The impact of educated labor on technology adoption and comparative advantage

Serge Shikher*

Research Division
U.S. International Trade Commission

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Abstract

Productivity differences across countries and industries play a major role in explaining international trade. This paper uses a new approach - a variant of the principal component analysis - to break down productivity differences into country- and industry-specific components. It finds strong evidence of log-supermodularity, which is a type of complementarity, of productivities with respect to country and industry characteristics, irrespective of whatever these characteristics may be. The paper then considers several candidates to explain country- and industry-specific components of productivity: physical capital, labor with various levels of education, and institutions. It finds that labor with tertiary education, especially labor with an equivalent of an Associate's degree, is the main determinant of productivity and does a good job explaining comparative advantages. The paper suggests that the main function of labor with tertiary education is to enable technology adoption.
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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 pattern of exports across countries. For example, countries with low GDP per capita tend to export products in certain industries, such as textile, basic metals, and food. Countries with high GDP per capita, on the other hand, tend to export certain types of machinery, such as medical equipment.

What explains the pattern of exports? Is it technology, abundance of some factors, or something else? The Ricardian model explains the pattern of trade by productivity differences, which determine comparative advantages. Empirical studies show that productivity differences are some of the

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most influential, maybe even the most influential, determinants of trade.[1] The goal of this paper is to characterize the pattern of productivities and then go beyond the productivity explanation and look for the causes of productivity differences across countries and industries.

The paper makes contributions to several literatures. It introduces a novel empirical approach to break down productivities into country- and industry-specific components. This approach does not require taking a stand apriori on which factors determine trade. The results provide strong evidence for log-supermodularity of productivity, which is a particular way in which country and industry characteristics interact to determine productivity, as explained below. The paper also contributes to the development accounting literature by adding the industry dimension. It shows that there is additional information contained in the industry dimension that can help us understand the sources of productivity differences across countries.

The paper finds that labor with tertiary education, especially labor with an equivalent of an Associate's degree, is the key determinant of productivity differences across industries and countries. The evidence suggests that the main contribution of this type of labor is to enable technology adoption.

The first step in the paper is to estimate productivities in each industry and country of the dataset. Comparative advantages are determined by productivities in autarky, also known as fundamental productivities (Costinot, Donaldson and Komunjer, 2012). These fundamental productivities are normally different from the productivities observed with trade. The paper uses the Eaton-Kortum model to estimate fundamental productivities in each country and industry.

When calculating productivities, the paper takes care to account for key factors of production. In addition to physical capital, the paper accounts for three types of labor distinguished by education: labor with primary, secondary, and tertiary education. In order to account for the contributions of these types of labor to production, the paper uses data on wages and employments in a wide set of countries. The paper is the first to the author's knowledge to calculate shares for these types of labor using data for a wide set of countries, not just the U.S.

The paper also accounts for differences in education quality across countries. Recent literature presents evidence on education quality differences from international test scores and earnings of immigrants (Hanushek and Kimko, 2000; Hendricks, 2002; Schoellman, 2012). Consistent with that literature, this paper finds that ignoring education quality differences substantially overestimates productivity gaps across countries.

The next step in the paper is to study the pattern of estimated productivities across industries and countries. The key finding is that productivity gaps between countries are systematically different across industries. Countries that are further away from technological frontier have productivities that are lower in certain industries than in others. Since distance to technological frontier has a high negative correlation with GDP per capita, another way of stating the key finding is that productivity gaps between rich and poor countries are systematically greater in some industries than in others. For example, productivity gaps between rich and poor countries are usually small in food manufacturing and large in medical equipment manufacturing.

The next challenge is to parsimoniously describe the observed pattern of productivities. I use a log-supermodular combination of country and industry characteristics to describe productivities. Log-supermodularity is a type of complementarity between two inputs of a mathematical function: it means that the impact from increasing one input is greater when other inputs are high.[2] Log-

[1] See for example Trefler (1995), Harrigan (1997), Davis and Weinstein (2001), and Eaton and Kortum (2012).

[2] Mathematically, function f is log-supermodular if for all $x' > x$ and $y' > y$ $f(x', y')f(x, y) \geq f(x, y')f(x', y)$.

supermodularity is the key unifying feature of the neoclassical trade theory. It characterizes the relationship between factor, industry, and country characteristics in a way that is more general than the Heckscker-Ohlin model: it provides more concrete results with an arbitrary number of countries, factors, and industries (Costinot, 2009a). An example of log-supermodularity is countries with more skilled workers having greater output in sectors which use skilled workers more intensively.

Since we do not know which country and industry characteristics may be affecting productivities, the first question is whether a combination of any country and industry characteristics can do a good job explaining productivities. To answer this question, I use a statistical technique called singular value decomposition (SVD), a variant of principal component analysis. The answer to the above question is a resounding "yes". A combination of just one country characteristic and one industry characteristic estimated by SVD can explain 92% of the variation of 742 productivities in 53 countries and 14 industries.

This result provides strong evidence for log-supermodularity. Until now, evidence of log-supermodularity existed only in cases of particular factors of production, such as institutions (Nunn, 2007; Levchenko, 2007; Chor, 2010; Costinot, 2009b). This paper is the first to provide evidence of log-supermodularity in general, irrespective of whatever country, industry, or factor characteristics affect trade.

I then proceed to search for real-life counterparts of the country and industry characteristics estimated by SVD. I investigate various factor endowments and measures of institutions. I find that the endowment and intensity of labor with tertiary education have the highest correlations with country and industry characteristics, respectively, estimated by SVD.

The central role of educated labor connects this paper with the literature focusing on the role of educated labor in technology adoption (Nelson and Phelps, 1966; Benhabib and Spiegel, 2005). In that literature, the lack of educated labor is a key reason for slow productivity convergence of developing countries to the technology frontier. The role of educated labor in technology adoption is motivated by the evidence from licensing of foreign technology, presented in detail in the appendix. In the industries that extensively use highly educated labor, we observe high levels of foreign technology adoption in the countries with high endowments of educated labor and very low levels of foreign technology adoption in the countries with low endowments of this labor. By contrast, in the industries that use little educated labor the levels of foreign technology adoption are equal across all countries.[3]

I estimate the fraction of the variation of productivities across countries and industries that can be explained by differences in endowments and intensities of labor with tertiary education. I find that labor with tertiary education alone is able to explain 50% of the variation of productivities across both countries and industries.

The particular pattern of productivities across countries and industries found in this paper connects it to the model of Krugman (1986). In both papers, technological gap between developed and developing countries varies systematically across industries. Both papers provide a "ladder" for development: as they develop, countries move from manufacturing one bundle of goods to another bundle of goods. In this world, technological progress is a vector rather than a number. In Krugman (1986), countries that lag further behind technological frontier have comparative disadvantage in the industries with high technological intensity. This paper presents empirical evidence that this is the case and relates technological intensity to human capital intensity.

[3] While this paper focuses on technology adoption, Somale (2014) focuses on innovation as the source of comparative advantage.

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. Even though the Ricardian model does well empirically, there is something unsatisfying about it.[4] 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. However, studies done until now have shown that factor endowment differences can explain only a fraction of comparative advantages. Productivity differences are still needed to explain the rest (Trefler, 1995; Harrigan, 1997; 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 comparative 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".[5]

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; Acemoglu and Zilibotti, 2001). There are also many papers that investigate the effects of human capital on output (Barro, 1991; Bils and Klenow, 2000; Barro and Lee, 2001; Erosa, Koreshkova and Restuccia, 2007; Manuelli and Seshadri, 2010; Schoellman, 2012).[6]

In international economics there are several papers that empirically investigate 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. Other papers that studied the relationship between human capital and trade are Keesing (1966), Baldwin (1971), Baldwin (1979), and Harrigan (1997).

One issue with the above literatures is that there is no widely agreed on measure of human capital. With very few exceptions, the existing literatures have not focused on workers with tertiary education. Typical measures of human capital are average years of schooling, fraction of workers

[4] 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 data well. Eaton and Kortum (2012) provide a review of the recent literature.

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

[6] Older literature finds the effect of education on output growth to be weak. Several reasons for this finding have been suggested: (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 et al., 2007; Manuelli and Seshadri, 2010; Schoellman, 2012).

with secondary education, fraction of skilled workers, and fraction of non-production workers. These measures are much less correlated with productivity than the fraction of workers with tertiary education.[7]

In addition to labor with tertiary education, this paper finds that institutions also play an important role in determining the pattern of productivities. Therefore, it confirms the findings of several previous papers that looked at the effects on institutions on trade (Nunn, 2007; Levchenko, 2007; Chor, 2010; Costinot, 2009b). However, this paper presents evidence that education plays a greater role in determining productivity than institutions.

Another study that analyzed various determinants of trade within the same methodology is Chor (2010). There is overlap in objectives between the our papers, but they ask somewhat different questions and use different empirical approaches. This paper looks to decompose productivities into country-specific and industry-specific determinants without taking a stand on what the determinants may be. Chor (2010), on the other hand, assumes specific determinants of trade from the beginning. To decompose productivities this paper uses a novel empirical approach and shows log-supermodularity of productivities. While Chor (2010) uses the fraction of non-production workers as the proxy for human capital, I use a much more detailed measure, which separates education into several levels, to more accurately pinpoint the effects of different levels of education on productivity.[8]

It is also interesting to compare the results of this study with the results in Levchenko and Zhang (2016). They estimate a measure of productivity for each industry and country following the same Eaton-Kortum methodology as this paper, but without distinguishing different types of labor. They estimate productivity for a number of countries and industries over several decades and find strong evidence of relative productivity convergence. Their result is consistent with the findings of this paper if the number of highly educated workers grew in developing countries relative to the developed countries.[9]

The results of this paper are relevant for applied trade analysis. Understanding causes of productivity differences makes it possible to predict changes in comparative advantages, trade flows, and specialization that will occur in the future. It also improves accuracy with which trade economists can predict the effects of trade policy changes. Policy implications are discussed in the conclusion.

2 Estimation of productivity

The first step is to estimate country- and industry-specific productivity levels. I follow a standard approach, using an extension of Eaton and Kortum (2002) to multiple industries and factors, similar

[7] Nunn (2007) distinguished between high school graduates and those that did not graduate from high school at the country level and looked at the fraction of non-production workers in the U.S. at the industry level. Levchenko (2007) and Chor (2010) looked at the fraction of non-production workers in U.S. data. Costinot (2009b) used average educational attainment for a country. At the industry level, he used a measure of on-the-job training.

[8] Chor uses trade as the dependent variable, whereas the dependent variable in this paper is productivity that is already net of factor price differences. Without taking a stand on the determinants of productivities, the methodology of this paper can explain 92% of the variation of productivities. Chor's R^2 is 0.6.

[9] Another related paper is Hanson, Lind and Muendler (2015) who estimate export capability (measured by the exporter fixed effect in the gravity regression) in each country and industry for a number of years. These export capabilities differ from the productivities measured in this paper by not accounting for differences in factor prices and intermediate goods costs across countries and industries. The authors find that countries' exports are highly concentrated in a few industries. They also find continual turnover in a country's top export products.

to Shikher (2012), Caliendo and Parro (2015), Chor (2010), and Levchenko and Zhang (2016). The model includes many countries, denoted by i, and industries, denoted by j. In each industry, there is a continuum of producers, each producing its own product with its own productivity, using a constant returns to scale production function.

The standard Eaton-Kortum methodology is applied at the industry level. Each industry j has a continuum of goods indexed by $u \in [0,1]$ and produced with its own productivity $\chi_{nj}(u)$. These productivities are the result of the R&D process and probabilistic, drawn independently from the Fréchet distribution with parameters $T_{ij} > 0$ and $\theta > 1$, with θ being the dispersion parameter.[10] The cdf of this distribution is $F_{ij}(\chi) = e^{-T_{ij}\chi^{-\theta}}$.

As in the Eaton-Kortum model, total imports of industry j goods by country n from country i, X_{nij}, as a share of total spending by country n on industry j goods, X_{nj}, is given by

$$\frac{X_{nij}}{X_{nj}} = \frac{T_{ij}\left(c_{ij}d_{nij}\right)^{-\theta}}{\sum_m T_{mj}\left(c_{mj}d_{nmj}\right)^{-\theta}} \tag{1}$$

where c_{ij} is the cost of production inputs and d_{nij} is the "iceberg" trade cost. Dividing trade shares (1) by their domestic counterpart, we obtain

$$\frac{X_{nij}}{X_{nnj}} = \frac{T_{ij}c_{ij}^{-\theta}}{T_{nj}c_{nj}^{-\theta}}d_{nij}^{-\theta} \tag{2}$$

The mean productivity in industry j of country i is denoted by $A_{ij} \equiv T_{ij}^{1/\theta}$. Costinot et al. (2012) call this measure the "fundamental" productivity of country i in industry j, which captures factors that affect all producers in that industry and country. This is also the productivity of an industry in autarky, when all goods are produced domestically.

