

How Important Is Human Capital for Development?

Evidence from Immigrant Earnings

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This paper offers new evidence on the sources of cross-country income differences. It exploits the idea that observing immigrant workers from different countries in the same labor market provides an opportunity to estimate their human-capital endowments. These estimates suggest that human and physical capital account for only a fraction of cross-country income differences. For countries below 40 percent of U.S. output per worker, less than half of the output gap relative to the United States is attributed to human and physical capital. (JEL O15, O41, F22)

Cross-country differences in per capita outputs are far larger than standard neoclassical growth models predict. In response, some authors have proposed to abandon the neoclassical framework in favor of theories where countries differ in their total factor productivities, possibly due to technology gaps (e.g., Paul Romer, 1993; Edward C. Prescott, 1998). An alternative approach, pioneered by N. Gregory Mankiw et al. (1992), is to augment the neoclassical model by adding human capital. Since the two approaches differ dramatically in their policy implications, it is important to determine the relative contributions of human capital and total factor productivity (TFP) to cross-country income differences.

Previous attempts at resolving this issue have encountered the problem of measuring countries' human-capital stocks. A common approach is to assume that workers of given age and education have the same human-capital endowments in all countries (e.g., Robert E. Hall and Charles I. Jones, 1999). A difficulty with this approach is that possible differences in unmeasured skills are not captured. Since mea-

sured skills account for only a relatively small fraction of earnings variation within countries, this could be an important omission. An alternative approach postulates a human-capital production function and constructs human-capital stocks based on a perpetual inventory method (e.g., Peter J. Klenow and Andrés Rodríguez-Clare, 1997a). A difficulty with this approach is that the implications may be sensitive to the human-capital production function chosen. Whether differences in human capital or in total factor productivity account for the bulk of cross-country income gaps remains therefore controversial (Robert Topel, 1998).

This paper offers a new empirical strategy which avoids these measurement problems. The idea is to estimate the human capital of workers from different countries by observing their earnings in the same labor market. Specifically, differences in labor earnings across U.S. immigrants with identical measured skills are used to infer their unmeasured human-capital endowments.¹ This approach has the benefit of capturing measured as well as unmeasured skill differences without having to impose a human-capital production function.

In order to quantitatively explore this idea, I develop a neoclassical growth model that incorporates both human capital and productivity gaps as sources of cross-country income differ-

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¹ The idea of using international migration as a natural experiment has been proposed a number of times (Mancur Olson, Jr., 1996 p. 16; Klenow and Rodríguez-Clare, 1997b p. 612) but it has apparently never been studied in detail.

ences. The model decomposes these income differences into the contributions of physical capital, observed skills (such as education and experience), unobserved skills as measured by relative immigrant earnings, and a total factor productivity residual.

Immigrant earnings are estimated from U.S. Census data (U.S. Department of Commerce, Bureau of the Census, 1990). A key observation is that the gap between immigrant and native earnings is less than 25 percent for most source countries, suggesting that cross-country differences in unobserved skills are much smaller than cross-country income gaps. As a result, human- and physical-capital accumulation account for only a fraction of cross-country income differences. For a sample of low-income countries, which produce on average 18 percent of U.S. output per worker, human and physical capital account for a reduction in output to 53 percent of the U.S. level, leaving a factor of 3 unexplained. For the poorest five countries in the sample, output per worker is overpredicted by a factor of 8.

A possible objection against this approach is that immigrant self-selection could drive a wedge between the unmeasured human-capital endowments of immigrants and source country workers. If immigrants are positively selected, then relative immigrant earnings overstate the human-capital endowments of the source countries. However, reasonable degrees of self-selection do not alter the qualitative findings. Fully accounting for observed cross-country income differences on the basis of human and physical capital implies that immigrants from poor source countries must possess several times more human capital than source country workers. Yet data on the earnings of emigrants and return migrants suggest that self-selection in unobserved skills is rather modest. Even allowing for degrees of self-selection that are larger than the data suggest implies that human- and physical-capital differences fail to account for large part of observed cross-country income gaps. For a sample of low-income countries, human and physical capital account for a reduction of output per worker to 36 percent of the U.S. level, compared with 18 percent in the data. For the poorest five countries in the sample, output per worker is overpredicted by a factor of 5.

The paper then considers whether skill

complementarities could increase the ability of human capital to account for large cross-country income differences. Scarcity of skilled labor may depress unskilled wages in poor countries. This might help explain why migrants experience large earnings gains, even though unskilled workers possess the same human-capital endowments in all countries. I find that skill complementarities improve the ability of human and physical capital to account for cross-country income differences, but output per worker remains overpredicted by factors of 2 or more for low-income countries.

I conclude that data on immigrant earnings are difficult to reconcile with the view that differences in human and physical capital account for the bulk of the observed cross-country income dispersion. The data are more consistent with Prescott's (1998) conclusion that accounting for large income differences across countries requires a theory of total factor productivity.

A number of other papers have recently offered empirical critiques of augmented neoclassical models (see Klenow and Rodríguez-Clare, 1997a; Prescott, 1998; Mark Bilal and Klenow, 2000). The main advantage of the approach taken here is that it requires few assumptions beyond those maintained in virtually all versions of neoclassical growth models (most importantly, that factors are paid their marginal products). It therefore avoids issues related to the measurement of human capital that underlie the current controversy about the importance of human capital for cross-country income differences.

The rest of the paper is organized as follows. Section I lays out the model and derives its implications for cross-country earnings differences. Section II describes the data and discusses measurement issues. The empirical findings are presented in Section III. Section IV concludes.

I. The Model

This section develops a model that encompasses the two competing hypotheses about cross-country income differences: human-capital gaps and productivity gaps. Output per worker depends on a country's stocks of human and physical capital, as for example in Mankiw et al.

(1992). But it also depends on a country's level of total factor productivity as suggested by Prescott (1998). A parameterized version of the model is used below to investigate to what extent capital accumulation can account for the large cross-country income differences observed in the data.

Each country, indexed by c , is inhabited by large numbers of workers indexed by i . Aggregate output is produced from physical capital (K_c) and labor (L_c) using a Cobb-Douglas production function

$$(1) \quad Y_c = K_c^\theta (A_c L_c)^{1-\theta}.$$

Labor input is an aggregate of skilled and unskilled labor inputs: $L_c = G(L_{c,H}, L_{c,L})$. This specification allows for complementarity between skilled and unskilled workers while retaining a constant capital share in national income. All markets are competitive. Firms rent physical capital and labor services from households so as to maximize period profits given factor prices. From the first-order condition, the rental price of labor of skill s is

$$(2) \quad \omega_{c,s} = (1 - \theta) A_c^{1-\theta} (K_c/L_c)^\theta G_s,$$

where G_s denotes the derivative of G with respect to labor of skill s . Competition in factor markets ensures that effective capital-labor ratios (K_c/L_c) and thus capital-output ratios ($\kappa_c = K_c/Y_c$) are equalized across workers within a country.² Hence, the wage rates may be written as functions of labor inputs and the capital-output ratio:

$$\begin{aligned} \omega_{c,s} &= \omega_s(\kappa_c, L_{c,H}, L_{c,L}; A_c) \\ &= (1 - \theta) A_c \kappa_c^{\theta/(1-\theta)} G_s(L_{c,H}, L_{c,L}). \end{aligned}$$

Earnings per worker in country c are then given by

$$(3) \quad w_{c,s} = \omega_s(\kappa_c, L_{c,H}, L_{c,L}; A_c) L_{c,s} / N_{c,s},$$

where $N_{c,s}$ denotes the number of workers with skill s in c . Within a skill class, individual earnings are thus proportional to workers' endowments of labor efficiency units. In what follows I shall assume that the labor aggregator is of the constant elasticity of substitution type

$$G(L_{c,H}, L_{c,L}) = (\rho_H L_{c,H}^\xi + \rho_L L_{c,L}^\xi)^{1/\xi},$$

with elasticity of substitution $\alpha = (1 - \xi)^{-1}$. The labor weights are normalized such that $\rho_H + \rho_L = 1$. I also consider the special case where the skill types are perfect substitutes: $G(L_{c,H}, L_{c,L}) = L_{c,H} + L_{c,L}$.

In the empirical implementation the skill types will be identified with education levels. In order to account for earnings differences within skill classes, for example by age, education, or sex, the labor force is further subdivided into J classes. Workers in classes j belonging to the set J_s are endowed with $h_j \eta_{c,j}$ efficiency units of labor of skill type s . The h_j capture relative labor efficiencies across skill classes that are common across countries, while the $\eta_{c,j}$ capture the efficiency of country c workers relative to a reference country within a skill class. This reference country will be the United States for which I normalize $\eta_{US,j} = 1$. If the number of class j workers in country c is denoted by $N_{c,j}$, then country c 's labor endowments are given by

$$L_{c,s} = \sum_{j \in J_s} N_{c,j} h_j \eta_{c,j}.$$

A number of reasons why observationally identical workers may differ in human-capital levels across countries have been suggested in the literature. Examples include differences in school quality or in the human capital of teachers (Bils and Klenow, 2000). I shall refer to differences in $\eta_{c,j}$ as unmeasured skill differences. In the empirical implementation, these will be estimated from immigrant earnings.

