Education and comparative advantages of rich and poor countries

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Abstract

Using data for 53 countries, this paper identifies and characterizes a set of industries in which rich countries have comparative advantages over poor countries. It finds that rich countries specialize in industries that make intensive use of workers with post-secondary education. The paper finds a remarkably close relationship between the share of these workers in production and the pattern of comparative advantages across countries. Poor countries are held back by the lack of highly educated workers and the poor quality of education they receive. The industries in which rich countries specialize are marked by more innovation and greater trade of technology between rich countries. These industries also require more sophisticated management techniques that poor countries lack. The paper emphasizes the central role of the workers with post-secondary education in production, innovation, and technology diffusion.
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1 Introduction

Different countries export different sets of products. The pattern of trade is not random, however, and the focus of this paper is on understanding the differences in the pattern of exports between rich and poor countries. Poor countries tend to export products in certain industries, such as textile, basic metals, and food. The share of these industries in total exports of developing countries is much higher than the share in rich countries. Rich countries, on the other hand, tend to export certain types of machinery, such as medical equipment.

What explains this pattern of trade? Is it technology, abundance of some factors, or something else? This paper shows that the comparative advantages of rich countries lie in the industries that make intensive use of highly educated workers. These industries can be called education-intensive. The highly-educated workers have at least some tertiary education from technical schools, colleges, and graduate schools. There is significant variation of education requirements across industries and rich countries produce and export goods that extensively use workers with tertiary education.

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This paper finds a remarkably close relationship between the education intensity of industries and the pattern of comparative advantages across countries.[1] Compared to the existing literature, this paper uses a methodology based on solid microfoundations that explicitly accounts for trade costs and costs of intermediate goods when considering the effects of factor endowments on comparative advantage and trade. Unlike previous literature, this paper considers workers with tertiary education as a separate factor of production and collects data on their use in a many industries and countries around the world. Also unlike most of the previous studies, this one focuses on the education of workers, rather than their classification as skilled/unskilled or production/non-production. There is little correlation between the skill or production classification and level of education.

I consider four reasons why rich countries have comparative advantages in education-intensive industries. First is that highly educated labor is relatively cheap in rich countries once the quality of education is taken into account. There are now many pieces of evidence that show that the quality of education varies significantly across countries. This evidence includes international test scores and earnings of immigrants (Hanushek and Kimko, 2000; Hendricks, 2002; Schoellman, 2012).

The second reason is that innovation proceeds the fastest in education-intensive industries of rich countries, as evidenced by the number of patents and computer use. The third reason is that technology adoption is slow in the education-intensive industries of poor countries. Licensing of foreign technology is much more prevalent in education-intensive industries of rich countries than in other industries and countries. The lack of highly educated labor is one of the reasons for slow technology adoption (Nelson and Phelps, 1966; Benhabib and Spiegel, 2005).

The fourth reason, the last strong empirically, is that education-intensive industries require more sophisticated management techniques. Using international data on management technology I find that education-intensive industries use management technology more intensively. At the same time, rich countries have higher-quality management technology.

This paper is related to the extensive literature that searches for the determinants of the pattern of trade and specialization. The Ricardian (1817) model tells us to look at comparative advantages driven by labor productivity differences. The Ricardian model does well empirically: early two-country studies of MacDougall (1951) showed good explanatory power of the Ricardian model and, more recently, the multi-country Ricardian model of Eaton and Kortum (2002) has been shown to fit the data well.

However, there is something unsatisfying about the Ricardian model. Labor productivity differences determine the pattern of trade, but what determines the labor productivity differences? Heckscher (1919) and Ohlin (1924) created a model that explained labor productivity differences by differences of factor endowments across countries and differences of factor use across industries. The problem is that the factor endowment explanation has not performed well empirically. Studies done until now have shown that factor endowment differences can explain only a small fraction of comparative advantages. Productivity differences are needed to explain the rest (Trefler, 1995; Davis and Weinstein, 2001).

The search for an explanation of the pattern of trade largely parallels macroeconomics' search for an explanation of per capita income differences across countries, also known as development accounting. In development accounting, large differences in total factor productivity across countries are needed to explain differences in per capita income (Hall and Jones, 1999; Caselli, 2005). These productivity differences are typically interpreted as differences in technology.

The empirical result that productivity differences play the greatest role in determining com-

[1] The dataset includes 15 industries in 53 rich and poor countries. It uses data for 2005.

parative advantage is akin to the result that total factor productivity (TFP) differences play the greatest role in explaining per capita income differences across countries. Ricardian productivity differences, just like TFP, are measured as residuals and, therefore, just like TFP, are "measures of our ignorance".[2]

Dissatisfaction with exogenous productivity differences as the explanation for the pattern of income across countries lead to the appearance of the endogenous growth literature. This literature aims to explain the differences in productivities across countries by accounting for additional factors, such as human capital (Mankiw, Romer and Weil, 1992), or by introducing mechanisms for technology production and transfer (Romer, 1990; Nelson and Phelps, 1966; Basu and Weil, 1998). This paper can be considered an extension of the development accounting literature to the industry dimension. It emphasizes the effects of human capital and education on the pattern of trade.

There is a literature that empirically investigates the effects of human capital on trade and specialization. Romalis (2004) finds that skill-abundant countries specialize in skill-intensive industries. Ciccone and Papaioannou (2009) find that countries with higher initial education levels experienced faster growth in schooling-intensive industries in the 1980s and 1990s. Their results are obtained using U.S. data on average years of schooling and fraction of workers with secondary education. Other papers that studied the relationship between human capital and trade are Keesing (1966), Baldwin (1971), Baldwin (1979), and Harrigan (1997).

There is a large empirical literature that investigates the effects of education on growth (Barro, 1991; Bils and Klenow, 2000; Barro and Lee, 2001). In general the effect of education on output growth is found to be weak. Several reasons for this finding have been suggested in the literature: (a) attenuation due to mismeasured schooling data (Krueger and Lindahl, 2001) and (b) cross-country difference in educational quality (Hanushek and Kimko, 2000; Hendricks, 2002). Once education quality differences are accounted for, the effects of education on output increase significantly (Erosa, Koreshkova and Restuccia, 2007; Manuelli and Seshadri, 2010; Schoellman, 2012).

This paper is connected to the literature on income inequality. Since income is related to education, changes in trade policy may have different effects on workers with different levels of education, thus affecting income inequality. The paper also has a connection to the literature on the Leontieff paradox.

The project described in this paper proceeds as follows. I start by estimating country- and industry-specific productivity measures, which provide information about Ricardian comparative advantages of countries. The results are shown in Section 2. Then in Section 3 I look for patterns in these competitiveness measures across industries and countries. The result suggest that there is one factor missing from the analysis that has an extremely large power to explain cross-industry and cross-country variation in productivity. I hypothesize that the "missing factor" is human capital. To study the effects of human capital, in Section 4 I break down labor into three types, based on the level of education: labor with no more than primary education, more than primary but less than tertiary education, and labor with at least some tertiary education. I collect data on the employment of these types of labor in 15 industries and many rich and poor countries. This is the first paper to much knowledge that collect this data. I also find earnings data for these types of labor in all the countries of the dataset. It turns out that the factor of production with large explanatory power for the pattern of trade is highly educated labor - labor with at least some tertiary education. Having determined that rich countries have comparative advantages in industries that use highly educated labor more intensively, I look for the explanations of this pattern in Section 5.

[2]The interpretation of TFP as a "measure of our ignorance" is due to Abramovitz (1956).

