about their size and form. The first two papers try to fill in this gap by using a hybrid Ricardo-Heckscher-Ohlin trade model and bilateral sectoral trade data. A comparable set of productivities for manufacturing sectors in more than sixty countries at all stages of development is provided, and estimates are applied to test theories on development that have implications for the patterns of sectoral productivities across countries. The third paper focuses on the effects of trade liberalization on countries' productive structures. Transition matrices that describe the specialization dynamics in liberalized countries are estimated. The final section of the paper empirically relates sectoral specialization with factor endowments and intensities.

Resumen

Aunque las diferencias entre países en la productividad total de los factores (TFP) sectorial está en el corazón de la teoría Ricardiana de comercio y en el de muchos modelos de crecimiento y desarrollo, muy poco se sabe acerca de su forma y tamaño. Los dos primeros artículos intentan rellenar esta brecha utilizando un modelo de comercio híbrido de Ricardo-Heckscher-Ohlin y datos bilaterales de comercio sectorial. Se brinda un conjunto comparable de productividades para sectores industriales en más de sesenta países en todas las etapas de desarrollo, y las estimaciones se aplican para probar teorías de desarrollo que tienen implicancias sobre el patrón de productividades sectoriales entre países. El tercer artículo se enfoca en los efectos de la liberalización comercial sobre la estructura productiva de los países. Se estiman matrices de transición que describen la dinámica de especialización en economías liberalizadas. La sección final del artículo relaciona empíricamente la especialización sectorial con la dotación e intensidad de factores.

Foreword

This thesis explores the links between trade, productivity, and specialization. The first part estimates sectoral productivities using bilateral trade data, while the second relates processes of trade liberalization with specialization within countries. There are several contributions: first, a Ricardian approach to trade is integrated into a general Heckscher-Ohlin model with monopolistic competition and trade cost. Second, we develop a methodology to estimate sectoral productivities that completely differs from the Solow residual approach, exploiting instead the information contained in trade data. This allows us to obtain a set of sectoral productivities for a large set of countries. Finally, there is an empirical application that allows us to better understand the relations between trade liberalization, specialization, factor endowments, and sectoral factor intensities.

The first two chapters[1] design and apply a methodology that uses bilateral trade data to estimate cross-country differences in sectoral productivity. We develop a model that integrates a Heckscher-Ohlin-Krugman-Ricardo approach, and then we explain how to estimate differences in sectoral productivity from this model. Intuitively, we associate sectoral productivity with observed trade that cannot be explained by differences in factor intensities and factor prices nor by differences in trade costs. The advantage of this endeavor is that it helps to overcome data problems that vitiate the application of standard methods for computing sectoral productivities, methods that require comparable information on inputs and outputs at the sector level, as that information is inadequate for most countries. We estimate total factor productivity for twenty-four manufacturing sectors in more than sixty countries at all stages of development. We also provide a series of alternative specifications that deal with some of the caveats of our benchmark model.

The second chapter describes the data used and estimates (using the framework of

[1] A joint work with Harald fadinger

the first chapter) a complete data-set of productivities. We show how productivity differences between rich and poor countries are not only substantial but also systematically more pronounced in sectors intensive in both human capital and research-and-development. Subsequently, these estimates are used to test theories from the growth and development literature that have implications for the patterns of productivity differences across sectors, such as the role of human capital for technology adoption, or the effect of financial development.

The third chapter represents an update of my thesis proposal. The basic idea is to exploit the information generated by the worldwide extended processes of trade liberalization in the '80s and '90s and thereby further investigate relations between openness and changes in the productive structure. As we have at our disposal data from several years before and after these given examples of trade reform, we can analyze whether medium-term changes during the last quarter of the last century are aligned with the main predictions of classical trade theory, i.e.: under free-trade conditions, countries specialize in sectors in which they have some kind of comparative advantage. In addition, I use transition-matrices analysis to describe the total dynamics of specialization in commercially liberalized countries.

Contents

1 CHAPTER ONE

1.1 Introduction

Differences in sectoral total factor productivity (TFP) across countries are at the heart of trade theory and of many theories of growth and development. Nevertheless, due to data limitations, very little is known about the form and the size of sectoral productivity differentials across countries outside the industrialized world.

In the next two chapters, we try to overcome the data problem faced by the traditional approach to TFP measurement, which requires comparable information on outputs and inputs at the sectoral level. We introduce a new method for estimating sectoral TFP levels that relies on information contained in bilateral trade.

The Ricardian approach to international trade emphasizes those productivity differences as the main reason for cross-country flows of goods, while the growth literature analyzes factors such as technology spillovers (Klenow and Rodriguez-Clare (2005)), human capital and technology adoption (Nelson and Phelps (1966)), or external financial dependence (Rajan and Zingales (1998)). All those theories have clear predictions on the form of sectoral differences in TFP. Moreover, information on sectoral productivity differences across countries is of interest not only to theorists but also to policy makers since it is important for the design of industrial and trade policy.

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

In the model, monopolistic firms produce differentiated varieties of a sectoral aggregate consumption good. Since varieties are gross substitutes, expenditure is higher on less expensive varieties and therefore countries that can produce more cheaply in a sector have larger sectoral export values. The market price of each variety in a given destination depends on factor prices, productivity and trade costs. The intutition behind our method for estimating sectoral productivities is to exploit variation in bilateral sectoral export values compared to a benchmark country (appropriately adjusted for total production and for input costs) across export markets. As an example, consider how we infer Italy's productivity (relative to the one of the US) in the sector Textiles: We could measure which fraction of its sectoral production value Italy exports to each market compared to the US, controlling for sectoral factor inputs and trade costs. If Italy exports more of its textile production to an average market than the US, once we have adjusted export values for relative input costs and relative bilateral sectoral trade costs, this indicates a higher level of sectoral TFP.

One main advantage of our procedure is that it does not require information on output prices, which is a prerequisite for computing comparable productivities with the standard production function approach. The idea is that in each market exporters face the same competitive environment as those from the benchmark country. Hence, even if firms charge different prices in different export markets because of differences in market structure, we do not need this information. If export values of a given country are higher than the ones of the benchmark in an average destination once we control for differences in market access this must be due to the fact that producers from that country are more competitive. Holding constant differences in factor input costs this happens if and only if productivity is higher. A further plus of our method is that it allows us to estimate productitivities rather than to calibrate them.

There is a large body of literature that studies sectoral productivity differences across countries by specifying a production possibility frontier, using data on sectoral inputs and outputs to calculate sectoral productivity indices.[1]. Because lack of data, those studies are limited to a number of OECD economies and do not disentangle sectoral price indices -which are usually unavailable- from output quantities. Therefore, variation in product prices across countries may wrongly be attributed to differences in TFP.

Besides problems with output prices, missing information on sectoral factor inputs is another serious issue for the standard approach, especially for developing countries. This problem can be overcome to some extent by assuming Cobb-Douglas production functions, mobility of factors across sectors and perfect competition in goods and factor markets. These assumptions allow to back out sectoral factor inputs by using aggregate factor endowments and sectoral factor income shares. Nonetheless, in addition to the distortions that arise from missing data on output prices this adds another potential error margin, the size of which is unknown because the model is exactly identified.[2] While we need to make similar assumptions on factor mobility and competition in factor markets, our methodology allows us to evaluate the statistical fit of our model.

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

In a very influential paper, Eaton and Kortum (2002) develop an alternative approach to

[1] Some of the earlier contributions that use sectoral value added as an output measure are Dollar and Wolff (1993) and Maskus (1991)

[2] A further challenge is that this method would also require information on how factor use is split between manufacturing and the rest of the economy.

construct sectoral productivity indexes from trade data. They construct a multi-country Ricardian model with a probabilistic technology specification that they calibrate to fit trade between OECD countries. Chor (2008) extends their model to Heckscher-Ohlin trade and differences in sectoral characteristics like financial dependence, volatility, etc. In our robustness checks we show that the productivity estimates obtained from the capital-augmented Eaton-Kortum model are very similar to the ones estimated with our methodology.

In parallel work to ours, Finicelli, Pagano and Sbracia (2008) apply the baseline Eaton-Kortum model to calibrate aggregate manufacturing TFPs for eighteen OECD economies. They do not include Heckscher-Ohlin motives for trade in their model and compute only aggregate manufacturing productivities, while we estimate productivity differences at a sectoral level and for a sample that includes a large number of developing countries. 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 the present paper.

The next section introduces the theoretical model and provides some intuition for the economic forces at work. Section three develops a methodology for computing sectoral productivity indices. In section four we present a series of alternative specifications which relax some assumptions of our original model or introduce alternative models to estimate productivities using the same data-set. Last section concludes the first chapter.

1.2 A Simple Model

In order to use trade data to estimate sectoral TFP differences we need a model in which bilateral trade is determined. A convenient way to achieve this is to follow Krugman (1979), assuming that consumers have love for variety and that production is monopolistic because of increasing returns.[3] We add three more ingredients to be able to talk about sectoral productivity differences. First, we assume that firms in different sectors use different factor proportions when faced with the same input prices, which gives rise to Heckscher-Ohlin 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.[4] Consequently, there is a cost advantage in producing more in those sectors that use the abundant factors intensively. This creates the prediction that countries export more in those sectors. Finally, we add sectoral differences in TFP, which introduces a motive for Ricardian style trade. Countries that have a high productivity in a sector have a cost advantage relative to their foreign competitors and charge lower prices. Because the elasticity of substitution between varieties is larger than one, demand shifts towards the varieties of that country and leads to a larger world market share in that sector.

To make our approach tractable we need to assume Cobb-Douglas cost functions in each sector. Even though in our model there are increasing returns to scale at the firm level because of a fixed cost, our setup with a constant price elasticity demand function implies de facto constant returns at the industry level, because firm size is fixed and any change in industry output occurs through entry and exit in the industry.[5] Consequently, an increase in industry output does not change firms' average cost and any internal (or external) increasing returns to scale that might exist in the real world will show up as larger sectoral productivities in the model. Note, however, that these

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

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

[5] In the baseline model, firms are homogeneous within a given sector in each country and we disregard firm heterogeneity in marginal costs and composition effects on sectoral TFP.

assumptions are standard in the literature on cross country TFP comparisons at the aggregate level.[6] Having explained the main features of the model, let us now develop the details.

a Demand

Our model generalizes the setup of Romalis (2004). We assume that all consumers in a given country have identical and homothetic preferences. These are described by a two-tiered utility function. The first level is assumed a Cobb-Douglas aggregator over K sectoral sub-utility functions. This implies that consumers spend a constant fraction of their income, σ_{ik}, which we allow to differ across countries on goods produced in each sector.[7]

$$U_i = \prod_{k=0}^{K} u_{ik}^{\sigma_{ik}} \tag{1.1}$$

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

$$u_{ik} = \left[\sum_{b \in B_{ik}} x_b^{\frac{\epsilon_k - 1}{\epsilon_k}} \right]^{\frac{\epsilon_k}{\epsilon_k - 1}} \tag{1.2}$$

Note that utility is strictly increasing in the number of sectoral varieties available in a country. Sector specific elasticity of substitution between varieties is denoted by ϵ_k,

[6] See, for example, Hall and Jones (1999), Caselli (2005).

[7] For our baseline specification preferences can be generalized to any country specific, strictly concave, homothetic and weakly separable utility function $U_i(u_{1i}, ..., u_{Ki})$, where the u_{ik}'s are CES indices over varieties as defined in (1.2). This would lead to demand functions of the form $x_{ijk} = \frac{\hat{p}_{ijk}^{-\epsilon_k}}{P_{ik}^{1-\epsilon_k}} E_{ik}(P_{1i}, ..., P_{iK})Y_i$, where $E_{ik}(P_{1i}, ..., P_{Ki})Y_i$ is expenditure on sector k goods in country i and the P_{ik}'s are CES price indices as defined in (1.4).

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 good produced by sector k of country j to arrive in destination i, τ_{ijk} units need to be shipped.

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

$$x_{ijk} = \frac{\hat{p}_{ijk}^{-\epsilon_k} \sigma_{ik} Y_i}{P_{ik}^{1-\epsilon_k}} \tag{1.3}$$

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[8] and P_{ik} is the optimal sector k price index in country i, defined as:

$$P_{ik} = \left[\sum_{b \in B_{ik}} \hat{p}_b^{1-\epsilon_k} \right]^{\frac{1}{1-\epsilon_k}} \tag{1.4}$$

b Supply

In each country, firms may be active in one of $k = 0, ..., K$ different sectors. Production technology differs across sectors due to differences in factor intensities and differences in sectoral TFP. In each sector firms can freely create varieties and have to pay a fixed cost to operate. Because of the demand structure and the existence of increasing returns,

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

production is monopolistic since 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 combine physical capital, $K_j(n)$, with price r_j[9], unskilled labor, $U_j(n)$ with price w_{uj}, and skilled labor $S_j(n)$ with price w_{sj} to produce.[10]

In addition, there is a country and sector specific total factor productivity term, A_{jk}. Firms' production possibilities in sector k of country j are described by the total cost function:

$$TC(q_{jk}) = (f_{jk} + q_{jk})\frac{1}{A_{jk}} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}} \tag{1.5}$$

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

Monopolistic producers maximize profits given (1.3) and (1.5). Their optimal decision is to set prices as a fixed mark-up over their marginal costs.

$$p_k = \frac{\epsilon_k}{\epsilon_k - 1} \frac{1}{A_{jk}} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}} \tag{1.6}$$

The combination of sectors with different factor intensities, and country-sector specific TFP differences gives the model Heckscher-Ohlin as well as Ricardian features. Since the elasticity of substitution across varieties, ϵ_k, is larger than one, consumers spend

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

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

more on cheaper varieties. This, together with the pricing structure, implies that lower production costs translate into larger market shares. Low production costs may be either because a sector is intensive in locally cheap factors, or because high productivity in this sector.

c A Two Country General Equilibrium Model

In this subsection, we present a two country general equilibrium version of the model based on Romalis (2004). There are two countries, Home and Foreign ($*$). Transport costs are allowed to be sector specific and asymmetric and are denoted by τ_k and τ_k^*. We assume in this section that there are only two factors of production, capital, K and labor, L The total number of varieties in each sector at the world level is $N_k = n_k + n_k^*$.

It follows from the definition of the sectoral price index in the main text that the Home price index in sector k is defined as:

$$P_k = \left[n_k p_k^{1-\epsilon_k} + n_k^* (p_k^* \tau^*)^{1-\epsilon_k} \right]^{\frac{1}{1-\epsilon_k}} \tag{1.7}$$

A similar expression holds for the Foreign price index.

The revenue of a Home firm is given by the sum of domestic and Foreign revenue and using the expressions for Home and Foreign demand in the main text, we get

$$p_k q_{jk} = \sigma_k Y \left(\frac{p_k}{P_k} \right)^{1-\epsilon_k} + \sigma_k^* Y^* \left(\frac{p_k \tau_k}{P_k^*} \right)^{1-\epsilon_k} \tag{1.8}$$

An analogous expression applies to Foreign Firms.

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

$$p_k = \frac{\epsilon_k}{\epsilon_k - 1} \frac{1}{A_{jk}} \left(\frac{w_j}{1 - \alpha_k} \right)^{1-\alpha_k} \left(\frac{r_j}{\alpha_k} \right)^{\alpha_k} \tag{1.9}$$

Since firms can enter freely, in equilibrium they make zero profits and price at their average cost. Combining this with (1.9), it is easy to solve for equilibrium firm size, which depends positively on the fixed cost and the elasticity of substitution.

$$q_{jk} = q_k = f_k(\epsilon_k - 1) \tag{1.10}$$

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

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

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

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

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

$$\frac{n_k}{n_k^*} = \frac{[\sigma_k Y(\tilde{p}_k \tilde{f}_k - \tilde{p}_k^{1-\epsilon_k}(\tau_k^*)^{\epsilon_k - 1}) + \sigma_k^* Y^*(\tilde{p}_k \tilde{f}_k - \tilde{p}_k^{1-\epsilon_k}\tau_k^{1-\epsilon_k})]}{[\sigma_k^* Y^* \tilde{p}_k^{1-\epsilon_k}(\tau_k^*)^{\epsilon_k - 1}(\tilde{p}_k \tau_k^{1-\epsilon_k} - \tilde{p}_k \tilde{f}_k) - \sigma_k Y \tilde{p}_k^{1-\epsilon_k}\tau_k^{1-\epsilon_k}(\tilde{p}_k \tilde{f}_k - \tilde{p}_k^{1-\epsilon_k}(\tau_k^*)^{\epsilon_k - 1})]} \tag{1.11}$$

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

$$\underline{p}_k = \left[\frac{(\sigma_k^* Y^* + \sigma_k Y)(\tau_k^*)^{\epsilon_k - 1} \tau_k^{1-\epsilon_k}}{\sigma_k Y \tau_k^{1-\epsilon_k} \tilde{f}_k + \sigma_k^* Y^* (\tau_k^*)^{\epsilon_k - 1} \tilde{f}_k} \right]^{1/\epsilon_k} \tag{1.12}$$

And

$$\bar{p}_k = \left[\frac{\sigma_k^* Y^* \tau^{1-\epsilon_k} + \sigma_k Y (\tau_k^*)^{\epsilon_k - 1}}{\tilde{f}_k \sigma_k^* Y^* + \tilde{f}_k \sigma_k Y} \right]^{1/\epsilon_k} \tag{1.13}$$

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

The model is closed by substituting the pricing condition (1.9) into $\tilde{p}$ and the expressions for v_k in the factor market clearing conditions for Home and Foreign.

$$\sum_{k=1}^{K} (1 - \alpha_k) v_k \sigma_k (Y + Y^*) + (1 - \alpha_{NT}) \sigma_{NT} Y = wL \tag{1.14}$$

$$\sum_{k=1}^{K} \alpha_k v(k) \sigma_k (Y + Y^*) + \alpha_{NT} \sigma_{NT} Y = rK \tag{1.15}$$

$$\sum_{k=1}^{K} (1 - \alpha_k)(1 - v_k) \sigma_k (Y + Y^*) + (1 - \alpha_{NT}) \sigma_{NT} Y^* = w^* L^* \tag{1.16}$$

$$\sum_{k=1}^{K} \alpha_k (1 - v_k) \sigma_k (Y + Y^*) + \alpha_{NT} \sigma_{NT} Y^* = r^* K^* \tag{1.17}$$

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

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

Romalis' Model

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

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

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

A Ricardian Model

If we make the alternative assumption that all sectors use labor as the only input, i.e.

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

The Hybrid Ricardo-Heckscher-Ohlin Model

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

$$\tilde{p}_k = \frac{\frac{1}{A_k}\left(\frac{w}{1-\alpha_k}\right)^{1-\alpha_k}\left(\frac{r}{\alpha_k}\right)^{\alpha_k}}{\frac{1}{A_k^*}\left(\frac{w^*}{1-\alpha_k}\right)^{1-\alpha_k}\left(\frac{r^*}{\alpha_k}\right)^{\alpha_k}} \tag{1.18}$$

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

The model is illustrated in Figure 1.1. In this example, $\epsilon_k = 4$, Home is relatively capital abundant, $\frac{K/L}{K^*/L^*} = 4$, and transport costs are high, $\tau_k = \tau_k^* = 2$. The panels of figure 1.1 plot Homes' relative productivity, Homes' sectoral revenue share, Homes' relative prices, as well as Homes' net exports, Homes' exports relative to production, and Homes' imports relative to production against the capital intensity of the sectors, which is ordered on the zero-one interval. In the first case (solid lines), there are no productivity differences between Home and Foreign. Because Home is capital abundant, it has lower rentals and higher wages which leads to lower prices and larger revenue shares in capital-intensive sectors. In addition, Home is a net importer in labor-intensive sectors and a net exporter in capital-intensive ones and its exports relative to production are larger in capital-intensive sectors, while its imports relative to production are much larger in labor-intensive sectors. This illustrates neatly the Quasi-Heckscher-Ohlin prediction of the model.

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

Figure 1.2 is an example of the Quasi-Rybczynski effect. Initially both Home and Foreign have the same endowments, $\frac{K/L}{K^*/L^*} = 1$, and Home has a systematically higher productivity than Foreign in capital-intensive sectors (solid lines), which explains Home's larger market share in those sectors. In the case with the dashed lines Home has doubled its capital stock, so that now $\frac{K/L}{K^*/L^*} = 2$. This leads to an expansion of production and revenue shares in the capital-intensive sectors and a decline of production in the labor intensive ones. The additional capital is absorbed both through more capital-intensive production and an expansion of production in capital-intensive sectors. The increased demand for labor in those sectors drives up wages and makes Home less competitive in labor-intensive sectors.

