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Ricardian-Heckscher-Ohlin Comparative Advantage: Theory and Evidence

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Abstract

This paper derives and estimates a unified and tractable model of comparative advantage due to differences in both factor abundance and relative productivity differences across industries. It derives conditions under which ignoring one force for comparative advantage biases empirical tests of the other. I emphasize two empirical results: First, factor abundance- and relative productivity-based models each possess explanatory power when nesting the other as an alternate hypothesis. Second, productivity differences across industries do not bias tests of the HO model in my sample. However, I find weak and mixed evidence that Heckscher-Ohlin forces can potentially bias tests of the Ricardian model.

JEL Codes: F10, F11, F12.
Keywords: Heckscher-Ohlin, Ricardian, Increasing Returns to Scale, Omitted Variable Bias.

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1 Introduction

Production patterns around the world exhibit tremendous heterogeneity and specialization. For example, the United States supplies 35.0% of the world's exports of aircraft while China provides only 0.1%. In contrast, China supplies 25.8% of the world's export supply of apparel and clothing while the United States only supplies 2.4%.[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). 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. Specifically, Heckscher-Ohlin predicts that countries will produce relatively more of the goods that use their relatively abundant factors relatively intensively. Neither model, in isolation, offers a unified theory as to why production patterns differ across countries and industries. Consequently, empirical tests of each model can be subject to omitted variable biases associated with ignoring the other.

Such a bias can emerge if countries that possess 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 seeking 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.[2] Thus, if the mechanisms in his model are pervasive in the data, economists will tend to confound the HO and Ricardian models when one is tested without the other as a meaningful alternate hypothesis. Simply put, it is possible that skilled labor-abundant countries will produce skilled labor-intensive goods both because of their relative abundance of skilled labor and high TFP in skilled labor intensive sectors.[3] There is anecdotal support for this idea. Although they do not examine productivity growth in

[1] Data taken from "World Trade Flows" bilateral trade data compiled by Robert Feenstra et al. (2005) for the year 2000. Aircraft is SITC code 792 and Clothing and Apparel is SITC code 84.

[2] However, he also shows that all predictions about *relative* TFP across sectors depend crucially on the existence of frictions in the international propagation of technology.

[3] This possibility has also been the subject of conjecture by authors such as Fitzgerald and Hallak (2004), although the modeling techniques have not been developed for empirical examination.

other countries, 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.[4]

This paper articulates a unified and tractable framework 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 can use traditional estimation techniques to separate out patterns of comparative advantage into those driven by Ricardian forces and those driven by HO. I also derive a condition under which tests of the HO model will not suffer from an omitted variable bias if they ignore Ricardian TFP differences.

Empirically, I estimate the model using panel data across 20 developed and developing countries, 24 manufacturing industries, and 11 years (1985-1995). The most binding constraint in assembling this data set is the availability of a continuous time series for investment necessary for creation of capital stock that is used for the creation of the TFP measures.

I highlight three important findings. First, both the Ricardian and HO models possess robust explanatory power in determining international patterns of production. Although this has been documented in past work, this is the first to model production and demand in a jointly HO/Ricardian setting where reduced-form coefficients can be mapped against structural parameters such as the elasticity of substitution or iceberg transportation costs.

Second, Ricardian productivity differences do not bias tests of the HO model in my data. Specifically, while both productivity differences and the interaction of factor abundance with factor intensity play a role in determining international specialization patterns, I find little evidence that relative productivity levels are systematically higher or lower for skilled labor abundant countries

[4]e.g. Bowen, Leamer and Sveikauskas (1987). While I do not offer a model of why TFP might be higher in unskilled labor intensive sectors for skilled labor abundant countries, one can imagine such a mechanism. For example, if labor saving technology is biased towards a country's relatively expensive (scarce) factor, this can deliver the result. Another mechanism would be if technological innovation is spurred by more stringent import competition at the industry level.

in skilled labor intensive sectors. This suggests that productivity levels that are non-neutral across industries have little influence over whether results consistent with HO appear in the data once country level productivity differences that do not vary across industries are taken into account. However, I find weak and mixed evidence that omission of HO forces can bias empirical tests of the Ricardian model.

Third, I find that a one standard deviation increase in relative factor abundance is approximately twice 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 second and third results are new and provide substantial insight into how we can integrate these two important models.

The key to nesting the Ricardian alternate hypotheses involves 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 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.

An important theoretical contribution of this paper is that when TFP is relatively uncorrelated with factor intensity, HO is valid as a partial description of the data. However, more complete industry-by-industry *level* predictions must take Ricardian differences into account. Examining if relative TFP is correlated with factor intensity in other data sets will suggest whether this orthogonality assumption is valid in other cases.

1.1 Relation to the Literature

This paper is related to two distinct strands of literature on the empirical determinants of specialization and trade and their occasional intermingling. The first strand documents the influence of Ricardian TFP on international production patterns. MacDougall (1951,1952) finds early evidence for 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.[5] The second related strand of literature documents the importance of factor abundance and includes Leontief (1954), Baldwin (1971), Davis and Weinstein (1999), Debaere (2003), and Romalis (2004).[6]

This is far from the first paper to examine empirically the interaction of productivity- and HO-based models. However, many prior explorations have been more concerned with improving the fit of the HO/HOV model than with considering the Ricardian hypothesis on its own merits. For example, Trefler (1993) shows how factor-augmenting technology differences can improve the fit of the HOV model by improving measurements of factor abundance.[7] Trefler (1995) shows how country-specific productivity differences can dramatically improve the results of the HOV model. However, because TFP differences in that paper are country-wide, they are not of the Ricardian nature that I examine here.

Harrigan (1997) is the closest antecedent to this paper. He examines the contributions of TFP and factor abundance in determining specialization. He does not examine the conditions under which the omission of Ricardian technology introduces systematic biases in tests of the HO model.[8] This paper contributes to the literature by deriving a condition under which ignoring one force for

[5]A limitation of this paper is that models based on Eaton and Kortum (2002) do not readily admit HO forces into their framework and, consequently, I work with a simple two country model that readily admits both HO and Ricardian forces as opposed to working with a formal multi-country model.

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

[7]Trefler concedes that it is difficult to untangle pure productivity effects from alternate hypotheses such as that the capital-labor ratio varies across countries (pg. 979-980).

[8]Rather, referring to HO and productivity based forces, he states “these forces must be considered jointly when formulating policies intended to affect the structure of production and trade. (pg. 492)” This implies that omitting consideration of one of these models when examining the other produces results that are incorrect at best or misleading at worst.

comparative advantage will or will not bias empirical tests of the other and finds that this condition holds empirically in the data set examined.

Earlier theoretical work on integrating HO and Ricardian models of comparative advantage includes 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. Bernard, Schott and Redding (2006) use Melitz's (2003) model of firm TFP heterogeneity with factor abundance differences to derive results consistent with the HO theorem.[9]

The paper is organized as follows. Section 2 sketches a simple two industry, two country, two factor version of the model. Section 3 extends the framework to a continuum of industries and derives empirically testable expressions. Section 4 describes the data and the construction of the total factor productivity measures used in the paper. Section 5 presents the baseline results. Section 6 presents robustness tests, and Section 7 concludes.

2 Theory: A Simple 2x2x2 Model

I first sketch a simple two country, two factor, two industry model to illustrate the insights of the more general model of Section 3. My model augments the quasi-Heckscher-Ohlin structure of Romalis (2004) with Ricardian TFP differences. This simple model uses two equilibrium conditions to extract the separate contributions of productivity and factor abundance on relative production patterns across industries in a country. 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 each of the two factors. I then illustrate conditions under which Ricardian productivity differences can introduce substantial biases in empirical tests of the HO model.

