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East is East and West is West: A Ricardian-Heckscher-Ohlin Model of Comparative Advantage

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Abstract

Models of comparative advantage are usually based either on differences in factor abundance or differences in total factor productivity within a country despite considerable empirical evidence that *both* matter. This paper articulates a unified and tractable model in which comparative advantage exists due to differences in factor abundance *and* relative productivity differences across a continuum of industries with monopolistic competition and increasing returns to scale. I provide evidence that both sources of comparative advantage shape international production patterns. In addition, I find that relative productivity differences across industries are uncorrelated with the factor intensities of these industries. Therefore, each of the two forces for comparative advantage offers valid partial descriptions of the data. Consequently, simply aggregating the predictions of the factor abundance-based and relative productivity-based models can be used to obtain a full description of industry-by-industry production patterns.

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1 Introduction

Production patterns around the world exhibit tremendous heterogeneity and specialization. For example, the United States supplies 16.2% of the world's exports of aircraft while China provides only 0.1%. On the other hand, China supplies 14.9% of the world's export supply of apparel and clothing while the United States only supplies 0.9%.[1] The Ricardian and Heckscher-Ohlin (HO) theories are the two workhorse models used to explain this specialization. The Ricardian model of international trade predicts that countries specialize in goods in which they hold the greatest relative advantage in total factor productivity (TFP).[2] The Heckscher-Ohlin model ignores differences in TFP across industries and assumes that all countries possess the same production function in a given industry. Heckscher-Ohlin asserts that differences in comparative advantage come from differences in factor abundance and in the factor intensity of goods. Neither model, in isolation, offers a complete description of why production patterns differ nor does either offer a unified theory of international specialization. Consequently, empirical tests of each model can be subject to the omitted variable problems associated with ignoring the other. Finally, little work has been done in assessing the relative empirical importance of the two models.

This paper presents a unified structural framework that nests each source of comparative advantage when there is a continuum of industries. The model's tractability allows me to estimate the relative contributions of Ricardian and HO forces through traditional estimation techniques. I highlight three important findings. First, both the Ricardian and HO models possess robust explanatory power in determining international patterns of production. Second, the two models are empirically separable in my broad sample in that the forces that determine comparative advantage in one model are orthogonal to the forces that determine comparative advantage in the other model. Finally, I find that a one standard deviation change in relative factor abundance is approximately twice as potent as affecting change in the industrial structure of an economy as a one standard deviation change in industry-specific relative TFP. Although the first result has been documented

[1]Data taken from "World Trade Flows" bilateral trade data compiled by Robert Feenstra et al. (2005) for the year 1990. Aircraft is SITC code 792 and Clothing and Apparel is SITC code 84.

[2]The original "Ricardian" model only focused on differences in opportunity cost across industries and did not explore from where these differences came. For the entirety of this paper, I take "Ricardian" technology differences to be differences in TFP as in Dornbusch, Fischer, and Samuelson (DFS) (1977).

in past reduced form estimation, this is the first to do so based on a unified structural model. The second and third results are new and provide substantial insight into how we can integrate these two important approaches.

More technically, I articulate a unified and tractable model in which comparative advantage exists due to differences in factor abundance *and/or* relative productivity differences across a continuum of monopolistically competitive industries with increasing returns to scale. In this manner, I rely on the quasi-Heckscher-Ohlin market structure of Romalis (2004) while augmenting his model with Ricardian TFP differences. By developing a tractable model that possesses theoretically meaningful nested hypotheses, I am able to dissect patterns of comparative advantage into those driven by Ricardian forces and those driven by HO. In addition, I derive conditions under which tests of the HO model will not suffer from an omitted variable bias in ignoring Ricardian TFP differences.

This unified model allows me to nest the precise alternate hypothesis that a country that possesses a relative abundance of a factor also possess levels of relative TFP that are systematically higher (or lower) in industries that use this factor relatively intensively. In trying to explain patterns of skill-biased-technical-change, Acemoglu (1998) suggests that skilled labor abundant countries will have higher levels of relative TFP in skilled-labor intensive industries than in unskilled labor intensive industries.[3] If the mechanisms in his model are pervasive in the data, economists will tend to confound the two models when one is tested without the other as a meaningful alternate hypothesis.[4] Empirically, Kahn and Lim (1998) find that TFP in the United States in the 1970s increased far more in skill-intensive industries than in industries that use unskilled labor relatively intensively. On the other side, if Ricardian TFP differences influence production patterns in a manner that is inconsistent with HO, this might suggest why HO results sometimes appear to be unstable.[5]

After solving the model, I estimate it using panel data across 20 developed and developing countries, 24 manufacturing industries and 11 years (1985-1995). I highlight three major findings. First, I find that both productivity differences and the interaction of factor abundance with factor

[3]However, he also shows that all predictions about *relative* TFP across sectors depend crucially on the enforcement of Northern property rights of technology in the South.

[4]This possibility has also been the subject of conjecture by authors such as Fitzgerald and Hallak (2004) although the modeling techniques have not existed for empirically examining this possibility.

[5]e.g. Bowen, Leamer and Sveikauskas (1987)

intensity play a role in determining international specialization patterns. Second, there is very little evidence that relative productivity is systematically correlated with factor intensity. This suggests that productivity levels that are non-neutral across industries have little influence on whether results consistent with HO appear in the data. Third, I find that a one standard deviation increase in relative factor abundance is 1.6 to 2.3 times as potent in affecting change in the commodity structure of the economy as a one standard deviation change in Ricardian productivity. This suggests that differences in factor abundance are more potent than differences in Ricardian productivity in determining patterns of specialization.

The key to nesting the Ricardian alternate hypotheses is decomposing industry-level TFP differences into three components: country-level TFP that differs across countries but is identical across industries within any given country, productivity that is correlated with factor intensity and is purged of country averages, and productivity that varies across industries but is orthogonal to factor intensity and is purged of country averages. If productivity is correlated with factor intensity, the two models can be confounded easily and tests of a single model will typically suffer from omitted variable bias. If TFP is orthogonal to factor intensity, it is reasonable to model TFP as consisting of a country-specific term that is neutral across industries and an idiosyncratic component that is orthogonal to factor intensity.

Empirically, when TFP is uncorrelated with factor intensity, HO is valid as a partial description of the data. Consequently, common tests of and the standard comparative statics associated with the HO model are valid (e.g. Rybczynski regressions) because Ricardian TFP predictions are not correlated with the factor intensity differences across goods that are the foundation of most of these empirical tests. However, industry-by-industry level predictions must take Ricardian differences into account. For example, the change in the commodity structure resulting from a change in number of skilled workers in a country can be estimated from a HO model but the level of production accruing to a certain industry must take HO and Ricardian considerations into account. Examining if relative TFP is correlated with factor intensity in other data sets will suggest if this orthogonality assumption is valid in other work.

This paper is related to two strands of literature on the empirical determinants of specialization and trade. The first strand documents the influence of Ricardian TFP on international production patterns. MacDougall (1951,1952) finds early evidence of the Ricardian model using data from the United Kingdom and the United States. Costinot and Komunjer (2007) augment the model of Eaton and Kortum (2002) to include industries and find that relative value added per worker possesses predictive power in determining patterns of industrial specialization in a broad panel of countries. The second related strand of literature documents the importance of factor abundance in determining country and industry level trade patterns. Early empirical investigations of the influence of factor abundance on production patterns include Leontief (1954) and Baldwin (1971).[6] More recently, Trefler (1995), Davis and Weinstein (1999), Debaere (2003) and Romalis (2004) document patterns of trade consistent with HO.

Based on these two strands of literature, there is broad agreement that both the Ricardian and HO models are important for understanding international patterns of production. Consequently, there is a need for a unified framework that can address the relative importance of these two forces as well as their potential interaction. Harrigan (1997) and Harrigan and Zakarasjek (2001) examine the contributions of TFP and factor abundance in determining specialization in a series of industry level studies that rely on reduced-form estimation based on translog approximations to the revenue function. Although they do not explicitly model the interaction of TFP and factor abundance in general equilibrium, these are the closest empirical antecedents to this paper. In addition, they do not examine when the omission of Ricardian technology introduces systematic biases in tests of the HO model. This paper is less related to Trefler (1993) who shows that taking country-level differences in TFP into account improves the performance of Heckscher-Ohlin-Vanek models by allowing for better measurement of factor abundance.

Theoretical antecedents of this paper include Findlay and Grubert (1959) who were among the first to use a two country, two good, two factor model to consider the effects of Ricardian productivity and factor abundance in jointly determining factor prices and production patterns. Xu (2001) works out a complete set of results regarding how technological progress impacts relative factor prices in a two country, two industry, two factor model. Bernard, Schott and Redding (2006)

[6] For thorough surveys of empirical tests of theories of trade, see Deardorff (1985) and Leamer and Levinsohn (1995).

use Melitz's (2003) model of firm heterogeneity to derive results consistent with the HO theorem. Although it provides substantial theoretical insights, their model requires data that is disaggregated to a level that is not available in international data sets that possess broad coverage.[7]

The paper is organized as follows. Section II sketches a simple two industry, two country, two factor version of the model. Section III extends the simple model to a continuum of industries and derives the empirically testable form. Section IV describes the data and the construction of the TFP measures used in the paper. Section V presents the baseline results. Section VI presents robustness tests, and Section VII concludes.

2 Theory: A Simple 2x2x2 Model

I first work through a simple two country, two factor, two industry model to illustrate the essence of a more general model. My model augments the quasi-Heckscher-Ohlin structure of Romalis (2004) with Ricardian TFP differences. This simple model solves for equilibrium factor prices and production as functions of exogenous factor abundance and productivity using two equilibrium conditions to extract the separate contributions of productivity and factor abundance on relative production patterns across industries in a country. I focus on the case where both countries produce in each industry such that intra-industry trade exists. I start by deriving a *goods market clearing condition* that maps relative factor prices to relative production values of goods demanded from skilled and unskilled labor intensive industries. I close the model by deriving a *factor market clearing condition* that assures full employment for both factors. I then show how Ricardian productivity differences can introduce substantial biases in empirical tests of the HO model.

2.1 Production

This section presents the supply side of the model including the production function and the pricing behavior of a firm. The two factors of production are skilled labor (S) and unskilled labor (U). The wages of these two factors are represented by w_s and w_u, respectively. Let $\omega \equiv \frac{w_s}{w_u}$. For simplicity,

[7] In addition, their model focuses on the case where firms take productivity draws from the same distribution across industries. Consequently, all differences in average TFP within a industry across countries are endogenous responses to exogenous differences in factor abundance.

define the two countries as the North and the South. All Southern values possess asterisks. Although this is relaxed completely in the more general model, assume for the moment that aggregate incomes in the two countries are identical ($Y = Y^*$).

The two industries are indexed by their Cobb-Douglas skilled labor factor cost shares, z, where $z = \frac{w_s S(z)}{w_s S(z) + w_u U(z)}$ and $0 < z < 1$. z_s is the skilled labor factor cost share of the skilled labor intensive good and z_u is the skilled labor factor cost share of the unskilled labor intensive good. Consequently, z is both a parameter and the index of industries. Without loss of generality, assume that $z_s > z_u$. Firms within each of the two industries each produce unique and imperfectly substitutable varieties. Hicks neutral TFP ($A(z)$) augments skilled and unskilled labor in production of a final good $x(z)$ and coverage of fixed costs $f(z) w_s^z w_u^{1-z}$ such that total cost for a given Northern firm i in industry z takes the following form:

$$TC(z,i) = [x(z,i) + f(z)] \frac{w_s^z w_u^{1-z}}{z^z (1-z)^{1-z} A(z)}. \tag{1}$$

As is common in the literature, I assume that skilled and unskilled labor are used in the same proportion in fixed costs as in marginal costs. Previewing the demand structure, prices are a constant markup over the Cobb-Douglas marginal cost. The markup is equal to $\frac{1}{\rho}$ where $0 < \rho < 1$ and $\frac{1}{1-\rho}$ is the elasticity of substitution between varieties within an industry. A zero profit condition solves for output per firm, $x(z) = \frac{\rho f(z)}{1-\rho}$. As is common in this class of model, all differences in international production patterns occur at the extensive margin as output per firm is pinned down by exogenous parameters. Assume that the elasticity of substitution and fixed costs are the same in the two countries for a given industry so that output per firm is constant across countries within an industry. I further assume that all firms within an industry and country have access to the same production function and face the same factor prices. Therefore, for a given industry z, the price of a Northern good relative to its Southern equivalent can be expressed as follows where Northern relative to Southern values are denoted with tildes:

$$\tilde{p}(z) = \frac{\tilde{w}_s^z \tilde{w}_u^{1-z}}{\tilde{A}(z)} = \frac{\tilde{\omega}^z \tilde{w}_u}{\tilde{A}(z)}. \tag{2}$$

The following notation introduces Ricardian productivity differences:

$$\tilde{\gamma} \equiv \frac{\tilde{A}(z_s)}{\tilde{A}(z_u)} = \frac{\frac{A(z_s)}{A(z_u)}}{\frac{A^*(z_s)}{A^*(z_u)}} \tag{3}$$

If $\tilde{\gamma} > 1$, the North is relatively more productive in the skill intensive industry than the unskilled intensive industry. If $\tilde{\gamma} < 1$, the North is relatively more productive in the unskilled labor intensive industry. If $\tilde{\gamma} = 1$, the North is equally relatively productive in the two industries.