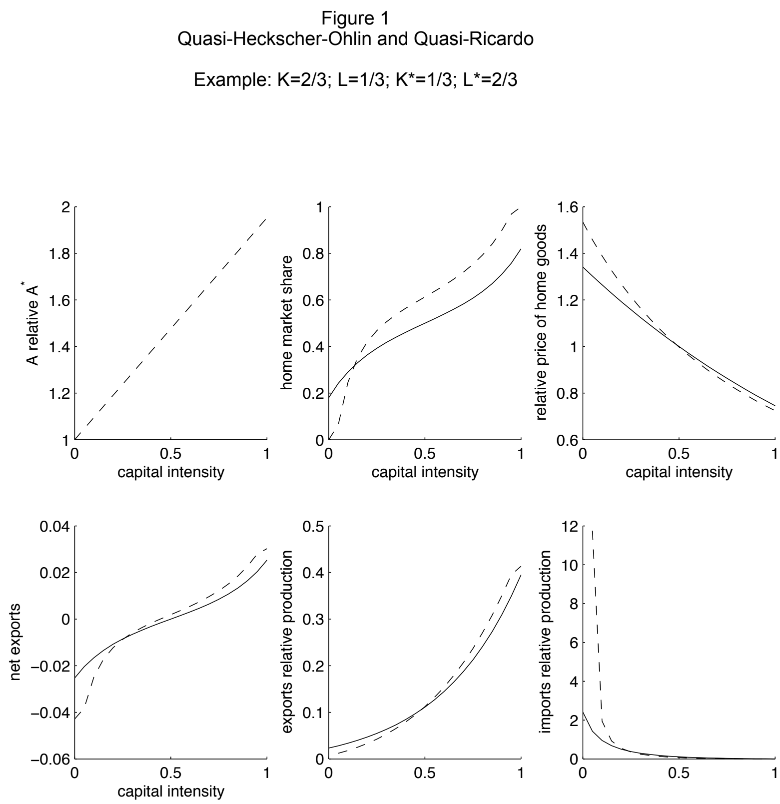

Figure 1.1: Quasi-Heckscher-Ohlin and Quasi-Ricardo Effects

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

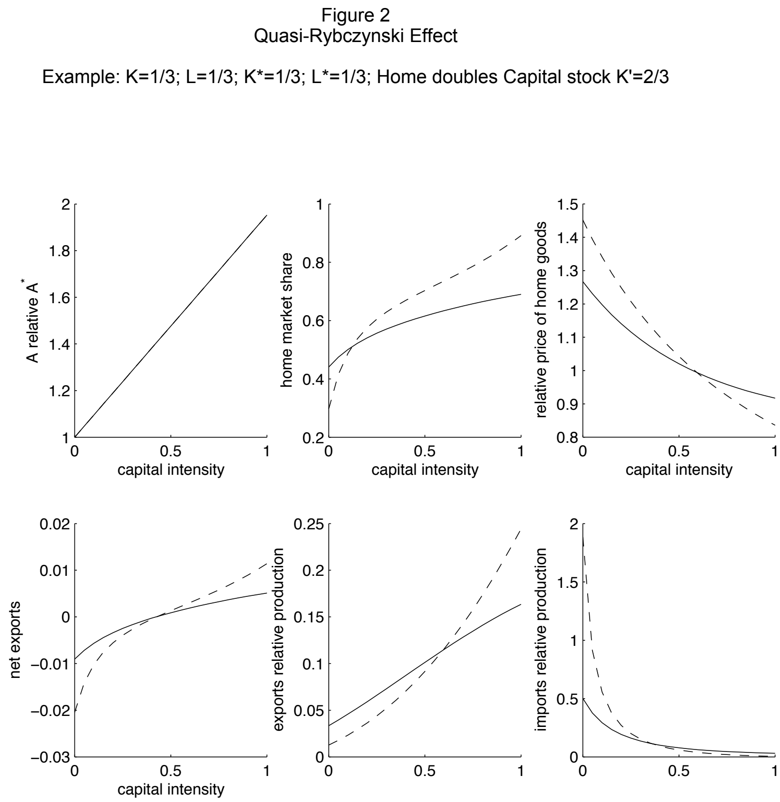

Figure 1.2: Quasi-Rybczynski Effect

1.3 A Methodology to Estimate Sectoral TFPs

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

$$M_{ijk} = \hat{p}_{ijk} x_{ijk} N_{jk} = p_{jk} \tau_{ijk} x_{ijk} N_{jk} \tag{1.19}$$

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

Substituting the demand function $x_{ijk}(\hat{p}_{ijk})$ from (1.3), we obtain:

$$M_{ijk} = \frac{(p_{jk}\tau_{ijk})^{1-\epsilon_k} \sigma_{ik} Y_i}{P_{ik}^{1-\epsilon_k}} N_{jk} \tag{1.20}$$

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 (1.5), we can write bilateral sectoral trade volume as:

$$M_{ijk} = \left[\frac{\frac{\epsilon_k}{\epsilon_k - 1} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}}}{A_{jk} P_{ik}} \right]^{1-\epsilon_k} \sigma_{ik} Y_i N_{jk} \tag{1.21}$$

Equation (2.2) makes clear that bilateral trade in sector k measured in dollars depends positively on the importing country consumers' expenditure share on sector k goods, σ_{ik}, and their total income, Y_i. On the other hand, because the elasticity of substitution between varieties is larger than one, the value of trade is falling in the price charged by exporting firms, p_{jk}. This, together with the pricing rule (1.6), implies 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 sectoral productivities, A_{jk}. If a country has a higher productivity in a sector relative to other exporters, it can charge lower prices and has a larger value of exports.

All of the previous statements hold conditional on the number of firms in sector k in the exporting country. Since we do not consider data on the number of firms active in the exporting countries as very reliable, but we observe the value of sectoral production, we can use the model to solve for the number of firms given total production.[11] 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.

$$p_{jk}q_{jk}N_{jk} = \tilde{Q}_{jk} \tag{1.22}$$

Assuming that new firms can enter freely, in equilibrium firms make zero profits and price at their average cost. Combining this with (1.6), it is easy to solve for equilibrium firm size, which depends positively on the fixed cost and the elasticity of substitution:

$$q_{jk} = f_{jk}(\epsilon_k - 1) \tag{1.23}$$

Using this result and plugging it into the definition of sectoral output, we get:[12]

$$N_{jk} = \frac{\tilde{Q}_{jk}}{p_{jk}(\epsilon_k - 1)f_{jk}} \tag{1.24}$$

Substituting for N_{jk} in the equation 2.2, we obtain:

$$M_{ijk} = \left[\frac{\frac{\epsilon_k}{\epsilon_k - 1}\prod_{f\in F}\left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}}}{A_{jk}}\right]^{-\epsilon_k}\left[\frac{\tau_{ijk}}{P_{ik}}\right]^{1-\epsilon_k}\sigma_{ik}Y_i\frac{\tilde{Q}_{jk}}{(\epsilon_k - 1)f_{jk}} \tag{1.25}$$

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

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

This equation can be rearranged to solve for the sector productivity A_{jk}. Because a productivity index needs to be defined relative to some benchmark, we measure productivity relative to a reference country. An advantage of choosing a reference country is that all the terms that are not indexed to the exporting country j (i.e. σ_{ik}, Y_i, P_{ik}) drop from the equation. For each importer i we can express the "raw" productivity of country j in sector k relative to a benchmark country (e.g. the US).

$$\begin{aligned}\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}} &\equiv \frac{A_{jk}}{A_{USk}}\left(\frac{f_{jk}}{f_{USk}}\right)^{-1/\epsilon_k}\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right)^{\frac{1-\epsilon_k}{\epsilon_k}} = \\ &= \left(\frac{M_{ijk}}{M_{iUSk}}\frac{\tilde{Q}_{USk}}{\tilde{Q}_{jk}}\right)^{1/\epsilon_k}\prod_{f\in F}\left(\frac{w_{fj}}{w_{fUS}}\right)^{\alpha_{fk}}\end{aligned} \tag{1.26}$$

Our "raw" productivity measure, $\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}}$, is a combination of relative productivities, fixed costs, and transport costs. Intuitively, country j is measured to be more productive than the US in sector k if, controlling for the relative cost of factors, j exports a greater fraction of its production in sector k to country i than the US. Note that we can compute this measure vis-a-vis every importing country using only relative imports and exporters' relative production and factor prices data.

This "raw" measure of relative productivities also contains relative sectoral transport costs and fixed costs of production. While relative transport costs vary by importing country, exporters' relative productivities and fixed costs are invariant to the importing country. Consequently, it is easy to separate the two parts by using regression techniques. Define relative productivity as the product of the relative productivity of variable production and weighted relative fixed cost: $\left(\frac{\breve{A}_{jk}}{A_{USk}}\right) = \left(\frac{A_{jk}}{A_{USk}}\right)\left(\frac{f_{jk}}{f_{USk}}\right)^{-1/\epsilon_k}$.

Taking logarithms, we get

$$\log\left(\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}}\right) = \log\left(\frac{\breve{A}_{jk}}{A_{US,k}}\right) + \frac{1-\epsilon_k}{\epsilon_k}\log\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right) \tag{1.27}$$

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

$$\begin{aligned} \log\left(\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}}\right) &= \log\left(\frac{A_{jk}}{A_{USk}}\right) + \beta_{1k}(\log Dist_{ij} - \log Dist_{iUS}) + \\ &+\beta_{2k}(\log Tariff_{ijk} - \log Tariff_{iUSk}) + \\ &+\beta_{3k}CommonLang_{ij} + \beta_{4k}CommonLang_{iUS} + ... + u_{ijk} - u_{iUSk} \end{aligned} \tag{1.28}$$

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

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

Let us discuss at this point why relative fixed costs could enter in our expression for relative productivity $\left(\frac{\breve{A}_{jk}}{A_{USk}}\right) = \left(\frac{A_{jk}}{A_{USk}}\right)\left(\frac{f_{jk}}{f_{USk}}\right)^{-1/\epsilon_k}$. We have that $\left(\frac{\breve{A}_{jk}}{A_{USk}}\right) < \left(\frac{A_{jk}}{A_{USk}}\right)$ whenever relative fixed costs are larger than one. In this case, we assign relatively too few firms to country j. The reason is that we have replaced the number of firms by (1.24), which depends on sectoral production and fixed costs. Higher relative fixed costs imply larger relative firm size (see (1.23)) and consequently a lower relative number of varieties produced given relative sectoral production. Given relative sectoral production, relative bilateral trade increases in the relative number of producers because love for variety. Hence, relatively higher fixed costs require a relatively higher productivity of variable production for a given ratio of exports relative to production.

The elasticity of substitution ϵ_k determines how sensitive the volume of relative bilateral sectoral trade is with respect to the relative price differences. Indeed, a lower elasticity implies less sensitivity to price differences. Thus, observed differences in export volumes relative to sectoral production must be caused by larger differences in variable productivity and the adjustment necessary to control for this effect (inverse weighting by elasticities) simultaneously increases the role of relative fixed costs in lowering relative productivity compared to relative productivity of variable production. 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 productivities can be interpreted as productivities of variable production.

Finally, productivity indices could alternatively be interpreted as differences in sectoral product quality across countries. Under this interpretation there would not exist any cost differences arising from TFP differentials across countries but consumers would be willing to spend more on goods of higher quality. Differences in M_{ijk} across countries would not arise because of differences in quantities shipped due to cost differentials but because of differences in quality. Since we look only at the value of trade, the two interpretations are equivalent.[13]

[13] An isomorphic model to the one presented in the main text is the following one. Replace sectoral subutility with the expression $u_{ik} = \left[\sum_{b \in B_{ik}} (\lambda_b x_b)^{\frac{\epsilon_k - 1}{\epsilon_k}}\right]^{\frac{\epsilon_k}{\epsilon_k - 1}}$, where $\lambda_b > 0$ is a utility shifter that measures product quality and let the cost functions be identical across countries for a given sector, such that $TC(q_{jk}) = (f_k + q_{jk}) \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}}$. Assuming that all firms within a sector of the exporting country produce varieties of the same quality, demand of country i consumers for sector k varieties produced in j is $x_{ijk} = \frac{\hat{p}_{ijk}^{-\epsilon_k} \lambda_{jk}^{\epsilon_k - 1} \sigma_{ik} Y_i}{\tilde{P}_{ik}^{1-\epsilon_k}}$, where $\tilde{P}_{ik} = \left[\sum_{b \in B_{ik}} (\frac{\hat{p}_b}{\lambda_b})^{1-\epsilon_k}\right]^{\frac{1}{1-\epsilon_k}}$ is the optimal quality adjusted price index. In this case the value of bilateral trade is $M_{ijk} = \frac{(p_{jk}\tau_{ijk})^{1-\epsilon_k} \lambda_{jk}^{\epsilon_k - 1} \sigma_{ik} Y_i}{\tilde{P}_{ik}^{1-\epsilon_k}} N_{jk}$. Comparing this expression with the one in the main text, (1.20), it becomes clear that productivity differences are indistinguishable from differences in product quality, because the value of bilateral trade is identical in both cases.

1.4 Alternative Specifications

In the previous section, we described how to estimate sectoral TFP using bilateral trade data, based on the simple model constructed in section 1.2. In order to make sure that our productivity estimates are not sensitive to the specific assumptions of this model we present a series of alternative specifications. Each of these alternatives generates also alternatives estimations. We will test the similarity between results under different specifications in the next chapter.

a A Hausman-Taylor Methodology

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

An alternative specification rearranges (2.4) such that we can write trade relative to production as a function of TFP, factor cost, and bilateral variables:

$$\left(\frac{M_{ijk}}{M_{iUSk}}\frac{\tilde{Q}_{USk}}{\tilde{Q}_{jk}}\right) = \left(\frac{A_{jk}}{A_{iUSk}}\right)^{\epsilon_k}\left[\prod_{f\in F}\left(\frac{w_{fj}}{w_{fUS}}\right)^{\alpha_{fk}}\right]^{-\epsilon_k}\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right)^{1-\epsilon_k} \tag{1.29}$$

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

$$\log\left(\frac{M_{ijk}}{\tilde{Q}_{jk}}\right) - \log\left(\frac{M_{iUSk}}{\tilde{Q}_{USk}}\right) =$$
$$\epsilon_k log\left(\frac{A_{jk}}{A_{USk}}\right) - \epsilon_k\left[\log\left(\frac{r_j}{r_{US}}\right) + \sum_{f\neq cap}\alpha_{fk}log\left(\frac{w_{fj}}{r_j}\right) - \alpha_{fk}log\left(\frac{w_{fUS}}{r_{US}}\right)\right] +$$
$$+(1-\epsilon_k)log\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right) \quad (1.30)$$

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

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

$$\log\left(\frac{M_{ijk}}{\tilde{Q}_{jk}}\right) - \log\left(\frac{M_{iUSk}}{\tilde{Q}_{USk}}\right) = D_{jk} + \beta_k log\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right) + u_{ijk} \quad (1.31)$$

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

$$\hat{D}_{jk} = D_j + D_k + \sum_{f\neq cap}\beta_{fk}\left[\alpha_{fk}log\left(\frac{w_{fj}}{r_j}\right) - \alpha_{fk}log\left(\frac{w_{fUS}}{r_{US}}\right)\right] + \nu_{jk} \quad (1.32)$$

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

$$\left(\frac{A_{jk}}{A_{iUSk}}\right) = exp\left[1/\epsilon_k(D_j + D_k + \nu_{jk}) + log\left(\frac{r_j}{r_{US}}\right)\right] \quad (1.33)$$

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

b Heterogeneous Firms and Zeros in Bilateral Trade

So far we have assumed that firms are homogeneous and that there are no fixed costs to export, thus all firms in a sector of country j are predicted to export to every country i. In reality, only a fraction of firms exports and very few firms export to several destinations.

Firm heterogeneity matters because the number of firms engaged in bilateral trade (the extensive margin) varies systematically with trade costs. Only the most productive firms can sell enough to recoup the fixed costs to export to destinations with high marginal trade costs. Not considering the extensive margin mixes the impact of trade barriers on the number of firms with the effect on exports per firm and it leads to biased estimates.

Thus, we want to check if our productivity estimates are robust once controlling for these factors. We follow the approach suggested by Helpman, Melitz and Rubinstein (2008), which forces us to use a somewhat different specification for our productivity estimates and obliges us to use information on the number of firms active in the exporting country, which we consider less reliable than the data on aggregate production.

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

$$MC(a) = \frac{a}{A_{jk}} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}} \tag{1.34}$$

Where a is an inverse measure of random firm productivity with sector specific cumulative distribution function $G_k(a)$ and support $[a_{Lk}, a_{Hk}]$ that is identical across countries. Aggregate sectoral productivity differences are measured by the term A_{jk},[14]. which can be interpreted as an average of the sectoral efficiency level in the exporting country.[15] In this way, we are able to measure which fraction of firms is engaged in bilateral trade once we filter out average sectoral productivity differences across countries.

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

$$\Pi_{ijk}(a) = \frac{1}{\epsilon_k} \left[\frac{\epsilon_k a \tau_{ijk} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}}}{(\epsilon_k - 1) A_{jk} P_{ik}} \right]^{1-\epsilon_k} \sigma_{ik} Y_i - f_{ijk} \tag{1.35}$$

Firms export from j to i in sector k only if they can recoup the bilateral fixed cost to export. This defines a cutoff productivity level a_{ijk} such that $\Pi_{ijk}(a_{ijk}) = 0$. Hence, only a fraction $G(a_{ijk})$ (potentially zero) of country j's N_{jk} firms export to country i. Define $V_{ijk} = \int_{a_{Lk}}^{a_{ijk}} a^{1-\epsilon_k} dG(a)$ if $a_{ijk} \geq a_{Lk}$ and zero otherwise. We assume that $G(a)$ is such that V_{ijk} is a monotonic function of $G(a_{ijk})$, the proportion of firms of country j exporting to country i in sector k.[16] The volume of bilateral trade can be written as:

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

[15] A more standard definition of sectoral productivity would be $\check{A}_{jk} \equiv A_{jk} \left(\int_{a_{Lk}}^{a_{jk}} a^{1-\epsilon_k} dG(a) \right)^{\frac{1}{1-\epsilon_k}}$, a weighted mean of firm productivities. The cutoff a_{jk} is endogenous and depends on the level of competition in the exporting country (see Melitz (2003)). Our definition disregards the effect of firm selection on the level of sectoral productivity.

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

$$M_{ijk} = \left[\frac{\frac{\epsilon_k}{\epsilon_k - 1} \tau_{ijk} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}}}{A_{jk} P_{ik}} \right]^{1-\epsilon_k} \sigma_{ik} Y_i N_{jk} V_{ijk} \tag{1.36}$$

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

$$\begin{aligned} \log(\tilde{A}_{ijk}) = \log(A_{jk}) + \frac{1}{\epsilon_k - 1} \log(\sigma_{ik} Y_i) + \log(P_{ik}) + \\ + \log \left(\frac{\epsilon_k - 1}{\epsilon_k} \right) + \log(\tau_{ijk}) + \frac{1}{\epsilon_k - 1} \log(V_{ijk}) \end{aligned} \tag{1.37}$$

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

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

$$Z_{ijk} = \frac{\frac{1}{\epsilon_k} \left[\frac{\epsilon_k a_{Lk} \tau_{ijk} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}}}{(\epsilon_k - 1) A_{jk} P_{ik}} \right]^{1-\epsilon_k} \sigma_{ik} Y_i}{f_{ijk}} \tag{1.38}$$

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

Using (1.35) and (1.38) one can show that $Z_{ijk} = \left(\frac{a_{ijk}}{a_L} \right)^{\epsilon_k - 1}$ and that consequently V_{ijk} is a monotonic function of Z_{ijk} if $V_{ijk} > 0$. Next, specifying z_{ijk} as the log of Z_{ijk}, we obtain:

$$rz_{ijk} = -log(\epsilon_k) + (1-\epsilon_k)log(\frac{\epsilon_k}{\epsilon_k - 1}) + (\epsilon_k - 1)log(P_{ik}) + log(\sigma_{ik}Y_i) + \\ +(1-\epsilon_k)log(p_{jk}) + (1-\epsilon_k)log(\tau_{ijk}) - log(f_{ijk}) \tag{1.39}$$

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

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

$$z_{ijk} = \xi_k + \xi_i + \xi_j - \gamma_k X_{ijk} + \eta_{ijk} \tag{1.40}$$

Where ξ_{jk} and ξ_{ik} are exporter, importer and sector specific effects[17] and $\eta_{ijk} = u_{ijk} + \nu_{ijk} \sim N(0, \sigma_u^2 + \sigma_\nu^2)$ is i.i.d (but correlated with the error term in the equation of trade flows). Hence $z_{ijk} > 0$ if $M_{ijk} > 0$ and zero else. As a next step define the latent variable T_{ijk}, which equals one if $z_{ijk} > 0$ and zero otherwise.

Specify the Probit equation

$$\rho_{ijk} = Pr(T_{ijk} = 1|X_{ijk}) = \Phi(\xi_k^* + \xi_i^* + \xi_j^* - \gamma_k^* X_{ijk}), \tag{1.41}$$

where starred coefficients are divided by the standard deviation of the error term, which

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

cannot be estimated separately. Finally, let $\hat{\rho}_{ijk}$ be the predicted probability of exports from j to i in sector k and let $\hat{z}^*_{ijk}$ be the predicted value of the latent variable z^*_{ijk}.

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

$$E[\log(\tilde{A}_{ijk})|X_{ijk}, T_{ijk} = 1] =$$
$$= \log(A_{jk}) + D_{ik} + \beta_k X_{ijk} + E[\frac{1}{\epsilon_k - 1} \log(V_{ijk})|T_{ijk} = 1] + E[e_{ijk}|T_{ijk} = 1] \quad (1.42)$$

Where $E[\log(\tilde{A}_{ijk})|.]$ is the mathematical expectation of "raw productivity" conditional on a vector of bilateral variables X_{ijk} and on observing positive trade flows, $T_{ijk} = 1$. The term $E[\log(V_{ijk})|T_{ijk} = 1]$ controls for the fraction and the productivity composition of exporters from country j that export to country i in sector k and $E[e_{ijk}|T_{ijk} = 1]$ controls for the sample selection because of unobservable trade barriers that affects both the decision to export and the volume of trade, while D_{ik} is a importer-sector dummy.

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

$$\log(\tilde{A}_{ijk}) = \log(A_{jk}) + D_{ik} + \beta_k X_{ijk} + \beta_{\eta,e,k}\frac{\phi(\hat{z}^*_{ijk})}{\Phi(\hat{z}^*_{ijk})} + \sum_{l=1}^{L} \gamma_{kl}(\hat{z}^*_{ijk})^l + \nu_{ijk} \quad (1.43)$$

c Eaton and Kortum's (2002) Model

An alternative model for estimating sectoral productivities from trade data is the Eaton and Kortum (2002) model of trade. Their Ricardian style model can easily be extended to the Heckscher-Ohlin style trade. Chor (2008) uses a version of this model to divide comparative advantage into different components by proxying for technology differences with observables but is not specifically interested in measuring sectoral TFPs. Finicelli et al. (2008) apply the baseline Eaton-Kortum model to calibrate aggregate manufacturing TFPs for a number of OECD economies, focusing on the role of competition on TFP, which we disregard in our discussion. While we define productivity as the average technology level, they focus on the effect of trade openness on the firm composition and hence on the aggregate productivity.

The model assumes a fixed measure of varieties $n \in [0,1]$ in each sector and perfect competition so that firms price at their (constant) marginal cost and countries source a given variety exclusively from the lowest cost supplier. The price of variety n of sector k produced in country j as perceived by country i consumers is:

$$\hat{p}_{ijk}(n) = \frac{1}{A_{jk}(n)} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}} \tau_{ijk} \tag{1.44}$$

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

Using the assumption of perfect competition and the properties of the extreme value distribution, it can be shown that exports of country j to country i in sector k as a fraction of $i's$ sectoral absorption are given by Π_{ijk}, the probability that country j is the lowest cost supplier of a variety n to country i in sector k.[18]

$$\frac{M_{ijk}}{\sum_{j \in J} M_{ijk}} = \Pi_{ijk} = \frac{\left[\prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}} \tau_{ijk}\right]^{-1/\beta_k} exp(1/\beta_k \lambda_{jk})}{\sum_{j \in J} \left[\prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}} \tau_{ijk}\right]^{-1/\beta_k} exp(1/\beta_k \lambda_{jk})} \tag{1.45}$$

[18] For the derivations, see Eaton and Kortum (2002) or Chor (2008).