[9] Their model focuses on the case where firms take productivity draws from the same distribution across industries. Consequently, any differences in average TFP across industries and countries are only endogenous responses to exogenous differences in factor abundance.

2.1 Production

The two factors of production are skilled labor (S) and unskilled labor (U). The wages of these two factors are w_s and w_u, respectively. Let $\omega \equiv \frac{w_s}{w_u}$. For simplicity, define the two countries as the North and the South. All Southern values are indicated by asterisks.

The two industries are indexed by their Cobb-Douglas skilled labor factor cost shares, $0 < z < 1$. z_s is the skilled labor cost share of the skilled labor intensive good and z_u is the skilled labor cost share of the unskilled labor intensive good. Consequently, z is both a parameter and an index of industries. Without loss of generality, assume that $z_s > z_u$. Hicks neutral TFP ($A(z)$) augments skilled and unskilled labor in production of a final good ($x(z)$) and coverage of fixed costs 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 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, $x(z) = \frac{\rho f(z)}{1-\rho}$. Assume that the elasticity of substitution and physical fixed costs do not vary across 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 indicated by 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

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 I completely loosen this assumption in the more general section, the expenditure share for each industry is constant and equal to 0.5. Each firm produces a unique imperfectly substitutable variety so that "firms" and "varieties" are synonymous. For a given industry z, $n(z)$ is the endogenously determined number of Northern firms. The total number of firms in a given industry is $N(z) = n(z) + n^*(z)$ where i indexes 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 $\tau > 1$. Romalis (2004) shows that the number of Northern (relative to Southern) firms can then be expressed as

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

where Y is total income in the North. Because output per firm is pinned down, aggregate Northern revenue relative to aggregate Southern revenue in industry z is

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

Romalis (2004) derives restrictions on $\tilde{p}(z)$ that provide necessary and sufficient conditions for $\tilde{R}(z) > 0$ and I assume that these conditions hold such that both the North and South produce in a given industry.[10] Romalis (2004) shows that both the relative number of firms and the relative aggregate revenue for the North are declining in the Northern price such that $\frac{\partial \tilde{n}}{\partial \tilde{p}} < 0$ and it is easily shown that

$$\frac{\partial \tilde{R}(\tilde{p}(z))}{\partial ln(\tilde{p}(z))} = \Gamma(\tilde{p}(z)) = \frac{-\sigma\tau^{1-\sigma}\left(\frac{Y^*}{Y}+1\right)\left[\tilde{p}(z)^{\sigma}\left(\tau^{2(1-\sigma)}+\frac{Y^*}{Y}\right)-2\tau^{1-\sigma}\left(\frac{Y^*}{Y}+1\right)+\tilde{p}(z)^{-\sigma}\left(\tau^{2(1-\sigma)}\frac{Y^*}{Y}+1\right)\right]}{\left[\tau^{2(1-\sigma)}+\frac{Y^*}{Y}-\tilde{p}(z)^{-\sigma}\tau^{1-\sigma}\left(\frac{Y^*}{Y}+1\right)\right]^2} < 0. \tag{8}$$

Consequently, the Northern share of revenue in industry $v(z)$ is also decreasing in $\tilde{p}(z)$ where $v(z) = \frac{R(z)}{R(z)+R^*(z)} = \frac{\tilde{R}(z)}{\tilde{R}(z)+1}$.

2.3 Equilibrium

To illlustrate the equilibrium, I start by deriving the *goods market clearing condition.* Factor price equalization fails due to transportation costs in this two country setting. Starting with the simple case where comparative advantage only comes from differences in factor abundance, 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 A shows this rigorously and Figure 1 depicts it graphically with the line DD.

A set of *factor market clearing conditions* close 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 unskilled labor in the North is

$$\frac{0.5\sum_{k\in s,u} v(z_k) z_k Y^w}{0.5\sum_{k\in s,u} v(z_k)(1-z_k)Y^w} = \frac{w_s}{w_u}\frac{S}{U} = \omega\frac{S}{U}. \tag{9}$$

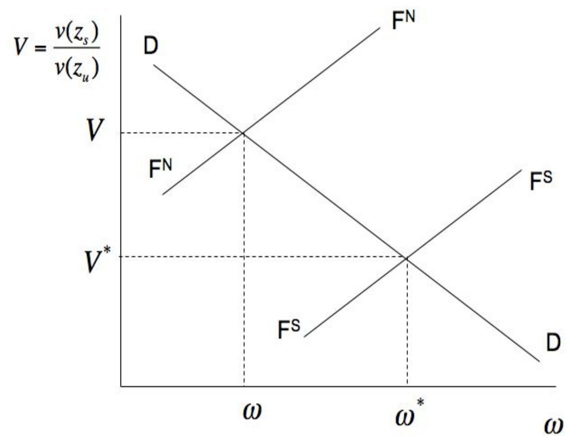
Simple manipulation gives

$$\frac{z_u + \frac{v(z_s)}{v(z_u)} z_s}{(1-z_u) + \frac{v(z_s)}{v(z_u)}(1-z_s)} = \omega\frac{S}{U}. \tag{10}$$

Define $V = \frac{v(z_s)}{v(z_u)}$ as a measure of specialization using the market share for the skilled labor-intensive

[10] The intuition for the model is unchanged when allowing for specialization although solving for equilibrium production patterns becomes more complex. Econometrically, it would involve introducing a selection equation as in Helpman, Melitz, and Rubinstein (2008) although finding econometrically valid first-stage instruments in extremely difficult for industry-by-industry observations.

Figure 1: Equilibrium: Heckscher-Ohlin Model



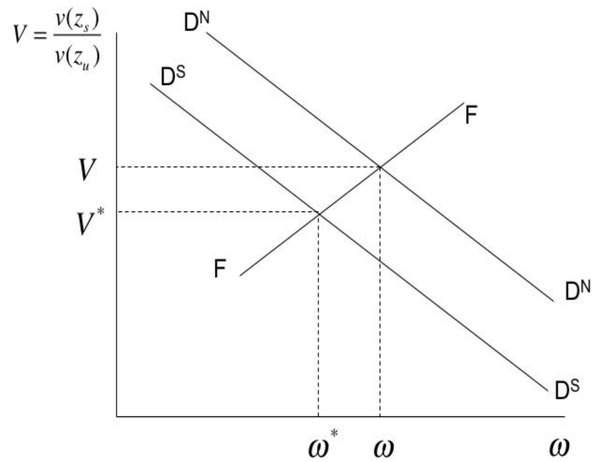
good relative to the market share of the unskilled labor-intensive good. Taking a total derivative of the above expression holding $\frac{S}{U}$ constant gives

$$\Omega d\frac{v(z_s)}{v(z_u)} = \Omega dV = \frac{S}{U}d\omega \tag{11}$$

where $\Omega = \frac{z_s - z_u}{\left[1-z_u+\frac{v(z_s)}{v(z_u)}(1-z_s)\right]^2} > 0$. Because $z_s > z_u$, the relative wage of the factor used relatively intensively in an industry will increase as productive factors are reallocated to that industry. Examining Figure 1, $F^N F^N$ is the factor market clearing condition for the Northern country and 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 10. 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 while the South relatively more of the unskilled labor intensive good.