Differences in A_{ij} across countries and industries create industry-level comparative advantages. For example, one country may have a comparative advantage in making textile products while another country may have a comparative advantage in making electronic components. The goal of this paper is to find and explain patterns in these industry-level comparative advantages.[11]

Taking logs of (2) and using the definition of A_{ij} we obtain

$$\log\frac{X_{nij}}{X_{nnj}} = \theta\log\left(A_{ij}/c_{ij}\right) - \theta\log\left(A_{nj}/c_{nj}\right) - \theta\log d_{nij}, \tag{3}$$

As in Eaton and Kortum (2002), I will assume that trade cost d_{nij} is represented by the following trade cost function:

$$\log d_{nij} = \mathrm{DIST}_{kj} + \mathrm{BORDER}_j + \mathrm{LANG}_j + \mathrm{FTA}_j + \mathrm{DEST}_{nj} + \delta_{nij} \tag{4}$$

where DIST_{kj} $(k = 1, ..., 6)$ is the effect of distance lying in the kth interval, BORDER_j is the effect of common border, LANG_j is the effect of common language, FTA_j is the effect of belonging to the

[10] The dispersion parameter θ is assumed to be the same across industries. Appendix A considers implications for the productivity estimates of allowing this parameter to vary across industries.

[11] There are also product level differences in productivities that create product-level comparative advantages. The focus in this paper is on the average productivity of an industry, rather than productivities of individual goods. In the context of the Eaton-Kortum model, the productivity of individual products within an industry are given by draws from the Fréchet distribution with mean A_{ij}. In autarky, two countries i and n with $A_{ij} = A_{nj}$ have the same average productivity across all goods in industry j, even if they may have different productivities for individual goods.

same free trade area, DEST_{nj} is the overall destination effect, and δ_{nij} is the sum of geographic barriers that are due to all other factors.[12] As typical in trade literature, international trade cost is measured relative to domestic trade cost: $\log d_{iij} \equiv 0$.

Plugging (4) into (3) we obtain

$$\begin{aligned}\log \frac{X_{nij}}{X_{nnj}} &= -\theta \text{DIST}_{kj} - \theta \text{BORDER}_j - \theta \text{LANG}_j - \theta \text{FTA}_j - \theta \text{DEST}_{nj} - \\ &\quad -\theta \delta_{nij} + \theta \log \left(A_{ij}/c_{ij} \right) - \theta \log \left(A_{nj}/c_{nj} \right)\end{aligned}$$

Collecting terms that become parts of importer and exports fixed effects, we get a gravity equation

$$\log \frac{X_{nij}}{X_{nnj}} = -\theta \text{DIST}_{kj} - \theta \text{BORDER}_j - \theta \text{LANG}_j - \theta \text{FTA}_j + D_{ij}^{exp} + D_{nj}^{imp} + \varepsilon_{nij}, \tag{5}$$

where $D_{ij}^{exp} = \theta \log \left(A_{ij}/c_{ij} \right)$ is the exporter fixed effect and $D_{nj}^{imp} = -\theta \text{DEST}_{nj} - \theta \log \left(A_{nj}/c_{nj} \right)$ is the importer fixed effect. The error term is $\varepsilon_{nij} = -\theta \delta_{nij}$.

The numbers for the left-hand side of (5) are obtained as follows: X_{nij} is from data and X_{nnj} is calculated as total output minus total exports of industry j in country n. The right-hand side of (5) consists of fixed effects. When estimating (5) the following normalization is used: $D_{us,j}^{exp} = D_{us,j}^{imp} = 0$. Consequently, the estimation produces fundamental productivities relative to the U.S., $A_{ij}/A_{us,j}$.

With estimates of exporter fixed effects D_{ij}^{exp} in hand, productivities $A_{ij}/A_{us,j}$ can be calculated using the definition of the exporter fixed effects as

$$\log \left(\frac{A_{ij}}{A_{us,j}} \right) = \frac{1}{\theta} D_{ij}^{exp} + \log \left(\frac{c_{ij}}{c_{us,j}} \right) \tag{6}$$

The production function in industry j of country i is Cobb-Douglas with physical capital, several types of labor, and intermediate goods as inputs.[13] The types of labor are differentiated by years of education and are imperfect substitutes in production. The cost of an input bundle in industry j of country n is

$$c_{ij} = r_i^{\alpha_j} \left(\prod\nolimits_e w_{ei}^{\lambda_{ej}} \right) P_{ij}^{1-\alpha_j-\beta_j}, \tag{7}$$

where r is the cost of capital, α is the share of capital, w_e is the cost of labor or type e, λ_e is the share of that type of labor, $\beta = \sum_e \lambda_e$ is total labor share, and P is the cost of the intermediate goods bundle.

Intermediate goods come from all industries and are aggregated in a Cobb-Douglas fashion:

$$P_{ij} = \prod\nolimits_m p_{im}^{\eta_{jm}}, \tag{8}$$

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 is calculated using the Eaton-Kortum model following Shikher (2012):

$$\log \frac{P_{ij}}{P_{us,j}} = \sum\nolimits_m \frac{\eta_{jm}}{\theta_j} \left(\log \frac{X_{iim}/X_{im}}{X_{us,us,m}/X_{us,m}} - D_{im}^{exp} \right). \tag{9}$$

[12] Note that unlike Eaton and Kortum (2002), trade costs here are industry-specific.

[13] Appendix A considers implications for the productivity estimates of allowing a more flexible production function.

2.1 Accounting for differences in education quality

I allow for the possibility that education quality can differ across countries. Measuring relative costs of labor in (7) only makes sense if labor quality is the same across countries. There is a growing body of literature that shows that education quality varies across countries and the variation helps explain GDP per capita differences across countries. The evidence of education quality differences includes international test scores (Hanushek and Kimko, 2000; Kaarsen, 2014) and earnings of immigrants (Hendricks, 2002; Schoellman, 2012). Whether education quality differences can help explain measured cross-industry productivity differences is a question that has not been asked until now.

To account for cross-country differences in education quality I use methodology from Schoellman (2012) and educational quality measures from Kaarsen (2014). The wage of workers with education level e in country i is given by $w_{ei} = \widetilde{w}_i h_{ei}$, where $\widetilde{w}_i$ is the base wage in country i and h_{ei} is the human capital of labor with education level e in country i. Human capital is a function of years and quality of education: $h_{ei} = e^{f(s_e, q_i)}$, where s_e is the number of year of education of level e and q_i is the quality of education in country i. Function f is given by $f(s_e, q_i) = \dfrac{\xi (s_e q_i)^\rho}{\rho}$, where ξ and ρ are parameters. With this specification, labor is differentiated by the level of schooling and also the quality of this schooling. So workers with secondary education in the United States and Brazil may have different levels of human capital for use in production.

If quality $q = 1$ for all countries, then the functional form for f is the one used in Bils and Klenow (2000) and, following their paper, much of the development accounting literature. Varying parameters ξ and ρ allows the model to fit the cross-country data on Mincerian returns to education.[14] Bils and Klenow note that ρ is probably less than one because of the diminishing Mincerian returns to schooling, which appear to exist based on the evidence from microdata from multiple countries. Schoellman (2012) extends the human capital production function of Bils and Klenow (2000) by introducing the quality of education q_i. By interacting education quality in the exponent, Schoellman (2012) produces the result that education quality and years of schooling are positively correlated as long as $0 < \rho < 1$, which is supposed by microeconomic evidence. The values of parameters ρ and ξ are estimated by Schoellman (2012) from earnings of immigrants and by Kaarsen (2014) from international test scores.[15]

The wages observed in data are w_{ei}^i, where the superscript represents the quality of education that workers received. In order to be comparable across countries, wages need to be for workers with the same level and quality of education. I use the quality of U.S. education as the level of quality at which I would compare the wages across countries. Therefore, I need to adjust wages from data w_{ei}^i to the equivalent wage at the U.S. quality of education, w_{ei}^{us}. If workers in country i had U.S.-quality education, they would have earned w_{ei}^{us}.

In order to obtain w_{ei}^{us}, I need to multiply the observed w_{ei}^i by w_{ei}^{us}/w_{ei}^i. Given the assumptions

[14] Following work of Mincer (1958), Mincerian returns are obtained by estimating an equation like this using microdata: $\log(w) = b_1 + b_2 s + b_3 B + \varepsilon$, where w is individual's wage, s is his years of schooling, B is the vector of other relevant personal characteristics, and b_2 is the estimated Mincerian return to schooling.

[15] Schoellman (2012) uses the returns to schooling of foreign-educated immigrants in the U.S. to measure the education quality of their birth countries. Kaarsen (2014) identifies differences in education quality from the increase in test scores obtained from an additional year of schooling.

above, this ratio is given by

$$\log \frac{w_{ei}^{us}}{w_{ei}^{i}} = \log \frac{\widetilde{w}_i h_{e,us}}{\widetilde{w}_i h_{ei}} = \log \frac{h_{e,us}}{h_{ei}} = f\left(s_e, q_{us}\right) - f\left(s_e, q_i\right) = \frac{\xi s_e^{\rho}}{\rho}\left[q_{us}^{\rho} - q_i^{\rho}\right] \tag{10}$$

The education quality in most countries is lower than that of the U.S., so their quality-adjusted wages are higher than non-quality-adjusted wages. Adjusting wages for quality in most countries leads to lower measured productivity differences with the United States in all industries. In other words, it helps explain productivity differences across countries. However, there are not enough differences in quality adjustment terms across industries to help explain the pattern of productivity differences across industries, i.e. the pattern of comparative advantages.

To summarize, the procedure for obtaining relative productivities $A_{ij}/A_{us,j}$ is to first estimate (5) in order to obtain the exporter fixed effects D_{ij}^{exp}. The second step is to calculate $A_{ij}/A_{us,j}$ using (6), with relative input costs calculated using (7) and wages for each labor type e adjusted for education quality using (10).

3 Data

I estimate country- and industry-specific productivities A_{ij} for 15 manufacturing industries in 53 countries in 2005. These productivities will inform us about the comparative advantages of countries. The countries include both rich and poor ones. For example, there are 30 countries with per capita 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 (5) was obtained from COMTRADE and concorded to 15 2-digit ISIC. 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).

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.[16] Rates of return to physical capital are calculated in two different ways using two different assumptions. Under the first assumption, rates of return 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). Under the second assumption, rates of return are given by $r = \alpha Y/K$, where α is the capital share in the economy, equal to 0.3, Y is GDP, and K is capital stock, obtained from Penn World Tables 8 (Feenstra, Inklaar and Timmer, 2013). The choice of the rate of return measure has little effect on the results and conclusions of this paper. Results presented in the rest of the paper are obtained using the first assumption. I set the value of θ equal to 8.28, which is the preferred value in Eaton and Kortum (2002). The appendix evaluates the robustness of the results to several assumptions made in the paper, including the value of θ.

[16] Some of these 43 countries are not in the dataset. However, since the assumption is that shares are the same in all countries, the set of countries is used to calculate the shares should not matter. I use this OECD data because it is the most reliable data on labor and capital shares for a wide set of countries. Also note that OECD data, in addition to intermediate and final goods, also has investment goods. Since there is no investment in the model, investment goods are treated as intermediate goods.

This paper considers three types of labor, differentiated by education: labor with no more than primary education ($e = 1$), labor with more than primary, but less than tertiary education ($e = 2$), and labor with at least some tertiary education ($e = 3$). One important issue with differentiating labor by level of education in the production function is that there is no readily available data on labor shares λ_{ej} by industry outside the U.S. This paper is the first to my knowledge to compile such data.[17] I also allow for differences in education quality across countries, as explained the previous section.

3.1 Data on the earnings of three types of labor

In order to operationalize (6) 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 that sometimes supplement each other and sometimes serve to cross-verify each other. What follows is fairly brief exposition of data sources. A more detailed review is presented in the data appendix.

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 (in ISIC classification) and level of education (in ISCED classification). 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.[18]

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 data from country-specific studies, documented in the data appendix. 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

[17] Previous studies used various measures of skill intensity. Some studies used skilled/unskilled classification of labor reported in some surveys. Other studies measured skill intensity by the proportion of non-production workers in the total labor. The WBES dataset classifies labor according to education, skilled/unskilled, and production/non-production status. Using WBES data, I find only a weak correlation between skilled status and education and between non-production status and education. In general, 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. The non-production status is a poor proxy for education because in industries with higher share of educated workers, both production and non-production are more educated than in other industries. For example, in some industries production workers are required to have post-secondary education.

