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ABSTRACT

The Effects of School Quality in the Origin on the Payoff to Schooling for Immigrants*

The payoff to schooling among the foreign born in the US is only around one-half of the payoff for the native born. This paper examines whether this differential is related to the quality of the schooling immigrants acquired abroad. The paper uses the Over-education/ Required education/Under-education specification of the earnings equation to explore the transmission mechanism for the origin-country school quality effects. It also assesses the empirical merits of two alternative measures of the quality of schooling undertaken abroad. The results suggest that a higher quality of schooling acquired abroad is associated with a higher payoff to schooling among immigrants in the US labor market. This higher payoff is associated with a higher payoff to correctly matched schooling in the US, and a greater (in absolute value) penalty associated with years of under-education. A set of predictions is presented to assess the relative importance of these channels, and the over-education channel is shown to be the more influential factor. This channel is linked to greater positive selection in migration among those from countries with better quality school. In other words, it is the impact of origin country school quality on the immigrant selection process, rather than the quality of immigrants' schooling per se, that is the major driver of the lower payoff to schooling among immigrants in the US.

JEL Classification: I21, J24, J31, J61, F22

Keywords: immigrants, schooling, school quality, earnings, selectivity

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THE EFFECTS OF SCHOOL QUALITY IN THE ORIGIN ON THE PAYOFF TO SCHOOLING FOR IMMIGRANTS

I. INTRODUCTION

Studies of immigrant economic adjustment have placed considerable emphasis on the less-than-perfect international transferability of immigrants' human capital. Starting with Chiswick (1978), this has been linked to the lower payoff to schooling for immigrants than for the native born. Chiswick (1978, p.919) concluded:

> The smaller partial effect of schooling on earnings in the United States is an important finding.. …The smaller effect of preimmigration schooling may be "explained" by country-specific aspects of the knowledge acquired in school, by a lower quality of foreign schooling, or by the poorer information it provides employers who use schooling as a screen….The weaker partial effect of schooling may in part reflect self-selection in migration in which only the most able and most highly motivated of those with little schooling migrate, while those with (or who subsequently acquire) higher levels of schooling came from a broader ability and motivation spectrum.

Empirical assessment of this important finding has proceeded along a number of lines. Chiswick and Miller (2008) use insights from the over-education/required education/under-education literature (Hartog, 2000) to assess the possible contribution of self-selection in migration and the less-than-perfect international transferability of immigrants' human capital. This is done indirectly, through linking these two aspects of the immigrant adjustment process to the patterns observed in the payoffs to over-education and under-education. They (2008, p.1339) argue: “The analysis also suggests that the two related issues of selectivity in migration and the international transferability of skills are both relevant, but their relative importance will vary by country of origin and educational attainment”.

Bratsberg and Terrell (2002) and Betts and Lofstrom (2000) provide direct evidence on the effect that characteristics of the immigrants’ country of origin might have on the payoff to schooling in the US. Bratsberg and Terrell (2002) link the payoff to schooling that the foreign born receive in the US to measures of the resources devoted to education (namely, the pupil-teacher ratio and relative expenditure per pupil in immigrants’ country of origin), a measure of the commitment to education (namely, years of compulsory education in the country of origin), and a number of other variables that cover differences in the transferability of immigrants’ schooling to the US labor market (*e.g.*, English as an official language in the origin labor market). They report (p.193):

> that differences in the attributes of educational systems account for most of the variation in rates of return to education earned by immigrants applying their source-country education in the U.S. labor market. We find a particularly robust inverse relationship between the rate of return to education and the pupil-teacher ratio in primary schools in the source country, and similarly robust direct relationships between the rate of return and relative teacher wages and expenditures per pupil in the source country.

Similar analyses by Betts and Lofstrom (2000, p.102) led them to conclude:

> …the characteristics of the source country affect immigrants' earnings substantially. Reductions in the pupil-teacher ratio and increases in the average level of educational attainment increase earnings of immigrants significantly, but only for the most highly educated workers….GDP per capita affects earnings positively for all immigrants, although it is the least well educated immigrants for whom the effect is the largest.

Sweetman (2004) extends this latter line of inquiry by focusing on an outcome measure, test scores from international standardized tests, rather than on input variables from the education production function. Thus, in his analysis of immigrant earnings in Canada, Sweetman relates the birthplace differences in the payoff to schooling to differences in the country-level average test scores compiled by Hanushek and Kimko (2000). Sweetman (2004) reports that the country of origin differences in the payoff to schooling are related to this measure of school quality, although the R^2s in the country-level regressions (of less than 0.2) were much lower than those reported by Bratsberg and Terrell (2002) where multiple input variables were used (of up to 0.84).[1]

In this paper we merge the approaches of Chiswick and Miller (2008) and Sweetman (2004). Thus we quantify birthplace differences in the payoff to schooling in the US using both conventional and Over-education/Required education/Under-education (ORU) models of earnings determination. These birthplace differentials are then related to measures of the quality of the immigrant source country human capital provided by the OECD Programme for International Student Assessment (or PISA) and the Hanushek and

[1] Hanushek and Kimko (2000) impute the majority of their country scores using educational input variables, and hence utilizing both the country-level average test scores and input variables in a single estimating equation has little merit.

Kimko (2000) data previously used by Sweetman (2004) in his analysis of immigrants' earnings in Canada.[2]

The structure of this paper is as follows. Section II provides a brief account of the methods that are employed in the statistical analysis. Section III reviews the PISA and Hanushek and Kimko (2000) data. Empirical findings are presented in Section IV. A summary and conclusion are provided in Section V.