Figure 2 illustrates a simple Ricardian model. Suppose that the North possesses the same factor endowments as the South but possesses TFP that is relatively higher in the skilled labor intensive sector than the unskilled labor intensive sector ($\tilde{\gamma} > 1$). If this pattern holds, the Northern goods

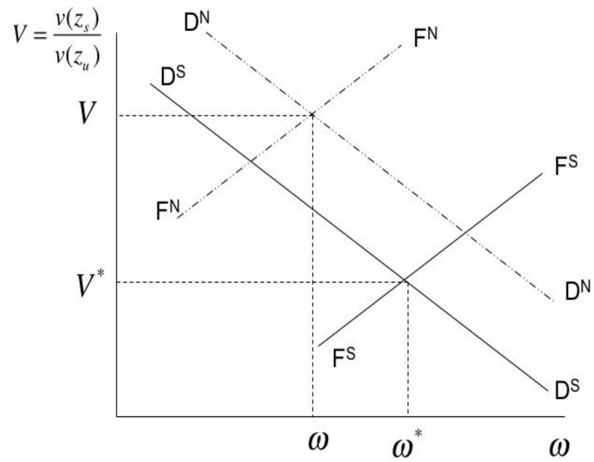
Figure 2: Equilibrium: Ricardian Model



market clearing condition $D^N D^N$ will be above and to the right of the goods market clearing condition for the South, $D^S D^S$. The fact that $D^N D^N$ lies above and to the right of $D^S D^S$ comes from the fact that for a given $\omega = \omega^*$, $V > V^*$ because TFP is systematically higher in the skilled labor intensive sector in the North. 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. 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 because we cannot distinguish shifts in the FF curve from shifts in the DD curve. If relative TFP is negatively correlated with skill intensity in the skill abundant country, HO mechanisms are less likely to appear in the data (i.e. the North produces a lower V than if productivity was distributed identically across industries). In the first case, the uni-

Figure 3: Hybrid Model



fied 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). 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 and $C(z)$ is the consumption aggregator for each industry. For a given industry, equation 7 still characterizes the relative value of production in a diversified equilibrium such that $\tilde{R}(\tilde{p}(z)) > 0$. As before, relative revenue in an industry is declining in its relative price. Relative prices reflect TFP differences and differences in factor prices

$$\tilde{p}(z) = \tilde{\omega}^z \frac{\tilde{w_u}}{\tilde{A}(z)}. \tag{13}$$

To keep track of productivity in many industries, I use a convenient parameterization of productivity as follows where $\tilde{a}(z) = ln\left(\tilde{A}(z)\right)$:

$$\tilde{a}(z) = \tilde{a} + ln\left(\tilde{\gamma}\right)z + \tilde{\epsilon}_{A(z)}; \quad \tilde{\epsilon}_{A(z)}\ i.i.d.(0, \sigma^2_{\tilde{A}(z)}), \tag{14}$$

$$ln(\tilde{\gamma}) = \frac{cov[z, \tilde{a}(z)]}{var(z)}. \tag{15}$$

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 ($\tilde{\epsilon}_{A(z)}$). The component of Ricardian TFP that is correlated with factor intensity is captured by $ln(\tilde{\gamma})z$. $ln(\tilde{\gamma})$ is just the coefficient of a linear projection $\tilde{a}(z)$ on skilled labor cost shares z. This poses problems for HO theory because it offers a well articulated hypothesis for why we do or do not find HO production patterns in data.

If $\tilde{\gamma} > 1$, then $cov[z, \tilde{a}(z)] > 0$ and skilled labor intensive industries will *on average* have higher relative TFP than unskilled labor intensive industries. If $\tilde{\gamma} < 1$, then $cov[z, \tilde{a}(z)] < 0$ and skilled labor intensive industries *on average* have lower relative TFP than unskilled labor intensive industries. If $\tilde{\gamma} = 1$, then $cov[z, \tilde{a}(z)] = 0$ and relative 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 empirically separable from HO forces.

I exploit the monotonic relationships between $v(z)$ and $\tilde{R}(z)$ and between $\tilde{R}(z)$ and $\tilde{p}(z)$ and take a first-order linear approximation around the skill labor intensity z_0 where $\tilde{p}(z_0) = 1$:

$$v(z) = v(z_0) + \frac{\partial v(z_0)}{\partial \tilde{R}(z_0)} \frac{\partial \tilde{R}(z_0)}{\partial ln(\tilde{p}(z_0))} (ln(\tilde{p}(z) - ln(\tilde{p}(z_0)). \tag{16}$$

Using the Cobb-Douglas structure of prices, the covariance of $v(z)$ with z gives the simple expression where $\Gamma'(z_0) = \frac{\tilde{R}(z_0)}{\left[1+\tilde{R}(z_0)\right]^2}\Gamma(z_0) < 0$ where $\Gamma(z_0)$ is as given in equation 8:

$$cov[z, v(z)] = \Gamma'(z_0) \ln\left(\frac{\tilde{\omega}}{\tilde{\gamma}}\right) var(z). \tag{17}$$

This is the continuum of industries analog of the goods market clearing condition DD from the two industry model. 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 ($cov[v(z), z] > 0$).[11] 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 ($\tilde{\gamma} > 1$).

The following equations present the continuum of industries analogs to the the factor market clearing conditions for the North for skilled and unskilled labor, respectively:

$$\int_0^1 b(z)v(z)zY^w dz = w_s S, \quad \int_0^1 b(z)v(z)(1-z)Y^w dz = w_u U.$$

Simple division of these two expressions and then division by the Southern analog yields the following *factor market clearing condition*:

$$\frac{\int_0^1 b(z)zv(z)dz}{\int_0^1 b(z)z(1-v(z))dz} \frac{\int_0^1 b(z)(1-z)(1-v(z))dz}{\int_0^1 b(z)(1-z)v(z)dz} = \tilde{\omega}\frac{\tilde{S}}{\tilde{U}}. \tag{18}$$

Proposition 1 states that when Ricardian productivity differences are uncorrelated with factor intensity, HO forces should be present and should contribute to the relative production structures of the two countries.

3.1 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

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

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 B.

This proposition shows that if TFP is uncorrelated with factor intensity, then basic HO results should hold in the data as differences in TFP across industries will not cause (nor prevent) empirical tests of Heckscher-Ohlin to find evidence of factor abundance based production and trade.[12]

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.

3.2 Empirical Application

I now derive two expressions that test for the contributions of Ricardian and HO forces in production data. 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 7) as a function of $ln\left(\tilde{p}(z)\right)$ with the appropriate subscripts for country c relative to c'.[13] I then take the covariance of this expression with z:

$$cov[z, \tilde{r}(z)_{cc't}] = \Gamma \ln\left(\frac{\tilde{\omega}_{cc't}}{\tilde{\gamma}_{cc't}}\right) var(z). \tag{19}$$

[12] It also provides a formalization of the assumption that Romalis makes in footnote 29 of his paper in support of his approach. I thank an anonymous referee for pointing this out. This should not be mistaken for how countrywide differences in TFP affect HOV predictions as in Trefler (1995).

[13] The use of log revenue and not market share more easily and transparently controls for country and industry fixed effects using country-time and industry-time fixed effects and allows easier interpretation of the regression coefficients.