Consequently, normalizing with imports from the US:

$$\frac{M_{ijk}}{M_{iUSk}} = \frac{\Pi_{ijk}}{\Pi_{iUSk}} = \frac{\left[\prod_{f\in F}\left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}} \tau_{ijk}\right]^{-1/\beta_k} exp(1/\beta_k \lambda_{jk})}{\left[\prod_{f\in F}\left(\frac{w_{fUS}}{\alpha_{fk}}\right)^{\alpha_{fk}} \tau_{iUSk}\right]^{-1/\beta_k} exp(1/\beta_k \lambda_{USk})} \tag{1.46}$$

Taking logs, we get:

$$\log\left(\frac{M_{ijk}}{M_{iUSk}}\right) = 1/\beta_k\left(\lambda_{jk} - \lambda_{USk}\right) - 1/\beta_k \sum_{f\in F} \alpha_{fk} \log\left(\frac{w_{fj}}{w_{fUS}}\right) - 1/\beta_k \log\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right) \tag{1.47}$$

Thus, we obtain $E\left[\frac{log(A_{jk})}{log(A_{USk})}\right] = \lambda_{jk} - \lambda_{USk}$.[19]

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

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

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

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

d Pricing to the Market and Endogenous Markups

Mark-ups charged by exporting firms may depend on the level of competition in the destination market (Sauré (2007), Melitz and Ottaviano (2008)). In this subsection, we study how our productivity estimation procedure is affected by the presence of pricing to the market. For doing so, we go back to our baseline model and slightly modify agents' utility function to make marginal utility bounded, so that consumers' demand drops to zero whenever a variety becomes too expensive.

$$u_{ik} = \left[\sum_{b\in B_{ik}} \ln(x_{bk}+1)\right] \tag{1.48}$$

The demand for a sector k variety produced in country j by consumers in country i is now given by:

$$x_{ijk} = \max\{\frac{1}{\mu_{ik}\tau_{ijk}p_{ijk}} - 1, 0\}, \tag{1.49}$$

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

$$M_{ijk} = \mu_{ik}^{-1}\left\{1 - \left[\mu_{ik}\tau_{ijk}\frac{1}{A_{jk}}\prod_{f\in F}\left(\frac{w_{fj}}{\alpha_{fk}}\right)^{\alpha_{fk}}\right]^{1/2}\right\}N_{jk} \tag{1.50}$$

Dividing by M_{iUSk}, taking logs and rearranging we get:

$$\log\left(\frac{M_{ijk}}{M_{iUSk}}\right) - \log\left(\frac{N_{jk}}{N_{USk}}\right) \approx \left(\frac{A_{jk}}{A_{USk}} \prod_{f\in F}\left(\frac{w_{fUS}}{w_{jk}}\right)^{\alpha_{fk}} \frac{\tau_{iUSk}}{\tau_{ijk}}\right)^{1/2} \tag{1.51}$$

We see that the shadow price, μ_{ik} (which is related to mark-ups and the level of competition in the export market) drops from the equation since exporters from country j and the US face the same level of competition in a given market i, but the relationship is no longer log linear. Moreover, N_{jk} cannot be replaced with aggregate production any more since the production level of individual firms q_{jk} depends on the trade weighted level of competition in the destination markets and prices charged in those markets, $N_{jk}\sum_{i\in I_{jk}} p_{ijk}q_{ijk}\tau_{ijk} = \tilde{Q}_{jk}$. Hence, our productivity estimation procedure remains approximately valid as long as we use the number of firms in the exporting country instead of aggregate production.

e Trade in Intermediates

In this subsection, we study how our specification is affected by the usage of tradable intermediate goods in production. Ethier (1982), Rivera-Batiz and Romer (1991), and others formalize the idea that having access to more varieties of differentiated intermediate goods through trade may boost sectoral productivity. Recently, Jones (2008) has emphasized that sectoral productivity may be crucially determined by linkages across sectors through the use of intermediate inputs, which may potentially lead to large multiplier effects of relatively small distortions. These ideas can easily be incorporated into our framework. We modify the production function in a way such that firms use not only capital and different labor types but also varieties of differentiated intermediates produced by other firms (and potentially in other countries) as inputs. Assuming that firms spend a fixed fraction of their revenues on intermediates of each sector the cost function now becomes:

$$TC(q_{ik}) = (f_{ik} + q_{ik})\frac{1}{A_{ik}}\left[\prod_{f\in F}\left(\frac{w_{fi}}{\alpha_{fk}}\right)^{\alpha_{fk}}\right]^{1-\beta_k}\left[\prod_{k'=1}^{K}\left(\sum_{b\in B_{ik'}}\hat{p}_{bk'}^{1-\epsilon_{k'}}\right)^{\frac{\sigma_{k'}}{1-\epsilon_{k'}}}\right]^{\beta_k} \tag{1.52}$$

Where $\sum_{k'=1}^{K}\sigma_{k'} = 1$ and $\epsilon_{k'} > 1$. Firms in sector k are assumed to spend a fraction, $\sigma_{k'}\beta_k$, of their revenues on a CES aggregate of differentiated intermediate inputs produced by sector k' with elasticity of substitution $\epsilon_{k'}$. Demand for intermediates by firms from sector k in country i for sector k' intermediates produced in country j can be found applying Shepard's Lemma to (1.52):

$$x_{ijkk'} = \frac{\hat{p}_{ijk'}^{-\epsilon_{k'}}\sigma_{k'}\beta_k N_{ik} TC(q_{ik})}{P_{ik}^{1-\epsilon_{k'}}} \tag{1.53}$$

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

Since we do not explicitly take into account that firms use intermediates our measured productivity is $\breve{A}_{jk} \equiv A_{jk}\left[\prod_{k'}\left(\sum_{b\in B_{jk}}\hat{p}_b^{1-\epsilon_{k'}}\right)^{\frac{\sigma_{k'}}{1-\epsilon_{k'}}}\right]^{-\beta_k}$. This implies that in countries and sectors where more varieties of intermediates are available and cheaper on average, measured productivity is higher. To the extent that intermediate inputs are non-tradable, like transport or government services, low productivity in other sectors leads to high prices of these intermediate inputs and consequently to lower measured sectoral productivity.

f Mismeasurement of Sectoral Factor Income Shares

In our modeling procedure, we have assumed that sectoral factor income shares do not vary across countries in order to be able to use the values of the US for these parameters, since reliable information on factor income shares at the sectoral level is not available for most countries. In this subsection, we investigate the bias that may arise from mismeasuring factor income shares. For concreteness, let us focus on income shares of skilled labor. Suppose $\alpha_{skj} = \alpha_{skUS} + \nu_{jk}$. Then with some manipulations productivities can be written as:[20]

$$E\left[log(\frac{A_{ijk}}{A_{iUSk}}|actual)\right] \approx E\left[log(\frac{A_{ijk}}{A_{iUSk}}|measured)\right] + E(\nu_{jk})log(\frac{w_{sj}}{w_{uj}}) + \\ E(\nu_{jk})(1-\alpha_{skUS}-\alpha_{capkUS}) + E[\nu_{jk}(\nu_{jk}-\alpha_{skUS}-\alpha_{capkUS})] \quad (1.54)$$

Consequently, if the intensity differences are random, i.e. ν_{jk} is i.i.d. with $E(\nu_{jk}) = 0$ and $Var(\nu_{jk}) = \sigma_{jk}$, we get $E\left[log(\frac{A_{ijk}}{A_{iUSk}}|actual)\right] = E\left[log(\frac{A_{ijk}}{A_{iUSk}}|measured)\right] + \sigma_{jk}$.

Hence, on average we tend to underestimate productivities in those sectors and countries that have very (but not systematically) different factor income shares than the US. Since this kind of measurement error is more likely to occur in poor countries, it may lead to underestimation of poor countries' productivities in specific sectors.

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

[20] In order to derive this, substitute the definition of skilled labor shares in the definition of "raw" productivity in the main text, divide by the value of the US, take logs, simplify, and use $log(1+x) \approx x$.

countries have a systematically larger skilled labor income share in more skill intensive sectors than the US. If technological change is skill biased, the gap in the wage share of skilled labor between rich and poor countries is larger in more skill intensive sectors, so that we actually tend to overestimate the productivity of poor countries in skill intensive sectors. The intuition is that in this case we overestimate the cost of skilled labor inputs in poor countries in skill intensive sectors, which have on average higher skill premia than rich ones.

1.5 Conclusion

In this chapter, we have developed a model that combines Heckscher-Ohlin trade, increasing returns and love for variety, trade costs, and sectoral differences in total factor productivity. Using, this model, we have shown how to back-out sectoral productivity differences as observed trade which cannot be explained by differences in factor intensities and factor prices or by differences in trade barriers across countries. The intuition behind our method for estimating sectoral productivities is to exploit variation in bilateral sectoral export values across export countries, instead of specifying a production possibility frontier.

Once explained a methodology to estimate sectoral TFPs, we have developed a series of alternative specification that address potential issues with our benchmark model. The next step, covered in the second chapter, will be to construct a data-set that gathers all the required information, and using it to obtain numerical estimations of sectoral productivities based on our benchmark and alternative specifications.

2 CHAPTER TWO

2.1 Introduction

In this chapter, we use the methodology exposed in the last chapter to estimate a set of sectoral productivities. Our results provide evidence that cross-country TFP differences in manufacturing sectors are large, on average of about the same order of magnitude as the substantial variation across countries at the aggregate economy level that has been found in the development accounting literature (for example, Hall and Jones (1999), and Caselli (2005)). In addition, we show that productivity differences between rich and poor countries are systematically larger in skilled labor and R&D intensive sectors. Productivity gaps are far more pronounced in sectors such as Scientific Instruments, Electrical- and Non-electrical Machinery, and Printing and Publishing, than in sectors such as Apparel, Textiles, or Furniture.

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

The next section briefly recalls the methodology. Section three describes the data and section four presents our empirical results on productivities. Section five is dedicated to robustness estimations, and section six discusses some applications of our productivity estimates in testing specific theories of development that have implications for the cross section of productivities within countries. The final section presents our conclusions.

2.2 The Basic Equation Revisited

We start with the sectoral volume of bilateral trade (measured at destination prices), defined as the value of imports of country i from country j in sector k.

$$M_{ijk} = \hat{p}_{ijk} x_{ijk} N_{jk} = p_{jk} \tau_{ijk} x_{ijk} N_{jk} \tag{2.1}$$

Substituting the demand function and 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, we can write bilateral sectoral trade volume as

$$M_{ijk} = \left[\frac{\frac{\epsilon_k}{\epsilon_k - 1} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}}}{A_{jk} P_{ik}} \right]^{1-\epsilon_k} \sigma_{ik} Y_i N_{jk} \tag{2.2}$$

Since we do not consider data on the number of firms active in the exporting countries as very reliable, but we observe the value of sectoral production, we can use the model to solve for the number of firms given total production. After some substitutions explained in detail in the previous chapter, we obtain:

$$M_{ijk} = \left[\frac{\frac{\epsilon_k}{\epsilon_k - 1} \prod_{f \in F} \left(\frac{w_{fj}}{\alpha_{fk}} \right)^{\alpha_{fk}}}{A_{jk}} \right]^{-\epsilon_k} \left[\frac{\tau_{ijk}}{P_{ik}} \right]^{1-\epsilon_k} \sigma_{ik} Y_i \frac{\tilde{Q}_{jk}}{(\epsilon_k - 1) f_{jk}} \tag{2.3}$$

This equation can be rearranged to solve for the sector productivity A_{jk}. Because a productivity index needs to be defined relative to some benchmark, we measure productivity relative to a reference country. We choose the US as a benchmark because they export to the greatest number of destinations in most sectors.[1] Another advantage

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

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

$$\begin{aligned}\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}} &\equiv \frac{A_{jk}}{A_{USk}}\left(\frac{f_{jk}}{f_{USk}}\right)^{-1/\epsilon_k}\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right)^{\frac{1-\epsilon_k}{\epsilon_k}} = \\ &= \left(\frac{M_{ijk}}{M_{iUSk}}\frac{\tilde{Q}_{USk}}{\tilde{Q}_{jk}}\right)^{1/\epsilon_k}\prod_{f\in F}\left(\frac{w_{fj}}{w_{fUS}}\right)^{\alpha_{fk}}\end{aligned} \tag{2.4}$$

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

Our "raw" productivity measure, $\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}}$, is a combination of relative productivities, fixed costs, and transport costs. Assuming that fixed cost are constant across countries and that transport costs are a log-linear function of a vector of bilateral variables plus a random error term, and taking logarithms, we get a three dimensional panel with observations that vary by industry, exporter, and importer.

$$\begin{aligned}\log\left(\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}}\right) &= \log\left(\frac{A_{jk}}{A_{USk}}\right) + \beta_{1k}(\log Dist_{ij} - \log Dist_{iUS}) + \\ &+\beta_{2k}(\log Tariff_{ijk} - \log Tariff_{iUSk}) + \\ &+\beta_{3k}CommonLang_{ij} + \beta_{4k}CommonLang_{iUS} + ... + u_{ijk} - u_{iUSk}\end{aligned} \tag{2.5}$$

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

The sector-country dummies are computed as:

$$\frac{A_{jk}}{A_{USk}} = exp\left[\log\left(\overline{\frac{\tilde{A}_{jk}}{\tilde{A}_{USk}}}\right) - \beta_k^{FE}\overline{X_{jk}}\right] \tag{2.6}$$

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

In summary, our methodology consists in two steps. In the first step, we compute "raw" productivities (i.e., TFP plus transport costs) using bilateral trade, production and factor prices data. In the second step we clean transport cost variables by regression, obtaining relative TFPs that do not depend on importer country i.

2.3 Data Description

We compute sectoral productivities for twenty-four (ISIC Rev. 2) manufacturing sectors in sixty-four countries at all stages of development for three periods: the mid-eighties, the mid-nineties, and the beginning of this century. In order to do so, we use data on bilateral trade at the sector level, information on sectoral production, factor prices, sectoral factor intensities, elasticities of substitution, and sectoral bilateral trade barriers (distance, tariffs, language, etc.).

Bilateral sectoral trade data, M_{ijk}, and sectoral production, $Output_{jk}$, are obtained from the World Bank's Trade, Production and Protection Database (Nicita and Olarreaga (2007)). 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. To mitigate problems of data availability and to smooth the business cycle, we average the trade and production data over three years. Thus, we collect data for the periods 1984-1986, 1994-1996 and 2002-2004, considering 36 importing countries and 64 exporting countries. The 36 importers represent more than $\frac{2}{3}$ of world imports[2]. We exclude, tobacco (314), petroleum refineries (353), miscellaneous petroleum and coal products (354) and other manufactured products not classified elsewhere (390) from the 28 sectors in the ISIC classification because trade data do not properly reflect productivity in those sectors.

For the monetary value of production, $Output_{jk}$, we use information on Gross Output from the Trade, Production and Protection Database.[3] The original source of this variable is the United Nations Industrial Development Organization's (UNIDO) Industrial Statistics. For the years 1994-1996 some data have been updated by Mayer and Zignago (2005).[4]

The production data published by UNIDO is by no means complete, and that is the main limitation in computing productivities.[5] UNIDO also collects data on establishments that we could have used directly, instead using Gross Output data. However, these data are less reliable than production data because different countries use different threshold

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

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

[4]They have updated a previous version of the Trade and Production Database. As in the latest version of the Trade, Production and Protection Database, data from years 94-96 remain the same, the Mayer and Zignago (2005) database is more complete than the one constructed by Nicita and Olarreaga (2007).

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

firm sizes when reporting data to the UNIDO.[6]

Sectoral elasticities of substitution, ϵ_k, are obtained from Broda and Weinstein (2006). They construct elasticities of substitution across imported goods for the United States at the Standard International Trade Classification (SITC) 5 digit level of disaggregation for the period 1990-2001. We transform those elasticities to our 3-digit ISIC rev. 2 level of disaggregation by weighting elasticities by US import shares.[7]

Factor intensities, $(\alpha_{ku}, \alpha_{ks}, \alpha_{kcap})$, are assumed to be fixed across countries. This assumption allows us to use data on factor income shares for just one country, namely the US. To proxy for skill intensity, we follow Romalis (2004), in using the ratio of non-production workers to total employment, obtained from the NBER-CES Manufacturing Industry Database constructed by Bartelsman, Becker and Gray (2000) and converting USSIC 87 categories to ISIC rev 2. Capital intensity is computed as one less the share of total compensation in value-added, using the same source. In our three factor model intensities are re-scaled such that $\sum_i \alpha_{k,i} = 1; \qquad i = u, s, cap$[8].

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

[7] We have also worked with elasticities obtained from Hummels (1999) at the SITC 2-digit level and from Broda and Weinstein (2006) at SITC 3-digit level. While computed elasticities are different depending on the source, final estimates of TFP are highly correlated. We prefer the SITC 5-digit level of disaggregation because there is an unique correspondence between SITC 5 digits and ISIC 3 digits (i.e., the SITC code 01111 maps only to ISIC code 311), but there is no unique mapping between ISIC 3-digit level and SITC 2 or 3 digits (for example, the SITC code 53 could correspond to ISIC codes 351 or 352). Thus, in the latter case choosing one specific ISIC code could lead to measurement bias, as we are defining more or less arbitrarily which code to choose (one reasonable option is to choose the ISIC code that has more correspondences at the SITC 5-digit level). Moreover, in some cases we still have to aggregate using imports shares. For example, ISIC sector 311 corresponds to SITC sectors 01-09, 21 and 22, so in that case (and others) we have again to weight somehow, so even working with SITC at a higher level of aggregation does not eliminate completely a potential measurement bias problem.

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

Table 2.1: Industry Statistics

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

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

Table 2.1 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 of 0.27. Capital intensity, measured as one minus labor compensation in value-added, varies from 0.56 (Fabricated Metals) to 0.85 (Beverages) with the mean being equal to 0.66. Finally, the elasticity of substitution varies between 1.90 (Pottery) and 12.68 (Non-Ferrous Metals) with an average of 4.36.

Wages and rental rates at the country level are computed using the methodology exposed in Caselli (2005), Caselli and Coleman (2006) and Caselli and Feyrer (2007). The definition of the rental rate is consistent with a dynamic version of our model in which firms solve an inter-temporal maximization problem and capital markets are competitive.[9] Total payments to capital in country j are $\sum_k p_{jk} MPK_{jk} K_k = p_j MPK_j \sum_k K_k = r_j K_j$ where K_j is the country $j's$ capital stock in physical units and the first equality follows from capital mobility across sectors. Since $\alpha_{j,cap} = \frac{r_j K_j}{P_Y Y}$, where Y is GDP in Purchasing Power Parities, the following holds:

$$r_j = \alpha_{j,cap} \frac{GDP_j}{K_j} \tag{2.7}$$

Capital stocks in physical units are computed with the permanent inventory method using investment data from the Penn World Table (PWT).[10] GDP_j is also obtained from the PWT and is expressed in current dollars. $\alpha_{j,cap}$ is country j's aggregate capital income share. We compute the capital share as one minus the labor share in GDP, which we take from Bernanke and Gürkaynak (2002) and Gollin (2002). In turn, the labor share is employee compensation in the corporate sector from the National Accounts plus a number of adjustments to include the labor income of the self-employed and non-corporate employees.

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

$$(1 - \alpha_{j,cap}) = \frac{w_u U + w_u \frac{w_s}{w_u} S}{GDP_j} \tag{2.8}$$

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

[10] For details see Caselli (2005)

The total labor share is equal to payments to both skilled and unskilled workers relative to GDP. Skilled and unskilled workers are expressed in efficiency units of non-educated workers and workers with complete secondary education.[11] Thus,

$$U = L_{noeduc} + e^{\beta * \frac{prim.dur.}{2}} L_{prim.incomp.} + e^{\beta * prim.dur.} L_{prim} + e^{\beta * lowsec.dur.} L_{lowsec} \quad (2.9)$$

and

$$S = L_{secondary} + e^{2\beta} L_{ter.incomp.} + e^{4\beta} L_{tertiary} \quad (2.10)$$

Educational attainment of workers over 25 years at each educational level are taken from Barro and Lee (2001) and Cohen and Soto (2001). Information on the duration of each level of schooling in years by country is provided by the UNESCO.[12] Skill premia β by country are obtained from Bils and Klenow (2000) and Banerjee and Duflo (2005). The wage premium $\frac{w_{skill}}{w_u}$ equals $e^{\beta * (prim.dur. + lowsec.dur.)}$.

The panels of figure 2.1 plot the computed skilled and unskilled wages, the wage premium, the capital stock per worker and the rental rate for the countries against log income per worker for the mid-nineties.

