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Global Wage Inequality and the International Flow of Migrants

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Abstract

A framework for understanding the determinants in the variation in the pricing of skills across countries and the model underlying the Mincer specification of wages that is used widely to estimate the relationship between schooling and wages are described. A method for identifying skill prices and for testing the Mincer model, using wages and the human capital attributes of workers located around the world, is discussed. A global wage equation that nests the Mincer specification is estimated that provides skill price estimates for 140 countries. The estimates reject the Mincer model. The skill price estimates indicate that variation in skill prices dominates the cross-country variation in schooling levels or rates of return to schooling in accounting for the global inequality in the earnings of workers worldwide. Variation in skill prices and GDP across countries has opposite and significant effects on the number and quality of migrants to the United States.

Although it is well known that global income inequality is high, the extent to which wage rates differ across persons with the same skill but located in different countries is not well understood. Because of data limitations, in practice measures of income inequality across countries are usually based on the per capita gross domestic product (GDP). Until recently, for many countries no data providing comparable cross-country information on worker earnings and their characteristics were available. Yet information on cross-country wage inequality for workers of a given skill is useful for three reasons. First, it helps to identify the sources of inequality. Average earnings differ across workers located around the world for two reasons: workers differ in average skill levels and the rewards to skill–skill prices–differ across countries. If the difference in average skill levels is the major reason for global wage or earnings inequality, a focus on upgrading skills might be a suitable remedy for ameliorating global income inequality. If, however, wage inequality is mainly due to the different pricing of skills across countries, the remedies might be quite different.

Labor force surveys providing wages by occupation such as that by Freeman and Oostendorp (2000) indicate that in 1995 a construction carpenter's wage in India was US$42 a month.[1] A worker in the same occupation in Mexico earned $125 a month, while his counterparts in Korea and the United States earned $1,113 and $2,299 a month, respectively. These are enormous differences in earnings. But it is not possible to know from these figures how much of the observed wage differentials are due to differences in skill and how much to the different prices of skill across countries. Surely the average construction carpenter in India has a lower level of schooling than, for example, a carpenter in the United States, and that may account for some part of the difference.[2]

A second reason that information on rewards to skill across countries is useful is that it helps analysts understand the magnitudes and patterns of the global migration of labor. Basic models of migration depict the choice of location of a worker with a given skill. Thus the relevant set of variables includes the wages a worker of a given skill would earn at different locations. Country-specific skill prices are central to understanding the individual gains from migration, and thus the quantity and the selectivity of international migration—that is, which

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[1] All dollar amounts are U.S. dollars unless otherwise indicated.

[2] These wages are not corrected for purchasing power parity.

workers of what skill levels move to which country. Whether a construction carpenter in India would want to move to, say, Korea depends on how much of the observed wage gap is a result of Koreans in the same occupation having more skill than their counterparts in India. If most of the difference stems just from a gap in skills, then for a typical low-skill Indian carpenter the incentives to migrate are low.

Yet as in the literature on global inequality, studies of the determinants of international migration do not use any cross-country wage data. Instead, they almost always rely on differences in country-specific levels of per capita GDP to explain, along with some other nonwage aggregate variables, cross-border migration. Per capita GDP is related to skill price, as discussed later in this chapter, but per capita GDP also differs across countries because of differences in the average domestic levels of human capital and because of differences in the proportion of the population that is employed because of differences, for example, in the labor force participation of women and in the proportion of the population of labor force age (dependency ratio). Variations in these cross-country factors for given skill prices do not have a strong direct bearing on individual migration decisions. Income also affects the ability to finance migration, so per capita income will imperfectly pick up both skill price and income effects, which may go in opposite directions.

A third reason it is important to have information on how skills are priced across countries is that inequality in skill prices indicates how well or how badly skill, or human capital, is allocated around the world. Large differences in skill prices imply there is a large global misallocation of labor (and perhaps other factors of production such as capital), and thus that total world income is substantially lower than it could be if labor were reallocated across countries. From a global efficiency point of view, if inequality in country-specific skill prices is high, then one might view statistics on the "brain drain"–the proportion of highly skilled persons born in "poor" countries who reside in "rich" countries–as a measure of the contribution of international migration to the alleviation of world income inequality. This would be particularly so if poor countries reward skills meagerly and rich countries reward skill with a high price. Thus from the perspective of global efficiency the statistic that, for example, 43 percent of tertiary-educated Ghanaians live in member countries of the Organisation for Economic Co-

operation and Development (OECD), would be seen not as alarmingly high but as alarmingly low, if the skill price in Ghana is still substantially lower than the average OECD skill price.[3]

In this chapter, I first set out a framework for understanding the determinants in the variation in the pricing of skills across countries and describe the model underlying the Mincer specification of wages that is used widely to estimate the relationship between schooling and wages. I then show how, using wages and the human capital attributes of workers located around the world, skill prices can be identified and the Mincer model can be tested. After describing the data sets that can be used to obtain estimates of skill prices, I estimate a global wage equation that is more general than the Mincer specification and provides estimates of skill prices for 140 countries. The estimates reject the Mincer model, implying that factors affecting the supply of schooling as well as schooling productivity need to be taken into account to understand the pricing of skill across countries.

The skill price estimates indicate that, as a first-order approximation, variation in skill prices substantially dominates the cross-country variation in schooling levels or rates of return to schooling in accounting for the global inequality in the earnings of workers around the world. I also show that the variation in skill prices and GDP across countries has opposite and significant effects on the number and quality of migrants to the United States, including employment migrants with permanent visas and persons with student visas. Skill prices also matter for which students return to their home countries. The migration findings indicate that among countries with the same GDP, low–skill price countries experience larger per capita outflows of total human capital–numbers of migrants multiplied by their average years of schooling–despite outmigration being more positively selective in higher–skill price countries. By contrast, countries with lower skill prices have, on net, larger populations of higher-educated persons trained outside their country, despite experiencing lower return rates of foreign students, which offsets the permanent outflow of "brains."

1. A Framework for Understanding the Proximate Determinants of Wages and Skill Prices across Countries

To understand the proximate determinants of the rewards to skills across countries, it is

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[3] This statistic is obtained from the database on stocks of educated foreign-born around the world assembled by Beine, Docquier, and Rapoport (2001 and 2006).

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useful to consider three functions. First, the aggregate production technology relates the total output of a country Y_j to the vector of aggregate skills of its labor force $\boldsymbol{X_j}$ and its capital stock and natural resources K_j to yield

$$Y_j = Y(\boldsymbol{X_j}, K_j, \boldsymbol{\Phi_j}) , \tag{9.1}$$

where $\boldsymbol{\Phi_j}$ are technology parameters, which may be country-specific. For purposes of exposition, I assume initially that there is one skill type (different types of skills are considered later in this chapter). The country-specific skill price ω_j is just the marginal value product of skill $\partial Y_j/\partial X_j$. The wage W_{ij} of a worker i in country j is then given by

$$W_{ij} = \omega_j x_{ij} , \tag{9.2}$$

where x_{ij} is the number of skill units of worker i in country j. Thus wage inequality within a country is due solely to differences in skills across workers. Differences in wages across workers in different countries stem from both differences in their skill levels and in the country-specific prices of skill. Skills are usually not measured directly or provided in most data sets. However, inputs to the production of skill, such as years of formal schooling S_{ij}, are measured. The skill production function for a country is

$$x_{ij} = S_j(S_{ij}, \boldsymbol{H_{ij}}, \boldsymbol{I_{ij}}) , \tag{9.3}$$

where $\boldsymbol{H_{ij}}$ is a vector of school inputs other than years of schooling attended, and $\boldsymbol{I_{ij}}$ is a vector of other human capital inputs, including training and work experience. A large literature has attempted to characterize (estimate) the skill production function, examining the effects of school inputs such as class size, textbooks, and teacher attributes. Substituting (9.3) into (9.2), one would get a wage function relating a worker's wage to his or her skill inputs and the skill price. Cross-country wage inequality would then be proximately determined by differences in cross-country skill prices, the technology of skill production, and differences in years of schooling, schooling inputs, and work experience across individuals.

