NBER WORKING PAPER SERIES

THE WORLD TECHNOLOGY FRONTIER

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Working Paper 7904
http://www.nber.org/papers/w7904

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2000

We are grateful to Ravi Bansal, Jess Gaspar, Aart Kraay, Philippe Martin, Pietro Peretto, James Schmitz, Jaume Ventura, Gianluca Violante and, especially, Peter Klenow for useful discussions and suggestions. We also thank Robert Barro and Jong-Wha-Lee for sharing their data on duration of schooling. Caselli thanks the University of Chicago Graduate School of Business, and Coleman thanks the Center for International Business and Economic Research, for financial support. The views expressed herein are those of the authors and not necessarily those of the National Bureau of Economic Research.

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NBER Working Paper No. 7904
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JEL No. E1, O3, O4

ABSTRACT

We define a country's technology as a triple of efficiencies: one for unskilled labor, one for skilled labor, and one for capital. We find a negative cross-country correlation between the efficiency of unskilled labor and the efficiencies of skilled labor and capital. We interpret this finding as evidence of the existence of a World Technology Frontier. On this frontier, increases in the efficiency of unskilled labor are obtained at the cost of declines in the efficiency of skilled labor and capital. We estimate a model in which firms in each country optimally choose from a menu of technologies, i.e. they choose their technology subject to a Technology Frontier. The optimal choice of technology depends on the country's endowment of skilled and unskilled labor, so that the model is one of appropriate technology. The estimation allows for country-specific technology frontiers, due to barriers to technology adoption. We find that poor countries tend disproportionately to be inside the World Technology Frontier.

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1 Introduction

Existing studies of the World income distribution decompose output differences across countries into a component due to differences in observed factors of production and a component due to differences in overall efficiency, or total factor productivity (TFP). These studies tend to find that poor countries have relatively low TFP, i.e. they are inefficient producers of goods and services. Since total factor productivity is factor neutral, this means that poor countries use all of their inputs inefficiently. Indeed, by construction the efficiencies of any two factors, e.g. skilled and unskilled labor, are perfectly positively correlated. Figure 1 depicts the relationship between the efficiencies of skilled and unskilled labor implied by the TFP approach to cross-country differences in technology.

This paper investigates an alternative framework where, rather than an overall level of total factor productivity, countries are characterized by different efficiencies of three different factors: skilled labor, unskilled labor, and capital. Far from confirming the perfect positive correlation predicted by the TFP approach, our evidence is strongly suggestive of a *negative* correlation between the efficiencies of skilled and unskilled labor (and between the efficiencies of capital and unskilled labor): countries that are the most efficient users of skilled labor and capital also tend to be the least efficient users of unskilled labor. In other words, we find that the cross-country pattern of relative efficiencies looks more like Figure 2 than Figure 1.

It also turns out that relative efficiencies are systematically related to relative factor endowments: countries that are abundant in unskilled labor are relatively efficient at using unskilled labor, while skilled-labor rich countries are relatively efficient at using skilled labor and capital. This motivates us to propose and estimate a model of appropriate technology, whereby firms in each country optimally choose their technology from a large menu of "blueprints." The choice of blueprint maps into a particular realization of the vector of efficiencies of the three inputs. Hence, firms in countries with a relatively large endowment of skilled workers will tend to choose skilled-labor (and capital) complementary technologies, while countries with more abundant unskilled labor will tend to operate unskilled-labor complementary technologies. In selecting the optimal technology, each country's choice set is bounded by a technological frontier, i.e. a locus of non-dominated technologies. Along this frontier increases in the efficiency of skilled labor and capital come at the cost of declines in the efficiency of unskilled labor. The observed negative correlations among the efficiencies of different factors emerges as different countries choose different points along their frontiers.[1]

[1]Note that the TFP approach generally implies that there is a unique best technology: the one used by

For the World as a whole, the location of this frontier depends on the current state of technological knowledge. By introducing new blueprints that dominate some of the pre-exisiting blueprints on the frontier, technological progress shifts this locus out. However, each country's frontier might differ from those of other countries for a variety of technological, institutional, and perhaps even cultural idiosyncracies that lead to differences in the set of blueprints countries can implement. Our model captures these differences by allowing for country-specific barriers to technology adoption. We find such barriers to be quantitatively very important. The technology frontiers of low-income countries are estimated to generally lie below the technology frontiers of high-income countries, indicating that – as in the TFP approach – barriers to technology adoption remain an important determinant of differences in per-capita income. Indeed, observed differences in endowments can account for an even smaller share of the cross-country income variance than implied by the TFP approach. The reason for this seemingly paradoxical result is that the appropriate choice of technology dampens the effects of differences in factor endowments.

A variety of papers have argued that different technologies may display different degrees of skill- or unskill- bias. For example, Katz and Murphy (1992), Berman, Bound and Griliches (1994), Kruger (1993), Acemoglu (1998), Caselli (1999), and several others have made the skilled-labor bias of recently developed technologies the centerpiece of explanations for the increase in wage inequality in many countries in the 1980s and 1990s. Also, Bartel and Lichtenberg (1987), Dunne and Schmitz (1995), Allen (1996), Doms, Dunne and Troske (1997), Dunne, Haltiwanger and Troske (1997), and others have documented with plant or firm level data that relative employment and relative wages of skilled workers vary systematically with the type of technology used. The new facts we uncover suggest that something similar is taking place at the country level.

The idea that countries with different factor endowments will use different technologies was first formalized by Atkinson and Stiglitz (1969), who thus gave rise to a tradition on "appropriate technology." This literature has been recently revived by Diwan and Rodrick (1991), Basu and Weil (1998), and Acemoglu and Zilibotti (1999).[2] Our contribution is especially close to Acemoglu and Zilibotti (1999) in that both papers focus on the role of the relative endowments of skilled and unskilled labor as the key determinant of each country's appropriate technology. However, in Acemoglu and Zilibotti (1999) developing countries are

the country with the highest level of TFP. In other words, in the space of efficiency levels of different inputs, the technology frontier is a singleton, and all countries but one lie inside the frontier.

[2]See also Caselli and Coleman (1999), and Zeira (2000).

forced to use the same technology as the developed ones - as R&D is targeted towards the needs of the countries with a large endowment of skilled labor. Instead, in our model all countries choose the technology most appropriate given their factor supplies.

The debate on the relative importance of factor endowments and productivity in explaining cross-country income differences started with Mankiw, Romer and Weil (1992), and featured contributions by, among others, Islam (1995), Caselli, Esquivel and Lefort (1996), Klenow and Rodriguez (1997), and Hall and Jones (1997). All these studies augment the production function by human capital, and use a TFP approach to differences in technologies. The emerging view attributes to (unexplained) TFP differences roughly 50% of the responsibility for GDP differences. Besides deviating from the TFP approach, our paper differs from these contributions in that it models the choice of technology as depending on observable inputs. As mentioned above, it turns out that this approach leads to a deepening of the puzzle: differences in factor endowments explain an even smaller share of differences in output.

Our paper is also closely related to work by Trefler (1993), who has argued that country-specific augmentation of factor supplies (which can be interpreted as country-specific efficiency levels) helps explain jointly the pattern of trade in factor services and cross-country differences in factor prices. A by-product of his technique is a full set of estimates of efficiency levels for each country and each factor, i.e. something analogous to the set of estimates we obtain. However, Trefler's disaggregation of the labor aggregate is very different from ours, so the two sets of estimates are not easily compared. The two study, however, share the basic conclusion that non-factor neutral technology differences across countries are critical to fit international data.[3]

In Section 2 we present some initial evidence suggesting that countries are typically observed to trade off the efficiency of one factor against another. In Section 3 we formalize a model in which countries choose a technology from a technology frontier, and we estimate this model using cross-country data on per-worker income, physical capital, skill-premia, and labor endowments. We then discuss the implications of our estimates. In Section 4 we perform a robustness check, and Section 5 concludes.

[3]See, however, Repetto and Ventura (1998) for an interesting critique of the Trefler method.

2 Relative Efficiency of Inputs

The goal of this section is to uncover cross-country patterns in the behavior of the efficiency of unskilled labor, skilled labor, and capital. Studies based on Cobb-Douglas specifications of production – for which there is no distinction between the efficiency of the different inputs – tend to show that overall efficiency is highly positively correlated with per-capita income. These findings are usually interpreted as showing that poorer countries use "backward," "inferior," or "inappropriate" technologies. In a more general framework in which different inputs are allowed to have different efficiencies, this interpretation would lead us to expect poor countries to have low levels of efficiency of all inputs relative to rich countries, or that these levels of efficiency are positively correlated across countries. In this section we present some evidence that just the opposite might be true.