2 Estimation of competitiveness and productivity

I start by estimating country- and industry-specific competitiveness measures for 15 industries in 53 countries. These competitiveness measures will be used to calculate productivities and Ricardian comparative advantages of countries. The competitiveness measures are obtained from the gravity equation derived from the multi-country Ricardian model of Eaton and Kortum (2002). This methodology is a great starting point because it incorporates influences of trade costs, cost of production inputs, and productivity on trade. It also naturally allows for two-way (intra-industry) trade between countries. The estimated competitiveness measures are net of trade costs, costs of intermediate goods, and costs of capital and labor.

Competitiveness measures are estimated using a gravity-like equation:

$$\log \frac{X_{nij}}{X_{nnj}} = -\theta \log d_{nij} + \theta \log R_{ij} - \theta \log R_{nj}, \tag{1}$$

where X_{nij} represents industry j imports from i to n, X_{nnj} represents purchases of domestically-produced goods in n, d_{nij} is the "iceberg" trade cost of delivering goods from i to n in industry j ($d_{nij} \geqslant 1$), θ is a parameter, and R_{ij} is the competitiveness of a mean producer in in industry j of country i ($R_{US,j} \equiv 1$).[3]

As in Eaton and Kortum, trade cost d_{nij} is represented by a trade cost function

$$\log d_{nij} = d^{phys}_{kj} + b_j + l_j + f_j + m_{nj} + \delta_{nij} \tag{2}$$

where d_{kj} ($k = 1, ..., 6$) is the effect of distance lying in the kth interval, b_j is the effect of common border, l_j is the effect of common language, f_j is the effect of belonging to the same free trade area, m_{nj} is the overall destination effect, and δ_{nij} is the sum of geographic barriers that are due to all other factors.[4] As typical in trade literature, international trade cost is measured relative to domestic trade cost: $\log d_{iij} \equiv 0$.

Combining (1) and (2), we obtain the estimating equation

$$\log \frac{X_{nij}}{X_{nnj}} = -\theta d^{phys}_{kj} - \theta b_j - \theta l_j - \theta f_j + D^{exp}_{ij} + D^{imp}_{nj} + \varepsilon_{nij}, \tag{3}$$

where $D^{exp}_{ij} = \theta \log R_{ij}$ is the exporter fixed effect and $D^{imp}_{nj} = -\theta m_{nj} - \theta \log R_{nj}$ is the importer fixed effect. The error term is $\varepsilon_{nij} = -\theta \delta_{nij}$. When estimating (3) the following normalization is used: $D^{exp}_{us,j} = D^{imp}_{us,j} = 0$. Consequently, the estimation produces the relative competitiveness measures $R_{ij}/R_{us,j}$.[5]

Equation (3) is estimated for 15 manufacturing industries in 53 countries and year 2005. The dataset includes both rich and poor countries. For example, there are 30 countries with per capita

[3] The "gravity-like" equation above is equation (25) in Eaton and Kortum (2002) with $R^{\theta}_{i} \equiv T_i w_i^{-\theta\beta} p_i^{-\theta(1-\beta)}$ applied at the industry level as in Shikher (2012) so that $R^{\theta}_{ij} \equiv T_{ij} w_i^{-\theta\beta_j} p_{ij}^{-\theta\left(1-\beta_j\right)}$. Note that in the Eaton-Kortum model productivity and therefore competitiveness are probabilistic. Therefore, individual producer's competitiveness can be larger or smaller than R_{ij}.

[4] Note that unlike Eaton and Kortum (2002), trade cost here is industry-specific.

[5] Note that the competitiveness measures are difference from the total factor productivities (TFPs). The competitiveness measures are derived from trade data while the TFPs are derived from production data. The TFPs are endogenous in models with trade since trade will cause least productive firms to exit and most productive firms to expand.

GDP less than 20% of the U.S. and 10 countries with GDP per capita less than 5% of the U.S. The bilateral trade data needed to estimate (3) was obtained from COMTRADE and concorded to 2-digit ISIC.[6] Imports from home X_{nnj} are calculated as output minus exports. Output data is originally from INDSTAT2-2010. The data on physical distance, common border, common language, and free-trade agreements is originally from the Gravity Database by CEPII. As in Eaton and Kortum, physical distance is divided into 6 intervals: [0,375), [375,750), [750,1500), [1500,3000), [3000,6000), and [6000,maximum).

In the Eaton-Kortum model, competitiveness R_{ij} is given by

$$R_{ij} = A_{ij}/c_{ij}, \tag{4}$$

where A_{ij} is the mean productivity of producers in industry j of i and c_{ij} is the unit cost of production inputs in industry j of country i.[7] At this point I assume Cobb-Douglas production with capital, labor, and intermediate goods:

$$c_{ij} = r_i^{\alpha_j} w_i^{\beta_j} \rho_{ij}^{1-\alpha_j-\beta_j}, \tag{5}$$

where r_i is the cost of capital, w_i is the cost of labor (earnings), ρ_{ij} is the cost of the intermediate goods bundle in j, α_j is capital share, and β_j is labor share. The relative mean productivity is calculated from (4) and (5) as the residual:

$$\log \frac{A_{ij}}{A_{us,j}} = \log \frac{R_{ij}}{R_{us,j}} + \alpha_j \log \frac{r_i}{r_{us}} + \beta_j \log \frac{w_i}{w_{us}} + \left(1 - \alpha_j - \beta_j\right) \log \frac{\rho_{ij}}{\rho_{us,j}} \tag{6}$$

Intermediate goods bundle is a Cobb-Douglas aggregation of goods from all industries:

$$\rho_{ij} = \prod_{m=1}^{J} p_{im}^{\eta_{jm}}, \tag{7}$$

where p_{im} is the price index in industry m of country i and η_{jm} is the share of industry m in industry j intermediate goods bundle. The price of the intermediate goods bundle in each country and industry can be calculated using the Eaton-Kortum model following Shikher (2004):

$$\log \frac{\rho_{ij}}{\rho_{us,j}} = \frac{1}{\theta} \sum_{m=1}^{J-1} \eta_{jm} \left(\log \frac{X_{iim}/X_{im}}{X_{us,us,m}/X_{us,m}} - \theta \log \frac{R_{im}}{R_{us,m}} \right) \tag{8}$$

Combining (6) and (8) we obtain the equation that lets us calculate relative productivities $A_{ij}/A_{us,j}$ from estimated relative competitiveness measures $R_{ij}/R_{us,j}$:

$$\begin{aligned} \log \frac{A_{ij}}{A_{us,j}} &= \log \frac{R_{ij}}{R_{us,j}} + \alpha_j \log \frac{r_i}{r_{us}} + \beta_j \log \frac{w_i}{w_{us}} + \\ &\quad + \frac{1}{\theta} \left(1 - \alpha_j - \beta_j\right) \sum_{m=1}^{J-1} \eta_{jm} \left(\log \frac{X_{iim}/X_{im}}{X_{us,us,m}/X_{us,m}} - \theta \log \frac{R_{im}}{R_{us,m}} \right) \end{aligned} \tag{9}$$

[6] Data needed to estimate (3) was taken from Yaylaci and Shikher (2014) and Yaylaci (2013).

[7] I will use the term "productivity" or "mean productivity" in this paper to describe A, but it should be remembered that this concept is distinct from Total Factor Productivity (TFP). The mean productivity A is derived from trade data while TFP is usually derived from production data. TFP is endogenous in models with trade since trade will cause the least productive firms to exit and the most productive firms to expand. In this paper, the productivity of a producer is a random variable drawn from a distribution with mean A_{ij}. Note the Eaton and Kortum use $T = A^{\theta}$ as a parameter of the productivity distribution.