In our estimations, wages of both skilled and unskilled workers are much higher in rich countries, but the wage premium is negatively related with income per worker, which gives rich countries a relative advantage in skilled labor-intensive sectors. The relation between the rental rate and income per worker is slightly positive. The absence of a strong relationship between the marginal product of capital and income per worker is similar to Caselli and Feyrer (2007) once they correct for price differences and natural

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

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

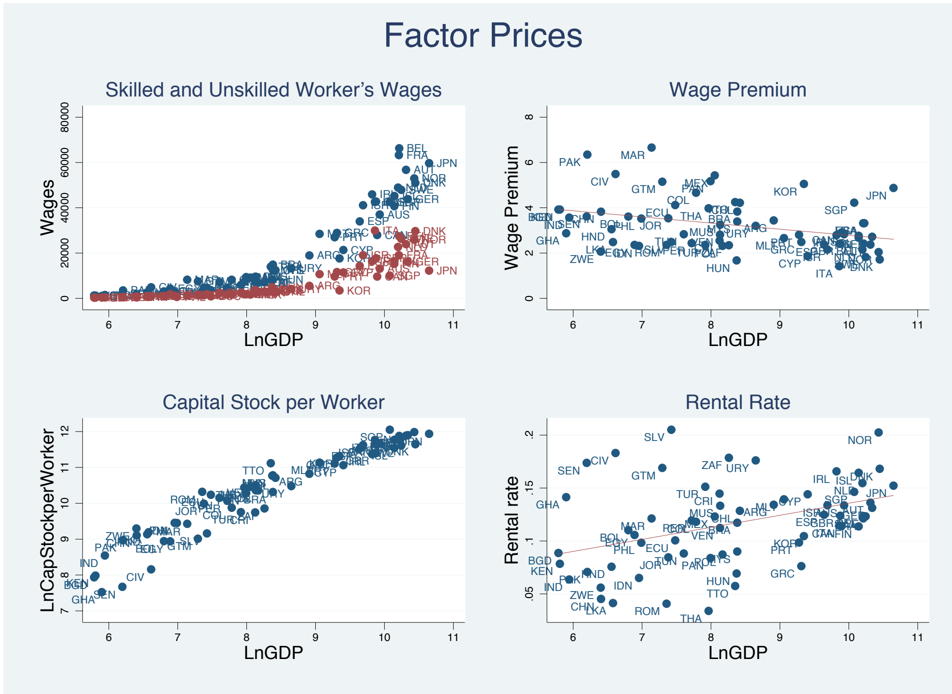

Figure 2.1: Factor Prices

capital. Although we do not adjust for the fraction of income that goes to natural capital in our three factor model, 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, who have developed a distance database which uses city-level data in the calculation of the distance matrix to assess the geographic distribution of population inside each nation. The basic idea is to calculate the distance between two countries based on bilateral distances between cities weighted by the share of each city in the overall country's population. CEPII also provides a bilateral sectoral tariff database. Tariffs are measured at the bilateral level and for each product of the HS6 nomenclature in the TRAINS database from UNCTAD. Those tariffs are aggregated from TRAINS data in order to match the ISIC Rev.2 industry classification using the world imports as weights for HS6 products. Other bilateral variables we use, the source of which is Rose

(2004), are the following: an indicator variable that equals one if two countries share a common border (common border), an indicator if two countries share a common language (common language), an indicator that equals one if one of the countries has ever been a colony of the other , an indicator for common membership in a regional trade agreement, and indicator for common membership in a currency union and an indicator for common membership in a general system of preferences.

2.4 Results

In this section, we report the results of computing productivities using our baseline specification (2.5). We use a simple stepwise linear panel estimation[13] with sector-country specific fixed effects. We limit the sample to exporter-sector pairs for which we observe exports to at least five destinations but ignore zeros in bilateral trade flows and issues of sample selection at this stage of our analysis. This leaves us with a sample of around 42000 observations for a given year.

Table 2.2 shows the regression results for our baseline model using data for the mid-nineties. The overall fit is very good with an R-square of 0.80 and a *within* R-square of 0.47. This implies that for a given sector's productivity $\frac{A_{jk}}{A_{USk}}$, trade costs due to the gravity type variables in our regression account for approximately half of the variation in $\frac{\tilde{A}_{ijk}}{\tilde{A}_{iUSk}}$ across importers. In addition ρ - the fraction of the variance of the error term that is due to $\frac{A_{jk}}{A_{USk}}$ - is 74%. Both 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 impact of the relevant variable on transport costs multiplied by the negative term $\frac{1-\epsilon_k}{\epsilon_k}$, so that a negative coefficient

[13]The stepwise procedure starts with the full model that includes all right hand side variables and one by one discards variables that are not significant at the ten percent 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.

implies that an increase in the dependent variable increases relative transport costs.

Differences in distance have a large and very significant negative effect on our relative raw productivity measure (i.e. increase trade costs) in all sectors. Differences in bilateral sectoral tariffs between country j and the US are also negative and significant for all sectors except Other Chemicals (sector 352). Indicators for common language between the importer and the exporter have a significant positive effect on raw productivity (i.e. reduce the transport cost) in all sectors but Iron and Steel (371) and Non-ferrous Metals (372), while having English as a common language with the importer has a negative effect in some sectors, since it is the language spoken in the US. 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 Footwear (324) and Paper (341).[14]

Having run regression (2.5), we use (2.6) to construct sectoral productivities. We compute almost 1500 sectoral TFPs for each period (twenty-four by country for sixty-four countries[15]). Table 2.3 summarizes some information about these productivities in the mid-nineties. We present the country mean of TFP across industries[16], the standard

[14]Overall, of all estimated significant coefficients, only one has a wrong sign: Common English Language in the sector Footwear. Note also that all the other bilateral variables that were in principle included in the regression (common regional trade agreement, common membership in a currency union, common membership in a generalized system of preferences), do not have a robust effect on relative raw productivities once we control for relative tariffs and distance, and therefore do not appear in the final specification.

[15]For some countries, we cannot compute TFP for all sectors either because of missing production data or because the country does not export to enough countries in a sector, so we drop the sector from (2.5). Ivory Coast is the country with the smallest number of sectors for which we obtain productivity measures (fifteen), and only in nine (out of sixty-four) countries we construct productivities for less than twenty sectors. The complete set of productivity estimates is available upon request and will soon be online under http://www.pablofleiss.com.

[16]Those averages of sector productivities cannot be interpreted as aggregate manufacturing produc-

Table 2.2: Regression Coefficients

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

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

deviation, and the sectors with maximum and minimum TFP for each country in our sample.

First, we observe that there is a strong correlation between a country's income per worker and average relative TFP in manufacturing. Poor countries tend to have far lower sectoral productivities than rich ones, but within countries relative productivities vary considerably across sectors. Taking for example Pakistan, we measure an average relative manufacturing TFP of 0.20 of the US level. This hides a large amount of heterogeneity across sectors: a productivity of 0.63 with respect to the US level in Furniture (322) and one of only 0.07 in the sector Printing (341). In general, Plastics (356), Fabricated Metals (381), and Transport Equipment (384) are sectors in which many of the poor countries tend to be least productive relative to the US, while Footwear (324) and Furniture (332) are the sectors in which rich countries seem to have their smallest productivities relative to the US, although these patterns are not as clear for poor nations. Many poor countries have their highest relative productivities in the sectors Food (311) and Apparel (322) while again, there is no clear pattern in which sectors rich countries are the most productive relative to the US.

In order to exemplify our results, the panels of Figure 2.2 and 2.3 show scatter plots of estimated sectoral productivities against the log GDP per worker in the mid-nineties for eight out of the twenty-four sectors. There is a high correlation between sectoral productivity and log GDP per capita in all sectors. However, the magnitude of productivity differences varies substantially across sectors. For example, the relation between log income per capita and productivity is much more pronounced in the sector Metal Products (381) than in Food (311). We also note that in general, the richest European countries tend to be more productive than the US in most manufacturing sectors.

tivity indices in terms of economic theory, since we would need to take into account agents' preferences for a proper aggregation. Nevertheless, they give some sense of the magnitude of average sectoral productivity differences across countries.

Table 2.3: Descriptive Statistics - Middle of the 90's

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

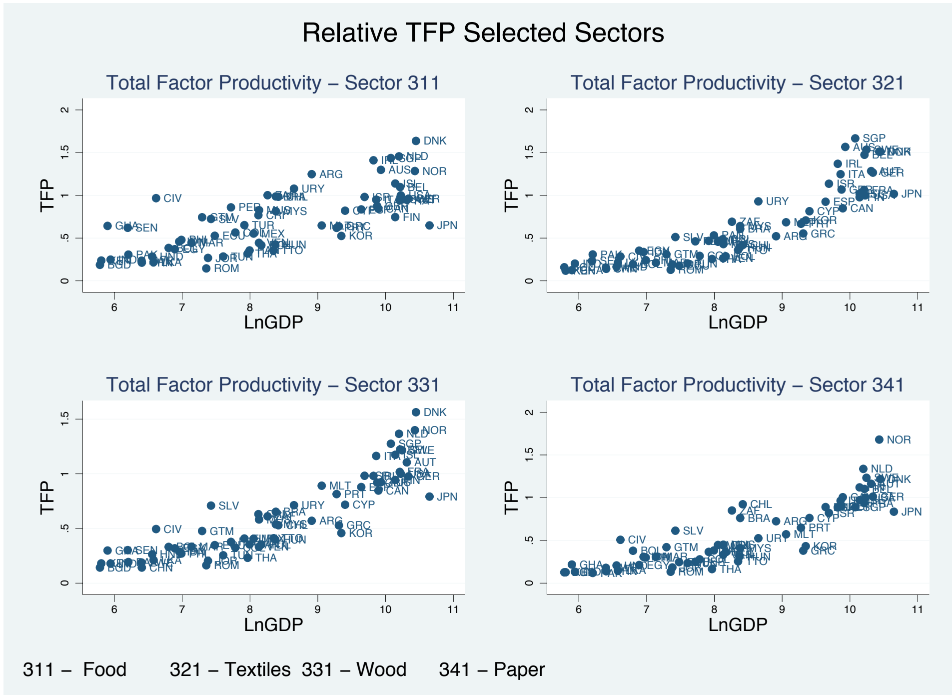

Figure 2.2: Relative TFP Selected Sectors

At this point, it seems interesting to compare our mean sectoral productivities in manufacturing with the aggregate productivities found in the Development Accounting literature. To this end we compute weighted averages (by value added) of our sectoral TFPs and correlate them with aggregate productivities constructed from production and endowment data.[17] Figure 2.4 shows a scatter plot of our aggregate manufacturing productivity against the aggregate economy productivity indices computed as Solow residuals. We note that there is a very strong correlation between the two sets of productivity estimates. The correlation coefficient between them is 0.68. Productivity differences in manufacturing tend to be even larger than aggregate ones. This is driven by the fact that European countries seem to be relatively more productive in manufacturing than at the aggregate economy level. Note also that a number of poor countries like Tunisia, Egypt, Guatemala, and Venezuela, that are close to the US productivity

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

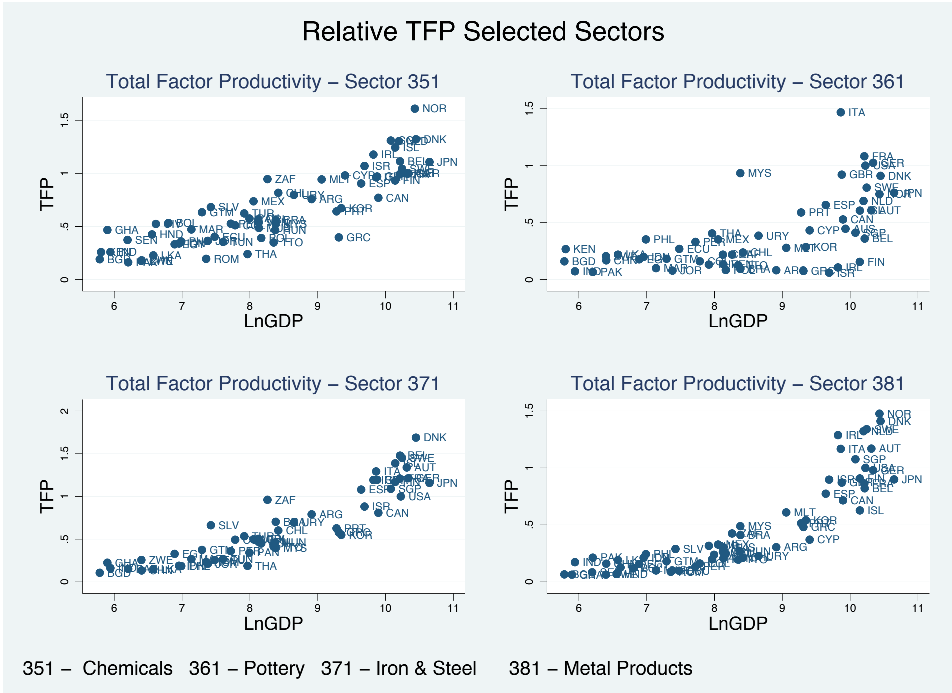

Figure 2.3: Relative TFP Selected Sectors (Continued)

level according to the Solow residual method, are estimated to be far less productive than the US in manufacturing when using our methodology.

To get an even better feeling for the productivity differences between rich and poor countries, we split the countries in two samples: developing countries (with income per worker below 8000 US Dollars in 1995) and developed countries. Figure 2.5 shows a histogram of sector productivities for the mid-nineties for both subsamples, where each observation is given by a sector-country pair. We observe that the productivity distribution of developing countries is left skewed, so that most sectoral productivities are far below the US level, with a long tail on the right, meaning that there are a few developing countries more productive than the US in certain sectors. Developed countries' have a relatively symmetric productivity distribution with a mean sectoral productivity that is slightly below one, and a significant variation to both sides, ranging from around 0.2 to 1.5 of the US level.

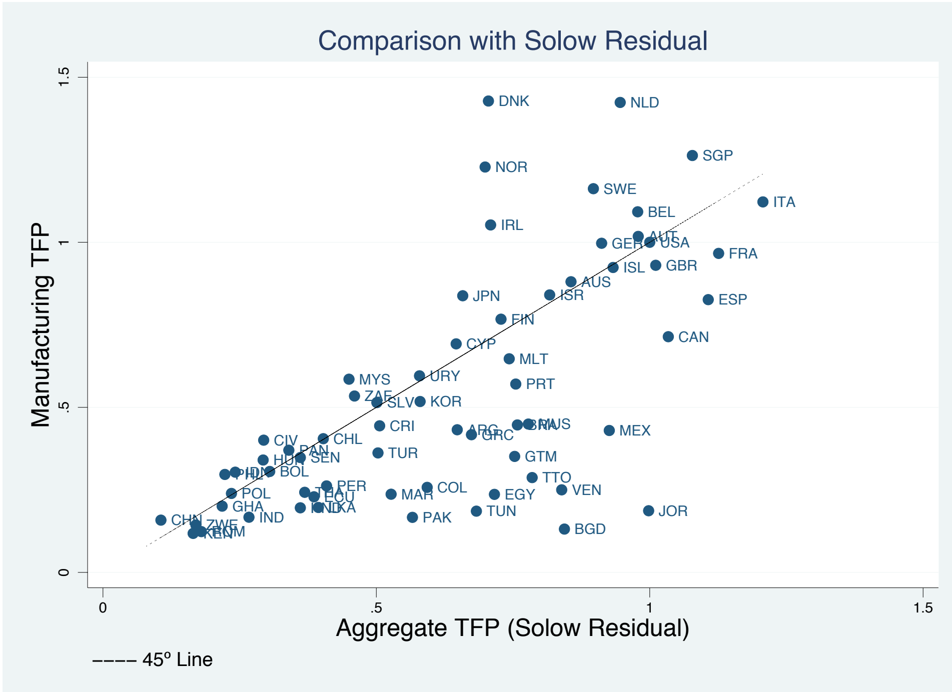

Figure 2.4: Aggregate Manufacturing TFP vs. TFP Solow Residual

Figure 2.6 shows the evolution of the relative productivities of developing countries over time. The dashed line is the histogram of developing countries' productivities in the mid-eighties, the solid line is the histogram for the mid-nineties and the dotted line the one for the beginning of this century for the sample of twenty-two developing countries for which we have data for all three periods. We see that the distribution is shifting to the right over time, meaning that over this twenty-year period, poor countries are slowly catching up in sectoral TFP relative to the US.[18] The countries in our sample that have on average experienced the fastest convergence in TFP towards the US level over these two decades (annualized growth rates in parenthesis) are China (5.1%), Uruguay (4.7%), Argentina (4.3%), Egypt (4.1%), and Poland (4%), while the countries with the greatest divergence were Jordan (-3.6%), Panama (-2%), Kenia (-1.2%), and Ecuador

[18] This finding is different from what is found with the Solow residual approach, according to which aggregate productivity differences have become larger in the last two decades. See, for example, (Acemoglu (2008)). However, our sample includes only two African economies (Kenia and South Africa), which is the continent that has fared by far worst during this period.

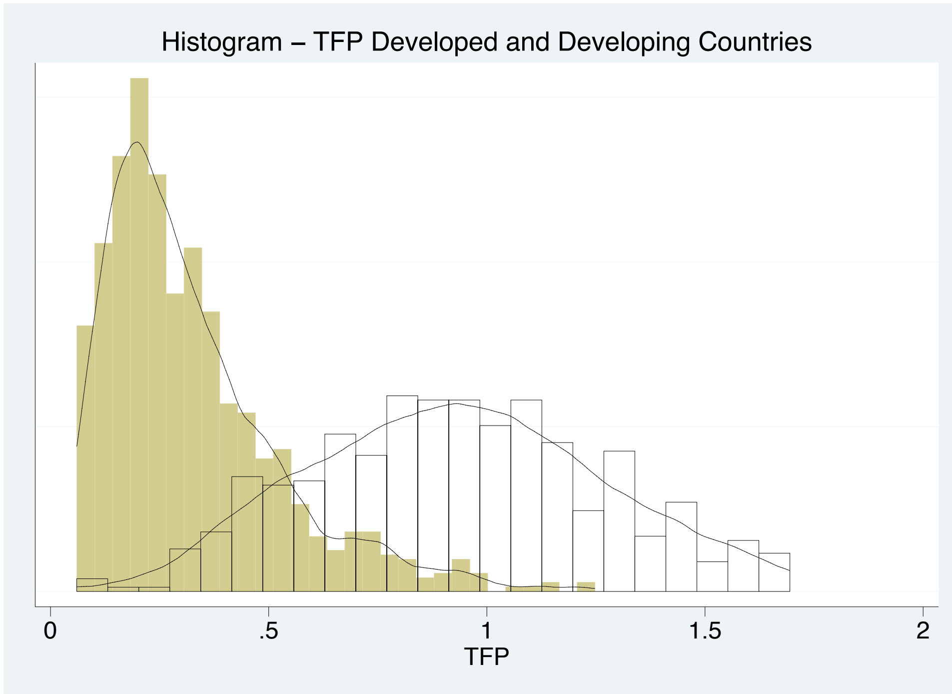

Figure 2.5: Histogram TFPs Rich and Poor Countries

(-0.3%). The sectors in which developing countries have on average experienced the fastest speed of catch up are Pottery (4.9%), Printing and Publishing (3.7%), Electrical Machinery (3.4%), and Other Chemicals (3.3%), while the ones with the lowest speed of convergence are Beverages (-0.8%), Transport Equipment (-0.7%), Food (-0.6%), and Industrial Chemicals (0.7%).

Our productivity estimates also allow us to construct "Ricardian" style curves of comparative advantage due to productivity differences for any country pair. The panels of Figure 2.7 depict productivities arranged in a decreasing order according to the magnitude of relative productivity differences with the US for four representative countries: Germany, Spain, Uruguay, and Zimbabwe. Here, for example, we see that Spain's comparative advantage relative to the US is greatest in the sectors Other Non Metallic Mineral Products (369), Iron and Steel (371), and Rubber Products (355), while the sectors with the greatest comparative disadvantage are Printing and Publishing (342), and Plastic Products (356). The comparative advantage of Zimbabwe, on the other

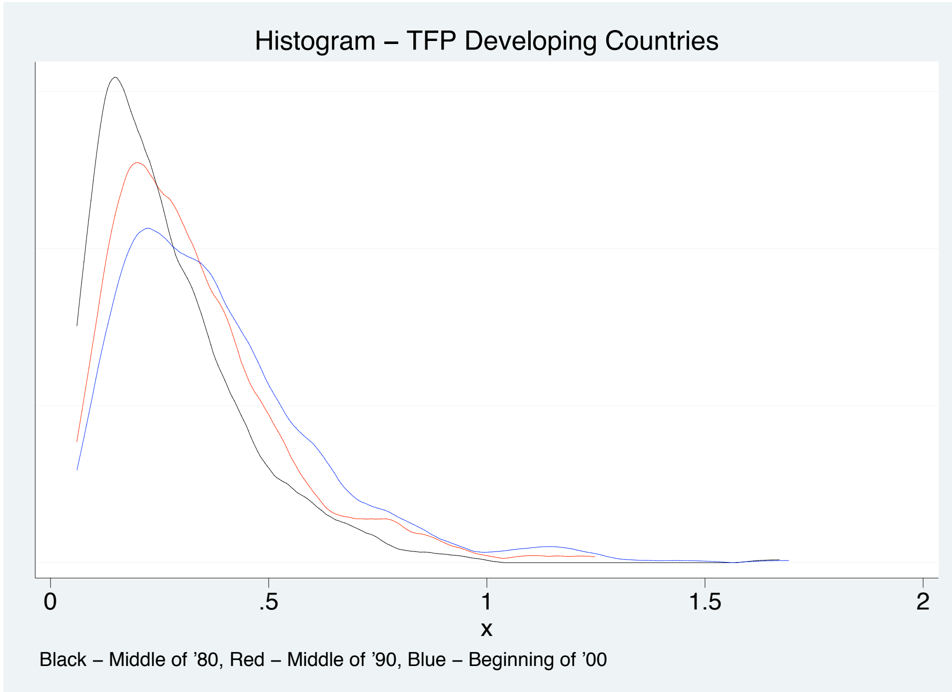

Figure 2.6: Histogram TFPs Evolution in Poor Countries

hand, is largest in the sectors of Apparel (322), with a productivity of less than 25% of the US level and Non Ferrous Metals (372), and smallest in the sectors of Plastic Products (356), and Footwear (324) with productivities around 5% of the US level.

As a further application, we check if productivity differences between developing and industrialized countries are systematically related to sector characteristics. Table 2.4 shows the result of a weighted regression[19] (with the inverse of the standard deviation of log(TFP)) of log(TFP) relative to the US in the mid-nineties on sectoral human capital intensity and the interaction of human capital intensity and log income per worker controlling for country fixed effects.[20] Productivity differences relative to the US in poor countries are systematically larger in human capital-intensive sectors but this

[19]Results also go through without weighting observations.