[18] The t-statistic for this correlation is 14.085 and p-value is <0.0001.

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.

Combining all the sources of earnings information, I obtain earnings for each of the 53 countries in my datasets and 3 levels 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 ("education premia").[19] The cross-country average premium for having secondary education is 34%. This number is not adjusted for differences in education quality. 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 one's standard of living.

In order to adjust wages for differences in education quality using equation (10) I use two sources of estimates of education quality: Schoellman (2012) and Kaarsen (2014). Schoellman (2012) estimates quality of education from earning of immigrants while Kaarsen (2014) estimates them from international science and math test results, as explained in Section 2.1. The choice of the source for the estimate of education quality makes only small difference in the results presented in this paper and does not affect the conclusions. When estimating productivities, I only present the results obtained using Kaarsen's estimates of q. When looking at the effects of country-specific determinants on productivities in Section 5.1 I show results obtained using both Schoellman's and Kaarsen's estimates. I use each author's corresponding estimates of parameters ρ and ξ. Schoellman estimates $\rho = 0.5$ while setting $\xi = 1$. Kaarsen estimates $\rho = 0.35$ and $\xi = 0.46$. I set $s_1 = 3$ for primary education, $s_2 = 9$ for secondary, and $s_3 = 15$ for tertiary.

3.2 Data on the employment and shares of 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.[20] 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} I calculate shares of each type of labor in total labor income, $w_{ei}L_{eij}/\left(w_{1i}L_{1ij} + w_{2i}L_{2ij} + w_{3i}L_{3ij}\right)$. The average of these shares across countries is equal to λ_{ej}/β_j from which I can back out λ_{ej} using data on β_j (described previously).

Table 1 shows factor shares in output. 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.[21] The share of capital in the most capital intensive industry,

[19] 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.

[20] The number of enterprises surveyed in some countries is small. This is compensated by the number of countries with the data. The total number of enterprises surveyed is 6,000. Note that I do not use the data on total employment from WBES, but only use the data on the share of each type of labor in total labor costs in each industry.

[21] 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).

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 least labor intensive industry, Food.[22]

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 ($e = 1$) is 1.65 times higher in Textile industry. At the same time, the share of labor with some tertiary education ($e = 3$) 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 1: 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}

3.3 Data for sixteen types of labor from the United States

I consider the shares obtained from the international data (described in the previous section) to be my primary source of information on the use of different types of labor, but I also use data from the United States to have a more detailed information on the use of different types of labor in manufacturing. The U.S. data provides information on 16 types of labor differentiated by level of education. The source of the U.S. data is the American Community Survey (ACS). I use microdata from that survey, which provides detailed information on about 3 million people. In addition to

[22] Petroleum Products industry is often an outlier and is omitted from much of the analysis done in this paper.

educational attainment, this survey collects data on employment status, industry of employment by 3 to 5 digit NAICS classification (which I concord to my 15 industries), salary/wages, and occupation by SOC code (465 non-military occupations).

For each industry, I calculate shares of each type of labor in total labor earnings λ_{ej}/β_j, $e = 1, ..., 16$. As a cross-check, I aggregate these shares into the three types of labor described in the previous section. I find that the shares from the ACS are correlated (across industries) with the shares from international data. The correlation is 0.78 for the first type of labor, 0.75 for the second, and 0.94 for the third.

4 What do estimated relative productivities tell us?

I estimate relative productivities $\log(A_{ij}/A_{us,j})$ using equations (5), (6), and data on 15 industries in 53 countries. The estimates of productivities for select countries are shown in Table 2.

Table 2: Productivities in select countries

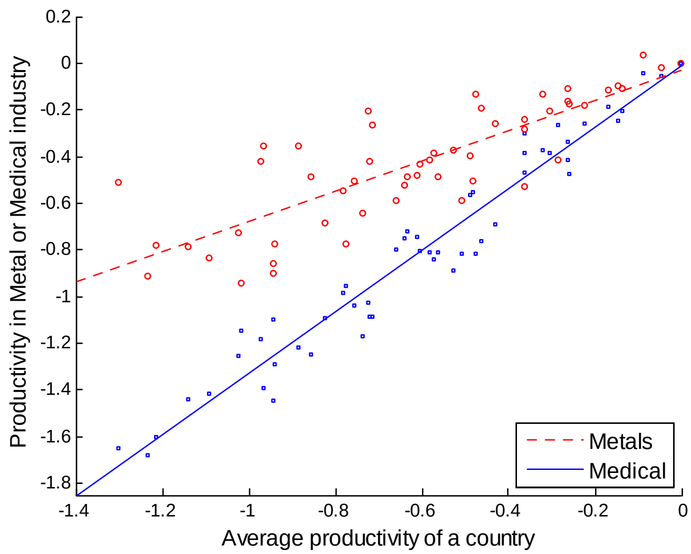
	China	Ethiopia	Germany	Korea	Mexico	Turkey	Vietnam
Food	0.66	0.48	0.88	0.60	0.57	0.67	0.56
Textile	0.80	0.42	0.96	0.91	0.59	0.78	0.54
Wood	0.74	0.33	0.98	0.60	0.47	0.53	0.46
Paper	0.59	0.25	0.95	0.73	0.49	0.49	0.33
Chemicals	0.66	0.39	0.91	0.72	0.62	0.59	0.37
Rubber	0.60	0.27	0.94	0.93	0.52	0.60	0.40
Nonmetals	0.71	0.30	1.01	0.77	0.53	0.66	0.40
Metals	0.77	0.46	0.98	0.90	0.62	0.69	0.42
Metal products	0.62	0.25	0.98	0.76	0.53	0.59	0.35
Machinery, other	0.58	0.21	0.97	0.75	0.54	0.54	0.31
Machinery, e&c	0.67	0.22	0.97	0.89	0.59	0.60	0.38
Medical	0.50	0.20	0.95	0.66	0.47	0.41	0.24
Transport	0.58	0.28	0.98	0.89	0.55	0.63	0.40
Other	0.67	0.26	0.91	0.76	0.54	0.59	0.41
AVERAGE	0.65	0.31	0.95	0.78	0.54	0.60	0.40

Looking at the industry-level productivities $\log(A_{ij}/A_{us,j})$ we can make several observations. First is that some countries have higher productivities than others in all industries. For example, productivity in Germany is higher than productivity in Ethiopia in all industries. The cross-industry average productivity in Germany is about 3 times higher than the average in Ethiopia.

The second observation is that in each country relative productivities vary significantly across industries. For example in Vietnam the Food industry is 56% as productive as the Food industry in the U.S. while the Metal Products industry is only 35% as productive as the Metal Products industry in the U.S. This within-country cross-industry variation represents industry-level comparative advantages enjoyed by each country.

The third observation, which is key to this paper, is that as the overall productivity of a country declines the productivities of individual industries decline at different rates. The productivity declines quickly in some industries and slowly in others. Figure 1 illustrates this phenomenon by

Figure 1: Productivity in two industries, in logs



plotting productivities in two industries, Metals and Medical, against a simple average productivity for each country, $\overline{A}_i = (1/J)\sum_j \log(A_{ij}/A_{us,j})$. As average productivity declines, the relative productivity falls much faster in Medical than in Metals industry. Productivity differences between these two industries are small in rich countries, but become obvious in middle-income countries. They are very large in poor countries. Clearly, the productivity-driven comparative advantage of poor countries lies much more in Metals industry than in Medical.[23] This implies that there is a pattern of productivity differences across countries.

This pattern is more clearly seen on Figure 2 which shows the productivities in all industries of all countries. The countries are sorted by the average (across industries) country productivity while the industries are sorted by the average (across countries) industry productivity.

4.1 A formal analysis of relative productivities

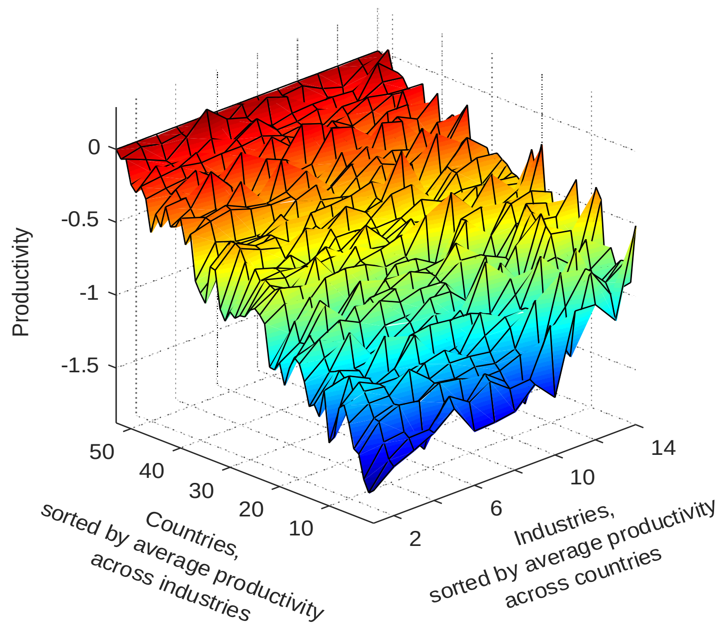
We will now proceed to characterize the pattern of productivities more formally. Let's see if we can decompose productivity differences into industry-specific components γ_j^k, $k = 1, ..., M$ and country-specific components ϕ_i^k, $k = 1, ..., M$, where M is the number of components.

I will assume a specific functional relationship between productivity differences, industry, and country components:

$$\frac{A_{ij}}{A_{us,j}} = f\left(\frac{\phi_i^1}{\phi_{US}^1}, ..., \frac{\phi_i^M}{\phi_{US}^M}, \gamma_j^1, ..., \gamma_j^M\right) = -\prod_{k=1}^{M}\left(\frac{\phi_i^k}{\phi_{US}^k}\right)^{\gamma_j^k} \tag{11}$$

[23] We can quantify how fast the technological gap grows as GDP per capita declines by the slope of the regression $\log(A_{ij}/A_{us,j}) = \mu_{0j} + \mu_{1j}\log(Y_i/Y_{us}) + \varepsilon_{ij}$, 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. Food and Metals industries have the lowest estimated elasticities μ_{1j} while Metal Products and Medical have the highest. The regression R^2 increases together with the slope (elasticity).

Figure 2: Pattern of industry productivities, in logs



or in logs

$$\log \frac{A_{ij}}{A_{us,j}} = -\sum_{k=1}^{M} \gamma_j^k \log \frac{\phi_i^k}{\phi_{US}^k}. \tag{12}$$

This functional form is called log-supermodular (Costinot, 2009a). As explained in the introduction, log-supermodularity is a type of complementarity between two inputs of a function. It is a mathematical property of a function that says that the impact from increasing one input is greater when other inputs are high. In (12), the impact of γ_j^k is high when ϕ_i^k/ϕ_{US}^k is high and vice versa.[24]

Equation (12) in a matrix form is

$$\underset{N\times J}{\mathbf{A}} = \underset{N\times M}{\mathbf{U}} \cdot \underset{J\times M}{\mathbf{V}}^{\mathsf{T}}, \tag{13}$$

where each row of $\mathbf{U}$ contains the values of M country-level determinants of productivity in country i, and each row of $\mathbf{V}$ contains the values of M industry-level determinants of productivity in industry j. To decompose $\mathbf{A}$ into $\mathbf{U}$ and $\mathbf{V}$ I use a statistical technique called Singular Value Decomposition (SVD). Since this procedure may be unfamiliar to some readers, I provide a brief description here.

A singular value and a pair of singular vectors of a rectangular matrix $\mathbf{A}$ are a nonnegative scalar σ and nonzero vectors u and v such that $\mathbf{A}v = \sigma u$ and $\mathbf{A}^{\mathsf{T}}u = \sigma v$. Written in matrix form, the defining equations for singular values and vectors are $\mathbf{AV} = \mathbf{U\Sigma}$ and $\mathbf{A}^{\mathsf{T}}\mathbf{U} = \mathbf{V\Sigma}^{\mathsf{T}}$. Here $\mathbf{\Sigma}$ is a matrix that is zero except on its main diagonal that contains the singular values of $\mathbf{A}$. Matrices $\mathbf{U}$

[24] By comparison, there is no complementary between country and industry characteristics in a fixed effects decomposition, such as $\log(A_{ij}/A_{us,j})$ =COUNTRY$_i$+INDUSTRY$_j + \varepsilon_{ij}$, where COUNTRY and INDUSTRY are the fixed effects and ε is the error term.

and $\mathbf{V}$, whose columns are the singular vectors, are orthogonal.[25] A singular value decomposition of matrix $\mathbf{A}$ is a factorization

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^{\mathsf{T}} \tag{14}$$

In other words, SVD decomposes $\mathbf{A}$ (in the least squared sense) into $\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^{\mathsf{T}}$, where $\mathbf{\Sigma}$ is a diagonal $M \times M$ matrix with each diagonal element (singular value) 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. SVD can be performed in MATLAB using the SVD command.