Capital shares α_j, labor shares β_j, and intermediate inputs shares η_{jm} are calculated as the average shares of 43 countries in the input-output tables collected by the OECD.[8] Data on wages is from INDSTAT2-2010. Rates of return to physical capital are assumed to be equal in all countries (meaning that capital is assumed to be internationally mobile, subject to transport costs, and economy is in a long-run equilibrium).[9]

To summarize, the procedure for obtaining the relative productivities $A_{ij}/A_{us,j}$ is to first estimate (3) in order to obtain the relative competitiveness measures $R_{ij}/R_{us,j}$. The second step is to calculate relative productivities $A_{ij}/A_{us,j}$ using (9). The relative productivities $A_{ij}/A_{us,j}$ represent the sources of comparative advantages not captured by trade costs and cost of labor, capital, and intermediate goods.

3 What do estimated relative productivities tell us?

The first notable thing about the relative productivities is that for each country they vary significantly across industries. This within-country cross-industry variation represents the industry-level comparative advantages enjoyed by each country. Table 1 shows the minimum and maximum relative productivity for each country in the dataset. For example, in Japan there is an industry with productivity that is 5.6% higher compared to the U.S. and another industry with productivity that is 35.5% lower.

The next step in the analysis is to look for any patterns in the variation of relative productivities across countries and industries. Looking at relative productivities, I noted that the productivity gap between rich and poor countries increases unevenly as the GDP per capita declines. The gap increases quickly in some industries and slowly in others.

Figure 1 illustrates this phenomenon by comparing the productivity gaps in two industries, Metals and Medical. As GDP per capita declines, the relative productivity falls much faster in Medical than in Metals industry. Rich countries have only small differences in relative productivities between the two industries. The differences between relative productivities of the two industries become obvious for middle-income countries. They are very large for poor countries. Clearly, the productivity-driven comparative advantage of poor countries lies much more in Metals industry than in Medical.

We can quantify how fast the technological gap grows as GDP per capita declines by the slope of the regression $\log\left(A_{ij}/A_{us,j}\right) = \mu_{0j} + \mu_{1j}\log\left(Y_i/Y_{us}\right) + \varepsilon_{ij}$, where Y_i is the GDP per capita of country i. This slope is the elasticity of relative productivity with respect to GDP per capita. Table 2 shows industries in the dataset ranked according to the estimated elasticity μ_{1j}. Food and Metals industries have the lower estimated elasticities while Metal Products and Medical have the highest. The regression R^2 increases together with the slope (elasticity).

What explains the differences in elasticities across industries? It is possible that the pattern of technological differences that drives productivity differences is such that poor countries have a greater technological gap in some industries than in others. We come back to this possibility later. Another possible explanation for the differences in elasticities is that there is a factor of production that is missing in out analysis.

[8] In the data, in addition to intermediate and final goods, there are also investment goods. Since there is no investment in the model, investment goods are treated as intermediate goods.

[9] As shown later, this assumption does not affect the conclusions of the paper.

Table 1: Range of estimated mean productivities across industries for each country (factors of production are capital and labor)

Code	Country	Min	Max	Code	Country	Min	Max
1	Australia	0.694	0.900	27	Kazakhstan	0.194	0.600
2	Austria	0.675	0.822	28	Kenya	0.205	0.502
3	Brazil	0.426	0.798	29	Korea	0.622	0.971
4	Bulgaria	0.265	0.465	30	Malaysia	0.439	0.670
5	Chile	0.335	0.768	31	Mauritius	0.281	0.493
6	China	0.423	0.704	32	Mexico	0.445	0.601
7	Colombia	0.267	0.596	33	Netherlands	0.749	0.896
8	Costa Rica	0.330	0.588	34	New Zealand	0.515	0.813
9	Czech Republic	0.426	0.631	35	Norway	0.628	0.795
10	Denmark	0.624	0.817	36	Peru	0.212	0.594
11	Ecuador	0.251	0.594	37	Philippines	0.341	0.513
12	Ethiopia	0.137	0.399	38	Poland	0.407	0.631
13	Finland	0.592	0.907	39	Portugal	0.396	0.761
14	France	0.802	0.914	40	Russia	0.317	0.759
15	Germany	0.869	0.997	41	Slovakia	0.363	0.570
16	Greece	0.437	0.690	42	Slovenia	0.414	0.618
17	Hungary	0.445	0.621	43	South Africa	0.405	0.841
18	Iceland	0.424	0.635	44	Spain	0.630	0.878
19	India	0.303	0.629	45	Sweden	0.664	0.864
20	Indonesia	0.268	0.572	46	Tanzania	0.153	0.442
21	Iran	0.266	0.533	47	Trinidad and Tobago	0.332	0.683
22	Ireland	0.535	0.837	48	Turkey	0.373	0.723
23	Israel	0.517	0.729	49	UK	0.779	0.900
24	Italy	0.747	0.982	50	Ukraine	0.221	0.654
25	Japan	0.645	1.056	51	Uruguay	0.273	0.578
26	Jordan	0.213	0.461	52	USA	1	1
				53	Vietnam	0.218	0.533

Note: Petroleum products industry is excluded

Figure 1: Mean productivity vs. GDP per capita in two industries

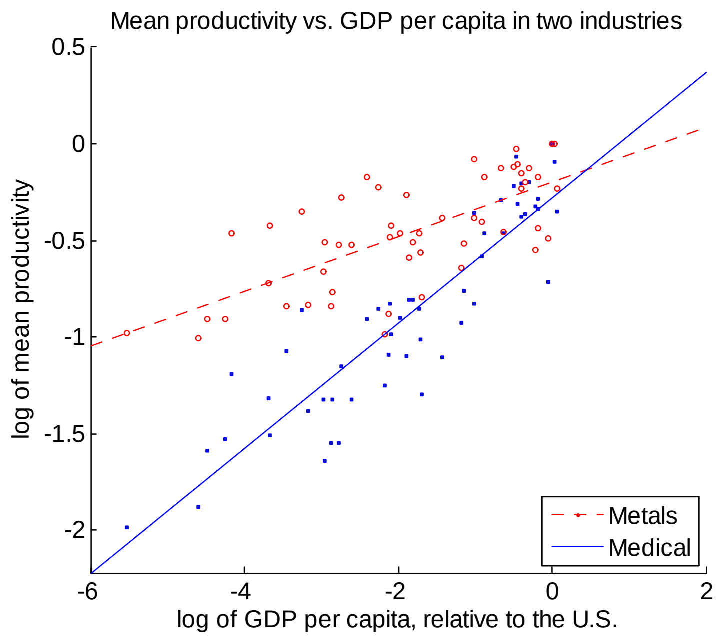


Table 2: Ranking of the industries

According to the slope of the regression of log(A) on log(GDP per capita)
Food
Metals
Textile
Chemicals
Wood
Transport
Nonmetals
Rubber
Machinery, e&c
Other
Paper
Machinery, other
Metal products
Medical

Before we start looking for a missing factor, we should check if it is even possible for one or several factors that are mobile across industries to explain the observed differences in productivities. Let's say that there are M factors of production not accounted for in (5) and (9). Let's denote the share of each missing factor k by γ_j^k and its price by ω_i^k. If the M missing factors can completely explain the relative productivities, then adding $\sum_{k=1}^{M} \gamma_j^k \log \omega_i^k / \omega_{US}^k$ to the right-hand side of (9) should make its left-hand side equal to zero. In other words, we should have

$$-\log \frac{A_{ij}}{A_{us,j}} = \sum_{k=1}^{M} \gamma_j^k \log \frac{\omega_i^k}{\omega_{US}^k}, \tag{10}$$

where $\log (A_{ij}/A_{us,j})$ is calculated from (9).

