"Brain Drain and Institutions of Governance: Educational Attainment of Immigrants to the US 1988-2000"

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Brain Drain and Institutions of Governance: Educational Attainment of Immigrants to the US 1988-2000

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Abstract

We use a fixed effects panel data model to investigate the impact of institutions of governance on the educational attainment of immigrants to the United States over the period 1988 – 2000. Distinguishing between the quality and stability of political institutions in the countries of origin, we find that the two characteristics of institutional structure have conflicting impacts on the nature of brain drain. Immigrants from countries with a higher quality of political institutions tend to be better educated, on the average, than immigrants from countries with institutions of lower quality. However, immigrants from countries with greater political instability tend to be better educated than immigrants from countries with more stable governments.

Keywords: *Immigration, institutions, political instability, brain drain*

JEL Codes: F22, J24, J61, J64

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I. INTRODUCTION

Immigration is a central theme in the globalization debate. Among the questions that have arisen in the discussion are: (1) what is the impact of immigration on welfare for the source and destination countries, and; (2) what are the distributional consequences of immigration for various interest groups? While most studies agree that there are net (but small) welfare gains for natives, the distributional question depends on many factors. One of these factors is whether or not the skill distribution of immigrants is representative of the distribution of skill in their respective home countries, or if immigrants are self-selected with some positive or negative skill bias. Because of its impact on the income distribution, selection bias may play a role in the politics of immigration policy.

The theoretical work on the selection of immigrants leaves the issue as an empirical question, and existing empirical tests have been inconclusive. The consensus is that the direction and magnitude of the selection bias depends on the conditions in the immigrants' home countries. This paper aims to complement the literature on immigrant selection bias. We find empirical evidence in support of the hypothesis that immigrants to the U.S. are favorably selected. We also find that favorable selection is stronger for immigrants who come from countries with more corrupt governments, who travel farther to get to the U.S., and whose home countries have higher average levels of educational attainment. The remainder of the paper is organized as follows: Section 2 reviews the literature on the selection and educational attainment of immigrants; Section 3 presents the empirical model and outlines the estimation methodology; Section 4 discusses the data; Section 5 explains the results, and; Section 6 concludes.

II. RELATED LITERATURE

At a theoretical level, the cornerstone of the immigration literature is Mundell (1957), who predicts negative selection using a factor-endowments approach. Skill-abundant countries will receive mostly low-skill workers as a complement to comparative advantage through trade in factors. However, Chiswick (1978; 2001) predicts positive selection using a human capital model in which migrants compare the returns from migration to its moving and opportunity costs. Borjas (1987) finds that both patterns are possible using the Roy (1951) model of occupational selection. The theoretical literature on brain drain, such as Chakraborty (2006) and Docquier and Rapoport (2003), predicts positive selection and deserves mention for explaining immigration from countries with poor institutions, corruption, or discrimination.

There has also been considerable debate in the empirical literature about the average skill level of immigrants to the United States. For our purpose, three sets of findings stand out: (1) Borjas (1999) and Betts and Lofstrom (2000) find a negative trend in the skill level of immigrants relative to the native U.S. population over the 1970s and 1980s; (2) Cohen, Zack and Chiswick (1997) and Barrett (1996) find that the decreasing trend in immigrant skill level over the 1970s ended by the mid-1980s, and; (3) Polgreen and Simpson (2006) confirm the trends found in the previous studies above using data from 1972-2000, but find that the upward trend that began in the mid-1980s reverted to a decline by 1994. For a more comprehensive survey of the empirical literature on immigrant self-selection, we refer the reader to Borjas (1994).

Polgreen and Simpson (2006) is an important launching point for this study because it covers the most comprehensive sample period and offers a technique for measuring the education levels of immigrants in the years they arrived. Previous studies measured immigrant education by using census data for the education of the foreign born population living in the U.S. or by using wages as a proxy. Neither of these measures directly addresses the issue of immigrant selection at the time they arrive.

III. EMPIRICAL MODEL AND ECONOMETRIC STRATEGY

The specification of the empirical model is a straightforward extension of the model in Polgreen and Simpson (2006), which includes immigrant type, visa class, and region to explain the variation in the education of immigrants over time. They are able to attribute the trends in immigrant selection to three sources: (1) changes in the education and visa status of non-immigrant residents; (2) policy changes, and; (3) demographic changes in immigrants' countries of origin.

Our goal is to investigate their third conclusion in greater detail to try to identify the country characteristics that affect the education of immigrants to the US. Specifically, we plan to evaluate whether the selection of immigrants is influenced more by the institutions and educational endowments in their countries of origin, or by the moving costs of immigrating relative to the benefits.

The model we estimate is:

$$(1)\ ln(ed_i) = \beta_0 + \beta_1 new_i + \sum_{p \in P} \beta_p year_t^p + \sum_{k \in K} \beta_k visa_i + \sum_{r \in R} \beta_r region_{ij} + \sum_{l \in L} \beta_l Z_{ljt} + \varepsilon_i$$

where *new* is a dummy variable indicating whether the visa is being issued to a new entrant; $\sum_{p \in P} \beta_p year_t^p$ is a time-trend polynomial chosen to approximate the trend in immigrant skill over time observed by the existing literature; *visa* is a set of dummy variables for the immigrants' visa class (family, employment, refugee, diversity, Immigration Reform and Control Act, or "other"); *region* is a set of region-of-origin dummy variables, and; *Z* are the country characteristics we are interested in. The details of these variables will be described in more detail in the next section.

We will employ a quantile regression as our estimation strategy to try to capture how the impacts of the variables vary for different levels of the distribution. Quantile regression estimates the treatment effects at a given quantile of the distribution by minimizing a weighted sum of the absolute deviations. Specifically, quantile regression solves:

(3) $min_{\beta}\{\tau(y - X\beta) - [I(s < 0)(y - X\beta)]\}$,

where $\tau \in (0,1)$ is the selected quantile and $I(*)$ is an indicator function equal to one if the error term, $y - X\beta$, is negative. A summary of this strategy can be found in Koenker (2005).

Quantile regression is useful because the explanatory variables of interest may have different marginal effects for observations in the tails of the distribution of immigrants than they do at the center. Quantile regression allows us to measure these differences without making restrictive assumptions. Also, quantile regression helps account for individual heterogeneity that cannot be easily corrected using instrumental variables (Arias et al. 2001). There are also economic reasons that quantile regression is useful for describing the skills of immigrants. First, the theories about selection have more to do with how variables affect skill selection in the tail of the distribution. Secondly, estimating the conditional quantile helps account for the fact that education may be a "lumpy" investment, in that individuals "drop out" after well-defined intervals.

IV. DATA

For the sample period 1988-2000, data for immigrants to the U.S. come from "Immigrants Admitted to the United States" published by the Immigration and Naturalization Service (INS).