2.2 Demand

This section links prices to consumption patterns. Demand is based on a two tier utility function. Consumers in each of the two countries have utility (Υ) that is Cobb-Douglas over the two industries but CES across varieties within each of the industries. Although it will be loosened in the more general section, assume for the moment that expenditure share for each industry is constant and equal to 0.5. For a given industry z, $n(z)$ is the endogenously determined number of Northern firms and $n^*(z)$ is the number of Southern firms and the total number of varieties/firms in a given industry is $N(z) = n(z) + n^*(z)$ where i indexes varieties/firms within industry z.

$$\Upsilon = C(z_s)^{0.5} C(z_u)^{0.5} \tag{4}$$

$$C(z_k) = \left[\int_0^{N(z_k)} x(z_k, i)^{\rho} di \right]^{\frac{1}{\rho}} \qquad k \in S, U \tag{5}$$

Consumers buying from a foreign firm incur iceberg transportation costs $\tau > 1$ such that if the price of a domestically produced good is $p(z)$ then the price of the same good abroad is $\tau p(z)$. Revenue accruing to a firm in the North is equal to its receipts from domestic and foreign consumers. Appendix A shows how Northern and Southern firms' revenue functions can be used to solve for the number of Northern firms relative to the number of Southern firms in a given industry $\left(\frac{n(z)}{n^*(z)}\right)$ as Romalis (2004):

$$\tilde{n} = \frac{\tau^{2(1-\sigma)} + 1 - 2\tau^{1-\sigma}\tilde{p}^{\sigma}}{\tilde{p}(\tau^{2(1-\sigma)} + 1) - 2\tilde{p}^{1-\sigma}\tau^{1-\sigma}}. \tag{6}$$

Because output per firm is pinned down, aggregate Northern revenue relative to aggregate Southern revenue in industry z is:

$$\tilde{R}(z) = \frac{n(z)p(z)x(z)}{n^*(z)p^*(z)x^*(z)} = \frac{\tau^{2(1-\sigma)} + 1 - 2\tau^{1-\sigma}\tilde{p}^{\sigma}}{\tau^{2(1-\sigma)} + 1 - 2\tau^{1-\sigma}\tilde{p}^{-\sigma}}. \tag{7}$$

I restrict my attention to the case where $\tilde{R}(z) > 0$ such that both the North and South produce in a given industry.[8] Romalis (2004) provides restrictions on $\tilde{p}(z)$ that give necessary and sufficient conditions for $\tilde{R}(z) > 0$.

Because firms produce on the elastic portion of their demand curve, $\frac{\partial \tilde{R}}{\partial \tilde{p}} < 0$.[9] As a country's relative price goes up its relative revenue in that industry falls. Finally, it is straightforward to show that the share of production in industry z accruing to the North is also decreasing in $\tilde{p}(z)$ where the share is defined as $v(z) = \frac{R(z)}{R(z)+R^*(z)} = \frac{\tilde{R}(z)}{\tilde{R}(z)+1}$.

2.3 Equilibrium

To solve for equilibrium production patterns and factor prices, I introduce price differences coming from Heckscher-Ohlin and Ricardian forces. To solve for the equilibrium, I start by deriving the goods market clearing condition. Starting with the simple case where comparative advantage only comes from differences in factor abundance, I show that if $\omega^* > \omega$ then $\frac{v(z_s)}{v(z_u)} > \frac{v^*(z_s)}{v^*(z_u)}$. That is, the relative value of goods demanded in an industry will be *declining* in the relative wage of the factor that is used relatively intensively in that industry. Appendix B derives this rigorously. As in Romalis (2004), factor price equalization fails due to transportation costs. This relationship is shown by the line DD in Figure 1 which depicts the *goods market clearing condition.* A *factor market clearing condition* closes the model. Define world income as $Y^w = Y + Y^*$. Based on Cobb-Douglas production, the ratio of aggregate payments to skilled labor relative to those to unskilled

[8] The intuition for the model is unchanged when allowing for specialization although solving for equilibrium production patterns becomes more complex.

[9] As Romalis (2004) notes, as $\sigma \to \infty$ and $\tau = 1$ the model becomes one of perfect competition as in DFS (1977) for the case of comparative advantage from Ricardian productivity and DFS (1980) for the HO case. With transportation costs and perfect competition, there are non-traded goods and no intra-industry trade. With monopolistic competition but no transportation costs, FPE results as long as factor endowments are not too dissimilar, the location of production becomes indeterminate for a given industry and we cannot make industry-by-industry predictions. Romalis (2004) also contains a proof that $\frac{\partial \tilde{R}}{\partial \tilde{p}} < 0$.

labor is

$$\frac{0.5\sum_{k\in s,u} v(z_k) z_k Y^w}{0.5\sum_{k\in s,u} v(z_k)(1-z_k) Y^w} = \frac{w_s}{w_u}\frac{S}{U} = \omega\frac{S}{U}. \tag{8}$$

Simple manipulation gives

$$\frac{z_u + \frac{v(z_s)}{v(z_u)} z_s}{(1-z_u) + \frac{v(z_s)}{v(z_u)}(1-z_s)} = \omega\frac{S}{U}. \tag{9}$$

Taking a total derivative of the above expression and setting $d\left(\frac{S}{U}\right) = 0$ gives the following expression

$$\Delta d\frac{v(z_s)}{v(z_u)} = \Delta dV = \frac{S}{U} d\omega \tag{10}$$

where

$$\Delta = \frac{z_s - z_u}{\left[1 - z_u + \frac{v(z_s)}{v(z_u)}(1-z_s)\right]^2} > 0. \tag{11}$$

Because $z_s > z_u$, $K > 0$ and the relative wage of the factor used relatively intensively in an industry will increase as productive factors are reallocated to that industry. This is the *factor market clearing condition FF*. Examining Figure 1, if $F^N F^N$ is the factor market clearing condition for the Northern country, the Southern factor market clearing condition $F^S F^S$ is below and to the right of $F^N F^N$. The location of $F^S F^S$ relative to $F^N F^N$ is given by solving for $\frac{d\omega}{d\frac{S}{U}}$ using equation 8.

Figure 1 confirms the intuition of the simplest HO model. The North possesses a relative abundance of skilled labor and its relative wage of skilled labor is less than in the South. Consequently, the North produces relatively more of the skill intensive good. The South produces relatively more of the unskilled labor intensive good.

I can also use this framework to illustrate a simple Ricardian model in Figure 2. Suppose that the North produces relatively more of the skill intensive good due to Ricardian TFP differences and possesses the same factor endowments as the South. If the North is systematically more productive

Figure 1: Equilibrium: Heckscher-Ohlin Model

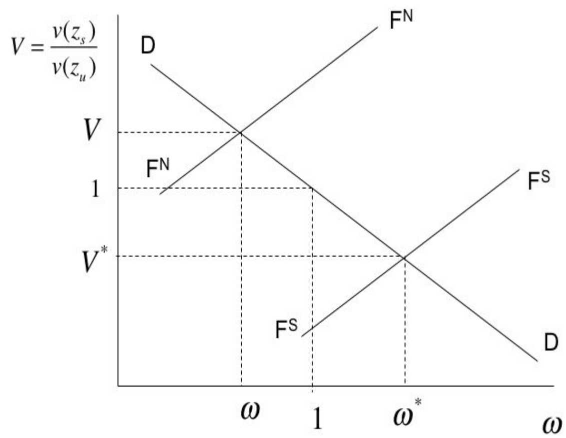


Figure 2: Equilibrium: Ricardian Model

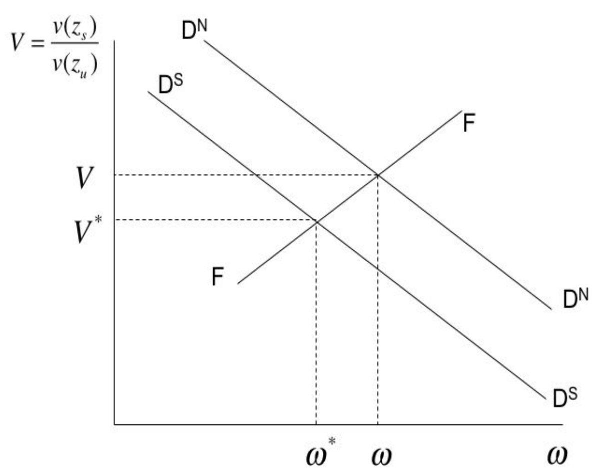
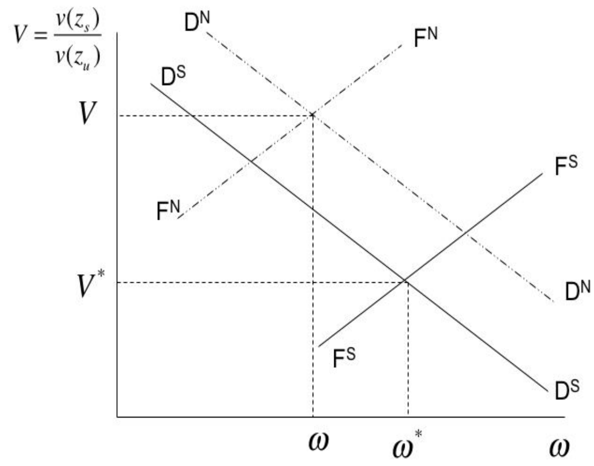


Figure 3: Hybrid Model



in the skill intensive industry, its goods market clearing condition $D^N D^N$ will be above and to the right of the goods market clearing condition for the South, $D^S D^S$. This is because the North generates higher demand at a given set of factor prices than the South in the skill intensive industry because it possesses relatively higher TFP in that industry. Because factor endowments are the same in each country, they share a common factor market clearing condition, FF. The North produces relatively more of the skill intensive good and the relative wage of skilled labor is bid up as resources are reallocated to the skill intensive industry.

Finally, consider a hybrid of the two models where Northern industry TFP is positively correlated with the skilled labor intensity of goods *and* the North possesses a relative abundance of skilled labor. This hybrid model is portrayed in Figure 3.

If we only observe differences in V and V^* and differences in factor abundance, we will confound the effects of high relative productivity and factor abundance when performing tests of HO because we cannot distinguish shifts in the FF curve from shifts in the DD curve. In this example, omitting productivity from empirical work when factor prices are unobserved will result in a substantial omitted variable bias in interpreting HO tests because the cumulative effect of factor abundance and productivity will be attributed to factor abundance.

If relative TFP is negatively correlated with skill intensity in the skill abundant country, the HO prediction is less likely to appear in the data (e.g. the North produces a lower V than if productivity was distributed identically across industries). In the first case, the unified Ricardian-HO model provides a meaningful alternate hypothesis for a given set of production patterns and a solution to an omitted variable bias. In the second case, it allows for the possibility that HO predictions can be rescued. Finally, if TFP is uncorrelated with factor intensity, we will not expect it to affect HO predictions at all.