2.1 Measurement of Relative Efficiencies

To compute different levels of efficiency for different inputs into production, we postulate a production function of the form proposed by Krusell, Ohanian, Rios-Rull and Violante (2000):

$$Y^i = [(A_u^i L_u^i)^\sigma + ((A_s^i L_s^i)^\rho + (A_k^i K^i)^\rho)^{\frac{\sigma}{\rho}}]^{\frac{1}{\sigma}}, \tag{1}$$

where $\sigma < 1$ and $\rho < 1$. In equation (1) Y^i is GDP per worker in country i, L_u^i, L_s^i, and K^i are per-worker inputs of unskilled labor, skilled labor, and capital, A_u^i is the efficiency of unskilled labor in country i, A_s^i is the efficiency of skilled labor, and A_k^i is the efficiency of capital. The parameters σ and ρ are assumed to be common across countries, while the efficiency levels A_u^i, A_s^i, and A_k^i can differ.

Equation (1) is a fairly general specification of the production process. It allows skilled and unskilled labor to be imperfect substitutes, and – even more importantly – it allows technological change to augment unskilled labor, skilled labor, and capital differently. The imperfect substitutability of the two labor aggregates and the differential effect of technologies on them accord well with the wide changes in the skill premum that have recently been observed in the US and many other countries. The widely popular Cobb-Douglas production function is nested in (1) as the special case in which both σ and ρ tend to 0. Equation (1) also allows for one of the labor aggregates to be more complementary with capital than the other. Specifically, if $\sigma > \rho$ then this production function exhibits capital-skill complementarity, in the sense that a rise in the capital stock raises the marginal productivity of skilled labor more than it raises the marginal productivity of unskilled labor.[4]

Assume that production of output takes place in perfectly competitive markets. Then in each country the marginal productivity of capital must equal r^i, which is the real interest rate plus the rate of depreciation on physical capital:

$$r^i = [(A_u^i L_u^i)^\sigma + ((A_s^i L_s^i)^\rho + (A_k^i K^i)^\rho)^{\frac{\sigma}{\rho}}]^{\frac{1}{\sigma}-1}((A_s^i L_s^i)^\rho + (A_k^i K^i)^\rho)^{\frac{\sigma}{\rho}-1}(A_k^i K^i)^{\rho-1} A_k^i. \tag{2}$$

Furthermore, from the condition that each of the two wage rates, w_s^i and w_u^i, equals the marginal productivity of the corresponding labor aggregate we get:

$$\frac{w_s^i}{w_u^i} = \frac{((A_s^i L_s^i)^\rho + (A_k^i K^i)^\rho)^{\frac{\sigma}{\rho}-1}(A_s^i L_s^i)^{\rho-1} A_s^i}{(A_u^i L_u^i)^{\sigma-1} A_u^i}. \tag{3}$$

Given data on labor endowments, output, and factor prices for a given country, and a choice of the parameters σ and ρ, equations (1), (2) and (3) constitute a system of 3 equations in the 3 unknowns A_u^i, A_s^i and A_k^i.[5] Essentially, then, for a given specification of the production function, along with observations for output (GDP), the inputs into production (unskilled labor, skilled labor, and capital), and prices (the skilled wage premium and the real interest rate), we determine the efficiency of each input such that a model with perfectly competitive markets is consistent with all these observations. Solving this system for each of a sample of countries allows one to examine the observed cross-country relationship among the relative efficiencies of unskilled labor, skilled labor, and capital.[6]

[4] Capital-skill complementarity has long been recognized as a potential feature of the production function. A considerable body of plant- or industry-level evidence exists to support this conjecture. See, e.g., Griliches (1969), Berman, Bound and Griliches (1994), Krusell, Ohanian, Rios-Rull and Violante (2000), Dunne, Haltiwanger and Troske (1997), Doms, Dunne and Troske (1997), and Caselli (1999). Flug and Hercowitz (2000) find evidence of capital-skill complementarity in cross-country data. We will see below that in our preferred estimates σ and ρ are approximately equal, which is inconsistent with capital-skill complementarity. The different result may be due to the fact that our K is total capital, while these studies focus on equipment.

[5] This system of equations has a closed-form solution. The solution is:.

$$A_u = \frac{Y}{L_u}(1-S)^{1/\sigma}, \qquad A_s = \frac{Y}{L_s}\left[1 - \frac{r(K/Y)}{S}\right]^{1/\rho} S^{1/\sigma}, \qquad A_k = \left[\frac{r(K/Y)^{1-\rho}}{S}\right]^{1/\rho} S^{1/\sigma}$$

where

$$S = \left(\frac{w + r(K/Y)L_u/L_s}{w + L_u/L_s}\right)$$

[6] Diamond, McFadden, and Rodriguez (1978) show that time-varying (country-varying) elasticities of substitution cannot be separately identified from time-varying (country-varying) efficiency parameters. We

2.2 The Data

Data for Y^i and K^i are obtained from Hall and Jones (1999): Y^i is GDP per worker in international dollars (i.e. PPP adjusted) and K^i is an estimate of the real per-worker capital stock obtained through a version of the perpetual-inventory method. The underlying data for both series come from Summers and Heston (1991). In order to construct L_u^i and L_s^i we use data collected by Barro and Lee (1993). The data break down the population of each country into seven categories: no education, some primary, completed primary education, some secondary, completed secondary education, some higher, and completed higher education. Our baseline experiments construct L_u^i as an aggregate of workers with no education and with some primary education, while L_s^i includes all other groups. Hence, we treat basic literacy as the key requirement for relatively skilled-labor complementary technologies. This particular choice does not turn out to be critical. We also perform many of our computations by including in L_u^i all workers with less than high-school completed, and we find no major change in results.[7] The data for Y^i and K^i are for the year 1988, while the data for L_s^i and L_u^i are for 1985.

To construct cross-country data for w_s^i/w_u^i we use the Mincerian coefficients collected by Bils and Klenow (1998). The Bils and Klenow data report the coefficient from regressing log-wages on schooling years. This number can be interpreted as the percentage wage gain associated with an extra year spent in school. Hence, if β^i is the Mincerian rate of return, and n is the difference in schooling years between workers in L_s^i and L_u^i, we estimate w_s^i/w_u^i as $\exp(\beta^i n)$.[8] Finally, there is no reliable cross-country data on r^i. We therefore assume that

follow the literature (e.g. Weitzman, 1970, Krusell, Ohanian, Rios-Rull, and Violante, 2000) in getting around this by assuming that σ and ρ do not vary across countries. Duffy and Papageorgiou (2000) show that a CES specification fits the cross-country data better than a Cobb-Douglas, but they also present some evidence that elasticities of substitution vary across countries. However, their specification differs considerably from ours, as theirs features only two inputs, and factor-neutral technology differences.

[7]In constructing the L_u^i and L_s^i aggregates there arises the problem of the weights to be assigned to the educational achievement sub-categories. How many more units of efficiency does a worker with a college education contribute to L_s^i relative to a worker with a high-school diploma? There is no entirely satisfying solution to this problem. Acemoglu and Zilibotti (1999) give equal weight to all categories, but this seems unrealistic. As we describe below we have country-level data on the returns to one extra year of education, so we weigh education sub-groups by combining these data with unpublished country-level data on length in years of each schooling level (collected by Robert Barro and Jong-Wha Lee). This amounts to assuming that log-wages are linear in years of schooling both within and between the sub-categories constituting L_u^i and L_s^i.

[8]When we measure L_u^i by the bottom two educational sub-groups (no education or some primary) we

physical capital is perfectly mobile across countries, so that there is a common world gross rate of return r. We set this common interest rate to the historically relevant value of 0.12. We report below on a robustness check using alternative data in which r^i sharply declines as per-capita income rises. There are 52 countries with complete data for Y^i, K^i, L_u^i, L_s^i, and w_s^i/w_u^i; this dataset is reproduced in Table A1.

Table 1 reports some basic statistics from the data set. In this sample of countries output per worker in the richest country is 19 times higher than that in the poorest country. The ratio of the supply of skilled workers to unskilled workers ranges from 0.32 to 36.11. Hence, our construction of the two labor aggregates implies a wide variation in the fraction of skilled vs. unskilled workers around the world. As for the skilled wage premium, in some countries skilled workers receive only a 10 percent higher wage rate than unskilled workers, whereas in other countries skilled workers receive over 3 times as much as a typical unskilled woker. Note also that, as expected, output is strongly positively correlated with both capital and the relative supply of skilled labor. As Bils and Klenow have documented, output is negatively correlated with the skilled wage premium. Not surprisingly, then, the relative supply of skilled labor is negatively correlated with the skilled wage premium. Finally, the skilled-labor wage bill relative to the unskilled-labor wage bill is positively correlated with output, an observation we will build upon in the next section.