The model nests the two competing hypotheses about cross-country income differences as special cases. In order to capture their implications clearly, I define two versions of the model meant to represent the two hypotheses. The *human-capital model* assumes that total factor

² A possible concern is that binding minimum-wage laws might drive a wedge between wage rates and marginal products for immigrants from poor source countries. However, in the data the bulk of immigrants earns considerably more than the minimum wage.

productivity does not differ across countries: $A_c = A$. The *total factor productivity* (TFP) *model* assumes that unmeasured skills do not differ across countries ($\eta_{c,j} = 1$).

A. A Decomposition of Cross-Country Income Differences

This section presents an empirical framework for quantifying the contributions of physical and human capital to cross-country income differences. The approach is to choose parameters of the production function such that U.S. labor and capital inputs yield the earnings received by U.S. native-born workers. The contributions of physical and human capital to cross-country earnings differences are then quantified by sequentially replacing the U.S. estimates of the capital-output ratio (κ_c), the population weights ($N_{c,j}$), and the unmeasured skill levels ($\eta_{c,j}$) with their source country counterparts in the production function. The implied sequence of earnings per worker, calculated from (3), decomposes the gap between U.S. and source country earnings per worker into the contributions of physical capital, measured and unmeasured skills. Specifically, I define the following earnings per worker concepts:

1. Earnings per worker of skill type s in the United States are given by

$$w_{US,s} = \omega_s(\kappa_{US}, L_{US,H}, L_{US,L}; A_{US}) L_{US,s} / N_{US,s},$$

which can be estimated from U.S. Census data.

2. Replacing the U.S. capital-labor ratio κ_{US} with its source country counterpart κ_c yields

$$w_{c,s}^\kappa = \omega_s(\kappa_c, L_{US,H}, L_{US,L}; A_{US}) L_{US,s} / N_{US,s}.$$

The ratio $w_{c,s}^\kappa / w_{US,s}$ measures the contribution of physical capital to cross-country earnings differences.

3. Using source country population weights to calculate labor endowments yields

$$w_{c,s}^N = \omega_s(\kappa_c, L_{c,H}^N, L_{c,L}^N; A_{US}) L_{c,s}^N / N_{c,s},$$

where $L_{c,s}^N = \sum_{j \in J_s} N_{c,j} h_j$. The ratio $w_{c,s}^N / w_{c,s}^\kappa$ measures the contribution of observed skills (education and experience) to earnings differences.

4. Using immigrants' unmeasured skills to calculate labor endowments yields

$$w_{c,s}^\eta = \omega_s(\kappa_c, L_{c,H}^\eta, L_{c,L}^\eta; A_{US}) L_{c,s}^\eta / N_{c,s},$$

where $L_{c,s}^\eta = \sum_{j \in J_s} N_{c,j} h_j \eta_{c,j} s_c$. The unmeasured skills of immigrants differ from source country efficiencies ($\eta_{c,j}$) by a factor of s_c reflecting self-selection. The ratio $w_{c,s}^\eta / w_{c,s}^N$ measures the contribution of unobserved skills to earnings differences before accounting for possible self-selection of immigrants.

5. Using source country unmeasured skills to calculate labor endowments yields

$$w_{c,s}^P = \omega_s(\kappa_c, L_{c,H}, L_{c,L}; A_{US}) L_{c,s} / N_{c,s},$$

where $L_{c,s} = \sum_{j \in J_s} N_{c,j} h_j \eta_{c,j}$ are the source country labor endowments. $w_{c,s}^P$ is the predicted level of earnings per worker in country c according to the human-capital model.

6. Measured earnings per worker in country c are denoted by $w_{c,s}$. The ratio $w_{c,s}^P / w_{c,s}$ represents the human-capital model's prediction error. One interpretation is that this residual is due to differences in total factor productivities across countries. Parameters of the production function are chosen such that for the United States the predicted and the measured earnings levels coincide: $w_{US,s}^P = w_{US,s}$. For each earnings concept I also define an average over skill types. For example, mean earnings per worker in the United States are given by $w_{US} = \sum_s w_{US,s} N_{US,s} / N_{US}$.

Strictly speaking, the predictions of the model apply only immediately after arrival in the host country. For earlier arrivals postmigration human-capital investments could break the relationship between source country and immigrant earnings. However, immigrant earnings growth does not differ sufficiently from native earnings growth to make a difference. George J. Borjas (1988) and Darren Lubotsky (2000)

estimate that immigrant earnings increase by 10–13 percent relative to native earnings during the first 20 years after migration. While these earnings changes are large in absolute terms, they are small compared with cross-country income differences of up to 30. It is therefore unlikely that postmigration skill investments invalidate the predictions of the human-capital model. In order to verify this conjecture, I restrict the sample to immigrants who arrived at most 10 years ago and confirm that this does not significantly alter the findings reported below.

A related concern is that some skills may not be fully transferable across borders (Rachel Friedberg, 1996). Immigrant earnings would then underestimate source country human-capital endowments. This would strengthen my main conclusion that human capital accounts for only moderate fractions of cross-country earnings gaps.

The TFP model matches cross-country earnings differences by construction: the A_c can be chosen such that predicted and measured earnings coincide. However, it makes a testable prediction about immigrant earnings: Immigrants should earn the same as natives with identical measured skills for all source and host countries.

II. Data and Empirical Implementation

This section provides an outline of the data and empirical procedures. Appendix B provides additional details as well as data for all countries contained in my sample (see Table B1). The *full sample* consists of 67 countries for which sufficient data are available. I also report results for a *low-income sample* which contains 37 countries with real per capita GDP per worker below 40 percent of the U.S. level. The objects to be estimated are the parameters of the production function (θ , A_c , ρ_H , ζ), the capital-output ratios (κ_c), the relative labor efficiencies of different skill classes (h_j , $\eta_{c,j}$), the degree of immigrant self-selection with respect to unmeasured skills (s_c), the population weights $N_{c,j}$, and source country mean earnings $w_{c,s}$.

Labor Efficiencies.—The relative labor efficiencies of workers from different countries are estimated from the earnings of U.S. immigrants. A sample of native- and foreign-born workers is

drawn from the 1990 U.S. Census of Population and Housing 5-percent State Sample data files. Results for 1980 are similar. All results are reported as averages over male and female workers. The sample is restricted to full-time workers between the ages of 20 and 69 who report positive earnings and who are not self-employed and do not live in group quarters. Only immigrants who arrived at age 20 or later are included so as to ensure that most schooling was completed in the source countries.³ Countries with fewer than 150 observations for each sex are dropped. For the two skill case the minimum number of observations is 40 per sex and skill class. The resulting sample consists of 106,263 immigrants.

For each sex and country of birth, workers are sorted into $J = 60$ classes according to age and education. The labor efficiency coefficients are calculated as mean earnings per hour in class j . For U.S. natives these represent h_j , while for immigrants they represent the products $\eta_{c,j}h_js_c$. Small sample sizes make it difficult to estimate immigrant earnings precisely for all J classes. I therefore assume that $\eta_{c,j}$ is the same for all classes within a given skill type ($j \in J_s$). Labor efficiencies are converted into annual earnings per worker assuming that mean hours worked equal 2,100 per year for all classes. A potential difficulty with the approach is self-selection. The unmeasured skills of immigrants may differ from those of source country natives. In terms of the model, the s_c factors could be different from one. This problem will be addressed in Section III, subsection B.

Production Function Parameters.—The productivity parameter A_{US} is chosen to match U.S. mean earnings per worker using (3). For the human-capital model, $A_c = A_{US}$ for all source countries. For the TFP model, A_c is chosen to match predicted earnings per worker in the source countries. The labor weight ρ_H matches the U.S. ratio of aggregate skilled to unskilled earnings. A normalization implies $\rho_L = 1 - \rho_H$. A number of alternative definitions of skilled versus unskilled labor and a range of substitution elasticities are explored.

³ Unfortunately, the Census data do not identify when or where schooling was completed.

The capital share parameter θ is set to a standard value of 0.33 for all countries. Douglas Gollin (1997) finds that capital shares do not systematically vary with per capita incomes. As a result, the decomposition of cross-country earnings gaps into the contributions of capital and TFP presented below also holds for cross-country income gaps. An alternative would be to assume that capital flows equalize rates of return across countries, in which case θ would be country specific. However, the human-capital model would then imply that migration has no effect on earnings, which is at variance with evidence presented below.

Source Country Statistics.—Data on source country real GDP per worker are taken from the Penn World Table Mark 5.6 for 1990. For five countries, data for 1987 through 1989 are used instead. Capital-output ratios are taken from Ellen R. McGrattan and James A. Schmitz, Jr. (1998). Lacking data on hours worked, mean annual earnings per worker are calculated as $(1-\theta)$ times real GDP per worker. Mean earnings by skill class are the computed from the identity $w_c L_c = \sum_s w_{c,s} L_{c,s}$ together with estimates of the source country skill premia $w_{c,H}/w_{c,L}$. The latter are calculated from source country Mincer regressions described in the Technical Appendix (available upon request).

Source country population weights are taken from Robert Barro and Jong-Wha Lee's (2000) data on educational attainment together with data on population age distributions from the U.S. Bureau of the Census International Data Base. The joint distribution of age and educational attainment is constructed from this data together with information on educational attainment by age taken from the Organization for Economic Cooperation and Development's (OECD) Education at a Glance 2001 database using an algorithm described in Appendix B. The findings change very little, if it is assumed instead that educational attainment is independent of age.