II. METHODOLOGY

Analyses of the birthplace differentials in the payoff to schooling have estimated both the conventional schooling and experience earnings equation and the Over-education/Required Education/Under-education (or ORU) earnings equation. The conventional earnings equation relates the natural logarithm of a measure of earnings (hourly, weekly, annual) to years of schooling (EDUC), years of labor market experience (EXP) and its square, and other variables that are generally held to affect earnings, such as marital status, official language skills and location and, among the foreign born, years since migration and citizenship. That is:

$$\ln \mathrm{Y_i} = \beta_0 + \beta_1 \mathrm{EDUC}_i + ... + \nu_i \quad . \tag{1}$$

The ORU modification of this earnings equation disaggregates the measure of years of schooling into three terms, namely a term for the years of education which are usual or standard in the worker's occupation, a term for any years of over-education possessed by the worker, and a term for any years of under-education. These terms for

[2] This relates standardized partial effects of education to standardized test scores. The partial effects of education are standardized in the sense noted by Bratsberg and Terrell (2002, p.179) "because the index is constructed on the basis of returns to education in a single market economy, it supplies a productivity-based estimate of the quality of educational institutions in foreign countries".

years of over- and under-education are measured relative to the central tendency for education in the respondent's occupation, which is what is referred to in the literature as the required, usual or standard level of schooling. For simplicity, occupation is treated as exogenous. Specifically,

$$\ln \mathrm{Y_i} = \alpha_0 + \alpha_1 \mathbf{O}\mathrm{ver\_Educ}_i + \alpha_2 \mathbf{R}\mathrm{eq\_Educ}_i + \alpha_3 \mathbf{U}\mathrm{nder\_Educ}_i + ... + u_i \quad (2)$$

where **O**ver_Educ = years of surplus or over-education,

Req_Educ = the usual or reference years of education,

Under_Educ = years of deficit or under-education, and

EDUC = **O**ver_Educ + **R**eq_Educ **–** **U**nder_Educ.

Note that for each individual, "**O**ver_Educ" and "**U**nder_Educ" cannot both be positive.[3] Either one or both must be zero. There are various ways of compiling a measure of "Req_Educ" (see Hartog, 2000; Chiswick and Miller, 2008). The measure used below is the modal educational attainment of workers in each of the approximately 500 occupations identified in the 2000 US Census.

When equations (1) and (2) are estimated on separate samples of the native born and foreign born, considerable interest had been focused on differences by nativity in the estimates of the payoff to schooling and the coefficients of the ORU variables. For the simple foreign-born/native-born dichotomy, the payoff to actual years of schooling for the foreign born is usually much less than the payoff to actual years of schooling for the native born. For example, in analyses of 2000 US Census data, Chiswick and Miller

[3] It will be apparent that the standard earnings equation in (1), $\ln \mathrm{Y}_i = \beta_0 + \beta_1 \mathrm{EDUC_i} + ... + \upsilon_i$, forces $\alpha_1 = \alpha_2 = |\alpha_3|$. As this condition does not hold, the ORU specification results in a higher R-squared and $\alpha_2 > \beta_1$.

(2008) report that the payoff to schooling for the native born was 10.6 percent, while that for the foreign born was only 5.2 percent. They also show that this payoff varies appreciably by country of origin, being relatively high for immigrants from developed, English-speaking countries, and relatively low for immigrants from less developed, non-English-speaking countries. For example, the payoff to schooling was just 1.8 percent for immigrants from Mexico, 4.3 percent for immigrants from Cuba as well as those from Eastern Europe, but as high as 11 percent for immigrants from Canada. Chiswick and Miller (2008) also report that the payoffs to the ORU variables, though particularly the earnings effects of the under-education and over-education variables, also vary by country of origin. In the analyses that follow, these variations are linked to direct measures of the quality of schooling in the immigrants' country of origin provided by the PISA and Hanushek and Kimko (2000) data.

The country-level information on the quality of schooling is incorporated into the study of immigrants' earnings using Card and Krueger's (1992) two-step approach. This involves augmenting the usual regression model with birthplace-schooling interaction terms, and then relating the estimated birthplace differentials in the payoff to schooling to the PISA scores and Hanushek and Kimko's (2000) human capital quality index in a second step or supplementary regression. The supplementary regressions may contain other country-level information, such as GDP per capital. This approach can be represented by two equations (for simplicity only the conventional schooling earnings equation and the PISA scores are considered here), namely:

$$\ln \mathrm{Y_i} = \beta_0 + \sum_{j=1}^{J} \left[\beta_{1j} (\mathrm{I}_j * \mathrm{EDUC}_{ij}) \right] + ... + \nu_i \qquad \mathrm{i} = 1, \ldots, \mathrm{n} \qquad (3a)$$

$$\beta_{1j} = \alpha_0 + \alpha_1 \mathrm{PISA_j} + ... + \eta_j \qquad \mathrm{j} = 1, \ldots, \mathrm{J} \qquad (3b)$$

where I_j is a vector of dichotomous variables with a value of one for each birthplace j, and zero otherwise, and β_{1j} are the separate birthplace effects on the payoff to schooling. This model can be generalized through the inclusion of birthplace intercept shifts. That is β_0 can be replaced by $\sum_{j=1}^{J}\left[\beta_{0j} I_j\right]$. The estimates in (3b) can be obtained using weighted least squares, where the weights are given by the sample sizes of workers from each country in the first-step regression, or the inverse of the variances of the slope estimates in the first-step regression.[4] Further details are provided in Section IV.

III. COUNTRY-LEVEL DATA

Two measures of school quality are employed in the analyses that follow. The first is provided by the reading, mathematics and science scores for countries in the PISA. The second is the human capital quality indices compiled by Hanushek and Kimko (2000).

The PISA is an international standardized assessment, coordinated by the OECD, to measure the outcomes of education systems. This assessment mechanism is administered every three years (first conducted in 2000) to 15-year-olds in schools of participating countries. Initially the assessment framework of the PISA covered only performance in reading, mathematics and science.[5] However, problem solving skills,

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[4] The use of weighted least squares in the second step mimics the more formal random parameters model, a single equation representation of which is:
$\ln Y_{ij} = \beta_0 + \alpha_0 EDUC_{ij} + \alpha_1 PISA_j \times EDUC_{ij} ... + \mu_{1j} EDUC_{ij} + \nu_{ij}$. The random parameters model can be estimated using maximum likelihood methods.