Immigrant characteristics in this dataset are: year of admission; visa class; countries of birth, last residence, and quota chargeability; age; occupation; marital status; gender; type (new admission or a visa adjustment non-immigrant foreign residents); intended US state and city of residence, and; labor certification status.

The INS data does not directly report immigrants' education levels, so we adopt the data constructed by Polgreen and Simpson (2006), who estimate immigrants' education based on their occupation and other characteristics in the INS dataset. Using data for U.S. natives from the *Current Population Survey* (CPS), they estimated the following equation for each occupation, *k*:

(4) $\widehat{ed}_{tk} = \beta_0 + \beta_1 age_{tk} + \beta_2 gender_{tk} + \beta_3 married_{tk}$.

The goal of constructing the education variable this way is to capture the variations in educational attainment caused by variations in observed characteristics.

This measure of immigrant education has disadvantages, which are discussed in Polgreen and Simpson (2006), and which we will summarize here. First, it only measures the education of immigrants who report a useful occupation. Immigrants who are children, retirees, students, unemployed, homemakers, or do not report an occupation comprise about 65% of the immigrants who entered during the sample period. Fortunately, these numbers have been relatively stable over that time so any bias that their omission may introduce is not fluctuating much. Secondly, immigrants are less likely to be matched into their primary occupation than natives. This may be related to licensing and other entry barriers. Chiswick (2008) finds that immigrants have a flatter distribution of wages across different skill levels, and partly attributes this to occupational mismatching. However, while skill mismatching may affect immigrants' *wage* distribution after they *arrive*, it does not necessarily reflect on their *ability* when they decided to *leave home*. Econometric problems with constructed variables include measurement error described by

Bollinger and Hirsch (2006). This may not seriously impact the elasticities we estimate as long as the bias is proportional to the actual levels of education.

Despite these shortcomings, we feel that the INS data still give the best snapshot at the time of arrival and therefore did a better job of addressing our main question. Some studies look at immigrants' occupations, wages and education levels using the CPS. While using the CPS might overcome some of the difficulties described above, it too is flawed because the CPS does not provide information about the characteristics of immigrants when they arrived and therefore does not answer the selection question. The CPS also includes undocumented immigrants, whose selection may be distorted by other factors.[1]

Summary statistics of the education variable are reported by country in Table 1. Columns (1) through (3) show the region, country, and number of immigrants from each country. The headcounts show that the countries which sent the most immigrants during this period were Mexico, The Philippines, and India. However, since the dataset deals specifically with legal immigration, it is not dominated by any single country or geographic region. This is because since 1965 U.S. immigration policy has set a single aggregate quota for the world, with a uniform percentage cap for the total from any single country.[2] Columns (4) through (7) report the mean, standard deviation, maximum and minimum values for the constructed education variable for immigrants from each of the countries. The last two columns of Table 1 show the average educational attainments of these immigrants' countries of origin in 1960 and 2000, respectively. Comparing these figures to column (4) of the table suggest that, while there may have been a downward *trend* in the education of immigrants at certain times during the sample period, it is

[1] For example, illegal immigrants may be selected because they have less to lose from being barred legal entry for life and thus tend to be lower-skilled.

[2] Quota exceptions include: (1) refugees, and; (2) the Western Hemisphere. Immigration from the Western Hemisphere had not fallen subject to quotas before 1965when a quota was added at a level of twice the quota allocated to the rest of the world.

unlikely that there was ever negative *selection* relative to the distribution of skill in immigrants' home countries.

The first group of explanatory variables we choose to include in our estimation of equation (1) are: type of case (new or adjusted), region of origin, visa class, and year from the INS dataset. Type of case is a dummy variable equal to one for new immigrants and zero for adjustments in the visa status of foreign residents already in the United States. Regions are included as dummy variables for immigrants coming from Western Europe, Eastern Europe, Asia, Africa, Oceania, and South America, leaving North America and the Caribbean as the benchmark group. Visa class includes dummy variables for family members of U.S. residents,[3] employment visas,[4] legalized status under the 1986 Immigration Reform and Control Act (IRCA),[5] "diversity" visas,[6] and "other" visas,[7] with refugees serving as the benchmark group. We also included polynomial function of the year the visa was issued to approximate the changes in the trends of immigrant education described in previous studies.

We then add several country characteristics. They are: population and real per capita gross domestic product (GDP) from the World Bank World Development Indicators (WDI); the corruption index from the *International Country Risk Guide* (ICRG); distance and dummy variables for English-speaking countries and countries with a shared colonial history with the US from the *Centre d'Etudes Prospectives et d'Informations Internationales* (CEPII), and; average educational attainment in each immigrant's home country from Barro and Lee (2001). Because of limited availability of the ICRG and education data for several countries, the final sample consisted of about 1.8 million legal immigrants between 1988 and 2000.

[3] Using the 29 classifications in the 2000 INS dataset, family visas included classifications 1-4, 14-18, and 21.
[4] Classifications 5-9.
[5] Classifications 22, 26, and 27.
[6] Classifications 13 and 23.
[7] Classification 29.

The variables we are most interested in are corruption, distance, and educational attainment in the immigrants' countries of origin. Corruption is included to determine how poor institutions in developing countries influence the problem of brain drain and is predicted to have a positive impact on immigrant education. Next, it is predicted that distance variable will not only reduce the quantity of immigrants in the context of "gravity," but it will also improve the quality of immigrants.[8] Chiswick (2000) predicts that higher moving costs will lead to favorable selection and rule out negative selection. Finally, average education in each immigrant's country of origin is used to measure that country's endowment of skilled labor relative to unskilled labor, which may impact the returns to human capital in that country and the incentives to emigrate. Mundell (1957) and Borjas (1987) predict immigrants from countries with more skilled workers will be better-educated in both absolute and relative terms. Summary statistics for all explanatory variables are reported in Table 2.

V. RESULTS

In this section, we highlight the empirical findings from: (1) OLS regression, to get an idea of the marginal effects around the mean, and; (2) quantile regression, to show how those impacts may vary at different levels of the skill distribution and; (3) ordered probit regression, to test the sensitivity of the results to small errors in the measurement of the education variable.

<u>OLS Results</u>

OLS estimation results for several specifications of equation (1) are reported in Table 3, with standard errors in parentheses. The specification in column (1) excludes country characteristics, *Z*. These results are consistent with Polgreen and Simpson (2006) in the sense that there is

[8] The relationship between trade cost and value is one common to the literature on trade in goods and services. A review by Leamer (2006) discusses various concepts of geography in economics in the context of Thomas Friedman's popular notion of "flatness."

similar variation on the basis of visa class, region, and type, and the time-trend displays similar breaks as those documented in their analysis.