3 Theory: A Continuum of Industries

I now generalize my analysis to a continuum of industries as in Dornbusch, Fischer, and Samuelson (1980) and Romalis (2004). I also derive estimable expressions for gauging the presence of Ricardian productivity and HO forces in determining international patterns of production. Industries with higher values of z use a more skill intensive production technique at a given set of factor prices than those with a lower z. With a continuum of industries, first tier utility (Υ) takes the form:

$$\Upsilon = \int_0^1 b(z) ln[C(z)]dz, \tag{12}$$

$b(z)$ is the exogenous Cobb-Douglas share of expenditures associated with each industry. The consumption aggregator for each industry, $C(z)$, is the same as in the simple model. I abandon the restriction that $Y = Y^*$ and define the relative value of production between the two countries as

$$\tilde{R}(\tilde{p}(z)) = \frac{n(z)p(z)x(z)}{n(z)^*p(z)^*x(z)^*} = \frac{\tau^{2(1-\sigma)}\frac{Y^*}{Y} + 1 - \tau^{1-\sigma}\tilde{p}(z)^{\sigma}(\frac{Y^*}{Y}+1)}{\tau^{2(1-\sigma)} + \frac{Y^*}{Y} - \tilde{p}(z)^{-\sigma}\tau^{1-\sigma}(\frac{Y^*}{Y}+1)}. \tag{13}$$

As before, I am particularly interested in the case where intra-industry trade occurs such that $\tilde{R}(\tilde{p}(z)) > 0$. Define $\tilde{r}(z) = ln\left(\tilde{R}(z)\right)$ and take a total derivative of this expression with respect to $ln\left(\tilde{p}(z)\right)$ to obtain the following expression:

$$d\tilde{r}(\tilde{p}(z)) = \Gamma(\tilde{p})d\ln(\tilde{p}(z)), \quad \Gamma(\tilde{p}) < 0 \tag{14}$$

where[10]

$$\Gamma(\tilde{p}(z)) = \frac{-\sigma\tau^{1-\sigma}\left(\frac{Y^*}{Y}+1\right)\left[\tilde{p}(z)^{\sigma}\left(\tau^{2(1-\sigma)}+\frac{Y^*}{Y}\right)-2\tau^{1-\sigma}\left(\frac{Y^*}{Y}+1\right)+\tilde{p}(z)^{-\sigma}\left(\tau^{2(1-\sigma)}\frac{Y^*}{Y}+1\right)\right]}{\tilde{p}(z)\left[\tau^{2(1-\sigma)}+\frac{Y^*}{Y}-\tilde{p}(z)^{-\sigma}\tau^{1-\sigma}\left(\frac{Y^*}{Y}+1\right)\right]^2} < 0. \tag{15}$$

Relative prices reflect differences in comparative advantage that come from TFP differences and differences in factor prices

$$\tilde{p}(z) = \tilde{\omega}^z \frac{\tilde{w_u}}{\tilde{A}(z)} \tag{16}$$

For a given set of relative factor prices, comparative advantage can emerge both because of the interaction of relative factor prices and factor intensity ($\tilde{\omega}^z$) or because of relative differences in TFP, $\tilde{A}(z)$. Because I need to keep track of productivity in many industries, I use a convenient parameterization of productivity as follows where $\tilde{a}(z) = ln\left(\tilde{A}(z)\right)$

$$\tilde{a}(z) = \tilde{a} + ln\left(\tilde{\gamma}\right)z + \tilde{\epsilon}_{A(z)}; \quad \tilde{\epsilon}_{A(z)}\ i.i.d.(0, \sigma^2_{\tilde{A}(z)}), \tag{17}$$

$$ln(\tilde{\gamma}) = \frac{cov[z, \tilde{a}(z)]}{var(z)}. \tag{18}$$

This conveniently breaks TFP into three components: country level differences that are neutral across industries ($\tilde{a}$), differences across industries that are correlated with factor intensity ($ln(\tilde{\gamma})z$), and differences across industries that are orthogonal to factor intensity ($\tilde{\epsilon}_{A(z)}$). Country level differences in relative productivity pose the fewest problems for HO theory in that they can easily be modeled as an increase in country size.[11] The component of Ricardian TFP that is correlated with factor intensity is captured by $ln(\tilde{\gamma})z$. $ln(\tilde{\gamma})$ is just the ordinary least squares (OLS) coefficient of a regression of $\tilde{a}(z)$ on skill intensity (z) under normal OLS assumptions. This poses problems for HO theory because it offers a well articulated alternate hypothesis for why we find HO production patterns in data.

If $\tilde{\gamma} > 1$, then $cov[z, \tilde{a}(z)]$ is positive and skilled labor intensive industries will *on average*

[10] Recall that this derivative is negative when $\sigma > 1$ and iceberg transportation costs exist.

[11] See Dornbusch, Fischer, and Samuelson (1980) for the simplest example of this.

have higher TFP than unskilled labor intensive industries. If $\tilde{\gamma} < 1$, then $cov[z, \tilde{a}(z)]$ is negative and skilled labor intensive industries *on average* have lower TFP than unskilled labor intensive industries. If $\tilde{\gamma} = 1$, then $cov[z, \tilde{a}(z)] = 0$ and productivity is uncorrelated with skill intensity.

TFP that is uncorrelated with factor intensity and purged of country level effects is represented by $\tilde{\epsilon}_{A(z)}$. Because this component of TFP is orthogonal to factor intensity and purged of country effects by assumption, it is part of a model that is separable from HO forces. Consequently, if TFP is uncorrelated with factor intensity, aggregate predictions can be made by simply aggregating the predictions of the two models.

I exploit the monotonic relationship between $v(z)$ and $ln(\tilde{p}(z))$ and take a first order linear approximation around the skill labor intensity z_0. Using the implicit function theorem, I can simplify $v(z)$ as a linear function of z.

$$v(z) = v(z_0) + \frac{\partial v(z_0)}{\partial ln(\tilde{p}(z_0))} \frac{\partial ln(\tilde{p}(z_0))}{\partial z_0} (z - z_0) \tag{19}$$

$$v(z) = v(z_0) + \frac{\tilde{R}(z_0)}{\left[1 + \tilde{R}(z_0)\right]^2} \Gamma(z_0) \ln\left(\frac{\tilde{\omega}}{\tilde{\gamma}}\right)(z - z_0) \tag{20}$$

Solving for the covariance of $v(z)$ with z gives the simple expression where $\Gamma'(z_0) = \frac{\tilde{R}(z_0)}{\left[1+\tilde{R}(z_0)\right]^2}\Gamma(z_0) < 0$

$$cov[z, v(z)] = \Gamma'(z_0) \ln\left(\frac{\tilde{\omega}}{\tilde{\gamma}}\right) var(z) \tag{21}$$

This expression is the continuum of industries analog of the goods market clearing condition DD from the two industry model. Although applicable to any two factors of production, this expression shows how a given correlation between skill intensity and production can occur for two reasons. First, if productivity is uncorrelated with factor intensity ($\tilde{\gamma} = 1$), relatively cheap skilled labor ($\tilde{\omega} < 1$) can lead countries to produce more skilled labor intensive goods ($cov[v(z), z] > 0$).[12] Second, even if factor prices do not differ ($\tilde{\omega} = 1$) production can be skewed towards skill intensive industries ($cov[v(z), z] > 0$) because productivity is systematically higher in skilled labor intensive industries ($\tilde{\gamma} > 1$).

[12] Recall that $\Gamma' < 0$.

I now present the continuum of industries analog of the factor market clearing condition. The following equations are the factor market clearing conditions for the North in skilled and unskilled labor,

$$\int_0^1 b(z)v(z)zY^w dz = w_s S, \tag{22}$$

$$\int_0^1 b(z)v(z)(1-z)Y^w dz = w_u U. \tag{23}$$

Dividing equation (22) by (23) gives

$$\frac{\int_0^1 b(z)zv(z)dz}{\int_0^1 b(z)(1-z)v(z)dz} = \frac{w_s S}{w_u U}. \tag{24}$$

I exploit the fact that $b(z)$ is everywhere non-negative and $\int_0^1 b(z)dz = 1$ and interpret $b(z)$ as a sample probability density. Therefore, the expressions can be rewritten using *sample* expectations. A Southern factor market clearing condition follows analogously so that the two factor market clearing conditions are:

$$\frac{E[zv(z)]}{E[(1-z)v(z)]} = \frac{w_s S}{w_u U} \tag{25}$$

$$\frac{E[z(1-v(z))]}{E[(1-z)(1-v(z))]} = \frac{w_s^* S^*}{w_u^* U^*}. \tag{26}$$

Taking the ratio of these two expressions and simplifying gives the following *factor market clearing condition*:

$$\frac{g + cov[v(z), z]}{g} = \tilde{\omega}\frac{\tilde{S}}{\tilde{U}} \tag{27}$$

where

$$g = E[z]E[v(z)] - E[v(z)]E[v(z)z] - E[z]E[v(z)z] + [E(v(z)z)]^2 .^{13} \tag{28}$$

Proposition 1 states that when Ricardian productivity differences are uncorrelated with factor in-

[13] Note that because it was derived from expectations of a product of strictly positive terms, both the numerator and denominator must be strictly positive.

tensity, HO forces should be present and should contribute to the relative production structures of the two countries.

3.1 Sufficient Conditions for "separability" between HO and Ricardian models.

Proposition 1: If productivity is uncorrelated with factor intensity and the relative abundance of factors differs among countries, then the relative wage of a country's abundant factor will be less than in the country where it is a relatively scarce factor. In addition, $cov[v(z), z] > 0$ where z is the Cobb-Douglas cost share of its relatively abundant factor and $cov[v(z'), z'] < 0$ where z' is the Cobb-Douglas cost share of its relatively scarce factor.

Proof: See Appendix

This proposition is important because it shows that if TFP is uncorrelated with factor intensity, then basic HO results should hold in the data. Intuitively, when relative TFP is uncorrelated with factor intensity, differences in TFP across industries will not cause (or prevent) empirical tests of Heckscher-Ohlin to find evidence of factor abundance based production and trade. Consequently, the effect of changes on the production structure coming from differences in factor abundance (i.e. Rybczynski regressions) or the net exporting position of a given factor (e.g. HOV tests) are unlikely to be affected by differences in relative TFP across industries if TFP is uncorrelated with factor intensity.

When TFP is correlated with factor intensity, any reduced form relationship between factor intensity, factor abundance and production will likely be due to both factor abundance and Ricardian TFP. It is also possible that relative Ricardian TFP differences will be large enough that a country that possesses a relative abundance of a factor will *not* produce relatively more of the good that uses that factor relatively intensively. For example, the South might have TFP that is systematically high enough in skill intensive industries that it will produce relatively more skilled labor intensive goods than the North. Intuitively, this is most likely to occur when differences in factor abundance are very small and/or differences in γ are very large. I now derive an empirically testable model that nests the separate contributions of Ricardian and HO forces to production patterns.

3.2 Empirical Application

I now derive two expressions that test for the contributions of Ricardian and HO forces in determining why different countries produce differing baskets of goods. I first derive a "restricted expression" that tests whether the relationship between factor intensity, factor abundance and production can be explained by HO and/or Ricardian forces. Unfortunately, it says nothing about the role of Ricardian productivity that is uncorrelated with factor intensity. To assess the role of productivity that is uncorrelated with factor intensity, I then derive an "unrestricted expression."

To derive the restricted expression, I log-linearize the expression for relative revenue in industry z (equation 13) as a function of $ln\left(\tilde{p}(z)\right)$ with the appropriate subscripts for country c relative to c'. The use of log revenue and not market share ($v(z)$) allows me to more easily and transparently control for country and industry fixed effects using country-time and industry-time fixed effects. I then take the covariance of this expression with z:

$$cov[z, \tilde{r}(z)_{cc't}] = \Gamma \ln\left(\frac{\tilde{\omega}_{cc't}}{\tilde{\gamma}_{cc't}}\right) var(z). \tag{29}$$

I further assume that the elasticity of relative factor prices with respect to relative endowments is constant and equal to $\kappa \leq 0$ where $ln(\tilde{\omega}) = \kappa ln(\tilde{S}/\tilde{U})$. This allows me to write the following expression:

$$cov[z, \tilde{r}(z)_{cc't}] = \kappa\Gamma \ln\left(\frac{\tilde{S}}{\tilde{U}}\right)_{cc't} var(z) - \Gamma \ln\left(\tilde{\gamma}_{cc't}\right) var(z) \tag{30}$$

This expression decomposes the covariance of production with skill intensity into that due to factor abundance and that due to Ricardian productivity differences. This expression can then be taken to the data using the following estimation equation where a vector of time fixed effects T allows the results to be invariant to the choice of numeraire:[14]

$$cov[z, r(z)_{ct}] = \beta_0 + \beta_1 \ln\left(\frac{S}{U}\right)_{ct} + \beta_2 \ln\left(\gamma\right)_{ct} + \beta_t' T_t + \zeta_{ct} \tag{31}$$

[14]This can be seen by rewriting $cov[z, \tilde{r}(z)_{cc't}]$ as $cov[z, r(z)_{ct} - r(z)_{c't}] = cov[z, r(z)_{ct}] - cov[z, r(z)_{c't}]$ and $\ln\left(\frac{\tilde{S}}{\tilde{U}}\right)_{cc't}$ as $\ln\left(\frac{S}{U}\right)_{ct} - \ln\left(\frac{S}{U}\right)_{c't}$.

$$\beta_1 = \kappa\Gamma var(z) > 0 \quad \beta_2 = -\Gamma var(z) > 0.$$

Under the null hypothesis that HO *alone* is responsible for any relationship between factor intensity, factor abundance and production, $\beta_1 > 0$ and $\beta_2 = 0$. Under the null hypothesis that there are no HO forces at work and that any differences in production are due to differences in Ricardian TFP, $\beta_1 = 0$ and $\beta_2 > 0$. If both HO and Ricardian effects explain why specialization occurs, then $\beta_1 > 0$ and $\beta_2 > 0$.