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

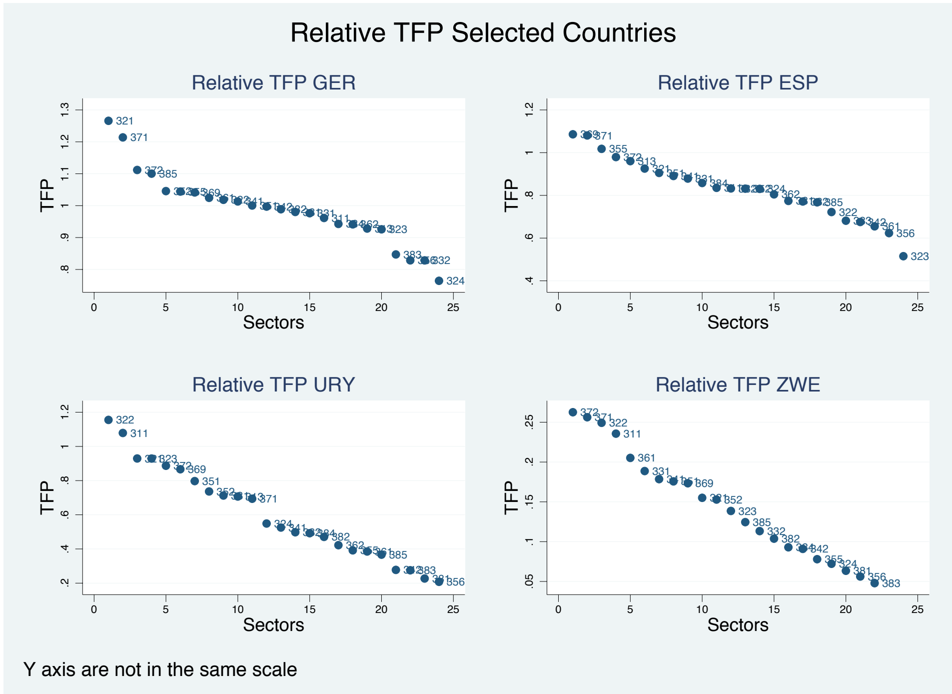

Figure 2.7: Ricardian Comparative Advantage Relative to US

effect disappears in richer countries. 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, poor countries have systematically larger productivity gaps in R&D intensive sectors, an effect that is mitigated as countries become richer.

2.5 Robustness

In this section, we will estimate productivities using the alternative specifications described in previous chapter (section 1.4). Then, we will compare the correlations between our baseline results and alternative procedures' results.

First, we check that results are robust to changing our econometric strategy. When we

Table 2.4: TFP and Sector Characteristics

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

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

directly estimate the Heckscher-Ohlin component of the model instead of calibrating it, we obtain significant results for the interaction of factor intensities and factor prices, indicating that countries indeed specialize in sectors that use their relatively cheap factors intensively.

As mentioned, this procedure is similar to the Hausman-Taylor GMM estimator, which allows some of the right hand side variables to be correlated with the fixed effects and at the same time to estimate the coefficients of the variables that do not vary by importing country.

In order to obtain a consistent estimator for $\left(\frac{A_{jk}}{A_{iUSk}}\right)$ under this procedure, we should assume that productivities are not correlated with relative factor prices within a country. Then, we follow the two-step procedure described in previous chapter: In the first step, we regress our dependent variable on sector-country dummies and bilateral variables. Having obtained the first stage estimates, in the second step we regress the sector-country dummy on factor prices weighted by factor intensities as well as country and sector dummies.

Table 2.5 reports the results of this regression. Differences in tariffs and in distance have a very significant negative impact on relative normalized trade in all sectors and the other bilateral variables have the expected sign and are mostly significant. The fit of the first stage has an R-square of 0.64. In the second stage, the interactions between factor intensities and the relative price of skilled and unskilled labor are highly significant. The R-square of the second stage is 0.55, implying that country and sector dummies and the Heckscher-Ohlin components explain around half of the country-sector specific variation.

This approach to 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 (1.31) with the one of a model with country specific productivities and a Heckscher-Ohlin component that ignores Ricardian productivities.[21]

$$\log\left(\frac{M_{ijk}}{\tilde{Q}_{jk}}\right) - \log\left(\frac{M_{iUSk}}{\tilde{Q}_{USk}}\right) = D_j + D_k + \tag{2.11}$$
$$+ \sum_{f \neq cap} \beta_{fk}\left[\alpha_{fk} log\left(\frac{w_{fj}}{r_j}\right) - \alpha_{fk} log\left(\frac{w_{fUS}}{r_{US}}\right)\right] + \beta_k log\left(\frac{\tau_{ijk}}{\tau_{iUSk}}\right) + u_{ijk}$$

The adjusted R-square of this model is 0.5 compared to the 0.63 obtained by using Ricardian productivities, so there is a 13% gain in fit by introducing Ricardian productivity differences.[22] Also the Akaike information criterion tells us that the Ricardian model does much better in terms of fit.[23]

The productivities obtained with this procedure are very similar to our baseline set of

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

[22] We obtain very similar results regarding the importance of Ricardian productivity differences when comparing (2.5) with a restricted version that allows only for country specific TFP differences.

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

Table 2.5: Coefficients, Hausman-Taylor Regression

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

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

productivities. The first row of Tables 2.6, and first two columns of table 2.7 show correlations and Spearman rank correlations between these two sets of productivities, for the whole sample and sector by sector. For most sectors, correlations are above 0.90 with an overall correlation of 0.98. Still, we prefer the mixed calibration and estimation approach of the baseline model because it does not require any assumptions on the correlations between the independent variables and the country-sector fixed effect and because not all of the coefficients in this specification have the correct magnitudes.

Table 2.6: Robustness of TFP Estimates

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

Tables 2.6 and 2.7 also show the correlations and rank correlations between our baseline productivity estimates and estimation considering number of firms instead of production data, zeros in bilateral trade, heterogeneous firms and the Eaton-Kortum model. The second specification considered ignores the issues of sample selection and heterogeneous firms to check how much results are affected by using the number of firms instead of aggregate production in our productivity estimations (columns labeled "number of firms"). We can see that the results are quite similar except for the sectors of Pottery and Scientific Equipment. Note that this specification, while using the number of firms instead of production, is also useful to observe the similarities between baseline estimations and the results considering pricing to the market and endogenous markup. In the next column, we take care of the issue of zero trade flows by estimating a standard Heckman-selection model (columns labeled "Heckman"). The inverse Mill's ratio[24] enters positively and significantly in all sectors, so that there is indeed sample selection towards countries with low unobserved trade barriers. However, results for productivities

[24]Results not reported

Table 2.7: Robustness of TFP Estimates - Sectoral Results

		Hausman-Taylor		Number of Firms		Heckman		Heterogeneous Firms		Eaton and Kortum	
isic	Sector Name	Correl	Spearman	Correl	Spearman	Correl	Spearman	Correl	Spearman	Correl	Spearman
311	Food	0.99	0.99	0.93	0.94	0.94	0.95	0.68	0.78	0.92	0.92
313	Beverages	0.97	0.96	0.91	0.95	0.91	0.94	0.81	0.85	0.91	0.89
321	Textiles	0.94	0.95	0.91	0.93	0.93	0.92	0.63	0.83	0.93	0.96
322	Apparel	0.99	0.99	0.70	0.78	0.71	0.72	0.61	0.68	0.85	0.85
323	Leather	0.98	0.99	0.71	0.83	0.79	0.81	0.78	0.82	0.82	0.86
324	Footwear	0.96	0.97	0.89	0.92	0.90	0.89	0.58	0.78	0.85	0.90
331	Wood	0.85	0.88	0.95	0.96	0.97	0.96	0.61	0.75	0.96	0.96
332	Furniture	0.98	0.97	0.52	0.76	0.68	0.73	0.73	0.72	0.72	0.64
341	Paper	0.90	0.92	0.94	0.97	0.92	0.97	0.70	0.78	0.97	0.96
342	Printing	0.97	0.97	0.75	0.90	0.88	0.86	0.80	0.83	0.92	0.91
351	Chemicals	0.97	0.97	0.93	0.94	0.93	0.92	0.57	0.66	0.93	0.95
352	Other Chemic	0.94	0.94	0.95	0.97	0.94	0.97	0.70	0.79	0.95	0.96
355	Rubber	0.90	0.91	0.89	0.93	0.93	0.94	0.74	0.82	0.96	0.96
356	Plastic	0.98	0.98	0.84	0.94	0.86	0.94	0.83	0.95	0.85	0.8
361	Pottery	0.97	0.98	0.36	0.63	0.19	0.54	0.25	0.54	0.79	0.72
362	Glass	0.96	0.97	0.83	0.88	0.82	0.85	0.68	0.76	0.96	0.95
369	Other Non-Metal	0.91	0.94	0.96	0.95	0.95	0.95	0.74	0.83	0.98	0.98
371	Iron and Steel	0.83	0.89	0.97	0.98	0.97	0.98	0.65	0.78	0.96	0.97
372	Non-Ferrous	0.85	0.88	0.97	0.97	0.98	0.98	0.67	0.74	0.95	0.94
381	Fabricated Metal	0.95	0.96	0.85	0.89	0.85	0.86	0.76	0.81	0.96	0.95
382	Machinery	0.93	0.95	0.88	0.93	0.85	0.92	0.73	0.84	0.96	0.95
383	Electrical Machinery	0.94	0.96	0.81	0.91	0.80	0.90	0.76	0.84	0.96	0.94
384	Transport	0.86	0.91	0.85	0.91	0.84	0.90	0.56	0.70	0.92	0.93
385	Scientific	0.96	0.97	0.35	0.78	0.39	0.79	0.40	0.80	0.86	0.81

change very little. Also, we simultaneously control for sample selection and the extensive margin of trade (via a 3rd order polynomial approximation of $E[log(V_{ijk})|T_{ijk} = 1]$, see eq. 1.43) - columns labeled “heterogeneous firms”. Even though these terms are all significant[25], correlations and rank correlations for our productivities remain around 0.8, so that our baseline specification seems to be robust.

Regarding the Eaton-Kortum model, when trying to estimate equation 1.47 with a two stage procedure, many of the coefficients of relative factor prices have the wrong sign, so this specification seems to be performing poorly. Alternatively, we can apply the hybrid calibration and estimation exercise by first constructing raw productivities and then regressing these on bilateral variables. In order to do so, we require estimates of β_k. Chor (2008) reports an aggregate value of β of around 12.41^{-1}, while Eaton and Kortum (2002) estimate β to lie between 2.44^{-1} and 12.86^{-1}. While the relative order of countries is meaningful for any β, the absolute size of productivity differences is very sensitive to the choice of β. Choosing a β of 12.41^{-1} (Chor's estimate) gives productivity estimates that are very similar to the ones obtained with our baseline model, as can be seen in last row of Table 2.6 and two last columns of Table 2.7. When setting β equal to 2.44^{-1}, absolute productivity differences explode.

Comparing Estimates with Solow Residuals

To assess the validity of our method for computing sectoral TFPs we compare our productivity estimates with TFPs constructed from the OECD STAN database for the few countries and sectors where this is feasible. We assume sectoral production functions to be Cobb-Douglas with sectoral factor income shares equal to the ones of the US. For reasons of data availability, we are limited to 11 countries,[26] two factors -capital and efficient labor-, and eight sectors[27].

[25] Results not reported

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

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

We compute the Cobb-Douglas value-added TFP index as

$$\frac{A_{jk}}{A_{USk}}\frac{p_{jk}}{p_{USk}} = \left(\frac{VA_{jk}}{VA_{USk}}\right)\left(\frac{K_{USk}}{K_{jk}}\right)^{\alpha_k}\left(\frac{H_{USk}}{H_{jk}}\right)^{1-\alpha_k} \tag{2.12}$$

Note that we do not have information on sectoral price indices, so that our TFP measures are contaminated by relative prices, which may potentially severely bias these productivity indices.[28] To make our baseline productivities comparable with the ones computed from STAN, we aggregate trade data to fit the STAN definitions and construct wages for workers with no education.

Table 2.8 we present correlations and Spearman rank correlations between TFPs computed with our baseline specification and from the STAN database. The overall correlation between the two measures is 0.34 and the rank correlation is 0.3. These aggregate numbers hide a large variation in fit by sector. Rank correlation are quite high for sectors 37 (Metals) and 31 (Food) but very low for other sectors.[29] Interestingly, the sectors with poor fit are those with high transport costs for which relative prices tend to vary much more across countries. Overall, the correlations are not overwhelming, but there clearly is a positive relation between the results of the two methods. One has to take into account that we have not only used a different approaches but also completely different datasets to compute the two sets of TFPs and that variation in relative prices may be severely distorting their comparability. In the end, the relative success of this robustness check together with the high correlation of our aggregate TFPs with the more reliable aggregate measures obtained using Hall and Jones' method makes us confident that we are indeed capturing productivity differences with our TFP measures constructed from trade data.

capital formation.

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

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

Table 2.8: Comparison with Solow Residuals

Isic	Name	Correl	Spearman
31	Food	0.55	0.49
32	Textiles	0.33	0.24
33	Wood	0.4	0.12
34	Printing	0.44	0.38
35	Chemicals	0.13	0.09
36	Pottery and Glass	0.15	0.19
37	Metals	0.78	0.73
38	Machinery	0.43	0.26

2.6 Productivity Differences and Theories of Development

In this section, we apply the estimates of sectoral productivity to test a number of development theories that have implications for sectoral productivity differences across countries. In our opinion, the following examples show particularly well the advantages of the sectoral productivity estimates.

a Research and Technology Spillovers

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) review a class of models where the world growth rate is driven by technological progress through research and development at the frontier. Cross country knowledge spill-overs guarantee a stable world income distribution even in the presence of persistent differences in R&D investment rates across countries. There is an advantage of backwardness in the sense that countries that are further away from the 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, Their model has several predictions that can be assessed using our sector productivities. First, the effect of a higher R&D investment rate on the steady state TFP level relative to frontier is larger in those sectors where the frontier grows faster. Second, since there is an advantage of backwardness, TFP growth will be higher the further away a sector is from the frontier - a convergence effect. Third, the impact of a higher R&D investment rate on the TFP growth rate relative to frontier is larger in those sectors where the frontier grows faster. 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, whereas Griffith, Redding and Reenen (2004) use sectoral TFP growth rates in manufacturing in 12 OECD countries for the period 1974-1990 and find support for the hypothesis that R&D investment facilitates technology adoption.

To examine the effect of R&D investment on technology adoption, we perform the following exercises: to check the first prediction, we regress the level of log TFP relative to the US in the mid-90's[30] on the interaction of countries' R&D investment rates, R_j/Y_j, and the sectoral R&D investment rate in the US, R_{USk}/Y_{USk}, which we take as a proxy for the growth rate of the sectoral technology frontier, controlling for sector- and country-specific effects.

$$\log\left(\frac{A_{jk}}{A_{USk}}\right) = \beta_1 X_{jk} + D_k + D_j + \epsilon_{jk} \qquad (2.13)$$

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

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

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

$$\Delta \log\left(\frac{A_{jk}}{A_{USk}}\right) = \beta_1 X_{jk} + \beta_2 \log\left(\frac{A_{jk0}}{A_{USk0}}\right) + D_k + D_j + \epsilon_{jk} \qquad (2.14)$$

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

The first two columns of table 2.9 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 strongly negatively in the growth rate specification.

b Financial Development

A second application relates our sectoral productivities to financial development. In a seminal article Rajan and Zingales (1998) show that industries which are more dependent on external finance grow faster in financially developed countries, thereby providing evidence for a causal relationship of finance on growth. The main advantage of our sectoral productivity estimates is that we can address the specific channel through which financial development affects growth. The empirical finance-growth literature has difficulties to assess whether financial development leads to growth by easing financial constraints and increasing the amount of investment firms are able to undertake or by channeling investment towards more efficient uses.[31] This is because reliable sectoral investment series are not available for most countries. We provide evidence for the second channel by showing that financial development leads to significantly higher relative productivity levels as well as growth rates in sectors that depend more on external finance. 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 from internal cash flow and is taken 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). First, we regress (log) sectoral productivity in the mid-90's on the $EXTFIN_k * PRIV_j$ interaction using specification (2.13) and controlling for sector and country fixed effects. Column three of table 2.9 shows that financial development has a significantly (at the one percent level) positive effect on relative productivities in sectors that depend more on outside finance. Next, in fourth column, we show the results of regressing the growth rate of sectoral TFP on the same interaction using specification (2.14), controlling for sector and country fixed effects. Again, we find a significant (at the one percent level) positive coefficient of the financial interaction variable, which corroborates the idea that financial development affects the efficiency of investment.

Note that our results on the significant positive impact of financial development on TFP in financially dependent sectors is different from the insignificant effect of the same variable other studies have found on sectoral value-added per worker. (see, for example Barone and Cingano (2008)). One conjecture why this is the case is that better financial development causes faster employment growth than growth in industry capital stocks in financially dependent sectors, so that industry capital labor ratios decrease

[31]An exception is Jayaratne and Strahan (1996) who exploit several bank liberalization episodes in different US states to show that bank branch deregulation has increased the efficiency but not the amount of bank credit in the US.

in those countries and sectors. In line with this interpretation, Rajan and Zingales (1998) provide some evidence that the effect of better external finance works through differentials in the growth rate of the number of firms rather than in value-added per firm. Hence, if higher financial development disproportionately benefits new, small firms, which operate at a lower capital intensity than large, established ones, industry capital labor ratios might well be lower in financially dependent sectors in countries with better financial systems. This mechanism would explain why financial development has no significant effect on value-added per worker but a positive impact on TFP. Indeed, Beck, Demirguc-Kunt, Laeven and Levine (2008) find that financial development has a differential impact on the growth rate of small firms. Industries that for exogenous technological reasons have smaller firms grow faster in countries with higher financial development. Guiso, Sapienza and Zingales (2004) provide similar evidence for Italy.

c Human Capital and Technology Adoption

A further application relates with the class of models emphasizes the role of human capital for the adoption of new technologies (e.g. Nelson and Phelps (1966), Caselli and Coleman (2006)). In a classical paper Nelson and Phelps (1966) develop a one sector economy where higher levels of human capital help to adopt new technologies from a world technology frontier that grows at an exogenous rate. The main predictions of their model are twofold. First, that countries with higher levels of human capital have higher productivity levels relative to the world technology frontier because new technologies are adopted faster. Second, countries with higher human capital levels experience faster aggregate TFP growth relative to the technology frontier.

Country level growth regressions that try to assess the effect of human capital levels on output or TFP growth provide only weak support for these predictions.[32] This may be

[32]Romer (1990), Barro (1991), and Benhabib and Spiegel (2005) find a significant effect of schooling levels on output growth, while Cohen and Soto (2001) find no link.

due to the usual problems faced by this type of regressions, like the limited number of observations and multi-collinearity (Durlauf, Johnson and Temple (2005)), as well as problems more specific to human capital, such as an attenuation bias due to mismeasured schooling data (Cohen and Soto (2001)), or missing information on differences in schooling quality (Hanushek and Kimko (2000)). Our productivity estimates allow us to test a sectoral version of the Nelson-Phelps model, which helps to overcome some of the above mentioned problems.

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 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 of 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 and find support for the hypothesis that countries with higher initial levels of human capital grow faster in human capital-intensive sectors.

Compared to Ciccone and Papaioannou (2009) our information on sectoral TFP relative to the US gives us several advantages. First, we can test if the *level* of sectoral TFP is significantly higher in skill-intensive sectors if countries have larger endowments of human capital. Second, we can test if sectoral growth rates of *productivity* are indeed higher in skill-intensive sectors if countries have larger endowments of human capital, while Ciccone and Papaioannou (2009) cannot control for accumulation of other factor inputs at the sectoral level, such as physical or human capital, that may affect sectoral value-added or employment growth.

To evaluate the predictions of the multi-sector Nelson-Phelps model, we regress both the level and the growth rate of sectoral TFP relative to the US, whose productivity we take as the one of the frontier, on the human capital interaction, $\alpha_{sk} * H_j$. For the regression in levels we consider the mid-nineties, while for the second specification we take the growth rate of sectoral TFP relative to the US between the mid-80's and the mid 90's. The econometric specification is again analogous to (2.13) and (2.14). Once more, we control for sector and country fixed effects in all regressions.

Looking at columns 5 and 6 of Table 2.9 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.[33] Finally, in last two columns of Table 2.9 we include all the previous dependent variables simultaneously in the level and the growth rate specification. In the both specifications all dependent variables have the expected sign and remain significant, except for the R&D interaction, which becomes insignificant.

d Adequate Technology

In order to explain cross country differences in income per worker, Acemoglu and Zilibotti (2001) develop a model of adequate technology which represents an alternative theory on human capital intensity and sectoral productivity differences related to technology adoption. Their hypothesis is that there is a mismatch between the skill requirements of frontier technologies that are developed in the industrialized world and the endowments of human capital in the developing countries. This in turn leads to sectoral

[33] While the results for TFP levels should be interpreted with some caution, since they may reflect a mismeasurement of the Heckscher-Ohlin effect in the construction of our productivity estimates, we are more confident about the validity of our results on TFP growth rates, where no such critique applies. Nevertheless, to be sure we are not measuring some kind of Rybczynski effects, 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 in levels.

Table 2.9: Productivity and Theories of Development

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

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

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

(and hence aggregate) productivity differences between rich and poor countries. Their model predicts that gaps in sectoral TFP between rich and poor countries are largest in sectors with intermediate skill intensity. The intuition is that while in sectors with extreme input requirements both rich and poor countries use the same inputs (either skilled or unskilled labor) in sectors with intermediate skill intensities production is performed by skilled workers in the rich countries and by unskilled workers in the poor countries because of differences in relative factor prices. Since technology for these sectors complement skilled labor, there is a technology-skill mismatch in these sectors. They are not able to test this prediction of their model since they lack a measure of sectoral TFP that would be not contaminated by differences in sectoral prices across countries.[34]

In a first attempt to scrutinize the prediction that productivity differentials between rich and poor countries are largest in sectors with intermediate skill intensity, we divide

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

our sample in two parts: developing countries (with a per capita GDP below 8000 International Dollars in 1995[35]) and industrialized countries. Figure 2.8 plots the average sector productivity for rich relative to poor countries against sectoral skill intensity, α_{ks}. We see that there is a hump shaped pattern and that productivity gaps tend to be largest in sectors with intermediate skill intensity, which provides some support for their model.