OLS estimates including country characteristics, *Z*, appear in columns (2) and (3) of Table 3. Column (2) includes only the control variables of GDP, population, language and colonial history variables and column (3) includes these characteristics as well as the corruption, distance and country of origin education variables we are interested in testing. Comparing these specifications the year, visa, and regional variables we see that there is not much change in the signs or magnitudes of their coefficients across specifications. The only place that we do notice some change is in the regional dummy variables, but these changes are not unexpected since distance and institutional quality are similar among geographic neighbors and political friends. The coefficients on the country control variables are virtually unchanged when we add corruption, distance and education in the country of origin.

Finally, column (4) shows the results from running OLS on equation (1) excluding the linear term of the polynomial time trend. The reason for including this specification is that quantile regression does not lead to an analytical solution, and therefore is both less stable and more sensitive to correlations among the explanatory variables than OLS is. Estimating equation (1), quantile regression was forced to drop the year variable. There are virtually no differences in the variables of interest between columns (3) and (4). Therefore, the rest of this subsection will focus on the results in Table 3, column (4).

The first group of country characteristics is the group of variables that control for population, GDP per capita, and dummy variables for English-speaking countries and countries that share a common colonial history with the United States. They tell us that immigrants from countries with historically large populations that speak English are more educated, while immigrants from countries whose populations have grown most, have the higher GDPs per capita, and which share a colonial history with the United States are less educated.

The coefficients on the corruption index, distance, and average educational attainment variables reveal that: (1) immigrants from more corrupt governments are better-educated; (2) moving costs improve immigrant quality, and; (3) immigrants from countries with higher education levels are themselves better educated. However, there is no evidence that this rises to the level of "positive selection" on the basis of skill endowments or the returns to human capital.

The corruption index's coefficient tells us that countries with higher levels of corruption in government send more educated immigrants to the United States. As a result, a one-point worsening in a country's ICRG corruption index will result in immigrants to the U.S. who are 11.3% more educated, on average. In years, a one standard deviation change in the corruption levels in a country will increase the expected educational levels of its immigrants by about 0.29 years. This result is consistent with the Docquier and Rappaport (2003) model of skilled migration. The sign of the distance variable is also positive and significant. Although the magnitude its elasticity is small (0.038), it is not of lesser importance. A one standard deviation change in the distance from the U.S. leads to about a 0.37 year increase in immigrants' education, which is more than the impact of corruption. This result supports the predictions of models involving moving costs, which include Chiswick (2000) and Borjas (1987).

The impact of education in immigrants' countries of origin is more complicated. Increases in a country's current average level of education increases the quality of its immigrants, even when controlling for 1960 educational attainment rates. The elasticity for country of origin average education in 1960 was about -0.007, meaning that slightly less-educated immigrants to the U.S. came from countries with higher initial education levels. At the same time, the elasticity of current educational attainment was estimated to be about 0.03. This shows that better-educated immigrants came from countries with higher current educational attainments and improvements in educational attainment rates since 1960. However, neither of these results supports the notion that immigrants from countries with higher skill endowments are positively selected. To determine this, we must test whether this elasticity is greater than one, which cannot be rejected. Therefore, even if negative selection from low-skill countries is *possible*, it seems unlikely that it follows the pattern described in Mundell (1957) or Borjas (1987).

Quantile Regression Results

The next step is to see how the marginal impacts of these variables vary throughout the distribution and then see what the predicted values from the quantile regressions show about the distribution of immigrants' skills. The Table 4 shows the estimated quantile coefficients for selected quantiles (τ = 0.05, 0.25, 0.50, 0.75, and 0.95) with standard errors in parentheses. This table tracks the changes in the impacts of various factors and the statistical significance of those factors at different quantiles. For example, 1960 educational attainment in an immigrant's country of origin stands out because its impact is significantly positive (0.011) for immigrants in the 5th percentile but significantly negative (-0.036) for immigrants in the 95th percentile. For other variables, the coefficients do not change in sign or significance, but nonetheless vary substantially, as corruption does (0.024 at the 5th percentile and rising to 0.169 at the 95th).

Figures 1 through 4 illustrate the variations in the coefficients for the four variables of interest (corruption, distance, average education, and average education in 1960) more clearly. In each figure the solid black line connects the observed values of the estimated quantile regression coefficients at every fifth percentile between the 5th and 95th. The smooth, grey curve fits a sixth-order polynomial trendline to the estimated quantile coefficients, and the horizontal dashed line references the OLS estimate. Confidence interval bands are not included because the standard errors are extremely small and the lines are almost indistinguishable.

First, Figure 1 shows the quantile regression coefficients for the corruption index in the immigrant's country of origin across quantiles. It shows that the impact of corruption is relatively weak for lower-skilled immigrants, but progressively stronger for immigrants at higher skill levels. This strengthens the case supporting models related to brain drain and institutions.

Next, Figure 2 plots the elasticity of distance on immigrants' education levels across quantiles. Moving costs improve the overall quality of immigrants at all skill levels, but its importance is less for low-skill immigrants. The upward trend in the value of the estimated coefficient is fairly consistent beginning with a value of 0.004 at the 5th percentile, and rising above 0.052 at the 95th. While this generally confirms theoretical predictions about the impact of moving costs, it is unclear why these costs would impact higher skill levels more than lower ones. One explanation is that for low skill immigrants living Mexico or other Latin American countries, waiting for the opportunity to migrate legally has a high opportunity cost. Instead of waiting, they can obtain similar benefits by exploiting legal seasonal opportunities in border communities that do not require a visa, or by immigrating illegally. These immigrants are not captured by the INS data.

Finally, Figures 3 and 4 show the effects of education levels in the immigrant's country of origin. Figure 3 graphs the coefficient for the elasticity of the 1960 average educational attainment in an immigrant's country of origin. It shows a declining trend and a reversal in sign for this coefficient across quantiles, starting at 0.011 at the 5th percentile and falling to -0.035 at the 95th. The OLS coefficient falls in between at -0.007. Figure 4 shows the quantile regression coefficients for average years of education in the immigrant's host country. In contrast to the previous three figures, this coefficient does not display a dominant upward or downward trend over the quantiles of immigrant skill. Also, the sign its impact is negative (and significant) for low skill levels (about -0.016), before becoming positive at about the 15th percentile, and remaining positive for middle and higher skill immigrants. The size of the impact of education peaks at a value of 0.058 in the 60th percentile of immigrant skill before falling to about 0.010 at the 95th percentile.

Robustness

The question next we ask is: How sensitive are the patterns described above slight changes in how we define the dependent variable? What if the education of a native-born construction worker poorly reflects the education of an immigrant construction worker? Are the marginal effects and trends described in this section still valid? To answer this, we converted the constructed education variable into a categorical variable with five different skill groups. These five skill categories are: (1) 11 or fewer constructed years of education; (2) between 11 and 13 constructed years of education; (3) between 13 and 15 constructed years of education; (4) between 15 and 17 constructed years of education, and; (5) more than 17 years of constructed education. The result is a variable that assigns individuals into broad skill classifications that mostly reflect their occupational selection.[9] Across the bottom row of Table 5 we report the number of immigrants who fall into each of the skill groups below each group's marginal effects coefficients.