This "restricted expression" does not allow for TFP that is uncorrelated with factor intensity to play any role in determining production patterns. To examine the contribution of TFP that is uncorrelated with factor intensity, I derive the "unrestricted expression" by again starting with a log-linearized version of equation 13 where the linearization occurs at the z_0 such that $\tilde{p}(z_0) = 1$:[15]

$$\tilde{r}(z) = \tilde{r}(z_0) + \frac{\partial \tilde{r}(z_0)}{\partial ln(\tilde{p}(z_0))} ln(\tilde{p}(z)). \tag{32}$$

Breaking $ln(\tilde{p}(z))$ into its components under Cobb-Douglas production gives

$$\tilde{r}(z) = \tilde{r}(z_0) - \frac{\partial \tilde{r}(z_0)}{\partial ln(\tilde{p}(z_0))} \left[\tilde{a} - \tilde{w}_u - ln(\tilde{\omega})z + ln(\tilde{\gamma})z + \epsilon_{\tilde{A}(z)} \right] \tag{33}$$

Revenue depends on country and industry level variables as might be expected. Revenue is increasing in country level productivity ($\tilde{a}$), decreasing in the absolute wage level ($\tilde{w}_u$), and increasing in industry specific relative productivity $\tilde{\epsilon}_{A(z)}$.[16] If the North possesses relatively cheap skilled labor, ($\ln(\tilde{\omega}) < 0$), then relative revenue is systematically increasing in z. If the North has systematically higher relative productivity in skill intensive industries, ($\ln(\tilde{\gamma}) > 0$), then relative revenue is also systematically increasing in z. Including fixed effects that make the results insensitive to the choice of numeraire country gives the following expression where ZT is a full vector of industry-time fixed effects (e.g. Industry 311 in 1990), CT is a full vector of country-time fixed effects (e.g. Japan in 1990), and ζ is an error term that is clustered by country-industry (e.g. Industry 311 in Indonesia):

[15] Taking the linearization around other relative prices does not affect the result.

[16] Recall that the derivative outside the brackets is negative.

$$\tilde{r}(z)_{ct} = \frac{\partial \tilde{r}(z_0)}{\partial ln(\tilde{p}(z_0))} \Big[ln(\omega)_{ct} z - ln(\gamma)_{ct} z - \epsilon_{A(z),ct} \Big] + \beta'_{zt} ZT_{zt} + \beta'_{ct} CT_{ct} + \zeta_{zct} \quad (34)$$

Again, assuming that the elasticity of relative factor prices with respect to relative endowments (κ) is constant transforms the expression into the following regression form

$$\tilde{r}(z)_{ct} = \beta_0 ln \left(\frac{S}{U} \right)_{ct} z + \beta_1 ln(\gamma)_{ct} z + \beta_2 \epsilon_{A(z),ct} + \beta'_{zt} ZT_{zt} + \beta'_{ct} CT_{ct} + \zeta_{zct} \quad (35)$$

where

$$\beta_0 = \kappa\Gamma > 0 \quad \beta_1 = -\Gamma > 0 \quad \beta_2 = -\Gamma > 0.$$

Thus, I can gauge the validity of HO as a driving force of comparative advantage through the coefficient β_0. The coefficient on the interaction term between $ln(\gamma)$ and skill intensity (z), β_1, allows me to gauge the importance of Ricardian productivity that is correlated with factor intensities of the goods. Finally, β_2 allows me to assess the importance of Ricardian productivity that is orthogonal to factor intensity in determining production patterns. All country level differences in productivity that are identical across industries in a year are absorbed into the country-time fixed effects. All industry-time characteristics (e.g. average scale of industry) will be absorbed by the industry-time fixed effects. Under the null that HO forces alone determine comparative advantage, $\beta_0 > 0$ and $\beta_1 = \beta_2 = 0$. Under the null that Ricardian forces alone determine comparative advantage but that they are *not* confounded with possible HO forces, $\beta_0 = \beta_1 = 0$ and $\beta_2 > 0$. Under the null that Ricardian TFP is comprised of components that are and are not correlated with factor intensity, $\beta_0 = 0$, $\beta_1 > 0$ and $\beta_2 > 0$. Finally, if there are both Ricardian and HO forces present but they are uncorrelated, $\beta_1 = 0, \beta_0 > 0$, and $\beta_2 > 0$.

4 Data and Results

This section outlines the data and variables used to estimate the model. The collected data set covers 24 3 digit ISIC revision 2 industries, 11 years (1985-1995), and the following 20 countries:

Austria, Canada, Denmark, Egypt, Finland, Great Britain, Hong Kong, Hungary, Indonesia, India, Ireland, Italy, Japan, Norway, Pakistan, Portugal, South Korea, Spain, Sweden, and the United States. All variables (except those explicitly mentioned) are taken from the World Bank's Trade and Production data set (Nicita and Olarreaga, 2001). All country-years for which complete data exist for at least 15 of the 24 industries in that country and year are kept.[17] Because not all countries have available data in all years, the dataset is an unbalanced panel. The Data Appendix lists the data availability for years and countries. The most binding constraint in assembling this data set was the availability of continuous time series for investment used to create the capital stock variables.

4.1 Factor Abundance

Although the model is applicable to any set of factors of production, I focus on skilled and unskilled labor as imperfectly substitutable factors of production as found in the Barro and Lee (2001) educational attainment dataset.[18] As a measure of $\frac{S}{U}$, I examine the ratio of the population that has obtained a tertiary degree to that which does not.[19] As might be expected, Canada and the United States have the highest (average) values with $\frac{S}{U} = 0.76$ for the United States and $\frac{S}{U} = 0.70$ for Canada. Pakistan and Indonesia have the lowest (average) values with $\frac{S}{U} = 0.02$ for both countries.

[17]There are 28 three digit ISIC manufacturing industries in the Trade and Production dataset. Four industries are excluded from the analysis: 314 (tobacco), 353 (petroleum refineries), 354 (misc. petroleum and coal production), 390 (other manufactures). The first three are excluded because their production values are likely to be substantially influenced by international differences in commodity taxation (Fitzgerald and Hallak, 2004). The last is excluded because its "bag" status makes comparability across countries difficult. All results are invariant to increasing the cutoff to having 18 of the 24 industries although the sample size and power of the empirical tests are obviously smaller.

[18]I select skilled and unskilled labor as the factors of production in this model for two reasons. First, recent work (e.g. Fitzgerald and Hallak (2004)) has shown that skilled and unskilled labor possess more explanatory power in differences in the structure of production than capital. Second, data on skilled labor abundance (as measured by educational attainment rates in Barro and Lee (2001)) is far more comprehensive than the Penn World Tables coverage of capital per worker.

[19]Data are only available at five year intervals. Data for the interim years are interpolated assuming that the growth rate of the variable is constant over the five years. No extrapolations are performed. Results using a broader definition of skilled labor are examined in the robustness section.

Table 1: Industry Skill Intensities

ISIC Code	Description	z_{narrow}	z_{broad}	ISIC Code	Description	z_{narrow}	z_{broad}
311	Food	0.16	0.36	355	Rubber Prod.	0.19	0.44
313	Beverages	0.35	0.57	356	Plastic Prod.	0.19	0.39
321	Textiles	0.13	0.28	361	Pottery, China etc.	0.21	0.50
322	Wearing Apparel	0.10	0.24	362	Glass and Prod.	0.18	0.41
323	Leather Prod.	0.12	0.31	369	Non-Metallic Mineral Prod.	0.20	0.37
324	Footwear	0.16	0.28	371	Iron and Steel	0.15	0.38
331	Wood Prod.	0.13	0.32	372	Non-ferrous Metals	0.19	0.41
332	Furniture	0.13	0.30	381	Fabricated Metal Prod.	0.18	0.40
341	Paper and Prod.	0.21	0.44	382	Machinery (non-elec)	0.20	0.47
342	Printing and Publishing	0.36	0.61	383	Elec. Machinery	0.36	0.60
351	Industry Chemicals	0.42	0.67	384	Transport Equip.	0.29	0.55
352	Other Chemicals	0.45	0.65	385	Prof. and Sci. Equip.	0.37	0.61
	Sample Average	0.23	0.44		Sample Std. Deviation	0.10	0.13

4.2 Skilled Labor Intensity of Industries

Data on the skilled labor cost share (z) for each of the 24 industries come from educational attainment data by worker in the United States Current Population Survey (CPS) dataset where workers are transformed into effective workers using a Mincerian wage regression. The regression is run on data pooled by years (1988-1992) and industries. The Data Appendix explains the procedure in detail. I examine narrow and broad definitions of skilled labor. The "narrow" definition defines a skilled laborer as a worker with four or more years of college. The "broad" definition defines a skilled laborer as one who has attended any college. Table 1 presents these measures of z along with their means and standard deviations.[20]

These measures line up with common priors. Among the most skill intensive industries are Scientific Equipment (385), Industrial and Other Chemicals (351,352), and Publishing (342). Among the least skill intensive industries are Textiles (321), Footwear (324) and Wearing Apparel (322).

[20]It is important to note that I assume that z is constant across countries. Similar results can be derived for CES production functions that allow both the factor intensities and the factor shares to vary across countries if the elasticity of substitution across factors is such that countries that possess relatively inexpensive skilled labor use techniques that produce more skill intensive factor shares in a given industry.

Table 2: $Cov[z, r(z)]$ Summary Stats (182 observations)

Measure of z	Mean	Std. Dev	Max	Min
Narrow	0.0284	0.0171	0.0556	-0.0198
Broad	0.0348	0.0246	0.0836	-0.0345

4.3 Production Covariances

I calculate the covariance of (log) revenue with the skill intensity of the industries ($cov[z, r(z)]$) using production value from the Trade and Production dataset. Table 2 presents summary statistics for $cov[z, r(z)]$ based on both the narrow and broad definitions of skill intensity. [21]

4.4 Factors of Production and TFP

I follow Caves, Christensen and Diewert (1983) and Harrigan (1997) in using the solution to an index number problem to calculate productivity levels.[22] This methodology is based on a translog functional form that allows the productivity calculation to be based on any production function up to a second order approximation. Based on this procedure, if capital (K) and homogenous labor (L) were used to produce value added (VA), the TFP productivity level between country a and a multilateral numeraire would be

[21] These measures are in line with measures from other studies. For example, Fitzgerald and Hallak (2004) use a slightly different measure of skilled labor and examine production in OECD countries. Using their data (table 7), I find that the country that is in the 25th percentile of skilled labor abundance has a covariance of 0.0377 and a country that is in the 75th percentile has a covariance of 0.0698. The values for the 25th and 75th percentile (using the broad definition) for my sample are 0.0206 and 0.0605, respectively. Appendix F contains a list of average $cov[r(z), z]$ by country.

[22] Basu and Kimball (1997) propose a method of measuring technology growth that addresses the endogeneity of factor demand and unobservable factor utilization. Unfortunately, there is a lack of demand shifting instruments that are strong both across industries and countries to control for the endogeneity of factor demand. I consider the issue of capacity utilization in the robustness section. Other estimators have been proposed in the firm level literature that do not rely on the need for instruments (e.g. Olley and Pakes (1996)). I choose not to use estimators in this class because their theoretical derivation is very much motivated for firm level studies and their use is inappropriate for industry-country level analysis. Required assumptions include that all "firms" possess the same demand function for investment or intermediate inputs and the same exogenous factor prices. The assumption that market structure and factor prices are the same across countries is highly questionable.

$$TFP(z)_{a,t} = \frac{VA(z)_{a,t}}{\overline{VA(z)_t}} \left(\frac{\overline{K(z)_t}}{K(z)_{a,t}} \right)^{\frac{\alpha_{K,a}+\alpha_{K,avg}}{2}} \left(\frac{\overline{L(z)_t}}{L(z)_{a,t}} \right)^{\frac{\alpha_{L,a}+\alpha_{L,avg}}{2}} \tag{36}$$

$\alpha_{i,j}$ represents the Cobb-Douglas revenue share of factor i in country j and $\alpha_{i,avg}$ is the average revenue share of factor i across all countries in the given industry.[23] $\overline{K}(z)_t = \frac{1}{N_{z,t}} \sum_c K(z)_{czt}$ and $\overline{L}(z)_t = \frac{1}{N_{z,t}} \sum_c L(z)_{czt}$ where $N_{z,t}$ is the number of countries in the sample in industry z in year t.

4.4.1 Deflators

Very few industry level deflators exist that allow comparison of output or value added across countries. One possibility is to assume that quality adjusted prices equate across countries due to a high substitutability and tradability of manufacturing goods and that all price differences should then be included as differences in quality. However, this relies more on conjecture than evidence. For this reason, I use the disaggregated PPP benchmark data provided by the Penn World Tables to deflate the data. These price indexes are constructed with an explicit eye toward comparing goods of similar quality across countries. The Data Appendix addresses this in detail.[24]

4.4.2 Labor and Capital Input

In measuring TFP, I consider differences in the effectiveness of labor across countries because it is not proper to interpret differences in the effectiveness of labor as differences in total factor productivity. Differences in the effectiveness of labor can be modeled as unmeasured differences in the abundance of labor and, therefore, can be easily written into an HO model. Following Bils and Klenow (2002) and Caselli (2005), I create measures of the effectiveness of labor using wage

[23] α is constrained within a country within an industry (e.g. Indonesia-311) with no time series variation. I do this because measured revenue shares are very noisy and there is little reason to think that they are allocative. Although they work with cost shares and not revenue shares, Basu, Fernald, and Kimball (2006) also constrain their factor shares. Labor's factor share of value added is calculated as wages' proportion of value added. Capital's share of value added is one minus labor's share. Observations where the factor share of any input is negative are dropped.