One limitation of Barro and Lee's data is that educational attainment is available only for the entire population over age 25, whereas for estimating source country human-capital stocks data on the educational composition of the working population would be desirable. For the United States this difference is small, but it may

be larger for other countries. Average years of schooling estimated from worker survey data typically exceed Barro and Lee's estimates by several years, even for rich countries (see Table B1). As a result, the contribution of education to cross-country income differences would be smaller than reported below, if educational attainment were taken from worker survey data.

III. Implications for Cross-Country Earnings Differences

This section investigates to what extent human- and physical-capital accumulation account for observed cross-country earnings differences. As a starting point, I consider a version of the human-capital model in which the skill types are perfect substitutes and in which immigrants do not differ from source country natives in their unmeasured skills ($s_c = 1$). Both assumption will be relaxed below.

A. One Skill Type—No Self-Selection

The model's implications for decomposing cross-country earnings differences into the contributions of physical capital, measured and unmeasured skills are shown in Table 1, which shows the relative earnings concepts defined in Section I for all countries in the sample. For example, mean earnings per worker in the Philippines equal $w_c/w_{US} = 0.13$ of the U.S. level. The lower Filipino capital-output ratio accounts for an earnings reduction of 6 percent ($w_c^k/w_{US} = 0.94$). The relative lack of measured skills reduces earnings further to $w_c^N/w_{US} = 0.72$. The fact that Filipino immigrants earn about 17 percent less than U.S. natives implies that lower unmeasured skills reduce earnings in the Philippines further to $w_c^7/w_{US} = 0.60$ of the U.S. level, leaving a factor of 4.6 unexplained. The last rows of Table 1 show the geometric means of these relative earnings concepts for the full sample, the low-income sample, and for the poorest five countries.

Figure 1 illustrates the data by plotting the earnings concepts reported in Table 1 against real source country earnings per worker relative to the United States (w_c/w_{US}). Panel (a) shows the effect of capital-output ratios on source country earnings, w_c^k/w_{US} . For most countries, physical capital accounts for only a small fraction

TABLE 1—DECOMPOSITION OF CROSS-COUNTRY EARNINGS GAPS

Country	PWT No.	w_c^K/w_{US}	w_c^N/w_{US}	w_c^η/w_{US}	w_c/w_{US}	w_c^η/w_c
Egypt	14	43.2	31.2	30.4	18.7	1.6
Ghana	18	55.3	37.4	29.5	5.1	5.8
Kenya	22	91.2	57.8	57.2	5.1	11.3
South Africa	41	95.7	66.5	83.8	26.1	3.2
Barbados	52	80.3	58.4	61.0	40.0	1.5
Canada	54	99.5	91.0	110.4	93.5	1.2
Costa Rica	55	86.0	62.4	55.0	27.3	2.0
Dominican Republic	57	84.9	59.7	48.8	18.8	2.6
El Salvador	58	68.3	47.3	35.9	14.9	2.4
Guatemala	60	70.0	47.9	36.4	20.2	1.8
Haiti	61	59.0	38.9	30.6	5.4	5.6
Honduras	62	77.2	52.7	39.3	12.1	3.2
Jamaica	63	112.1	76.1	73.7	14.0	5.3
Mexico	64	85.7	61.0	47.3	46.3	1.0
Nicaragua	65	80.8	56.5	38.8	11.3	3.4
Panama	66	92.8	70.9	66.6	21.8	3.1
Trinidad and Tobago	71	81.7	56.9	55.8	54.1	1.0
Argentina	73	100.3	74.7	75.7	36.5	2.1
Bolivia	74	90.5	65.5	52.1	14.5	3.6
Brazil	75	88.7	62.1	58.0	30.0	1.9
Chile	76	96.4	72.4	66.2	32.2	2.1
Colombia	77	82.3	58.0	49.3	27.5	1.8
Ecuador	78	97.4	73.9	61.6	24.6	2.5
Guyana	79	138.4	93.2	88.4	8.1	10.9
Peru	81	97.9	73.9	59.5	18.6	3.2
Uruguay	83	101.7	76.5	74.1	32.2	2.3
Venezuela	84	102.7	73.5	67.1	47.4	1.4
Bangladesh	86	46.3	31.2	24.5	13.0	1.9
China	88	82.6	58.3	47.3	6.0	7.9
Hong Kong	89	79.9	62.5	63.8	62.1	1.0
India	90	75.0	52.1	51.8	8.8	5.9
Indonesia	91	79.8	54.2	51.8	13.7	3.8
Iran	92	90.7	62.6	57.6	31.0	1.9
Iraq	93	89.5	61.7	56.1	32.3	1.7
Israel	94	99.7	81.3	88.4	64.7	1.4
Japan	95	114.1	98.0	122.3	61.5	2.0
Jordan	96	88.1	65.6	59.8	34.4	1.7
Korea, Republic of	97	89.3	72.3	59.2	43.6	1.4
Malaysia	100	96.1	66.7	65.2	34.1	1.9
Pakistan	105	59.6	41.1	36.4	12.6	2.9
Philippines	106	94.4	72.1	59.5	13.0	4.6
Sri Lanka	110	63.2	43.6	42.4	15.6	2.7
Syria	111	77.4	56.1	59.7	43.2	1.4
Taiwan	112	88.0	66.5	66.4	50.1	1.3
Thailand	113	78.7	55.8	48.1	18.4	2.6
Austria	116	110.9	89.0	105.3	72.6	1.4
Belgium	117	107.9	85.1	104.7	86.3	1.2
Denmark	121	109.4	94.1	120.1	67.9	1.8
France	123	113.6	87.8	105.2	82.6	1.3
Germany, West	125	116.7	93.8	104.2	80.3	1.3
Greece	126	104.8	81.0	84.1	48.2	1.7
Hungary	127	89.4	70.3	73.0	29.4	2.5
Ireland	129	108.4	85.0	100.2	65.4	1.5
Italy	130	110.3	83.0	96.2	83.8	1.1
Netherlands	133	107.1	86.1	93.1	85.0	1.1
Norway	134	113.0	97.6	123.0	79.5	1.5
Poland	135	83.4	64.2	60.0	20.3	3.0
Portugal	136	103.7	74.2	79.2	45.2	1.8
Spain	138	108.8	78.7	79.8	71.7	1.1

TABLE 1—*Continued.*

Country	PWT No.	w_c^k/w_{US}	w_c^N/w_{US}	w_c^η/w_{US}	w_c/w_{US}	w_c^η/w_c
Sweden	139	106.7	89.5	113.6	77.2	1.5
Switzerland	140	121.1	99.5	122.7	89.2	1.4
Turkey	141	95.1	65.4	71.1	23.5	3.0
United Kingdom	142	95.1	74.9	92.9	72.8	1.3
Yugoslavia	144	117.6	92.0	101.8	27.2	3.7
Australia	145	111.1	94.9	118.8	82.4	1.4
Fiji	146	94.1	65.4	56.4	32.1	1.8
New Zealand	147	109.7	96.4	117.8	69.1	1.7
Subsample means:						
Full sample		90.4	67.1	65.7	30.4	2.2
Low-income sample		83.4	59.2	53.1	17.7	3.0
Poorest five countries		80.6	54.0	46.4	5.8	8.0

Notes: PWT No. denotes the Penn World Table 5.6 country number. Columns 2–4 show the cumulative effects of K/Y , measured and unmeasured skills on source country earnings per worker. w_c/w_{US} denotes relative source country earnings in the Penn World Tables. w_c^η/w_c is the ratio of predicted to measured source country earnings.

of the observed earnings gap relative to the United States. For example, in the low-income sample, lack of physical capital reduces earnings by 17 percent, whereas measured earnings are only 18 percent of the U.S. level. The reason is that even low-income countries often have capital-output ratios greater than one-half of the U.S. level. According to (3), their earnings are reduced at most by a factor of $w_c^k/w_{US} = \sqrt{0.5}$. This is, of course, precisely the reason why a Solow growth model cannot account for large cross-country output differences.

The effect of measured skills on earnings, w_c^N/w_c^k , is shown in Panel (b). For all source countries, educational attainment in the Barro-Lee (2000) data is lower than in the United States. This reduces earnings per worker between 20 percent for the richest and 40 percent for the poorest countries. The combined effect of physical capital and measured skills [w_c^N/w_{US} , shown in Panel (c)], is to reduce earnings in the full sample to 67 percent of the U.S. level. For the poorest five countries, earnings are reduced to 54 percent.

Panel (d) shows the effect of unmeasured skills, w_c^η/w_c^N , estimated by the earnings of immigrants relative to U.S. natives with identical measured skills ($\eta_{c,c}$). In the one skill model, source country earnings are proportional to unmeasured human capital. Hence, the ratios plotted in Panel (d) equal the $\eta_{c,c}$ factors. The key insight from this data is that the gap between the earnings of immigrants and U.S. natives with identical skills is less than 25 percent for most source countries. Immigrants

from richer source countries earn more, but the relationship is weak. A tenfold increase of source country earnings (or source country output per worker) is associated with an immigrant earnings improvement of only around one-third.⁴ Accounting for this fact poses a challenge for models where productivity is embodied in workers, but it arises naturally if productivity is country specific as in the TFP model.