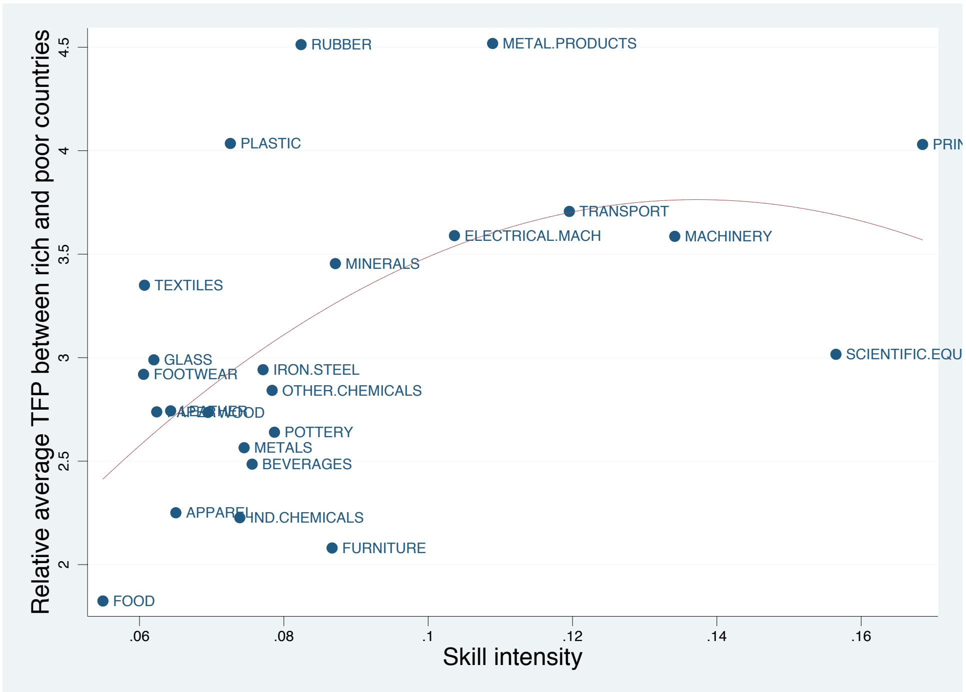

Figure 2.8: Skill Intensity and Relative TFP

To address the issue more formally, we regress $\log(\frac{A_{jk}}{A_{USk}})$ on skill intensity and the square of the same variable, to allow for a nonlinear relationship. We control for capital intensity and country specific effects. We run this regression separately for developing and developed countries. For the sample of developing countries there is indeed a very significant nonlinear relationship that gives us a hump shaped relation between the relative sectoral TFP of developing countries and the sectoral skill intensity. Moving from the 10th to the 50th percentile of skill intensity reduces sectoral productivity of

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

developing countries relative to the US by roughly 19%. Repeating the same regression for the sample of developed countries, we find no systematic relationship between productivity differences and skill intensity at all.

As a next step we use the whole sample and include - in addition to skill and physical capital intensity and theirs squares-, two interaction term between income per worker and skill and physical capital intensity. We observe that there is again the hump shaped relationship between productivity and skill intensity for poor countries but it disappears as income per worker increases.[36]

Table 2.10: Sectoral Productivity and Adequate Technology

	TFP	**TFP**	**TFP**
Human capital Intensity	-16.82	-0.42	-10.55
	(3.52)***	(2.52)	(2.14)***
Physical capital Intensity	-10.11	1.69	-3.99
	(3.65)***	(2.68)	(2.20)***
Human capital Intensity^2	66.93	-1.49	33.00
	(16.99)***	(11.92)	(9.96)***
Physical capital Intensity^2	7.56	-1.00	3.26
	(2.57)***	(1.91)	(1.54)***
Human capital*Income			4.82
			(1.18)***
Phys. capital*Income			-0.57
			(0.4)
Sample	Developing	Developed	All
Country Fixed Effects	Yes	Yes	Yes
Observations	735	736	1471

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

Even though productivity differences remain larger in very skill-intensive sectors than in very unskill-intensive ones, there is clearly a non-linear relationship between skill intensity and productivity gaps. This supports a theory on adequate technology that has been untestable up to now.

[36]While the coefficients imply a 17% difference in productivity relative to the US between a sector at the 10th and one at the 50th percentile of skill intensity for a for a country at the 5th percentile of income per worker, they imply no difference in productivity relative to the US between these sectors for a country at the 90th percentile of income per worker.

e Trade and Productivity

As a last application, we explore whether our productivity estimates can be used to study the effect of trade on productivity. Compared to previous work on this topic such as Frankel and Romer (2003) and Alcala and Ciccone (2004)[37], our estimates of TFP at the sector level make it easier to control for country-specific factors such as institutions, the inclusion of which tends to eliminate the effect of trade (policy) in regressions of income per worker on measures of trade and/or trade policy at the country level (Rodrik, Subramanian and Trebbi (2004)). Alcala and Ciccone (2004) argue that trade may raise aggregate productivity through specialization of countries in those sectors where they have higher productivities.[38] We briefly investigate, whether trade indeed tends to increase aggregate productivity by helping countries to concentrate their production in sectors in which they have relatively high productivities.[39]

We consider the following specification:

$$s_{VA,jk} = \beta_1 \frac{A_{jk}}{A_{USk}} + D_k + D_j + \epsilon_{jk} \tag{2.15}$$

where $s_{VA,jk}$ is the value-added share of sector k in country j's total manufacturing

[37] Earlier work on this topic is critically assessed in Rodrik and Rodriguez (2001).

[38] In a Ricardian model like ours trade need not lead to an increase in aggregate productivity, defined as a weighted average (e.g. by value-added) of sectoral productivities, because countries specialize in sectors where they have relatively high productivities compared to other countries. However, these might be sectors that, for technological reasons, have relatively low output per unit of input.

[39] This raises the further question which benchmark to use for productivity comparisons. In our theoretical model sectoral production shares are positively related to competitiveness in world markets. Countries have largest production shares in those sectors where their production prices are relatively low compared to the prices of competitors from all other countries. One determinant of relative prices is relative productivity. The identity of the fiercest competitors will depend in general on the specific sector, and so will the relevant benchmark. Since the US has one of the highest TFPs in all sectors, we believe that it provides a meaningful benchmark.

value-added. We estimate this regression separately for two subsamples of countries: those that are open according to the index constructed by Wacziarg and Welch (2003), who extend and update the popular index by Sachs and Warner (1995). Sectoral TFP relative to the US enters strongly significantly in the regression only in the subsample of countries that are open to trade. This provides some evidence for the hypothesis that countries do specialize in sectors where they are relatively more productive only if they are open to trade.

Table 2.11: Productivity and Openness

					Non Weighted Regression					
Variable	VA share Whole Sample	VA share No Open Before 90	VA share Open Before 90	VA share No Open Before 80	VA share Open Before 80	VA share	VA share	VA share	VA share	VA share
Ln(TFP)	0.005	-0.006	0.009	-0.005	0.013	0.006	0.005	0.006	0.007	0.006
relative to the US	(0.003)	(0.004)	(0.004)*	(0.003)	(0.006)*	(0.004)	(0.003)	(0.003)*	(0.003)**	(0.003)*
Ln(TFP)						-0.003				
*Open before 90						(0.005)				
Ln(TFP)							-0.002			
*Open before 80							(0.006)			
Import								-0.000		
over VA								(0.000)		
Ln(TFP)								-0.000		
*import over VA								(0.000)		
Export									-0.001	
over VA									(0.000)**	
Ln(TFP)									0.001	
*export over VA									(0.000)	
Total trade										-0.000
over VA										(0.000)
Ln(TFP)										-0.000
*trade over VA										(0.000)
Observations	1419	656	763	844	575	1419	1419	1418	1418	1418
Countries	63	30	33	38	25	63	63	63	63	63
					Weighted Regression					
Variable	VA share Whole Sample	VA share No Open Before 90	VA share Open Before 90	VA share No Open Before 80	VA share Open Before 80	VA share	VA share	VA share	VA share	VA share
Ln(TFP)	-0.002	-0.010	0.002	-0.008	0.005	-0.003	-0.003	-0.002	-0.001	-0.001
relative to the US	(0.002)	(0.003)***	(0.004)	(0.002)***	(0.007)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Ln(TFP)						0.002				
*Open before 90						(0.005)				
Ln(TFP)							0.003			
*Open before 80							(0.008)			
Import over								-0.000		
Over VA								(0.000)		
Ln(TFP)								0.000		
*import over VA								(0.000)		
Export									-0.001	
over VA									(0.000)***	
Ln(TFP)									0.000	
*export over VA									(0.000)	
Total trade										-0.000
over VA										(0.000)
Ln(TFP)										0.000
*trade over VA										(0.000)
Observations	1395	632	763	820	575	1395	1395	1395	1395	1395
Countries	62	29	33	37	25	62	62	62	62	62

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

2.7 Conclusion

In this chapter we have estimated sectoral manufacturing total factor productivities (TFP) for more than sixty countries at all stages of development by using information contained in bilateral sectoral trade data. To this end, we have derived structural estimation equations from a hybrid Ricardo-Heckscher-Ohlin model with transport costs constructed in the last chapter. The main advantage of our methodology is that it allows us to overcome severe data limitations that render the application of traditional methods for TFP computations that rely on information on sectoral inputs and outputs in physical units unfeasible for virtually all developing countries. To compute sectoral productivities, we only need data on bilateral trade, aggregate factor prices, and sectoral production values.

Our results show that productivity differences in manufacturing sectors are large and systematically related to income per capita. In addition, differences in productivity between rich and poor countries are more pronounced in skilled labor and R&D intensive sectors. We also find that some poor countries have higher productivities than the US in a small set of sectors. Moreover, our methodology allows us to compute bilateral rankings of comparative advantage due to productivity for any pair of countries.

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

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

3 CHAPTER THREE

3.1 Introduction

Inspired by the idea that trade liberalization is a policy reform essential to promoting growth, a large number of developing countries undertook important trade reforms during the last quarter of the 20th century. For example, Wacziarg and Welch (2008) count almost 70 countries that liberalized their economies in the late '80s and early '90s. As a result, in the year 2000 almost 75% of countries could be considered open, compared with only 25% in 1980. This spate of massive trade liberalization represents an excellent field for analyzing openness' manifold effects on national economies.

In this paper, I will focus specifically on one such effect: trade liberalization's impact on national productive structure. Classical trade theory suggests that gains from trade are obtained by moving economic resources toward those sectors in which a country enjoys comparative advantage. The resultant expectation is that moving from restricted to freer trade will entail observable changes in countries' respective economic structures. Moreover, in the Heckscher-Ohlin model, these changes are related to relative factor endowments.

Exploiting a relatively rich sectoral data for a large set of countries, this paper attempts to answer the following questions: a) do we in fact see trade liberalization bring about major structural changes in national productive structure? and b) when observable, do those changes conform to the patterns that classical trade theory would predict?

Many specialized studies have explored the relationship between trade liberalization and aggregate economic growth.[1] While a number of these inquiries do conclude that

[1]Earlier contributions include Dollar (1992), Sachs and Warner (1995), and Edwards (1998) . Later Rodrik and Rodriguez (2001) survey skeptically this literature. Some papers that try to address the problems stated in the latter are Greenaway, Morgan and Whright (2002), Giavazzi and Tabellini

there is a positive correlation between trade policy openness and growth, various other studies find no such correlation, and some even judge the association negative. Various factors explain why this literature is so inconclusive: difficulties in measuring trade policy adequately; the simultaneous action of several different policies, and reforms, susceptible of impacting growth; the frequent impossibility of analyzing all the relevant controls; absence of a testable counterfactual; endogeneity of the liberalization decision; etc.

Because these facts make it almost impossible to arrive at a final conclusion in studies of the sort, I have chosen to focus instead on whether or not liberalization episodes do in fact generate significant changes in the productive structure of the economy, independently of the possible correlation between applied liberalism and growth. To be sure, we cannot be certain those structural changes are exclusively due to trade liberalization (because of the simultaneousness of reforms as described in the last paragraph). As long as those changes prove consistent with the predictions of classical trade theory, nonetheless, at least we cannot fail to recognize that trade liberalization is a meaningful influence on industrial reconfiguration.

I will briefly discuss what this paper is not. It is not a direct test of comparative advantage. In order to test that, I would be obliged to deal somehow with data on typically unobservable autarky prices, in the vein of Bernhofen and Brown (2004). This is an approach that I have not found practicable for the countries and the period in the sample. Also, this paper is not a direct test of the effect of endowments on the localization of production, something that has already been extensively studied.[2]

Rather, this paper is an attempt to advance in the analysis of the changes in economic structure induced by a policy of trade liberalization. In that regard, there are certain

(2005) Wacziarg and Welch (2008) and Estevadeordal and taylor (2008).

[2]See Harrigan (2002) for a complete survey. A major criticisms of this methodology is found in Bernstein and Weinstein (2002).

papers that can be considered relevant for the analysis developed here. For example, Wacziarg and Seddon (2004) examine the impact of trade liberalization episodes on the cross-sector movement of labor. Unlike their paper, nevertheless, mine focuses on productive specialization and not resource movements, and I also consider changes over longer periods of time. So too, Estevadeordal and Volpe (2008) have a paper similar in spirit, but their focus is on the impact of relative prices on sectoral production specialization patterns, exclusively in Latin America.

In order to answer the proposed questions, I will advance in two directions. First, I will use a transition-matrices analysis to model the dynamics of industrial specialization. In this way, I can capture the principal features of the evolution of the entire distribution of specialization indexes, addressing issues such as persistence versus mobility of industrial structure and changes in the overall degree of specialization over time.

Second, following a very simple neoclassical model linking production to endowments, I will construct growth regressions where changes in the degree of specialization are related to the level of, and changes in, relative endowments. Then I will use those results to study the relationship between endowments, specialization, trade cost and industry characteristics in a multi-country multi-good framework. Here, my methodology is inspired by Markusen and Venables (2007).

Overall, evidence suggests that countries which liberalized their economies in the last quarter of the past century experienced a substantial degree of mobility, at least if we consider large transitional periods. In those countries, mobility is higher than in countries already open by that time, and those which continued to be closed. Finally, it is patent that changes in the degree of specialization depend in part on degree of capital intensity. In the sample of liberalized economies, changes from a lower level of specialization toward a higher one are more frequent than the opposite, save that the reverse is true in capital-intensive sectors.

Moreover, changes in specialization are related to countries' capital abundance only in non capital-intensive sectors. The data show no relationship between specialization and endowments in capital-intensive sectors, as when trade costs decrease the countries concerned tend not to specialize in those particular sectors. In addition, the explanatory power of endowments on specialization is higher in non capital-intensive sectors.

The next section will proceed to descriptive analysis of the transition matrices used. Section three will present the results of the econometric specification process by which I relate specialization to endowments. The final section concludes.

3.2 Transitional Dynamics in the Liberalized Economies

In this section, I will use a statistical model of distribution dynamics to study production specialization patterns. This methodology has been developed by Quah (1993) and Quah (1996) in the context of cross-country growth literature, and by Proudman and Redding (2000) and Redding (2002), among others, in the context of comparative advantages and specialization. Using an industry's GDP share as a measure of a country's degree of specialization, I construct transition-probability matrices that provide an accurate picture of specialization's dynamics. The main advantage of this approach is that, instead of using a particular moment of a distribution, transition matrices allow us to analyze the evolution of the entire distribution of industrial sectors' shares. Thus, it becomes possible to address issues such as persistence versus mobility in productive structure, changes in the overall degree of specialization across countries and time, and whether or not there is an increase in the degree of long-run specialization.

The choice of the measure of productive specialization $s_{ict} = \frac{Value\,Added_{ict}}{GDP_{ct}}$ (the share of industry i in country c GDP at time t) is motivated by Harrigan (1997).[3] Using the

[3] Other papers that use the same framework are Harrigan and Zakrajsek (2000), Redding (2002), and Estevadeordal and Volpe (2008).

dual representation of aggregate technology, and assuming that the revenue function can be adequately approximated by a translog functional form, he shows how industry share is a theory-consistent measure of sectoral specialization and relates to relative prices, technology and factor endowments. In the next section I will come back to this model in order to test the effect of factor endowments on specialization after trade liberalization.

As we are interested in specialization within manufacturing, and given that a decline in the manufacturing sector's average share of the whole economy could drive the results, I will normalize all the data by dividing, at each point in time, the share of a sector in a country's GDP by total manufacturing's share in GDP:

$\tilde{s_{ict}} = s_{ict} \backslash \frac{\sum_i VA_{ict}}{GDP_{ict}} = \frac{VA_{ict}}{\sum_i VA_{ict}}$

Thus the normalized measure of specialization $\tilde{s_{ict}}$ is the share of industry i in the total manufacturing sector of country c at time t.

The main sample is the set of countries that, according to Wacziarg and Welch (2008), opened their economies in the '80s and '90s. Using a comprehensive survey of country case studies of liberalization, they determine the year which uninterrupted openness began.[4] At times, I will compare the results in that sample with the sample of countries that opened their economies in prior decades, and also the sample of countries that at the end of last century were still closed. Altogether, I will work with twenty-four separate industrial sectors.[5]

[4]This is the list of countries that liberalized since the end of the '70s and having data of industry value added for the beginning of the '80s and end of the '90s: Argentina, Bangladesh, Bolivia, Brazil, Bulgaria, Cameroon, Chile, Colombia, Costa Rica, Cote d'Ivoire, Czech Republic, Dominican Republic, Ecuador, Egypt, Arab Rep., El Salvador, Ethiopia, Ghana, Guatemala, Honduras, Hungary, Kenya, Latvia, Macedonia, FYR, Madagascar, Mexico, Morocco, Nepal, Nicaragua, Panama, Peru, Philippines, Poland, Romania, Slovak Republic, Slovenia, South Africa, Sri Lanka, Tanzania, Trinidad and Tobago, Tunisia, Turkey, Uganda, Uruguay, and Venezuela.

[5]ISIC rev.2. I exclude, tobacco, petroleum refineries, miscellaneous petroleum and coal products and other manufactured products not classified elsewhere.

a Construction of Transition Matrices

Following Redding (2002), let s_{ict} denote the extent of specialization of country c in industry i at time t. We can characterize the pattern of specialization at any point in time by the cumulative distribution function of s_{ict} across countries and industries $F_t(s)$. We can define a probability density function λ_t such that: $\lambda_t((-\infty, s]) = F_t(s)\, \forall s \in \Re$. The dynamics of a country's pattern of specialization correspond to the evolution of the entire cross section distribution of s over time.

This evolution can be modelled using a stochastic difference equation in the form:

$$\lambda_t = P(\lambda_{t-1}, u_t), integer\, t \tag{3.1}$$

where $\{u_t : integer\, t\}$ is a sequence of disturbances to the entire distribution and P maps disturbances and probability measures into probability measures. Absorbing the disturbances into the definition of the operator and assuming that this stochastic difference equation is first-order, operator P is time-invariant, and the space of possible values of s is divided into a number of N discrete cells. Then P becomes a matrix of transition probabilities.

$$\lambda_{t+1} = P^T(\lambda_t) \tag{3.2}$$

$$\begin{bmatrix} \lambda_{t+1}^1 \\ \vdots \\ \lambda_{t+1}^N \end{bmatrix} = \begin{bmatrix} p^{11} & \ldots.. & p^{1N} \\ & \ddots & \\ p^{N1} & \ldots.. & p^{NN} \end{bmatrix}^T \begin{bmatrix} \lambda_t^1 \\ \vdots \\ \lambda_t^N \end{bmatrix} \qquad p^{kl} \geq 0, \sum_l p^{kl} = 1$$

Now λ_t is a $N \times 1$ vector of probabilities that an industry occupies a given grid cell at time t and p^{kl} denotes the probability that an industry that is in grid k at time t moves to grid l. Each element of this vector, λ_t^i defines a particular level of specialization and a movement from one state to another implies a change in the degree of specialization. Thus, higher values along the diagonal of the transition matrix denote persistence, while larger off-diagonal terms indicate mobility. There exist several ways of dividing the space of possible values for s into a number of intervals. One possibility would be to make the space discrete in terms of uniformly defined states (i.e., country-industry-year observations would be divided roughly equally between the cells, generally quintiles or deciles).[6]

Note that I have implicitly assumed common distribution function of s and common stochastic process across countries (i.e., $F_{ct}(s) = F_t(s)$, $\lambda_{ct} = \lambda_t$ and $P_c = P$ $\forall c$. Thus, we can pool observations across countries and industries, estimating a single transition probability matrix. We can also extend the analysis to allow for cross country heterogeneity in the stochastic process, such that different sets of countries (e.g., open vs. closed countries) have different transition matrices.

In summary, what we want to know is: given that sector i in country c is in the $k-th$ quintile/decile of the pooled distribution of specialization indexes in year t, what is the probability that this sector will be in the $l-th$ quintile/decile of the distribution in year $t+n$?

The matrix of transition probabilities could be estimated by Maximum Likelihood. (Anderson and Goodman (1957)) Denoting n_{kl} the empirically observed number of transition from state k to l, then:

$$\underset{p^{kl}}{Max} \ln L = \sum_k \sum_l n_{kl} \ln p^{kl}$$

$$s.t \quad p^{kl} \geq 0, \sum_l p^{kl} = 1$$

The solution is: $\overset{\wedge}{p^{kl}} = \frac{\sum_t n_{kl,t}}{\sum_t \sum_l n_{kl,t}}$: the number of changes from k to l in all periods divided by the total number of observations that at any point of time begin in k. The standard

[6] Alternatively, one could work in terms of proportionally defined states. Additionally, with a large number of observations, it is possible to analyze the evolution of continuous probability measures and estimate the stochastic kernel associated with P^*

deviation can be estimated as: $\hat{\sigma}_{\hat{p}^{kl}} = \sqrt{\frac{\hat{p}^{kl}(1-\hat{p}^{kl})}{n_k}}$

Once the transition matrix is estimated, we can obtain the ergodic (stationary) distribution of λ. This represents the long-run distribution towards which pattern of specialization evolve, and it is presumed to remain unaltered in time. When it is compared with the initial state, the ergodic distribution provides information on the evolution of the external shape of our measures of specialization distribution. Furthermore, the ergodic distribution gives us insights into convergence or polarization in specialization across different sectors.

The stationary distribution must satisfy: $\lambda = P^T\lambda \Rightarrow (I - P^T)\lambda = 0$. Here λ is an eigenvector associated with a unit eigenvalue of P^T If there is only one unit eigenvalue, then the stationary distribution is unique and the limit stationary distribution does not depend on the initial distribution. We say in this case that the process is asymptotically stationary. The fact that P is a stochastic matrix (i.e., $p^{ij} \geq 0, \sum_j p^{ij} = 1$) guarantees that it has at least one unit eigenvalue, and that there is some λ that satisfies $(I-P^T)\lambda$. Moreover, if P is a stochastic matrix with $(p^{ij})^n > 0 \quad \forall (i,j)$ for some value of $n \geq 1$ then it has a unique stationary distribution, and the process is asymptotically stationary (see Ljungqvist and Sargent (2000)).