[24] Country level PPP price deflators are incorrect because of the weight that they assign to non-traded goods which leads to a greater dispersion in price indexes than occurs in manufacturing which is highly traded. In addition, any country level output deflators will be differenced out by the country-year fixed effects. See Kravis, Heston and Summers (1982) for a thorough discussion of the process behind the collecting of the data and the preparation of the price indexes that are behind this study and the Penn World Tables. Country averages only capture 35% of the variance of relative prices across countries and industries in the disaggregated PWT data. This suggests that using country level price deflators will not capture substantial within-country variation.

Table 3: Effective Labor Across Countries

Country	E	Country	E
Austria	2.55	Ireland	2.60
Canada	2.99	Italy	1.96
Denmark	2.91	Japan	2.73
Egypt	1.59	Korea	2.74
Finland	2.78	Norway	3.06
Great Britain	2.64	Pakistan	1.35
Hong Kong	2.58	Portugal	1.72
Hungary	2.64	Spain	1.95
Indonesia	1.54	Sweden	2.80
India	1.61	United States	3.32

premium and educational attainment data. Define E as the effectiveness of labor per worker so that EL is the effective labor input. Using the Barro and Lee data on average years of schooling, I normalize the effectiveness of labor with "no schooling" (0 years) to be $E = 1$. Following Caselli (2005), I assume that labor becomes 13% more effective per year for the first four years of schooling, 10% per year for years 4-8, and 7% per year after that. Because the evolution of the skill level of labor in a country is likely to be slow, I use average years of schooling in 1990 for these calculations. Table 3 presents measures of E based on this methodology. These measures line up with commonly held priors.

Unlike work such as Harrigan (1999) and Keller (2002), I do not consider differences in days or hours worked. Practically, hours worked data that is sufficiently comparable across industries and countries is not available. Harrigan (1999) and Keller (2002) sidestep this issue by imposing measures of hours worked in aggregate manufacturing on all sectors within manufacturing. My interest in cross-industry TFP comparisons allows me to not include these measures. This is because hours of labor input will be highly correlated with (if not identical to) hours of capital service. If the production function is constant returns to scale, then it will also be homogenous of degree one in hours worked. If I use the same measure of hours worked in manufacturing across all manufacturing industries, I will multiply each production function in a given country-year group by the same scalar. This scalar will then be differenced out by a country-year fixed effect as derived in section 3.1.[25]

Labor is decomposed into operatives (U) and non-operatives (S) using data from the United Nations General Industrial Statistical Database.[26] The effectiveness of labor is assumed to augment both operatives and non-operatives. Capital is calculated using the perpetual inventory method.[27] The (value added) measure of productivity between country a and the multilateral numeraire is then

$$TFP_{a,t} = \frac{VA_{a,t}}{\overline{VA_t}} \left(\frac{\overline{S_t E_t}}{S_{a,t}E_{a,t}}\right)^{\frac{\alpha_{S,a}+\alpha_{S,avg}}{2}} \left(\frac{\overline{U_t E_t}}{U_{a,t}E_{a,t}}\right)^{\frac{\alpha_{U,a}+\alpha_{U,avg}}{2}} \left(\frac{\overline{K_t}}{K_{a,t}}\right)^{\frac{\alpha_{K,a}+\alpha_{K,avg}}{2}}. \tag{37}$$

4.4.3 Plausibility of TFP Measures

Because of the importance of TFP measures in this paper, I check their plausibility. First, I compare my measures to those calculated by others for consistency. Second, I check the correlation of TFP across industries with revenue. If Ricardo's original insight is fundamentally true, this correlation should be positive. Last, I check how much these measures fluctuate over time because large fluctuations would suggest substantial noise in my calculations. My measures meet all of these criteria for desirability.

First, Table 4 presents my estimates of industry level productivity against similar measures calculated by Harrigan (1999) (Table 1). I compare *all* industries and countries for which our

[25]This can also be applied to the adjustment to the effectiveness of the labor force. If both capital and labor are equally more effective in some countries, this country specific term will be differenced out by the country-year fixed effects.

[26]These UNGISD data on operatives and non-operatives are commonly used to distinguish skilled and unskilled workers within a given country as in Berman, Bound and Machin (1998). However, using it to compare skilled and unskilled workers across countries is highly dubious. For example, the ratio of non-operatives (commonly thought to be "skilled") to operatives (commonly though to be "unskilled") is 0.21 in Indonesia, 0.38 in the United States, 0.85 in Japan, and 0.45 in Italy (U.N., 1995). Given the levels of effective labor calculated in Table 3, these numbers are not likely to represent differences in average skill across countries. Comprehensive data on operatives and non-operatives are not available from year to year. For this reason, I calculate the average proportions of employment that are operatives and non-operatives for each country-industry. Using the available data, these average measures capture 95% of the year to year variation in a fixed effects regression. I then apply these constant proportions to annual employment data from the Trade and Production dataset to create annual measures of operatives and non-operatives. I follow a similar procedure to decompose wages into those paid to operatives and non-operatives to calculate the measures α_S and α_U.

[27]See the Data Appendix for more details.

calculations of TFP overlap. I calculate TFP of industries 382 (Machinery, non-electric), 383 (Machinery, Electric), 384 (Transport equipment), and 385 (Professional and Scientific Equipment). I then calculate them relative to the average across these four industries and then relative to the United States in that industry. I then compare these to similar measures from Harrigan (1999).[28]

Despite differences in our calculations (e.g. labor input and industry level deflators), our measures of relative TFP line up broadly. The rank correlation between the two measures based on the 24 observations is 0.74.[29] In addition, although not presented, selected industrial levels line up with other work. For example, Japan is the world leader in TFP for Iron and Steel (371) and Non-Ferrous Metals (372) which is consistent with Dollar and Wolff (1993) and Harrigan (1997). One discrepancy between the calculations here and those of Harrigan (1999) is the lower average TFP level in scientific and professional equipment (ISIC 385) that I calculate relative to his calculations. However, some consolation should be taken from the fact that both calculations find that the United States, Canada and Finland are among the most productive while Italy and Great Britain are among the least productive.

I also examine $\frac{cov[\tilde{a}(z),\tilde{r}(z)]}{var(\tilde{a}(z))}$ to gauge the explanatory power of productivity across industries. I calculate this measure for two reasons: first, this statistic should be positive for any non-pathological model. Second, it can be shown that this number should be equal to $-\Gamma$ as defined in equation 15. For 182 observations, each indexed by country-year, the mean is 0.3572 and significantly different from zero at the 1% level of certainty ($t = 3.24$).[30] Because this is a reduced form combination of structural parameters, it is difficult to interpret. However, Anderson and van Wincoop (2004) estimate that international trade barriers impose a total of a 74% ad valorem tax equivalent. Relating this number to the expression for Γ evaluated at $\tilde{p}(z) = 1$ and $Y/Y^* = 1$, this value implies a value

[28] I compare my measure for ISIC 382 to Harrigan's (1999) "Non-electrical machinery", ISIC 383 to his "Electrical machinery", ISIC 384 to his "Motor vehicles" and 385 to his "Radio, TV, & communications Equip." Although our methods for calculating TFP differ somewhat, our measures should line up broadly. He also calculates TFP for "Office and Computing Equipment" and "Aircraft" but my industrial classification does not allow for easy comparison of these industries. In addition, he also calculates TFP for Australia, Germany and the Netherlands, none of which I calculate because of data constraints. Finally, I drop his 1988 measure for Motor Vehicles in Italy which increases four-fold from the previous year in his measures and is unlikely to be accurate.

[29] This is obviously excludes the values for the United States that are set equal to 1.00 for normalization. Without the normalization, I can also compare each measure relative to country mean and include the measures for the United States. The rank correlation for these measures is 0.76 based on 28 observations.

[30] With standard errors clustered by country.

Table 4: Comparing Relative TFP Measures

					Harrigan (1999)			
	ISIC Industry				ISIC Industry			
Country	382	383	384	385	382	383	384	385
Canada	0.980	1.005	0.681	0.335	0.952	1.663	0.688	0.755
Finland	1.009	0.934	0.244	0.334	0.981	2.325	0.468	0.945
Great Britain	0.613	1.116	0.425	0.321	0.596	1.361	0.294	0.655
Italy	0.782	0.904	0.377	0.221	0.760	1.807	0.477	0.673
Japan	0.861	0.818	0.586	0.287	0.837	1.711	0.826	0.691
Norway	0.811	0.621	0.277	0.326	0.788	1.771	0.339	0.664
United States	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Rank correlation between constructed measures and those of Harrigan (1999): 0.74

of $\sigma = 9.5$ if $\tau = 1.74$. Although this is in the upper range of values for σ, it is within reason.[31]

Third, the measures of total factor productivity are also relatively stable over time. Running a regression of $\tilde{a}(z)_{ct}$ on a full set of country-industry fixed effects (e.g. Indonesia, ISIC-311) explains 91% of the variance as measured by the unadjusted R^2. Therefore, although these measures almost surely capture some business cycle fluctuations, the variance is dominated by the larger differences that exist across countries and industries rather than fluctuations over time within a country and industry.

The covariance terms (γ) are then calculated using the skill labor shares (z) and value added productivity. Recall that γ is defined as follows:

$$\gamma_{ct} = exp\left[\frac{cov[z, a_{czt}]}{var(z)}\right] \tag{38}$$

where

$$cov[a_{czt}, z] = \frac{\sum_z \left(a_{czt} - \overline{a}_{czt}\right)\left(z - \overline{z}\right)}{N_{ct}} \tag{39}$$

where $\overline{a}_{czt}$ is average (log) productivity across all industries for country c in year t, $\overline{z}$ is the average

[31] Broda and Weinstein (2006) estimate σ for 256 industries and find that the 5th and 95th percentiles of the distribution are 1.2 and 9.4, respectively.

skilled labor intensity across industries and N_{ct} is the number of industries that the summation is taken over. Because the covariance is between z and $a(z)$, all country specific effects are differenced out (e.g. country level business cycles).

In conclusion, although all comparisons of TFP across countries, industries and time are subject to some difficulties in measurement, the measures presented here are very likely to reflect real differences in TFP based on similarity to previous studies, the positive correlation of productivity and revenue across industries within a country in a given year, and the stability of the estimates over time. Because all measures are relative to a numeraire, the means of $ln(\tilde{\gamma}_{narrow})$, $ln(\tilde{\gamma}_{broad})$, and $ln(\frac{\tilde{S}}{\tilde{U}})$ lose meaning but their standard deviations are 1.29, 1.00, and 0.901 based on 182 observations. Consequently, no force for comparative advantage possesses substantially more variance than others.

5 Results

I present two sets of results. First, I present a "restricted" version of the model where the dependent variable is $cov[z, r(z)_{ct}]$. This expression allows me to ask to what degree a country specializes in the production of skill intensive goods due to HO and Ricardian effects. Second, I present "unrestricted" results where the dependent variable is $r(z)_{ct}$. This allows me to gauge the determinants of revenue, industry by industry instead of based on country level covariances. Finally, I present a robustness section to show that the results are insensitive to using IV regression to correct for classical measurement error in the productivity measures, a broader definition of skilled labor abundance, exchange rate volatility, and capacity utilization. I also show that the dynamic correlation of the error terms in the panel regression does not affect the resulting coefficients. In addition, I show that my results are not sensitive to the imposition of the Cobb-Douglas cost shares for the U.S. by obtaining similar results using the skill *rank* of the industry both within the U.S. and within each country.

5.1 Results: Restricted

Recall that the "restricted" regression equation is:

Table 5: Restricted Regression

	Dependent Variable: $cov[r(z), z]$			
	Narrow z		Broad z	
Variables	(1)	(2)	(3)	(4)
$ln(S/U)_T$	0.0109***	0.0115***	0.0174***	0.0175***
	(0.0033)	(0.0025)	(0.0041)	(0.0036)
$ln(\gamma)$		0.0031		0.0033
		(0.0018)		(0.0028)
Obs	182	182	182	182
Time Fixed Effects	yes	yes	yes	yes
R^2	0.3477	0.3996	0.4230	0.4411

*** estimated at the 1% level of certainty, ** estimated at the 5% level of certainty
Robust standard errors clustered by country. Each observation is indexed by country-year.

$$cov[z, r(z)_{ct}] = \beta_0 + \beta_1 \ln\left(\frac{S}{U}\right)_{ct} + \beta_2 \ln(\gamma)_{ct} + \beta_t' T_t + \zeta_{zct} \tag{40}$$

Column (1) of Table 5 tests the hypothesis that the abundance of skilled labor as measured by the proportion of workers with a tertiary education or higher, $(\frac{S}{U})_T$, predicts how skewed productive resources are towards relatively skill intensive industries ($cov[z, r(z)]$). Column (2) includes $ln(\gamma)$ to assess the importance of productivity that is correlated with skill intensity. Columns (3)-(4) do the same except that skilled labor intensity now uses the broad definition of skilled labor. Robust standard errors are clustered by country and presented in parentheses.