The human-capital model's predicted source country earnings per worker, w_c^η/w_{US} , are shown in Panel (e). They represent the joint effect of physical capital, measured and unmeasured skills. In the full sample, human capital accounts for a 27-percent reduction in output per worker. The joint effect on human and physical capital is to reduce relative earnings to 0.66, leaving on average a factor of 2.2 unexplained. Figure 2 shows the ratio of predicted to measured immigrant earnings [w_c^η/w_c , or the ratio of the data shown in Panel (e) of Figure 1 to the 45-degree line]. Consistent with theories that attribute cross-country income differences to total factor productivity, the degree of overprediction is larger for poorer countries. In the low-income sample, earnings per worker implied by the model (0.53) overpredict measured earnings by a factor of 3. For the poorest five countries, predicted earnings of 0.46 exceed measured earnings by a factor of 8.

⁴ Borjas (1988 Table 5) has a similar finding.

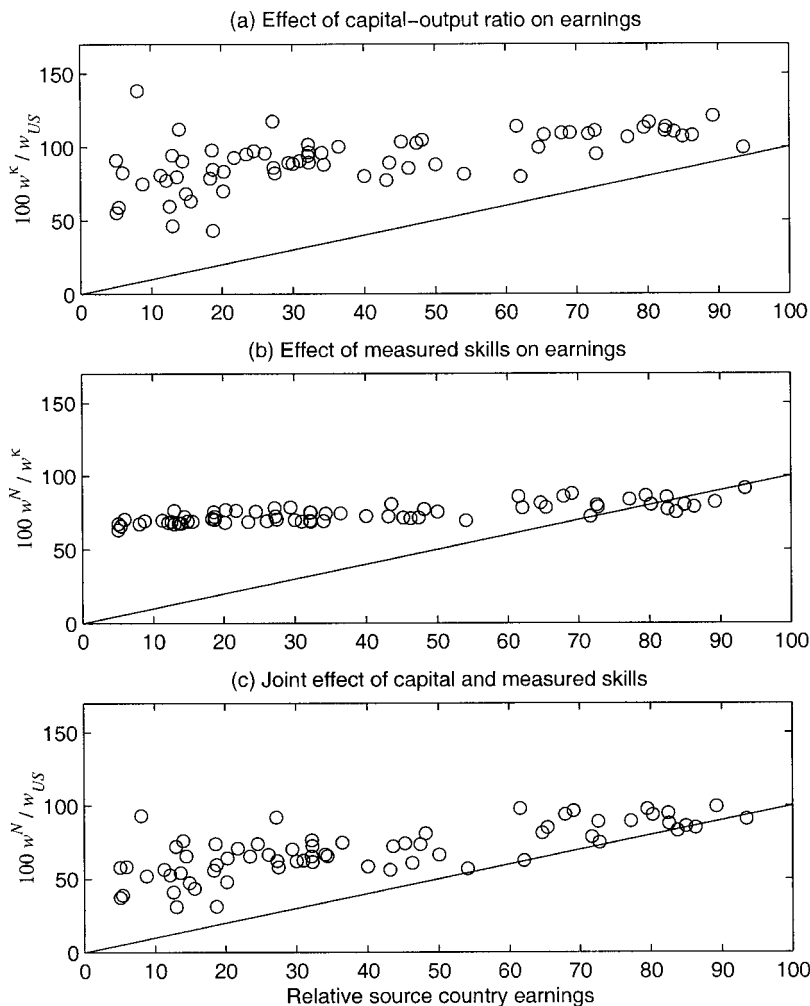


FIGURE 1. DECOMPOSITION OF CROSS-COUNTRY EARNINGS DIFFERENCES: ONE SKILL MODEL

Other Host Countries.—There are reasons to believe that similar findings are valid for a variety of host countries, not only for the United States. In particular, the observation that immigrants earn within 25 percent of natives with identical measured skills is common in the literature. For example, Borjas (1988 Table 6.1) reports that the typical immigrant with 12 years of schooling at age 50 earns 9 percent more than observationally similar natives in the United States, 10 percent less in Canada, and 5 percent less in Australia [see also David E. Bloom and Morley Gunderson (1991 Table 12.5) for Canada and see John J. Beggs and

Bruce J. Chapman (1991) for Australia]. Similar findings hold for the United Kingdom (Brian D. Bell, 1997, especially Table 5), Italy (Alessandra Venturini and Claudia Villosio, 1998 Table 4.1), Denmark (Leif Husted et al., 2000), Norway (John E. Hayfron, 1998), Sweden (Per-Anders Edin et al., 2000), and Germany (Christoph M. Schmidt, 1997 Table 4).

Importantly, the observation remains valid for poorer host countries as well. For Israel, Friedberg (1996 Table 4) reports that, controlling for individual characteristics, earnings of immigrants from all regions are very similar to those of natives. For example, with 12 years of

FIGURE 1—Continued.

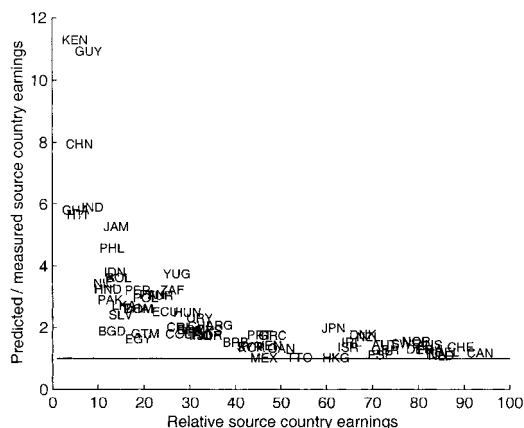
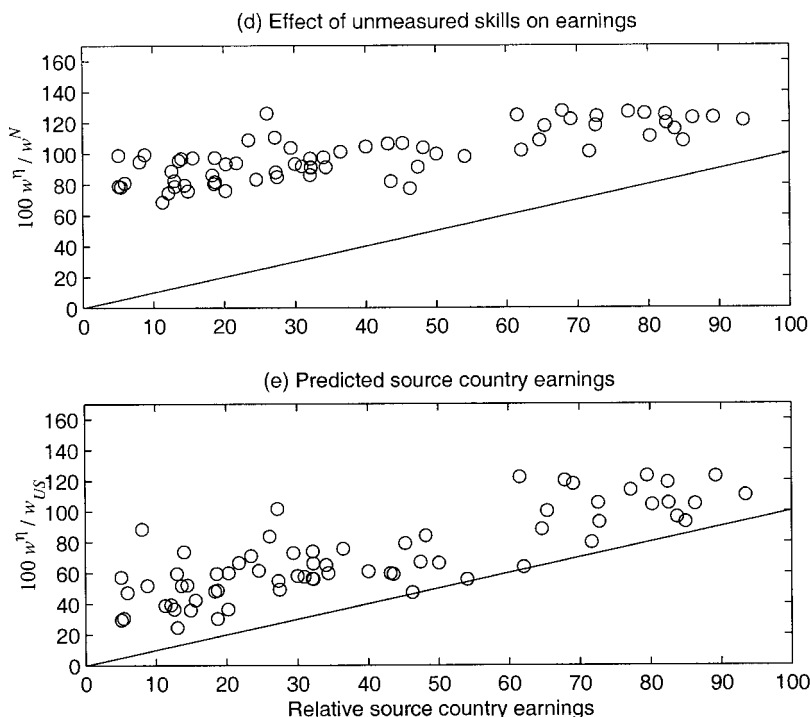


FIGURE 2. RATIO OF PREDICTED TO MEASURED SOURCE COUNTRY EARNINGS

schooling and 20 years of experience the ratio of immigrant to native earnings is 99 percent for Western Europeans, 96 percent for Eastern Europeans, 101 percent for Soviets, and 86 percent for Asians/Africans.

Discussion.—In order to understand why human and physical capital fail to account for large parts of cross-country income differences, consider the model's implications for migrant earnings gains. If there is only one skill type and if countries share identical production functions, migration affects earnings of a given worker only by changing the capital-output ratio. Specifically, moving from country c to country s increases earnings by a factor of $(\kappa_s / \kappa_c)^{\theta/(1-\theta)}$ according to (3). For a capital share of $\theta = 1/3$ and a source country with one-half the U.S. capital-output ratio, migration increases earnings by 40 percent. Hence, the predicted earnings gains from migration are much smaller than observed cross-country earnings differences for workers with identical measured skills, so that immigrants should earn much less than U.S. natives. By contrast, in the data immigrants typically receive at least 75 percent of native earnings. Successfully accounting for cross-country income differences without appealing to TFP gaps therefore either requires larger earnings gains from migration or that

migrants differ in their unmeasured skills from nonmigrants.

An additional challenge for the human-capital model is to account for the variation of immigrant earnings across host countries. The fact that immigrant earnings cluster around native earnings in poor as well as in rich host countries arises naturally in the TFP model, but poses a problem for models in which productivity is embodied in workers. For example, Israel's capital-output ratio is close to that of the United States. Hence, the human-capital model does not provide any reasons why the earnings of immigrants with identical measured skills should differ between Israel and the United States by a factor of 2.

The following subsections examine whether two extensions help reconcile the model with the data. These extensions are self-selection of emigrants in terms of unmeasured human-capital and skill complementarities.⁵

B. One Skill Type—Nonrandom Selection of Migrants

A possible defense of the human-capital model is that migrants are self-selected so that they possess more *unmeasured* human capital than nonmigrants. The large earnings gap between U.S. immigrants and nonmigrants in poor source countries (Figure 2) would then reflect strong self-selection instead of large earnings gains. In other words, the reason why immigrants earn several times more than predicted by the human-capital model would then not be that migration leads to large earnings gains, but that immigrants possess several times more unmeasured human capital (s_c) than nonmigrants with identical characteristics. However, several pieces of evidence suggest that unmeasured self-selection is likely much smaller than necessary for reconciling the model with large cross-country earnings gaps.⁶

⁵ Given the limited evidence, it is difficult to quantify the role of possible human-capital spillovers. See James E. Rauch (1993) and Daron Acemoglu and Joshua Angrist (2000) for attempts at measuring such spillovers.