The most popular wage function used in empirical studies of wage determination is the Mincer wage function, which is

$$log\ W = w_j + \beta_j S_{ij} + \boldsymbol{I}_{ij}\gamma_j , \tag{9.4}$$

where w_j is an intercept, perhaps specific to country j, and β_j is the rate of return to schooling in each country. If this is the correct wage function, then to completely characterize global wage inequality one would need to know just three parameters: the intercepts and the country-specific rates of return to schooling β_j and work experience γ_j. Conspicuously absent from the Mincer

specification are school quality variables—that is, the inputs to schooling. Is this just a mis-specification? And what is the relationship between variation in skill prices across countries and the parameters of the Mincer wage function? For example, if the rate of return to schooling is higher in country A compared with country B, does that mean that skill is more rewarded in country A?

The original specification of the wage function derived by Jacob Mincer (1958) was based on the assumption that individuals discount future income and that there are no nonmarket barriers to schooling—that is, the amounts of schooling chosen by individual workers are not constrained by school availability or by access to finance (credit constraints). In particular, lifetime income y for an infinitely lived agent i who spends S_{ij} years in school is by definition

$$y(S_{ij}) = \int_S W(S_{ij}) e^{-r(j)t} dt \,, \tag{9.5}$$

where $r(j)$ is the subjective discount rate in j. Relationship (9.5) embodies the assumption that earnings are zero when schooling is being acquired—the only cost to schooling is thus the foregone wage. With no barriers to schooling, lifetime wages must be equal for all workers no matter what their schooling level—that is, for example, if college graduates had higher lifetime earnings, then more persons would go to college, driving down the wages of college graduates until lifetime incomes are the same. This arbitrage assumption means that

$$y(S'_j) = y(S''_j), \tag{9.6}$$

for any S, S', including $S = 0$. Moreover, because agents would compare the returns to schooling with the returns to capital, the discount rate would be equated to the cost of capital. Thus in the Mincer earnings function (9.4), the parameters have a structural interpretation in terms of the model: the intercept is the wage a worker who had no schooling would earn in country j; $w_j = W(0)_j$, the base wage for country j; and the rate of return to schooling is actually the rate of return to capital in the economy, $\beta_j = r_j$.

Thus in the Mincer model the rate of return to schooling says nothing about the scarcity of skill, just the scarcity of capital! And variables reflecting the quality of schooling do not belong in the specification, even if inputs to schools vary a lot across countries or even individuals. The reason is that the Mincer wage equation is an equilibrium condition that always holds no matter what happens to school quality or in labor markets, so long as the return to capital or the base wage is not affected. Consider, for example, a country in which the government raises the quality of its universities. This higher quality, by definition, increases the wages of university graduates compared with the wages earned by them in the past, but the

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higher wages of graduates then attract more students to the universities (remember that there are no entry barriers to schooling in the model), and thus eventually the wages of the university graduates are driven down, until the return to schooling for everyone again equals the discount rate and the return to capital.

If the actual world conformed to the Mincer model, analysts would need to know the country-specific heterogeneity in base wages, returns to capital, and schooling to fully account for world wage inequality. Existing data sets provide information on average years of schooling across countries (e.g., Barro and Lee 2001). The average years of schooling for the population aged 15 and over vary from about 3 to 14 years across countries. Estimates of returns to schooling (capital) from Mincer wage regressions estimated from labor force data from 52 countries, as reported in Bils and Klenow (2000), suggest a range from 0.024 to 0.28. Interestingly, Bils and Klenow do not report the intercepts (base wages) from those regressions. However, it would be a straightforward exercise to back out the intercepts (base wages) given the information on average wages, average schooling levels, and the estimated β_j's for the 52 countries.

That said, this imputation exercise is not worth carrying out for three reasons. First, it is not at all clear that the data used for each of the 52 countries are comparable. They were obtained by different researchers, who may have dealt differently with the thorny problem of attributing wages to, for example, the self-employed (a large part of low-income country labor forces), or who are using data sets that differentially exclude certain workers such as part-time or informal. Second, this sample of 52 countries represents less than one-third of countries. Third, and perhaps most important, the Mincer model may be inappropriate to characterize the determinants of wages around the world.

Putting aside the issue of data for the moment, two alternative approaches to the highly restrictive Mincer model exploit the relationships given in equations (9.1), (9.2), and (9.3). The first approach uses aggregate data on outputs Y, the labor force L, and schooling S across countries. For example, assume that the aggregate production function (9.1) is Cobb-Douglas, so that

$$Y_j = A_j L_j^{a} \prod K_{nj}^{\gamma}, \tag{9.7}$$

where A_j characterizes the technology level (TFP) of the country, K_{nj} is the vector of capital stock and natural resources, and $L_j = N_j (s(x_{ij}))$, where N_j is the total number of workers in country j and the s function relates the average skills of the work force in j to observables such as

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schooling

years and school inputs—the inverse of (9.3). The skill price for country j, the marginal product of a unit of skill, is then

$$\omega_j = \alpha Y_j / N_j \ (s(x_{ij})). \tag{9.8}$$

Taking logs of (9.8) yields

$$log(\omega_j) = log \ \alpha + Ln(Y_j / N_j) - Ln(s(x_{ij})) \ . \tag{9.9}$$

Thus assuming the popular Cobb-Douglas functional form, all that is needed to compute skill prices across countries are data on output *per worker*, estimates of the coefficients α (labor share) from aggregate production function estimates, and information on schooling, given assumptions about the *s* function.

Equation (9.9) is also useful in showing how skill prices are related to per capita GDP, which is typically used to characterize both global income inequality and the determinants of migration. As can be seen, the skill price of a country is positively associated with its GDP per worker, which is only imperfectly correlated with its GDP per capita. More important, the skill price, given GDP per worker, is negatively associated with the average level of human capital. Thus high-GDP countries with unusually high levels of schooling will have a relatively low skill price. Conversely, poor countries that have unusually low levels of schooling will have high returns to skill. Differences in per capita GDP across countries are therefore not very informative about the efficiency of the distribution of skilled workers around the globe, nor are they good measures, used alone, of the gains from international migration for workers of different skill levels.

A second approach to estimating global, country-specific skill prices uses individual worker data from different countries on wages and human capital inputs, including schooling years and schooling quality variables. For example, assume that the skill production function has the form

$$x_{ij} = \mu_{ij} exp(\beta_j S_{ij} + I_{ijk}\gamma_k + H_{ijn}\delta_n), \tag{9.10}$$

where μ_{ij} is an unobserved component of skill for a worker i in country j. Note that the coefficient β_j is not the return to schooling (capital) as in the Mincer model, but expresses how a unit increase in schooling years augments skill. Replacing (9.10) in (9.2) and taking logs yields

$$log(W_{ijz}) = log \ \omega_j + \beta_j S_{ij} + I_{ijk}\gamma_{jk} + H_{ijn} \ \delta_n + log \ \mu_{ij} \ . \tag{9.11}$$

The estimated country-specific intercepts from wage relationship (9.11) estimated across individual workers from different countries yield directly the (log) skill prices, one for each

country represented. With multiple workers for each country, it is also possible to allow the coefficients on schooling and the other human capital variables to vary across countries.