The information about the degree of mobility or persistence in the pattern of specialization could be summarized by mobility indexes, defined as a continuous real function $M(\cdot)$ over the set of transition matrices, such that $0 \leq M(P) \leq 1$, where 0 implies immobility and 1 perfect mobility. Among several possibilities (See Shorrocks (1978) and Geweke, Marshall and Zarkin (1986)), we will compute the following indexes of mobility:

$M1 = \frac{K-tr[P]}{K-1}$. This index captures the relative magnitude of diagonal and off-diagonal terms (recall that the diagonal elements of P give the probability of staying in the same class). In the case of total persistence, the elements of the diagonal are equal to 1 (and then $M1 = 0$). In the perfect mobility case, all of the cells have the same value and $trace = 1$, and $M^1 = 1$. Notice that that the mean length of stay in state k is $\frac{1}{1-p^{kk}}$ so M^1 is just the inverse of the harmonic mean of these lengths, scaled by $\frac{n}{n-1}$.

$M2 = 1 - |det(P)|$. Since P is a transition probability matrix there is always one eigenvalue equal to 1 and the other eigenvalues have modulus lower than one The smaller the modulus of an eigenvalue, the faster its corresponding component converges toward an ergodic distribution. Moreover, the product of the eigenvalues is equal to the determinant of the matrix, which explains the logic of this mobility index.[7]

Finally, as the dominant (i.e., the slowest) convergence term is given by the second largest eigenvalue (ξ_2), a final index of mobility is computed as $M3 = 1 - |\xi_2|$.

Using the transition matrices, spatial homogeneity could be tested by dividing the whole sample into R mutually exclusive and exhaustive subsamples (set of countries), and testing whether transition matrices estimated for each of the subsamples are significantly different from the entire sample's estimated matrix.

In this case the null hypothesis is: $H_0)\ p^{kl}(r) = p^{kl}\ \forall r = 1...R$ and $H_A)\ \exists r : p^{kl}(r) \neq p^{kl}$. If in each row of transition matrix for the entire sample there are at least two non-zero transition probabilities, and each of the R subsamples has a positive number of observations, then the statistic:

$$Q^{(R)} = \sum_{r=1}^{R}\sum_{k=1}^{N}\sum_{l\in B_k} n_k(r)\frac{(\overset{\wedge}{p^{kl}}(r) - \overset{\wedge}{p^{kl}})^2}{\overset{\wedge}{p^{kl}}} \sim\ asy\ \chi^2\left(\sum_{k=1}^{N}(a_k - 1)(b_k - 1)\right) \tag{3.3}$$

where $\overset{\wedge}{p^{kl}}$ is the probability transition estimated for the whole sample, and $\overset{\wedge}{p^{kl}}(r)$ is the corresponding transition probability estimated for the r-th sub-sample. $B_k =$

[7] A problem of $M2$ is that it gives the completely mobile value when any two rows or columns of the matrix are identical.

$\left\{ l : \hat{p}^{kl} > 0 \right\}$; is the set of nonzero transition probabilities in the $k-th$ row of the transition matrix estimated for the entire sample (i.e., transitions for which no observations are available in the entire sample are excluded) and $b_k = \#B_k$ the number of elements in the set B_k. Similarly $a_k = \#A_k; whereA_k = \{r : n_k(r) > 0\}$ is the number of sub-samples in which observations for the $k-th$ row are available. $n_k(r)$ denotes the number of observations initially falling into the $k-th$ class within the $r-th$ sub-sample.

b Results

I estimate transition probabilities over different periods of time and dividing the space of possible values of the specialization measure into five discrete grid cells.[8] Recall that the distribution of quintiles has been constructed considering the entire sample of countries that liberalized their economies since the '80s. The Value-added data are collected from Nicita and Olarreaga (2007) for the years 1980-2004.

Table 3.1 shows estimates for 2, 10, and 20 transition periods (i.e., we estimate the changes in value-added share for a given industry between t and $t+2$, $t+10$, and $t+20$ respectively). The first row and column of numbers denote the upper endpoint of the corresponding grid cell (for example, one quintile of all the country-year-industries have a share lower than 0.8% and one quintile have a share higher than 6.4%) . Thereafter, each row reports the estimated probability of having passed from one state into another after two, ten or twenty years. For example, cell (1,1) of the matrix is the probability that a sector in the lowest quintile of the distribution remains there, while cell (1,2) represents the probability that a sector in the lowest quintile will ascend to the second quintile after the transition period.

Comparison of the three previous tables reveals an obvious but useful result: the difference in the degree of mobility when we analyze dynamics using different transition

[8] Results do not change if deciles are considered instead.

Table 3.1: Transition Matrices
Countries with Trade Liberalization in the '80s and the '90s

	0.008	0.019	0.035	0.064	>0.064
0.008	0.87	0.11	0.01	0.01	0.00
0.019	0.13	0.71	0.15	0.01	0.00
0.035	0.01	0.15	0.65	0.18	0.01
0.064	0.01	0.02	0.17	0.69	0.12
> 0.064	0.00	0.00	0.01	0.12	0.87

Transition period: 2 years

	0.008	0.019	0.035	0.064	>0.064
0.008	0.76	0.17	0.03	0.02	0.01
0.019	0.21	0.50	0.21	0.06	0.02
0.035	0.05	0.23	0.40	0.27	0.05
0.064	0.02	0.06	0.27	0.47	0.19
> 0.064	0.00	0.01	0.04	0.22	0.72

Transition period: 10 years

	0.008	0.019	0.035	0.064	>0.064
0.008	0.70	0.20	0.03	0.06	0.00
0.019	0.35	0.33	0.20	0.08	0.04
0.035	0.10	0.20	0.38	0.28	0.05
0.064	0.05	0.14	0.26	0.34	0.22
> 0.064	0.01	0.02	0.08	0.24	0.66

Transition period: 20 years

periods. Values along the main diagonal (which indicates persistence) are much higher when we consider two-year changes than when we consider ten or twenty years. The estimated probability of moving out of one quintile of the distribution varies from .13 to .35 when we consider two-year changes, and from .30 to .67 for twenty-year changes. In fact, considering 20 years' transition, it is more probable that an industry in the second quintile of the distribution will descend to the first quintile than that it will remain in the second one.

Here we have an obvious finding which (Shorrocks (1978) expresses thus:"...there will be a tendency to give an inflated mobility value to the structure defined over the longer period. In a short space of time there is little opportunity for movement, even if the structure is inherently very mobile"). This result is nonetheless useful in explaining why many studies that try to link trade liberalization to either reallocation or structural transformation of the economy find little in the way of conclusive results: most of them use differences in differences or compare situations a few years before and after an episode of liberalization, considering one-, two- or at most five-year changes.

For example, Wacziarg and Seddon (2004) employ internationally comparable panel data for a broad sample of liberalization episodes in order to examine the impact of trade liberalization episodes on movements of labor across sectors. They find a positive but relatively small-scale and statistically less than robust effect of trade liberalization on sectoral 3-digit level labor reallocation. Combining results at a 1-digit level of disaggregation and a 4-digit level for the manufacturing sector, they have concluded that episodes of trade liberalization do not appear to be followed by structural upheaval.

They compute measures of structural change (specifically the magnitude of changes in sectoral employment shares) and job reallocation (to isolate the fraction of jobs that move from sector to sector independently of overall employment gains or losses) in the pre- and post-liberalization regimes, using two variants of the measures: differences in shares or reallocation over two and five years.

However, transition-dynamics analysis shows that working only with differences in two or five years creates a bias toward finding no upheaval. Factors such as previous expectations of liberalization, persistence of labor response, and counteractive policies and barriers to factor mobility could explain the (lack of) results obtained. In the robustness check portion of the paper, they do try to control for these factors, but the lack of data makes it difficult to arrive at any valid conclusions in this respect. In that sense, exploiting the fact that we now have several years of data before and after liberalization episodes, we can consider changes over larger periods of time and compare results using different spans of time.

In order to explore further the differences that arise when consider different time intervals, Table 3.2 presents the three mobility indexes (see previous subsection) computed for various transition periods. All the three indexes increase monotonically with the length of the transition period. According to Shorrocks (1978), M2 and M3, while taking into account the characteristic roots of the transition matrix, have the advantage of somehow compensating for the length of the time interval. Therefore, the table shows how productive structures in the liberalized economies appear to be much less rigid when our analysis embraces enough time to observe changes in them.

Table 3.2: Mobility Indexes over Different Transition Periods

	M1	M2	M3
1year	0.23	0.68	0.05
2years	0.30	0.80	0.07
5years	0.42	0.92	0.12
10years	0.53	0.98	0.18
15years	0.58	0.99	0.21
20years	0.65	1.00	0.25

The foregoing analysis strongly suggests that an adequate time frame for observing significant changes in productive structure after an episode of trade liberalization is longer than those the literature usually considers. However, once having enough data to consider larger transition periods, one can ask whether or not the countries that liberalized their economies have experienced more transformations that have other economies.

Table 3.3 shows the mobility index (M1)[9] computed for various transition periods for three groups of countries: those that liberalized in the '80s and '90s, those that were already open before the last quarter of the past century; and those that remain closed today.

For any transition period, mobility is higher in the group of liberalized economies. Note that results for 1- and 2-year changes are very similar between liberalized and closed economies, probably because many of the transitions in the liberalized countries were computed while they were still closed (e.g., for a given country liberalized in 1990, all

[9]Results are equivalent when one considers M2 or M3.

Table 3.3: Mobility Index M1 over Different Set of Countries and Transition Periods

	Open90	Open60	Never
1year	0.23	0.13	0.23
2years	0.30	0.19	0.29
5years	0.42	0.29	0.36
10years	0.53	0.40	0.44
15years	0.58	0.48	0.52
20years	0.65	0.55	0.57

the data, and hence transitions, of the '80s correspond to a closed economy). Yet, when we analyze more extensive periods, the evidence shows that countries opened in this period did in fact experience deeper changes in their economic structures. On the other hand, countries that were already open seem to have shown less mobility, probably because their economic structures were already shaped before the '80s.

To further explore the differences between liberalized economies and those who were already open in the '70s, I compare transition matrices for both sets of countries and test spatial homogeneity. Table 3.4 shows the results, using 10-year transition periods.[10] Elements along the main diagonal are higher in the sample of economies already open in the '70s, indicating liberalized economies tended to have more mobility in their pattern of specialization during this period. To test whether both subsamples are statistically different from each other, we use 3.3 and obtain Q=180.77 which clearly rejects the null hypothesis of spatial homogeneity ($\chi^2_{20}(0.995) = 40.0$).

Table 3.4: 10 years Transition Matrices

	0.008	0.019	0.036	0.066	>0.066
0.008	0.81	0.14	0.03	0.02	0.01
0.019	0.20	0.57	0.17	0.05	0.01
0.035	0.04	0.21	0.49	0.22	0.03
0.066	0.01	0.04	0.24	0.52	0.20
>0.066	0.00	0.00	0.03	0.19	0.77

Sample: All Countries

[10]The results do not change when different transition periods are considered.

	0.008	0.019	0.036	0.066	>0.066
0.008	0.78	0.16	0.03	0.02	0.01
0.019	0.21	0.51	0.20	0.06	0.02
0.035	0.05	0.24	0.40	0.26	0.05
0.066	0.01	0.06	0.27	0.46	0.20
>0.066	0.00	0.01	0.05	0.22	0.72

Sample: Liberalized Countries

	0.008	0.019	0.036	066	>0.066
0.008	0.84	0.12	0.03	0.01	0.00
0.019	0.20	0.62	0.15	0.03	0.00
0.035	0.02	0.19	0.57	0.19	0.02
0.066	0.00	0.03	0.21	0.56	0.20
>0.066	0.00	0.00	0.02	0.17	0.81

Sample: Open Economies

As a last exercise, I use the ergodic distribution to study specialization in the liberalized economies. Considering the 10-year transition matrices, ergodic distribution for the whole sample is vector: $\lambda'_\infty = \begin{pmatrix} 0.22 & 0.19 & 0.19 & 0.21 & 0.20 \end{pmatrix}$. Thus in the long run, there is no trend toward specialization (for in that case, we should observe higher values in the first and last quintile). So, in these liberalized economies considered as a whole, there is no indication of polarization between industries.

However, the aggregate analysis conceals the dynamics of specialization according to sector characteristics. Therefore, I will divide the sectors into two categories according to their capital intensity: low and high. Then I compare the changes from one quintile to another for each group of industries. The results are shown in Table 3.5

Table 3.5: Quintile Change/Persistence and Capital Intensity

	Non Capital Intensive	Capital Intensive	Average
Decrease	0.181	0.235	0.209
Maintains	0.594	0.564	0.579
Increase	0.224	0.201	0.212
Total	1.00	1.00	1.00
Ratio Increase-Decrease	1.239	0.852	1.019

The table shows how the change from one quintile to another differs according the capital intensity of the sectors. For non capital-intensive ones (e.g., food, garment, wood and furniture, metal products) there is a 24% more changes from a lower quintile toward a higher than from a higher toward a lower. Yet, the opposite occurs in capital-intensive sectors (typically chemicals and machinery). For the whole sample of liberalized countries, the number of increases and decreases cancels out, generating the ergodic result I commented above.

In summary, this section has made several points. a) Mobility in liberalized economies does prove significant if the analysis covers a period long enough to allow for measuring transitions. b) Mobility is higher in economies that experienced a trade reform in the '80s and '90s than in either closed economies or already open ones. c) In particular, dynamics are statistically different between economies that were liberalized in the last quarter of the twentieth century and economies that had already been liberalized before. d) Finally, the data do show a tendency toward specialization in capital-non intensive industries.

3.3 Trade Liberalization, Endowments, and Specialization

In this section, I will describe a precise econometric relationship between specialization and factor endowments that arises from a very simple neoclassical model. Then, I will briefly present the main results of a generalized multi-countries and multi-good factor proportion model in which specialization is determined by the interaction between relative endowments and trade costs (Markusen and Venables (2007)). Results obtained from data on liberalized countries will be compared to the main points of this model.

a Econometric Specification

The starting point is a simple neoclassical model inspired by Harrigan (1995), who focuses empirically on the production side of factor-proportions theory. International differences in production are determined by international differences in factor supplies.

Assuming constant return to scale and also a perfect competitive markets for inputs and outputs, a country's national product is given by its revenue function:

$$\pi(p, v) = \max_{y}\{p \cdot y \mid y \in Y(v)\} \tag{3.4}$$

where p, v and y are vectors of prices, productive factors and net output, and $Y(v)$ is a compact production set.

The gradient of π w.r.t p[11] gives the net supply vector:

$$y = \pi_p(p, v) = \pi_{pv}(p, v) \cdot v = R \cdot v \tag{3.5}$$

Where R represents the matrix of Rybczynski derivatives, whose i, kth element is: $\frac{\delta^2 \pi(p,v)}{\delta p_i \delta v_k}$. Because of that, these linear relationship between gross output and factor endowment are called Rybczynski equations.

With factor price equalization, R matrix is the same in all countries. Thus, (net) outputs[12] in each country are the same linear function of national factor endowments. The assumption of identical R turns this model from a standard neoclassical formulation into a model of the international location of production. Moreover, by adding very simple assumptions about consumption we can obtain the Hecksher Ohlin theorem.

Note that this result is also attainable from full-employment condition of factors: $v = A \cdot y$. Assuming there are equal numbers of goods and factors, we can invert the matrix A of cost-minimizing input coefficients, so $y = A^{-1} \cdot v \Rightarrow R = A^{-1}$.

Moreover, differences in technology can be introduced in the model (Fitzgerald and

[11] Assuming differentiability as well as linear homogeneity of y w.r.t v

[12] One can also consider gross output, since in this simple model the share of value added in gross output is common across countries.

Hallak (2004)). Hicks-Neutral productivity differences are such that one unit of factor f in country c is equivalent to a_c units of that factor in a benchmark country. Hence 3.5 becomes:

$$y^c = R\tilde{v^c} = Ra^c v^c \tag{3.6}$$

Where $\tilde{v^c}$ is the vector of productivity-adjusted factors, and I explicitly introduced the superscript c to denote countries. Working with industries' value-added and three sectors (physical capital, skilled and unskilled workers[13]), and adding a disturbance term to 3.6 we can estimate the following regressions:

$$y_i^c = r_{ik} a^c K^c + r_{is} a^c S^c + r_{iu} a^c U^c + \epsilon_i^c \tag{3.7}$$

Where the subscript i refers to each of the twenty-four industries studied here. These are precisely the same regressions that Harrigan (1995) worked on.[14] Considering $L^c = S^c + U^c$ the total number of workers in country c, we can rewrite 3.7 as:

$$\frac{y_i^c}{a^c L^c} = r_{iu} + r_{ik} \frac{K^c}{L^c} + (r_{is} - r_{iu}) \frac{S^c}{L^c} + \tilde{\epsilon}_i^c \tag{3.8}$$

According to Fitzgerald and Hallak (2004) this lead to a reduced form that relates specialization to factor proportions and captures the intuition of the Heckscher-Ohlin model yet preserving a close relation to the Rybczynski estimates. They find that the term $a^c L^c$ is highly correlated with country GDP. As it is also highly correlated with total manufacturing value-added, and modifying the subscripts to explicitly allow for the time dimension, I arrive to the following regressions:

[13] The stock of arable land, sometimes considered a proxy for natural-resources endowment, does not add explanatory power in any of the further regressions.

[14] All his regressions has a constant that accounts for omitted endowments

$$\tilde{s_{ict}} = \beta_{it}^{0} + \beta_{it}^{1}\frac{K_{ct}}{L_{ct}} + \beta_{it}^{2}\frac{S_{ct}}{L_{ct}} + \mu_{ict} \tag{3.9}$$

Thus, β coefficients relate changes in relative factor abundance to changes in relative sectoral value added at any moment in time. It is important that these coefficients, being related to the r_{iv} of the Rybczynski R matrix, somehow reflect production techniques in a very broad sense. But what 3.9 actually represents is the existence of a common underlying structural relationship between factor endowments and specialization.

We are interested in the effect of the endowments over the changes in specialization in those countries liberalized in the '80s and '90s. Notice that time differences of 3.9 can be expressed in the following way:

$$\Delta^{t}\tilde{s_{ic}} = \gamma_i^{0} + \gamma_i^{1}\overline{\left(\frac{K_{ct}}{L_{ct}}\right)} + \gamma_i^{2}\overline{\left(\frac{S_c}{L_c}\right)} + \gamma_i^{3}\Delta^{t}\left(\frac{K_c}{L_c}\right) + \gamma_i^{4}\Delta^{t}\left(\frac{S_c}{L_c}\right) + \Delta^{t}\mu_{ic} \tag{3.10}$$

Where the differences are taken between 2000 and 1980, and the bars represent averages over that period. γ^1 and γ^2 represent the impact of relative endowments over changes in specialization over the period. For example, a (significant) positive value for γ^1 in an industry i implies that specialization (measured as growth in value-added share) in that industry was stronger in countries that on average have higher levels of capital per worker. γ^3 and γ^4 control for the Rybczynski effect of factor accumulation over industry growth.

I will estimate 3.10 using the data explained in past chapter[15] and then I will compare the results with the prediction of a model that interacts factor endowments and trade cost in a multi-country and multi-god approach.

[15]See Chapter 2, section 3.

b A Model of Trade Cost, Endowments, and Specialization

As stated in the previous subsection, we need a model against which results can be compared. A tractable model linking factor endowments to trade cost and to both production and trade specialization occurs in Markusen and Venables (2007). It deals with a multi-country world where countries differ in factor endowments and trade costs alike. In this scenario, there are two factors (Labor and Capital) and production has constant return to scale and is perfectly competitive. Unit cost functions for each good i are the same in all countries and depend on factor prices: $b_i(w, r)$. There are three produced goods, varying in factor intensities. Trade in these goods is subject to iceberg trade costs varying across countries but constant within any given country.

The equilibrium location of production satisfies a set of inequalities relationships. The lower boundary of unit cost is the export price, and each good will be produced in a country only if unit cost is less than or equal the import price: $p_i t \geq b_i(w, r) \geq p_i/t, \quad i = 1, 2, 3$

Under these circumstances, equilibrium is described numerically.[16] The authors assume that preferences and production of three goods are Cobb-Douglas (the latter with symmetric factor shares, being X_1 is the most capital-intensive), and that countries are uniformly distribute over the parameter space of factor endowments and trade costs, solving for world general equilibrium for all countries simultaneously.

The following graph (taken from their paper) shows the main findings:

The horizontal axis represents country's labor abundance (one minus capital abundance) and the vertical axis represents trade cost. A given country is a point on the graph. Higher trade costs are associated with a region of autarky. As trade costs fall,

[16] In the second part of the paper they characterize the different regimes of specialization analytically, showing how they depend on key parameters of the model.

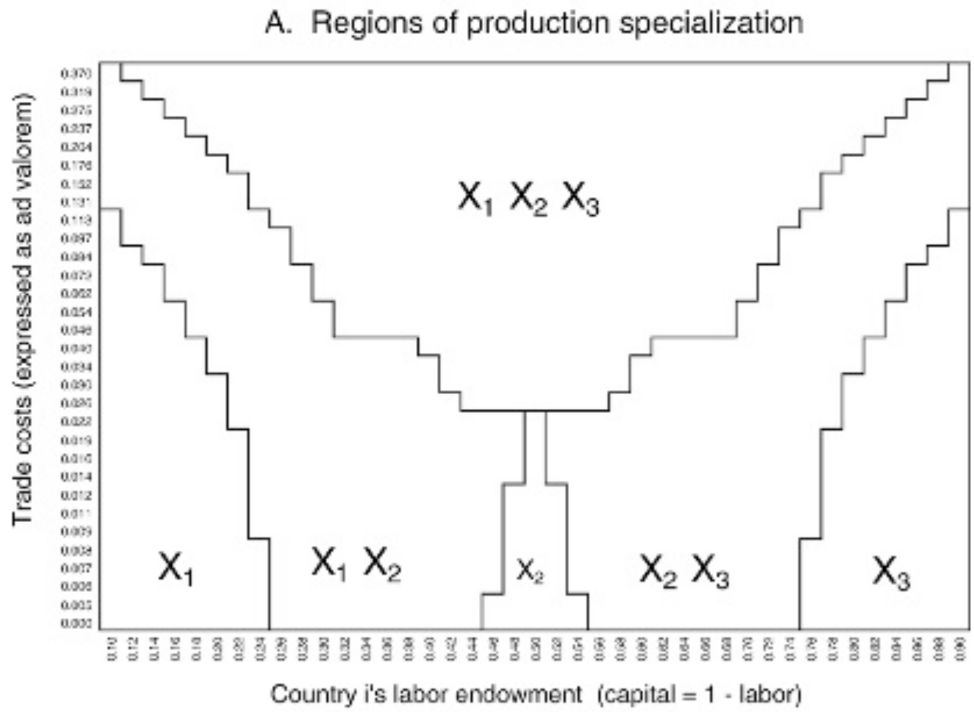

Figure 3.1: Regions of Production Specialization in Markusen and Venables (2007)

countries become more specialized, Under these conditions, capital scarce (i.e., labor-abundant) countries are first seen to produce goods 2 and 3 (that is, the less capital intensive ones) and further falling implies total specialization in good 3 for those same less capital-abundant countries. Countries with lower than the average capital abundance produces goods 2 and 3, and average countries specialize in good 2. Finally, relatively capital-abundant countries either produces goods 1 and 2 or exclusively good 1. A zero trade-cost situation is characterized by multiple cones of partial diversification bounded by regions of complete specialization.