⁶ Section III, subsection D, builds on the evidence presented here to quantify the contributions of human and physical capital to cross-country income differences in the presence of plausible degrees of self-selection.

Self-Selection Implied by the Model.—It is instructive to ask what degree of immigrant self-selection would be required to fully account for cross-country income gaps based on human and physical capital alone. First, I calculate the predicted earnings of immigrants at source country skill prices from (3):

$$w_c^{\text{lm}} = \omega(\kappa_c, L_{c,H}, L_{c,L}; A_{US}) \\ \times \sum_j N_{c,j}^{US} h_j \eta_{c,j} s_c / \sum_j N_{c,j}^{US}.$$

Hence the predicted ratio of immigrant to mean source country native earnings is given by

$$(4) \quad ER_c = \frac{w_c^{\text{lm}}}{w_c} = \frac{\sum_j N_{c,j}^{US} h_j \eta_{c,j} / \sum_j N_{c,j}^{US}}{\sum_j N_{c,j} h_j \eta_{c,j} / \sum_j N_{c,j}} s_c.$$

The interpretation is that immigrants should earn ER_c times mean earnings, if they returned to their source countries. The first ratio reflects measured skill differences. It can be calculated directly from population weights in source countries and of immigrants. The factor s_c reflects self-selection in unmeasured skills. If human and physical capital fully account for cross-country earnings differences, then $s_c = w_c^{\eta}/w_c$. In other words, the self-selection factors s_c equal the unexplained earnings gaps shown in Figure 2.

These figures are easier to interpret when expressed as the implied positions of immigrants in the source country earnings distribution. I assume that the distribution of earnings in each country is lognormal with a standard deviation that matches the quintile ratios reported in Klaus Deininger and Lyn Squire's (1996) data set of inequality measures. The lognormal distribution approximates the earnings distributions of several countries fairly closely, except for the very highest earnings levels (John Creedy, 1985). Using Deininger and Squire's inequality measures likely understates the degree of migrant self-selection implied by the model, as their estimates represent income inequality across the entire population which is typically larger than earnings dispersion among the labor force. Figure 3 shows the implied

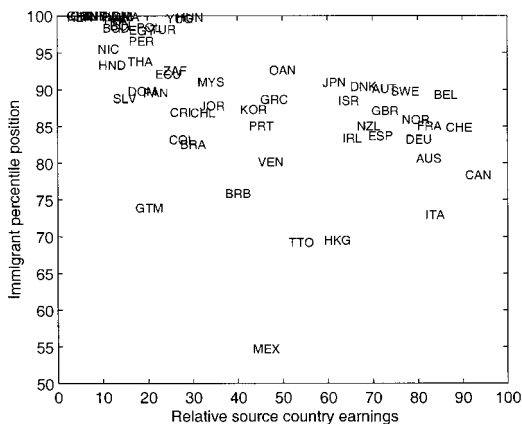


FIGURE 3. PREDICTED POSITION OF IMMIGRANTS IN SOURCE COUNTRY EARNINGS DISTRIBUTION

percentile positions of immigrants in the source country earnings distributions. For several low-income countries the model predicts that the typical immigrant should be drawn from the top 1 percent of the observed earnings distribution (which does not include expatriates).

This strong degree of self-selection appears especially implausible for source countries with large emigrant populations. The most striking case is Jamaica, where 14.5 percent of the population resided in the United States in 1990, yet the mean immigrant must be drawn from the top 0.1 percent of the earnings distribution. Other countries for which the fraction of the population residing in the United States exceeds the predicted degree of self-selection include Guyana (15.2 percent vs. 0.1 percent), Nicaragua (4.7 percent vs. 0.4 percent), the Philippines (1.6 percent vs. 0.6 percent), and Hungary (1.1 percent vs. 0.2 percent). Another case in which strong self-selection is unlikely is El Salvador. Edward Funkhouser (1992) estimates that 35 percent of households have family members living abroad. Furthermore, he finds little self-selection of emigrants within households. Yet the human-capital model implies that the 9.1 percent of the population residing in the United States in 1990 must be drawn from the top 11.1 percent of the earnings distribution. In these countries, accounting for cross-country earnings differences based on human and physical capital alone would require that the entire top of the earnings distribution (and only the top) has em-

igrated to the United States. However, other evidence suggests that self-selection in unmeasured skills is generally quite weak.

Estimates of Emigrant Self-Selection.—The most direct evidence suggesting weak self-selection in unmeasured skills comes from studies that follow individual workers across borders. Based on a sample of 490 recent U.S. immigrants, Guillermina Jasso et al. (1998) find that migrants on their last source country jobs earned 75 percent more than the mean source country worker. However, this gap is largely accounted for by differences in measured skills. Immigrants in their sample possess almost eight years more schooling than nonmigrants. With a Mincerian return to schooling of 9.9 percent per year, which is the average in the 56-country sample of George Psacharopoulos (1994), immigrants' higher education accounts for more than the entire earnings gap, leaving little room for self-selection with respect to unmeasured skills. For Egypt, Richard H. Adams, Jr. (1993) finds that emigrants tend to be poorer than nonmigrants.⁷

An indirect measure of self-selection can be obtained from return migrants. If emigrants were strongly self-selected, return migrants should earn substantially more than never migrants. However, in the data the earnings of both groups are very similar, suggesting that self-selection is weak. For Hungary, Catherine Y. Co et al. (1999) find that female return migrants earn slightly more than never migrants, whereas the difference is insignificant for male workers. G. M. Arif (1998) estimates that Pakistani return migrants earn less than those who never migrated. Alan Barrett and Philip J. O'Connell (2000) find that male return migrants in Ireland earn 10 percent more than never migrants, although no wage premium is found for women. For Puerto Rico, Fernando A. Ramos (1992) finds that whether a worker is a

⁷ Earnings of political refugees provide another opportunity for observing immigrant earnings where nonrandom selection appears unlikely. For Cuban refugees arriving during the Mariel boatlift, David Card (1990) finds that, after controlling for measured skills, their earnings differ only by 18 percent from those of previous Cuban immigrants in Miami. A more systematic investigation of refugee earnings would be a useful task for future research.

return migrant or even whether a person was born in the United States has little effect on earnings. This pattern is precisely what the TFP model predicts: earnings are determined by where a person works, not by place of birth.

Of course, the fact that return migrants do not earn much more than those who never left the source countries could be due to the fact that return migrants are strongly negatively selected in terms of unmeasured skills. However, recent longitudinal studies of U.S. immigrants find that this is not the case. Lubotsky (2000) estimates that return migrants earn around 15 percent less than immigrants who stay in the United States.

Additional evidence suggesting that self-selection is weak comes from estimates of migrant earnings gains. Except for some very poor countries with unusually low capital-output ratios, the human-capital model predicts that immigration should raise earnings by modest amounts or even not at all. Yet empirical estimates of the earnings gains associated with migration are typically large. Jasso et al. (1998) find that, controlling for purchasing power differences, Chinese immigrants earn three times more in the United States than they did on their last home country job. By contrast, the model predicts earnings gains of only 21 percent. Similarly, Filipinos earn 2.5 times more in the United States while the model predicts an earnings improvement of only 6 percent. The only low-income source country for which Jasso et al. (1998) do not find large earnings gains is Mexico. However, their finding contrasts with other studies, such as Richard W. Cuthbert and Joe B. Stevens (1981) or Douglas S. Massey et al. (1987), who find that Mexican immigrants earn around six times more in the United States than in Mexico, compared with a predicted gain of 17 percent. For Puerto Ricans, Ramos (1992) finds that, controlling for migrant self-selection, working in the United States doubles earnings, whereas the model predicts an earnings gain of only 8.4 percent. Large earnings gains due to migration are also found for Pakistani workers in Saudi Arabia (around 800 percent; Hafiz A. Pasha and Mir Anjum Altaf, 1987) and in the Middle East (Nadeem Ilahi and Saqib Jafarey, 1999), and for Egyptian emigrants (Adams, 1993). This evidence suggests that migrating from poor to rich countries results in earnings

gains that are considerably larger than the human-capital model predicts.

One possible way of reconciling the human-capital model with large immigrant earnings gains is self-selection based on job matches.⁸ If migration occurs because workers have received attractive job offers, then the earnings gap between immigrants and source country natives may in part reflect the high quality of immigrant job matches instead of differences in human capital. Consistent with this hypothesis, Arnold De Silva (1997) finds that immigrants who are admitted into Canada with prearranged employment enjoy higher earnings. However, the estimated earnings benefit of 17 percent accounts for only a small fraction of the unexplained gap between immigrant and source country earnings. Moreover, only around one in five Canadian immigrants arrive with prearranged employment.