Consider for example equation (12) with $M = 1$:

$$\log \frac{A_{ij}}{A_{us,j}} = -\gamma_j^1 \log \frac{\phi_i^1}{\phi_{US}^1} + \varepsilon_{ij}, \tag{15}$$

where ε_{ij} is the residual. We can use SVD to estimate γ_j^1 and ϕ_i^1 that would best explain the variation of productivities A_{ij} (in the least squared sense).

Table 3: Singular value decomposition results

1	19.16
2	1.43
3	1.30
4	1.05
5	0.95
6	0.67
7	0.52
8	0.46
9	0.45
10	0.39
11	0.36
12	0.34
13	0.28
14	0.21

I apply singular value decomposition (14) to the matrix of relative productivities $\log(A_{ij}/A_{us,j})$. Table 3 shows the estimated diagonal elements of $\mathbf{\Sigma}$. We immediately notice the very large explanatory power of the first factor. This means that the elements of $\mathbf{A}$ are not random, but have a structure.[26] This structure is given by (12) and is log-supermodular. Robustness checks performed in the appendix show that log-supermodularity of the productivity matrix is robust to the choice of the production function and dispersion parameter θ.

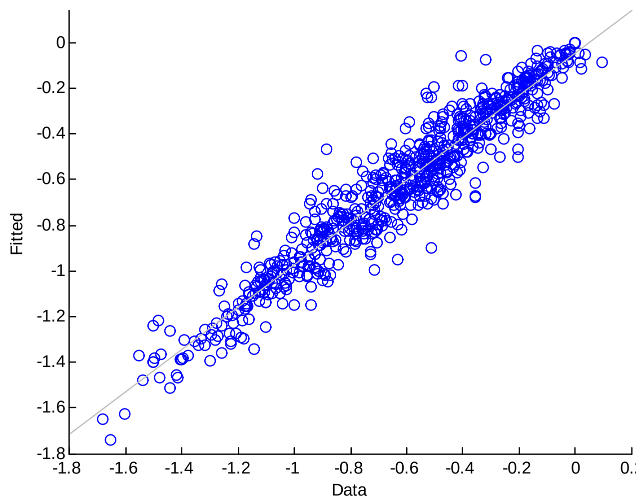
The results in Table 3 imply that there is one component with a very large explanatory power for both cross-industry and cross-country variation of relative productivities. The R^2 of the fit with

[25] Singular values and eigenvalues are related: the singular values of matrix $\mathbf{A}$ are the positive square roots of the nonzero eigenvalues of $\mathbf{A}^{\mathsf{T}}\mathbf{A}$. If $\mathbf{A}$ is a real symmetric $N \times N$ matrix with non-negative eigenvalues, then its eigenvalues and singular values are the same.

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

only the first factor, as in (15), is 0.92.[27] Figure 3 plots the fitted vs. actual productivities in all industries and countries in this case. Table 4 shows the ranking of the industries according to the estimated first industry component, γ_j^1.

Figure 3: Fitted vs. actual productivities



If we find one or more industry characteristics that are highly correlated with γ_j^1 and one or more country characteristics that are highly correlated with ϕ_i^1/ϕ_{US}^1 then we would be able to explain most of the variation in productivities $A_{ij}/A_{us,j}$.[28] In the next sections we will be looking for such industry and country characteristics.

Krugman (1986) described a model in which productivity differences across countries and industries have a pattern. In that model, rich countries have comparative advantages in certain industries, which Krugman calls "technology-intensive". The results of this section show that there is a pattern of productivities across countries and industries in which the level of economic development of a country leads to a particular set of industries in which that country has comparative advantages. The next section will characterize the industries in which rich and poor countries have comparative advantages.

[27] This corresponds to the correlation equal to 0.96. I investigate whether it is the country or industry component of this first factor that accounts for most of its explanatory power. I set the industry component γ_j^1 equal to its mean value across all industries and compute a counterfactual set of productivities based on just the variation in the country component ϕ_i^1/ϕ_{US}^1. The correlation between the counterfactual and actual productivities is 0.9. Similarly, I set ϕ_i^1/ϕ_{US}^1 equal to its mean value across countries and compute a counterfactual set of productivities based on just the variation in the industry component. The correlation between counterfactual and actual productivities in this case is 0.27. Therefore, cross-industry differences are more important for explaining relative productivity differences. This is partially due to the fact that there are more countries than industries in the dataset. If the number of countries (chosen randomly) is reduced, the importance of cross-country differences decreases and the importance of cross-industry differences increases.

[28] Estimated components γ_j^1 and ϕ_i^1/ϕ_{US}^1 can be linear combinations of several real-world determinants of productivity.

Table 4: Ranking of industries according to the first industry-specific factor γ_j^1

Metals
Food
Textile
Chemicals
Wood
Machinery, e&c
Rubber
Nonmetals
Transport
Other
Paper
Machinery, other
Metal products
Medical

5 In search of key determinants of productivity

In this section, we will search for country- and industry-level determinants of productivity. The industry determinant(s) should be highly correlated with γ_j^1 while the country determinant(s) should be highly correlated with ϕ_i^k/ϕ_{US}^k. I am especially looking for factor(s) that affects both country and industry dimensions of productivity differences.

Literature, reviewed in the Introduction, suggests several possible causes of productivity differences across countries and industries. Factor endowment differences across countries and factor intensity differences across industries can lead to productivity differences. Since factor prices and shares have been accounted for when calculating productivities, the remaining effects of factor endowments and intensities may be externalities. There are many examples of externalities coming from factor accumulation in the literature, so we will discuss if they play a role here.

Productivity can also be caused by differences in institutions. Countries may differ in the quality of their institutions and industries may differ in the degree to which they rely on institutions. Finally, productivity differences can come from differences in technology production or technology adoption. This section will present evidence, building on the results of the previous section, to help us evaluate these and other alternative explanations. Section 6 will discuss the evidence.

5.1 Country-level determinants

In this section I will look for country characteristics that are correlated with ϕ_i^1/ϕ_{US}^1. The most obvious country characteristic that is commonly used in macroeconomics is GDP per capita. The correlation between ϕ_i^1/ϕ_{US}^1 and $\log(y_i/y_{US})$, where y_i/y_{US} is the GDP per capita of country i relative to the U.S., is 0.8.

5.1.1 Factor endowments

I check if factor endowments are correlated with ϕ_i^1/ϕ_{US}^1. I consider physical capital, labor with primary education, secondary education, and tertiary education. Data on physical capital per person is from Penn World Tables 8 (Feenstra et al., 2013). The correlation between physical capital per capita, $\log(k_i/k_{us})$, where k_i is capital per capita in country i, and ϕ_i^1/ϕ_{US}^1 is 0.75. All correlations are summarized in Table 6.

Table 5: Quality and endowments of labor with tertiary education in select countries

	China	Ethiopia	Germany	Slovakia	Norway	Turkey	Vietnam
Quality of education: human capital per person with tertiary education, relative to the U.S., in logs	-0.462	-0.930	-0.059	-0.206	0.013	-0.564	-1.280
Endowments: fraction of population over 25 with tertiary education in 2005							
Data from from IIASA	0.052	0.014	0.219	0.130	0.267	0.089	0.042
Relative to the U.S., in logs	-1.633	-2.933	-0.201	-0.723	-0.002	-1.097	-1.843
Adjusted for education quality, relative to the U.S., in logs	-2.094	-3.864	-0.260	-0.929	0.011	-1.662	-3.123

Table 6: Correlations between various country-level determinants and ϕ_i^1/ϕ_{US}^1

GDP per capita	0.8
Capital stock per capita	0.75
Labor with primary education	(-0.23)-(-0.09)
Labor with primary education (outliers removed)	(-0.30)-(-0.18)
Labor with secondary education	0.48-0.55
Labor with secondary education (outliers removed)	0.56-0.69
Labor with tertiary education	0.55-0.65
Labor with tertiary education (outliers removed)	0.67-0.76
Rule of law	0.69
Quality of legal system	0.65
WB Doing Business Overall Distance To Frontier 2010	0.7
WB Doing Business Distance To Frontier 2006	0.26-0.61

Note: For labor with tertiary education, Russia, Ukraine, Kazakhstan, and Bulgaria are outliers

I consider two measures of educational attainment, one from Barro and Lee (2013) and the other from IIASA/VID[29]. The measures of skilled labor endowments need to be adjusted for cross-country

[29] Described in Lutz, Goujon, K.C. and Sanderson (2007).

differences in education quality. I use estimates of education quality from Schoellman (2012) and Kaarsen (2014) as follows. Let L_{3i}^{i} be the quantity of labor with tertiary education in country i. Subscript denotes location of labor while superscript denotes quality of education. Each worker has human capital h_3^i so the total human capital embodied in L_{3i}^i is $H_{3i} = h_3^i L_{3i}^i$. The same human capital can be embodied in L_{3i}^{us} workers with U.S.-quality education: $H_{3i} = h_3^{us} L_{3i}^{us}$. While L_{3i}^i is observed in the data, I need L_{3i}^{us} to make meaningful comparisons of skilled labor endowments across countries. It is obtained as $L_{3i}^{us} = L_{3i}^i \left(h_3^i / h_3^{us}\right)$, where following Schoellman (2012) and Kaarsen (2014) $h_3^i / h_3^{us} = \exp\left(\left(\xi/\rho\right) s_3^{\rho} \left(q_i^{\rho} - q_{us}^{\rho}\right)\right)$, where q_i is the quality of education in country i.

I look at the correlations between ϕ_i^1/ϕ_{US}^1 and $\log\left(l_{ei}^{us}/l_{e,us}^{us}\right)$, where labor endowments l are measured in per capita terms. There are two sources of information on educational attainment (Barro-Lee and IIASA/VID) and two measures of educational quality (Schoellman and Kaarsen).[30] Table 5 shows endowments of labor with tertiary education for select countries using IIASA/VID data and Schoellman's measure. The first row shows $\log\left(h_3^i/h_3^{us}\right)$, the second row l_{3i}^i, the third row $\log\left(l_{ei}^i/l_{e,us}^{us}\right)$, and the last row $\log\left(l_{ei}^{us}/l_{e,us}^{us}\right)$. We can see that differences in education quality amplify gaps in effective endowments of educated labor between rich and poor countries.

Table 6 shows the range of correlations for all possible combinations of data sources, 0.55-0.65. Barro-Lee measures produce lower correlations than IIASA/VID measures. There are several countries that are outliers in terms of the relationship between ϕ_i^1/ϕ_{US}^1 and $\log\left(l_{3i}^{us}/l_{3,us}^{us}\right)$. They are the former Soviet republics in my dataset (Russia, Ukraine, and Kazakhstan), and Bulgaria. These countries have high educational attainment, but relatively low ϕ_i^1/ϕ_{US}^1 (and low GDP per capita).[31] Dropping these four countries raises the correlations to 0.67-0.76.

5.1.2 Role of institutions

I check how country institutional quality correlates with ϕ_i^1/ϕ_{US}^1. I use a measure of the rule of law in 1998 from Kaufmann, Kraay and Mastruzzi (2003) and the measure of the quality of legal system in 1995 from Gwartney and Lawson (2003). Both of these measures were used in Nunn (2007). I also use several measures from the World Bank's Doing Business report. One is the "overall distance to the frontier" in 2010. It is a score between 0 and 100 with 100 being the highest. Ideally, I would use data for 2005 since this is the year for which productivities were estimated. However, the overall distance to the frontier is not available for years prior to 2010 so I use distances to frontier in 9 different Doing Business report topics for 2006.[32]

The first three measures of institutions (Kaufmann, Kraay, and Mastruzzi's, Gwartney and Lawson's, and World Bank's overall distance to frontier) have similar correlations with ϕ_i^1/ϕ_{US}^1, between 0.65 and 0.7. The correlations between 9 different distances to frontier and ϕ_i^1/ϕ_{US}^1 vary between 0.26 ("paying taxes") and 0.61 ("trading across borders").

Of all the variables reviewed in this section, GDP per capita has the highest correlation with ϕ_i^1/ϕ_{US}^1, so higher overall productivity is associated with higher GDP per capita. Physical capital, skilled labor, and institutional endowments have similar correlations with ϕ_i^1/ϕ_{US}^1, around 0.7.

[30] Both Barro-Lee and IIASA/VID educational attainment datasets combine census and other data with estimates.