Categorizing the estimated skill will sort them mostly on the basis of occupation and make the results less sensitive to small discrepancies in education levels across immigrants from different countries or the choice of conditioning variables used in its construction. Since we control for most other attributes, the only reason this approach should be a problem would be if the ordering of occupations on the basis of skill differed greatly across countries. In other words, the fact that German and Chinese engineers and construction workers have different absolute

[9] We could have simply subjectively assigned each occupation as "skilled" or "unskilled" and run a logit regression. In fact, this was one of our first experiments. The results were similar to those obtained from performing OLS on the constructed years of education.

levels of education would not necessarily pose a problem, as long as engineers and construction workers are ranked similarly relative to other occupations in each country.

The coefficients in column (1) of Table 5 are the coefficients of the ordered probit regression using this measure categorical skill as the dependent variable. Comparing these results to column (3) of Table 3, there do not seem to be any differences that would seem to invalidate the basic conclusions from the OLS in terms of signs or significance levels. Columns (2) through (6) of Table 5 show the marginal effects of these variables throughout the distribution. In these columns the signs of the marginal effects are expected to vary some from the coefficients obtained in the quantile regression because the probabilities must sum to one (and therefore each set of marginal effects must sum to zero). Looking across the rows for corruption, distance, and educational attainment, the marginal effects follow similar patterns to those plotted in Figures 1 through 4. This suggests that measurement errors and bias introduced by the construction of the variable we use for immigrants' education are unlikely to be having extreme consequences for the qualitative nature of our results.

VI. CONCLUSION

In the Mundell and Borjas-Roy models of immigration, higher skill endowments in the immigrants' country of origin lead to higher education levels for immigrants and even positive selection. Our results support the hypothesis that higher attainment rates produce a higher quality of immigrants, but this effect is not strong enough to support positive selection relative to the average non-migrant. This affirms the interpretation of the data offered by Jasso and Rosenzweig (1990). On the other hand, the human capital model advocated in Chiswick (2000) suggests that moving costs play a more prominent role and that positive selection is the most likely outcome of migration. Our results are more consistent with these predictions. Moving costs such as distance, language, and colonial history *did* play an important role. Finally, our results offer strong support for the role of institutions in the quality of immigrants in a way that is consistent with models of brain drain and discrimination.

More importantly, this paper raises some new and important questions for the direction of research in the area. First, immigration policy and human capital investment choices may both play roles in explaining why negative self-selection is so unlikely. Introducing these factors as part of the decision sequence may shed light on the results we have found. Yet another question concerns welfare and income distribution for natives in the receiving country. While it is often presumed that stricter immigration quotas will foster positive selection and would therefore benefit natives more, the case for this is not clear cut, and the potential impacts of these policy choices on selection need to be investigated carefully. A third issue concerns welfare and development in poor countries, and the problem of brain drain. We have found evidence that immigrants from poorer countries are well-educated relative to those who do not migrate and this selection bias is magnified by poor institutions and low rates of overall educational attainment in those countries. This may pose an obstacle to development in these countries.

Our results generally agree with Polgreen and Simpson (2006), who show that much of the difference in the education of immigrants can be explained by changes in the countries of origin from which immigrants have come over time. We advance the literature by describing what some of those country characteristics are.

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TABLE 1

Summary Statistics for Education of Immigrants by Country of Origin

Region	Immigrants' Countries of Origin	Number of Immigrants	Constructed Immigrants' Years of Education				Country of Origin Ave. Education	
			Mean	S.D.	Min	Max	1960	2000
Afr.	Algeria	2,019	14.12	2.15	9.17	18.73	0.97	4.72
Afr.	Botswana	37	14.18	1.92	10.96	18.16	1.46	5.35
Afr.	Cameroon	1,429	13.82	2.11	9.76	18.72	1.37	3.17
Afr.	Congo	53	14.13	1.94	11.16	18.48	1.93	4.68
Afr.	Egypt	16,167	14.39	2.24	9.15	19.52	1.32	5.05
Afr.	Gambia	463	12.72	1.62	9.59	18.43	0.50	1.86
Afr.	Ghana	10,466	12.96	1.94	9.40	19.08	0.69	4.01
Afr.	Kenya	4,211	13.85	1.97	9.70	18.66	1.20	3.99
Afr.	Liberia	4,079	12.99	1.98	9.12	19.08	0.56	2.26
Afr.	Malawi	214	13.98	2.10	10.62	18.62	1.70	2.58
Afr.	Mali	295	12.56	1.65	10.57	18.48	0.17	0.76
Afr.	Mozambique	245	12.89	1.77	10.46	18.61	0.26	1.19
Afr.	Niger	602	13.63	2.23	9.52	18.56	0.20	.
Afr.	Senegal	1,173	12.83	1.69	9.47	18.42	1.60	2.23
Afr.	Sierra Leone	3,425	13.07	1.86	9.30	18.73	0.53	1.99
Afr.	South Africa	8,928	14.36	1.84	9.50	18.75	4.08	7.87
Afr.	Sudan	3,439	12.92	2.12	9.45	18.93	0.29	1.91
Afr.	Togo	316	12.94	1.95	10.32	18.57	0.32	2.83
Afr.	Tunisia	920	13.92	1.98	9.77	18.93	0.54	4.20
Afr.	Uganda	1,812	13.78	2.02	9.60	18.64	1.10	2.95
Afr.	Zaire	844	13.12	2.02	9.77	18.50	0.56	3.18
Afr.	Zambia	693	14.32	1.80	10.40	18.55	1.60	5.43
Afr.	Zimbabwe	1,237	14.22	1.77	10.08	18.83	1.54	4.88
Asia	Bahrain	144	14.55	1.78	11.00	18.55	1.37	6.09
Asia	Cyprus	889	13.95	2.04	9.66	18.65	4.29	8.77
Asia	Hong Kong	33,212	13.70	1.66	9.57	19.43	4.74	9.47
Asia	India	110,804	14.33	2.33	8.73	19.92	1.45	4.77
Asia	Indonesia	6,260	13.80	1.84	9.57	19.18	1.11	4.71
Asia	Iran	38,431	13.54	2.11	8.93	19.57	0.63	4.66
Asia	Israel	11,945	13.94	2.00	9.48	19.18	6.99	9.23
Asia	Japan	19,689	13.58	1.69	9.54	19.33	6.87	9.72
Asia	Jordan	10,704	13.21	2.08	9.04	18.98	1.40	7.37
Asia	Korea	41,355	13.60	2.17	9.09	19.67	3.23	10.46
Asia	Kuwait	918	13.84	1.89	10.80	18.46	2.59	7.05
Asia	Malaysia	7,065	14.00	1.85	9.84	18.70	2.34	7.88
Asia	Pakistan	25,114	13.82	2.44	8.97	19.72	0.63	2.45
Asia	Philippines	178,353	13.19	2.15	8.69	19.47	3.77	7.62
Asia	Singapore	2,253	14.27	1.72	9.80	20.03	3.14	8.12
Asia	Sri Lanka	4,477	14.20	2.11	9.85	18.98	3.43	6.09
Asia	Syria	7,313	13.84	2.53	9.33	19.23	0.99	5.74
Asia	Thailand	9,438	12.98	1.73	9.06	18.78	3.45	6.10
Asia	Turkey	9,142	13.55	2.11	8.95	19.53	2.00	4.80