Note that in this one skill case, the wage equation (9.11) looks identical to the Mincer wage equation (9.4) except that inputs to schooling appear in the specification. Of course, if the skill production function had a different functional form, the specification would look very different. With the specific functional form for the skill production function chosen in (9.10), the Mincer model is then nicely nested within the specification (9.11). If the Mincer model is correct, the coefficient vector δ associated with the vector of school quality inputs H_{ijn} should be zero (school quality does not matter in the Mincer model). Using appropriate comparable data on wages of workers around the world one can thus also test the Mincer model.[4]

It is also possible to obtain estimates of the relationships between skill prices and aggregate country variables and test the Cobb-Douglas functional form of the aggregate production function. Substituting (9.9), the skill price relationship with aggregate income, into (9,11), yields

$$log(W_{ijz}) = log\ \alpha + Ln(Y_j/N_j) - Ln(s(x_{ij})) + \beta_j S_{ij} + I_{ijk}\gamma_k + H_{ijn}\delta_n + log\ \mu_{ij.}\ (9.12)$$

This hybrid equation contains both individual worker variables, characterizing the worker's own schooling years and school quality, and country-level variables, characterizing output and the quality of the country's aggregate work force. If the Cobb-Douglas functional form is true, the coefficient on per worker GDP should be equal to one in this global wage regression. More important, estimates of equation (9.12), obtained from a subsample of countries for which there is both individual wage and human capital information as well as aggregate income and labor force variables, can be used to predict skill prices for countries in which there are no individual worker wages but only the aggregates, which are more generally available.

Up to this point, I have assumed that there is only one type of skill. In the Mincer model it does not matter, again, how many different types of skill there are; the equilibrium relationship between years of schooling and wages characterized by the Mincer wage equation remains the same. For any integrated domestic economy, as assumed in the model, there is only one rate of return, that to capital. In the more agnostic approach in which markets can be imperfect, one can easily incorporate multiple skill types, but for empirical applications it is necessary to take a stand on how many skill types there are and which laborers fit into which category of skill. For

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[4] There are other tests: the returns to capital should equal the Mincer schooling return and the Mincer schooling return should be the same for every schooling level.

example, with suitable data it is possible to distinguish skill prices for, say, those workers with less than a high school education and those with at least some college. Then the parameters of equations (9.11) and (9.12) would have to be estimated for each of the two groups.[5]

2. Global Wage Data Sets

To quantify the global inequality in wages and to account for how much of world wage inequality is due to variations across countries in skill prices and how much to differences in human capital, data are needed that provide comparable wage and human capital information for representative workers for most countries—that is, a global wage data set that is comparable, comprehensive, and representative in countries and workers. Only three data sets, all of which have become available in recent years, can be used to obtain estimates of world skill prices and their determinants and to carry out tests of the Mincer model. They are the New Immigrant Survey Pilot, Occupational Wages Around the World, and the New Immigrant Survey.

The New Immigrant Survey Pilot (NISP) is a random sample of new permanent resident aliens in the United States who obtained the permanent visa (green card) in 1996 (Jasso et al. 2000). The relevance of this sample for gauging global inequality in wages is that the survey obtained information on the earnings of these new immigrants in their last jobs in their home countries before coming to the United States and on their complete employment histories. Thus information on wages worldwide is taken from a common questionnaire, which provides information as well on workers' schooling, including the location of schooling, and work experience. The disadvantage of the data set is that it is a small sample—it consists of only 332 workers who worked prior to coming to the United States (the total number of respondents is 800), and these workers represent only 54 countries. However, the subsample of countries with wage data on migrants and aggregate information on incomes and the labor force can be used to estimate hybrid equation (9.11), enabling predictions of skill prices for those countries on which information on per worker GDP and aggregate schooling measures is available. This procedure was carried out in Jasso and Rosenzweig (2009), and the predicted skill prices for 125 countries were used to examine the determinants of immigration in both Australia and the United States. The other drawback of this sample is that it is selective, including only workers who were able to

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[5] This discussion ignores how heterogeneity in unobservable skills might affect schooling choices, which has implications for how the relevant parameters are estimated.

emigrate to the United States.

The data set Occupational Wages Around the World (OWW) is based on International Labor Organization (ILO) labor force surveys, put together and made more comparable by Freeman and Oostendorp (2000). Many years are covered, and there are a large number of observations in any given year—for example, 4,942 observations in 1995. Each survey is meant to represent the workers in each country. The main shortcoming of this database is that the observations are average wages in an occupation. There are no other variables characterizing human capital—that is, there is no information on age, work experience, or schooling. The number of countries represented in any given year is also small; the maximum number is 67. However, there is an incomplete overlap in country coverage across years, so that one can, combining years, achieve a larger set of countries. Again, using the hybrid equation relating aggregate country variables to wage data it is possible to estimate skill prices for many more countries, but it is necessary to assume that the one occupational variable captures all of a worker's human capital attributes.

The New Immigrant Survey (NIS) baseline data set is a larger and more comprehensive version of the NISP. It contains information on a probability sample of new immigrants to the United States in 2003. Home country wages, adjusted for purchasing power parity (PPP) and inflation, for over 4,000 workers representing 140 countries are contained in these data, along with comprehensive migration and schooling histories. Thus it is possible to use the NIS data to estimate skill prices, without any information on aggregate country variables, for as many as 140 countries.

Table 9.1 provides descriptive statistics for the three data sets. The average annualized earnings of the sampled immigrants is predictably higher than the earnings of those respondents represented in the OWW data set, given that immigrants to the United States have higher schooling levels than the average person in the world—in the NISP and NIS samples average years of schooling are 14.4 and 13.8, respectively. These figures can be compared with the population-weighted world average, based on the Barro-Lee data (Barro and Lee 2001) of 6.3 years. That immigrants are positively selected for schooling is an implication of most standard migration models (see later discussion), because the United States has a higher skill price than most countries of the world (Jasso and Rosenzweig 2009). When estimating country-specific skill prices from these data, as noted, schooling and other human capital variables are controlled.

3. Estimates of Worldwide Skill Prices and Tests of the Mincer Model

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Using the three global wage data sets, it is possible to estimate country-specific skill prices. In this section I report results from estimating skill prices using the NIS data. Country-specific skill prices were obtained based on a specification of the log wage equation (9.11) in which each country is allowed to have a unique intercept (the skill price) and a unique coefficient on the individual schooling (β_j) and labor force experience variables (the γ_{jk}). Working within the constraints of missing variables, I obtain 139 estimated skill prices. The estimates indicate that, unsurprisingly, I can soundly reject the hypothesis that skill prices are the same across countries, but I cannot reject the hypothesis that the schooling and work experience coefficients are identical across countries. Bils and Klenow (2000) do not carry out a statistical test of whether the schooling coefficients estimated for each of the 52 countries were not statistically significantly different, so that it is not clear whether the global variance in schooling returns is essentially zero or my estimates of schooling returns by country lack precision.

The NIS data can also be used to test whether the Mincer model is the appropriate model for specifying and interpreting the relationship between wages and schooling. To carry out the test, I allow the country-specific schooling coefficient β_j to vary with measures of school quality in each country. Eight measures are used: average class sizes, average teacher salaries, and pupil/teacher ratios in primary and secondary schools and the number of ranked universities and the average rank of the ranked universities based on the *Times Higher Education* survey. As noted, in the Mincer equilibrium model school quality should be unrelated to the returns to schooling, which is anchored by the return to capital. Table 9.2 reports estimates of the log wage equation. In the first column, a bare specification is used in which the coefficient on schooling is assumed to be the same across countries and no school quality variables are included, but intercepts differ by country. Interestingly, in this Mincer specification the global coefficient on schooling of 0.095 is almost identical to the average of the 52 country schooling returns in the Bils and Klenow collection of estimates—0.096. However, based on the test statistic reported in the second column of the table, I strongly reject the hypothesis that the schooling coefficients do not vary by schooling quality. The Mincer model, assuming perfectly functioning labor, credit, and capital markets, is thus rejected.