[5] The PISA also collects information on a wide range of factors thought to have a bearing on student performance, namely: (i) characteristics of individual students (*e.g.*, their home background, learning approach); (ii) characteristics of schools (*e.g.*, school/classroom atmosphere, school resources); and (iii)

designed to assess cross-curriculum competencies, were also covered in the 2003 survey. The PISA covers both OECD (*e.g.*, France, UK, Australia, USA) and non-OECD (*e.g.*, Brazil, Chile, Peru, Thailand) countries. Further details are available from the PISA web site: www.pisa.oecd.org.

The reading, mathematics and science literacy scores from the 2000 PISA survey form the basis of the main set of analyses presented below. Reading literacy in the PISA is defined as the ability to understand, to use and to reflect on written texts in order to fulfill one's goals, to develop one's knowledge and potential, and to use written information to function or participate effectively in complex modern societies.

Mathematical literacy is defined in the PISA as the capacity to identify, understand and engage in mathematics, as well as to use mathematical knowledge and skills in one's life. These skills incorporate simple calculations, posing and solving mathematical problems in various situations, and being able to take a point of view and appreciate things expressed numerically.

Scientific literacy is defined in the PISA as the capability to use scientific knowledge, to identify questions/issues and to draw evidence-based conclusions in order to understand and help make decisions about the natural world and human interactions with it.

Table 1 lists information on the mean reading, mathematics and science literacy scores by country from the 2000 PISA. This table also includes an average score for the OECD. This score is computed using a simple average of the scores for all OECD countries. These scores have been normalized so that the OECD average is 500.

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characteristics of school systems (*e.g.*, the degree to which individual schools are given autonomy within the education system).

Table 1

Mean PISA Scores, 2000

Country	Reading	Mathematics	Science
Albania	349	381	376
Argentina	418	388	396
Australia	528	533	528
Austria	507	515	519
Belgium	507	520	496
Brazil	396	334	375
Bulgaria	430	430	448
Canada	534	533	529
Chile	410	384	415
Czech Republic	492	498	511
Denmark	497	514	481
Finland	546	536	538
France	505	517	500
Germany	484	490	487
Greece	474	447	461
Hong Kong	525	560	541
Hungary	480	488	496
Iceland	507	514	496
Indonesia	371	367	393
Ireland	527	503	513
Israel	452	433	434
Italy	487	457	478
Japan	522	557	550
Korea	525	547	552
Latvia	458	463	460
Liechtenstein	483	514	476
Luxembourg	441	446	443
FYR Macedonia	373	381	401
Mexico	422	387	422
New Zealand	529	537	528
Norway	505	499	500
Peru	327	292	333
Poland	479	470	483
Portugal	470	454	459
Russian Federation	462	478	460
Spain	493	476	491
Sweden	516	510	512

Switzerland	494	529	496
Thailand	431	432	436
United Kingdom	523	529	532
United States	504	493	499
OECD Average	*500*	*500*	*500*

Source: *Literacy Skills for the World of Tomorrow- Further Results from PISA 2000* (OECD and UNESCO Institute for Statistics).

The mean reading score for the US, at 504, is only slightly above the 500 benchmark average across the OECD countries in the survey. There is considerable variation is the reading scores, with the standard deviation of the scores in Table 1 being 54. The reading literacy scores range from below 400 (Peru has a score of 327, Albania 349, Indonesia 371, Macedonia 373 and Brazil 396) to values over 525 (Finland has a score of 546, Canada 534, New Zealand 529, Australia 528 and Ireland 527). The reading score for Mexico, which is the largest source region for immigrants in the US, is a relatively low 422.

The mathematics literacy score for the US is 493, below the OECD average, while the score for Mexico is 387, which represents a relatively weaker position in mathematics than that reported for reading literacy. The mathematics scores listed in Table 1 are characterized by greater variation than is the case for the reading score: The lowest mathematics score is the 292 for Peru and the highest is Hong Kong's 560. The range in the scores is thus 268 points, compared to the range of 219 points for reading literacy. Brazil also has a relatively low mathematics score (334), as does Indonesia (367). Countries other than Hong Kong with relatively high mathematics scores are Japan (557) and Korea (547). The standard deviation of the PISA mathematics scores across countries is 65, which is somewhat higher than the standard deviation of the PISA reading scores across countries of 54. There is, however, a very high correlation between the reading and mathematics scores, with the Pearson correlation coefficient between the values in Table 1 being 0.95.

The science literacy scores range from Peru's value of 333 through to the 552 for Korea. Other countries with relatively low scores are Brazil (375), Albania (376), Indonesia (393) and Argentina (396). Other countries with relatively high scores are Japan (550), Hong Kong (541), Finland (538), the UK (532), Canada (529), Australia (528) and New Zealand (528). Thus, the range for the science literacy scores is 219, which is the same as for the reading literacy scores. The standard deviation of the science literacy scores in Table 1, at 53, is also similar to that for the reading scores. The science literacy scores are highly correlated with each of the other measures, with pair-wise correlation coefficients of 0.97 in each instance. The science literacy score for the US is 499, close to the OECD average. The science literacy score for Mexico is 422, the same distance from the OECD average as characterized the reading literacy data.

These country data on student performance in reading, mathematics and science are positively correlated with typical indicators of economic progress or educational status. For example, the correlation of the country test scores with GDP per capita is between 0.61 (science) and 0.68 (reading). The correlation of the country test scores with educational expenditure per student is between 0.70 and 0.79, for the subgroup of 29 countries for which the educational expenditure data are available. Note, however, that while these correlation coefficients are quite high, the correlations are far from perfect, suggesting that the average test scores may have information content on the school quality differences across countries that varies from the information in the input variables used in previous studies.[6]

Hanushek and Kimko (2000) base their measure of human capital quality on six international tests of student achievement in mathematics and science undertaken between 1965 and 1991.[7] A total of 26 performance series were collected, and converted to a common scale. Country averages were then obtained for the scores available for each country. Scores for 39 countries were compiled this way. Then, these scores were related to a number of input variables, including the primary school enrolment rate, pupil-teacher ratio in primary school and expenditure on education, and the estimates of this educational quality production function used to infer quality scores for a further 51 countries.[8] The data for Hanushek and Kimko's (2000) preferred human capital quality series are presented in Table 2. This table also contains information on whether the data for a particular country were imputed using the procedure described above.