2.3 Results

Table 2 summarizes the results of computing efficiency levels for unskilled labor, skilled labor, and capital with the methodology and data described above. The exercise is repeated for a wide range of values of σ and ρ, and each row of the table corresponds to a particular choice of these parameters.

The second, third, and fourth columns report cross-country correlations among A_u, A_s, and A_k. The striking finding from Table 2 is that for almost all choices of σ and ρ at least one of the correlations between the efficiencies of the different inputs is negative, and large in absolute value. For moderately high values of σ countries that use unskilled labor efficiently also appear to use skilled labor efficiently. However, they use capital relatively

set $n = 4$, because this is the shortest duration of primary school across the countries in the sample. This might seem a small number but keep in mind that – by the aggregation procedure described in the previous footnote – L_u^i and L_s^i are in units of workers with no schooling and with just a primary school diploma, respectively. When we include all groups with less than a high-school diploma in L_u^i the two aggregates are in units of workers with a primary and a secondary school diploma, respectively, and $n = 5$.

inefficiently. For anything less than moderately high values of σ, instead, countries that are efficient at using unskilled labor are inefficient at using both skilled labor and capital. We view this overwhelming prevalence of negative correlations as suggestive of the existence of a Technology Frontier. Along this frontier increases in the efficiency of one input come at the cost of losses of efficiency of another input.[9]

In the rest of the paper we develop and estimate a simple model of technology choice that rationalizes these findings. As prelude and motivation for some of our modeling choices, the last two columns of Table 2 report additional results that highlight important features of the data. In the sixth column we report the correlation between $\ln(A_s^i/A_u^i)$, and the relative supplies of the two labor types, $\ln(L_s^i/L_u^i)$. For all values of $\sigma > 0$ ($\sigma < 0$) we find a strong positive (negative) relationship: the relative efficiency of skilled labor is strongly positively related to the relative supply of skilled workers if the skilled-unskilled elasticity is less than 1 ($\sigma > 0$), and negatively if the elasticity is greater than 1 ($\sigma < 0$). Either way, this result suggests to us that the heterogeneity in technology uncovered in Table 2 is driven by factor supplies, and supports the choice of an appropriate technology model.

In the last column (denoted "Frac. Dom.") is the fraction of countries that use a technology that is dominated by the technology of at least one other country in the sample. Country i's technology is dominated by country j's if $A_z^i < A_z^j$ for every z $(= u, s, k)$. The fraction of countries using dominated technologies varies considerably with the values of σ and ρ (from 14 to 79 percent for the values in Table 2). It is clear that only rarely we observe the pattern implied by the TFP approach, whereby all countries but one use less-than-best practice technologies. This further supports an appropriate technology explanation. On the other hand, it is clear that several countries do use inferior technologies. A simple model of technology choice where all countries have access to the same set of technologies would fail to capture this important feature of the data. Hence, the model we propose below features potential country-specific barriers to technology adoption.

[9]Are there values of σ and ρ that seem more relevant than others? The only estimate that we are aware of is due to Krusell, Ohanian, Rios-Rull, and Violante (2000) who place σ at 0.36 and ρ at -0.67. With these numbers we have that $\text{Corr}(A_u, A_s) = -.27$, $\text{Corr}(A_u, A_k) = -.31$, and $\text{Corr}(A_s, A_k) = .11$. These estimates of σ and ρ, however, are obtained from US time series data, they are based on a college vs. high-school criterion for construction of L_u and L_s (while our assification is based on basic literacy), and they include only equipment as capital (while our figures incluse equipment and structures). Hence, it is not obvious that these particular numbers are necessarily relevant for our purposes.

3 Endogenous Choice of Technology

In this section we lay out a simple model in which firms in a given country choose from a "menu" of available technologies (blueprints) the one that maximizes their profits given factor prices. This model is consistent with the facts of Table 2. Estimating this model allows us to: (i) obtain an estimate of the parameters σ and ρ, so that it is possible to determine which particular row of Table 2 is the empirically relevant one; (ii) characterize the set of technologies available to each country in the sample; and (iii) obtain quantitative measures of the role of barriers to technology adoption in explaining cross-country income differences.

3.1 The Model

We continue to assume that in each country competitive firms obtain output according to the production function (1). Capital continues to move freely across countries so that the first order conditions (2) and (3) for optimal choices of capital and labor inputs must still hold. However, we now add to the model a choice of technology. Specifically, instead of treating A_s^i, A_u^i, and A_k^i as given, each firm in country i faces a menu of feasible (A_s, A_u, A_k) triples. We have in mind firms choosing from a set of available blueprints, where each blueprint describes a particular method of obtaining output from skilled labor, unskilled labor, and capital. Different methods imply different values for the triple (A_s, A_u, A_k). For example, a firm might produce cars in an assembly line operated by blue-collar workers wielding hand tools; or in a computer-controlled plant mainly operated by engineers. The former technology might be expected to imply relatively high A_u and low A_s and A_k; the latter, low A_u and high A_s and A_k.

Because (at a given point in time) scientific and technical knowledge are not unlimited, the set of available blueprints is bounded. The size of the set is further reduced if a country faces additional barriers (e.g. institutional or cultural) to technology adoption. Formally, this means that the set of feasible (A_s, A_u, A_k) combinations is bounded. We therefore describe the set of feasible technologies for country i by the relationships:

$$(A_s^i)^\omega \leq a_0^i - a_1^i \left(A_u^i\right)^\omega , \tag{4}$$

$$(A_k^i)^\omega \leq b_0^i - b_1^i \left(A_u^i\right)^\omega , \tag{5}$$

where $\omega > 0$, $a_0^i > 0$, $a_1^i > 0$, $b_0^i > 0$, $b_1^i > 0$. On the boundary of the feasible menu (the technology frontier) technologies involve a trade-off between unskilled labor and skilled labor and between unskilled labor and capital. Clearly, no firm will choose a dominated technology so combinations of (A_s, A_u, A_k) that are not on the frontier are irrelevant. Notice that the parameters of the frontier are country-specific (except ω): we do this to allow for country-specific barriers to technology adoption.

Since equations (4)-(5) describe monotonic relations between A_s and A_u and between A_k and A_u, the optimal choice of technology is found by maximizing profits with respect to A_u, subject to (4)-(5). The first order condition is:

$$\frac{\partial Y^i}{\partial A_u^i} = -\frac{\partial Y^i}{\partial A_s^i}\frac{dA_s^i}{dA_u^i} - \frac{\partial Y^i}{\partial A_k^i}\frac{dA_k^i}{dA_u^i}. \tag{6}$$

This condition says that at an optimum a unit increase in A_u^i has no effect on output: the increase through larger efficiency of unskilled workers (left hand side) is completely offset by the corresponding decline through lower efficiency of skilled workers and capital.

Using the first order conditions with respect to L_u^i, L_s^i, and K^i, equation (6) can be rewritten as:

$$w_u^i L_u^i = w_s^i L_s^i a_1^i \left(\frac{A_u^i}{A_s^i}\right)^{\omega} + rK^i b_1^i \left(\frac{A_u^i}{A_k^i}\right)^{\omega} \tag{7}$$

To interpret this equation, it helps to think of two special cases. Suppose, first, that $b_1^i = 0$. Recall that $a_1^i > 0$ and $\omega > 0$. This relationship then says that in equilibrium countries with a relatively large skilled-labor wage bill will tend to choose relatively skill-complementary technologies. Countries that have a large relative cost of production due to skilled labor (the skilled labor wage bill) will find it advantageous to implement technologies that save on skilled labor. Recall that, as shown in Table 1, rich countries tend to have a large fraction of their wage bill going to skilled labor (as measured by $w_s L_s / w_u L_u$) – even though they have a low skill premium (as measured by w_s/w_u). For the other special case, suppose that $a_1^i = 0$. Recall here that $b_1^i > 0$ and $\omega > 0$. In this case this relationship says that in equilibrium countries with a relatively large expense due to capital will tend to choose technologies that raise the relative efficiency of their capital stock. The intermediate case in which $a_1^i > 0$ and $b_1^i > 0$ is then some combination of these two cases.[10]

[10] The existence of a solution to the firm's problem, and hence of an equilibrium given a world interest rate, follows from the continuity of the objective function and compactness of the constraint set. The uniqueness of a solution may depend on values of the parameters of the model. Indeed, for some parameter values the objective function as it depends on A_u^i (using eqs. (4) and (5) to substitute out A_s^i and A_k^i) may become convex over some range. We have checked (numerically) that at the estimated parameter values the solution is indeed a global optimum and is unique.