The above equation can be written in matrix form as

$$\underset{N \times J}{\mathbf{A}} = \underset{N \times M}{\mathbf{U}} \cdot \underset{J \times M}{\mathbf{V}}^{\mathrm{T}}, \tag{11}$$

where each row of $\mathbf{U}$ contains the prices of M factors in country i, and each row of $\mathbf{V}$ contains shares of M factors in industry j. We can use a statistical technique called Singular Value Decomposition (SVD) to decompose $\mathbf{A}$ into $\mathbf{U}$ and $\mathbf{V}$. More precisely, SVD decomposes $\mathbf{A}$ (in the least squared sense) into $\mathbf{A} = \mathbf{USV}^{\mathrm{T}}$, where $\mathbf{S}$ is a diagonal $M \times M$ matrix with each diagonal element showing the importance or weight of each factor. SVD tries to explain as much as possible of $\mathbf{A}$ by the first factor, then uses other factors to tweak the fit.

Table 3 shows the estimated diagonal elements of $\mathbf{S}$. We immediately notice is the very large explanatory power of the first factor. The means that the elements of $\mathbf{A}$ are not random, but follow a structure.[10] The results also imply that there is one factor with very large explanatory power for both cross-industry and cross-country variation of relative productivities. Table 4 shows the ranking of the industries according to the estimated shares of the first factor, γ_j^1, side-by-side with the ranking according to the estimated elasticity of relative productivity with respect to GDP per capita μ_{1j} (previously shown in Table 2). We can see that the rankings are very similar. The correlation between the estimated shares and elasticities is 0.97.

In summary, the purpose of this section was to look for a pattern in the variation of relative productivities $A_{ij}/A_{us,j}$ across industries and countries. We learned that there is a pattern. We also learned that there is one factor of production that is missing from our analysis that can explain much of this variation. What is this factor?[11]

4 In search of the mysterious missing factor

I hypothesize that this missing factor is human capital. While human capital has been studied extensively in macroeconomics, its effects on international trade have been studied relatively little.[12]

[10] If the elements of $\mathbf{A}$ were random, the estimated diagonal elements of $\mathbf{S}$ would have been slowly declining.

[11] We have assumed that θ is the same in all countries and industries. If θ were different across industries and countries, could its variation explain the pattern of competitiveness that we observe? In order to explain the pattern described in this section, θ would have to be the same across industries in the richer countries. It would need to be lower in Metals than Medical in poor countries. Parameter θ is related to the variable of the productivity distribution of the firms in the Eaton-Kortum model. Lower θ leads to high variance of the distribution. There is not reason for θ to vary in such a way across countries and industries.

[12] Romalis's (2004) and Ciccone and Papaioannou's (2009) are the few examples.

Table 3: Singular value decomposition results

1	20.79
2	1.45
3	1.30
4	1.05
5	0.93
6	0.66
7	0.53
8	0.48
9	0.45
10	0.38
11	0.36
12	0.34
13	0.29
14	0.20

Table 4: Rankings of the industries

According to the slope of the regression of log(A) on log(GDP per capita)	According to the shares estimated by SVD
Food	Metals
Metals	Food
Textile	Textile
Chemicals	Chemicals
Wood	Wood
Transport	Machinery, e&c
Nonmetals	Rubber
Rubber	Nonmetals
Machinery, e&c	Transport
Other	Other
Paper	Paper
Machinery, other	Machinery, other
Metal products	Metal products
Medical	Medical

One immediate problem with introducing human capital into our analysis is that there is no readily available data on human capital intensity by industry outside the U.S. This paper is the first to my knowledge to compile such data.[13]

In order to study the effects of human capital, I distinguish three types of labor: labor with no more than primary education, denoted by L_1, labor with more than primary, but less than tertiary education, denoted by L_2, and labor with at least some tertiary education, denoted by L_3. The basis for these levels of education is the International Standard Classification of Education, ISCED-97.

With three types of labor the input cost function becomes

$$c_{ij} = r_i^{\alpha_j} w_{1i}^{\lambda_{1j}} w_{2i}^{\lambda_{2j}} w_{3i}^{\lambda_{3j}} \rho_{ij}^{1-\alpha_j-\beta_j} \tag{12}$$

where λ_e is the share of labor with level of education e, w_e represents the earnings of labor with level of education e, and $\beta = \lambda_1 + \lambda_2 + \lambda_3$ is total share of labor.

4.1 Data on the earnings of the three types of labor

In order to operationalize (12), I need to know the earnings by country and labor type, w_{ei}, and income shares by labor type in every industry, λ_{ej}. The earnings are obtained from data. The income shares are calculated from earnings w_{ei} and data on employment by labor type, industry, and country, L_{eij}. I use multiple data sources for earnings and employment which sometimes supplement each other and sometimes serve to cross-verify each other. What follows is fairly brief exposition of data sources. A much more detailed review is presented in the Data Appendix, available upon request.

There are three data sources for earnings. The first is the Freeman-Oostendorp's Occupational Wages Around the World (OWW) database, which takes its data from the ILO's October Inquiry. It has data for 1983-2008 and 44 countries out of 53 countries in my dataset. For each country, it reports earnings for up to 161 occupations. Each occupation (coded according to the ISCO-88 standard) is related to an industry (ISIC) and level of education (ISCED). For example, occupation number 52 in OWW is a Chemical Engineer employed in the Manufacture of Industrial Chemicals industry who has tertiary education.

To obtain average earnings for a given level of education in a country, I take an average of earnings of all occupations with that level of education in the country. While OWW has many occupations, it does not cover all occupations and does not represent a random sample. Therefore, to check how accurate the average earnings produced by OWW are, I use data from Eurostat's Structure of Earnings Survey (SES). It has 2006 data for 22 out of 53 countries in my dataset. For 15 of those countries, there is earnings data in both OWW and SES datasets. The earnings for each level of education and country are similar in the two datasets with correlation being 0.92.

Two countries in my dataset have no earnings data in either OWW or SES dataset. In addition, data for five countries in OWW is suspect or missing. For these seven countries, I obtain earnings

[13] Previous studies used various measures of skill intensity. Some studies used skilled/unskilled classification of labor reported in some surveys. However, I find there is only weak correlation between skill and education. Skill is typically defined as knowledge of a particular complicated procedure, such as welding. Education, on the other hand, is a much more broad set of knowledge. Some studies measured skill intensity by the proportion of non-production workers in the total labor. I find this statistics also has only a very weak correlation to the level of education of the workforce. For example, in some industries production workers are required to have post-secondary education.

data from country-specific studies. There is a large literature that uses microdata to estimate returns to education, also known as Mincerian returns. These returns are slopes from the regression of the log of earnings on the number of years of education (Mincer, 1974). In addition to the seven countries already mentioned, I calculate earnings by education from Mincerian returns for two more (randomly chosen) countries to see how similar the calculated earnings are to those in OWW. Altogether, I have six countries for which I calculated earnings from Mincerian returns and have earnings data from OWW. The correlation between the earnings obtained from the two sources is 0.9.

Table 5 shows hourly earnings for each country and level of education. As expected, earnings vary significantly across countries. The cross-country variation in hourly earnings is highly correlated with GDP per capita. Within each country, earnings increase with education.[14] Table 5 also shows the increases in earnings in each country that come with getting more education ("education premia"). The cross-country average premium for having secondary education is 34%. The average earnings premium of workers with tertiary education over those with secondary education is 84%. The average earnings premium of workers with tertiary education over those with primary or no education is 149%. Therefore, having additional education, especially college education, significantly improves ones's standard of living.

There is significant variation in education premia across countries in the sample. The secondary education premium varies between -13% (in Ukraine) and 187% (in Ethiopia). The premium for tertiary education over secondary varies between 25% (in Vietnam) and 247% (in Tanzania). The premium for tertiary education over primary or no education varies between 23% (in Ukraine) and a whopping 519% (in Brazil).