The mean score on the Hanushek and Kimko (2000) quality index is 45.18. There is considerable variation across countries in the scores. There are scores below 25 and scores above 65, and the standard deviation is 13.25. Countries with scores below 25 are Iran (18.26), Kuwait (22.50), Papua New Guinea (22.58), Bahrain (23.19), Chile (24.74) and Central Africa (24.77). Countries with scores above 65 are Singapore (72.13), Hong

[6] Random measurement error could also result in the correlation coefficients being less than one.

[7] Four of these tests were administered by the International Association for the Evaluation of Educational Achievement and two by the International Assessment of Educational Progress.

[8] Hanushek and Kimko (2000) use the human capital quality variable in cross-country growth regressions. Estimation of models based only on countries with observed human capital quality indicators, and with the broader sample that includes countries where the variable is imputed, led Hanushek and Kimko (2000, p.1196) to conclude "The estimates using this augmented sample confirm the appropriateness of projection to the expanded set of countries". They also compare a number of their imputed scores with evidence from independent tests, and again confirm the appropriateness of the imputation procedure.

Kong (71.85), New Zealand (67.06) and Japan (65.50). Thus the score for the US, at 46.77, is slightly above the overall mean. The score for Mexico, at 37.24, is about one-half of a standard deviation below the mean.

Table 2

Hanushek and Kimko's (2000) Human Capital Quality Index

Country	Imputed Score	Score	Country	Imputed Score	Score
Algeria	✓	28.06	Kenya	✓	29.73
Argentina	✓	48.50	Republic of Korea		58.55
Australia		59.04	Kuwait	✓	22.50
Austria	✓	56.61	Lesotho	✓	51.95
Bahrain	✓	23.19	Luxembourg		44.49
Barbados	✓	59.80	Malaysia	✓	54.29
Belgium		57.08	Malta	✓	57.14
Bolivia	✓	27.47	Mauritius	✓	54.95
Botswana	✓	31.71	Mexico	✓	37.24
Brazil		36.60	Mozambique		27.94
Cameroon	✓	42.36	Netherlands		54.52
Canada		54.58	New Zealand		67.06
Republic of Central Africa	✓	24.77	Nicaragua	✓	27.30
Chile		24.74	Nigeria		38.90
China		64.42	Norway		64.56
Colombia	✓	37.87	Panama	✓	46.78
Congo	✓	50.90	Papua New Guinea	✓	22.58
Costa Rica	✓	46.15	Paraguay	✓	39.96
Cyprus	✓	46.24	Peru	✓	41.18
Denmark	✓	61.76	Philippines		33.54
Dominican Republic	✓	39.34	Poland		64.37
Ecuador	✓	38.99	Portugal		44.22
Egypt	✓	26.43	Singapore		72.13
El Salvador	✓	26.21	South Africa	✓	51.30
Fiji	✓	58.10	Spain		51.92
Finland		59.55	Sri Lanka	✓	42.57
France		56.00	Swaziland		40.26
West Germany		48.68	Sweden		57.43
Ghana	✓	25.58	Switzerland		61.37
Greece	✓	50.88	Syria	✓	30.23
Guyana	✓	51.49	Taiwan		56.31
Honduras	✓	28.59	Thailand		46.26
Hong Kong		71.85	Togo	✓	32.69
Hungary		61.23	Trinidad and Tobago	✓	46.43
Iceland	✓	51.20	Tunisia	✓	40.50
India		20.80	Turkey	✓	39.72
Indonesia	✓	42.99	Uruguay	✓	52.27
Iran		18.26	UK		62.52

Iraq	✓	27.50	USA		46.77
Ireland		50.20	USSR		54.65
Israel		54.46	Venezuela	✓	39.08
Italy		49.41	Yugoslavia	✓	53.97
Jamaica	✓	48.62	Zaire	✓	33.53
Japan		65.50	Zambia	✓	36.61
Jordan		42.28	Zimbabwe	✓	39.64

Source: Hanushek and Kimko (2000), Table C1.

The Hanushek and Kimko (2000) quality index, being based on standardized tests undertaken between 1965 and 1991, appear to have an advantage over the PISA scores for 2000 in that they relate to a period when many of the immigrants in the US labor market in 2000 would have been enrolled in school in their country of origin. The extent of this advantage will depend on the magnitude of the across-country variation in the inter-temporal changes in school quality. Where such variation is modest, the PISA data might be preferred, as these data relate to single tests for a specific age group, whereas the Hanushek and Kimko (2000) data are averages for a number of age groups, test types and years of test assessment.

There are two pieces of evidence that may be advanced on this. First, PISA scores are also available for 2003 and 2006, and one can therefore look at the relatedness of the scores for 2000 and those for these later years, although this is a short time span. Correlation coefficients between the PISA scores for 2000 and 2003/2006 (listed in Table 3) indicate that there is a very high degree of stability in the PISA scores across time, at least for the six years covered in this presentation.

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Table 3

Correlation Coefficients Between 2000 PISA Scores and PISA Scores for 2003 and 2006

Score for 2000	**Score for 2003**	**Score for 2006**
Reading	0.955	0.927
Mathematics	0.979	0.970
Science	0.948	0.943

Note: Correlations based on 29 observations for both the 2000-2003 and 2000-2006 comparisons.

Second, Hanushek and Kimko (2000, Figure 1) present a visual display of test scores for various countries across time, ranging from 1965 to 1991 (a time span of 26 years). This also conveys the clear impression of stability in the relative standing of various countries with respect to student achievement. As Hanushek and Kimko (2000, p.1186) state in relation to their Figure 1:

> The test performance in Figure 1 provides some evidence about the stability (over time) of scores. The United States and United Kingdom participate in all six testing programs. Throughout the period, the United Kingdom consistently performs a little better than the United States. Further, with a few exceptions, countries that outperform either the United States or United Kingdom on one test also tend to do so when they participate in other tests and vice versa.