Because sufficiently comparable international factor prices are unavailable and because equilibrium factor prices are likely to be related to both relative factor abundance (which will lead to lower relative wages of the relatively abundant factor *ceteris paribus*) and the industry structure of TFP (which will lead to higher relative wages for factors used relatively intensively in high relative TFP sectors *ceteris paribus*), I use observed relative factor abundance and productivity distributions as proxies for unobserved factor prices.[14] With a slight abuse of theory, I represent this relationship by $ln\left(\tilde{\omega}\right)_{cc't} = \kappa_0 ln\left(\tilde{S}/\tilde{U}\right)_{cc't} + \kappa_1 ln\left(\tilde{\gamma}\right)_{cc't} + \epsilon_{\omega,cc't}$ where $\kappa_0 < 0$, $\kappa_1 > 0$, and ϵ_ω is a random disturbance to factor prices uncorrelated with relative skilled labor abundance and the covariance of productivity with skilled labor intensity.[15] Appendix C discusses in further detail using observed relative factor abundance and productivity distributions as proxies for unobserved endogenous relative factor prices. This allows for equilibrium wages to be determined by both factor abundance and by the industrial structure of productivity differences. This allows for the following expression:

$$cov[z, \tilde{r}(z)_{cc't}] = \kappa_0 \Gamma \ln\left(\frac{\tilde{S}}{\tilde{U}}\right)_{cc't} var(z) - \Gamma\left(1-\kappa_1\right)\ln\left(\tilde{\gamma}\right)_{cc't} var(z). \tag{20}$$

This expression decomposes the covariance of production with skill intensity into that due to factor abundance and that due to Ricardian productivity differences. Somewhat uncomfortably, I assume that this two-country model can be re-interpreted as one in which we examine production patterns in country c relative to a world aggregate that can be taken as constant across countries.[16] 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:

$$cov[z, r(z)_{ct}] = \beta_0 + \beta_1 \ln\left(\frac{S}{U}\right)_{ct} + \beta_2 \ln\left(\gamma\right)_{ct} + \beta_t' T_t + \zeta_{ct}, \tag{21}$$

[14] Ideally, we would want an instrument that moves relative factor prices or abundances around in a manner that is exogenous from the model but I am unaware of any such instruments.

[15] Generally, the relationship between relative factor prices, endowments, and relative productivity differences is likely to be complex and non-log-linear. In addition, it is well-known (e.g. Jones,1965) that the relative size of a country will play a major role in how autarky factor prices relate to factor prices in a trading equilibrium. I have experimented with the expression $ln\left(\tilde{\omega}\right) = \kappa_0 ln\left(\tilde{S}/\tilde{U}\right) + \kappa_1 ln\left(\tilde{\gamma}\right) + \kappa_2 ln\left(\tilde{S}/\tilde{U}\right) ln\left(G\tilde{D}P\right) + \kappa_3 ln\left(\tilde{\gamma}\right) ln\left(G\tilde{D}P\right) + \kappa_4 ln\left(G\tilde{D}P\right)$ and the results are unchanged.

[16] This assumption would be especially problematic for more structural numerical analysis. This is because assuming a constant rest of the world aggregate assumes complete factor mobility within that world aggregate and, consequently, extremely strong home market effects for the rest of the world.

where $\beta_1 = \kappa_0 \Gamma var(z) > 0$ and $\beta_2 = -\Gamma(1-\kappa_1)var(z) > 0$ if $0 < \kappa_1 < 1$. This is the "restricted expression." A richer and more realistic treatment of the interaction between Ricardian and Heckscher-Ohlin forces would allow explicitly for arbitrarily many asymmetric countries. Recent advances in this direction such as Eaton and Kortum (2002) and Anderson and Van Wincoop (2003) have been fruitful but have not yet been able to integrate Heckscher-Ohlin and Ricardian forces in a tractable manner.[17]

To examine the contribution of TFP that is uncorrelated with factor intensity, I derive the "unrestricted expression" by again log-linearizing equation 7 where the linearization occurs at z_0 such that $\tilde{p}(z_0) = 1$:[18]

$$\tilde{r}(z) = \tilde{r}(z_0) + \frac{\partial \tilde{r}(z_0)}{\partial ln(\tilde{p}(z_0))} ln(\tilde{p}(z)). \tag{22}$$

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

$$\tilde{r}(z) = \tilde{r}(z_0) - \frac{\partial \tilde{r}(z_0)}{\partial ln(\tilde{p}(z_0))} \left[\tilde{a} - \tilde{w}_u - ln(\tilde{\omega})z + ln(\tilde{\gamma})z + \epsilon_{\tilde{A}(z)}\right]. \tag{23}$$

Revenue depends on country and industry level variables as might be expected. Revenue is increasing in country level productivity ($\tilde{a}$), decreasing in the relative unskilled labor wage level ($\tilde{w}_u$) and increasing in industry specific relative productivity ($\tilde{\epsilon}_{A(z)}$).[19] 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. Fixed effects that make the results insensitive to the choice of numeraire country give the following expression where ZT is a vector of industry-time fixed effects (e.g. Industry 311 in 1990), CT is a vector of country-time fixed effects (e.g. Japan in

[17] Although Romalis (2004) allows for an arbitrary number of countries each country must fall into one of two types "North" or "South" such that there are only two unique country types with an arbitrary number of countries of each type. In addition, the assumption of uniform and multiplicitive iceberg transportation costs ignores the full matrix of bilateral transportation costs that are at the heart of multi-country models such as Eaton & Kortum (2002) and Anderson & Van Wincoop (2003).

[18] Taking the linearization around other relative prices does not affect the result as long as it is around a price at which production occurs in both countries.

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

1990), and ζ is an error term that is clustered by country-industry (e.g. Industry 311 in Japan):

$$r(z)_{ct} = \frac{\partial \tilde{r}(z_0)}{\partial ln(\tilde{p}(z_0))} \left[ln(\omega)_{ct} z - ln(\gamma)_{ct} z - \epsilon_{A(z),ct} \right] + \beta'_{zt} ZT_{zt} + \beta'_{ct} CT_{ct} + \zeta_{zct}. \tag{24}$$

Again, assuming that the elasticity of relative factor prices with respect to relative endowments and patterns of industry TFP can be expressed as in the "restricted" expression, I can specify the following expression:

$$r(z)_{ct} = \beta_0 ln \left(\frac{S}{U} \right)_{ct} z + \beta_1 ln(\gamma)_{ct} z + \beta_2 \epsilon_{A(z),ct} + \beta'_{zt} ZT_{zt} + \beta'_{ct} CT_{ct} + \zeta_{zct} \tag{25}$$

where $\beta_0 = \kappa_0 \Gamma > 0$, $\beta_1 = -\Gamma(1 - \kappa_1) > 0$, and $\beta_2 = -\Gamma > 0$. This is the "unrestricted expression." As with the "restricted expression", an ideal multi-country estimation would use estimating equations explicitly derived from a multiple country framework that includes both Ricardian and Heckscher-Ohlin forces in a tractable and general manner.

As before, β_0 gauges the validity of the HO models and β_1 assesses the importance of TFP that is correlated with skill intensity. β_2 assesses the importance of Ricardian productivity that is orthogonal to factor intensity in determining production patterns. All country-year and industry-year factors are absorbed into the included vectors of fixed effects.

4 Data

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).[20] All country-years for which complete

[20] Because I am concerned with the supply side of models of comparative advantage, both the model and data deal with production data. I briefly examine trade data in the Robustness section.

Table 1: Sample

Country	Years	Obs	Median. Ind.	Country	Years	Obs	Median Ind.
Austria	1985-1994	239	24	Ireland	1985-1991	154	22
Canada	1985-1990	138	23	Italy	1985-1994	190	19
Denmark	1985-1991	168	24	Japan	1985-1995	264	24
Egypt	1985-1995	247	22	Korea	1985-1995	264	24
Finland	1985-1995	261	24	Norway	1985-1995	246	23
Great Britain	1985-1992	192	24	Pakistan	1985-1988	96	24
Hong Kong	1985-1995	184	17	Portugal	1985-1989	120	24
Hungary	1985-1993	216	24	Spain	1985-1995	176	16
Indonesia	1985-1995	242	22	Sweden	1985-1990	138	23
India	1985-1995	264	24	United States	1985-1995	264	24

data exist for at least 15 of the 24 industries in that country and year are kept.[21] Because not all countries have available data in all years, the dataset is an unbalanced panel.[22] Table 1 lists the data availability for years and countries as well as the median number of industries by country. The most binding constraint in assembling this data set and a major reason for its unbalanced nature is the availability of a continuous time series for investment necessary for creation of capital stock that is used for the creation of the TFP measures.