Richer countries tend to have smaller education premia than poorer countries. The correlation between the secondary education premium and GDP per capita is -0.38. The correlation between the premium for tertiary education over secondary and GDP per capita is -0.38 and the correlation between the premium for tertiary education over primary or no education and GDP per capita is -0.48. This is consistent with existing literature on return to education that finds that returns to education decline with the level of development (Psacharopoulos and Patrinos, 2002). The relationship between the education premia and GDP per capita is noisy, especially for poorer countries, which is also consistent with previous literature (King, Montenegro and Orazem, 2012).

4.2 Data on the employment and shares of the three types of labor

The main source of data for the employment by country, industry, and level of education, L_{eij}, is the World Bank Enterprise Surveys (WBES). The surveys were conducted during 2002-05 and have data on 6,000 enterprises from 21 countries out of 53 studied in this paper.[15] Half of these 21 countries are low and low-middle income countries. In addition, World Management Survey (WMS) data is used to check the WBES data. WMS was conducted during 2004-2010 and has data on 10,000 enterprises in 20 countries. It only collected employment data on workers with tertiary education, which can be compared to the data from WBES. The correlation is 0.89.

Using data on earnings w_{ei} and employment L_{eij} we calculate shares of each type of labor in total labor income, $w_{ei}L_{eij}/(w_{1i}L_{1ij} + w_{2i}L_{2ij} + w_{3i}L_{3ij})$. The average of these shares across

[14] The only exception is Ukraine where the average worker with secondary education earns a little less than the average worker with primary or less education.

[15] This means that the shares are calculated for 21 countries, not for all 53 countries. The model assumes that the shares are the same in all countries and the average shares across the 21 countries are used the analysis.

Table 5: Hourly earnings of workers in USD by educational attainment; earnings premia

		Level of education			Education premia			Educational premia rankings		
Code	Country	Primary	Secondary	Tertiary	Sec/Prim	Tert/Sec	Tert/Prim	Sec/Prim	Tert/Sec	Tert/Prim
1	Australia	12.93	15.11	21.61	16.84%	43.04%	67.14%	38	42	45
2	Austria	9.74	11.93	21.43	22.39%	79.71%	119.94%	32	25	29
3	Brazil	1.30	2.33	8.08	78.62%	246.59%	519.06%	3	1	1
4	Bulgaria	0.84	0.91	1.60	7.88%	76.12%	89.99%	45	28	39
5	Chile	2.90	3.68	8.50	27.12%	130.76%	193.36%	24	10	13
6	China	0.93	0.96	1.74	3.49%	81.28%	87.61%	49	23	40
7	Colombia	1.31	2.03	3.76	55.63%	85.21%	188.24%	9	19	14
8	Costa Rica	1.43	1.80	4.60	25.17%	156.11%	220.57%	27	5	9
9	Czech Rep.	3.19	4.13	7.20	29.48%	74.38%	125.79%	23	30	27
10	Denmark	23.66	25.27	34.59	6.82%	36.91%	46.24%	47	46	49
11	Ecuador	1.51	2.26	2.98	49.30%	32.05%	97.15%	11	49	36
12	Ethiopia	0.22	0.64	0.96	186.98%	49.23%	328.25%	1	39	5
13	Finland	15.63	17.05	25.12	9.06%	47.38%	60.73%	44	41	47
14	France	13.91	16.77	26.70	20.58%	59.17%	91.92%	34	35	38
15	Germany	18.63	19.19	34.73	2.99%	81.03%	86.45%	50	24	41
16	Greece	9.49	9.52	12.39	0.26%	30.22%	30.56%	52	51	52
17	Hungary	2.71	3.26	7.07	20.44%	116.67%	160.95%	35	13	18
18	Iceland	13.86	19.62	25.11	41.53%	27.95%	81.09%	15	52	42
19	India	0.37	0.54	1.27	47.47%	135.49%	247.27%	12	9	7
20	Indonesia	0.48	0.67	1.13	38.70%	69.11%	134.55%	16	33	20
21	Iran	3.75	4.64	8.69	23.55%	87.47%	131.62%	30	16	22
22	Ireland	19.29	20.64	29.26	7.03%	41.77%	51.74%	46	43	48
23	Israel	5.29	9.06	13.45	71.12%	48.57%	154.23%	5	40	19
24	Italy	11.54	13.44	25.43	16.42%	89.23%	120.30%	39	14	28
25	Japan	14.31	15.90	24.59	11.11%	54.72%	71.92%	42	37	44
26	Jordan	1.01	1.35	2.33	33.19%	72.74%	130.08%	19	32	24
27	Kazakhstan	0.72	1.15	1.51	59.37%	31.06%	108.87%	8	50	32
28	Kenya	0.47	0.77	2.06	64.56%	166.26%	338.16%	6	4	4
29	Korea	6.08	7.96	13.29	30.88%	66.95%	118.50%	20	34	30
30	Malaysia	1.39	1.75	4.77	25.13%	173.32%	242.00%	28	3	8

		Level of education			Education premia			Educational premia rankings		
Code	Country	Primary	Secondary	Tertiary	Sec/Prim	Tert/Sec	Tert/Prim	Sec/Prim	Tert/Sec	Tert/Prim
31	Mauritius	1.69	2.20	5.29	29.58%	140.68%	211.86%	22	7	11
32	Mexico	1.83	3.25	5.73	76.99%	76.52%	212.41%	4	27	10
33	Netherlands	12.43	16.18	25.69	30.20%	58.73%	106.67%	21	36	34
34	New Zealand	9.89	11.23	20.55	13.54%	83.01%	107.79%	41	21	33
35	Norway	23.90	24.56	34.54	2.76%	40.66%	44.54%	51	45	50
36	Peru	1.31	2.09	4.95	59.79%	137.48%	279.48%	7	8	6
37	Philippines	0.83	1.12	1.95	34.60%	73.69%	133.80%	18	31	21
38	Poland	3.06	3.79	7.00	23.60%	84.95%	128.61%	29	20	26
39	Portugal	5.18	6.54	14.94	26.21%	128.34%	188.19%	25	11	15
40	Russia	1.59	2.30	3.07	44.53%	33.33%	92.69%	13	48	37
41	Slovakia	2.35	2.97	5.39	26.14%	81.87%	129.40%	26	22	25
42	Slovenia	5.24	6.28	15.46	20.02%	146.04%	195.31%	36	6	12
43	South Africa	2.20	5.65	9.89	156.35%	74.96%	348.50%	2	29	3
44	Spain	10.13	11.15	16.79	10.04%	50.60%	65.71%	43	38	46
45	Sweden	17.01	17.97	24.13	5.65%	34.26%	41.84%	48	47	51
46	Tanzania	0.32	0.49	1.44	51.95%	195.17%	348.50%	10	2	2
47	Trin. and Tob.	5.09	5.88	10.39	15.64%	76.75%	104.40%	40	26	35
48	Turkey	2.93	3.58	8.06	22.11%	125.21%	175.00%	33	12	16
49	UK	14.82	17.44	32.29	17.62%	85.23%	117.87%	37	18	31
50	Ukraine	1.15	1.00	1.41	-12.86%	41.06%	22.92%	53	44	53
51	Uruguay	2.97	4.26	8.00	43.43%	87.68%	169.19%	14	15	17
52	USA	14.75	18.14	33.99	23.02%	87.35%	130.49%	31	17	23
53	Vietnam	0.31	0.43	0.53	37.77%	24.80%	71.94%	17	53	43
	AVERAGE	6.41	7.60	12.59	33.81%	84.13%	148.52%			
	MINIMUM	0.22	0.43	0.53	-12.86%	24.80%	22.92%			
	MAXIMUM	23.90	25.27	34.73	186.98%	246.59%	519.06%			

countries is equal to λ_{ej}/β_j from which we can back out λ_{ej} using data on β_j (described previously).