There is no a priori way of evaluating the relative merits of the two data series, and hence both are used in the analyses below. There are 32 countries for which there are both PISA scores and a value for the Hanushek and Kimko (2000) human capital quality index.[9] The simple correlation coefficients between the Hanushek and Kimko (2000) index (covering 1965 to 1991) and the PISA reading, mathematics and science scores (for 2000) for this group of countries are 0.774, 0.765 and 0.777, respectively. This, like the correlations for the PISA scores for 2000, 2003 and 2006, suggests only modest across-country variation in inter-temporal changes in school quality. In other words, the standardized tests of 15-year-olds in 2000 should provide an extremely useful measure of across-country differences in student achievement as far back as 1965.

To minimize any unintended consequence associated with the use of the contemporary school quality data, they are entered into the second step of the model along with per capita GDP data for each country. These per capita GDP information are defined with respect to 1980. The use of a 20-year lag in this analysis follows Bratsberg and Terrell (2002. p.182) who argue "We lag the educational quality data by 20 years to better capture differences in school quality at the time immigrants undertook their schooling…".[10] The changes in the estimated effects of the PISA variables as the per capita GDP data are included in the model will inform on whether the contemporary PISA scores are a proxy for origin-country characteristics linked to school quality 20 years ago.

Finally, as a further way of ascertaining the nature of the effects captured by the PISA data for 2000, the sample used in the statistical analysis can be restricted to the one-

[9] Only nine of these countries have imputed values in the Hanushek and Kimko (2000) index.

[10] Betts and Lofstrom (2000), who use a single-equation approach in which origin-country information is interacted with the immigrant's pre-immigration level of education, reference their variables to the time when the immigrant would have been 10 years old.

quarter (or other fraction) of immigrants with the most recent exposure to the origin-country school system.[11] Results from this extension are discussed below.

IV. EMPIRICAL ASSESSMENT

The estimating equation used in the first step of the assessment of the reasons behind the differences by country of origin in the payoff to schooling in the US is a standard human capital earnings equation (equation 1 above). In particular, using data from the 2000 US Census, the natural logarithm of annual earnings in 1999 for males aged 25 to 64 who had non-zero earnings in that year is related to educational attainment, potential labor market experience (computed using the proxy Age – Years of Schooling – 6), the natural logarithm of weeks worked, dummy variables for married (spouse present), race, US armed forces veteran status, resident of a metropolitan area, resident of a southern state, and English language skills, and, among the foreign born, variables for duration of residence in the US and citizenship. The data are described in detail in Chiswick and Miller (2009). For the foreign born, the main set of analyses are based on immigrants aged 18 or more at the time of arrival in the US. This is to ensure that the individuals will typically have completed secondary school in their country of origin, as this is the level that the school quality data refer to. Definitions of variables are presented in Appendix A.

The Card and Krueger (1992) two-step approach was applied using both the PISA scores in Table 1 and the larger number of countries (73) with information on the Hanushek and Kimko (2000) index (Table 2). These separate estimates suggested that the

[11] This sample selection is based on the gap between the immigrant's age and an assumed school leaving age associated with their highest grade of secondary or primary schooling.

PISA scores had far greater information content for understanding the variation in the payoff to schooling that immigrants receive in the US. For example, the R^2 in the second-step of the Card and Krueger (1992) two-step approach in aggregate-level models based on the Hanushek and Kimko (2000) data were very low: they were even lower than the values reported by Sweetman (2004), and only one-eighth of the R^2 in some of the models based on the PISA scores.

However, when the analyses were based on the smaller group of 32 countries for which there are both PISA and Hanushek and Kimko scores, the results from the alternative measures are comparable:[12] in models where the PISA scores are statistically insignificant, the Hanushek and Kimko (2000) index is also statistically insignificant. Where the alternative origin school quality measures are both statistically significant, the coefficients are of the same sign. Moreover, the relative magnitudes of the estimated effects on the various payoffs (to actual years of schooling, years of required schooling, years of under-education and years of over-education) are similar, regardless of whether the analysis is based on the Hanushek and Kimko (2000) index or the PISA reading, mathematics or science literacy scores. This similarity in findings presumably follows from the high simple correlation (above 0.76) between the alternative measures noted in Section III.

Given the similarity in statistical findings, any preference between the measures can be made on other grounds. As the standardized PISA scores are for specific tests for 15-year-olds in 2000, whereas the Hanushek and Kimko index is based on results from

[12] The difference in the results from analyses for this smaller group of countries and from analyses for all countries with Hanushek and Kimko scores may be associated with either the greater prevalence of imputed values of the Hanushek and Kimko index when using the larger sample (see footnote 9), or simply different roles for origin-country school quality for the purged countries.

different tests, conducted on various age groups, and in various years, and the majority of which were imputed, ease of interpretation suggests a preference for the PISA scores. The remainder of this paper, therefore, is based on the PISA scores. Selected findings from the analysis using the Hanushek and Kimko (2000) data are reported in Appendix B.

(i) Aggregate-Level Analyses

There is information in Table 1 on the PISA scores for 40 countries other than the US. However, the sample of 25-64 year old males who worked in the US during 1999 does not contain any immigrants from Iceland, Liechtenstein or Luxembourg. Hence the analyses below are based on the remaining 37 countries.

Only findings from the second step of the model (*i.e.*, estimation of equation 3b) are presented here. There are two sets of results in Table 4 for each PISA score (Reading, Mathematics, Science). The first, in column (i), is based on the payoff to schooling across birthplace groups without country fixed effects in the first-step regression (*i.e.*, the intercept is simply β_0). The second, in column (ii), is for the analogous set of analyses where the first step model takes account of birthplace fixed effects (*i.e.*, the intercept is generalized to $\sum_{j=1}^{J}\left[\beta_{0j}\mathrm{I}_j\right]$).