Rejection of the Mincer model means that the country-specific intercepts can be interpreted as skill prices and that it is necessary to account for schooling quality variables in estimating the determinants of wages. However, by estimating one skill price per country I am

assuming there is only one type of skill. To see whether ignoring skill type heterogeneity will seriously affect inferences about either world inequality or incentives for migration, I reestimated wage equation (9.11) separately for two groups of workers, those with 12 years of education or less and those with 16 years of education or more—yielding two sets of country-specific skill prices. Figure 9.1 shows the correlation between the college graduate skill prices and the skill prices obtained assuming one skill. As can be seen, the two series co-move strongly; the correlation is over 0.74. Given this high correlation, it is not possible to assess the contribution of variations in the pricing of skills across countries by skill type. As will become clear, however, cross-country differences in skill prices in the one skill price framework account for a large component of the variance in earnings across countries as well as the quantity and human capital intensity of cross-border labor flows.

4. Proximate Determinants of Global Earnings Inequality

It is useful to compare the cross-country variation in estimated skill prices from the NIS with the global variation in average years of schooling from Barro and Lee (2001), the schooling returns from the 52-country table in Bils and Klenow (2000), and the GDP per adult equivalent in order to understand the proximate determinants of world inequality in incomes.[6] Because differences in GDP across countries reflect differences in schooling levels and the rewards to skills as well as the variability in labor force participation, it is expected that the global variation in GDP will exceed that of the other variables, unless there are strong negative covariances across human capital levels, skill prices, and returns.[7]

Table 9.3 reports three inequality statistics for each variable: the coefficient of variation (CV), the span (ratio of highest to lowest value), and the ratio of highest to lowest value in the interquartile range (IR). The three statistics generally show the same patterns across the four global variables: GDP per adult equivalent and country-specific skill prices exhibit the most global variation, and schooling levels and returns the least. Indeed, the coefficient of variation of schooling is less than 60 percent of that for GDP, whereas the CV for skill prices is over 85 percent of the CV for GDP. Thus variability in schooling levels across countries is 44 percent of

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[6] Nine outliers were removed from the set of skill price estimates. The formula was to remove the topmost and bottommost values obtained from countries with only one person represented in the data. Thus my estimate of the global variation in skill prices is conservative.

[7] Both the schooling level and the schooling return variables are positively correlated with skill prices.

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the variability in country-specific skill prices. The span statistic, in which the variation in skill prices exceeds the variation in incomes across countries, suggests that despite trimming there may be outliers in the set of skill price estimates, which will in part contaminate the CV comparisons. The IR measure is insensitive to outliers in any of the variables. However, the patterns are similar for this inequality measure—the IR statistic for average schooling is only 44 percent of the IR of GDP, while the IR for skill prices is 73 percent of the IR of GDP. For this statistic, then, the cross-country variability in skill prices is 66 percent higher than the intercountry variability in schooling attainment.

Based on equation (9.11), the set of estimated worldwide skill prices can be used to compute the hourly wage of any worker of given schooling for any rate of return (β). Thus, for example, the earnings of high school or college graduates for 140 countries could be constructed. To illustrate the importance of skill price variability in world wage inequality relative to both variability in schooling levels and schooling returns (the coefficient on schooling), I use the skill price estimates to predict earnings for persons with both 12 and 16 years of education for a given schooling return, using equation (9.11), for a subset of countries. I then alter the schooling coefficient differentially across countries to assess how such a change would affect cross-country earnings gaps by schooling level. For this comparison, I select five countries with low and intermediate levels of skill prices: Nigeria, India, Indonesia, Mexico, and Korea. Figure 9.2 reports the predicted annualized earnings for high school and college graduates for each of these countries based on their estimated skill prices and an assumed schooling return of 0.07.

Four features of figure 9.2 are notable. First, earnings differences across the countries, for either schooling level, are enormous. For example, a Korean high school graduate earns 10 times more than a high school graduate in India; a college graduate in Mexico earns almost three times more than a college graduate in Indonesia, and so on. The cross-country misallocation in skill is evidently very high. Second, a pattern evident in figure 9.2 is that differences in earnings across countries within each schooling level dominate differences in earnings within countries across schooling levels. Providing a Nigerian high school graduate with a college education (with a 7 percent return), for example, raises his or her earnings by $200 a year. If that high school graduate migrates to Indonesia or Mexico, his or her earnings rise by $1,200 or $5,400 a year. Put another way, if everyone in the world obtained a college degree but stayed in place, even ignoring standard within-country general equilibrium effects that would depress the return to schooling, world wage inequality would not be substantially altered. The gaps in wages between

persons in poor (low–skill price) and rich (high–skill price) countries would not be affected significantly by improvements in schooling attainment in poor countries, unless such improvements affected skill prices positively.

A third feature of figure 9.2 is that the higher the skill price the larger are the absolute gains from increasing schooling. In India, for example, the annual gain in earnings from obtaining a college degree over a high school diploma is just $190. The same additional four years of schooling yields a gain of $1,600 a year in Korea and $500 a year in Indonesia, but only $120 a year in Nigeria. Yet the rate of return to schooling is the same in all four countries. These cases illustrate the point that rates of return to schooling provide no information on differences in the productivity or value of schooling across countries. It is necessary to know how skills are priced in each country—skill prices.

Finally, figure 9.2 shows that the absolute differences in earnings across the countries are always higher for the college graduates compared with the high school graduates. The gap between what a high school graduate earns in Korea and Indonesia is $3,700 a year; the cross-country earnings gap for the same two countries for a college graduate, however, is $4,850 a year. Similarly, a high school graduate working in Mexico earns $2,900 more a year than one working in Indonesia; a college graduate would earn $3,800 more. Put another way, the absolute gains from migration are higher for the more educated. As I discuss and test more formally shortly, as long as schooling is not strongly positively correlated with migration costs, international migration will tend to be positively selective—that is, the more educated in a population are more likely to emigrate to a country with a higher skill price.

The patterns of earnings by country and schooling level depicted in figure 9.2 were constructed based on the assumption that the return to schooling was identical across countries. How is intercountry inequality, and the gains from crossing borders by schooling level, affected if heterogeneity in schooling returns is increased, leaving skill price differences the same? Figure 9.3 reports the results of this counterfactual for two countries, Bangladesh and Korea, again based on their estimated skill prices. However, in this case earnings are computed for the two schooling groups within each country for two rates of return to schooling, 0.07 (as before) and 0.10. For both rates of return the patterns in figure 9.2 are apparent in figure 9.3—the differences in earnings across the two countries within schooling groups dominate strongly differences in earnings across schooling groups within each country; the gains from schooling investment are higher in the higher–skill price country; and the gains from moving to the higher–skill price

country are higher for the more educated.

The most interesting experiment is one in which the return to schooling in the lower–skill price country, in this case Bangladesh, is increased, while leaving the return at the same (lower) level for the higher–skill price country, Korea. Does this experiment alter any of the conclusions made under the assumptions of equal returns? First, the figure reveals that the increase in the return to schooling increases both high school and college graduate earnings in Bangladesh and lowers the earnings gap between the two countries for both groups. However, despite the relatively larger increase in the earnings of college graduates, the gap in earnings between Korean and Bangladesh college graduates is still larger than the gap between high school graduates across the two countries. And despite the fact that the return to schooling is 43 percent higher in Bangladesh than in Korea, the gains from migration are still higher for the college graduates than for the high school graduates.

5. Skill Prices, GDP, and International Migration

In this section I use the estimated skill prices, combined with other country-specific information, to examine the determinants of international migration. This exercise is useful from two perspectives. First, if one accepts the estimates of skill prices as being accurate, they can be used to appropriately test models of migration and to assess how differing prices of skill across countries affect the quality and amount of migration. Or, accepting models of migration, one can view this exercise as validating the skill price estimates, which should significantly affect the choices of migrants.