3.2 Estimation of the Model

We now turn the theoretical model into a statistical model in order to obtain estimates of the unknown parameters. We assume that the country-specific parameters of the technology frontier are realizations from log-normal distributions. In particular, our statistical model assumes:

$$
\begin{aligned}
a_0^i &= a_0 e^{\varepsilon_s^i}, \qquad & b_0^i &= b_0 e^{\varepsilon_k^i} \\
a_1^i &= a_1 e^{\varepsilon_u^i}, \qquad & b_1^i &= b_1 e^{e_u^i}
\end{aligned}
$$

where

$$
(\varepsilon_s^i, \varepsilon_k^i, \varepsilon_u^i) \sim N(0, \Sigma).
$$

Σ is unrestricted. Hence, there are "average" values of the parameters of the technology frontier – defining an "average" World Technology Frontier – but individual countries' frontiers may differ from the average one because they have differential access (or differential ability to implement) the various best practices. Notice that we have assumed that deviations from the average frontier (i.e. realizations of ε's) are known to firms at the time of their choice of technology. However, they are not observed by the econometrician.

We estimate this model by maximum likelihood. Given values of σ and ρ equations (1)-(3) imply values of A_u^i, A_s^i, and A_k^i (as we have seen in Section 2). These, in turn, together with choices of the remaining parameters, can be plugged into equations (4) and (5) (which hold with equality), and (7) to back out the $\varepsilon's$. With the ε's at hand, one can construct the log-likelihood for that particular choice of parameters.[11]

3.3 Results

Maximum Likelihood estimates for the parameters of interest are reported in Table 3. The point estimate of σ is .24, and that of ρ is .25. Hence, at the estimated parameter values the model does not exhibit capital-skill complementarity. As noted above, we conjecture that this finding might reflect the inclusion of structures in the capital stock. Most of the parameters are estimated relatively precisely.

[11] Our approach to modeling the frontier is close in spirit to the literature on frontier production functions in empirical production economics (see Greene (1997) for an especially useful survey). The difficulties associated with extending that approach to a setting with non-factor neutral technology differences dictates our focus on an "average" – as opposed to "global" – frontier.

Figure 3 plots against each other the realized levels of the efficiency of skilled labor (A_s^i) and unskilled labor (A_u^i), as implied by our estimates of σ and ρ. This reproduces graphically the negative association already uncovered in (the relevant row of) Table 2. The figure also draws the average frontier, as given by equation (4), with $\epsilon_s^i = \varepsilon_u^i = 0$, given the estimated values of a_0, a_1, and ω. Figure 4 does the same for the relationship between A_k^i and A_u^i. Here we can see graphically the estimated tradeoff among the efficiency levels of the various factors of production. As discussed above, no individual country's technology lies on the average frontier, as barriers to technology adoption vary from country to country. But each country's technology lies on that country's frontier. To illustrate, we have also plotted some sample frontiers for a few representative countries (in Fig. 3 the ordering of the lines, from bottom to top, is Average, US, Hong Kong; in Fig. 4 the ordering is US, Average, Italy).

Having estimated the model allows us to quantitatively investigate the importance of appropriate technology. In order to do so we perform the following experiments. In the first experiment we ask what would be a country's output (given its labor endowments) if it had access to the technological menu of the US. Specifically, we compute the level of GDP associated with an appropriate choice of technology on the US technology frontier. We then compare this number with the level of GDP the same country would have if forced to use the technology of the United States. In other words, for each country we compare two points on the US technology frontier: the one corresponding to that country's optimal choice, and the one corresponding to the optimal choice of the US. The result of this experiment is plotted in Figure 5, where the vertical axis measures the ratio of US-technology GDP to appropriate-technology (on US frontier) GDP; and the horizontal axis measures actual per-capita output. As can be seen, the adoption of an inappropriate technology involves very large output losses – up to 50% of GDP – the more so the more different the levels of development (and hence factor endowments). A similar experiment, with a similar message, is reported in Figure 6. Here, instead of comparing points on the US frontier, we compare points on the average frontier. For country i the vertical axis measures GDP at US-appropriate technology (on the average frontier) as a ratio of GDP at country i-appropriate technology (on the average frontier). Again, forcing countries to deviate from their appropriate technology causes spectacular output losses.

Our method assumes that each country uses the optimal (appropriate) technology from the set of technologies that are available to it, i.e. each country is on its own technology frontier. However, we have allowed for idiosyncratic factors that cause the set of available technologies to differ across countries. We think of these factors as barriers to technology adoption. Since we have implicitly estimated each country's own frontier, we can also investigate the quantitative importance of such barriers. Figure 7 compares each country's observed level of GDP with the level of GDP that country would obtain if it had access to the US technology frontier. Hence, we now compare two points on different technology frontiers: the one corresponding to that country's optimal choice on the US frontier, and the one corresponding to its optimal choice on its own frontier. Both points are "appropriate," but they are conditional on different choice sets. The Figure shows staggering effects from barriers to technology adoption, with output increasing by up to a factor of 7 if such barriers were removed. Figure 8 shows that the barriers are very severe even just to reach the average frontier: just by obtaining access to the average frontier countries can obtain output gains of up to a factor of 4.

It is clear from the last two figures that poor countries tend to disproportionately be the ones that would gain the most by having access to the technological menu of the US, or indeed the technological menu of the average country. Hence, there is clearly support for the standard view according to which poor countries are generally inside the "world" technology frontier. This finding calls for a more general framework that nests the models in which some countries are pushed to use less-than-best-practice technologies by barriers to technology adoption, together with the present framework of appropriate technology. This is a challenging problem that is beyond the scope of the present paper.

An additional perspective on the relationship between appropriate technology and barriers to technology adoption can be obtained by computing the fraction of the cross-country variation of per-capita income that would be explained by a deterministic model of appropriate-technology adoption, in which all countries had access to the same set of potential technologies. For example, if each country could choose the point on the *average* frontier that maximizes its output – given its labor endowments – the standard deviation of the log of per capita GDP would be 0.26. This compares to a value of 0.8 in the data. Hence, differences in inputs explain only little more than a quarter of the observed disparity of incomes, with the rest explained by barriers to technology adoption – i.e. by the fact that different countries have different frontiers.

As discussed in the Introduction, models in which technological choice is factor neutral, such as the Cobb-Douglas model, lead to a roughly 50-50 split of the responsibility for the variation of income between factor endowments and differences in technology. It may therefore seem paradoxical that a model of appropriate technology attributes an even smaller share of the overall variation to differences in endowments. But in fact this result is not surprising: when countries are allowed to choose optimally from a menu of technologies, this optimal choice will dampen, and not exacerbate, the effect of differences in endowment on differences in income. In a way, therefore, our results deepen the puzzle of the great dispersion of per-capita income around the world, and make it even more important that we understand deviations from best practice at the country level.

Before concluding, we return to the properties of the estimated technology frontier. Figures 9 and 10 present characteristics of countries that chose different technologies. Figure 9 shows that countries with a large labor bill for skilled labor relative to their labor bill for unskilled labor tend to be those countries that adopted a technology more complementary to skilled labor (their skilled-labor efficiency level is relatively high). Figure 10 shows that countries with a large capital expense (rK) relative to their unskilled wage bill are countries that adopted a technology more complementary to capital (their capital efficiency level is relatively high). Both results are consistent with our model of appropriate-technology adoption.

As a final check, Figure 11 graphs the relationship between the wage rates for unskilled and skilled labor implied by our data set. It is surely the case that both skilled and unskilled wage rates are higher in rich countries than in poor countries, and the Figure shows that our data are consistent with this fact. This is especially notable for the unskilled wage, since we have estimated rich countries to have the least efficient unskilled labor. The explanation is that this inefficiency is more than compensated by complementarity with skilled labor and capital, which are more abundant in rich countries, as well as the relatively low supply of unskilled workers in rich countries. Figure 11 also shows that there is no problem reconciling the fact that rich countries have the lowest skilled wage premium but also the highest skilled wage rate.[12]

[12] An alternative interpretation of some of our results is that the efficiencies A_s^i and A_u^i are exogenous and factor supplies respond endogenously. In this view high values of $\ln(A_s^i/A_u^i)$ lead to large relative wages for skilled workers, and hence to greater investment in human capital. However, as shown in Table 1, $\ln(L_s^i/L_u^i)$ and $\ln(w_s^i/w_u^i)$ are negatively correlated: countries in which skilled workers are relatively efficient generally have a low skilled-wage premium. It does not appear that relative labor supplies are driven only by incentives. This result is also consistent with the related findings of Caselli and Coleman (1999) on US wages and relative labor supplies over the last century.