E. Eur.	Bulgaria	5,097	13.76	2.24	9.77	18.98	6.08	9.74
E. Eur.	Former USSR	24,784	12.83	2.02	8.66	19.08	7.59	10.49
E. Eur.	Hungary	4,713	13.32	2.20	9.11	19.47	6.65	8.81
E. Eur.	Malta	279	13.36	1.90	10.27	18.56	5.64	7.57
E. Eur.	Poland	80,642	12.84	2.01	9.00	19.33	6.74	9.90
E. Eur.	Romania	18,677	12.95	2.16	8.86	19.28	5.33	9.51
E. Eur.	Yugoslavia	8,047	13.09	2.23	8.94	19.08	5.08	7.48
N. Am.	Canada	55,629	14.01	1.83	9.15	19.42	8.37	11.43
N. Am.	Costa Rica	3,930	12.46	1.86	9.04	18.57	3.86	6.01
N. Am.	Dominican Republic	98,132	12.15	1.82	8.54	19.18	2.38	5.17
N. Am.	El Salvador	62,989	11.56	0.91	8.91	18.59	1.70	4.50
N. Am.	Guatemala	23,747	11.80	1.43	8.84	19.03	1.43	3.12
N. Am.	Haiti	28,665	12.07	1.80	8.58	19.87	0.70	2.67
N. Am.	Honduras	17,960	11.94	1.55	9.00	19.28	1.69	4.08
N. Am.	Jamaica	68,728	12.08	1.54	8.61	18.87	2.46	5.22
N. Am.	Mexico	279,495	11.55	1.08	8.50	18.72	2.41	6.73
N. Am.	Nicaragua	26,714	11.98	1.53	8.81	18.73	2.09	4.42
N. Am.	Panama	6,887	13.04	1.86	9.02	18.93	4.26	7.90
N. Am.	Trinidad & Tobago	19,863	12.56	1.75	8.60	18.83	4.19	7.62
N. Am.	United States	295	14.19	2.09	9.54	19.23	8.66	12.25
Ocean	Australia	8,626	14.03	1.81	9.70	18.98	9.43	10.57
Ocean	New Zealand	3,964	13.81	1.83	9.97	19.42	9.56	11.52
Ocean	Papua New Guinea	51	14.09	1.83	10.97	18.42	1.13	2.39
S. Am.	Argentina	9,471	13.74	2.13	9.02	18.93	4.99	8.49
S. Am.	Bolivia	4,846	12.55	1.88	9.18	19.42	4.22	5.54
S. Am.	Brazil	13,800	13.27	2.02	9.42	19.03	2.83	4.56
S. Am.	Chile	5,812	13.03	2.01	8.96	19.33	4.99	7.89
S. Am.	Colombia	38,349	11.98	1.85	9.04	19.62	2.97	5.01
S. Am.	Ecuador	21,202	12.29	1.70	8.88	18.72	2.95	6.52
S. Am.	Guyana	26,979	12.32	1.75	8.98	19.13	3.50	6.05
S. Am.	Paraguay	1,017	12.52	1.89	9.67	18.60	3.35	5.74
S. Am.	Peru	32,367	12.41	1.85	8.54	19.57	3.02	7.33
S. Am.	Uruguay	2,236	12.77	1.97	9.62	18.78	5.03	7.25
S. Am.	Venezuela	7,159	13.77	2.04	9.34	19.28	2.53	5.61
W Eur.	Austria	2,199	13.75	1.86	9.20	19.28	6.71	8.80
W Eur.	Belgium	2,342	14.27	1.88	9.65	19.47	7.46	8.73
W Eur.	Denmark	2,718	13.82	1.77	9.43	18.70	8.95	10.09
W Eur.	Finland	1,889	13.86	1.82	9.46	18.88	5.37	10.14
W Eur.	France	10,837	13.90	1.79	9.54	19.23	5.78	8.37
W Eur.	Germany	23,226	13.55	1.82	8.99	19.08	8.40	9.75
W Eur.	Greece	5,659	13.29	2.24	9.29	19.57	4.64	8.51
W Eur.	Iceland	557	14.03	2.05	10.23	18.51	5.63	8.75
W Eur.	Ireland	51,564	13.03	1.73	9.27	18.83	6.45	9.02
W Eur.	Italy	9,108	13.22	2.04	8.69	18.98	4.56	7.00
W Eur.	Netherlands	5,857	14.04	1.82	9.64	19.03	5.27	9.24
W Eur.	Norway	1,989	13.85	1.73	9.89	18.68	6.11	11.86
W Eur.	Portugal	10,161	11.82	1.28	9.07	19.40	1.94	4.91
W Eur.	Spain	5,174	13.74	2.14	8.77	19.23	3.64	7.25
W Eur.	Switzerland	4,014	14.04	1.83	9.46	18.59	7.30	10.39

TABLE 2
Summary Statistics for Explanatory Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
New Immigrants	0.657	0.475		
Asia Region	0.299	0.458		
Regions				
East Europe	0.082	0.275		
West Europe	0.080	0.271		
Africa	0.036	0.187		
Oceania	0.007	0.085		
South America	0.094	0.292		
Visa Classes				
Family	0.658	0.474		
Employment	0.141	0.348		
Immigration Reform and Control Act (IRCA) Amnesty	0.017	0.128		
"Other" Visa Classes	0.055	0.229		
Diversity	0.064	0.245		
Country of Origin Characteristics				
ln(Population)	17.180	1.601	12.429	20.688
ln(Population in 1960)	8.714	1.594	4.078	12.133
ln(GDP per capita)	7.834	1.202	3.799	10.519
Corruption Index	0.556	0.201	0.000	1.000
ln(Average Education)	1.733	0.407	-0.868	2.500
ln(Average Education in 1960)	1.030	0.675	-1.772	2.258
English-Speaking Country of Origin	0.781	0.413	0.000	1.000
Shared Colonial History (with U.S.)	0.112	0.316	0.000	1.000
Distance from U.S. (miles)	7,160	4,240	1,850	1,550
Number of Observations	1,729,019			