A. Framework.

The simplest framework for understanding the forces affecting migration and that incorporates skill prices begins with agent i residing in country j with a given number of skill units x_i. That agent earns $W_{ij} = \omega_j x_i$ at home, from (9.2), but can earn $W_{iu} = \omega_u x_i$ in country u. The net gain from migration G_{ij}, ignoring issues of skill transferability, is then

$$G_{ij} = [\omega_u - \omega_j]x_i - C_{ij} , \tag{9.13}$$

where C_{ij} is the direct cost of migration. The agent migrates from j to u if $G_{ij} > 0$.

Equation (9.13) has several testable implications for both the quantity and selectivity of migration. Given a distribution of private costs within a country, it can be shown easily that, first,

the larger the skill price gap $\omega_u - \omega_j$, the greater is the gain from migration and thus the more migration. Countries with the lowest skill prices will experience the highest rates of out-migration. Second, agents with more skill units have greater gains from migration, as was seen in figure 9.2. As a consequence, for given fixed costs of migration, as the skill price gap narrows, migration becomes more positively selective—only those agents with the highest levels of skills still experience a gain from migration net of costs. Migrants from countries with the highest skill prices will be highly skilled, but there will be fewer of them. Third, increases in the cost of migration will lower the number of migrants, but also increase the average skill levels of those who migrate, because only those with the highest levels of skill will experience a net gain from migration. Migrants from nearby countries will be numerous and relatively low skill. A key point is that changes in the skill price gap and in the costs of migration will have opposite effects on the quantity and quality of migration flows.

A more elaborate model would incorporate country-specific amenities in a utility-maximizing framework, but the basic implications from (9.13) would still hold (see Jasso and Rosenzweig 2009). In an empirical study of international migration, (9.13) suggests that variables are needed that measure skill prices at destination and origin, the determinants of human capital production, as in (9.3), as well as migration costs. A major issue in examining the determinants of international migration is that, unlike domestic migration in most countries, international migration is heavily regulated, subject, for example, to quotas by country of origin and restrictions based on family relationships to destination country citizens. Characterizing the costs and opportunities of international migration are thus complex. In addition, the model ignores uncertainty and thus the costs of search. One related important aspect of migration is that it tends to depend on networks, which play an important role in reducing search and other migration costs. Therefore migration is a dynamic phenomenon, with today's migration costs related to past migration histories to particular destinations.

U.S. immigration is an example of a heavily regulated system. More than 90 percent of U.S. immigrants qualify for a visa because of a family relationship. To minimize the complexities associated with international migration, I look at two types of international migrants to the United States: migrants who obtain an employment visa and migrants who obtain a student visa. Migrants who obtain an employment visa are not required to have family members in the United States to qualify, and visa qualification in this category is based on the human capital characteristics of the potential migrant and the willingness of a U.S. employer to

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hire the migrant. Jobs that qualify in this category are the kinds in which the role of networks is minimal. Those who qualify can also bring their immediate relatives (children and spouses). The appropriate category that comes closest to the "economic" migrant to which the model pertains is the "principal applicant"—that is, the person who receives the job offer as opposed to the relative of someone who does. Principal applicant visas make up less than 5 percent of all U.S. permanent resident visas. Fortunately, the NIS oversampled immigrants in this category, so that sufficient numbers represent most countries. Moreover, country quotas were not binding in the period covered by the NIS for this category of immigrant. Because the NIS provides the number of employment principal immigrants by country and their schooling, it is possible to look at the determinants of both the quantity and quality of immigrants in this category.

U.S. student visas are relatively unregulated and not subject to country quotas. Generally, all that is necessary to qualify for a student visa is to have obtained admission to one of the thousands of qualifying U.S. educational institutions. The two sources of annual information on foreign students by country of origin are (1) the student visas issued by the State Department each year and (2) the number of foreign students studying in the United States by both U.S. institution and country of origin, which is provided in the Student and Exchange Visitor Information System (SEVIS). The United States is the most popular destination for foreign students; approximately 250,000 came to the United States to study in 2004.

A somewhat different model is required to examine student migration decisions—that is, the decisions on where to acquire schooling. The model incorporates, besides the attributes of the schools at both the origin and the potential destinations, the skill prices at home and in potential destinations because of the possibility that acquiring schooling abroad increases the probability of obtaining a job offer where one is studying (this model is set out in Rosenzweig 2007, 2008). If so, part of the gain from acquiring schooling in destination country u as opposed to in home country j will be determined by the gap in skill prices between the two countries, as in (9.13). Based on the NIS information on the prior visas held by immigrants and the SEVIS data on stocks of foreign students, I constructed country-specific measures of the fraction of foreign students who were able to stay permanently in the United States (Rosenzweig 2008). On average, 20 percent of students stayed, suggesting that studying in the United States hugely increases the probability of immigrating there. Stay rates, however, differed greatly across countries. It is possible to use these measures of student stay rates to also examine determinants of the fraction of U.S. foreign students returning to their home countries.

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To estimate the determinants of migration to the United States incorporating country skill prices, I use two measures of migration costs: distance of each country's capital to the nearest port of entry to the United States and GDP per adult equivalent. I expect that the distance from origin to destination is positively associated with the costs of migration. For GDP, I expect that wealthier households are more able to bear the immediate costs of migration, so that richer countries, among those with the same skill prices, will experience higher rates of outmigration. I also include as determinants the school quality variables used in the tests of the Mincer model and the size of the home country population. To extend the number of countries beyond the 139 for which I have direct estimates of skill prices in order to minimize country selectivity, I estimated an auxiliary equation predicting skill prices based on equation (9.12), using information on each country's per worker GDP, its average schooling levels, and the school quality variables. Based on these estimates, I predicted skill prices for 168 countries.

B. Estimates

Table 9.4 reports the estimates of the effects of origin country skill prices per adult-equivalent GDP and distance, all in logs, on the log of the number of employment visa principal migrants to the United States in 2003 and the log of the average years of schooling of those migrants.[8] The coefficient signs conform perfectly to the model: skill prices are negatively related to the number of migrants but positively related to their average schooling; distance reduces migration but raises the quality of those who do migrate; and GDP is positively associated with outmigration but negatively associated with the schooling of the outmigrants. Thus GDP and skill prices have opposite effects on the quantity and quality of migration. Studies that use only origin country GDP as a determinant of migration are thus confounding the effects of financial constraints with the gains associated with increased wages.

What do these estimates imply for a "brain drain" from low– and high–skill price countries? One measure of skill outflow is the total number of years of schooling of the migrants—the number of migrants multiplied by their average schooling. Although the point estimate of the effect of variations in the skill price on the number of employment migrants is not

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[8] The number of countries in the analysis of the schooling of the employment migrants is reduced because some countries did not have any employment migrants. A more sophisticated analysis would take into account the selectivity associated with nonmigration. However, it is an implication of the model that factors affecting the decision to migrate also affect who migrates (selectivity).

estimated with precision, the magnitude is high in absolute value, suggesting that a doubling of the skill price would reduce outmigration by 83 percent. The average schooling of the outmigrants, column (2), would increase by 50 percent, however. The net effect of increasing the origin country skill price on the total outflow of human capital, measured by the total years of schooling of all migrants, is thus negative. Doubling the skill price reduces the total human capital outflow by 33 percent. Thus less human capital flows out of high–skill price countries compared with low–skill price countries. Put another way, even though outmigration is more skill-intensive in high– than in low–skill price countries, because far more migrants leave from low–skill price countries the total loss in human capital is greater. From the perspective of poor countries that subsidize education, this is a loss. From the perspective of global efficiency, however, that more human capital flows out of places where skill is rewarded less to places where it is more valuable is good news.