4 Robustness

One restrictive assumption we have employed is undoubtedly that the cost of acquiring capital goods in units of consumption goods is equalized across countries (or that the required rate of return to capital is higher for some countries, which has a similar effect). If the cost of capital goods for country i is p^i, then all the equations of the model hold with

$$r^i = rp^i.$$

We computed p^i from the Summers and Heston (1991) dataset as the ratio of the price of investment goods to the price of consumption goods in 1988. Clearly this price will also be affected by the fact that not all countries purchase the same kinds of capital (or consumption), but we will nevertheless use it here as an estimate of differences in the relative price of the same capital good. The value of this price generally falls with per-capita income, and ranges from 2.26 for Kenya to .79 for France (the value for the U.S. is .81).[13] When using this price data, the correlations between the estimated efficiency levels for various values of σ and ρ exhibit the same pattern of positive and negative values as does Table 2, and mostly the numbers are not substantially different. We also re-estimated the model using this relative price data. All the graphs exhibit the same relationships as the ones that are reported. The main difference is in the value of the estimated parameters. The estimated value of $\sigma = .31$ and $\rho = -1.39$, hence the model with these parameter estimates exhibits capital-skill complementarity. The central message of our paper concerning the properties of a Technology Frontier, though, are unaltered.

5 Conclusions

The main message of this paper is that there seems to exist a World Technology Frontier. Points on this frontier represent a menu of best practice technologies. Along the frontier countries trade off the efficiency with which different inputs are used. A model in which countries optimally choose an appropriate technology from this menu was used to identify this frontier. In this model, countries with relatively large endowments of skilled labor, and consequently large skilled-labor wage bills, find it optimal to adopt a technology that makes skilled labor and capital relatively more efficient. Countries for which unskilled labor

[13] Hence the implied estimate of r^i varies from .27 to .09. This alternative estimate has the intuitive property that the cost of capital is much higher in poor countries than in rich ones.

represents a large fraction of their workforce find it optimal to adopt less sophisticated technologies (and accumulate less capital). In sum, choice of technology and capital-stock levels are driven by human capital endowments.

Yet some features of the results suggest that the appropriate technology view of the World adopted in this paper is complementary, not alternative, to the standard view of technological backwardness, in which poor countries are poor because they are afflicted by barriers to technology adoption. Poor countries do generally choose technologies that are inside the technology frontier of rich countries. Hence, the challenge for future progress in this field is to develop a framework that nests both mechanisms. A complementary area for future research is the source of cross-country differences in skill levels.

As virtually all papers in this literature, our work rests on very restrictive aggregation assumptions. A legitimate question is whether these restrictions are driving some of our results. Answering this question would involve studying a multi-good version of the model in this paper, and work out the implications for factor-specific efficiency levels. This is a complex task that is beyond the scope of the present paper. A priori, however, we see no obvious reason why our aggregation assumption would bias our estimates towards finding a negative cross-country correlation between the efficiencies of different factors. On the other hand, a potentially fruitful way to interpret the frontier we identify is not that countries are faced with different ways of producing the same good, but rather that goods may differ in the relative efficiency of different factors. Countries abundant in skilled labor may then tend to specialize in the production of goods that use skilled labor efficiently, etc. This would provide our model of appropriate technology with roots in the Heckscher-Ohlin tradition.[14] Again, whether or not this is a useful way to interpret our findings will have to await results on computing efficiency levels of various factors for a variety of goods, and relating this to cross-country production patterns, but this seems a worthwhile project.

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[14] Indeed, the work by Trefler discussed in the Introduction suggests that embedding our results into a multi-good setting may help explain trade flows as well.

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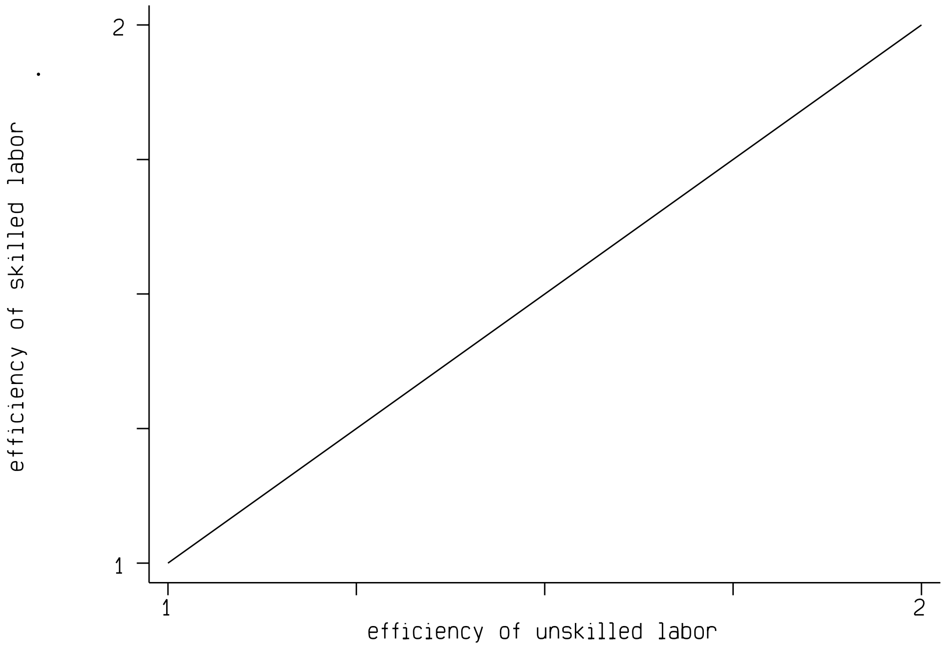