4.1 Factor Abundance

Although the model is applicable to any set of factors of production, I focus on skilled and unskilled labor.[23] As a measure of $\frac{S}{U}$, I examine the ratio of the population that has obtained a tertiary degree

[21] 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.

[22] In unreported results, the probability of a country-industry-year observation being in the sample is uncorrelated with the right hand side variables of interest.

[23] 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. Third, measurement of capital cost share in an industry requires data on the user cost of capital and capital stock. While the latter is available, the earlier is not.

Table 2: 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	0.49
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.	0.19	0.37
324	Footwear	0.15	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.	0.17	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	0.66	384	Transport Equip.	0.29	0.55
352	Other Chemicals	0.45	0.65	385	Prof. and Sci. Equip.	0.37	0.61

to that which does not as found in the Barro and Lee (2001) educational attainment dataset.[24] Results using a broader definition of skilled labor are examined in the robustness section.

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 online 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 2 presents these measures of z.[25] I loosen the assumption of a constant z across countries in a given industry in the Robustness Section (Section 6).[26]

[24]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.

[25]I assume that z is constant across countries. Similar theoretical results can be derived for CES production functions if skilled and unskilled labor are more substitutable than the Cobb-Douglas case.

[26]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 and likely to induce non-trivial measurement error. 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).

4.3 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 relative productivity levels.[27] 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) are used to produce value added (VA), the TFP productivity level between country a and a multilateral numeraire is $TFP(z)_{a,t} = \frac{VA(z)_{a,t}}{\overline{VA(z)_t}} \left(\frac{\overline{K(z)_t}}{K(z)_{a,t}}\right)^{\frac{\alpha_{K,a}+\alpha_{K,avg}}{2}} \left(\frac{\overline{L(z)_t}}{L(z)_{a,t}}\right)^{\frac{\alpha_{L,a}+\alpha_{L,avg}}{2}}$, $\alpha_{i,j}$ 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.[28] $\overline{K}(z)_t = \frac{1}{N_{z,t}} \sum_c K(z)_{czt}$ 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.

4.3.1 Deflators

Very few industry level deflators exist that allow comparison of output or value added across countries with this limitation being more binding for developing countries. For this reason, I use *disaggregated* PPP benchmark data provided by the Penn World Tables to construct country-industry level deflators. These price indexes allow PPP price comparisons across goods and countries and are constructed with an explicit eye toward comparing goods of similar quality. The online data appendix addresses this in detail.[29]

[27] I do not to use estimators that are often used in the firm level literature (e.g. Olley and Pakes (1996)) because the assumptions that legitimize their use do not hold in 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.

[28] Because year-to-year measured revenue shares are extremely noisy, I constrain α within a country within an industry (e.g. Indonesia-311) as a five year moving average. 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.

[29] 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. Further, 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.

4.3.2 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 can be easily written into an HO model.

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. The online data appendix discusses these measures in more detail.

Unlike 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 are 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 not to 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 value added function is constant returns to scale, then it will also be homogenous of degree one in hours worked. Consequently, a constant measure of hours worked in manufacturing across all manufacturing industries for a country-year panel will then be differenced out by country-year fixed effects.

Labor is decomposed into operatives (U) and non-operatives (S) using data from the United Nations General Industrial Statistical Database.[30] The effectiveness of labor is assumed to augment

[30] Comprehensive data on wages for operatives and non-operatives are not available from year to year for my broad sample. For this reason, I calculate the average wage shares for operatives and non-operatives in total wages 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 total wage share data from the Trade and Production dataset to create measures of operatives' and non-operatives' wage shares in value added to calculate the measures α_S and α_U.

both operatives and non-operatives. Capital is calculated using the perpetual inventory method.[31] The final (value added) measure of productivity between country a and the multilateral numeraire is then

$$TFP_{a,t} = \frac{VA_{a,t}}{\overline{VA}_t}\left(\frac{\overline{S_tE_t}}{S_{a,t}E_{a,t}}\right)^{\frac{\alpha_{S,a}+\alpha_{S,avg}}{2}}\left(\frac{\overline{U_tE_t}}{U_{a,t}E_{a,t}}\right)^{\frac{\alpha_{U,a}+\alpha_{U,avg}}{2}}\left(\frac{\overline{K}_t}{K_{a,t}}\right)^{\frac{\alpha_{K,a}+\alpha_{K,avg}}{2}}. \qquad (26)$$

The covariance terms (γ) are then calculated using the skill labor shares (z) and TFP and equation 15 such that $\gamma_{ct} = exp\left[\frac{cov[z,a_{czt}]}{var(z)}\right]$ where $cov[a_{czt}, z]$ is an unweighted covariance of (log) productivity with z. This differences out all country specific effects (e.g. country level business cycles).

5 Results

First, I present a "restricted" version of the model where the dependent variable is $cov[z, r(z)_{ct}]$. These results appear in Table 4. Second, I present the "unrestricted" results where the dependent variable is $r(z)_{ct}$. These results appear in Table 5. Extensive robustness checks are presented in Section 6.

5.1 Results: Restricted

Recall that the "restricted" regression equation is:

$$cov[z, r(z)_{ct}] = \beta_0 + \beta_1 \ln\left(\frac{S}{U}\right)_{ct} + \beta_2 \ln(\gamma)_{ct} + \beta_t' T_t + \zeta_{ct}. \qquad (27)$$

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 ($ln(\frac{S}{U})_T$) predicts how skewed productive resources are towards relatively skill intensive industries ($cov[z, r(z)]$). Column (2) includes $ln(\gamma)$ alone to assess the importance of productivity that is correlated with skill intensity. Column (3) includes both $ln(\frac{S}{U})_T$ and $ln(\gamma)$. Columns (4)-(6) perform the same regressions using the broad

[31] See the online data appendix for more details.

Table 3: Restricted Regression

	Narrow z			Broad z		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
$ln(S/U)_T$	0.0109***		0.0118***	0.0174***		0.0177***
	(0.0033)		(0.0026)	(0.0041)		(0.0036)
$ln(\gamma)$		0.0021	0.0036		0.0031	0.0041
		(0.0021)	(0.0022)		(0.0038)	(0.0033)
Obs	182	182	182	182	182	182
Time Fixed Effects	yes	yes	yes	yes	yes	yes
R^2	0.3477	0.0388	0.4121	0.4230	0.0300	0.4481

*** estimated at the 1% level, ** estimated at the 5% level. Robust standard errors clustered by country. Observations indexed by country-year. Equation (27) gives the estimation equation for this table. Dependent Variable: $cov[r(z), z]$

definition of skilled labor intensity. Robust standard errors are clustered by country and presented in parentheses.