What about the flows of foreign students to rich countries and back? Table 9.5 reports estimates from Rosenzweig (2008) that look at the effects of skill prices (estimated from the NISP and OWW), per capita GDP, and distance on the number of foreign students to the United States and their return rates. The first two columns indicate that higher skill prices at origin, whether estimated from the NISP or the OWW world wage data sets, reduce the number of students who seek schooling abroad. Because these estimates control for measures of school quality, the estimates suggest that foreign schooling is in part a job-seeking phenomenon. The estimates also suggest, parallel to those obtained for permanent migrants, that for given skill prices countries that are richer experience greater outflows of migrants. Countries with lower skill prices experience more student outmigration. Moreover, the students from these countries are also less likely to return. As seen in the third and fourth columns of table 9.5, student return rates are higher back to countries that have higher skill prices, that reward skill.

Outsourcing of schooling may be a benefit for poor countries, which cannot afford to supply a sufficient quantity of high-quality schools, but only if students return. Is foreign schooling relatively beneficial for poorer countries? The point estimates suggest that a doubling of the home skill price lowers the outflow of students by from 26 to 73 percent and also increases their return rates by from 1.5 to 1.9 percent. The net effect is that the total number of students who receive their higher levels of schooling abroad are significantly greater in low–skill price countries. Although such countries lose a greater fraction of their best and brightest because they "outsource" far more students compared with high–skill price countries, the total numbers that

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return are higher. Outsourcing higher education thus appears to benefit, on net, poorer countries.

6. Conclusion

Global inequality in incomes can be viewed from various perspectives—for example, as an indicator of global unfairness, as a measure of the challenge for development policy, or as a measure of the inefficient global allocation of labor or capital. Understanding the proximate determinants of income inequality is useful for all of these perspectives. In this chapter, I use newly available data on the wages and human capital of workers across the countries to shed light on how much of inequality in incomes across countries is due to inequality in human capital and how much from differential rewards to the same skills—that is, the cross-country variation in skill prices. I showed how the global wage data can be used to identify skill prices worldwide and to test the Mincer model of schooling and wages that has been used pervasively to specify and interpret wage functions estimated within countries. I also used estimates of the set of country-specific skill prices to quantify the relative importance of skill and skill price variation in explaining income inequality and to assess how variation in the rewards to skill across countries affects the quantity and quality of cross-border migrant flows, including permanent employment and student migrants to the United States from around the world.

The data reject the model underlying the Mincer wage specification, which assumes perfect capital and labor markets and no barriers to schooling acquisition (and no permanent differences in lifetime earnings), suggesting that a framework incorporating the determinants of the supply and pricing of skills is better suited to accounting for wage inequality. My estimates also indicate that domestic rates of return to schooling across countries are relatively uninformative about differences in the rewards to skill across countries. To fully characterize the global wage distribution, one needs to know how schooling affects wages, levels of schooling, and skill prices for each country. My estimates indicate that the global variation in skill prices is significantly greater in magnitude than either the variation in schooling levels or schooling returns. In particular, my estimates of country-specific skill prices suggest that global inequality in the price of skill exceeds global inequality in either average per country schooling levels or returns by as much as 70 percent, depending on the measure. That most of global inequality in incomes is due to intercountry differences in the prices of skills suggests that greater equalization of schooling levels arising from domestic schooling policies will have only marginal effects on global inequality, that domestic development policies in poor countries should focus on the
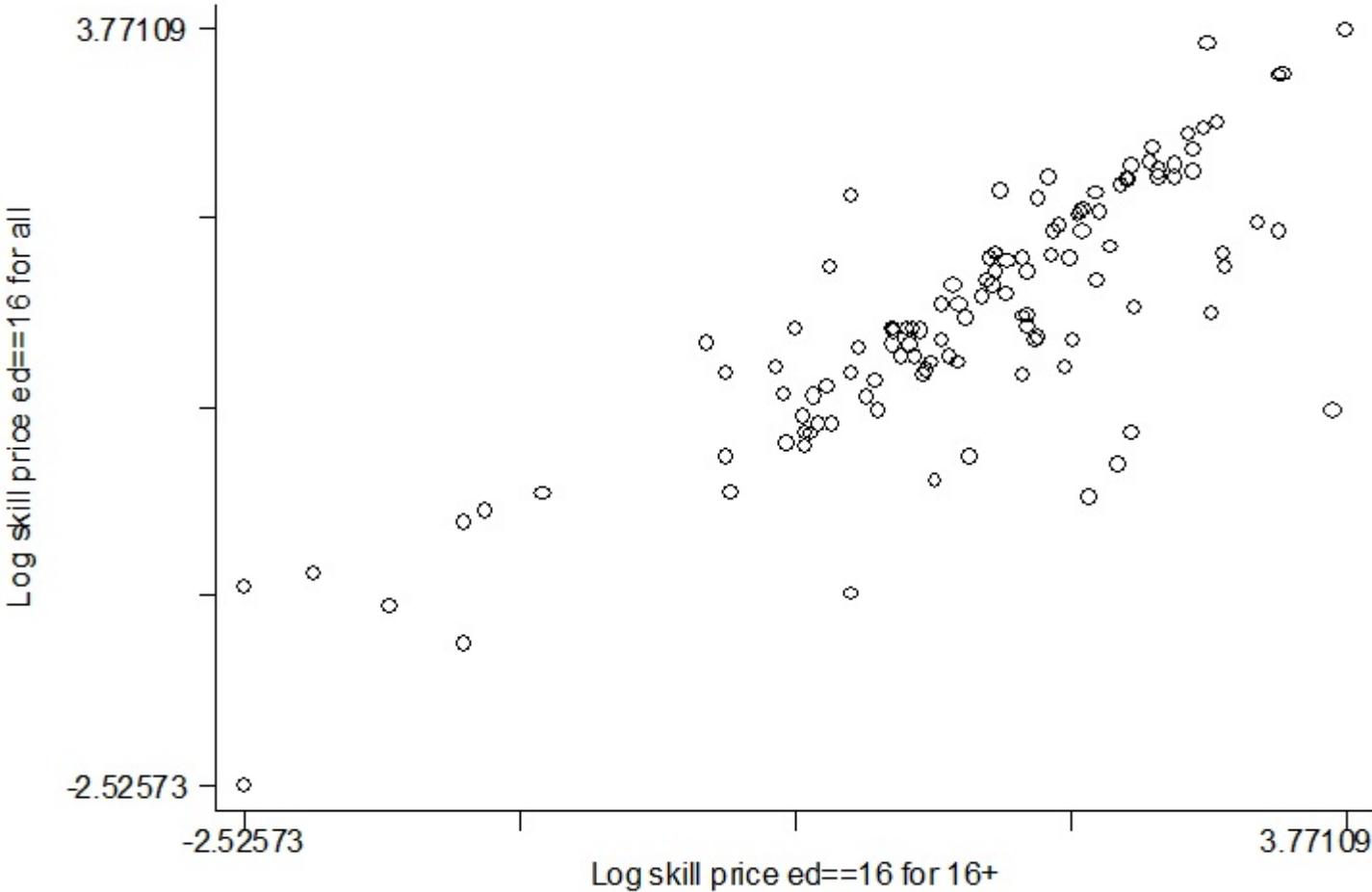
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underlying reasons skills are less valued, and that, given the structure of skill prices, labor is poorly distributed across countries based on global efficiency criteria.