Fig. 1: Labor Efficiencies Implied by a TFP Approach

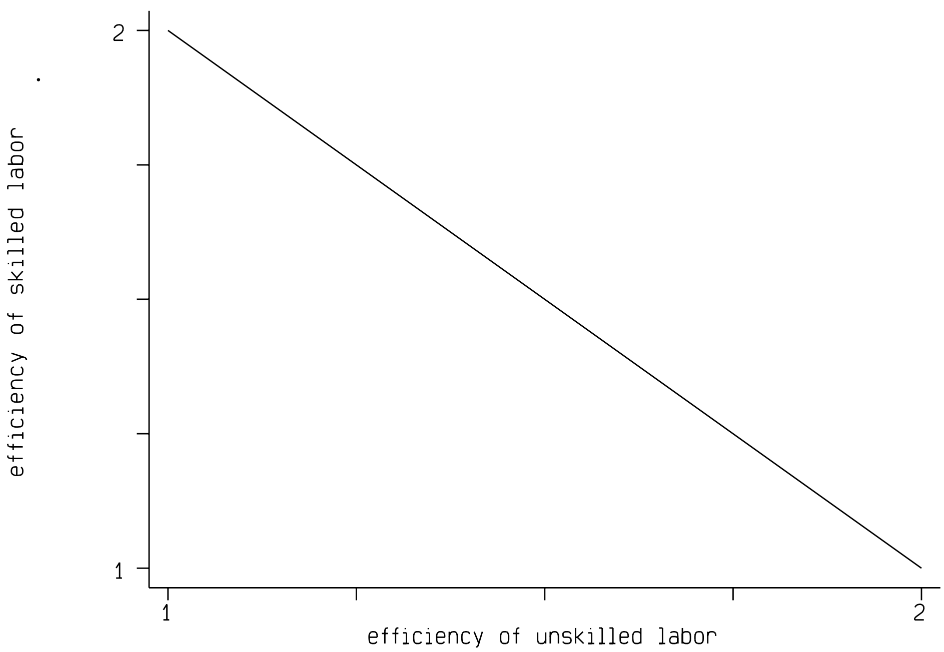

Fig. 2: Labor Eff. Possible with a Multi-Efficiency Approach

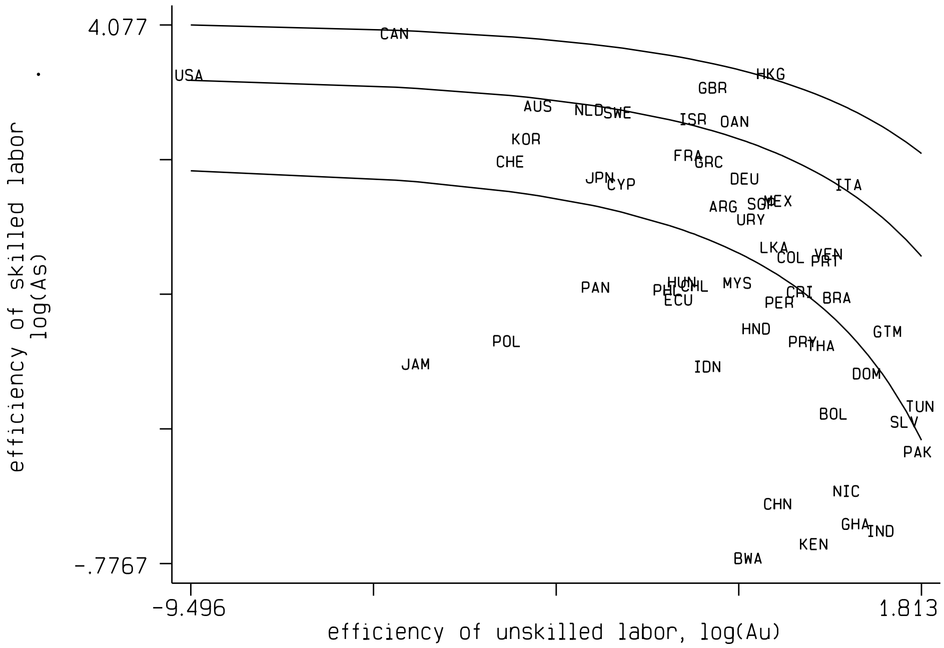

Fig. 3: The Technology Front.: Skilled & Unskilled Labor

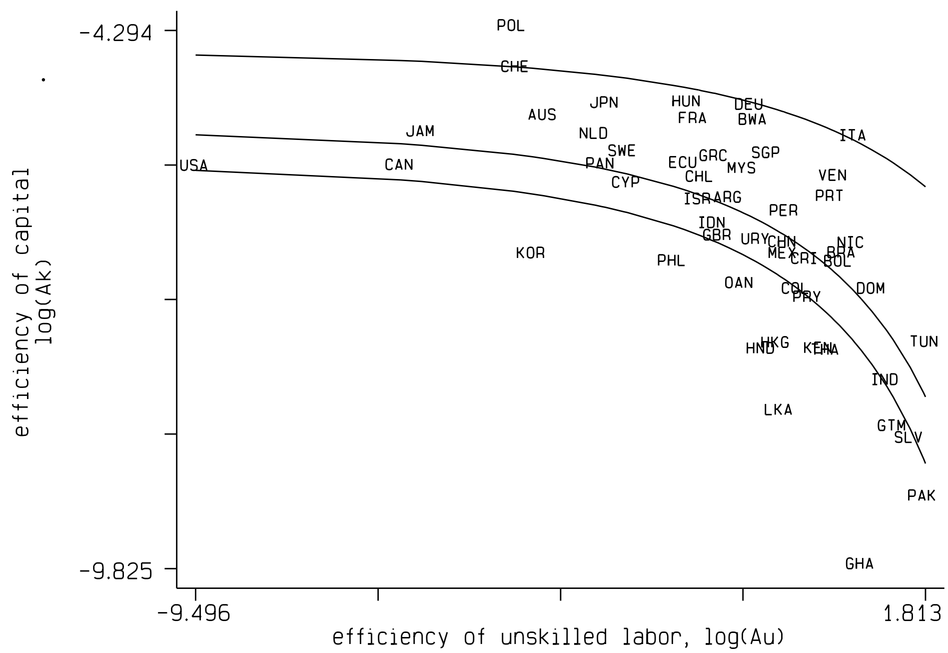

Fig. 4: The Technology Frontier: Capital & Unskilled Labor

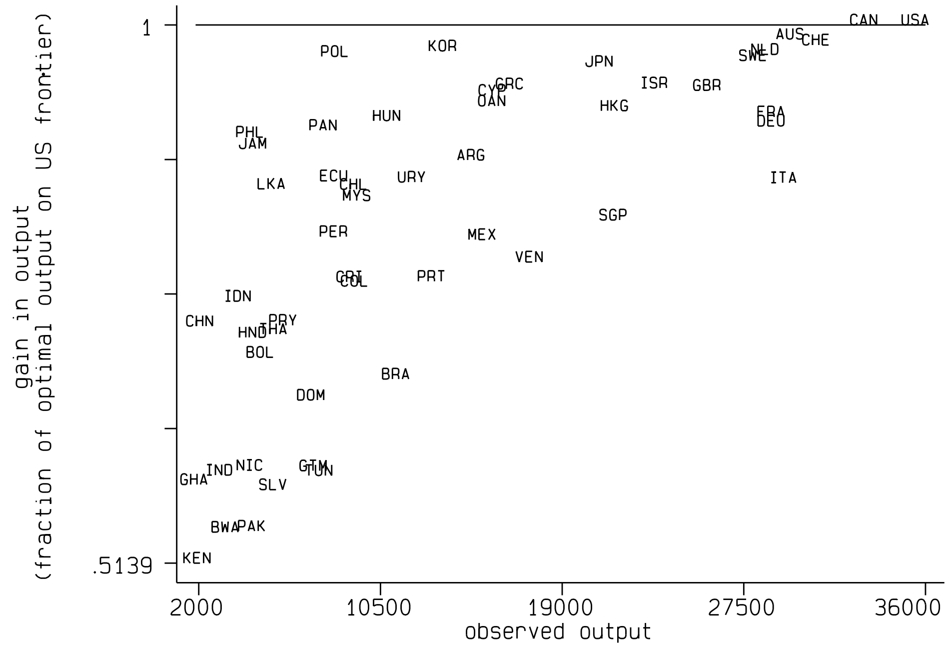

Fig. 5: Output Gain by Moving to US tech. on US Front.

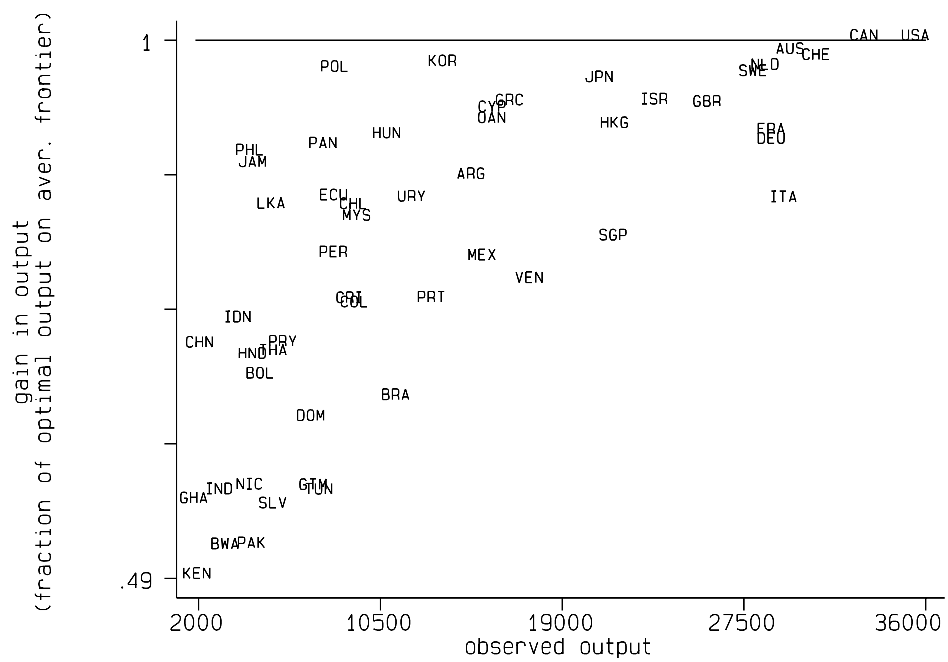

Fig. 6: Output Gain by Mov. to opt. US tech. on aver. Front.