I highlight three results. *First*, the familiar HO result holds where 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. The estimate from Column 1 implies an elasticity of substitution (σ) of 5.4.[32] This is generally in line with prior estimates.[33]

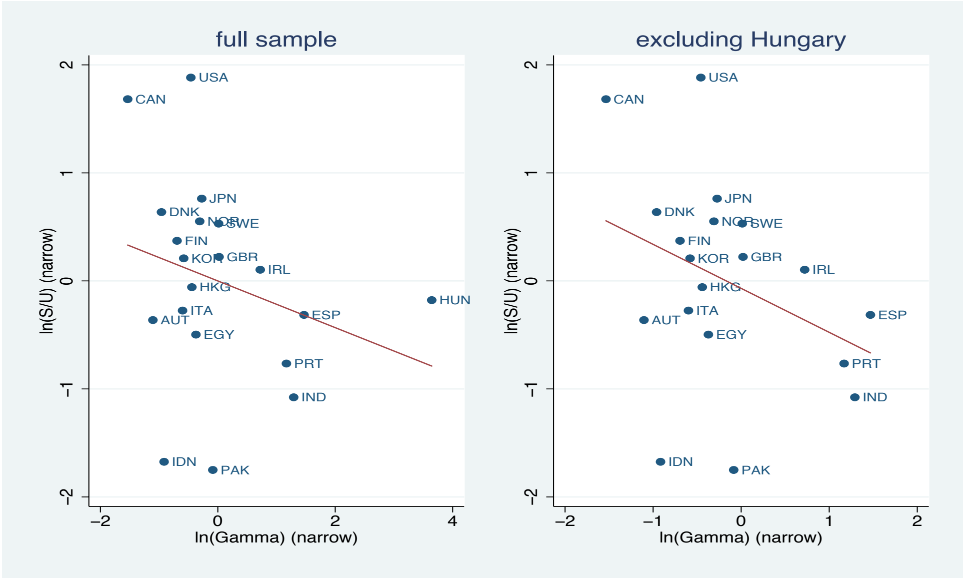
Second, the inclusion of $ln(\gamma)$ does not significantly change the coefficient on $ln(S/U)$. This suggests that Ricardian productivity differences are not biasing the tests of HO effects in this sample. This suggests that skilled labor abundant countries possess weakly greater productivity in unskilled labor-intensive sectors although this relationship is insignificantly different from zero.[34] *Third*, the coefficient on $ln(\gamma)$ is statistically indistinguishable from zero. This suggests that Ricar-

[32]This can be calculated by evaluating the expression for $-\kappa_0\Gamma$ at $\tilde{p}(z) = 1$, assigning $\tau = 1.74$, $Y^*/Y = 30$, assigning a value of $-\kappa_0 = 0.95$ and $\kappa_1 = 0$, and noting that var(z)=0.0106 from table 1, and solving for the σ that is consistent with the coefficient. See Appendix C for a discussion of the decision to set $-\kappa_0 = 0.95$ and $\kappa_1 = 0$. Note that this assumes that Γ is constant over time.

[33]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.

[34]This relationship is robust to setting the effectiveness of labor (E) to 1 for all countries in the TFP measurements.

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



dian productivity is relatively uncorrelated with skill intensity.

The scatterplots in Figure 4 present the same information graphically. 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. This is confirmed by regressing $ln(\gamma)$ on $ln(S/U)$ which yields a coefficient of -0.2332 with a robust standard error of 0.2635 with clustering by country and inclusion of time fixed effects to control for each annual numeraire. Although there is a gently downward sloping relationship, these results suggest that TFP that is correlated with factor intensity is unlikely to bias HO results.

Table 4 presents standardized coefficients to assess how important variation in relative factor abundance is in explaining specialization. The standardized coefficients on relative factor abundance range from 0.58 to 0.65. Under an assumption of a normally distributed right hand side variable this implies that a one standard deviation change in relative factor abundance is the difference between the median country in the sample and one in the 84th percentile. Maintaining the assumption of a normally distributed dependent variable, this implies that $cov[r(z), z]$ moves from the median to between the 70th and 74th percentiles. Put another way, a movement into the top quintile of relative skilled labor abundance implies a movement into the top quartile of skilled

Table 4: Restricted Regression (Standardized Coefficients)

Variable	Narrow z		Broad z	
$zln(S/U)_T$	0.5861	0.6309	0.6489	0.6594
$zln(\gamma)$		0.2582		0.1592

labor intensive good specialization. A one standard deviation in $ln(\gamma)$ only moves specialization to approximately the 60th percentile however the point estimate the latter is based on is insignificant from zero.

5.2 Results: Unrestricted

I now estimate the "unrestricted" expression where observations are indexed by country-industry-year as below:

$$r(z)_{ct} = \beta_0 ln\left(\frac{S}{U}\right)_{ct} z + \beta_1 ln(\gamma)_{ct} z + \beta_2 \epsilon_{A(z),ct} + \beta'_{zt} ZT_{zt} + \beta'_{ct} CT_{ct} + \zeta_{zct}. \quad (28)$$

Examining Table 5, 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.[35] *Second*, the inclusion of $ln(\gamma)z$ adds very little explanatory power in terms of its significance and effect on the coefficient on $zln(S/U)_T$. While the coefficient on $\ln(\gamma)z$ is greater in value when $\ln(S/U)z$ is included, we cannot reject the null that it is always equal to zero in all specifications. *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 in section 5.1, the coefficients in Column 3 imply a value of $\sigma = 5.3$ if calculated off of the coefficient on $ln(S/U)z$ or $\sigma = 8.3$ if it is identified off of $\epsilon_{A(z),ct}$. Again, each is reasonable based on prior estimates. This confirms previous findings that Ricardian productivity

[35] These coefficients appear to be larger than those in the restricted regressions. However, in the restricted regressions, $\beta_0 = \kappa_0 \Gamma var(z)$ but in the unrestricted regression $\beta_0 = \kappa_0 \Gamma$. Dividing the coefficient on $zln(S/U)_T$ from Table 4, Column 1 by the variance of z from Table 1 gives a value of 1.0228 which is extremely close to its counterpart in Column 1 of the unrestricted regression (1.0870).

Table 5: Extended Regression

	Narrow z			Broad z		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$zln(S/U)_T$	1.0870***		1.2118***	1.0720***		1.0961***
	(0.3818)		(0.3910)	(0.3060)		(0.2995)
$zln(\gamma)$		0.1494	0.3118		0.2895	0.3607
		(0.2144)	(0.2342)		(0.2356)	(0.2401)
$\epsilon_{A(z),ct}$		0.3011***	0.3110***		0.3033***	0.3032***
		(0.0947)	(0.0933)		(0.0948)	(0.0935)
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	0.8890	0.8919	0.8895	0.8892	0.8929

*** estimated at the 1% level, ** estimated at the 5% level. Robust standard errors clustered by country-industry. Observations indexed by country-industry-year. Equation 28 gives the estimation equation for this table. Dependent Variable: $r(z)$

Table 6: Unrestricted Regression (Standardized Coefficients)

Variable	Narrow z		Broad z	
$zln(S/U)_T$	0.1648	0.1837	0.2602	0.2661
$zln(\gamma)$		0.0469		0.0769
$\epsilon_{A(z),ct}$		0.1185		0.1155

possesses explanatory power in explaining relative production patterns. However, it offers the new contribution that Ricardian productivity explains very little (if any) of why HO results do or do not appear in this sample.

Table 6 presents standardized coefficients to assess the relative strength of these forces in determining production patterns. The coefficient 0.1837 should be interpreted as that a one standard deviation change in the interaction of factor intensity and factor abundance moves a country-industry from the median to the 84th percentile but only moves production to the 60th-62nd percentile. A similar movement in Ricardian productivity only moves the left hand side variable to approximately the 54th percentile. In this sense, the effects of Heckscher-Ohlin and Ricardian forces are relatively small. The table also shows that a one standard deviation increase in relative factor abundance is approximately 1.6 (0.1837/0.1185) to 2.3 (0.2661/0.1155) times as potent as a one standard deviation in Ricardian productivity in a given industry. Consequently 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.