Table 6 shows factor shares in value added while Table 7 shows factor shares in output. Focusing on Table 7, we see that Nonmetals, Chemicals, and Paper industries are the most capital intensive while Textile, Other Machinery, and Transport industries are the least capital intensive industries.[16] The share of capital in the most capital intensive industry, Nonmetals, is 1.84 times higher than the share in the least capital intensive industry, Transport.

Looking at the total shares of labor, we see that Medical, Metal Product, and Textile industries are the most labor intensive while Metals, Food, and Petroleum Products are the least labor intensive. The share of labor in the most labor intensive industry, Medical, is nearly five times higher than in the least labor intensive industry, Petroleum products. It is 1.93 times higher than in the second most labor intensive industry, Food.[17]

We can also look at the shares of each type of labor. It is interesting, for example, to compare Textile and Medical industries. Both are very labor intensive. However, they use different types of labor. The share of labor with primary or less education (L_1) is 1.65 times higher in Textile industry. At the same time, the share of labor with some tertiary education (L_3) is 2.45 times higher in Medical industry. In addition to Medical, Other Machinery and Paper industries use highly educated labor intensively. Textile, Wood, and Nonmetals industries use least educated labor intensively.

Table 6: Factor shares in value added

Code	Industry	Capital	Lab-Tot	Lab-Pri	Lab-Sec	Lab-Ter
1	Food	0.492	0.508	0.059	0.305	0.144
2	Textile	0.341	0.659	0.068	0.459	0.132
3	Wood	0.425	0.575	0.064	0.386	0.125
4	Paper	0.444	0.556	0.029	0.327	0.200
5	Petroleum products	0.688	0.312	0.000	0.153	0.159
6	Chemicals	0.539	0.461	0.018	0.247	0.196
7	Rubber	0.394	0.606	0.042	0.378	0.186
8	Nonmetals	0.461	0.539	0.068	0.341	0.130
9	Metals	0.464	0.536	0.056	0.352	0.128
10	Metal products	0.365	0.635	0.053	0.393	0.190
11	Machinery, other	0.342	0.658	0.038	0.370	0.250
12	Machinery, e&c	0.393	0.607	0.037	0.351	0.218
13	Medical	0.379	0.621	0.033	0.325	0.262
14	Transport	0.353	0.647	0.026	0.423	0.198
15	Other	0.403	0.597	0.051	0.384	0.162

Note: Share of capital is $\alpha_j/\left(\alpha_j+\beta_j\right)$, share of labor is $\beta_j/\left(\alpha_j+\beta_j\right)$, share of labor with level of education e is $\lambda_{ej}/\left(\alpha_j+\beta_j\right)$

[16] The Paper industry is dominated by the Printing and Publishing (sub)industry (ISIC 22). Other Machinery industry includes office and computing machinery industries (ISIC 29 and 30).

[17] Petroleum Products industry is often an outlyer and is omitted from much of the analyis done in this paper.

Table 7: Factor shares in output

Code	Industry	Capital	Lab-Tot	Lab-Pri	Lab-Sec	Lab-Ter
1	Food	0.123	0.127	0.015	0.076	0.036
2	Textile	0.110	0.211	0.022	0.148	0.042
3	Wood	0.136	0.184	0.021	0.123	0.040
4	Paper	0.156	0.195	0.010	0.115	0.070
5	Petroleum products	0.114	0.052	0.000	0.025	0.026
6	Chemicals	0.162	0.139	0.005	0.074	0.059
7	Rubber	0.126	0.193	0.013	0.121	0.059
8	Nonmetals	0.173	0.203	0.026	0.128	0.049
9	Metals	0.115	0.133	0.014	0.087	0.032
10	Metal products	0.130	0.226	0.019	0.140	0.068
11	Machinery, other	0.108	0.207	0.012	0.117	0.079
12	Machinery, e&c	0.118	0.182	0.011	0.105	0.066
13	Medical	0.150	0.246	0.013	0.129	0.104
14	Transport	0.094	0.172	0.007	0.113	0.053
15	Other	0.142	0.210	0.018	0.135	0.057

Note: Share of capital is α_j, share of labor is β_j, share of labor with level of education e is λ_{ej}

4.3 Have we found the mysterious factor?

In Section 3 we found that there are regularities in how estimated productivities vary across industries and countries. Countries with lower incomes have lower productivities than countries with higher incomes and the productivity differences between rich and poor countries are systematically higher in some industries than in others. I hypothesized that the industries with greater productivity gaps are more intensive in some factor of production not accounted for in the analysis. I used the singular value decomposition to see if there such a factor. The results showed that one factor of production missing from the analysis can explain a great deal of variation of productivities across countries and industries. I suspected that this missing factor could be human capital and broke down labor into three types, based on education. We can now check if human capital is the factor of production that we were looking for.

Table 8 shows the correlations between factor shares α_j, λ_1, λ_2, λ_3 and two measures representing the pattern of productivities across industries and countries: elasticity of productivity with respect to GDP per capita, μ_{1j}, and share of the first factor estimated by SVD, γ_j^1. The correlation between α_j and μ_{1j} is -0.54 meaning the industries with greater capital intensity have lower productivity gap between rich and poor countries.[18] This is consistent with what has been previously suggested in the literature (Bardhan, 1996). Productive physical capital with embodied advanced technology can be imported whereas labor cannot.[19] The correlation between μ_{1j} and shares of

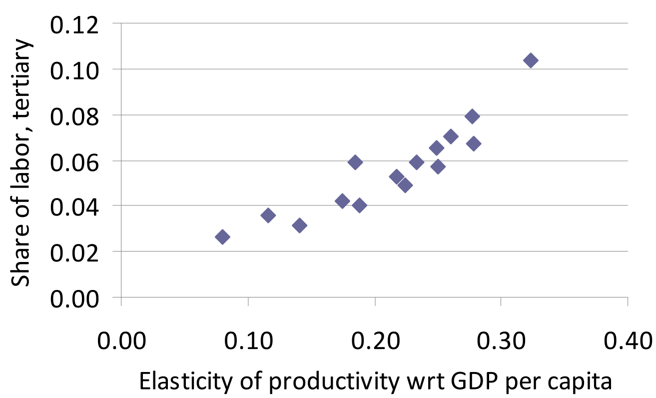
[18] Since the cost of physical capital is already accounted for explicitly when calculating productivities, any remaining effect of capital on productivity must be an externality.

[19] Bardhan looks at this issue from the point of view of a Lerner diagram: greater technological gap in labor-intensive industries helps explain why wages are so different between rich and poor countries while rates of return

Table 8: Is human capital the missing factor?

	Factor shares obtained from data			
	Capital, α_j	Labor, primary, λ_{1j}	Labor, secondary, λ_{2j}	Labor, tertiary, λ_{3j}
Elasticities of productivity with respect to GDP per capita, μ_{1j}	-0.54	-0.07	0.56	0.91
Shares of the first factor estimated by SVD, γ_j^1	0.23	-0.06	0.54	0.88

Figure 2: Education intensity and comparative advantage



labor with primary education is close to zero, so this type of labor is not a significant determinant of the pattern of productivity differences between rich and poor countries. The correlation between μ_{1j} and shares of labor with secondary education is positive, but not very strong. This means that this factor of production can help explain the pattern of productivity differences, but its explanatory power is weak.