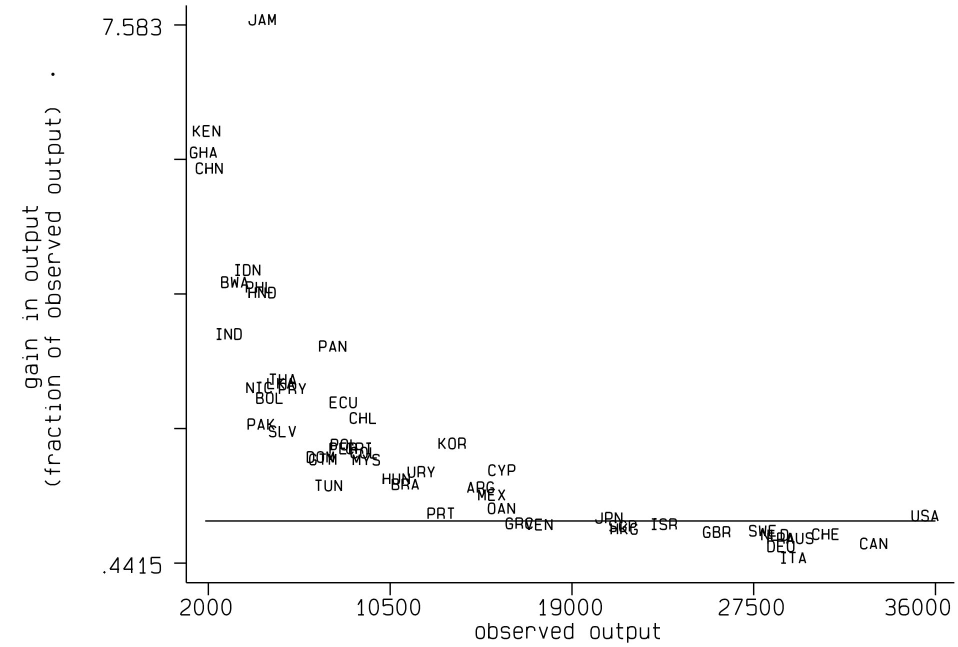

Fig. 7: Output Gain by Moving to the US Frontier

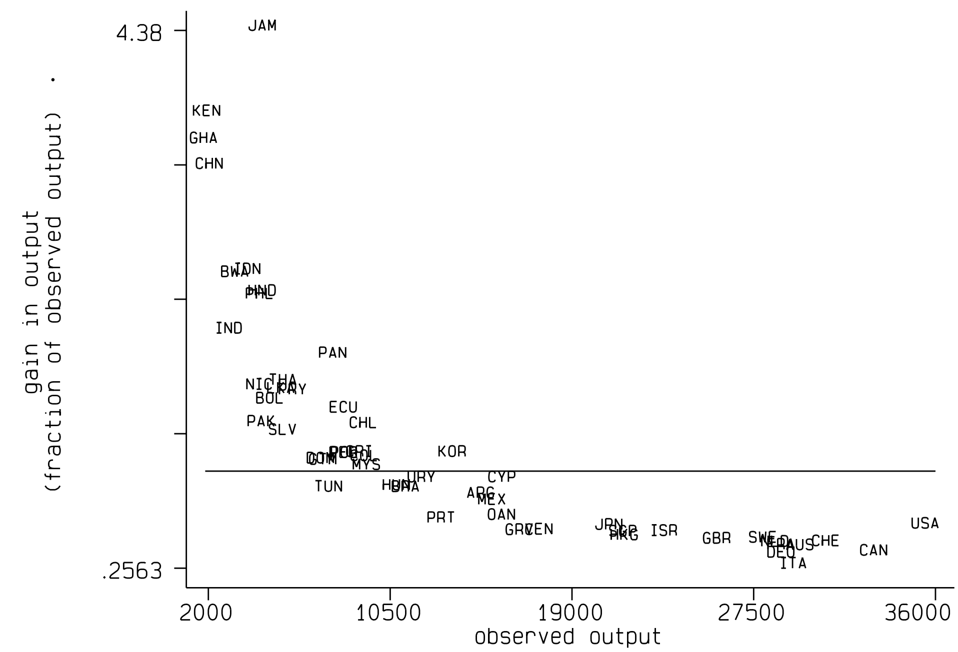

Fig. 8: Output Gain by Moving to the Aver. Frontier

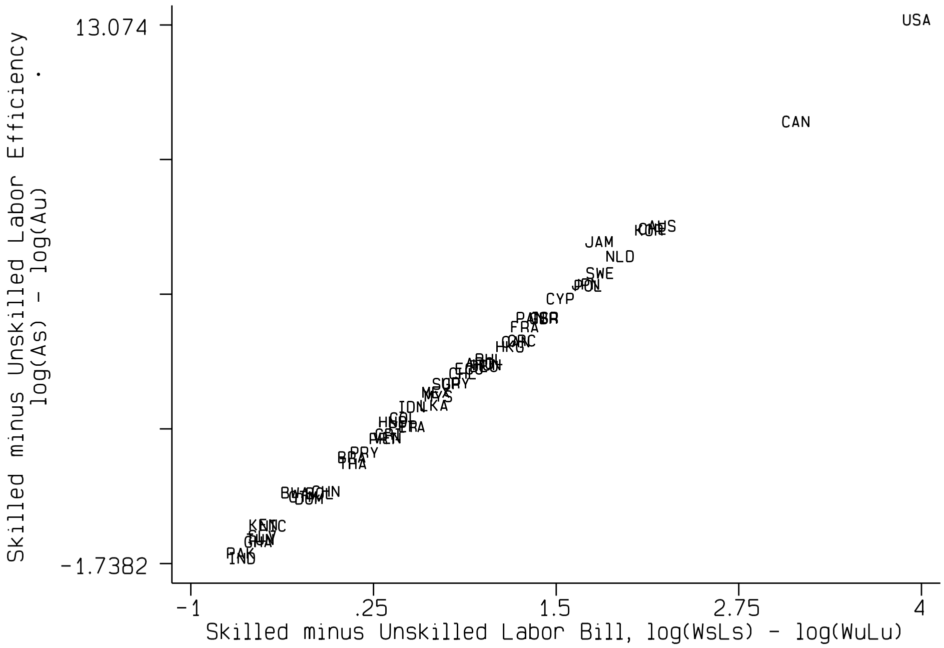

Fig. 9: Technology and Relative Wage Bills

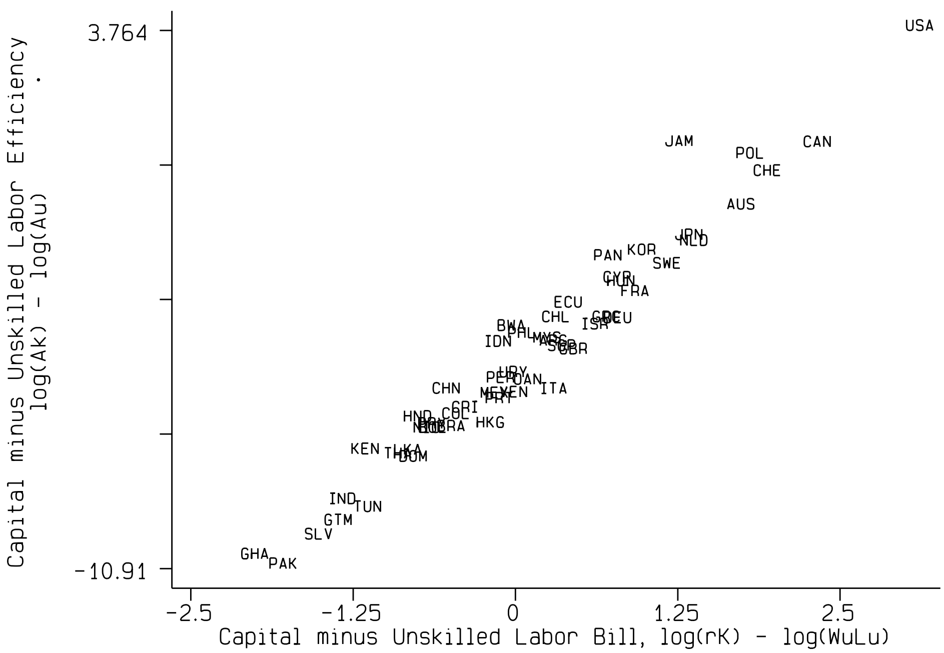

Fig. 10: Technology and Capital Share

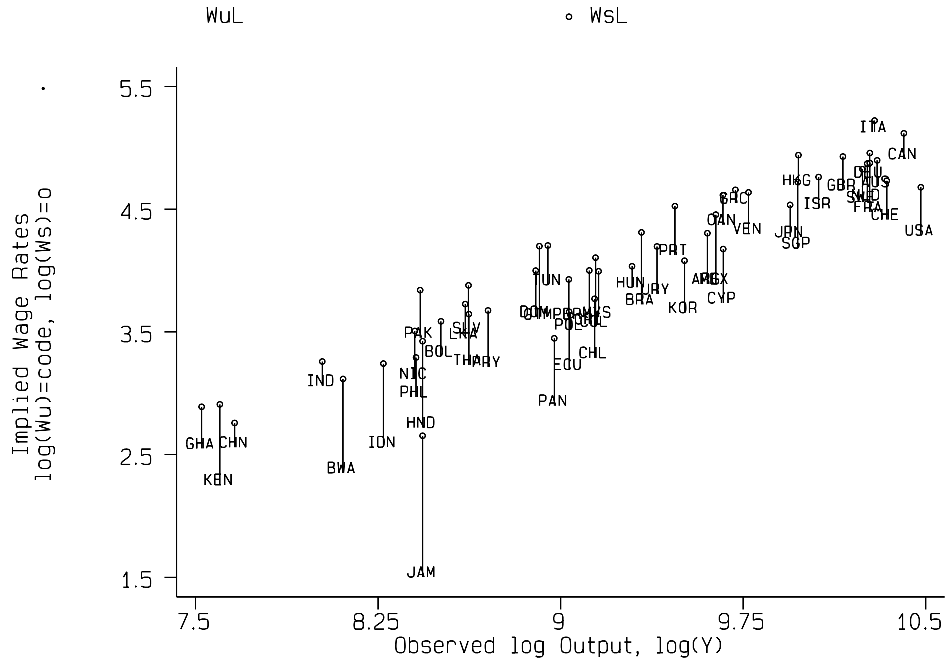

Fig. 11: Implied Wage Rates and Output

Table 1: Summary Statistics of the Data

variable	mean	std.dev.	minimum	maximum
output	13506	9717	1854	35440
capital	32271	28994	1218	107900
L_s/L_u	2.93	5.52	.32	36.11
w_s/w_u	1.50	.33	1.10	3.16
w_sL_s/w_uL_u	4.14	7.86	.52	53.45