I highlight three results. *First*, each column contains the familiar HO result that countries with a relative abundance of skilled labor produce relatively more skilled intensive goods. As before, because the coefficients are reduced form combinations of structural parameters, it is impossible to identify any of these structural parameters. However, I can gauge their plausibility. For example, the estimate from column 1 implies an elasticity of substitution (σ) of 7.1 using the estimate of

Anderson and van Wincoop of $\tau = 1.74$.[32]

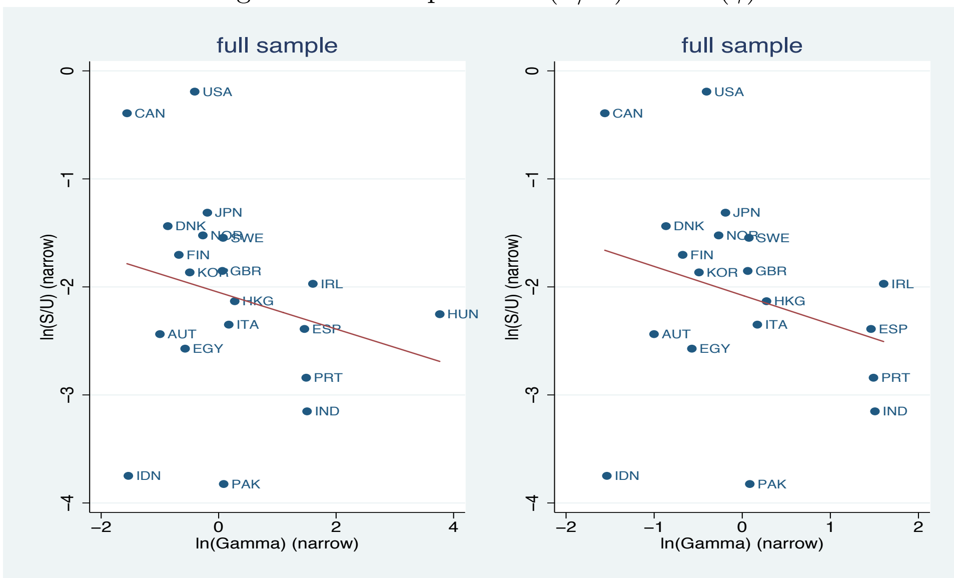
Second, the inclusion of $ln(\gamma)$ does not substantively change the coefficient on $ln(S/U)$. This suggests that skill abundant (or scarce) countries do not have productivity that is systematically higher in skill intensive (or unskilled intensive) industries. *Third*, the coefficient on $ln(\gamma)$ is statistically indistinguishable from zero. This suggests that Ricardian productivity is relatively uncorrelated with skill intensity. This is confirmed by regressing $ln(\gamma)$ on $ln(S/U)$ which yields a coefficient of -0.1935 with a robust standard error of 0.3494 with clustering by country and inclusion of time fixed effects to control for each annual numeraire. Figure 4 presents scatterplots that present the same information graphically. For brevity, it only includes measures of $ln(S/U)$ based on the tertiary measure of skilled labor abundance and measures of $ln(\gamma)$ based on the narrow measure. Because the observation for Hungary is an outlier in the left hand panel, it is excluded in the right hand panel with the same qualitative results. Similar qualitative results hold for the broad measures of each variable. As a whole, these results suggest that TFP that is correlated with factor intensity is unlikely to bias HO results. Consequently, this is one piece of evidence that the Ricardian and HO models are likely to be empirically uncorrelated.

5.2 Results: Unrestricted

Unfortunately, the "restricted" expression says nothing about how Ricardian productivity influences patterns of specialization when relative TFP is uncorrelated with factor intensity. To combat this problem, I use an "unrestricted" expression where observations are indexed country-industry-year. I estimate the following equation where ZT is a vector of industry-time fixed effects and CT is a vector of country-time fixed effects and the standard errors are clustered by country-industry and presented in parentheses. As noted before, ZT controls for all numeraires and CT controls for all country-time effects such as aggregate TFP. Recall that $\epsilon_{A(z)}$ is the component of TFP that is uncorrelated with factor intensity and is purged of country averages.

[32]This can be calculated by evaluating the expression for $-\Gamma$ at $\tilde{p}(z) = 1$, plugging in $\tau = 1.74$, noting that var(z)=0.0106 from table 1, and solving for the σ that is consistent with the coefficient.

Figure 4: Scatterplot of $ln(S/U)$ and $ln(\gamma)$



$$r(z)_{ct} = \beta_0 ln\left(\frac{S}{U}\right)_{ct} z + \beta_1 ln(\gamma)_{ct} z + \beta_2 \epsilon_{A(z),ct} + \beta_{zt}' ZT_{zt} + \beta_{ct}' CT_{ct} + \zeta_{zct} \tag{41}$$

Examining Table 6, I highlight three results. *First*, the coefficient on relative factor abundance is still positive and significant and does not change significantly when productivity measures are included in the regression. These coefficients appear to be larger than those in the restricted regressions. However, in the restricted regressions, $\beta_1 = \kappa\Gamma var(z)$ but in the unrestricted regression $\beta_1 = \kappa\Gamma$. Dividing the coefficient on $zln(S/U)_T$ from Table 5, Column 1 by the variance of z from Table 1 gives a value of 1.0254 which is extremely close to its counterpart in column 1 of the unrestricted regression (1.0870). *Second*, the inclusion of $ln(\gamma)z$ adds very little explanatory power in terms of its significance and effect on the coefficient on $zln(S/U)_T$.

Third, the residual productivity term, $\epsilon_{A(z)}$, is estimated precisely at the 1% level of certainty, is the expected sign, and changes little over different specifications. Following the algorithm as in section 5.1, the coefficients in column 3 imply a value of $\sigma = 6.78$ if calculated off of the coefficient on $ln(S/U)z$ and a value of $\sigma = 9.80$ if it is calculated off of the coefficient on $\epsilon_{A(z)}$. Again, these implied values fall within a reasonable range.

Table 6: Extended Regression

	Dependent Variable: $r(z)$					
	Narrow z			Broad z		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$zln(S/U)_T$	1.0870***		1.2040***	1.0720***		1.0815***
	(0.3817)		(0.3895)	(0.3060)		(0.2980)
$zln(\gamma)$		0.2074	0.3293		0.2915	0.3179
		(0.2194)	(0.2355)		(0.2375)	(0.2354)
$\epsilon_{A(z),ct}$		0.2966***	0.3079***		0.2999***	0.3001***
		(0.0997)	(0.0984)		(0.0997)	(0.0988)
Obs	4063	4063	4063	4063	4063	4063
Country-Time FE	yes	yes	yes	yes	yes	yes
Industry-Time FE	yes	yes	yes	yes	yes	yes
R^2	0.8883	0.8888	0.8917	0.8895	0.8889	0.8926

*** estimated at the 1% level of certainty, ** estimated at the 5% level of certainty
Robust standard errors clustered by country-industry. Each variable is indexed by country-industry-year.

Table 7: Unrestricted Regression (Standardized Coefficients)

Variable	Narrow z		Broad z	
$zln(S/U)_T$	0.1762	0.1952	0.2782	0.2806
$zln(\gamma)$		0.0548		0.0754
$\epsilon_{A(z),ct}$		0.1223		0.1192

This confirms previous findings that Ricardian productivity possesses explanatory power in explaining relative production patterns. However, it offers the new contribution that Ricardian productivity is uncorrelated with factor intensity and explains very little (if any) of why HO results do or do not appear. The forces that determine comparative advantage in the HO model seem to be orthogonal to those that determine comparative advantage in the Ricardian model in my sample. Therefore, it is a reasonable approximation to consider the two models as being separable and equally valid when contributing to production patterns as stated in Proposition 1. Aggregate predictions can then be made by simply aggregating the two models.

Table 7 presents standardized coefficients to assess the relative strength of these forces in determining production patterns. The proposition that a one standard deviation change in relative factor endowments is more potent than a one standard deviation change in industry level relative TFP in determining production patterns continues to hold. It suggests that a one standard deviation increase in relative factor abundance is approximately 1.6 (0.1952/0.1223) to 2.4 (0.2806/0.1192) times more potent than a one standard deviation in Ricardian productivity in a given industry.

5.3 Results: Size of the Coefficients

It is interesting that while theory suggests that the coefficient on factor abundance should be the same size or smaller than that on TFP, the empirical result is that it is substantially larger in all specifications. One plausible explanation is that production is closer to CES than it is to Cobb-

Douglas. Consequently, there will be an omitted variable that captures the effect of a higher S/U on a larger value of z and not just its effect on relative factor prices. If factors are more substitutable than the Cobb-Douglas case, a country will use techniques that produce larger factor shares with respect to their relatively abundant factor.

6 Robustness Checks

I explore the robustness of these results in seven ways in Table 8. First, I use a simple IV regression to consider the role of classical measurement error in the productivity measures. Second, there are many developing countries in my sample that suffer from exchange rate volatility. I drop countries and years for which exchange rate volatility might induce measurement error and show that the results are unchanged. Third, influential work has demonstrated the importance of capacity utilization at the business cycle frequency. Because I am most interested in the cross section, it is not clear that capacity utilization should make a difference but its importance in past studies merits examination. Next, I show that these results are robust to a broader measure of skilled labor abundance. In Table 9, I also show that the dynamic correlation of the error term is sufficiently accounted for by standard clustering of the error terms. Finally, I show that the results are not sensitive to replacing the Cobb-Douglas cost shares with the rank of the cost shares both in the U.S. and in each country. I find that these seven factors affect the results very little, if at all. For parsimony, all robustness checks (except that for secondary educational attainment) use the "narrow" definition of skill intensity although the results do not change substantively when the "broad" measure is used.

I start by using the one year lagged values of $a(z)_{ct}$ and $ln(\gamma_{ct})z$ as instruments for their current values to gauge the importance of classical measurement error in the TFP measures. Column 1 presents these results. The estimated coefficient on $\epsilon_{A(z),ct}$ changes very little from the baseline result suggesting that classical measurement error does not play an important role in the baseline results.

Because some countries are vulnerable to large exchange rate movements, this can induce sub-

Table 8: Robustness Check I

Variable	IV	Exchange Rate		Utilization	Secondary	Secondary	Secondary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$ln(S/U)_T z$	1.2781***	1.0943***	1.2259***	1.2027***			
	(0.3982)	(0.3816)	(0.3877)	(0.3892)			
$ln(S/U)_S z$					0.8451***		0.9315***
					(0.3085)		(0.3049)
$ln(\gamma)z$	0.3516		0.3796			0.2915	0.4541*
	(0.2482)		(0.2357)			(0.2375)	(0.2470)
$ln(\gamma_{util})z$				0.3232			
				(0.2326)			
$\epsilon_{A(z),ct}$	0.3131***		0.3388***			0.2999***	0.3002***
	(0.1081)		(0.1043)			(0.0997)	(0.0992)
$\epsilon_{A(z),util,ct}$				0.3119***			
				(0.0947)			
Obs	3601	3711	3711	4063	4063	4063	4063
Country-Time FE	yes	yes	yes	yes	yes	yes	yes
Industry-Time FE	yes	yes	yes	yes	yes	yes	yes
R^2	0.8911	0.8873	0.8912	0.8919	0.8883	0.8889	0.8919

*** estimated at the 1% level of certainty, ** estimated at the 5% level of certainty
Robust standard errors clustered by country-industry.

stantial measurement error in measures of value added and inputs. Columns 2 and 3 drop all country-year observations in which a country experienced a 20% appreciation or depreciation of their nominal exchange rate in the prior twelve months.[33] The results are unchanged.

Basu (1996) and Basu, Fernald, and Kimball (2006) have shown that incorporating capacity utilization is important for reducing the spurious correlation between output and "productivity" at the business cycle frequency. It is less obvious that it should matter in this context where the cross section is the primary dimension of identification. I use the following proxy for capacity utilization

$$util = \frac{\frac{M_{czt}}{K_{czt}}}{\left(\frac{M_{cz}}{K_{cz}}\right)_{med}} \tag{42}$$

where M is a broad measure of intermediate inputs that is defined as the difference between output and value added. Because the ratio of materials to capital is likely to vary broadly across countries for reasons unrelated to capacity utilization, I divide it by the median value for that country-industry. Therefore, the proper interpretation is that if materials use has increased relative to capital use relative to other years, this can be a signal of an increased workweek of capital and utilization. I then multiply the capital stock of the industry-country-year observation by this value. Column 4 shows that does not change the results.

Columns 5, 6 and 7 measure skilled labor abundance by the relative abundance of workers with at least a secondary education as defined in the Barro and Lee dataset. I use the broad measure of skilled labor intensity because it is closer in comparability than the narrow measure. In column 7, it appears that $ln(\gamma)z$ does possess some explanatory power when included with factor abundance. However, Column 6 shows that this is only when it is conditioned on factor abundance and that its explanatory power falls when it is not conditioned on factor abundance.