TABLE 3

OLS Results (Dependent Variable = ln[Constructed Immigrant Education]).[b]

Variable	(1)	(2)	(3)	(4)
Constant	-98.913** (5.558)	-85.456** (5.500)	-135.753** (5.507)	2.638** (0.050)
New Immigrants	-0.023** (0.000)	-0.023** (0.000)	-0.022** (0.000)	-0.022** (0.000)
Year	3.244** (0.180)	2.823** (0.178)	4.479** (0.178)	
$Year^2$	-0.035** (0.002)	-0.030** (0.002)	-0.048** (0.002)	6.30e-5** (0.000)
$Year^3$	1.22e-4** (0.000)	1.06e-4** (0.000)	1.73e-4** (0.000)	-5.68e-7** (0.000)
Asia	0.105** (0.000)	0.107** (0.000)	0.035** (0.001)	0.034** (0.001)
East Europe	0.068** (0.000)	0.001 (0.001)	-0.080** (0.001)	-0.080** (0.001)
West Europe	0.088** (0.000)	0.024** (0.001)	-0.031** (0.001)	-0.030** (0.001)
Africa	0.119** (0.001)	0.123** (0.001)	0.057** (0.001)	0.057** (0.001)
Oceania	0.124** (0.001)	0.083** (0.001)	-0.004 * (0.002)	-0.005 * (0.002)
South America	0.030** (0.000)	0.028** (0.000)	0.000 (0.001)	-0.001 (0.001)
Employment	0.125** (0.001)	0.111** (0.001)	0.117** (0.001)	0.116** (0.001)
Family	0.036** (0.000)	0.030** (0.000)	0.040** (0.000)	0.039** (0.000)
Other	0.064** (0.001)	0.057** (0.001)	0.068** (0.001)	0.068** (0.001)
Diversity	0.058** (0.001)	0.049** (0.001)	0.060** (0.001)	0.058** (0.001)
IRCA Amnesty	0.008** (0.001)	0.007** (0.001)	0.024** (0.001)	0.023** (0.001)
ln(Population in 1960)		0.077** (0.000)	0.072** (0.001)	0.072** (0.001)
ln(Population)		-0.074** (0.000)	-0.067** (0.001)	-0.067** (0.001)
ln(GDP per capita)		-0.002** (0.000)	-0.016** (0.000)	-0.016** (0.000)
English-Speaking		0.006** (0.000)	0.001** (0.000)	0.001** (0.000)
Shared Colonial History		-0.021** (0.000)	-0.023** (0.001)	-0.024** (0.001)
Corruption Index			0.115** (0.001)	0.113** (0.001)
ln(Distance from U.S.)			0.037** (0.001)	0.038** (0.001)
ln(Ave. Education in 1960)			-0.007** (0.001)	-0.007** (0.001)
ln(Average Education)			0.029** (0.001)	0.030** (0.001)
Adjusted R^2	0.188	0.205	0.216	0.216
Log-Likelihood	983,594	1,002,141	1,014,200	1,013,884
Akaike Info Criterion				

[b] Standard errors in parentheses. * Indicates significance at the 10% level. ** Indicates significance at the 1% level.

TABLE 4

Selected Quantile Regression Results (Dependent Variable = ln[Immigrants' Education]), Unrestricted Model.[b]

Variable	0.05		0.25		0.50		0.75		0.95	
Constant	1.412**	(0.055))	1.715**	(0.032)	2.564**	(0.037)	4.734**	(0.044)	4.609**	(0.116)
New Immigrants	-0.028**	(0.000)	-0.026**	(0.000)	-0.022**	(0.000)	-0.013**	(0.000)	0.007**	(0.001)
$Year^2$	3.84e-4**	(0.000)	3.27e-4**	(0.000)	1.09e-4**	(0.000)	-4.54e-4**	(0.000)	-4.52e-4**	(0.000)
$Year^3$	-2.85e-6**	(0.000)	-2.46e-6**	(0.000)	-8.68e-7**	(0.000)	3.16e-6**	(0.000)	3.20e-6**	(0.000)
Asia	0.022**	(0.001)	0.025**	(0.001)	0.055**	(0.001)	0.097**	(0.001)	0.047**	(0.003)
East Europe	-0.023**	(0.001)	-0.078**	(0.001)	-0.116**	(0.001)	-0.063**	(0.001)	-0.049**	(0.003)
West Europe	0.003**	(0.001)	-0.036**	(0.001)	-0.034**	(0.001)	-0.008**	(0.001)	-0.049**	(0.002)
Africa	0.065**	(0.002)	0.051**	(0.001)	0.068**	(0.001)	0.120**	(0.001)	0.049**	(0.003)
Oceania	0.023**	(0.002)	0.010**	(0.001)	0.006**	(0.001)	0.027**	(0.002)	-0.031**	(0.004)
South America	0.000	(0.001)	-0.019**	(0.000)	-0.021**	(0.000)	0.051**	(0.001)	0.051**	(0.002)
Family	0.004**	(0.001)	0.024**	(0.000)	0.043**	(0.000)	0.033**	(0.000)	0.045**	(0.001)
Employment	0.042**	(0.001)	0.087**	(0.000)	0.150**	(0.000)	0.106**	(0.000)	0.082**	(0.001)
IRCA Amnesty	0.024**	(0.001)	0.027**	(0.001)	0.049**	(0.001)	0.015**	(0.001)	-0.090**	(0.002)
Other	0.001	(0.001)	0.024**	(0.000)	0.082**	(0.000)	0.068**	(0.001)	0.035**	(0.002)
Diversity	0.030**	(0.001)	0.037**	(0.000)	0.069**	(0.000)	0.052**	(0.001)	0.031**	(0.002)
ln(Population in 1960)	0.019**	(0.001)	0.047**	(0.000)	0.085**	(0.000)	0.116**	(0.000)	0.111**	(0.001)
ln(Population)	-0.020**	(0.001)	-0.043**	(0.000)	-0.077**	(0.000)	-0.115**	(0.000)	-0.110**	(0.001)
ln(GDP-per capita)	0.007**	(0.000)	-0.003**	(0.000)	-0.020**	(0.000)	-0.031**	(0.000)	-0.018**	(0.001)
English-Speaking	-0.002**	(0.000)	0.002**	(0.000)	0.009**	(0.000)	-0.009**	(0.000)	0.004**	(0.001)
Colonial History	-0.030**	(0.001)	-0.048**	(0.000)	-0.015**	(0.000)	-0.007**	(0.000)	-0.023**	(0.001)
ln(Distance from US)	0.004**	(0.001)	0.019**	(0.001)	0.031**	(0.001)	0.027**	(0.001)	0.052**	(0.002)
Corruption Index	0.024**	(0.001)	0.055**	(0.001)	0.108**	(0.001)	0.165**	(0.001)	0.169**	(0.002)
ln(Education in 1960)	0.011**	(0.001)	0.009**	(0.000)	-0.007**	(0.000)	-0.013**	(0.000)	-0.036**	(0.001)
ln(Ave. Education)	-0.012**	(0.001)	0.009**	(0.001)	0.041**	(0.001)	0.051**	(0.001)	0.010**	(0.002)
Pseudo-R^2	0.058		0.061		0.177		0.180		0.084	

[b] Standard errors in parentheses. * Indicates significance from zero at the 10% level. ** Indicates significance from zero at the 1% level.