A related concern is that skill-based admissions could induce strong immigrant self-selection. This could be a problem for countries such as Canada, which admits around 40 percent of immigrants based on skill or employment criteria. However, it is much less of a concern for the United States where, since the 1965 Immigration Act, the bulk of immigrants are admitted as relatives or family members of U.S. residents. The fraction of skill-based admissions never exceeded 16 percent during the period 1988–1998 and most of these come from rich source countries (U.S. Immigration and Naturalization Service, 1998). Moreover, while skill-based immigrants enjoy an initial earnings advantage over family migrants, the gap vanishes after some years of U.S. experience (Jasso and Mark R. Rosenzweig, 1995; Harriet O. Duleep and Mark C. Regets, 1996).

A final reason to doubt the hypothesis of strong self-selection is that the earnings of immigrants cluster around native earnings in all host countries. This arises naturally in a TFP model, where the earnings of immigrants and natives benefit equally from the country-specific productivities of the host countries. By contrast, if productivity is embodied in workers,

⁸ I am grateful to an anonymous referee for pointing out this possibility.

the fact that immigrant earnings are close to native earnings requires a specific pattern of self-selection. In particular, immigrants from poorer countries must be more positively selected (as measured in Figure 2), and immigrants in poorer host countries must be less positively selected.

Accounting for Cross-Country Earnings Gaps with Stronger Migrant Self-Selection.—Taken together, this evidence suggests that migrant self-selection in unmeasured skills is likely weak. If this is the case, then the estimates of Section III, subsection A, quantify the contributions of human and physical capital to cross-country earnings gaps. It is, however, useful to examine the robustness of these findings against the possibility of stronger self-selection in unmeasured skills. The evidence reviewed earlier indicates that unmeasured self-selection is weaker than measured self-selection. In terms of the model this means that the s_c factors are smaller than the ratio of measured skills of immigrants relative to source country natives [the first term in equation (4)]. Setting the s_c equal to these ratios should therefore overstate unmeasured selection. It implies that immigrants are drawn from the top 5 percent of the source country earnings distribution for eight countries in the sample, and that immigrants in the low-income sample possess 2.3 times more human capital than nonmigrants. This degree of self-selection is far greater than the evidence presented earlier suggests. Still, large cross-country income gaps remain unaccounted for. Output per worker is overpredicted by a factor of 2 for the low-income sample and by a factor of 5 for the poorest five countries. I conclude that plausible degrees of unmeasured self-selection do not overturn the finding that physical- and human-capital accumulation fail to account for a large part of cross-country income differences.

C. Multiple Skill Types

In neoclassical growth models, it is typically assumed that workers of different skill levels are perfect substitutes in production. Relaxing this assumption might help reconcile the model with the data. If skilled and unskilled labor are poor substitutes, countries where skilled labor is

scarce may have low average earnings, even though a typical unskilled worker possesses the same amount of human capital in all countries. Migration then leads to large wage gains for unskilled workers because they benefit from the larger supply of skilled labor in the host country.⁹

In order to empirically implement the model with two skill types, it is necessary to define which education classes belong to each skill. Barro and Lee's (2000) data distinguish seven education classes for the source countries (no formal schooling; primary, secondary, or higher schooling attained or completed). A common approach is to count only college graduates as skilled. For this case Per Krusell et al. (2000) estimate a substitution elasticity between skilled and unskilled labor of 1.67. However, when applied across countries, these parameters yield skill premia in poor countries that are up to ten times larger than in the United States. Obtaining reasonable skill premia requires a broader definition of skill and a higher substitution elasticity. In what follows I define workers with at least completed secondary education as skilled. The substitution elasticity is set to 5, so that the model matches the mean skill premium in the low-income sample. Experimentation with alternative skill definitions or substitution elasticities either reduces the explanatory power of the model or results in unreasonable skill premia.¹⁰

The implications of the two skill model for source country earnings are shown in Figure 4.¹¹ Comparing the findings with those of Figure 1 for the one skill model reveals that imperfect substitutability of skills improves the model's ability to account for large cross-country income differences. However, the gaps between source country earnings in the data and the model predictions, shown in Figure 5, remain large. In the full sample, physical and human capital account for a reduction in relative earnings to 0.58, leaving an unexplained ratio of

⁹ I am grateful to Michele Boldrin for suggesting this extension.

¹⁰ The Technical Appendix (available upon request) shows that the qualitative conclusions reported here carry over to the case where skill types are not observed by the econometrician.

¹¹ The Technical Appendix (available upon request) reports the underlying data.

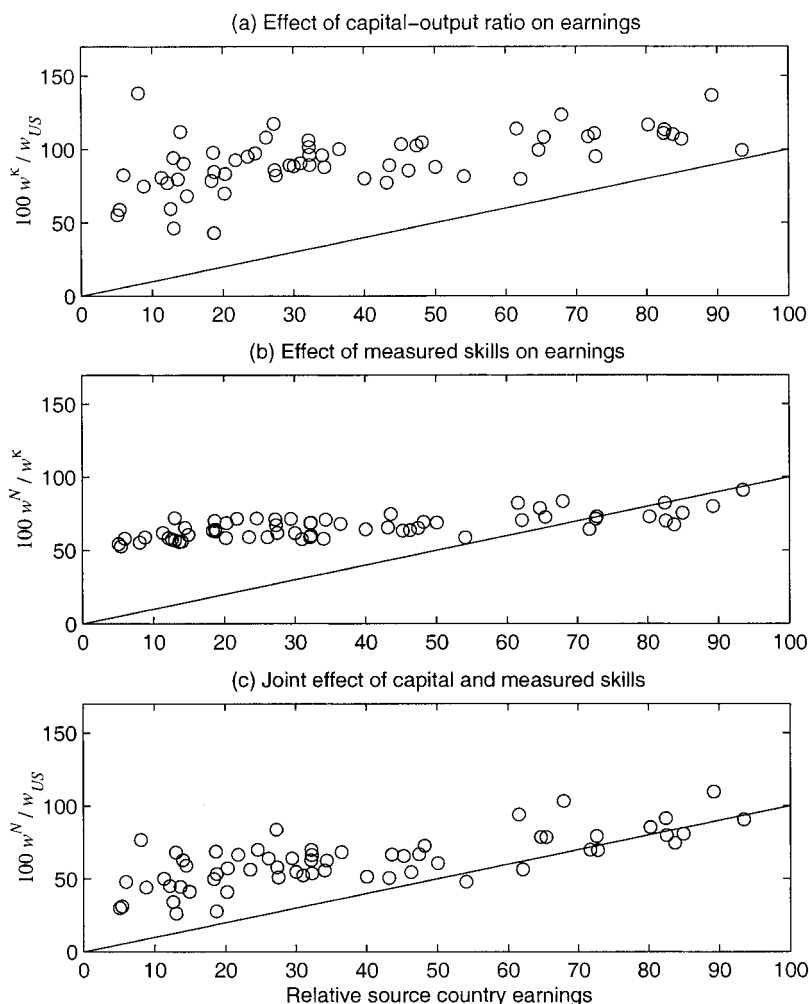


FIGURE 4. DECOMPOSITION OF CROSS-COUNTRY EARNINGS DIFFERENCES: TWO SKILL MODEL

1.9. As in the one skill case, the unexplained gaps are larger for poorer countries. In the low-income sample, predicted earnings are 2.6 times larger than measured earnings, and for the poorest five countries, the factor of overprediction is 5.6.

The reason for the limited improvement is the high substitution elasticity of skilled and unskilled labor. However, the skill premia predicted for poor countries are, on average, close to those calculated from source country Mincer regressions. This indicates that reducing the substitution elasticity substantially below 5 would lead to unreasonable skill premia. To

illustrate, reducing the substitution elasticity to 3 raises skill premia roughly 50 percent above those observed in the data.

As in the one skill model, it is useful to ask whether stronger migrant self-selection increases the ability of human and physical capital to account for cross-country earnings gaps. As a proxy for unmeasured self-selection I again set the s_c factors equal the ratios of measured skills of immigrants relative to source country natives. Consistent with the findings for the one skill case, the implied ratios of predicted to measured earnings per worker remain large. For the low-income sample, output per worker is

FIGURE 4—Continued.

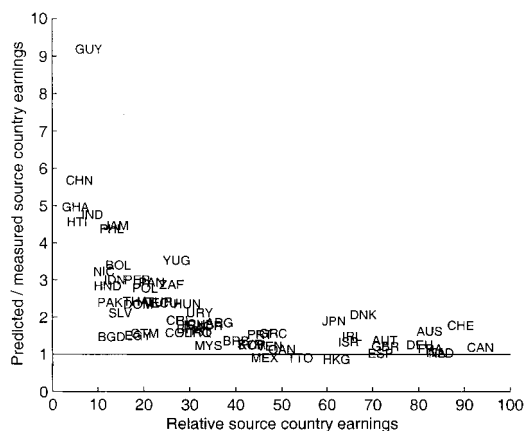
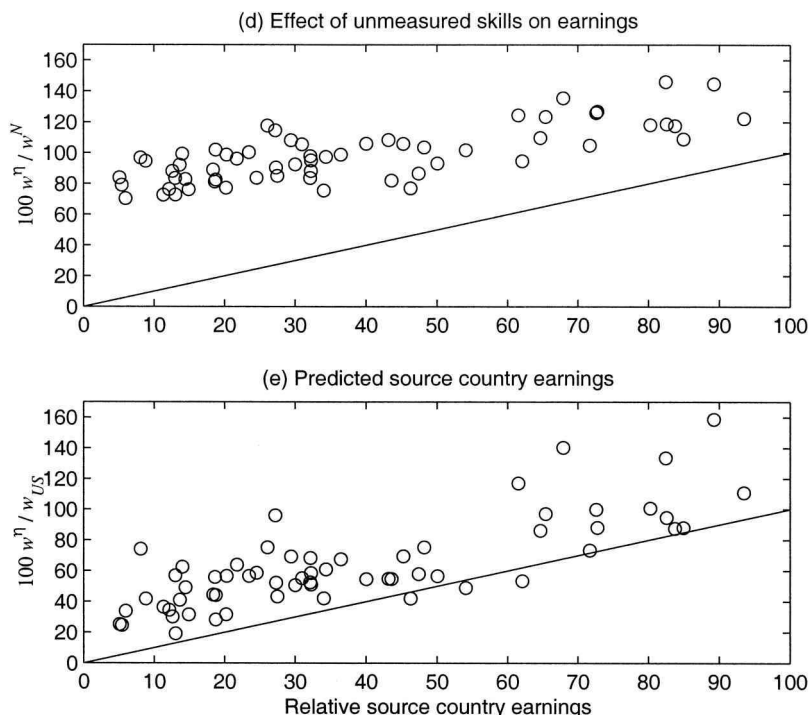