The precision of the estimates of the payoff to schooling will vary across countries. Therefore, weighted least squares is used to compute the second-step equations, where the weights are the number of workers for each country of origin in the first-step regressions. Hence, important immigrant source countries, such as Mexico, Canada and Korea, are assigned relatively more weight than minor source countries, like Denmark and Latvia. An alternative set of weights that was investigated involved the inverse of the variances of the estimates of the birthplace interaction terms in the first step. This alternative gives more weight to birthplace effects that are precisely estimated (*e.g.*, for Mexico, Korea, Russia) and less weight to birthplace effects that are estimated less precisely (*e.g.*, for Belgium, Denmark, New Zealand). The two sets of weights are highly correlated (correlation coefficient of 0.983 for the column (i) specification) and so similar results emerge. For simplicity, only those using the country sample sizes are reported here.

Table 4

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses

	Reading Literacy		**Mathematics Literacy**		**Science Literacy**	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
Constant	-0.100	-0.173	-0.079	-0.145	-0.091	-0.162
	(6.28)	(4.73)	(8.53)	(6.81)	(6.44)	(5.05)
PISA/100	0.018	0.029	0.014	0.024	0.016	0.026
	(4.42)	(3.07)	(5.45)	(4.07)	(4.36)	(3.16)
1980 GDP per	0.018	0.031	0.018	0.029	0.020	0.034
capita/10000	(3.88)	(2.88)	(4.42)	(3.04)	(4.68)	(3.43)
Country fixed effects in first step	No	Yes	No	Yes	No	Yes
R^2	0.744	0.598	0.785	0.655	0.741	0.604
Sample Size	37	37	37	37	37	37

Notes: Model (i) has a single intercept, β_0, in the first-step regression. Model (ii) is based on the flexible specification in the first-step regression, where the intercepts are given by $\sum_{j=1}^{J}\left[\beta_{0j}\mathrm{I}_j\right]$. The dependent variable for each model is the estimated partial effects of education for the countries for which there are PISA scores. Absolute values of 't' statistics in parentheses.
Source: Authors' calculations.

For the first-step regression for specification (i), the payoffs to schooling for the 37 countries that are the focus of this analysis range from 2.7 percent (for Mexico) to 7.9 percent (for Japan), a range of 5.2 percentage points. The standard deviation of the differentials in the payoff to schooling across the 37 countries is 1.4 percent. According to the Table 4 column (i) results, the birthplace differences in the payoff to schooling are positively associated with both the country-level average PISA scores and with 1980 GDP per capita. Up to 79 percent of the variation in the payoffs to schooling is accounted for by the two regressors, with the level of explanation being highest for mathematical literacy and lowest for science literacy. In alternative estimations (not shown here), the 1980 per capita GDP variable was omitted from the model: this change to the model was associated with an increase in the partial effects of the PISA variables by between 50 and 56 percent. This suggests that the effects of the PISA variables in Table 4 are net of the effects of the level of economic development in the country of origin when many immigrants would have been attending school.

Each 100-point increase in the PISA scores is associated with between 1.4 and 1.8 percentage points increase in the payoff to schooling in the US. Hence a 200-point change in the PISA, which is about the range in the data, is associated with around a three and one-half percentage points increase in the payoff to schooling. These relationships are described in Figure 1 in the case of the PISA reading literacy scores.[13]

In the column (ii) results in Table 4 the first-step regression has been augmented with 37 country fixed effects. This less-restrictive specification is associated with a greater spread in the estimated payoffs to schooling. For example, the payoff for Mexico is now estimated to be 1.6 percent (compared with 2.7 percent with the common intercept) and that for Japan 8.8 percent (compared with 7.9 percent with the common intercept). The standard deviation of the estimates of the payoff to schooling is 3.2, over two times that when it is assumed that there is a common intercept, as in column (i). While this greater variation in the dependent variable in the second-step regression is associated

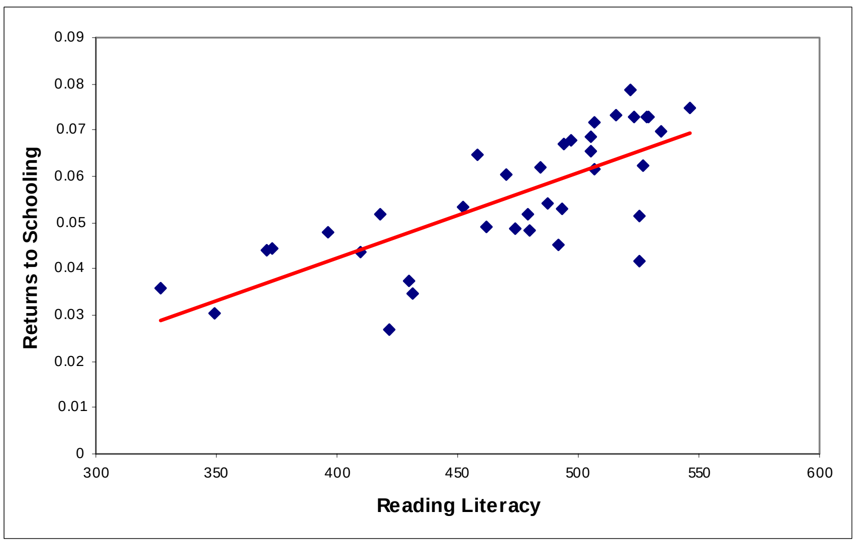
[13] Given the broad similarity of the findings for reading, mathematics and science, Figure 1 contains only information on the relationship across countries between the payoff to schooling and reading literacy.

with a smaller explanatory power of the model, the PISA scores and 1980 per capita GDP variable both remain highly significant, with partial effects that are—following the greater range in the dependent variable—appreciably greater than under the first specification. Specifically, the effect of changes in the PISA scores range from 0.024 to 0.029, with the smallest and largest impacts again being associated with mathematics and reading literacy, respectively.