My estimates based on patterns of migration to the United States indicate that skill price variation is an important determinant of the variation in the number and schooling levels of migrants. In conformity with a simple model of migration choice, the estimates indicate that among countries with similar levels of per capita income, countries with low skill prices experience greater rates of outmigration than countries with high skill prices, but the average schooling levels of those leaving low–skill price countries are lower than those from high–skill price countries. Despite this selectivity, the estimates suggest that the total amount of human capital—the total schooling years of migrants—exiting countries is greater per capita in low– than in high–skill price countries. By contrast, low–skill price countries appear to gain more from the migration of persons to acquire schooling abroad. Although more students from low–skill price countries study abroad and the return rates of those students are also lower for such countries compared with those for countries in which skills are more favorably rewarded, on net larger stocks of foreign-trained, tertiary-educated persons are in low–skill price countries than in high–skill price countries. Existing estimates of the brain drain from low-income countries thus need to take into account both phenomena—the permanent outflow of those who have acquired their schooling in the home country and the numbers of persons in home countries who received their subsidized schooling elsewhere. Finally, my estimates indicate that rising incomes accompanied by stagnant skill prices will lead to greater outmigration. Thus, for example, humanitarian aid, which increases incomes in poor countries but does little to increase the rewards to skills, can worsen the brain drain, although it would also increase global efficiency and therefore output. How individual countries increase incomes will then significantly affect the global mobility of workers and total world output.

References

Barro, Robert J., and Jong-Wha Lee. 2001. "International Data on Educational Attainment: Updates and Implications." *Oxford Economic Papers* 53 (3): 541−63.

Bartik, Alex. 2008. "New International Data on Schools." Senior thesis, Yale University, New Haven, CT.

Beine, Michel, Frédéric Docquier, and Hillel Rapoport. 2001. "Brain Drain and Economic Growth: Theory and Evidence." *Journal of Development Economics* 64 (1): 275−78.

_____. 2006. "Measuring International Skilled Migration: New Estimates Accounting for Age of Entry." Research Report, World Bank, Washington, DC.

Bils, Mark, and Peter J. Klenow. 2000. "Does Schooling Cause Growth?" *American Economic Review* 90 (5): 1160−83.

Freeman, Richard B., and Remco Oostendorp. 2000. "Wages round the World: Pay across Occupations and Countries." NBER Working Paper 8058, National Bureau of Economic Research (NBER), Cambridge, MA, December.

Jasso, Guillermina, and Mark Rosenzweig. 2009. "Selection Criteria and the Skill Composition of Immigrants: A Comparative Analysis of Australian and US Employment Immigration." In *Skilled Immigration Today*, ed. Jagdish Bhagwati and Gordon Hanson, New York: Oxford University Press.

Jasso, Guillermina, Doug Massey, Mark Rosenzweig, and James Smith, 2000. "The New Immigrant Survey Pilot: Overview and New Findings about Legal Immigrants at Admission." *Demography* 37 (1): 127-138.

Mincer, Jacob. 1958. "Investment in Human Capital and Personal Income Distribution." *Journal of Political Economy* 66 (4): 281−302.

Rosenzweig, Mark R. 2007. "Global Wage Differences and International Student Flows." In *Brookings Trade Forum: Global Labor Markets*, ed. Susan Collins and Carol Graham. Washington, DC: Brookings Institution Press.

_____. 2008. "Higher Education and International Migration in Asia: Brain Circulation." In, *ABCDE World Bank Conference*, ed. François Bourguignon. New York: Oxford University Press.

Figure 9.1 Relationship between Log Skill Price (One Skill) and Log of College Plus Skill Price

Figure 9.2 Predicted Annual Earnings (PPP-Adjusted) of High School and College Graduates Based on NISP Skill Prices, across Selected Countries ($r = 0.07$)
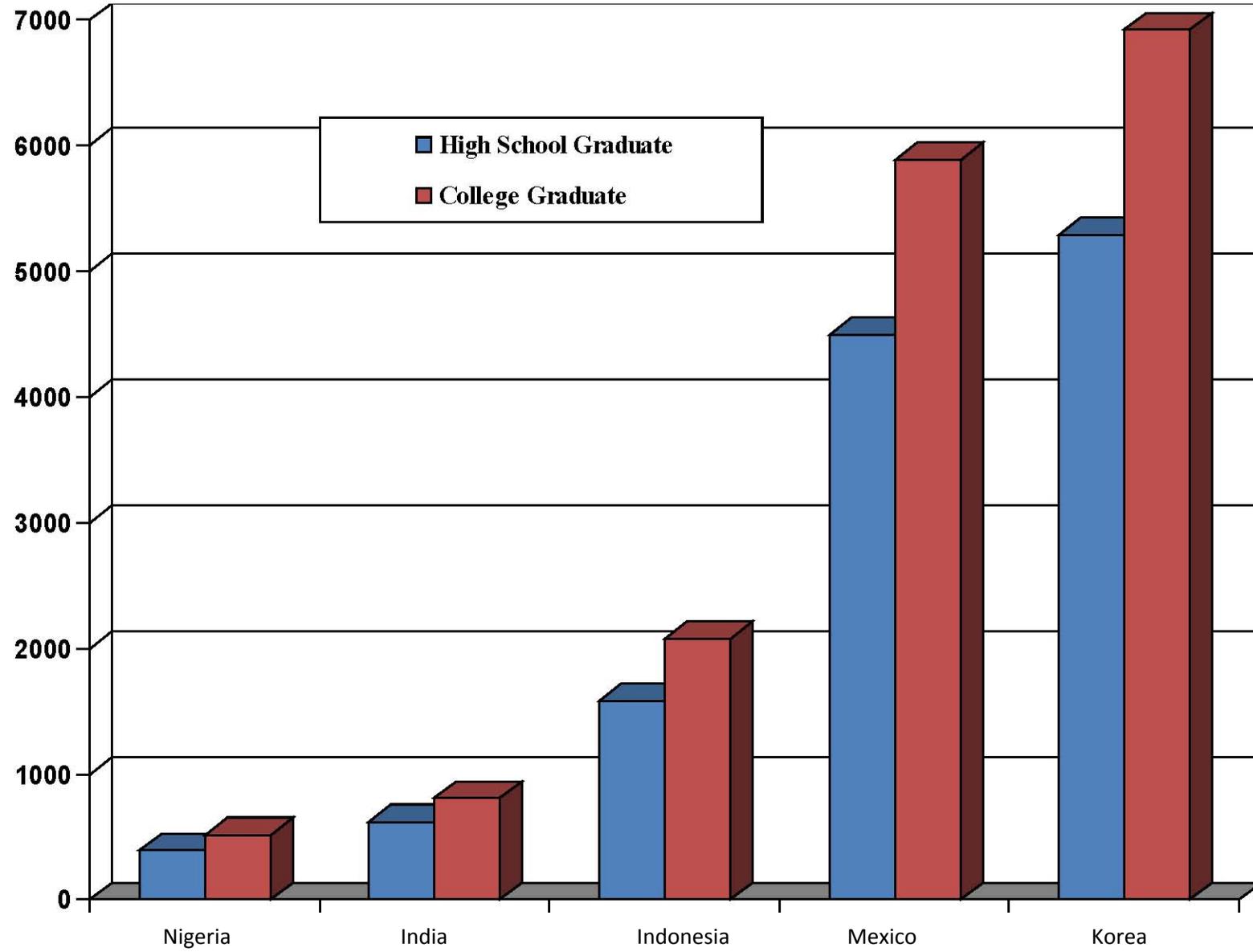
Figure 9.3 Predicted Annual Earnings (PPP-Adjusted) Based on NISP Skill Prices by Schooling Level and Schooling Return, Bangladesh and Korea
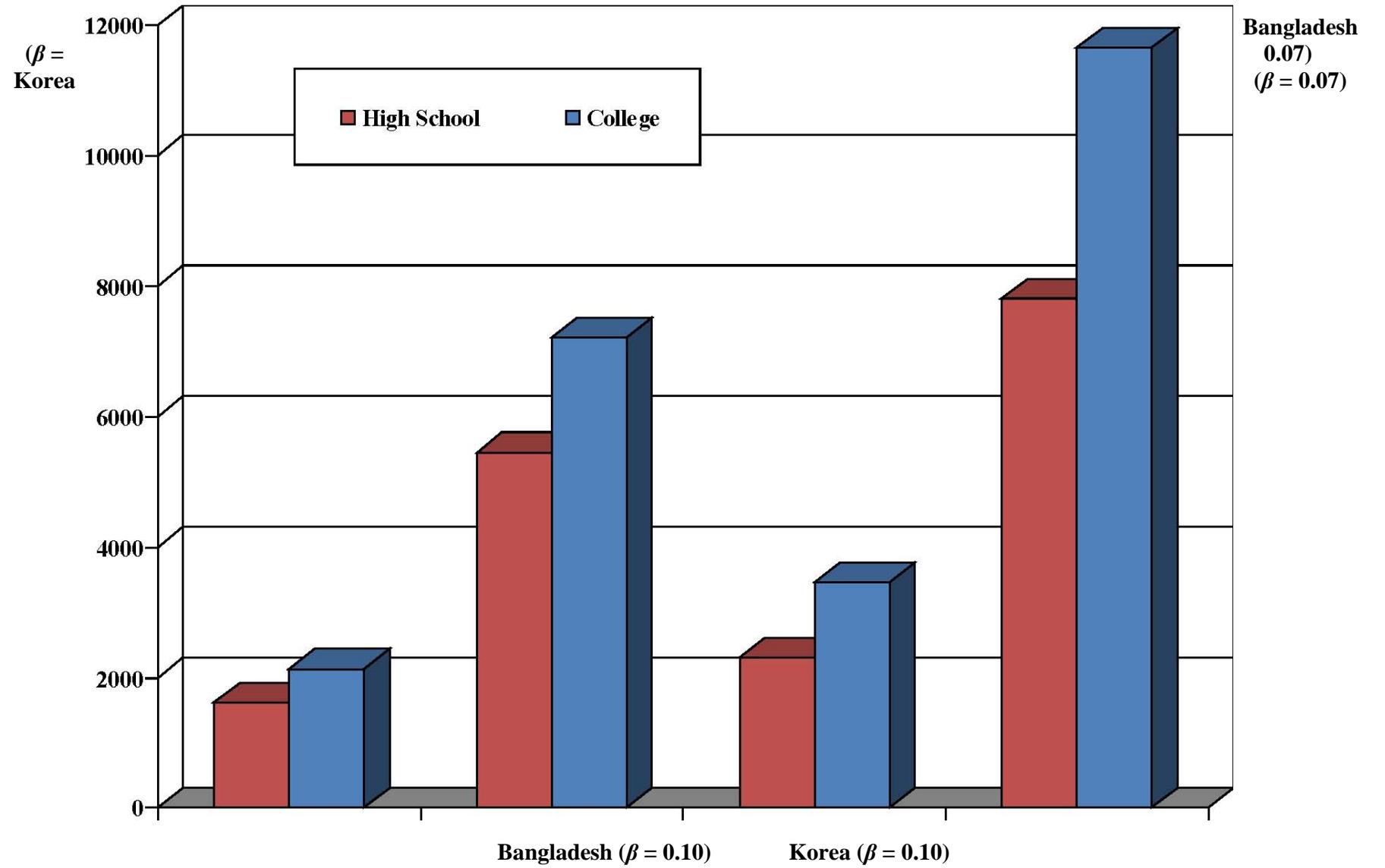
Table 9.1 Characteristics of Global Earnings Data Sets