[31] Schoellman's educational quality measure, which is based on earnings of immigrants, produces lower measures quality of education does a better job of accounting for lower quality of education in those four countries than Kaarsen's measure, which is derived from science and math test results. However, Schoellman's measure produces slightly lower correlations between ϕ_i^1/ϕ_{US}^1 and $\log\left(l_{ei}^{us}/l_{e,us}^{us}\right)$ when outliers are dropped.

[32] Those are Starting a Business, Dealing with Construction Permits, Registering Property, Getting Credit, Protecting Minority Investors, Paying Taxes, Trading Across Borders, Enforcing Contracts, and Resolving Insolvency.

These three measures are also highly correlated with each other.

5.1.3 Altogether

The first principal component ϕ_i^1/ϕ_{US}^1 can actually be a linear combination of several country-level determinants. To see if this is the case, I regress it on factor endowments and a measure of institutions. Table 7 shows the results.

Table 7: Regression of ϕ_i^1/ϕ_{US}^1 on various country-level determinants

Source of education quality data	Schoellman	Shoellman	Kaarsen
Source of institutions data	DTF10	DTF10	qc
Constant	-0.043 (0.000)	-0.044 (0.000)	-0.049 (0.000)
Physical capital per capita	0.030 (0.001)	0.032 (0.000)	0.022 (0.047)
Fraction of population with primary education, quality adjusted	0.001 (0.552)	0.000 (0.814)	0.001 (0.497)
Fraction of population with secondary education, quality adjusted	-0.014 (0.342)	-0.006 (0.627)	0.011 (0.363)
Fraction of population with tertiary education, quality adjusted	0.019 (0.052)	0.023 (0.012)	0.017 (0.045)
Institutions	0.104 (0.037)	0.027 (0.654)	0.030 (0.276)
R squared	0.65	0.71	0.71
N	53	49	47

p-values in parentheses
Source of educational attainment data is IIASA
DTF10 is Overall distance to frontier in 2010 from WB
qc is Quality of Legal System in 1995 from Gwartney and Lawson (2003)

When physical capital is included in a regression, it is always statistically significant. Fraction of labor force with tertiary education is also statistically significant in all regressions, regardless of the source of data or measure of education quality used. Institutions are significant when all observations are included, but become insignificant when the four outlier countries are omitted. This finding is robust to the measure of institutions used. It seems that physical capital and labor with tertiary education can explain average productivity differences across countries, except in the four outlier countries. In those countries, poor institutions help explain low average productivity.[33]

5.2 Industry-level determinants

This section looks at several sets of industry characteristics that can be correlated with γ_j^1. It will look at intensities with which industries use capital and labor. I have accounted for capital and labor costs when calculating productivity (6), but there could be effects of these factors on productivity not accounted for in the production function. I discuss in the next section what these effects may be.

The section will also look at the effects of institutions. Several recent papers found that industries vary in the degree to which they rely on institutions (Nunn, 2007; Levchenko, 2007; Costinot,

[33] An appendix performs a variety of the robustness checks for these results.

2009b; Chor, 2010; Nunn and Trefler, 2015). These differences in institutional reliance, called institutional intensities, can lead to productivity differences.

5.2.1 Factor intensities

I start by checking if intensities of some factor of production correlate with the estimated γ_j^1. Table 8 shows the correlations between factor shares α_j, λ_{1j}, λ_{2j}, λ_{3j} and γ_j^1. The correlation between α_j and γ_j^1 is very low at 0.27. The correlation between γ_j^1 and shares of labor with primary education, λ_{1j}, 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 γ_j^1 and shares of labor with secondary education, λ_{2j}, is 0.51, so it 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.

Table 8: Correlations between various industry-level determinants and γ_j^1

Capital	0.27
Labor, primary	-0.08
Labor, secondary	0.51
Labor, tertiary	0.88
Contract intensity, z^{rs1}	0.65-0.69
Contract intensity, z^{rs2}	0.76-0.78
Input concentration	0.67
External financial dependence	0.53
Job complexity	0.47

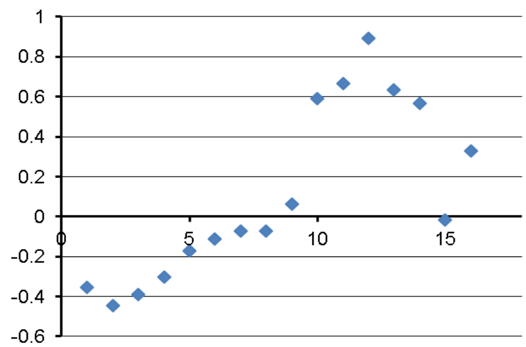
z^{rs1}: fraction of inputs not sold on exchange and not reference priced
z^{rs2}: fraction of inputs not sold on exchange
Input concentration: one minus the Herfindahl index of intermediate input use
External financial dependence is capital expenditure minus cash flow, divided by capital expenditure
Job complexity is a measure of on-the-job training required to become fully qualified

The correlation between γ_j^1 and shares of labor with at least some tertiary education, λ_{3j}, is 0.88, so it is positive and high. Since γ_j^1 is closely related to λ_{3j} and ϕ_i^1/ϕ_{US}^1 is closely related to GDP per capita, we can say that as GDP per capita decreases relative productivity falls faster in the education-intensive industries.

The high correlation between λ_{3j} and γ_j^1 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 an post-secondary education.

I will now use the U.S. data on labor shares to learn more precisely which type of labor is the key to the pattern of productivity. While using U.S. data to proxy for international data is not ideal, I have shown that labor shares obtained from the U.S. data are closely correlated with the shares obtained from international data, especially for the labor with tertiary education, which is our focus.

Figure 4: Correlations between γ_j^1 and shares of 16 types of labor (from the U.S. data)



1	No school completed
2	Nursery school to grade 4
3	Grade 5 or grade 6
4	Grade 7 or grade 8
5	Grade 9
6	Grade 10
7	Grade 11
8	Grade 12 no diploma
9	High school graduate
10	Some college, but less than 1 year
11	One or more years of college, no degree
12	Associate's degree
13	Bachelor's degree
14	Master's degree
15	Professional school degree
16	Doctorate degree

The U.S. data provides us with shares of 16 types of labor shown on Figure 4. For each type of labor, I calculate the correlation between its share λ_{ej}, $e = 1, ..., 16$, and γ_j^1. Figure 4 plots the correlations with the type of labor on the horizontal axis and correlation between labor shares and γ_j^1 on the vertical.

The figure shows a very clear pattern. The correlation is negative for low levels of education until $e = 8$ (12th grade, no diploma). There is a big jump between levels 9 (high school graduate) and 10 (some college, but less than one year). The correlation peaks at level 12 (Associate's degree) and drops after that. The correlation is close to zero for level 15 (professional degrees). The correlation for level 16 (doctorate degree) is higher than for level 9 (high school graduate), but lower than for level 10 (some college). The correlation for labor with Associate's degrees is high, 0.89.

The U.S. data also makes it possible to break down shares by educational attainment and occupation. The data shows that people with Associate's degrees work in many occupations: management, office support, production, maintenance, engineering, technicians, and others. The data also shows that industries that are more education-intensive use more educated workers in all occupations. In other words, administrators, engineers, maintenance workers, production workers, technicians, and sales people are all more educated in the education-intensive industries.

The evidence presented in Figure 4 supports the idea that labor with Associate's degrees is key for the U.S. and other developed countries' competitiveness in manufacturing. The manufacturing operations that exist in developed countries are highly computerized and use sophisticated equipment that requires labor with specialized technical education. This education is provided by technical schools, community colleges and other institutions. In the U.S., this education can also be obtained in the armed forces.

5.2.2 Role of institutions

I also explore if γ_j^1 is correlated with some measure of institutional intensity or institutional dependence of industries. I use two industry-level measures of institutional intensity from Nunn (2007): a measure of contract intensity and one minus the Herfindahl index of intermediate input use. Chor

(2010) also uses both of these measures and Levchenko (2007) uses the latter measure. In addition, I use a measure of external financial dependence used in Do and Levchenko (2007) and a measure of job complexity from Costinot (2009b). In the appendix, I describe three additional industry characteristics that I analyzed: patenting, computer use, and management technology.

The first measure, contract intensity or relationship specificity, is based on Rauch's (1999) classification of goods into those sold on exchange, reference priced, or neither. Nunn (2007) combines this information with the U.S. I-O use table to calculate, for each industry, the fraction of inputs not sold on organized exchange, denoted z^{rs2}, and the fraction of inputs not sold on organized exchange or reference priced, denoted z^{rs1}. Greater z^{rs1} (or z^{rs2}) implies greater dependence on institutions. Since Rauch created two classifications of goods, conservative and liberal, depending on how he treated ambiguous cases, there are actually two measures, conservative and liberal, of z^{rs1} and two measures of z^{rs2}.

Another measure of institutional intensity is the Herfindahl index of intermediate input use, which tells us how concentrated (across industries) are the intermediate goods used by an industry. An industry that sources many of its intermediate goods from other industries will have a high value of (1 − Herfindahl index) and will depend more on institutions.

External financial dependence is a measure of dependence on external financing for capital investment.[34] An industry in which firms require more external financing is more dependent on the financial sector, which may not be up to the task.

Job complexity is a measure of on-the-job training required in an industry to become fully qualified.[35] On-the-job training is another way of acquiring human capital, besides education.[36]

Table 8 shows the correlations between various industry characteristics and γ_j^1. The correlations range between 0.65 and 0.78. The fraction of inputs not sold on organized exchange, z^{rs2}, has a fairly high correlation with γ_j^1, 0.76 or 0.78, depending on whether we use the conservative or liberal measure of z^{rs2}. Two other measures of institutional intensity, z^{rs1} and one minus the Herfindahl index, have slightly lower correlations with γ_j^1, between 0.65 and 0.69. The two remaining industry characteristics considered, external financial dependence and job complexity, have even lower correlations with γ_j^1, 0.53 and 0.47. The results in Table 8 are similar to Chor (2010) who finds that Nunn's (2007) and Levchenko's (2007) measures are the most important regressors.

5.2.3 Altogether

Similarly to the first country-specific principal component, ϕ_i^1/ϕ_{US}^1, the first industry-specific principal component γ_j^1 can be a linear combination of industry-specific variables. Therefore, I regress γ_j^1 on several variables that I suspect may be important. I consider intensities of several factors of production: physical capital, labor with primary education, secondary education, and tertiary education. I also consider several measures of institutional reliance of industries: contract intensity,

[34] External dependence is equal to capital expenditure minus cash flow, divided by capital expenditure. This measure is due to Rajan and Zingales (1998). The numbers I use are from Do and Levchenko (2007), who in turn source them from Klingebiel, Kroszner, and Laeven (2005), who calculated them using US firm-level data.

[35] Costinot (2009) uses data from the PSID surveys of 1985 and 1993 that ask workers the following question: "Suppose someone had the experience and education needed to start working at a job like yours. From that point, how long would it take them to become fully trained and qualified (to do a job like yours)?"

[36] Compared to on-the-job training, education provides a broader set of knowledge that may be more useful to a worker when adopting new technologies. The correlation between the job complexity measure and the share of labor with tertiary education is 0.64.

input concentration, external financial dependence, and job complexity. Since the conservative measure of z^{rs2} has the highest correlation with γ_j^1, I concentrate on this measure of contract intensity.[37]

Table 9: Regression of γ_j^1 on various industry-level determinants

Constant	-0.018 (0.796)
Share of physical capital	0.107 (0.763)
Share of labor with primary education	0.439 (0.855)
Share of labor with secondary education	0.228 (0.743)
Share of labor with tertiary education	1.634 (0.008)
Contract intensity*	0.150 (0.228)
R^2	0.89
N	14

p-values in parentheses
*The measure of contract intensity is z^{rs2} (conservative)

Table 9 summarizes the results.[38] The first column shows the results of a regression of γ_j^1 on four factor intensities and a contract intensity. It shows that this model has high explanatory power ($R^2 = 0.89$), but only the share of labor with tertiary education is statistically significant.

6 Explaining the variation of productivities by human capital

Sections 4 and 5 have presented many pieces of evidence. What did we learn from them? We learned that industry productivities are not random, but have a structure. The results of the singular value decomposition have shown that productivities exhibit log-supermodularity, as theoretically proposed by Costinot (2009b). As average productivity of a country declines, productivities in some industries decline faster than in others. This pattern of productivity differences is a feature of the Krugman (1986) model. In that model, a country's technological lag behind the frontier is greater in the industries with higher technology intensity.

We decomposed the matrix of productivities into industry and country components without taking a stand on what those components may represent. The next challenge was to identify the real-world determinants of productivity that match the principal components.