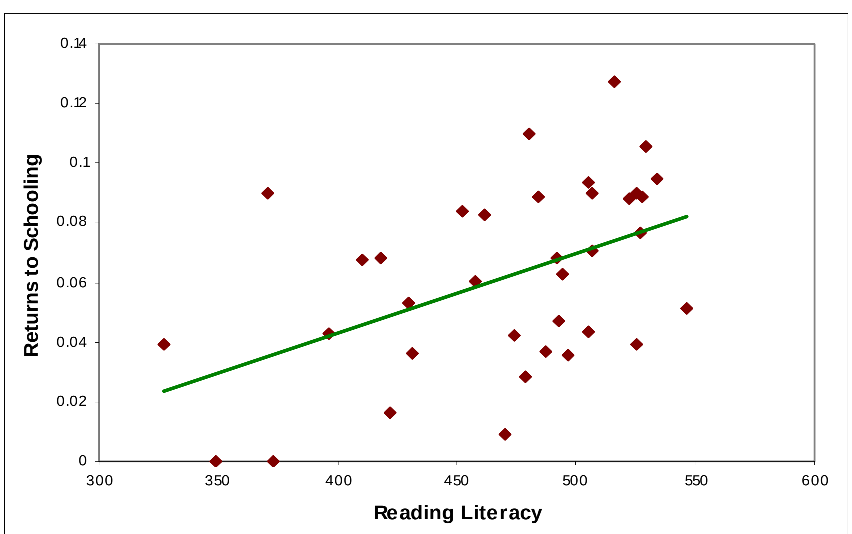
Figure 1

Relationship Between the Payoff to Schooling and PISA Reading Literacy

(a) Without country fixed effects in first-step regression



(b) With country fixed effects in first-step regression



The first-step regression results were also derived in an alternative way to examine the robustness of the findings. Thus, the models were estimated without the approximately 51 percent of the data where there are no PISA scores. This change in the sample was also associated with a widening of the range in the estimated payoffs to schooling. It was also associated with a reduction in the explanatory power of the second step of the model compared to the results in Table 4, of around 15 percentage points for specification (i) and by 2 to 4 percentage points for specification (ii). The partial effects of the PISA variables (not reported here) following this change to the sample, however, were larger than in the benchmark models of Table 4.

The analyses were also conducted on sub-samples formed using the years since the immigrant would have attended school in the country of origin. Two sub-samples were formed: the 25 percent of the original sample with the most recent exposure to the origin-country school system, and the remaining 75 percent. Some of the findings from this disaggregated analysis (particularly those based on the column (i) specification in Table 4) showed that the models had greater explanatory power for immigrants with the most recent exposure to the origin-country school system, whereas other results from the disaggregated analysis (those based on the column (ii) specification in Table 4) were opposite this. This ambiguity presumably follows from the PISA scores offering a very useful measure of the across-country differences in school quality up to four decades ago.

One issue that needs to be addressed in this preliminary set of aggregate-level analyses relates to the role of Mexico. Mexico is the dominant source of immigrants in the US. In the sample of adult males used above, 29.2 percent are from Mexico. Among immigrants from countries where there are PISA scores, 60.7 percent of the sample are from Mexico. Accordingly, the analyses can be dominated by this group, particularly where the second-step results are weighted by the size of the birthplace groups.[14] There are various ways this issue can be assessed, for example, through conducting the analyses of Table 4 for the 36 countries other than Mexico, or undertaking the analyses without weights (so that Mexico counts the same as any other country). The latter approach is adopted here, as this will also provide the opportunity to illustrate the impact that weighting has on the analyses. Table 5 replicates Table 4 for this set of analyses.

Table 5

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses, Without Weights

	Reading Literacy		Mathematics Literacy		Science Literacy	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
Constant	-0.047	-0.110	-0.036	-0.087	-0.040	-0.106
	(3.55)	(2.31)	(3.48)	(2.32)	(3.15)	(2.32)
PISA/100	0.010	0.023	0.007	0.018	0.008	0.021
	(3.01)	(1.97)	(2.82)	(1.90)	(2.59)	(1.97)
1980 GDP per capita/10000	0.012	0.008	0.013	0.010	0.014	0.011
	(3.92)	(0.73)	(4.41)	(0.96)	(4.84)	(1.11)
Country fixed effects in first step	No	Yes	No	Yes	No	Yes
R^2	0.699	0.268	0.691	0.262	0.681	0.267
Sample Size	37	37	37	37	37	37

Note: For notes and source for the table, see Table 4.

The results in Table 5 are broadly the same as those reported in Table 4. The PISA scores remain as a statistically significant determinant of the across-country variation in the payoff to schooling among immigrants in the US. The 1980 GDP per capital variable, however, while having a positive impact in each equation, is significant only for the first-step equation without country fixed effects, that is the equation has a

[14] Antecol *et al*. (2003) have previously drawn attention to the important role that immigrants from Mexico can have in aggregate-level analyses for the foreign born.

common intercept for all countries. In the model where the across-country variation in the payoff to schooling is obtained from first-step equation with country fixed effects (*i.e.*, the intercept is generalized to $\sum_{j=1}^{J}\left[\beta_{0j}\mathrm{I}_j\right]$) , these fixed effects apparently capture all of the influence of the different stages of economic development of the origin on the earnings of immigrants in the US (that is, this effect applies to immigrants of all levels of schooling).

The analyses were also undertaken with the estimating equation for the second step augmented with a dummy variable for Mexico. This enables the distance of the data for Mexico from the regression line to be assessed. In these analyses, whether conducted using the PISA scores or the Hanushek and Kimko (2000) index, the dummy for Mexico was associated with a significant negative coefficient, of around two percentage points. In other words, given the quality of the schooling in Mexico (as measured in this study), and the relative level of economic development of Mexico, immigrants from Mexico would need to gain an extra two percentage points payoff to their education in the US labor market (that is, it should be around five percent rather than three percent) in order to conform to the estimated pattern for other countries. The two percentage point shortfall in the payoff to schooling for immigrants from Mexico may be associated with the illegal status in the US of many from that country.