FIGURE 5. RATIO OF PREDICTED TO MEASURED SOURCE COUNTRY EARNINGS IN THE TWO SKILL MODEL

tory power of the model, large income gaps remain unaccounted for.

D. Comparison with Other Estimates

This subsection compares the decomposition of cross-country income gaps presented in this article with estimates reported in the literature.¹² My findings are directly comparable to those of Hall and Jones (1999). Except for the method of measuring human capital, their accounting framework is the same as the one described in Section I. As a result, their estimates of the contribution of physical capital to cross-country output differences are close to mine. Hall and Jones estimate human-capital stocks based on Mincer regressions that are common to all countries together with mean years of schooling taken from an earlier version

overpredicted on average by a factor of 1.7, while the corresponding factor for the poorest five countries is 3.6. I conclude that while imperfect skill substitution improves the explana-

¹² An interesting attempt at quantifying the role of human capital in an environment with skill-specific technologies is presented in Acemoglu and Fabrizio Zilibotti (2001).

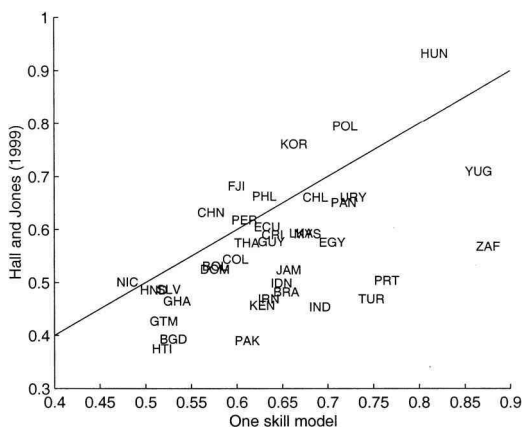


FIGURE 6. CONTRIBUTION OF HUMAN CAPITAL TO OUTPUT PER WORKER DIFFERENCES

Notes: The vertical axis shows source country output per worker relative to the United States implied by the human-capital stock estimates of Hall and Jones (1999). The horizontal axis shows the corresponding values predicted by the one skill model.

of Barro and Lee's data. Figure 6 plots their estimates of human capital per worker relative to the United States against those derived here for the one skill model. In spite of this very different estimation method, the two estimates are highly correlated (the correlation coefficient is 0.82). For countries in the low-income sample, human capital accounts for a reduction in output per worker relative to the United States of 44 percent according to Hall and Jones's estimates, compared with 36 percent based on the one skill model. It is easy to see why the two estimates are close. Hall and Jones's estimation framework *assumes* that the human-capital endowments of workers with identical schooling are the same in all countries. The approach pursued here *estimates* these human-capital endowments from immigrant earnings, but reaches a similar conclusion.

My findings are also consistent with those of Klenow and Rodríguez-Clare (1997a), who develop measures of country human-capital stocks based on a Mincerian earnings function. The contribution of human and physical capital to cross-country output differences is measured by regressing the logarithm of predicted output per worker on the logarithm of observed output per worker. In my notation, the regression equation is given by $\ln(w_c^\eta) = \beta_0 + \beta_1 \ln(w_c) + \varepsilon_c$,

where ε_c is a stochastic error term. One interpretation is that the fraction β_1 of the cross-country variance in log output is accounted for by physical and human capital. Klenow and Rodríguez-Clare find that β_1 is likely less than 0.5, with the exact figure depending on assumptions about the production and measurement of human capital. Replicating this regression in my full sample yields an estimate of $\beta_1 = 0.38$ (standard error 0.04) for the one skill model and of $\beta_1 = 0.45$ (standard error 0.05) for the two skill model. Consistent with the finding that the unexplained output gaps are larger for poorer countries, the low-income sample yields smaller estimates of β_1 (0.27 in the one skill model and 0.38 in the two skill model). The fact that my estimates are consistent with those of Hall and Jones (1999) and Klenow and Rodríguez-Clare (1997a) suggests that the implications for the sources of cross-country income gaps are robust against alternative methods of constructing country human-capital stocks.

IV. Conclusion

This paper offers new evidence on the sources of cross-country income differences. It exploits the idea that immigrant workers provide an opportunity to estimate the human-capital endowments of workers from a variety of source countries based on earnings attained in a common labor market. This approach captures both observed and unobserved skill differences without having to postulate a particular human-capital production function. Immigrant earnings data suggest that cross-country differences in unobserved skills are much smaller than cross-country income gaps. As a result, my estimates strongly reject the hypothesis that human and physical capital account for the bulk of cross-country income differences.

For a sample of low-income countries, human and physical capital account for a reduction in output per worker to one-half of the U.S. level, compared with one-fifth in the data. Allowing for skill complementarities and stronger immigrant self-selection still leaves an average income gap of 1.7 unexplained. For the poorest five countries in the sample, output per worker implied by human- and physical-capital differences is at least 3.6 times larger than in the data. This evidence is consistent with Prescott's

(1998) conclusion that accounting for cross-country income differentials requires a theory of total factor productivity.

APPENDIX A: CENSUS DATA

Census data are taken from the 1990 PUMS 5-percent State Sample data files. Individuals are excluded from the sample if they reside in group quarters, are younger than 20 years or older than 69 years, do not work at least 30 hours per week and 40 weeks per year, or are self-employed. In addition, observations are deleted if weekly hours exceed 120 or annual earnings are less than \$500. Such cases are exceedingly rare and likely due to measurement error. Immigrants are also dropped if they arrived in the United States before age 20. This excludes immigrants who attained most of their education in the United States. Increasing the lowest arrival age to 24 makes little difference. The resulting sample contains 2.2 million natives and 178,000 immigrants. When averaging over male and female workers, fixed weights of 0.6 and 0.4 are used. This avoids counting differences in gender ratios as differences in human capital. Observations are sorted into the following classes:

- Years of schooling: 0–4, 5–8, 9–11, 12, 13–14, 15+.
- Age: 20–24, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, 64–69.
- Sex: Male or female.
- Birthplace: According to Penn World Table country codes.

Annual work hours are calculated from “weeks worked last year” and “hours usually worked per week.” Labor earnings are calculated from “wage and salary income,” which does not include self-employment income. The variable “educational attainment” gives years of schooling in an intervallic format. Each person is assigned its interval midpoint as years of schooling.

APPENDIX B: SOURCE COUNTRY DATA

Data on source country aggregates are generally taken from the Penn World Table Mark 5.6. Capital-output ratios are taken from McGrattan and Schmitz (1998), but results are

very similar if Penn World Table data are used instead. For four countries capital stock data are not available (Belize, Dominica, Hungary, and Poland). In these cases I impute a capital-output ratio by regressing $\ln(\text{capital stock per worker})$ on $\ln(\text{real GDP per worker})$.

For the two skill model it is necessary to calculate source country earnings by skill type. Mincer regressions are used to calculate the relative earnings of skilled to unskilled workers in the source countries. Psacharopoulos (1994) provides sources for a large number of countries, which are updated in Bils and Klenow (2000). Only earnings regressions that do not control for additional variables which might be correlated with education/experience are used. Moreover, the underlying samples must be representative for a significant fraction of the source country workforce. Additional detail is provided in a Technical Appendix, which is available from the author.

Educational Attainment.—In order to calculate the contribution of measured skills to cross-country income differences, it is necessary to construct the joint distribution of age and educational attainment for each country. Data from three sources are used. Barro and Lee (2000) report the population fractions, π_c , in each of $c = 1, \dots, 7$ educational attainment classes. The U.S. Bureau of the Census International Data Base provides the population fraction, μ_a , in each of $a = 1, \dots, 9$ age classes. The objective is to construct the joint distribution, $\Pr(c, a)$, in such a way that the marginal distributions π_c and μ_a are respected.

The algorithm draws on OECD data, which provide conditional fractions $\Pr(j|a)$ for a subset of 39 countries, where $j = 1, \dots, 3$ indexes education classes. Following Barro and Lee (2000), I map the c classes into the j classes as follows. Class $j = 1$ captures persons with less than upper secondary education and is mapped into Barro-Lee classes $c = 1, \dots, 4$. Class $j = 2$ contains persons who completed upper secondary education and corresponds to $c = 5$. Finally, $j = 3$ refers to tertiary education and corresponds to $c = 6, 7$.