Looking at the first country principal component, we found that many variables are correlated with it. These variables include physical capital, educated labor, and institutions. This result is typical in growth and development literatures. However, when all determinants are included jointly in a regression, only physical capital and labor with tertiary education are robust and consistently statistically significant determinants of the first country principal component. Institutions are only statistically significant when the four Eastern European countries are included in the regression.

Looking at the first industry principal component, we found that the share of labor with tertiary education has the highest correlation with it. Measures of institutional dependence and share of labor with secondary education have lower correlations. However, only the share of labor with

[37] Other measures of institutional reliance are less statistically significant than z^{rs2} when included in the regression.
[38] An appendix performs a variety of the robustness checks for these results.

tertiary education is significant when all determinants are included together in a regression.[39]

Physical capital can help explain cross-country variation of productivities, but not cross-industry variation. Highly educated labor, on the other hand, can explain both cross-country and cross-industry variations of productivities. This additional information obtained when using the industry dimension in development accounting shows the advantage of looking at the industry dimension.

Putting together the above results, labor with tertiary education is the most robust and significant determinant of both country and industry principal components. Why does labor with tertiary education have such a strong effect on industry productivities? It cannot be the differences in cost of this labor because the cost has been taken into account when calculating productivities. In other words, the direct effect of human capital, which can be called Heckscher-Ohlin or Becker-Mincer effect, has been already accounted for by including human capital into the production function.

Therefore, there may be an externality associated with this type of labor. Several models in macroeconomics (Nelson-Phelps and others) have previously suggested that the main role of human capital is to enable technology adoption (see Doms, Dunne and Troske (1997) for plant-level evidence). In those models, countries with high stocks of educated labor are able to adopt the latest technologies while other countries are not.

Enterprise-level evidence on licensing of foreign technology helps to motivate the technology adoption story. Using the World Bank Enterprise Surveys data, I calculate the percentage of plants that report usage of foreign technology for each country and industry. This data shows that rich and poor countries are about equal in their use of foreign technology in the industries with low education intensity. About 12-15% of all plants report using foreign technology in those industries. However, there is a big difference in the use of foreign technology between the rich and poor countries in the industries with high education intensity. Poor countries have about 13% of plants in those industries using foreign technology. In the rich countries, this number is 34%. This evidence suggests that the poor countries cannot use the latest technology in the education-intensive industries because they do not have the pool of educated workers to use it.[40]

If the benefits of highly educated labor occur within the firm's boundary, then why would the firm not compensate these workers properly? One possibility is that the externality of the educated labor takes place outside the firm's boundaries. For example, there may be learning from others (as in Foster and Rosenzweig (2010)). More generally, there may be local labor market effects (Moretti, 2004). There may also be labor market imperfections, such as high search costs, that prevent good matches between employers and workers. These factors reduce the wage premium of well educated workers in the poor countries and create a gap between private and social returns to education. While this paper presents new evidence that suggests externality of educated labor in technology adoption, the exact mechanism of this externality is still to be completely understood.[41]

[39] Therefore, this paper finds that education of the labor force is a more important determinant of productivity than institutions. Intuitively, before contract disputes can even arise, there needs to be a highly educated labor force that can read and implement complex blueprints. In modern world, contractual relationships can be substituted by networks and vertical integration (see Nunn and Trefler (2015) for discussion). Many of supplier relationships are international and disputes are increasingly resolved through international arbitration rather than domestic court systems, thus decreasing the importance of domestic institutions.

[40] If bad institutions were to blame for lower incidence of foreign licensed technology use in poor countries, we would see lower incidence in all industries, not just the education-intensive ones. In this case, innovators would not want to license their technology to the poor countries in all industries, not just the education-intensive ones.

[41] It is possible that there is a reverse causation in which higher levels of productivity are correlated with higher skilled wages. With reverse causation, there is a pattern of productivities such that rich countries have comparative advantages in education-intensive industries. This pattern of productivities leads to higher education premia in the

6.1 Evaluating the fit

In Section 4 we learned that the matrix of productivities can be well explained by one country-specific and one industry-specific factor. Then in Section 5 we learned that human capital in the form of labor with tertiary education is the real-life factor that most closely resembles the estimated factor from Section 4. This section will check how much of the productivity variation across countries and industries in the dataset can be explained by this form of human capital.

The goal is to explain the variation of mean productivityA_{ij}, across countries i and industries j. We will be evaluating the fit of the following equation:

$$\frac{A_{ij}}{A_{us,j}} = \mu \left(\frac{H_i}{H_{us}} \right)^{\psi \lambda_{3j}}, \tag{16}$$

which is very similar to equation (15) with the one factor being human capital H. As in the previous sections, the U.S. is the proxy for technological frontier.

I assume that frontier technology is available to all countries around the world through various means, such as licensing, foreign direct investment, import of capital goods, and publicly available information.[42] However, as in Krugman (1986), countries vary in their abilities to use technologies. As in Nelson and Phelps (1966), technology adoption is enabled by labor with tertiary education. More sophisticated technology requires more workers with post-secondary education.

Educated labor requirements vary across industries. Some industries have technologies that require more educated labor to use. The ability of producers in industry j of country i to use technology depends on country i availability of educated labor and industry j requirements for educated labor. The average productivity in industry j of country i relative to the technology frontier in industry j is a function of (a) the stock of educated labor in country i, H_i, relative to the stock of educated labor required by the frontier technology, H_{us}, and (b) industry j requirements for educated labor, λ_{3j}. The relationship between the endowment of educated labor in i and intensity of its use in j is log-supermodular, as in Costinot (2009a). In equation (16) μ and ψ are (scaling) parameters.

An implication of 16 is that countries with higher stocks of labor with tertiary education have comparative advantages in more education-intensive industries. This is what was found in the previous sections of the paper.

We proceed to evaluate how well equation (16) fits the pattern of productivities across countries and industries. We use the results of the singular value decomposition with only the first principal components ($M = 1$), given by equation (15), as the benchmark.

As was reported in Section 4, the R^2 of (15) is 0.92. This means that the first principal component can explain 92% of the variance of productivities across countries and industries. There

rich countries, which in turn leads to greater accumulation of human capital in the rich countries. The pattern of productivities like this could exist, for example, because of greater exogenous technological progress in education-intensive industries. This mechanism would lower the gap between education premia in the rich and poor countries. While I cannot rule this mechanism out, the correlation between patenting intensity (a measure of innovation, presented in the appendix) and the first industry factor γ_j^1 is between 0.52 and 0.6 (depending on how patenting intensity is measured), which is not very high. In addition, the correlation between γ_j^1 and the share of workers with Ph.D.'s (who would presumably be leading research) is 0.33 (Figure 4), which is low and much lower than the correlation between γ_j^1 and the share of workers with Associate's degrees, which is 0.89. Finally, the correlation between γ_j^1 and research intensity (R&D spending as a share of last year's sales), reported in WBES, is close to zero.

[42] I do not specify how new technologies arrive. An example of a model of innovation is Eaton and Kortum (2001). Technology (productivity) in their model is developed in each country by scientists through R&D.

are 53*14=742 productivities $A_{ij}/A_{us,j}$ on the left-hand side of (15). They are explained by the first principal component vectors ϕ_i^1 and γ_j^1 that have 53+14=67 elements in total.

The stock of educated labor in (16) is measured by the stock of labor with tertiary education adjusted for education quality, $l_{3i}^{us}/l_{3,us}^{us}$, described in Section 5.1.1. Data on educational attainment is from IIASA/VID and educational quality is from Schoellman. Taking logs of (16) we have

$$\log \frac{A_{ij}}{A_{us,j}} = \log \mu + \psi \lambda_{3j} \log \frac{l_{3i}^{us}}{l_{3,us}^{us}} \tag{17}$$

The R^2 for this equation is 0.41. If the four outlier countries (Russia, Ukraine, Kazakhstan, and Bulgaria) are dropped, the R^2 increases to 0.50. So labor with tertiary education can explain 50% of the variation in the productivities. Full results of this regression are shown in Table 10.[43]

Table 10: Regression of $\log A_{ij}/A_{us,j}$ on $\log l_{3i}^{us}/l_{3,us}^{us}$

$\log \mu$	-0.300 (0.000)
ψ	3.812 (0.000)
R^2	0.5
N	686

p-values in parentheses

One of the goals of this paper is to explain the productivity gaps across countries. Table 11 shows productivity gaps between the most productive and least productive countries in every industry, $\max_i A_{ij}/\min_i A_{ij}$. The first three columns show productivity gaps estimated from data using different production functions. The first column uses the production function with capital and labor, measured by the number of workers. The labor in this case is not disaggregated by education, as in the rest of this paper. Stocks of labor are not adjusted for educational attainment, either. This is the most basic approach to incorporating labor into the production function when calculating productivities. The second column uses the production function with three types of labor, but without accounting for differences in education quality across countries. The third column uses three types of labor and accounts for education quality differences. This is the approach taken in this paper to calculate productivities.

Comparing columns 1 and 2, we can see that disaggregating labor into three types makes little difference to the productivity gaps, which are under 3 in the Metals industry and about 7 in the Medical industry.[44] Accounting for differences in education quality makes a noticeable reduction in productivity gaps. The gap in the Medical industry falls from 7.28 (calculated using the "basic approach") to 5.37. The average reduction going from column 1 to column 3 is 16%.

Columns 4 and 5 show productivity gaps predicted by the first SVD factor and the labor with tertiary education. The gaps predicted by the first SVD factor track fairly closely those estimated from the data, shown in column 3.

[43] I also estimated equation (17) with the actual productivities on the left-hand side replaced by the predicted productivities from the first factor in the decomposition exercise, $\gamma_j^1 \log\left(\phi_i^1/\phi_{US}^1\right)$. The coefficients are the same up to the second decimal point. R^2 is a little higher with predicted productivities, 0.44 vs 0.41 (0.53 vs 0.50 with the 4 outlier countries omitted).

[44] It increases productivity gaps in the industries with low gaps and decreases productivity gaps in the industries with high gaps.

Table 11: Accounting for productivity gaps between the most and least productive countries in each industry, $\max_i A_{ij} / \min_i A_{ij}$

	Data			Model	
	Capital and one type of labor	Capital and three types of labor	Labor adjusted for differences in education quality	First SVD factor	Labor with tertiary education
Food	3.27	3.29	3.10	2.66	2.03
Textile	3.30	3.21	3.10	2.81	2.30
Wood	4.40	4.60	4.40	3.38	2.21
Paper	5.39	5.06	4.40	4.33	3.99
Chemicals	3.98	4.07	3.55	3.15	3.21
Rubber	4.92	4.66	4.45	3.93	3.23
Nonmetals	4.45	4.70	4.52	3.98	2.62
Metals	2.73	2.90	2.65	2.45	1.87
Metal products	5.71	5.57	4.67	4.40	3.79
Machinery, other	6.52	6.11	4.72	4.33	4.75
Machinery, e&c	5.95	5.61	4.49	3.77	3.65
Medical	7.28	6.83	5.37	5.70	7.74
Transport	5.00	4.86	4.03	4.04	2.83
Other	5.34	4.99	4.50	4.06	3.08

7 Conclusion

Productivity determines the comparative advantages of countries, but productivity is calculated as a residual and, therefore, is a "measure of our ignorance". The goal of this paper is to endogenize the industry-level productivities that determine comparative advantages.

The approach of this paper is different from the existing literature. I start by estimating fundamental (autarky) productivity for each industry and country following Eaton and Kortum's methodology. Then I look for a pattern in these productivities across industries and countries, without making assumptions regarding the determinants of productivities. I find that certain industries consistently have greater productivity gaps between rich and poor countries than other industries. In other words, comparative advantages of a country are fairly predictable given its average productivity across industries.

I assume that the relationship between country and industry components is log-supermodular and decompose productivities into industry and country-specific components using a statistical technique called singular value decomposition. This approach turns out to be very successful empirically. The main departure from the previous literature is that I do not take a stand apriori on what the industry and country determinants of productivity are. I find that the interaction of the first principal industry and country components can explain the vast majority of variation in the productivity matrix. In fact, the first country-specific component and the first industry-specific component can explain 92% of the variation in the productivities of 14 industries and 53 countries. This result provides strong evidence for log-supermodularity of productivity in country and industry determinants irrespective of what those determinants are.

Having decomposed productivities in this manner, I look for country- and industry-specific variables that correlate highly with the country- an industry-specific components produced by the singular value decomposition. I consider physical capital, labor with three different levels of education, and various measures of institutions. An appendix considers additional determinants of productivity. I find that among all of these variables, the endowment of labor with tertiary education has the highest correlation with the country-specific component while the intensity of labor with tertiary education has the highest correlation with the industry-specific component. Breaking down educational attainment further, I find that the intensity of labor with an equivalent of an Associate's degree has the highest correlation with the industry-specific component.