Thus, according to the model, a trade liberalization reform that could be associated with a fall in trade cost would cause liberalized economies (typically those less capital-abundant than the average) to specialize in a subset of capital non-intensive goods. Within this range of countries and goods, Rybczynski effects will prevail. Thus, relatively more capital-abundant countries will produce relatively more capital-intensive goods (always excluding the most capital-intensive goods).

Having explained the main features of a model that links both trade cost and factor endowments to specialization, I will describe the main results of the regression analysis and how they relate to the main conclusion of the model.

c Results and Discussion

The table 3.6 shows the results obtained for regressing 3.10 for each one of the twenty-four sectors in the sample of countries that liberalized their economies in the '80s and '90s. As comparable data on industrial value-added[17] from the beginning of the '80 and end of the century are needed, I provide data on twenty five countries.[18] Many countries have missing values in some sectors, and differences in shares have been considering over the same set of sectors.[19]

The table shows the standardized coefficients of the regression (for each sector) of variations in the sectoral value-added share between early 80's (on average data from 1980-1983) and the late '90s (average 1998-2001) with respect to averages and differences in capital per worker, and proportion of skilled over total labor. An explanation of how those variables were constructed, and the sources for the data is found in the previous chapter, section 2.3.[20]

[17]Using production output gives like results. I prefer to work with value-added as it is the adequate theoretical measure of specialization

[18]This is the list of the countries: Argentina, Bangladesh, Bolivia, Cameroon, Chile, Colombia, Costa Rica, Ecuador, Egypt, El Salvador, Ethiopia, Hungary, Kenya, Madagascar, Mexico, Panama, Poland, South Africa, Sri Lanka, Tanzania, Trinidad and Tobago, Tunisia, Turkey, and Uruguay.

[19]This means that if, for example, a country has data for one sector for the '80s but not for the '2000s, that sector is excluded, and total manufacturing value-added is computed summing the remaining sectors.

[20]It is important to recall, for example that skilled and unskilled workers are expressed in efficiency units.

Table 3.6: Regression Coefficients

Isic	Sector Name	Average $\frac{K}{L}$	Average $\frac{S}{L}$	$\Delta\frac{K}{L}$	$\Delta\frac{S}{L}$	R2	Obs
311	Food	.525**	.164	-.277*	-.054	.446	23
313	Beverages	.195	.104	-.16	.021	.076	23
321	Textiles	.392*	.316	-.148	-.072	.305	24
322	Apparel	-.542***	.308	.136	-.341	.289	22
323	Leather	-.207	-.13	-.033	.278	.072	21
324	Footwear	-.417*	.238	-.025	-.369	.247	20
331	Wood	.194	-.602	-.009	.211	.164	22
332	Furniture	-.435	.525	-.04	-.262	.14	24
341	Paper	.025	.055	-.112	-.17	.021	25
342	Printing	.228	.063	.085	-.129	.074	24
351	Ind.Chemichals	.13	.117	-.233	.12	.117	21
352	Other.Chemicals	-.13	.224	.101	-.013	.04	24
355	Rubber	-.412	-.092	.511*	.439	.209	21
356	Plastic	.418*	.122	.21	-.043	.348	24
361	Pottery	-.831*	.07	.356	.242	.347	21
362	Glass	.072	-.066	.172	.147	.049	24
369	Minerals	-.125	-.233	.175	.311	.039	21
371	Iron.Steel	.006	.126	-.157	-.173	.022	25
372	Metals	-.096	-.764**	-.069	.561*	.286	24
381	Metal.Products	-.124	.19	.576***	-.147	.344	21
382	Machinery	.414	.409	-.341	-.406	.182	21
383	Electrical.Mach	.191	-.424	.523	.191	.26	21
384	Transport	.191	-.091	.253	.369	.266	22
385	Scientific.Equipm	.228	.158	.079	-.203	.074	24

Standardized Coefficient. Dependent variable is $\Delta^t \tilde{s_{ic}}$, the growth in sectoral value added share in total manufacturing value added between the early '80s and late '90s. ***Significant at 1%, **5%, *1%. Significance obtained using robust standard errors.

Although initially it seems not much information can be extracted for the table, my contention is that the results (more especially those related to the average capital abundance of a country) are consistent with the main conclusions of the model presented in the previous sub-section.

To see that, first consider the relative capital abundance of the countries in the sample (i.e., those that opened their economies in the last quarter of the last century). Figure 3.2 shows the histogram of their capital abundance, measured as average capital per worker for the world and for the liberalized economies. It is clear that the sample of the latter (transparent bars) are located at the left tail of the distribution.

According to the Markusen and Venables (2007) model, capital-scarce countries do not

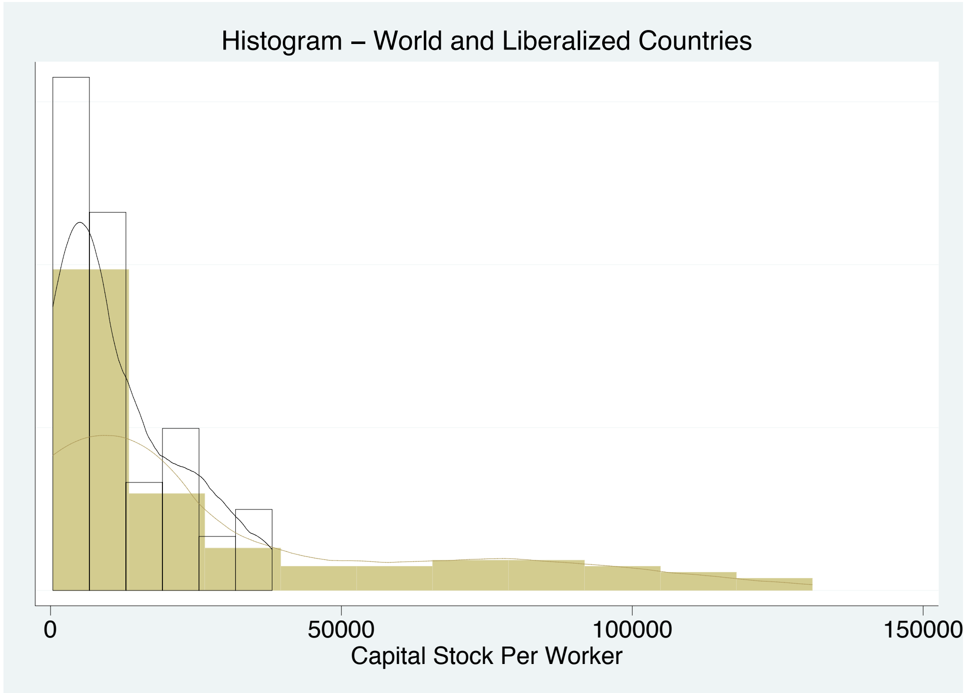

Figure 3.2: Histogram - Capital Stock per Worker

specialize in products which are capital intensive. Instead, they specialize in less capital-intensive sectors as trade costs decrease, there being a positive relationship between relative capital abundance and capital intensity of goods (within that range of less capital-intensive goods). Thus, if we graph a scatter of γ_i^1 (the coefficient that relates specialization to capital abundance) and sector capital intensity, we should observe a positive relation for lower levels of capital intensity. We do not necessarily observe any kind of relationship for capital intensive-sectors, as none of the countries studied specialize in those sectors.

Figure 3.3 confirm this intuition. The first column of table 3.6, showing standardized coefficient (γ_i^1 in 3.10) are plotted against sectoral capital intensity, measured as real capital per employee ratio expressed relative to the same ratio for US manufacturing as a whole. Broadly, sectors are divided into: capital-intensive (above-average ratios of of $\frac{K}{L}$), and intermediate and non-capital intensive (ratio lower than half the average).

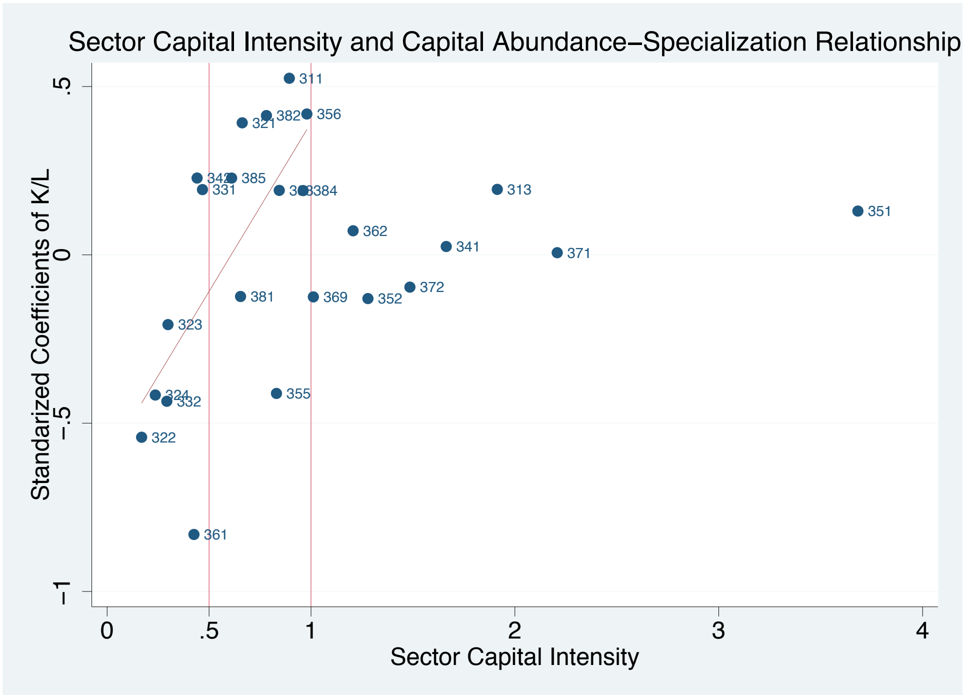

Figure 3.3: Scatterplot - γ_i^1 and sector capital intensity

High capital-intensive sectors have in general coefficients close to zero. For those sectors relatively less capital-intensive (i.e., below the average) there is a clear positive relationship between intensity and the coefficient linking endowment with specialization. In general, the less capital-intensive sectors have a negative coefficient (i.e., the more capital-abundant a country, the less it specializes in this sector), while intermediate capital-intensive sector generally have positive coefficients. The only sector that appears not to follow the rule would be Rubber (355). In the graphs, regression lines are computed only for those sectors with a below-average capital ratio.[21]

These findings are clearer if, instead of using the coefficient value, we graph the t statistic against capital intensity (Figure 3.4). Even tough the small sample size makes most of the coefficients being non-significant, there are some sectors with negative significance of the coefficients relating specialization to endowments at lower levels of capital intensity,

[21] Alternatively, one could work with other measures of capital intensity, like ratio of real capital to value-added. Results does not vary significantly, since the order in practically the same.

and there are also some sectors with positive significance at sectors with intermediate levels of capital per worker ratio. No one sector with a ratio of capital per worker higher than the average has a significant coefficient, and in general, t statistics related to those sectors are close to zero.

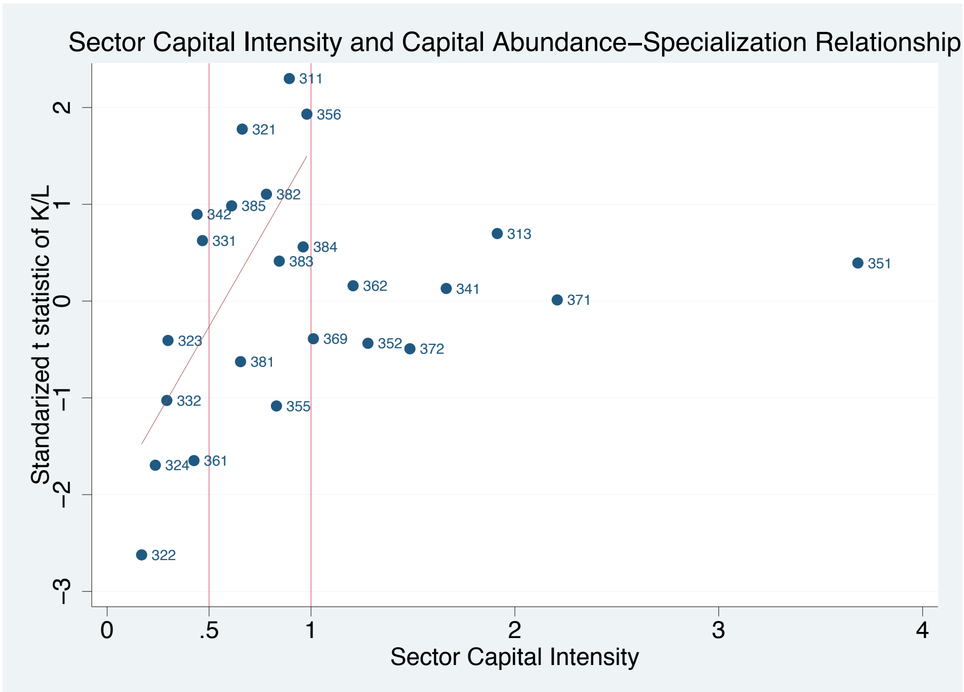

Figure 3.4: Scatterplot - $\frac{\gamma_i^1}{\sigma_{\gamma_i^1}}$ and Sector Capital Intensity

Thus, the data would seem to indicate that there is indeed a positive correlation between capital abundance and specialization, and sector capital intensity, once one controls for the accumulation of factors. However, this relationship is to be found only in the relative non capital-intensive sectors. This is precisely what the model of Markusen and Venables (2007) predicts for those countries that experience a reduction in trade costs, a situation that I relate to the process of trade liberalization. Countries with a lower level of capital abundance specialize in non capital-intensive sectors such as Apparel, Footwear or Pottery, and intermediate capital-abundant countries (relatively speaking, the capital-abundant ones in the sample) specialize in intermediate capital-intensive sectors such as Food, Textiles or Plastic. There is simply no pattern whatever in capital-intensive sectors like Chemicals or Steel, because no country in the sample is capital-abundant relative to the rest of the world.

However, when one scatters the second coefficient of regression 3.10 (the one related with skilled-labor abundance) with a measure of sectoral skilled intensity (ratio of non-production workers over total employees), the results exhibit no clear pattern. Both skilled and non-skilled intensive sectors show a (non-significant) positive correlation between relative abundance and specialization. Clearly these results fit better when we analyze the relationship between specialization and relative capital abundance.

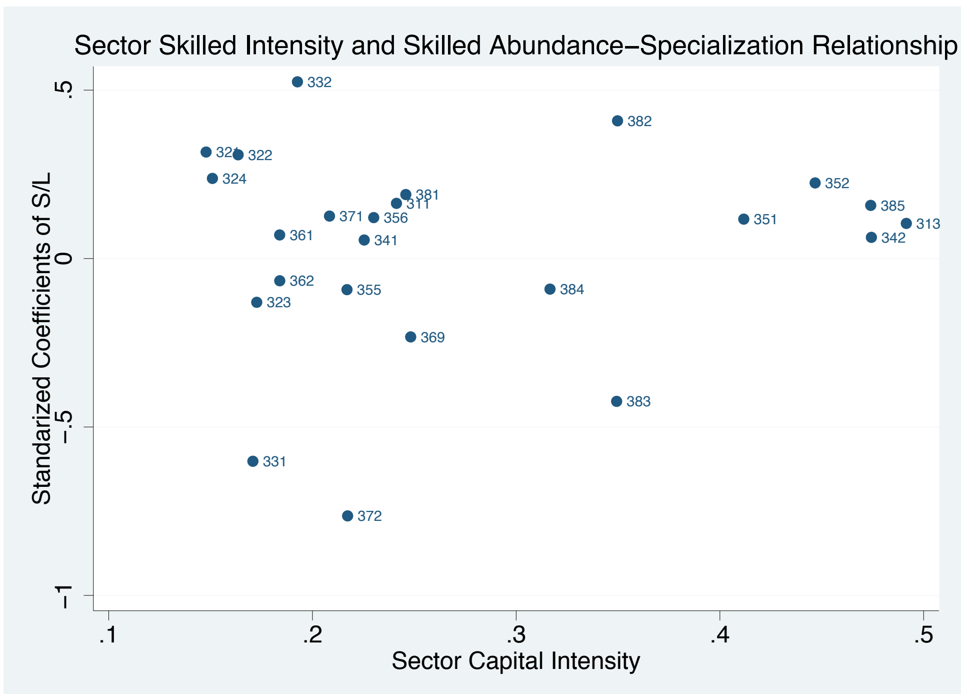

Figure 3.5: Scatterplot - γ_i^2 and sector skilled labor intensity

Finally, Figure 3.6 graphs the R^2 of the regressions in 3.10 against sectoral capital-intensity. The explanatory power of average levels, and of changes in endowments (capital and skilled labor) with regard to specialization is higher (for the sample of liberalized countries) in non capital-intensive sectors. Actually, in most of the capital intensive ones, R^2 is lower than .10, while in the rest of the sectors it averages 0.24. In summary, data seem to support the main prediction of a simple multi-country multi-

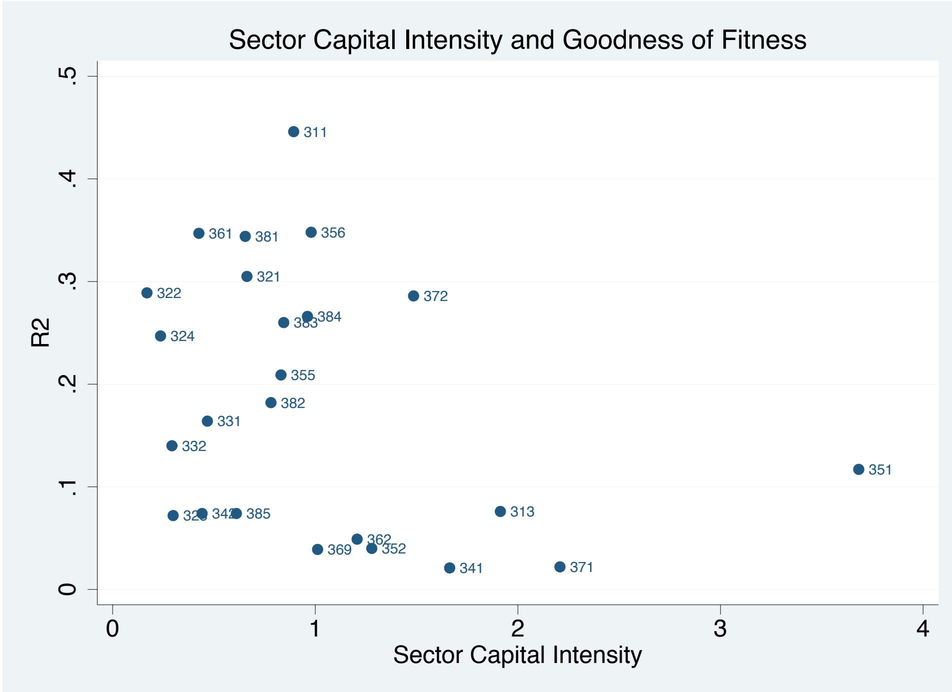

Figure 3.6: Scatterplot - R^2 and sector capital intensity

good factor proportion model. For countries that reduced their trade cost significantly in the period, through a process of trade liberalization, there exists a positive relationship between capital abundance and specialization only in some set of sectors, those with lower levels of capital intensity. No relationship is found in capital-intensive sectors, as the countries in the sample did not specialize in those sectors. The relationship can be observed if we rank the sectors according to their capital-labor intensity, but not if we rank them according to their skilled or non-skilled labor intensity. Finally, the explanatory power of endowments (both levels and changes) with regard to specialization is higher in labor-abundant sectors.

3.4 Conclusion

Considering that the massive trade-liberalization episodes at the end of the last century could help us to understand better some openness' effects on national economies, this paper has focused on the liberalization's effects on given countries' productive structures. Having twenty years of value-added data for a number of trade-liberalized countries, one can compare how the productive structure was before with respect to the situation existing several years after the reforms took place. Thus, I have been able to study the medium-run changes that compensate from those short-run adjustments that frequently biases the results of previous studies.

In particular, the paper had tried to answer two questions: a) do we observe major structural changes in the productive structure within countries after a process of trade liberalization? and b) do such changes in the productive structures conform to the pattern that classical trade theories would predict?

In order to resolve the first one, I have conducted a descriptive analysis using transition matrices and a dynamic model of specialization. This has shown that, when one analyzes sufficiently large transition periods, mobility in liberalized countries is relatively high, in particular higher than in already open or non-liberalized economies.

To answer the second question, I based my regression strategy on a neoclassical model of production. Then I compare the results obtained with a multi-country multi-good factor proportion model showing the interaction of factor endowments and trade cost with production specialization. The data used have confirmed the basic intuition of the model: i.e., for relative capital-scarce countries, reduction in trade cost provokes specialization in a set of non capital-intensive goods, and (for this set of goods) there is an observable positive relationship between capital abundance and specialization. This relationship however, is not seen in the set of capital-intensive sectors, as none of the countries in the sample were specialized in that kind of activity.

Overall, we can not rule out the effects of trade liberalization on productive structure. Changes in such structure seem to be correlated with endowments, as classical theories predict, but this last finding is far from conclusive.

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