correlation matrix

	log output	log capital	log L_s/L_u	log w_s/w_u	log w_sL_s/w_uL_u
log output	1.0000				
log capital	0.9567	1.0000			
log L_s/L_u	0.7555	0.7808	1.0000		
log w_s/w_u	-0.3781	-0.3244	-0.3410	1.0000	
log w_sL_s/w_uL_u	0.7197	0.7566	0.9834	-0.1648	1.0000

Table 2: Cross-Country Efficiency Patterns

σ	ρ	$Corr(A_u^i, A_s^i)$	$Corr(A_u^i, A_k^i)$	$Corr(A_s^i, A_k^i)$	$Corr(As/Au, Ls/Lu)$	Frac.Dom.
0.5	0.25	0.298	-0.188	-0.098	0.895	0.75
0.5	0.05	0.186	-0.106	-0.882	0.333	0.442
0.5	-0.25	0.149	0.014	-0.554	0.753	0.635
0.5	-0.5	0.199	-0.037	-0.286	0.838	0.692
0.5	-0.75	0.216	-0.073	-0.141	0.864	0.692
0.5	-5	0.245	-0.198	0.258	0.9	0.788
0.25	0.5	-0.555	-0.735	0.785	0.967	0.635
0.25	0.25	-0.519	-0.586	0.428	0.970	0.635
0.25	0.05	-0.138	-0.261	-0.759	0.789	0.308
0.25	-0.25	-0.532	-0.298	-0.095	0.923	0.365
0.25	-0.5	-0.556	-0.506	0.325	0.943	0.423
0.25	-0.75	-0.562	-0.596	0.5	0.949	0.481
0.25	-5	-0.566	-0.735	0.773	0.957	0.615
0.05	0.5	-0.849	-0.849	0.989	0.976	0.231
0.05	0.25	-0.849	-0.835	0.966	0.977	0.288
0.05	-0.25	-0.836	-0.837	0.921	0.971	0.135
0.05	-0.5	-0.842	-0.851	0.968	0.972	0.231
0.05	-0.75	-0.844	-0.853	0.978	0.973	0.25
0.05	-5	-0.845	-0.855	0.988	0.973	0.255
-0.25	0.5	-0.589	-0.855	0.773	-0.98	0.558
-0.25	0.25	-0.559	-0.739	0.451	-0.972	0.462
-0.25	0.05	-0.324	-0.064	-0.811	-0.855	0.192
-0.25	-0.5	-0.56	-0.737	0.53	-0.989	0.365
-0.25	-0.75	-0.575	-0.772	0.633	-0.988	0.385
-0.25	-5	-0.591	-0.826	0.77	-0.986	0.442
-0.5	0.5	-0.229	-0.824	0.441	-0.98	0.596
-0.5	0.25	-0.231	-0.561	-0.056	-0.965	0.519
-0.5	0.05	-0.169	0.025	-0.904	-0.746	0.231
-0.5	-0.25	-0.088	-0.511	-0.323	-0.989	0.442
-0.5	-0.75	-0.166	-0.683	0.185	-0.993	0.5
-0.5	-5	-0.196	-0.781	0.418	-0.99	0.519

Table 3: Estimated Parameter Values

parameter	value	std.err.	description
σ	.240	.074	prod. curvature parm.
ρ	.252	.072	prod. curvature parm.
ω	.317	.128	tech. curvature parm.
a_0	2.440	1.208	technology frontier for (A_u,A_s)
a_1	.747	.198	technology frontier for (A_u,A_s)
b_0	.185	.049	technology frontier for (A_u,A_k)
b_1	.061	.045	technology frontier for (A_u,A_k)
		52	number of observations

Table A.1: Raw Data

country	code	GDP	capital	L_u	L_s	w_s/w_u
Argentina	ARG	14804.7	33151.4	59.9	106.45	1.51
Australia	AUS	29858.1	88075.5	17.08	128.79	1.24
Bolivia	BOL	4952.5	9076.4	74.91	50.74	1.33
Botswana	BWA	3315.8	9884.9	115.07	40.73	2.15
Brazil	BRA	11297	21226.6	99.61	61.97	1.8
Canada	CAN	33336.9	82442.8	7.04	133.7	1.23
Chile	CHL	9323.1	22451.9	72.64	107.74	1.62
China	CHN	2123.7	4156.4	64.89	49.85	1.22
Colombia	COL	9360.2	15433.7	83.39	76.07	1.75
Costa Rica	CRI	9118.2	16695.3	82.61	76.78	1.55
Cyprus	CYP	15804.7	37046.2	47.87	143.77	1.55
Dom. Rep.	DOM	7314.3	12231.8	84.97	48.74	1.46
Ecuador	ECU	8388.1	21190.1	68.52	106.87	1.6
El Salvador	SLV	5548.5	5617.3	92.26	38.05	1.47
France	FRA	28971.6	84929	45.53	111.7	1.49
Ghana	GHA	1853.9	1217.9	83.85	35.24	1.4
Greece	GRC	16607.3	42802.4	26.54	85.39	1.11
Guatemala	GTM	7430.5	7772.6	98.19	43.36	1.81
Honduras	HND	4596.5	6174.7	102.17	74.94	2.02
Hong Kong	HKG	21532.3	29127.6	38.21	98.99	1.28
Hungary	HUN	10868.9	33857	37.43	88.94	1.19
India	IND	3045.7	3775.5	79.29	34.47	1.22
Indonesia	IDN	3914.3	8083.8	84.62	72.29	1.97
Israel	ISR	23362.3	51767.6	36.53	118.69	1.29
Italy	ITA	29552.4	82317.6	42.94	66.22	1.1
Jamaica	JAM	4595.5	12830.9	96.17	184.72	3.16
Japan	JPN	20807.3	64180.8	27.87	119.16	1.3
Kenya	KEN	1997.8	2748.3	108.77	34.46	1.93
Malaysia	MYS	9471.6	23542.7	58.8	81.76	1.46
Mexico	MEX	15329.6	28448.8	81.22	92.07	1.76
Netherlands	NLD	28549.7	79069.3	24.43	127.68	1.34
Nicaragua	NIC	4452.8	8762.3	90.85	40.19	1.47
Pakistan	PAK	4551.6	3793.2	85.09	30.24	1.47
Panama	PAN	7897.9	19793.9	63.3	139.12	1.73
Paraguay	PRY	6015.4	9689	87.77	67.7	1.58
Peru	PER	8386.6	18075.5	65.24	75.06	1.38
Philippines	PHL	4472.8	8042.3	46.46	96.98	1.38

Table A.1: Raw Data (continued)

country	code	GDP	capital	L_u	L_s	w_s/w_u
Poland	POL	8438.8	33948.8	19.5	98.1	1.12
Portugal	PRT	12960.5	29436.8	63.82	59.47	1.49
S. Korea	KOR	13483.3	24650.9	28.46	159.26	1.53
Singapore	SGP	21470.4	56218.5	71.33	89.34	1.71
Sri Lanka	LKA	5476.3	5919.5	51.12	75.99	1.32
Sweden	SWE	27886	72777.3	28.28	132.6	1.31
Switzerland	CHE	30964.9	107869.8	22.21	142.18	1.37
Taiwan	OAN	15787.3	26240	35.82	96.91	1.27
Thailand	THA	5557.7	7477.4	86.78	64.52	1.52
Tunisia	TUN	7695.7	10823.4	82.32	35.73	1.38
UK	GBR	25775.3	50408.8	36.38	115.32	1.31
USA	USA	35438.7	87330.1	6.33	228.61	1.48
Uruguay	URY	12036.3	23397.6	62.49	96.67	1.47
Venezuela	VEN	17529.1	42713.1	69.46	70.71	1.4
W. Germany	DEU	28992.2	89368.2	41.19	93.7	1.22