The conditional fractions $\Pr(j|a)$ are extended to the finer c classes according to $\Pr(c|a) = \Pr(j|a)\pi_c/\sum_{c \in J_j}\pi_c$, where J_j denotes the set of c classes that are mapped into

class j . This scales the marginal fractions π_c such that the $\Pr(j|a)$ are respected. Constructing the joint distribution according to $\Pr(c, a) = \Pr(c|a)\mu_a$ would respect the age marginals μ_a , but not the education marginals π_c . Therefore, a correction term $\Delta\pi_c = \pi_c - \sum_a \Pr(c, a)$ is added to each column of $\Pr(c, a)$, so that the resulting joint distribution respects both μ_a and

π_c while capturing the observation that younger persons have higher educational attainment contained in the OECD data. Countries not contained in the OECD data set are divided into three classes based on whether real GDP per worker is below or above one-third of the U.S. level. Their $\Pr(j|a)$ are replaced by the averages across countries in their income class.

[Table B1 follows.]

TABLE B1—SOURCE COUNTRY AND IMMIGRANT CHARACTERISTICS

Country	PWT No.	Relative RGDPW	K/Y	Immigrant Earnings		Years of Schooling			N
				Unadjusted	Adjusted	BL	Mincer	Immigrant	
Egypt	14	18.7	0.4	128.7	93.7	4.9	—	15.5	812
Ethiopia	15	2.1	0.5	80.2	73.8	—	—	13.8	303
Ghana	18	5.1	0.7	87.3	70.4	4.2	—	14.9	242
Kenya	22	5.1	1.6	126.4	99.0	3.8	—	15.6	124
Nigeria	34	5.7	1.8	81.4	67.1	—	—	15.8	694
South Africa	41	26.1	2.2	175.7	135.9	5.3	—	15.4	297
Barbados	52	39.9	1.5	95.6	95.5	8.2	—	11.7	314
Belize	53	30.5	1.9	80.2	84.6	—	—	11.4	173
Canada	54	93.5	2.4	150.2	125.8	10.6	—	13.7	3214
Costa Rica	55	27.3	1.8	80.9	86.4	5.5	6.4	11.7	274
Dominica	56	18.2	1.5	73.5	85.4	—	—	10.4	102
Dominican Republic	57	18.8	1.7	65.9	79.1	4.5	8.4	9.7	1575
El Salvador	58	14.9	1.1	57.0	74.7	3.8	7.0	8.7	3251
Guatemala	60	20.2	1.2	59.1	75.9	3.0	4.0	9.2	1615
Haiti	61	5.4	0.8	66.4	72.7	3.3	—	10.9	1704
Honduras	62	12.1	1.4	61.2	73.0	3.8	6.1	10.3	570
Jamaica	63	14.0	3.0	87.6	90.4	4.2	—	11.5	1890
Mexico	64	46.3	1.8	56.1	76.5	6.3	—	7.5	25799
Nicaragua	65	11.3	1.6	62.1	66.5	3.5	—	11.6	1069
Panama	66	21.8	2.1	101.4	90.6	7.2	8.6	13.3	463
Puerto Rico	67	70.9	2.0	77.8	85.3	—	—	10.8	4247
Trinidad and Tobago	71	54.1	1.6	94.9	91.9	6.7	—	12.2	655
Argentina	73	36.5	2.4	115.5	102.6	7.8	8.7	13.1	789
Bolivia	74	14.5	2.0	82.6	78.6	5.6	9.5	12.9	248
Brazil	75	30.0	1.9	92.4	94.1	3.8	5.0	12.8	620
Chile	76	32.2	2.2	101.1	90.7	7.2	8.2	13.2	509
Colombia	77	27.5	1.6	80.9	83.9	4.3	8.1	11.8	2069
Ecuador	78	24.6	2.3	74.3	82.2	6.4	9.7	10.9	1016
Guyana	79	8.1	4.6	88.4	88.7	5.4	—	11.9	814
Peru	81	18.6	2.3	80.2	77.3	6.6	10.2	12.7	1199
Uruguay	83	32.2	2.5	91.9	96.3	6.5	8.7	11.3	195
Venezuela	84	47.4	2.5	100.2	89.2	5.0	7.9	14.3	235
Bangladesh	86	13.0	0.4	89.8	78.8	3.2	—	14.3	248
China	88	6.0	1.6	88.4	77.3	6.8	—	12.3	4080
Hong Kong	89	62.1	1.5	111.0	98.3	9.2	—	13.9	690
India	90	8.8	1.3	131.8	97.5	5.0	—	15.6	5374
Indonesia	91	13.7	1.5	124.5	96.7	4.1	—	14.7	340
Iran	92	31.0	2.0	118.0	91.2	4.4	8.0	15.3	1557
Iraq	93	33.9	1.9	100.8	88.3	4.4	—	13.1	307
Israel	94	64.7	2.4	127.1	109.7	9.4	12.6	14.2	579
Japan	95	61.5	3.1	173.5	136.4	9.7	—	15.4	1908

TABLE B1—Continued.

Country	PWT No.	Relative RGDPW	K/Y	Immigrant Earnings		Years of Schooling			N
				Unadjusted	Adjusted	BL	Mincer	Immigrant	
Jordan	96	34.4	1.4	98.2	91.3	6.7	—	13.6	191
Korea, Republic of	97	43.6	1.9	95.1	77.6	10.5	8.0	14.2	396
Malaysia	100	34.1	2.2	106.1	93.5	6.7	—	14.7	188
Pakistan	105	12.6	0.8	98.1	81.9	3.5	—	14.6	938
Philippines	106	13.0	2.1	94.8	76.4	7.1	9.0	14.3	7737
Sri Lanka	110	15.6	0.9	131.7	100.0	5.7	—	15.3	155
Syria	111	43.2	1.4	118.1	106.2	5.9	—	13.5	266
Taiwan	112	50.1	1.9	132.9	99.4	8.6	—	15.9	1930
Thailand	113	18.4	1.5	101.6	83.0	5.8	—	14.2	486
Austria	116	72.6	3.0	164.0	126.3	9.3	9.7	14.3	251
Belgium	117	86.3	2.8	162.2	126.5	8.9	—	14.6	160
Czechoslovakia	120	21.0	3.1	128.2	100.5	—	—	13.9	477
Denmark	121	67.9	2.9	160.4	131.4	11.2	12.4	14.2	195
France	123	82.6	3.1	153.1	126.5	7.9	—	14.6	678
Germany, West	125	80.3	3.3	142.4	117.0	9.5	11.2	14.3	727
Greece	126	48.2	2.6	102.6	102.6	9.0	—	11.0	1092
Hungary	127	29.4	1.9	125.9	100.4	9.4	—	13.4	568
Ireland	129	65.4	2.8	127.4	119.3	8.5	11.6	12.9	1252
Italy	130	83.8	2.9	112.6	119.1	6.8	—	9.9	2790
Netherlands	133	85.0	2.8	140.8	110.2	9.0	—	14.3	508
Norway	134	79.5	3.1	166.5	131.0	11.2	11.8	14.3	165
Poland	135	20.3	1.7	98.0	92.3	9.9	11.1	12.4	2474
Portugal	136	45.2	2.6	87.2	109.4	4.7	—	7.4	1494
Romania	137	11.2	2.5	114.0	97.8	—	—	13.3	710
Spain	138	71.7	2.9	113.2	105.5	6.3	8.0	11.9	541
Sweden	139	77.2	2.7	165.6	129.2	9.7	—	15.1	257
Switzerland	140	89.2	3.5	169.7	131.4	10.6	11.0	15.0	319
Turkey	141	23.5	2.2	127.0	107.0	5.0	—	14.1	363
United Kingdom	142	72.8	2.2	165.1	130.5	8.8	11.8	14.6	4068
U.S.S.R.	143	41.6	3.7	118.9	93.0	—	—	14.1	1157
Yugoslavia	144	27.2	3.3	114.5	111.4	8.6	—	11.2	976
Australia	145	82.4	3.0	162.5	131.3	10.5	10.3	14.9	306
Fiji	146	32.1	2.1	73.3	81.4	7.9	—	11.1	144
New Zealand	147	69.1	2.9	148.9	126.2	11.6	—	14.7	140
Mean		38.1	2.1	109.9	97.6	6.8	9.1	13.1	1417

Notes: PWT No. is the Penn World Table 5.6 country number. Relative RGDPW denotes real GDP per worker relative to the United States in 1990. Data for 1990 are not available for five countries. In four of these cases, 1989 RGDPW is used instead. For Iraq, 1987 RGDPW is reported. K/Y is the capital-output ratio taken from McGrattan and Schmitz (1998). Two definitions of relative immigrant earnings are shown. Unadjusted relative earnings denote mean earnings per immigrant divided by mean earnings per native-born worker. Adjusted relative earnings are defined as the ratio of immigrant earnings per worker relative to native-born workers with identical age, education, and sex. Average years of schooling are taken from Barro and Lee (2000; column BL), from a sample of source country Mincer regressions (column Mincer; not available for all countries), and from immigrant data (Immigrant). The figures shown in column BL are calculated by assigning respectively the values 0, 2.5, 6.5, 10, 12, 13, and 17 years of schooling to the seven education categories reported in Barro and Lee (2000). N denotes the number of immigrants observed in the Census sample.

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