Data set/variable	NISP home country workers	OWW, 1995	NIS home country workers
Mean annualized earnings of respondents (US$)	14,719[a] (2,602)	10,208[b] (13,289)	17,803[a] (29,410)
Mean age of respondents	34.6 (8.53)	–	39.7 (11.5)
Mean years of schooling of respondents	14.4 (4.5)	–	13.8 (3.82)
Number of industries	–	49	–
Number of occupations	–	161	–
Number of countries	54	67	140
Number of workers	332	4,924	4,455

Note: NISP = New Immigrant Survey Pilot; OWW = Occupational Wages Around the World; NIS = New Immigrant Survey.

[a] PPP-adjusted.
[b] Exchange rate-adjusted, country-specific calibration with lexicographic imputation.

Table 9.2 Test of Mincer Model: Fixed Effcts Country Log Wage Regression Coefficients from NIS using Bartik School Quality Data and Log of Hourly Wage for Men at Last Job before Coming to United States

Origin country variable	(1)	(2)
Total years of schooling completed	0.0948 (6.12)[a]	0.0721 (3.30)
Work experience	0.0298 (2.24)	0.0339 (2.30)
Work experience squared ($\times 10^{-3}$)	−0.0697 (2.59)	−0.0664 (2.19)
Interactions with Bartik school quality variables?[b]	No	Yes
F-test: $\hat{E} = 0$ [p-value] (d.f., d.f.)	–	2.50 [0.006] (10, 1,226)
Number of sending countries	112	112

Sources: New Immigrant Survey (NIS) and Bartik 2008.

[a] Absolute value of t-ratio is in parentheses.
[b] The school quality measures are pupils per teacher, spending per pupil, and average teacher salaries in primary and secondary schools; the number of ranked universities; and the average rank of ranked universities, if any.

Table 9.3

Global Inequality: Comparisons of the Global Variation in Schooling, Schooling Returns, Per Capita GDP, and Skill Prices

	Number of countries	Coefficient of variation	Span (ratio)	Interquartile range (ratio)
Average years of schooling, 15+ population	106	0.474	14.4	2.2
Mincer schooling return	52	0.494	11.7	1.7
GDP per adult equivalent	139	0.948	76.7	4.9
Skill price	130	0.807	108.9	3.6

Sources: Average years of schooling: Barro and Lee 2001; Mincer schooling return: Bils and Klenow 2002; GDP: World Tables 2003; skill price: estimated by the author using the New Immigrant Survey.

Table 9.4
Effects of Home Country Skill Price, GDP, and Distance on Log of Number and Average Schooling Attainment of U.S. Employment Visa Principal Immigrants in 2003

	Log number of employment visa principal immigrants	Log average schooling of employment visa principal immigrants
Log skill price (NIS, 2003)	−0.827	0.499
	(1.23)[a]	(2.83)
Log GDP per adult equivalent	0.604	−0.108
	(2.74)	(1.60)
Log distance of country to the United States	−0.248	0.0377
	(4.98)	(4.43)
R-squared	0.611	0.112
Number of sending countries	168	94

Source: New Immigrant Survey.

Note: The specification also includes whether there is a military base in the home country, the log of the home country labor force size, and measures of the quality of primary and secondary schools.

[a] Absolute values of bootstrapped t-ratios in parentheses are based on the multiple imputation method.

Table 9.5

Effects of Home Country Skill Price, GDP, and Distance on Log of Number and Exit Rate of Foreign University Students in United States, 2004

Dependent variable	Log number of U.S. foreign students		Log exit rate of foreign students	
Basis for skill price	NISP	OWW	NISP	OWW
Log skill price	–0.259	–0.730	0.0152	0.0193
	(2.17)[a]	(2.14)[a]	(2.31)	(3.61)
Log GDP per adult equivalent	0.516	1.06	0.00145	–0.00137
	(2.85)	(2.71)	(0.56)	(0.42)
Log distance of country to United States	–0.298	–0.309	0.00163	0.00237
	(4.30)	(4.44)	(0.52)	(0.75)
R-squared	0.766	0.766	0.183	0.202
Number of sending countries	125	125	125	125

Source: New Immigrant Survey Pilot, Occupational Wages Around the World, and the Student and Exchange Visa Information System, 2004.

Note: The specification also includes the log of the home country population and measures of the number and quality of home country universities. NISP = New Immigrant Survey Pilot; OWW = Occupational Wages Around the World.

[a] Absolute values of bootstrapped t-ratios in parentheses are based on the multiple imputation method.