Several important conclusions emerge from the analysis. First, countries with high average productivity have comparative advantages in the industries that use highly educated labor more intensively. These countries also have high GDP per capita. Second, highly educated labor is a key determinant of productivity across both countries and industries. Previous macro literature found that human capital explains the pattern of productivities across countries. This paper finds that human capital also explains the pattern of productivities across industries.

The fourth conclusion is that industry matters as a unit of analysis. The productivity differences across industries are not random, but contain important information. 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 finds that while some types of labor have little explanatory power for the pattern of trade, labor with tertiary education can explain a significant portion of the pattern of trade in manufactures. Classification of labor by education is the one most suited for the analysis of productivity. Classifications of labor as production/non-production and skilled/unskilled are less relevant.

Even though highly educated labor is an important determinant of trade, the effect of this labor is not through its wage. In other words, differences in marginal product of labor across different levels of education and countries are not big enough to explain productivity differences. Therefore, there may be an externality associated with highly educated labor.

Existing literature tells us that educated labor is not just a factor of production, but also a factor that facilitates technology adoption. This has important policy implications because the benefits of educated labor extend beyond its marginal product. This function of educated labor was modeled by Nelson and Phelps, Acemoglu and Zilibotti, and others for the whole economy.

This function of educated labor is also motivated by evidence on licensing of foreign technology presented in this paper. While there are several ways that technology can diffuse across countries, licensing is the most direct route. I find that foreign technology licensing is the most prevalent in the education-intensive industries of the rich countries. While poor countries license as much foreign technology as the rich countries in the non-education-intensive industries, they license much less in the education-intensive ones. This is consistent with a view that poor countries have little educated labor and are not able to adopt the latest technology in the education-intensive industries, which requires more educated labor.

I find that labor with tertiary education can explain 50% of the variation in productivities across countries and industries. I also find that there are four countries in Eastern Europe in which institutional deficiencies seem to play an important role.

There are several important implications of these results. First, since the endowments of educated labor change slowly, so does the pattern of comparative advantages. Second, governments that wish to change the comparative advantage of their countries should focus on growing the pool of labor with tertiary education and improving the quality of education. More specifically, they should focus on increasing the number of workers with an equivalent of an Associate's degree. This level of education provides the necessary skills to operate and maintain the sophisticated computerized machinery used in modern manufacturing.

Appendix A Robustness of productivity estimates

This appendix reports several robustness checks of the results obtained in the paper. First, it checks the effects of allowing a more flexible production function. Then it checks the effects of setting different values of the dispersion parameter θ.

A.1 Production function

I relax the assumption of Cobb-Douglas production function made in Section 2 when estimating productivities. Instead, I use the multilateral translog index derived by Caves, Christensen and Diewert (1982) to compare relative costs of production inputs across countries. This index is an extension of the bilateral Törnqvist index. The multilateral translog index is exact for the translog cost function, which is an extremely flexible functional form. CES and Cobb-Douglas cost functions are special cases of the translog cost function. In each industry j, the relative cost of country i with respect to the reference point (in this paper the United States) is given by

$$\begin{aligned} \log c_{ij} - \log c_{us,j} \quad = \quad & \widehat{\alpha}_{ij} \left(\log r_i - \overline{\log r}\right) + \widehat{\alpha}_{us,j} \left(\overline{\log r} - \log r_{us}\right) \\ & + \sum\nolimits_e \left(\widehat{\lambda}_{eij} \left(\log w_{ei} - \overline{\log w_e}\right) + \widehat{\lambda}_{e,us,j} \left(\overline{\log w_e} - \log w_{e,us}\right)\right) \\ & + \left(1 - \widehat{\alpha}_{ij} - \widehat{\beta}_{ij}\right) \left(\log P_{ij} - \overline{\log P_j}\right) + \left(1 - \widehat{\alpha}_{us,j} - \widehat{\beta}_{us,j}\right) \left(\overline{\log P_j} - \log P_{us,j}\right) \end{aligned} \tag{18}$$

where $\widehat{\alpha}_{ij} = 0.5\left(\alpha_{ij} + \overline{\alpha_j}\right)$, α is the share of capital, a bar indicates the arithmetic mean over all countries, r is the cost of capital, w_e is the cost of labor or type e, λ_e is the share of that type of labor, $\beta = \sum_e \lambda_e$ is total labor share, and P is the cost of the intermediate goods bundle. For Cobb-Douglas cost function, this expression collapses to (7). A more flexible functional form, such as (18), allows us to consider the effects of cross-country differences in factor shares on estimated fundamental productivities $A_{ij}/A_{us,j}$.

In order to calculate cost indices according to (18) I need information on factor shares in output for all countries and industries in the dataset, α_{ij} and λ_{eij}. These shares are obtained from the Industrial Statistics (IndStat) database of the United Nations and the World Bank Enterprise Surveys (WBES) dataset described in the paper. IndStat and WBES do not have the complete coverage of the countries and industries studied in this paper so some imputation was performed to assemble the data. The country- and industry-specific factor shares they produce are noisy (see also Levchenko and Zhang (2016)). For these reasons these factor shares are not used in the main results reported in the paper.

Allowing a more flexible functional form of the production function does not alter the results presented in the paper. The productivity matrix still looks like Figure 2. The results of singular value decomposition, shown in the second column of Table A1 still show log-supermodularity of the productivity matrix. For comparison, the main results from the paper are shown in the first column of that table.

Allowing a more flexible production function does not affect the relationships between the first country determinant ϕ_i^1/ϕ_{US}^1 and various country characteristics. Regression results are shown in the first two columns of Table A2. Compare these results to the results shown in the first two columns of Table 7.

Similarly, the relationships between the first industry determinant γ_j^1 and various industry characteristics are not affected. Regression results are shown in the first column of Table A3. Compare these results to the results shown in Table 9.

Table A1: Singular value decomposition results

Value or source of theta	8.28	8.28	4	12	CP
Production function	CD	TL	TL	TL	TL
Factor 1	19.16	16.44	29.19	12.80	68.38
Factor 2	1.43	1.44	2.98	0.99	4.79
Factor 3	1.30	1.25	2.67	0.84	3.41
Factor 4	1.05	1.03	2.26	0.70	2.46
Factor 5	0.95	0.93	1.94	0.63	1.97
Factor 6	0.67	0.64	1.31	0.46	1.52
Factor 7	0.52	0.51	1.09	0.36	0.90
Factor 8	0.46	0.46	0.95	0.32	0.83
Factor 9	0.45	0.42	0.87	0.29	0.62
Factor 10	0.39	0.40	0.80	0.29	0.51
Factor 11	0.36	0.36	0.76	0.25	0.51
Factor 12	0.34	0.32	0.63	0.23	0.44
Factor 13	0.28	0.27	0.54	0.21	0.35
Factor 14	0.21	0.24	0.46	0.16	0.23

CD is Cobb-Douglas production function, TL is translog production function.
CP is Caliendo and Parro (2015).

A.2 Dispersion parameter

The results in the main paper are obtained by setting the dispersion parameter θ equal to 8.28, which is the preferred estimate in Eaton and Kortum (2002). However, there is some uncertainly regarding the value of this parameter. Therefore, I reestimate the results using two more values of θ: 4 and 12, which roughly represent the range of estimates in the literature. The third and fourth columns of Table A1 show that the log-supermodularity is still present. The third and fourth columns of Table A2 show that physical capital per capita and labor with tertiary education are most closely related to the first country-level determinant ϕ_i^1/ϕ_{US}^1.[45] The second and third columns of Table A3 show that the share of labor with tertiary education is most closely related to the first industry-level determinant γ_j^1. Therefore, values of θ within a reasonable range do not affect the results presented in the paper.

[45] To save space, only the regression results with the outliers omitted are presented in this case.

Table A2: Regression of ϕ_i^1/ϕ_{US}^1 on various country-level determinants

Value of source of theta	8.28	8.28	4	12	CP	CP
Constant	-0.052	-0.053	-0.061	-0.048	-0.068	-0.072
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Physical capital per capita	0.024	0.026	0.025	0.027	0.025	0.026
	(0.023)	(0.012)	(0.034)	(0.005)	(0.066)	(0.041)
Fraction of population	0.001	0.000	0.000	-0.000	0.002	
with primary education	(0.682)	(0.957)	(0.830)	(0.936)	(0.554)	
Fraction of population	-0.010	-0.003	-0.001	-0.004	0.004	
with secondary education	(0.538)	(0.854)	(0.960)	(0.772)	(0.848)	
Fraction of population	0.019	0.023	0.022	0.024	0.018	0.020
with tertiary education	(0.094)	(0.033)	(0.074)	(0.018)	(0.207)	(0.108)
Institutions	0.094	0.009	-0.013	0.024	-0.037	-0.051
	(0.103)	(0.900)	(0.870)	(0.717)	(0.702)	(0.580)
R squared	0.52	0.57	0.45	0.64	0.32	0.32
N	53	49	49	49	49	49

p-values in parentheses.
Source of educational attainment data is IIASA.
Educational attainment is adjusted for quality of education. Source of educational quality data is Schoellman.
Institutions are measured by the Overall distance to frontier in 2010 from WB.
CP is Caliendo and Parro (2015).
N=53 means that all countries are included while N=49 means that 4 outlier countries are excluded.

Table A3: Regression of γ_j^1 on various industry-level determinants

Value or source of theta	8.28	4	12	CP
Constant	-0.045	-0.040	-0.048	-0.000
	(0.599)	(0.675)	(0.545)	(1.000)
Share of physical capital	0.117	0.131	0.103	-1.694
	(0.784)	(0.785)	(0.793)	(0.668)
Share of labor with primary education	0.407	0.194	0.560	-27.474
	(0.888)	(0.953)	(0.834)	(0.320)
Share of labor with secondary education	0.175	-0.124	0.382	3.988
	(0.834)	(0.895)	(0.623)	(0.607)
Share of labor with tertiary education	1.771	1.699	1.804	-6.865
	(0.014)	(0.028)	(0.008)	(0.223)
Contract intensity*	0.175	0.212	0.150	0.774
	(0.242)	(0.211)	(0.275)	(0.561)
R squared	0.86	0.82	0.89	0.41
N	14	14	14	14

p-values in parentheses.
*The measure of contract intensity is z^{rs2} (conservative).
CP is Caliendo and Parro (2015).

In addition to the uncertainty to the true value of the dispersion parameter θ, there is also uncertainty regarding the equality of its true value across industries. Therefore, I redo the analysis in this paper using industry-specific estimates of θ from Caliendo and Parro (2015). Their estimates of θ_j vary between 0.69 and 51.08 across industries, i.e. by two orders of magnitude.[46] The matrix of productivities is still strongly super-modular, as shown in the last column of Table A1. However, the labor with tertiary education is only marginally related to the first country determinant. None of the industry determinants studied in this paper are related to the first industry determinant. The values of θ_j determine the pattern of productivities at the industry dimension in this case.

Appendix B Additional determinants of productivity

This appendix presents analysis of several possible determinants of productivity not included in the main text: patenting intensity, computer use, and management technology. Because of low number of observations in the industry dimension and because these industry characteristics did not turn out to have a high correlation with the first industry determinant γ_j^1, they were not included in the regression analysis in the paper.

B.1 Patenting

I investigate if there is more innovation in the industries with high γ_j^1. 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. I use data on the number of granted patents from the U.S. Patent and Trademark Office (USPTO). 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. The data is for the period from 1963 to 2008.[47]

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.

The correlation across industries between the (scaled) number of patents and γ_j^1 is 0.52-0.6, depending on how patenting intensity is measured.[48] There are exceptions to the relationship between patenting intensity and γ_j^1. For example, the Paper industry has high γ_j^1 (and high educational intensity λ_{3j}), but low innovation, as least as measured by the patenting intensity. The first industry determinant γ_j^1 is more correlated with educational intensity than patenting intensity. Therefore, educational intensity seems to be a better measure of complexity of an industry's technology than patenting intensity.[49]

[46] This variation of trade elasticities (dispersion parameters) across industries is very large compared to other estimates in the literature. For example, standard Global Trade Analysis Project (GTAP) elasticities vary at most by a factor of 2 across industries. There is evidence that a multi-industry extension of the Eaton-Kortum model with elasticities set to 8.28 in all industries performs well in predicting the effects of NAFTA. There is also evidence that the GTAP model performs better in predicting the effects of NAFTA when all its trade elasticities are set equal to 8 instead of its standard values (Fox, Shikher and Tsigas, 2017).

[47] 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.

[48] The number of patents can be 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.

[49] 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.