TABLE 5

Ordered Probit Results (Dependent Variable = Skill Category)[b]

	(1)		(2)	(3)	(4)	(5)	(6)
					Marginal Effects		
			1	2	3	4	5
Year^2	5.82e-4**	(0.000)	-1.24e-4	-9.05e-5	9.13e-5	9.30e-5	3.06e-5
Year^3	-5.12e-6**	(0.000)	1.09e-6	7.96e-7	-8.03e-7	-8.18e-7	-2.69e-7
New Immigrants	-0.181**	(0.002)	0.037	0.030	-0.028	-0.030	-0.010
Asia	0.226**	(0.010)	-0.046	-0.039	0.034	0.037	0.013
East Europe	-0.491**	(0.009)	0.129	0.034	-0.081	-0.064	-0.017
West Europe	-0.190**	(0.008)	0.044	0.023	-0.031	-0.028	-0.009
Africa	0.392**	(0.010)	-0.068	-0.084	0.052	0.071	0.030
Oceania	-0.029 *	(0.014)	0.006	0.004	-0.005	-0.005	-0.001
South America	-0.002	(0.005)	0.000	0.000	0.000	0.000	0.000
Family	0.269**	(0.004)	-0.060	-0.037	0.043	0.041	0.013
Employment	0.832**	(0.004)	-0.125	-0.196	0.087	0.154	0.080
Other	0.448**	(0.005)	-0.076	-0.098	0.057	0.081	0.035
Diversity	0.434**	(0.005)	-0.074	-0.094	0.056	0.078	0.033
IRCA Amnesty	0.122**	(0.008)	-0.024	-0.022	0.018	0.020	0.007
ln(Population)	-0.458**	(0.004)	0.098	0.071	-0.072	-0.073	-0.024
ln(Population in 1960)	0.484**	(0.004)	-0.104	-0.075	0.076	0.077	0.025
ln(GDP per capita)	-0.097**	(0.002)	0.021	0.015	-0.015	-0.016	-0.005
English	0.012**	(0.003)	-0.003	-0.002	0.002	0.002	0.001
Colonial History	-0.186**	(0.004)	0.043	0.024	-0.030	-0.028	-0.008
ln(Distance from US)	0.269**	(0.006)	-0.058	-0.042	0.042	0.043	0.014
Corruption Index	0.790**	(0.007)	-0.169	-0.123	0.124	0.126	0.042
ln(Ave. Education)	0.184**	(0.006)	-0.039	-0.029	0.029	0.029	0.010
ln(Education in 1960)	-0.081**	(0.004)	0.017	0.013	-0.013	-0.013	-0.004
Constant			0.132	0.520	0.217	0.109	0.022
c_1	-1.360**	(0.396)					
c_2	0.149	(0.396)	0.160	0.479	0.199	0.126	0.036
c_3	0.879 *	(0.396)					
c_4	1.770**	(0.396)					
Pseudo R^2	0.071						
Log-Likelihood	-2,164,953						
LR chi2(23)	332,956						
Number of Observations	1,729,019		275,768	828,234	343,677	218,434	62,906

[b] Standard errors in parentheses. * Indicates significance at the 10% level. ** Indicates significance at the 1% level.

FIGURE 1

Coefficient on Impact of Corruption Index of Immigrants' Country of Origin on the Log of Immigrants' Education vs. Quantile

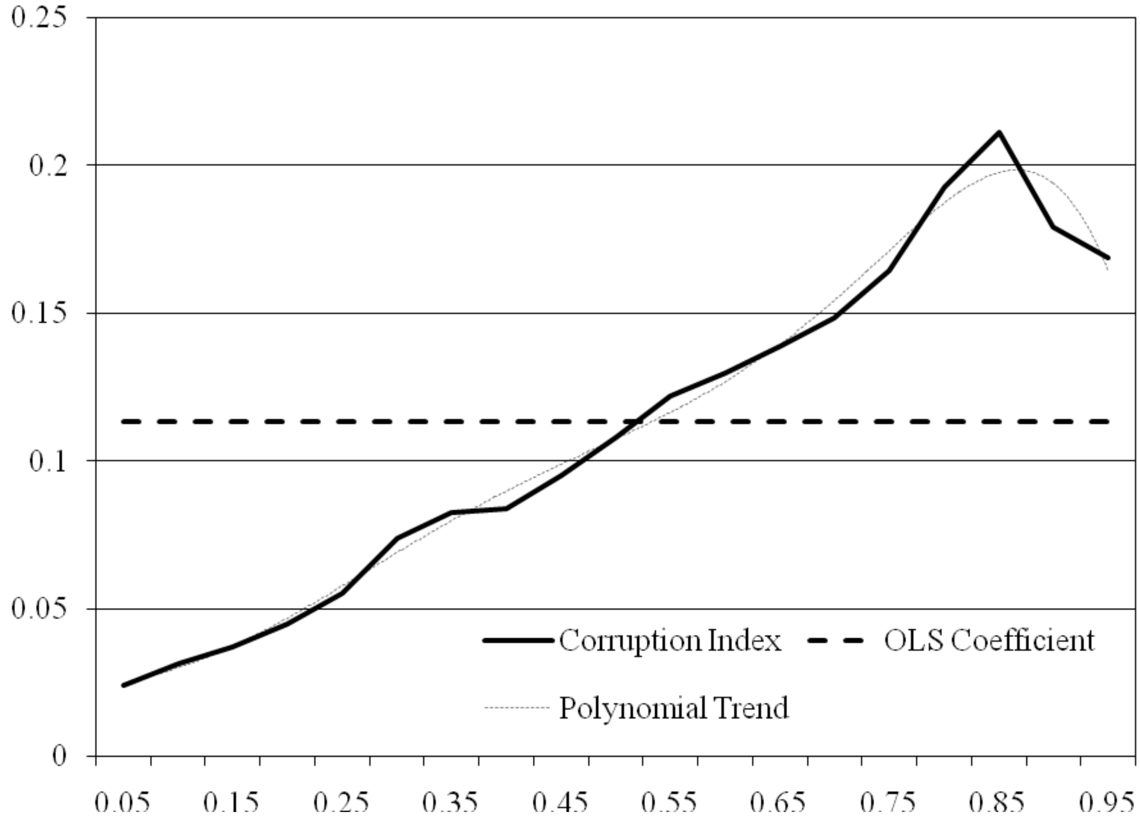

FIGURE 2
Elasticity of Immigrants' Education with Respect to Distance of their Country of Origin from the U.S. vs. Quantile