6 Robustness

I explore the robustness of these results in six ways in Tables 7 and 8. *First*, I use a simple IV regression to consider the role of classical measurement error in the productivity measures. *Second*, I drop countries and years for which exchange rate volatility might induce measurement error. *Third*, I show that these results are robust to a broader measure of skilled labor abundance. *Fourth*, I also show that the dynamic correlation of the error term is sufficiently accounted for by standard clustering of the error terms. *Fifth* and *sixth*, I show that the results are not sensitive to replacing the Cobb-Douglas cost shares with the skill rank of the cost shares both in the U.S. and in each country.[36]

Table 9 steps away from the model and estimates similar relationships using U.S. import data instead of domestic production data. While I continue to find that Ricardian productivity forces do not bias tests of HO effects in my sample, I do find weak evidence of the opposite. I find weak evidence that estimation of the Ricardian model that does not include HO effects may suffer from an omitted variable bias.

Table 7, Column 1 starts 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. 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 substantial measurement error in measures of inputs (i.e. capital) that will not be differenced out the TFP measures using

[36] 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.

Table 7: Robustness Check I

Variable	IV	Exchange Rate		Secondary	Secondary	Secondary
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(S/U)_T z$	1.2810***	1.0943***	1.2317***			
	(0.3985)	(0.3816)	(0.3887)			
$ln(S/U)_S z$				0.8451***		0.9399***
				(0.3085)		(0.3050)
$ln(\gamma)z$	0.3300		0.3570		0.2895	0.4821*
	(0.2476)		(0.2327)		(0.2356)	(0.2494)
$\epsilon_{A(z),ct}$	0.3145***		0.3384***		0.3033***	0.3030***
	(0.1032)		(0.0989)		(0.0948)	(0.0941)
Obs	3601	3711	3711	4063	4063	4063
Country-Time FE	yes	yes	yes	yes	yes	yes
Industry-Time FE	yes	yes	yes	yes	yes	yes
R^2	0.8913	0.8873	0.8913	0.8883	0.8892	0.8921

*** estimated at the 1% level, ** estimated at the 5% level, * estimated at the 10% level.
Robust standard errors clustered by country-industry.

country-year fixed effects. 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.[37] The results are unchanged.

Columns 4, 5 and 6 use the relative abundance of workers with at least a secondary education as defined in the Barro and Lee data set as an alternate measure of skilled labor abundance. I use the broad measure of skilled labor intensity because it is closer in comparability than the narrow measure. In Column 6, $ln(\gamma)z$ does possess some explanatory power when conditioned on $\ln(S/U)z$. This suggests that while HO tests on the sample do not suffer from omitted variable bias, Ricardian tests might based on how the coefficient on $\ln(\gamma)z$ changes when HO forces are or are not included in columns 5 and 6. This comes from the weak downward sloping relationship between $\ln(\gamma)$ and $\ln(S/U)$. Intuitively, unskilled labor abundant countries in this sample tend to have high relative productivity in skilled labor intensive sectors being offset by "stronger" HO forces.

The error terms in the panel regressions presented above are undoubtedly correlated. The

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

Table 8: Robustness Check II

Variable	1988 (1)	US Rank (2)	US Rank (3)	US Rank (4)	US Rank (5)	Own Rank (6)	Own Rank (7)	Own Rank (8)
$ln(S/U)_T z$	1.1145***							
	(0.3627)							
$rank(S/U)$		0.0125***		0.0131***	0.0109***	0.0058**	0.0061**	0.0048**
$*rank(z)$		(0.0025)		(0.0022)	(0.0021)	(0.0023)	(0.0027)	(0.0022)
$ln(\gamma)z$	0.1529							
	(0.2290)							
$rank(ln(\gamma))$			0.0040	0.0060	0.0046		-0.0020	-0.0016
$*rank(z)$			(0.0031)	(0.0027)	(0.0025)		(0.0026)	(0.0022)
$\epsilon_{A(z),ct}$	0.4242***							
	(0.1196)							
$rank(a(z))$			0.0702***	0.0695***	0.0679**		0.0656**	0.0641**
			(0.0265)	(0.0282)	(0.0303)		(0.0251)	(0.0282)
Obs	454	4063	4063	4063	454	4063	4063	454
Country-Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry-Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Sample	1988	Full	Full	Full	1988	Full	Full	1988

*** estimated at the 1% level of certainty, ** estimated at the 5% level of certainty, * estimated at the 10% level of certainty. Robust standard errors clustered at the country-industry level

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. Generally, if errors are correlated due to a specific dynamic structure of the underlying economic model, clustering of the standard errors will yield inconsistent point estimates.[38] The first column of Table 8 explores this question. Using data for 1988, I show that nearly all of the variation comes from the cross section and, consequently, this concern is unfounded. I choose this year because it contains the most observations of any single year.[39] 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.[40]

The imposition of a constant z across countries in a given industry is unlikely to be completely

[38]See Maddala (1988), page 200.

[39]Similar results hold using pooled time averages and are available upon request.

[40]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.

true but it is less obvious how severe a bias this introduces. Columns 2-8 in Table 8 address this problem. Columns 2-4 replicate Columns 1-3 of Table 5 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 world rank in that statistic in that year. 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. $ln(\gamma)$ is replaced by its world rank in that year. Because I am now dealing with rank orderings I perform an ordered logit which makes comparison to OLS coefficients inappropriate. However, the same general patterns of magnitude and significance hold. Column 5 performs the same exercise on cross sectional data from 1988.

Columns 6-8 perform the same exercises as 2-4 except that the skill rank of the industry in the United States is now replaced by the rank of the proportion of non-operative wages in total wages of the industry in that country as measured by the United Nations General Industrial Statistical Dataset.[41] Consequently, it is less constrained than columns 2-4. Although the point estimates on factor abundance are now smaller, the same patterns of magnitude hold. The smaller coefficients are possibly due to measurement error in representing skilled labor intensity by the proportion of non-production workers across industries in different countries.[42]

While the theoretical motivation is based on production data as in Harrigan (1997), Table 9 examines the same question using U.S. import data from Feenstra, Romalis, and Schott (2002).[43] HS6 data is aggregated to the 3-digit ISIC level using a concordance from Jon Havemen.[44] All right hand side variables are the same as in Table 5. The value of production on the left hand side is now replaced by the value of imports into the United States for the period 1989-1995. It is also important to note that because I am stepping away from the model in these tables, the coefficients

[41] I am 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.

[42] I also estimated Columns (4) and (8) using pooled time averages of country-industry values. The results are nearly identical and available upon request.

[43] I thank an anonymous referee for suggesting this.

[44] Available at http://www.macalester.edu/research/economics/page/haveman/Trade.Resources/tradeconcordances.html

Table 9: Robustness Check III: Trade Data (Pooled)

Variable	Narrow z			Broad z		
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(S/U)_T z$	5.5126***		5.7363***	5.2654***		5.7132***
	(0.9535)		(0.9773)	(0.7745)		(0.7477)
$ln(\gamma)z$		-0.0494	0.5484		1.0572	1.2524**
		(0.4778)	(0.5057)		(0.6468)	(0.6231)
$\epsilon_{A(z),ct}$		0.5449**	0.5807***		0.5454**	0.5364**
		(0.2358)	(0.2227)		(0.2330)	(0.2149)
Obs	3784	3784	3784	3784	3784	3784
Country-Time FE	yes	yes	yes	yes	yes	yes
Industry-Time FE	yes	yes	yes	yes	yes	yes

*** estimated at the 1% level of certainty, ** estimated at the 5% level of certainty, * estimated at the 10% level of certainty, Robust standard errors clustered at the country-industry level

based on trade data are not directly comparable to those based on production data. The different sample comes from the fact that there is not a concordance from the TS system to the ISIC code as there is for the HS to the ISIC code and HS import data only begins in 1989 and because the use of U.S. import data forces me to throw out the U.S. as an observation. Similar results hold as before. The coefficient on factor abundance changes insignificantly with the inclusion of $\ln(\gamma)$ suggesting that omitted variable bias is less likely to be a problem for HO tests in this sample but that an omitted variable bias might be a problem for tests of the Ricardian model in the specifications using the broad measure of z.