The error terms in the panel regressions presented above are undoubtedly correlated. The more substantive question is if the correlation emerges from repeatedly observing a slow moving equilibrium relationship or if the correlation emerges due to a specific dynamic economic structure of the error terms. Generally, if errors are correlated due to a specific dynamic structure of the

[33] All monthly exchange rate data is from IMF's International Financial Statistics Database $ifs.apdi.net/imf/logon.aspx$.

Table 9: Robustness Check II

Variable	1988 (1)	US Rank (2)	US Rank (3)	US Rank (4)	Own Rank (5)	Own Rank (6)	Own Rank (7)
$ln(S/U)_T z$	1.1178*** (0.3638)						
$rankS/U * rankz$		0.0127*** (0.0028)	0.0136*** (0.0031)	0.0113*** (0.0027)	0.0125*** (0.0027)	0.0137*** (0.0031)	0.0115*** (0.0027)
$ln(\gamma)z$	0.1884 (0.2278)						
$(ln(\gamma)z)_{rank}$			0.0349 (0.0467)	0.0096 (0.0497)		0.0468 (0.0511)	0.0130 (0.0527)
$\epsilon_{A(z),ct}$	0.4098*** (0.1253)						
$rank(a(z))$			0.0618*** (0.0197)	0.0630*** (0.0192)		0.0616*** (0.0197)	0.0630*** (0.0192)
Obs	454	4063	4063	454	4063	4063	454
Country-Time FE	yes	yes	yes	yes	yes	yes	yes
Industry-Time FE	yes	yes	yes	no	yes	yes	no
Sample	1988	Full	Full	1988	Full	Full	1988

*** estimated at the 1% level of certainty, ** estimated at the 5% level of certainty
Robust standard errors clustered by country-industry observation

underlying economic model, clustering of the standard errors will yield inconsistent point estimates. The first column of Table 9 explores this question. I show that nearly all of the variation comes from the cross section from the year 1988 and, consequently, this concern is unfounded. I choose this year because it contains the most observations of any single year. The coefficients and standard errors are extremely similar to those in other regressions suggesting that the correlation of the error terms is sufficiently accounted for by clustering of the error terms.[34]

It is obvious that the imposition of a constant z in a given industry is unlikely to be completely true but it is less obvious how severe a bias this introduces. Columns 2-7 in Table 9 address this problem. Columns 2 and 3 replicate Columns 1 and 3 of Table 6 except that they replace all numerical values with their rank. Output is replaced by the rank of output in each country industry after it has been purged of country-year and industry-year fixed effects. Educational attainment is replaced by its rank in that statistic. Each z is replaced by the skill rank of that industry in the United States as measured by the proportion of non-operative wages in total wages in the United Nations General Industrial Statistical Dataset. $a(z)$ is replaced by the TFP rank of that country industry across all countries in that industry in that year after it has been purged of country-year and industry-year fixed effects. γ is created using the above mentioned ranks. Because I am now dealing with rank orderings, OLS is not appropriate and I perform an ordered logit. Although the coefficients are not comparable, the same patterns of magnitude and significance continue to hold. Column 4 performs the same exercise on data from 1988.

Columns 5-7 perform the same exercises as 2-4 except that the skill rank of the industry in the United States is now replaced by the skill rank of the industry in that country as measured by the United Nations General Industrial Statistical Dataset.[35] Consequently, it is less constrained than columns 2-4. However the results do not change.

[34]Nickell (1981) suggests that other methods such as including a lagged endogenous term are likely to introduce more problems than they solve when the time dimension of the sample is sufficiently short. The same criticism applies to a GLS estimation of the system.

[35]Note that we are not comparing industries across countries but industries within a country so that the objection to using the UNGISD data raised in footnote 26 is not valid.

7 Conclusion

The Ricardian and Heckscher-Ohlin (HO) theories are the workhorse models of international trade. Neither model, in isolation, offers a complete description of the data, nor does either model offer a unified theory of international trade. This paper presents a unified framework that nests these two models in determining comparative advantage when there is a continuum of industries if countries differ both in factor abundance and relative TFP patterns across industries. In addition, the model's tractability allows me to estimate it easily and to assess the relative contributions of HO and Ricardian forces. I highlight two results.

First, both the Ricardian and HO models possess robust explanatory power in determining international patterns of production. However, I find that a one standard deviation change in relative factor abundance is 1.6 to 2.4 times as potent in changing the structure of an industry in an economy as a one standard deviation change in the relative productivity of that industry. Second, these two models are separable in the sense that the forces that determine comparative advantage in one are orthogonal to the forces that determine comparative advantage in the other in my broad sample. Although the first result has been documented in past reduced form estimation, my paper is the first to do so based on a unified structural model where the estimated coefficients can be mapped against structural parameters. More importantly, this suggests conditions under which the two models are orthogonal in that Ricardian TFP differences do not cause or prevent HO effects in the data. The second result is new and provides substantial insight into how we can combine these important models.

If TFP is distributed orthogonally to factor intensity, it is reasonable to model productivity using two components: a country specific term that is neutral across industries and an idiosyncratic component that is orthogonal to factor intensities. Simply examining if relative TFP is relatively more positively or negatively correlated with factor intensity in countries that possess a relative abundance of that factor is a good starting point for assessing if this is likely to be a reasonable assumption.

If TFP is orthogonal to factor intensity, HO is empirically valid as a partial description of the data and the standard comparative statics associated with the HO model are valid (e.g. Rybczynski regressions). In addition, if TFP is uncorrelated with factor intensity, HOV predictions will not be biased by differences in relative Ricardian TFP across industries. However, even if TFP is uncorrelated with factor intensity, industry-by-industry predictions must take Ricardian differences into account.

The key to nesting the alternate hypotheses is decomposing industry level TFP differences into three components: country level productivity that is neutral across industries, productivity that is correlated with factor intensity, and productivity that varies across industries but is orthogonal to factor intensity. If one is trying to make industry by industry predictions, HO models will be misspecified if they omit TFP differences even if TFP is uncorrelated with factor intensity. However, if one is trying to identify coefficients such as those that occur in Rybczynski regressions, this will be a valid exercise if TFP is uncorrelated with factor intensity but not if TFP is correlated with factor intensity. Although I find that TFP is uncorrelated with factor intensity in my sample, the obvious caveat applies that such a (zero) correlation is ultimately an empirical question that depends on the data set.

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A Relative Number of Firms

Romalis (2004) (equation 14) solves for the relative number of firms/varieties produced in the North relative to the South in a given industry z. He starts with the fact that firms' income in the North and South equal revenue from Northern and Southern consumers as reflected in the below equations:

$$p(z)x(z) = \frac{1}{2}\left(\frac{p(z)}{P(z)}\right)^{1-\sigma} Y + \frac{1}{2}\left(\frac{p(z)\tau}{P^*(z)}\right)^{1-\sigma} Y^*$$

$$p^*(z)x^*(z) = \frac{1}{2}\left(\frac{p(z)^*\tau}{P(z)}\right)^{1-\sigma} Y + \frac{1}{2}\left(\frac{p^*(z)}{P^*(z)}\right)^{1-\sigma} Y^*$$

Using the fact that $P(z)^{1-\sigma} = n(z)p(z)^{1-\sigma} + n^*(z)\left(p^*(z)\tau\right)^{1-\sigma}$ and that an analogous expression holds for $P^*(z)$, we can solve for $\tilde{n}(z) = \frac{n(z)}{n^*(z)}$:

$$\tilde{n} = \frac{\tau^{2(1-\sigma)}\frac{Y^*}{Y} + 1 - \tau^{1-\sigma}\tilde{p}^{\sigma}(\frac{Y^*}{Y} + 1)}{\tilde{p}(\tau^{2(1-\sigma)} + \frac{Y^*}{Y}) - \tilde{p}^{1-\sigma}\tau^{1-\sigma}(\frac{Y^*}{Y} + 1)}. \tag{43}$$

Romalis emphasizes that the above expression is not guaranteed to be positive. When it is positive, intra-industry trade exists, otherwise specialization occurs with only one country producing in the industry. I examine the case of intra-industry trade in this paper. A necessary and sufficient condition for this to hold is that $\tilde{p}(z)_{lower} < \tilde{p}(z) < \tilde{p}(z)_{upper}$ where

$$\tilde{p}_{upper} = \left[\frac{\tau^{2(1-\sigma)}\frac{Y^*}{Y} + 1}{\tau^{1-\sigma}\left(\frac{Y^*}{Y} + 1\right)}\right]^{\frac{1}{\sigma}} > 1 \tag{44}$$

$$\tilde{p}_{lower} = \left[\frac{\tau^{1-\sigma}(\frac{Y^*}{Y} + 1)}{\tau^{2(1-\sigma)} + \frac{Y^*}{Y}}\right]^{\frac{1}{\sigma}}. \tag{45}$$

Romalis also shows how to prove that the derivative of the number of firms with respect to relative prices is negative. For a more in depth discussion of this, the interested reader is directed to the Technical Appendix of Romalis (2004). Dropping the z notation, recall that the derivative is as follows:

$$\frac{d\tilde{R}(\tilde{p})}{d\ln(\tilde{p})(z)} = \frac{-\sigma\tau^{1-\sigma}\left(\frac{1-\pi}{\pi} + 1\right)\left[\tilde{p}_0^{\sigma}\left(\tau^{2(1-\sigma)} + \frac{1-\pi}{\pi}\right) - 2\tau^{1-\sigma}\left(\frac{1-\pi}{\pi} + 1\right) + \tilde{p}_0^{-\sigma}\left(\tau^{2(1-\sigma)}\frac{1-\pi}{\pi} + 1\right)\right]}{\tilde{p}_0\left[\tau^{2(1-\sigma)} + \frac{1-\pi}{\pi} - \tilde{p}_0^{-\sigma}\tau^{1-\sigma}\left(\frac{1-\pi}{\pi} + 1\right)\right]^2}$$

B Derivation of Goods Market Clearing Condition

To show that the goods market clearing condition is downward sloping in $\tilde{\omega} - V$ space, I simply show that if $\omega < \omega^*$, then $V > V^*$. Start by noting that $V > V^*$ if and only if $\tilde{R}(z_s) > \tilde{R}(z_u)$. Therefore, It is sufficient to show that if $\omega < \omega^*$, then $\tilde{R}(z_s) > \tilde{R}(z_u)$ or simply that $\tilde{R}(z)$ is increasing in z if and only if $\omega < \omega^*$. Taking the derivative of $\tilde{R}(z)$ with respect to z yields the following expression

$$\frac{\partial \tilde{R}(z)}{\partial z} = \frac{-\sigma\tau^{1-\sigma}\left(\frac{Y^*}{Y}+1\right)\left[\tilde{p}(z)^{sigma}\left(\tau^{2(1-\sigma)}+\frac{Y^*}{Y}\right)-2\tau^{1-\sigma}\left(\frac{Y^*}{Y}+1\right)+\tilde{p}(z)^{sigma}\left(\tau^{2(1-\sigma)}\frac{Y^*}{Y}+1\right)\right]}{\tilde{p}(z)\left[\tau^{2(1-\sigma)}+\frac{Y^*}{Y}-\tau^{1-\sigma}\tilde{p}(z)^{-\sigma}\left(\frac{Y^*}{Y}+1\right)\right]} ln(\tilde{\omega})\tilde{p}(z)$$

Note that the large fraction is unambiguously negative as noted in Appendix A and Romalis (2004), therefore $\tilde{R}(z)$ is increasing in z if and only if $\omega < \omega^*$.

C Proof of Proposition 1

Proposition 1 If productivity is uncorrelated with factor intensity and the relative abundance of factors differs among countries, then the relative wage of a country's abundant factor will be less than in the country where it is a relatively scarce factor. In addition, $cov[v(z), z] > 0$ where z is the Cobb-Douglas cost share of its relatively abundant factor and $cov[v(z'), z'] < 0$ where z' is the Cobb-Douglas cost share of its relatively scarce factor.

Proof of Proposition 1: This is a proof by contradiction. Without loss of generality, assume that the North has a relative abundance of skilled labor such that $\frac{S}{U} > \frac{S^*}{U^*}$ and that productivity is uncorrelated with factor intensity so that $\tilde{\gamma} = 1$. Suppose that the relative wage of skilled labor is lower in the South than in the North ($\tilde{\omega} > 1$). By equation, 21, $cov[z, v(z)] < 0$. Applying this to equation 27, this implies that the relative wage of skilled labor in the North is lower than in the South ($\tilde{\omega} < 1$) which is a contradiction. Now suppose that the relative wage of skilled labor is the same in the North and South such that $\tilde{\omega} = 1$. By equation 21, $cov[z, v(z)] = 0$. Applying this to equation, 27, this implies that $\tilde{\omega} < 1$ which is a contradiction. Therefore, $\tilde{\omega} < 1$ and, by equation 21, $cov[z, v(z)] > 0$. The production structure of the South follows trivially from the fact that $cov[z, v(z)] > 0$ and the covariance of Southern production with skill intensity is $cov[z,(1 - v(z))] = -cov[z, v(z)]$.