B.2 Computer use

I look for evidence on computer use across industries since 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 percentage of the workforce that regularly uses a computer in their jobs. This percentage 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. The correlation between computer use intensity and γ_j^1 is 0.38. The correlation between computer use intensity and the share of workers with tertiary education is 0.62, so education-intensive industries are characterized by higher use of computers.[50] The most education-intensive industries have lower incidence of computer use in lower income countries, while the least education-intensive industries have about the same incidence. This evidence is similar to the evidence on licensing (below), but, unfortunately, only a few countries collected data on computer use, so this evidence should be taken with a grain of salt.

B.3 Management technology

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 high-γ_j^1 (and 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 high-γ_j^1 (and education-intensive) industries. Therefore, there is little support for the management technology explanation of the pattern of comparative advantage.

Appendix C Evidence on technology adoption from licensing

In this appendix I review evidence on technology adoption through licensing. This evidence comes from data on the use of licensed foreign technology collected by the World Bank Enterprise Surveys. For each country and industry I calculate the percentage of plants that report usage of foreign licensed technology. The average percentage of plants in the data (across all industries and countries) that report using foreign licensed technology is about 16%. This percentage varies across industries. The correlation, across industries, between the fraction of plants which report usage of foreign technology licensing and share of workers with tertiary education is 0.6. Food and Metals industries have 13.3% and 14.6% of plants using licensed foreign technology, while Medical and Other Machinery have 24.6% and 27.1%. Therefore, education-intensive industries have much more foreign technology adoption through licensing.

However, if we decompose this data by country income we see that greater licensing in education-intensive industries occurs only in richer countries. The average percentage of plants that use foreign technology licensing is 21.6% in the upper middle income countries, 13.8% in the lower

Slightly higher fraction of enterprises answered 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 that said "yes") across industries is small.

[50] 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.

Table C4: Pattern of foreign technology licensing

	Country income		
	Upper middle income	Lower middle income	Low income
High education intensity	34%	13%	13%
Low education intensity	15%	12%	14%
Correlation between education intensity and use of licensed foreign technology			
	0.84	-0.07	0.06
Number of countries reporting data			
	14	21	11

middle income countries, and 12.8% in the low income countries.[51] The correlation between the fraction of plants which report using licensed foreign technology and share of workers with tertiary education is 0.84 in the upper middle income countries and about zero in the lower middle income and low income countries. This information is summarized in Table C4. 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 plants 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 that there is much more technology diffusion through licensing in rich countries. The difference in licensing of foreign technology between rich and poor countries is much greater in the education-intensive industries. There are two possible explanations of these observations. First is that for some reason, most likely bad institutions in poor countries, innovators do not want to license technology to firms in poor countries. Since they cannot license the latest technology, poor countries cannot develop comparative advantages in the industries with high rates of innovation.

The second explanation is that poor countries have comparative disadvantage in education-intensive industries and, therefore, have much less demand for foreign-licensed technology in those industries. Poor countries cannot use the latest technology of the education-intensive industries because they do not have the pool of educated workers to use it.

Can we distinguish between these two explanations using available data? Table C4 summarizes the incidence of foreign licensed technology in different types of industries and countries. We can see that in the industries with low education intensity, the incidence of foreign licensed technology does not drop as country income drops. In the industries with high education intensity, it drop significantly, decreasing by half, as we go from upper-middle income countries to low-middle income countries. It seems reasonable to think that if bad institutions were to blame for lower incidence of foreign licensed technology use in poor countries, we would see lower incidence in all industries,

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

not just the education-intensive ones. The observed pattern of licensing is most likely caused by the pattern of the demand for licensed technologies which, in turn, is driven by countries' abilities to implement these technologies.

In other words, the pattern of foreign technology licensing suggests that the countries with low GDP per capita (and low endowment of labor with tertiary education, since the two measures are highly correlated) are not able to absorb the latest technology in the education-intensive industries.

References

Abramovitz, M. (1956). Resource and output trends in the United States since 1870, *American Economic Review* **46**(2): 5–23.

Acemoglu, D. and Zilibotti, F. (2001). Productivity differences, *Quarterly Journal of Economics* **116**(2): 563–606.

Baldwin, R. E. (1971). Determinants of the commodity structure of U.S. trade, *The American Economic Review* **61**(1): 126–146.

Baldwin, R. E. (1979). Determinants of trade and foreign investment: Further evidence, *The Review of Economics and Statistics* **61**(1): 40–48.

Barro, R. (1991). Economic growth in a cross section of countries, *Quarterly Journal of Economics* **106**: 407–444.

Barro, R. J. and Lee, J.-W. (2001). International data on educational attainment: Updates and implications, *Oxford Economic Papers* **53**: 541–563.

Barro, R. J. and Lee, J.-W. (2013). A new data set of educational attainment in the world, 1950-2010, *Journal of Development Economics* **104**: 184–198.

Basu, S. and Weil, D. (1998). Appropriate technology and growth, *The Quarterly Journal of Economics* .

Benhabib, J. and Spiegel, M. M. (2005). Human capital and technology diffusion, *in* P. Aghion and S. N. Durlauf (eds), *Handbook of Economic Growth*, Vol. 1A, Elsevier B.V., chapter 13.

Bils, M. and Klenow, P. J. (2000). Does schooling cause growth?, *American Economic Review* **90**(5): 1160–1183.

Bloom, N., Genakos, C., Sadun, R. and Reenen, J. V. (2012). Management practices across firms and countries, *NBER Working Paper No. 17850* .

Caliendo, L. and Parro, F. (2015). Estimates of the trade and welfare effects of NAFTA, *The Review of Economic Studies* **82**(1): 1–44.

Caselli, F. (2005). Accounting for cross-country income differences, *in* P. Aghion and S. N. Durlauf (eds), *Handbook of Economic Growth*, Vol. 1A, Elsevier B.V., chapter 9.

Caves, D. W., Christensen, L. R. and Diewert, W. E. (1982). Multilateral comparisons of output, input, and productivity using superlative index numbers, *The Economic Journal* **92**(365): 73–86.

Chor, D. (2010). Unpacking sources of comparative advantage: A quantitative approach, *Journal of International Economics* **82**(2): 152–167.

Ciccone, A. and Papaioannou, E. (2009). Human capital, the structure of production, and growth, *The Review of Economics and Statistics* **91**(1): 66–82.

Costinot, A. (2009a). An elementary theory of comparative advantage, *Econometrica* **77**(4): 1165–1192.

Costinot, A. (2009b). On the origins of comparative advantage, *Journal of International Economics* **77**: 255–264.

Costinot, A., Donaldson, D. and Komunjer, I. (2012). What goods do countries trade? A quantitative exploration of Ricardo's ideas, *Review of Economic Studies* **79**: 581–608.

Davis, D. R. and Weinstein, D. E. (2001). An account of global factor trade, *The American Economic Review* **91**(5): 1423–1453.

Do, Q.-T. and Levchenko, A. (2007). Comparative advantage, demand for external finance, and financial development, *Journal of Financial Economics* **86**(3): 796–834.

Doms, M., Dunne, T. and Troske, K. R. (1997). Workers, wages, and technology, *The Quarterly Journal of Economics* **112**(1): 253–290.

Eaton, J. and Kortum, S. (2001). Technology, trade, and growth: A unified framework, *European Economic Review* **45**: 742–755.

Eaton, J. and Kortum, S. (2002). Technology, geography, and trade, *Econometrica* **70**(5): 1741–1779.

Eaton, J. and Kortum, S. (2012). Putting Ricardo to work, *Journal of Economic Perspectives* **26**(2): 65–90.

Erosa, A., Koreshkova, T. and Restuccia, D. (2007). How important is human capital? A quantitative theory assessment of world income inequality, *University of Toronto mimeo* .

Feenstra, R. C., Inklaar, R. and Timmer, M. P. (2013). The next generation of the Penn World Table, *Available for download at www.ggdc.net/pwt* .

Foster, A. D. and Rosenzweig, M. R. (2010). Microeconomics of technology adoption, *Annual Review of Economics* **2**: 395Ű424.

Fox, A., Shikher, S. and Tsigas, M. (2017). How to evaluate computable models of trade, *in* F. L. Rivera-Batiz (ed.), *Encyclopedia of International Economics and Global Trade*, World Scientific Publishers, forthcoming.

Gwartney, J. and Lawson, R. (2003). Economic freedom of the world: 2003 annual report, *Fraser Institute Mimeograph* .

Hall, R. E. and Jones, C. I. (1999). Why do some countries produce so much more output per worker than others?, *The Quarterly Journal of Economics* .

Hanson, G. H., Lind, N. and Muendler, M.-A. (2015). The dynamics of comparative advantage, *NBER Working Paper No. 21753* .

Hanushek, E. A. and Kimko, D. D. (2000). Schooling, labor-force quality, and the growth of nations, *American Economic Review* **90**(5): 1184–1208.

Harrigan, J. (1997). Technology, factor supplies, and international specialization: Estimating the neoclassical model, *The American Economic Review* **87**(4): 475–494.

Heckscher, E. (1919). The effects of foreign trade on the distribution of income, *Ekonomisk Tidskrift* **21**: 497–512.

Hendricks, L. (2002). How important is human capital for development? Evidence from immigrant earnings, *American Economic Review* **92**(1): 198–219.

Kaarsen, N. (2014). Cross-country differences in the quality of schooling, *Journal of Development Economics* **107**: 215–224.

Kaufmann, D., Kraay, A. and Mastruzzi, M. (2003). Governance matters III: Governance indicators for 1996-2002, *World Bank Policy Research Working Paper No. 3106* .

Keesing, D. B. (1966). Labor skills and comparative advantage, *The American Economic Review* **56**(1/2): 249–258.

Krueger, A. B. and Lindahl, M. (2001). Education for growth: Why and for whom?, *Journal of Economic Literature* **39**(4): 1101–1136.

Krugman, P. R. (1986). A "technology gap" model of international trade, *in* K. Jungenfelt and D. Hague (eds), *Structural adjustment in advanced economies*, Macmillan.

Levchenko, A. A. (2007). Institutional quality and international trade, *Review of Economic Studies* **74**(3): 791–819.

Levchenko, A. A. and Zhang, J. (2016). The evolution of comparative advantage: Measurement and welfare implications, *Journal of Monetary Economics (forthcoming)* .

Lutz, W., Goujon, A., K.C., S. and Sanderson, W. (2007). Reconstruction of populations by age, sex and level of educational attainment for 120 countries for 1970-2000, *Vienna Yearbook of Population Research* **5**: 193–235.

MacDougall, G. D. A. (1951). British and American exports: A study suggested by the theory of comparative costs, *The Economic Journal* **61**(244).

Mankiw, G. N., Romer, D. and Weil, D. N. (1992). A contributionn to the empirics of economic growth, *Quarterly Journal of Economics* **107**: 407–437.

Manuelli, R. E. and Seshadri, A. (2010). Human capital and the wealth of nations, *University of Wisconsin mimeo* .

Mincer, J. (1958). Investment in human capital and personal income distribution, *Journal of Political Economy* **66**(4): 281–302.

Mincer, J. A. (1974). *Schooling, Experience, and Earnings*, NBER Books, National Bureau of Economic Research.

Moretti, E. (2004). Workers' education, spillovers, and productivity: Evidence from plant-level production, *The American Economic Review* **94**(3): 656–690.

Nelson, R. R. and Phelps, E. S. (1966). Investment in humans, technical diffusion, and economic growth, *American Economic Review* **56**(2): 69–75.

Nunn, N. (2007). Relationship-specificity, incomplete contracts, and the pattern of trade, *Quarterly Journal of Economics* **122**(2): 569–600.

Nunn, N. and Trefler, D. (2015). Domestic institutions as a source of comparative advantage, *in* E. Helpman, K. Rogoff and G. Gopinath (eds), *Handbook of International Economics*, Vol. 4, Elsevier, pp. 263–315.

Ohlin, B. (1924). *Handelns Teori*, AB Nordiska Bokhandeln.

Rauch, J. E. (1999). Networks versus markets in international trade, *Journal of International Economics* **48**: 7–35.

Ricardo, D. (1817). *The Principles of Political Economy and Taxation*, John Murray, London.

Romalis, J. (2004). Factor proportions and the structure of commodity trade, *American Economic Review* **94**(1).

Romer, P. M. (1990). Endogenous technological change, *Journal of Political Economy* **98**: S71–S102.

Schoellman, T. (2012). Education quality and development accounting, *Review of Economic Studies* **79**: 388–417.

Shikher, S. (2012). Putting industries into the Eaton-Kortum model, *Journal of International Trade and Economic Development* **21**(6): 807–837.

Somale, M. (2014). Comparative advantage in innovation and production, *Manuscript* .

Trefler, D. (1995). The case of the missing trade and other mysteries, *The American Economic Review* **85**(5): 1029–1046.