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 three results.

First, both the Ricardian and HO models possess robust explanatory power in determining international patterns of production when nesting the other as an alternate hypothesis. Second, Ricardian productivity differences do not bias tests of HO effects in my sample. However, I find weak and mixed evidence that omission of HO forces may bias empirical estimation of the Ricardian model. Although the first result has been documented in past reduced form estimation, my paper is the first to do so based on a unified model where the estimated coefficients can be mapped against structural parameters. The second result is new and suggests that Ricardian TFP differences do not cause nor prevent HO effects from holding in the data. Third, I find that a one standard deviation change in relative factor abundance is approximately twice 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.

The theoretical contributions of this paper are twofold. First, if TFP is orthogonal 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.

Second, when trying to make industry by industry *level* predictions, HO models will be misspecified if they omit TFP differences even if TFP is uncorrelated with factor intensity. However, HO remains valid as a partial description of the data. Although I find that TFP does not bias HO tests 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 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

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

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 $\omega < \omega^*$.

B 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 proof proceeds in two steps and closely resembles a similar proof in Romalis (2004). First, I show that FPE breaks down. Second, I show that the North possesses relatively cheap skilled labor. First, based on the expression for $\tilde{p}(z)$, if FPE results $v(z)$ is constant across sectors and uncorrelated with $b(z)$ and z. Consequently, the left hand side of equation 18 is equal to unity and the right hand side is greater than unity. This is a contradiction. Consequently, FPE breaks down. Second, given assumptions about factor abundance, full employment of each factor implies that the North either *i*) has a larger share of relatively skilled labor intensive industries or *ii*) use more skilled labor intensive techniques. If TFP is uncorrelated with z, the first statement requires that $\tilde{\omega} < 1$ based on equation 17. Second, based on Cobb-Douglas production, the use of more skilled labor intensive techniques in each industry also requires that $\tilde{\omega} < 1$. Consequently, $\tilde{\omega} < 1$ and $cov[z, v(z)] > 0$ by equation 17. $cov[z', v(z')] < 0$ follows trivially.

C Empirical Representation of Equilibrium Factor Prices

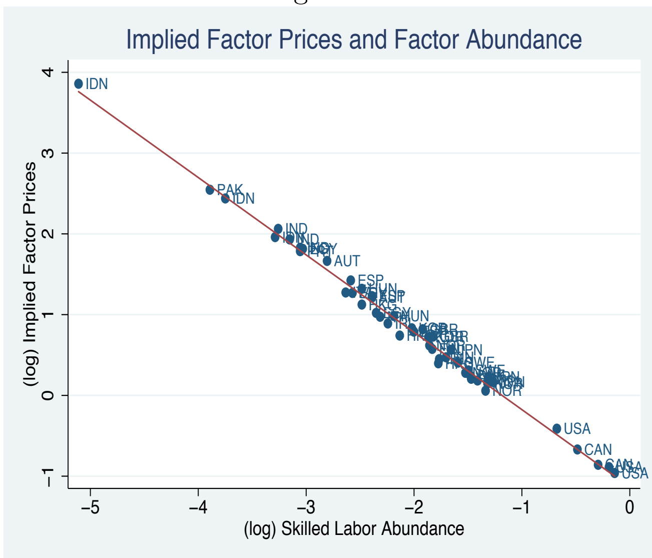
This section deals with the relationship between relative factor prices, relative endowments, and the industrial structure of productivity differences and the question of if $ln\left(\tilde{\omega}\right) = \kappa_0 ln\left(\tilde{S}/\tilde{U}\right) + \kappa_1 ln\left(\tilde{\gamma}\right)$ is a reasonable empirical representation. Specifically, I combine production data, relative endowments, and the factor market clearing condition (equation 18) and calculate the equilibrium factor prices that are implied by these patterns. I then show that the vast majority of the cross sectional variation in relative implied factor prices is accounted for by relative endowments, thus validating the approach in the text.

Specifically, I use the Trade and Production data to calculate market shares for each country in each industry ($v(z)$) and to calculate world expenditure shares by industry ($b(z)$). I combine these data with the data on skill intensity from Table 1 and the relative endowments data with equation 18 and calculate ω. Figure 5 below plots the implied values of $ln(\omega)$ against $ln(\frac{S}{U})$ for 1985, 1990, and 1995 pooled together. Table 10 shows the estimated coefficients from the following simple regressions to judge the empirical validity of the linear expression proposed in the text in columns (1)-(3) respectively:

$$ln(\omega_{ct}) = \beta_0 ln(S_{ct}/U_{ct}) + \beta_T T' + \epsilon_{ct}$$

$$ln(\omega_{ct}) = \beta_0 ln(S_{ct}/U_{ct}) + \beta_2 ln(GDP) ln(S_{ct}/U_{ct}) + \beta_4 ln(GDP) + \beta_T T' + \epsilon_{ct}$$

Figure 5:



$$ln(\omega_{ct}) = \beta_0 ln(S_{ct}/U_{ct}) + \beta_1 ln(\gamma_{ct}) + \beta_2 ln(GDP) ln(S_{ct}/U_{ct}) + \beta_3 ln(GDP) ln(\gamma_{ct}) + \beta_4 ln(GDP) + \beta_T T' + \epsilon_{ct}$$

Based on the extremely high R^2 in the first column and the only marginal improvements in the second and third columns. A simple log-linear specification with endowments alone is likely to be reasonable as a reduced form characterization of factor prices. It is useful to define two special cases that bound the estimates of κ_0. First, if factor abundance has no effect on production patterns such that the left hand side of equation 20 is constant across countries, the estimated coefficient should be unity. If we observe FPE due to strong HO effects, we would expect to observe a coefficient close to or equal to zero. The value of $\kappa_0 = -0.95$ suggests that trade has little effect on relative factor prices. Note that all estimates for $ln(\gamma)$ are not significantly different than zero informing my decision to set $\kappa_1 = 0$. However, it is consistent with some effect in that the coefficient is not equal to one which would be the case if endowments had no effect on patterns of specialization. In addition, implied relative factor prices are lower more negatively related to endowments for larger countries which is consistent with traditional theory in which free trade relative factor prices more closely resemble autarky relative factor prices the larger the country.

Table 10: Determinants of Equilibrium Implied Factor Prices

Variable	(1)	(2)	(3)
$ln(S/U)$	-0.9540^{***}	-0.9537^{***}	-0.9562^{***}
	(0.0128)	(0.0143)	(0.0100)
$ln(\gamma)$		0.0095	
		(0.0019)	
$ln(GDP)$		$2.03e-11$	$1.14e-11^{**}$
		$(2.75e-11)$	$(4.65e-12)$
$ln(S/U)ln(GDP)$		$-1.50e-11$	$-1.99e-11^{*}$
		$(1.84e-11)$	$(1.05e-11)$
$ln(\gamma)ln(GDP)$		$8.52e-12$	
		$(2.58e-11)$	
Time Fixed Effects	Yes	Yes	Yes
R^2	0.9932	0.9950	0.9950

*** estimated at the 1% level, ** estimated at the 5% level
* estimated at the 10% level. Standard errors clustered by country.