The correlation between μ_{1j} and shares of labor with at least some tertiary education is positive and high. Figure 2 shows the scatter plot of the shares of labor with tertiary education, λ_{3j}, against the elasticities of productivity with respect to GDP per capita, μ_{1j}. It shows the remarkably close relationship between between the intensity of use of the highly educated labor and the rate of fall of productivity with respect to GDP per capita. The industries in which relative productivity (measured using capital and combined labor) falls the fastest with GDP per capita are the ones in which highly educated labor is used most intensively.

The second column of Table 8 shows the correlations (across industries) between the shares of the most significant factor estimated by SVD, γ_j^1, and the shares of capital and three types of labor. The correlations are negative or low for all factors except for the labor with tertiary education. This suggests that the highly educated labor is the missing factor suggested by SVD that we have

are fairly similar. Of course, the fact that physical capital is mobile across countries while labor is not helps explain this fact too.

been looking for.

This result may be surprising to some. It is important to remember that tertiary education includes many types of post-secondary schooling. Workers with technical-school education and Associate's degrees constitute a large portion of the labor force in many industries. For example, aircraft assembly typically requires workers to have at least an Associate's degree.

The information presented in Table 8 and Figure 2 has several implications. First, rich countries have comparative advantages in the industries which use highly educated labor more intensively (education-intensive industries). This is the case because the relative productivity of poor countries with respect to rich is much lower in the education-intensive industries. This pattern of comparative advantage is quite robust, as shown by the high correlation and the graph, which leads us to the next implication, that highly educated labor is an important determinant of the pattern of trade. Highly educated labor can explain the pattern of trade much better than all the other factors of production considered in this paper.

The third implication is that human capital can help explain the pattern of productivity across both countries and industries. This is the case because the shares of labor with tertiary education are highly correlated with the shares of the first factor estimated by SVD, while this first factor was shown able to explain much of the variation of productivities across countries and industries. Previous macro literature found that human capital helps explain the pattern of productivities across countries. This paper finds that human capital can also explain the pattern of productivities across industries.

The fourth implication is that industry matters as a unit of analysis. The productivity differences across industries are not random. Previous literature has found that capital and labor intensities have little explanatory power for the pattern of trade. Those results could lead one to conclude that the industry dimension is not important. This paper has found while some types of labor have little explanatory power, labor with tertiary education can explain much of the pattern of trade. The next question is what are the mechanisms through which highly educated labor affects comparative advantages.

5 Explaining the pattern of trade

In Section 3 we found that a pattern exists to comparative advantages of rich and poor countries. Rich countries tend to have comparative advantages in one set of industries while poor countries in another. In Section 4 we found that this pattern is strongly related to industries' intensity of use of workers with tertiary education. Why do rich countries have comparative advantages in education-intensive industries? This section considers several possibilities.[20]

5.1 Factor endowment differences

First, we will consider a simple factor endowment story: rich countries are more competitive in education-intensive industries because they have more workers with tertiary education. For this, we recalculate relative mean productivities $A_{ij}/A_{US,j}$ using the production function with three types

[20] What this section does is somewhat similar to development accounting at the industry level.

of labor.

$$\log \frac{A_{ij}}{A_{US,j}} = \log \frac{R_{ij}}{R_{US,j}} + \alpha_j \log \frac{r_i}{r_{US}} + \lambda_{1j} \log \frac{w_{1i}}{w_{1,US}} + \lambda_{2j} \log \frac{w_{2i}}{w_{2,US}} + \\ + \lambda_{3j} \log \frac{w_{3i}}{w_{3,US}} + \left(1 - \alpha_j - \beta_j\right) \log \frac{\rho_{ij}}{\rho_{US,j}} \tag{13}$$

Measuring relative costs of labor by $w_{3i}/w_{3,US}$ only makes sense if the labor quality is the same across countries. But, the literature finds that the quality of education varies significantly across countries. The evidence includes international test scores (Hanushek and Kimko, 2000) and earnings of immigrants (Hendricks, 2002; Schoellman, 2012). If the quality of education is indeed different across countries, we need to adjust wages to account for these differences.[21]

I use educational quality measures from Schoellman (2012). He estimates quality of education for 130 countries using data on the earning of immigrants in the United States. After adjusting wages using his quality measures, I calculate the contribution of relative wages by education to the pattern of mean productivities. I find that while relative wages can explain some of the variation of relative mean productivities across industries and countries, there remain a significant unexplained component. Therefore, I consider other explanations.

5.2 Technology differences

If the prices of highly educated labor do not fully explain the comparative advantages then there must be productivity differences across industries such that productivity gaps between rich and poor countries are greater in the education-intensive industries. I use the Nelson and Phelps (1966) model of technology diffusion to make a connection between education intensities and technological differences.

In the Nelson-Phelps model, the evolution of technology in industry j of country i is given by

$$A_{ij,t+1} = \sigma_{ij} \left(A_{jt} - A_{ijt}\right) + \left(1 + \mu_{ij}\right) A_{ijt}, \tag{14}$$

where A_{ijt} is the state of technology in industry j of country i at time t, A_{jt} is the state of technology at the world technological frontier in industry j, σ_{ij} is the technology absorption rate, and μ_{ij} is the rate of local technological research and development. Defining $a_{ijt} \equiv A_{ijt}/A_{jt}$ as the distance between country i's technology and technology at the world frontier, we rewrite the above expression as

$$a_{ij,t+1} = \sigma_{ij} - \left(\sigma_{ij} + g_j - \mu_{ji} - 1\right) a_{ijt}, \tag{15}$$

where g_j is the rate of growth of the world technological frontier in industry j. The equilibrium distance to the technology frontier is

$$a^*_{ij} = \frac{\sigma_{ij}}{\sigma_{ij} + g_j - \mu_{ij}}. \tag{16}$$

According to the above equation, the technological gap between rich and poor countries will be greater in the education-intensive industries if (a) the rate of growth of technological frontier g_j

[21] Calculating relative mean productivities without adjusting for the quality of education produces the results similar to those shown in Section 3. The pattern of this variation remains the same and elasticities and results of the SVD analysis do not change. While λ_{3j} are highly influential for the pattern of productivities, relative wages $w_{3i}/w_{3,US}$ do no vary enough across countries to make a difference.

is higher in the education-intensive industries, (b) rate of domestic technological innovation μ_{ij} is higher in rich countries and education-intensive industries, and (c) rate of technology absorption σ_{ij} is higher in rich countries and education-intensive industries. Parts (a) and (b) are basically the same since nearly all world innovations are made in rich countries.

5.2.1 Evidence on innovation from patenting and computer use

I start by investigating if there is more innovation in the education-intensive industries. There are several approaches to measuring innovation used in the literature. I use the number of patents as a measure of output of the research and development activity in an industry. Since all the patents are granted by the same patent office, there is no problem with inconsistency that arises when one compares the number of patents granted by different countries.

I use data on the number of granted patents from the U.S. Patent and Trademark Office (USPTO). The data is for the period from 1963 to 2008, according to state or country of origin. The number of patents is calculated as fractional or whole counts. Using whole counts allows the same patent to be counted in several industries while using fractional counts eliminates this multiple counting. I use the total number of patents granted between 1963 and 2008 and the number of patents granted during the last 10 years of the data, between 1999 and 2008. Since industries are different in size, I scale the number of patents by output or employment. I then calculate the correlation across industries between the (scaled) number of patents and λ_3, the share of workers with tertiary education.

The results show that the correlation between the number of patents and λ_3 is high, around 0.75-0.81. This is true whether the number of patents is measured in whole counts or fractional counts, per output or per worker, for the U.S. or the whole world, for 1963-2008 or 1999-2008. For example, the number of patents granted by the USPTO to residents of any country between 1963 and 2008 per 1 million dollars of output (using fractional count) is 0.04 and 0.19 in the Food and Metals industries, the two least education-intensive industries, and 2.99 and 4.29 in the Medical and Other Machinery industries, the two most education-intensive industries.[22] This means that the education-intensive industries are characterized by much higher rate of growth of technological frontier g_j.