D Data Appendix: Sample

See Table 10.

E Data Appendix: Calculating the Cobb-Douglas Cost Share of Skilled Labor

I calculate Cobb-Douglas factor cost shares of the total wage bill for skilled and unskilled labor. Suppose that s indexes the different types of skilled labor. For any level of skill s, its Cobb-Douglas factor cost share of wage will be:

$$z_s = \frac{w_s L_s}{\sum_{s'} w_{s'} L_{s'}} \tag{46}$$

To calculate this value, I estimate a Mincerian wage regression of the form

$$ln(w_{it}) = \beta_0 + \beta_1 age_{it} + \beta_2 age_{it}^2 + \beta'_{edu} EDU_{it} + \beta' T_{it} + \epsilon_{it} \tag{47}$$

Table 10: Sample

Country	Years Available	Obs	Country	Years Available	Obs
Austria	1985-1994	239	Ireland	1985-1991	154
Canada	1985-1990	138	Italy	1985-1994	190
Denmark	1985-1991	168	Japan	1985-1995	264
Egypt	1985-1995	247	Korea	1985-1995	264
Finland	1985-1995	261	Norway	1985-1995	246
Great Britain	1985-1992	192	Pakistan	1985-1988	96
Hong Kong	1985-1995	189	Portugal	1985-1989	120
Hungary	1985-1993	216	Spain	1985-1995	176
Indonesia	1985-1995	242	Sweden	1985-1990	138
India	1985-1995	264	United States	1985-1995	264

Table 11: Sample by Year

Year	Observations	Year	Observations
1985	451	1991	359
1986	452	1992	312
1987	451	1993	282
1988	454	1994	257
1989	430	1995	210
1990	405		

w is the hourly wage based on data on income, weeks worked, and average work week. Age is the age of the worker. EDU_{it} is a vector of dummy variables indicating education attainment of different levels. T is a series of time fixed effects. All data comes from the March U.S. Current Population Surveys for the years 1988-1992. The regression itself is run on data that is pooled over industries and years. The data is available for download from $http://www.ipums.umn.edu/usa/data.html$.Wage and salary income is $incwage$. Weeks worked is $wkswork1$. Average work week is $uhrswork1$. Age is age. The variable $educrec$ indicates the highest education level of the worker in the survey. The levels of educational attainment indicated are:

- None of Preschool
- Grades 1-4
- Grades 5-8
- Grade 9
- Grade 10
- Grade 11
- Grade 12
- 1-3 years of college
- 4 or more years of college

When running the wage regression, a vector of coefficients will be returned that give the skill premium for different levels of educational attainment. Because they are dummy variables, they will state the wage of a person of that educational attainment relative to the omitted level. I use the variable $educrec$ and define four types of labor: 0-11 grades of school completed, 12th grade completed, 1-3 years of college, and 4 or more years of college). Applying this to the definition of z given above, this is equivalent to dividing the numerator and denominator by a given (omitted) wage level:

$$z_{s''} = \frac{\frac{w_{s''}}{w_s} L_{s''}}{\sum_{s' \neq s} \frac{w_{s'}}{w_s} L_{s'} + L_s} \tag{48}$$

By dividing through by a numeraire wage, the physical workers are converted to effective workers. Although this will be invariant to the omitted skill level, I do need to take a stand on what comprises skilled and unskilled labor. Suppose that the factor share of "skilled labor" is the sum of the factor shares of the types of labor deemed to be skilled:

$$z_{skill} = \sum_{s \in skilled} z_s \tag{49}$$

Unfortunately, there must still be an arbitrary cut between "skilled" and "unskilled" labor in order to retain the two-factor model. Having a spectrum of skilled labor is desirable but it makes relative abundances of skilled labor more difficult to define. I use two measures of skilled labor: a "narrow" measure that only counts those in the final category as skilled labor and a "broad"

Table 12: Wage Regression Coefficients

Dependent Variable	
Age	0.0636^{***}
	(0.0010)
Age^2	-0.0006^{***}
	(0.00001)
$edu_{highschool,it}$	0.2939^{***}
	(0.0001)
$edu_{1-3years,it}$	0.4755^{***}
	(0.0071)
$edu_{4+years,it}$	0.8128^{***}
	(0.0074)
Time Fixed Effects	Yes
Observations	65,853
$\overline{R}^2$	0.2625

measure for those who have any college and fall into the last two groups. If I divide the numerator and denominator by the amount of total labor employed in a industry and define $\alpha_s = \frac{L_s}{L_{total}}$, the skilled labor share is:

$$z_{s''} = \frac{\frac{w_{s''}}{w_s}\alpha_{s''}}{\sum_{s' \neq s} \frac{w_{s'}}{w_s}\alpha_{s'} + \alpha_s} \tag{50}$$

Therefore, I can calculate skilled labor intensity using data on the proportion of workers in a given industry of differing education levels and the coefficients from the wage regression. I use pooled data from the years 1988-1992 for the regression and obtain the following regression coefficients:

The below table shows the proportion of different types of workers employed in different ISIC industries $\frac{L_s}{L_{total}}$. The last three columns sum to 100 to reflect that of this survey all workers fall into one of the three groups. The CPS industry classifications are mapped against the ISIC classifications based on verbal definitions that are available on my website.

F Country Level Covariances

See Table 14.

Table 13: Shares of Employment for Different Categories of Workers

Industry	Obs.	High School or Less	Some College	4+ Years of College
311	5763	0.7336	0.1706	0.0958
313	664	0.5482	0.2063	0.2455
321	3059	0.7980	0.1272	0.0749
322	3369	0.8341	0.1098	0.0561
323	57	0.7719	0.1579	0.0702
324	544	0.8033	0.1048	0.0919
331	1891	0.7573	0.1618	0.0809
332	2118	0.7771	0.1454	0.0774
341	2358	0.6518	0.2120	0.1361
342	6132	0.5011	0.2456	0.2533
351	1910	0.4346	0.2529	0.3126
352	1863	0.4600	0.2061	0.3339
355	752	0.6529	0.2247	0.1223
356	2316	0.7029	0.1770	0.1200
361	163	0.6135	0.2515	0.1350
362	573	0.6841	0.2024	0.1134
369	1208	0.7235	0.1540	0.1225
371	1388	0.6981	0.2089	0.0929
372	1012	0.6808	0.1986	0.1206
381	3911	0.6883	0.2012	0.1105
382	3179	0.6241	0.2425	0.1334
383	10699	0.5009	0.2429	0.2562
384	7501	0.5529	0.2510	0.1961
385	2225	0.4935	0.2458	0.2607

Table 14: Country Level Covariances

Country	Cov (narrow)	Cov (broad)	Country	Cov (narrow)	Cov (broad)
Austria	0.0183	0.0206	Ireland	0.0366	0.0438
Canada	0.0267	0.0436	Italy	-0.0006	0.0059
Denmark	0.0450	0.0500	Japan	0.0421	0.0605
Egypt	0.0252	0.0258	Korea	0.0152	0.0166
Finland	0.0278	0.0383	Norway	0.0425	0.0636
Great Britain	0.0397	0.0508	Pakistan	0.0245	0.0206
Hong Kong	0.0300	0.0356	Portugal	0.0031	-0.0051
Hungary	0.0262	0.0309	Spain	0.0334	0.0246
Indonesia	-0.0070	-0.0165	Sweden	0.0473	0.0713
India	0.0381	0.0464	United States	0.0520	0.0659

G Data Appendix: Deflators from the Penn World Tables Disaggregated Benchmark Data

I use the Penn World Tables benchmark data to deflate value added across countries. This is obviously not a first best outcome but it represents a substantial improvement on the literature. The benchmark data is available at *http://pwt.econ.upenn.edu/Downloads/benchmark/benchmark.html*. This data was collected by examining very narrowly defined goods across a number of countries with specific attention paid to the quality of goods across countries. See Kravis, Heston and Summers (1982) for a thorough explanation of the process of creating the price indexes. Because of substantially finer disaggregation across goods, I use the benchmark data from 1985 instead of 1996. I also use the 1980 data to fill in missing observations for Indonesia. I also assume that all prices increase at the same rate as the PPP GDP price deflator which allows me to fill in observations for other years. Because all country-year level price differences are differenced out through the use of logs, this filling in of the interim years assumes that the relative prices across industries in a country in 1985 (and 1980 in Indonesia) persist throughout the sample.

As noted in Harrigan (1997b), these measures are subject to the following criticisms as to why they might not truly reflect country-industry level deflators. First, these prices include import prices and exclude export prices. Second, these prices include transport and distribution margins. Third, they include indirect taxes and exclude subsidies. Finally, fourth, these prices only refer to final output and not intermediate goods. For these reasons, these deflators should only be taken as approximations to actual deflators. For this reason, he constructs actual deflators from the OECD national accounts data. Because of the severe limitations that this places on the data, I choose to use the ICP data and compare my results to his. As shown in Table 5, this appears to be a reasonable approximation.

The original data was collected via the United Nations International Comparison Programme (ICP) classification level which is available at *http://unstats.un.org/unsd/methods/icp/ipc8_htm.htm*. Because there is no clean concordance between this classification and the ISIC classification used in the Trade and Production dataset, I created a concordance that is available on my website. The only departures from this process were Iron and Steel (ISIC 371) and Non-Ferrous Metals (ISIC 372). These goods have no convenient analog in the ICP project and they are relatively homogenous and highly traded. Therefore, I assume that the appropriate cross country deflator for these industries is unity.

Unlike other authors (e.g. Dollar and Wolff), I do not use the country level PPP price levels because this is highly influenced by the non-traded industries. This will lead to output being deflated "too much" in poor countries which will understate their productivity levels. In addition, even if a researcher possesses a PPP deflator for traded goods, there is substantial heterogeneity in the PPP price deflator across ICP industries. A simple fixed effects regression of all logged PPP deflators across industries and countries on a series of country level fixed effects only captures 35% of the variation in estimations that I have carried out.

H Data Appendix: Effective Labor

The employment measure L does not differentiate between skilled and unskilled labor. However, I follow Caselli (2005) and Bils and Klenow (2002) and use educational attainment and wage premium data to construct measures of the effectiveness of labor. The most basic specification would be a log-linear structure in which the effectiveness of a measured unit of labor (E) is affected by years of schooling (s) according to the semi-elasticity ϕ.

$$ln(E) = \phi_0 + \phi_1 s \tag{51}$$

The parameter ϕ_1 is taken to be the coefficient on years of schooling in a Mincerian wage regression. However, country level data on ϕ are likely to be incomparable for two reasons. First, the samples from which these estimates are drawn might differ even controlling for the level of development in the country. Secondly, even if the economic relationship is stable across countries, ϕ_1 is likely to be higher for less developed countries due to the relative paucity of skilled workers. This is confirmed by examining the data presented in Psacharopoulos (1994). For this reason, I follow Casellli (2005) and assume that each additional year of education makes a worker 13% more effective for the first four years of schooling, 10% for years 4-8, and 7% a year after that. In addition to having published data on the educational attainment rates for different levels of education, Barro and Lee also possess average years of schooling. This data is available at $http://www.cid.harvard.edu/ciddata/ciddata.html$.

I Data Appendix: Capital Stock Calculation

Capital is calculated using the perpetual inventory method where investment is deflated across countries using the Penn World Tables PPP investment price deflator and the United States implicit price deflator for non-residential investment from the Bureau of Economic Analysis to achieve comparability across time.

To attain the least sensitivity, I merge the Trade and Production dataset with the United Nations General Industrial Statistical Dataset used by Berman, Bound and Machin (1998). All data begins in 1976 for the Trade and Production dataset, however, merging it with the UNGISD database gives earlier initial years. The following data gives the average initial capital stock remaining in 1985 (from its initial year) and the initial year from which the capital stock calculations is made (t_0): Austria (0.238,1967), Canada (0.106,1967), Denmark (0.114,1967), Egypt (0.044,1967), Finland (0.067,1967), Great Britain (0.151,1968), Hong Kong (0.22,1973), Hungary (0.140,1970), Indonesia (0.199,1970), India (0.279,1977), Ireland (0.124,1969), Italy (0.084,1967), Japan (0.106,1967), South Korea (0.019,1967), Norway (0.114,1967), Pakistan (0.61,1976), Portugal (0.151,1971), Spain (0.10,1967), Sweden (0.126,1967), United States (0.010,1967). Initial Capital stock is calculated as follows:

$$K(z)_{c,t_0} = \frac{I_{cz,t_0}}{\delta + g} \tag{52}$$

where g is the median growth of gross investment over the available sample for a country and $\delta = 0.125$.[36] Starting from this point, I calculate the capital stock as the sum of flow investment net depreciation as below.

$$K(z)_{c,t+1} = (1 - \delta)K(z)_{c,t} + I(z)_{c,t} \tag{53}$$

[36]This is similar to the approach taken by Hall and Jones (1998). In some cases, the growth rate of the gross investment over the sample was negative enough to result in estimates of the starting value of the capital stock being negative. In these cases, I set $g = 0$