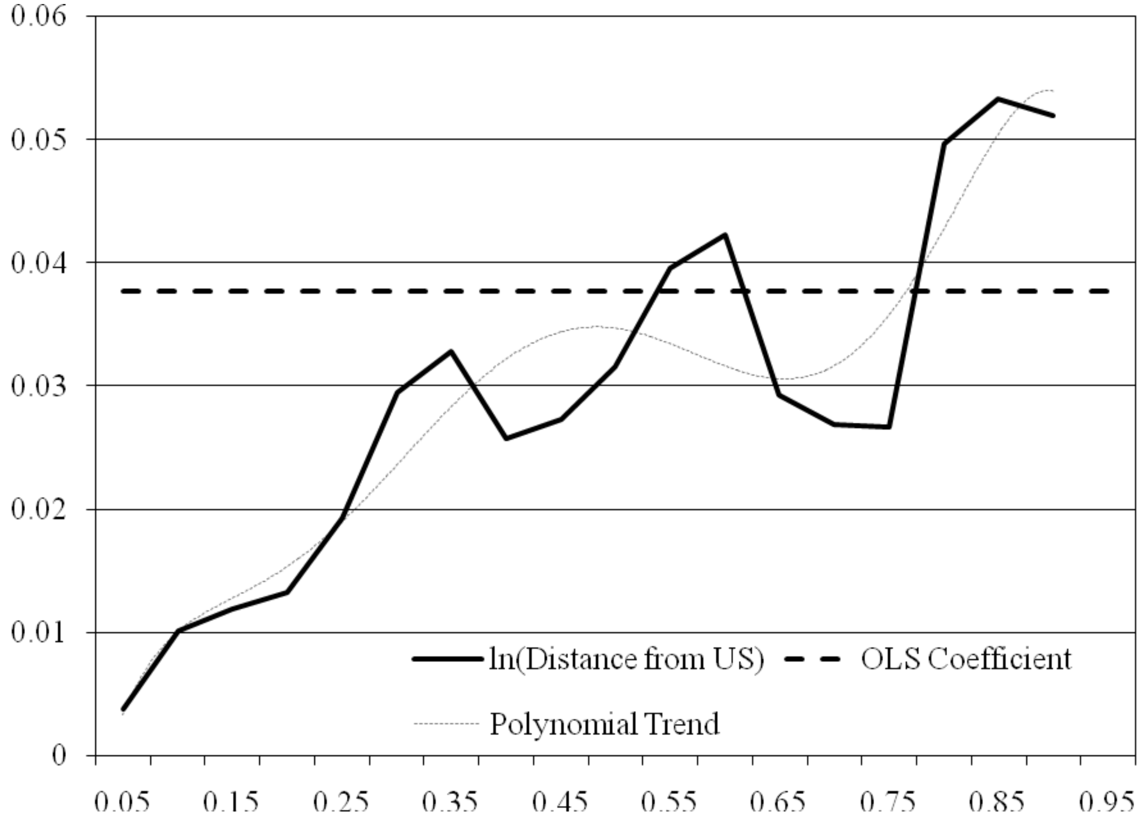

FIGURE 3

Elasticity of Immigrants' Education with Respect to Average Education in their Countries of Origin in 1960 vs. Quantile

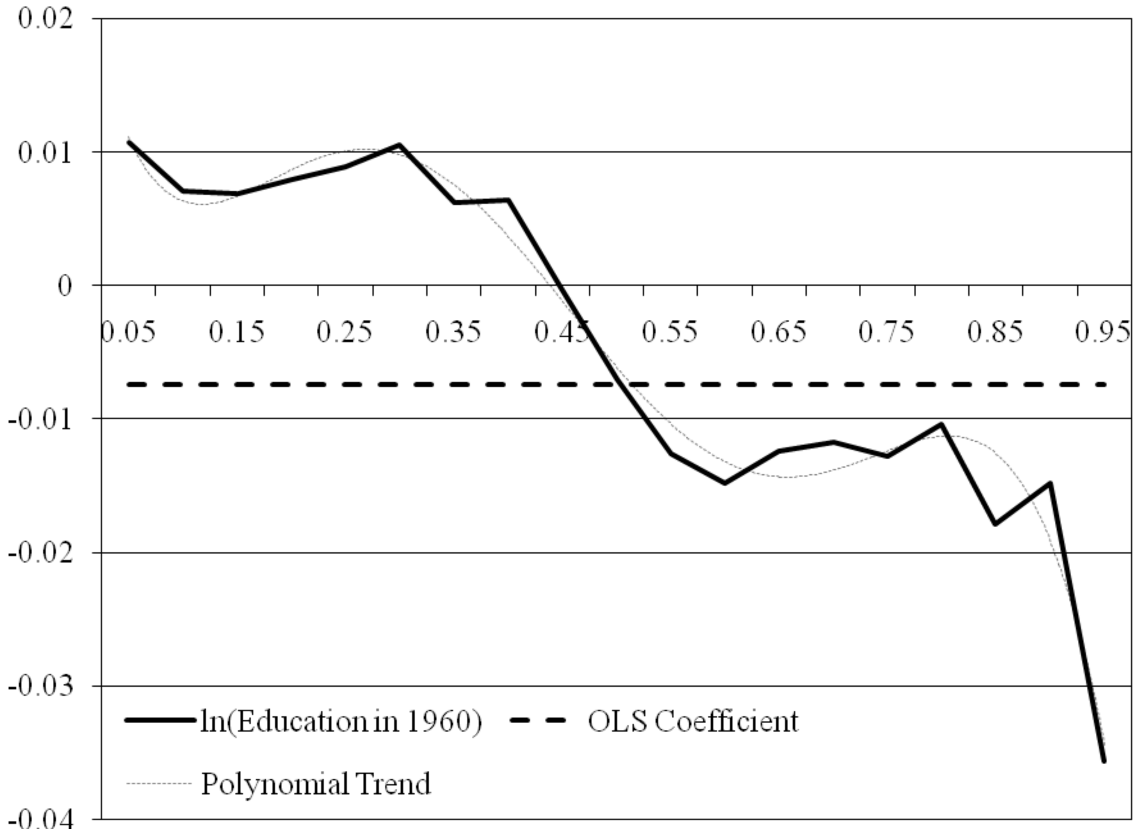

FIGURE 4
Elasticity of Immigrants' Education with Respect to Average Education in their Countries of Origin vs. Quantile