Moreover, the rate of growth of technological frontier seems to be accelerating in the education-intensive industries. I calculate the fraction of the number of patents issued between 1963 and 2008 that has been issued between 1999 and 2008. This fraction is noticeably higher in the education-intensive industries. It is 0.21 and 0.24 in the Metals and Food industries and 0.41 in the Other Machinery and Medical industries. The correlation between the fraction and share of workers with tertiary education is 0.69.

The education-intensive industries are also characterized by higher use of computers. While the use of computers may not be the best proxy for innovation, a large fraction of productivity-enhancing innovations in recent years require computer use. I use data from World Bank Enterprise Surveys to calculate industry-level measures of computer use. The surveys ask for the percent of the workforce that regularly uses a computer in their jobs. This percent ranges from 13.3 and 13.5 in the Food and Metals industries to 17.8 and 27.1 in the Other Machinery and Medical industries.

[22] The number of patents (fractional count, 1963-2008, granted to residents of any country) per 1,000 workers is 13.3 and 56.5 in the Food and Metals industries and 802.3 and 471.5 in the Other Machinery and Medical industries.

The correlation between computer use and share of workers with tertiary education is 0.62.[23,24]

5.2.2 Evidence on technology adoption from licensing data

In this section I present evidence that there is more technology adoption in the education-intensive industries and between rich countries. I use data on licensing of foreign technology from the World Bank Enterprise Surveys. The surveys ask if an enterprise uses technology licensed from a foreign-owned company. The average (across industries) share of enterprises which answer this question in the affirmative is about 16%. The correlation between the fraction of enterprises which report using foreign technology through licensing and share of workers with tertiary education is 0.6. Food and Metals industries have 13.3% and 14.6% of enterprises using foreign technology, while Medical and Other Machinery have 24.6% and 27.1%. Therefore, education-intensive industries have much more technology adoption through licensing of foreign technologies.

However, if we decompose this data by country income we see that the licensing occurs mostly in richer countries. The average percentage of enterprises that use foreign technology through licensing is 21.6 in the upper middle income countries, 13.8 in the lower middle income countries, and 12.8 in the low income countries.[25] The correlation between the fraction of enterprises which report using foreign technology through licensing and share of workers with tertiary education is 0.84 (0.71 with Medical industry omitted) in the upper middle income countries, 0 (0.14 with Medical industry omitted) in the lower middle income countries, and 0.128 (with Medical industry omitted) in the low income countries. Richer countries have more foreign technology licensing in most of the industries. However, the difference in the prevalence of foreign technology licensing between rich and poor countries is much greater in the industries with high shares of workers with tertiary education. For example, 40.5% and 50.0% of enterprises in Other Machinery and Medical industries of the upper middle income countries report using technology licensed from a foreign-owned company. These numbers for the low middle income countries are 17.1% and 8%.

These numbers tell us there is much more technology diffusion through licensing in rich countries. The difference in the licensing of foreign technology between rich and poor countries is much greater in the education-intensive industries. Putting this information together with the information discussed in the previous section, we can say that the education-intensive industries have more innovation, greater computer use, and greater technology diffusion through licensing in rich countries. Poor countries participate much less in technology diffusion through licensing, probably because they lack human capital needed to use foreign technology and because of weak institutions (such as weak protection of intellectual property) that raise problems with appopriability in the use of foreign technology.

[23] There is no correlation between the computer use and the share of workers with secondary education or capital share. There is a negative correlation -0.76 between the computer use and share of workers with primary education.

[24] Education-intensive industries introduce new product lines somewhat faster than the other industries. One of the WBES questions asked whether an enterprise has developed a major new product line in the past three years. Slightly higher fraction of enterprises aswered this questions positively in the education-intensive industries. The correlation between the share of enterprises who answered this question positively and share of workers with tertiary education is 0.6, but the difference in magnitudes (of fractions who said “yes”) across industries is small.

[25] The surveys in high income countries did not ask the question about use of technology licensed from a foreign-owned company.

5.3 Other explanations: management technology and government subsidies

I consider two additional determinants of productivity gaps between rich and poor countries: management technology and government support. There is evidence that management technology varies across countries (Bloom, Genakos, Sadun and Reenen, 2012). I use enterprise-level management techniques data from the World Management Survey to compile industry- and country-specific indicators of management quality. The results show that education-intensive industries have higher quality management. Data also shows that rich countries have better management across all industries. However, the correlations are not very strong and there is no evidence that management quality gaps between rich and poor countries are greater in the education-intensive industries. Therefore, there is only a weak support for the quality of management explanation for the pattern of comparative advantage so far.

Another possible determinant of the pattern productivity gaps between rich and poor countries is government support. I use data on the effective tax rates and subsidies in the U.S. industries (9 of them in manufacturing) in 2008-10 from the Institute on Taxation and Economic Policy. The effective tax rates vary widely, but I did not find a correlation between education intensity and effective tax rate of industries. More evidence is needed to study effects of government policy on relative industry productivities.

6 Conclusion

Rich and poor countries specialize in exporting products from different industries. What are these industries and what are their defining characteristics? I start investigating this issue by estimating country- and industry-specific productivity measures, which provide information about Ricardian comparative advantages of countries. I then look for patterns in these productivities across industries and countries. A key finding is that productivity falls with country's per capita income in all industries, but does so much faster in some industries than others. In other words, the elasticity of productivity with respect to per capita income is higher in some industries than others. What makes the industries with high elasticity different from those with low elasticity? Could it be that some factor that is in short supply in poor countries is used more intensively in the industries with high elasticity?

To answer this question, I use a statistical technique called singular factor decomposition or SVD. The result show that there is one factor with an extremely large power to explain cross-industry and cross-country variation in productivity. The statistical analysis also shows that the industries with the high intensity of this factor are the ones with high elasticity of productivity with respect to per capita income, meaning that there is a shortage of this factor in poor countries. I hypothesize that the "missing factor" is human capital, which has been largely missing from the empirical analysis in international trade until now.

To study the effects of human capital, I break down labor into three types, based on the level of education: labor with no more than primary education, more than primary but less than tertiary education, and labor with at least some tertiary education. I collect data on the employment of these types of labor in 15 industries and many rich and poor countries. I also find earnings data for these types of labor in all the countries of the dataset.

It turns out that the factor of production with large explanatory power for the pattern of trade is highly educated labor - labor with at least some tertiary education. The industries which use this factor intensively are the ones with high elasticity of productivity with respect to per capita income. These are the industries in which rich countries have comparative advantages over poor countries.

Why do rich countries specialize in education-intensive goods? This paper finds that a number of explanations contribute to this result. Highly educated workers are relatively cheaper in rich countries than in poor ones if the differences in quality of educated are accounted for. Innovation occurs primarily in rich countries and it occurs faster in education-intensive industries than in other industries, as measured by the number of patents and extent of computer use. There is also more licensing of foreign technology in the education-intensive industries. There is much less licensing in poor countries for various reasons. Therefore, technology adoption in education-intensive industries occurs much faster in rich than in poor countries for two reasons. First, rich countries have more educated workers which are necessary for technology adoption and second, technology licensing is much more widespread between rich countries than between rich and poor countries. As the result, the technological gap between rich and poor countries is wider in education-intensive industries.

In addition, I find that education-intensive industries use management technology more intensively. Combined with the observation that rich countries use more management technology, this also provides an explanation for the observed pattern of comparative advantages. Empirically, this seems to be the least significant explanation.

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