These preliminary results provide strong support for the hypothesis that origin country school quality, as proxied by the PISA scores, affects the payoff to schooling for immigrants in the US. The evidence derived using the Hanushek and Kimko (2000) index, reported in Appendix B, reinforced this conclusion. This suggests that the lower payoff to schooling for immigrants in the US reflects, in part, a lower quality of education acquired in the country of origin.

(ii) The Role of Age at Migration

Sweetman (2004) conducts analyses of the links between indicators of origin country school quality and the payoff to immigrants' schooling in Canada on sub-samples defined using age at migration. Sweetman (2004, p.30) argues "If it is the quality of the education system that is driving these results, and not other factors, such as discrimination, then immigrants educated primarily in the Canadian system should not be affected by the source country school quality index". He shows that the payoffs to schooling are greatest for those educated primarily in Canada, and smallest for the foreign born educated abroad. The payoffs to schooling for those with a mix of pre-immigration and post-immigration schooling were of intermediate size. Origin-country school quality had no impact on the payoffs to schooling in Canada among immigrants educated primarily in Canada, whereas the payoff to schooling in Canada for immigrants mostly educated abroad was positively related to origin-country school quality.[15]

In the current study the analyses were repeated for several child immigrant groups. Selected results by age at immigration are presented in Table 6. The first set of results presented in this table is the benchmark set of findings for adult immigrants, from Tables 4 and 5. The other sets of results are for the two samples of child immigrants, namely those who arrived before their tenth birthday, and the more restrictive definition of those who arrived before their sixth birthday. Two sets of analyses are presented in this table:

[15] Bratsberg and Terrell (2002) focus only on those who were likely to have obtained their education abroad.

the first (on the left-hand-side) is based on the second-step regression models that are weighted according to the number of workers in each country of origin, and the second (on the right-hand-side) is from un-weighted regressions.

Table 6

Estimate of PISA Effect from Second Step of Two-Step Model, by Age at Migration, Weighted and Un-Weighted Regressions

	With Weights			Without Weights		
Variable	Reading (i)	Mathematics (ii)	Science (iii)	Reading (iv)	Mathematics (v)	Science (vi)
Age at Migration 18 or more (from Tables 4 and 5)						
PISA/100	0.029	0.024	0.026	0.023	0.018	0.021
	(3.07)	(4.07)	(3.16)	(1.97)	(1.90)	(1.97)
1980 GDP per capita/10000	0.031	0.029	0.034	0.008	0.010	0.011
	(2.88)	(3.04)	(3.43)	(0.73)	(0.96)	(1.11)
R^2	0.598	0.655	0.604	0.268	0.262	0.267
Age at Migration ≤ 10						
PISA/100	0.037	0.031	0.034	0.010	0.013	0.016
	(3.25)	(4.48)	(3.68)	(0.81)	(1.23)	(1.36)
1980 GDP per capita/10000						
R^2	0.653	0.714	0.675	0.064	0.087	0.095
Age at Migration ≤ 5						
PISA/100	0.024	0.023	0.023	0.004	0.005	0.009
	(1.95)	(2.90)	(2.25)	(0.27)	(0.39)	(0.59)
1980 GDP per capita/10000						
R^2	0.594	0.638	0.607	0.055	0.058	0.063
Sample Size	37	37	37	37	37	37

Note: The first-step regression is the flexible specification where the intercepts are given by $\sum_{j=1}^{J}\left[\beta_{0j} I_j\right]$.

Second step regression also includes 1980 GDP per capita variable. The dependent variable for each model is the estimated partial effects of education for the countries for which there are PISA scores. Absolute values of 't' statistics in parentheses.
Source: Authors' calculations.

The weighted regressions (where considerable weight is given to Mexico) indicate that the school quality effects are at least as strong among child immigrants as they are among adult immigrants (Table 6, columns i, ii , iii). This suggests that factors other than pure school quality effects must also be playing a role. We consider one of these, selectivity in migration among less-well educated immigrants (many of whom will be from Mexico), below. In the un-weighted regressions, however, the PISA variables are statistically insignificant (Table 6, columns iv to vi). The PISA variable is also insignificant for these two "child immigrant" samples if weighted regressions are estimated on the 36 countries other than Mexico. That is, when Mexico is excluded from the sample, there is evidence that school quality effects on the payoff to schooling dissipate as younger age-at-migration cohorts are considered. That is, school quality in the origin is not relevant for the payoff to schooling in the US for those who migrate as young children and therefore have little or no exposure to school quality in the origin.

(iii) <u>Reference Education, Over-education and Under-education and PISA scores</u>

It has been shown here that immigrants from countries that perform poorly on standardized tests are associated with lower payoffs to schooling in the US. Chiswick and Miller (2008) link the low payoff to schooling among the foreign born in the US to a lower payoff to immigrants' schooling that is surplus to the standard in their occupations, and to a lower penalty to years of under-education among immigrants compared to the native born. This section examines the links between the returns to immigrants' over-education and under-education and school quality, as measured by the PISA scores.

Chiswick and Miller (2008) show that the payoff to schooling in the conventional earnings equation can be linked to the estimated effects on earnings of the education variables in the ORU model. In particular, greater estimated partial effects of the reference education and over-education variables are shown to be associated with a higher payoff to education in the conventional earnings equation. A more negative earnings effect of under-education is also associated with a higher payoff to schooling in the conventional human capital earnings model.

To quantify the link between the ORU and conventional earnings equations in the current study of origin-country school quality effects, it is first necessary to estimate the ORU model (*i.e.*, estimate equation (2) as the first step in the two-step approach). Then the analyses reported above need to be repeated replacing in the second step the payoff to schooling from the conventional (first step) earnings function with the payoffs to over-education, required education and under-education from the ORU specification of the earnings function.

Table 7 presents results from the second step of the model where the variations across birthplaces in the payoffs to years of over-education are related to the PISA scores. The structure of this table is the same as Table 4. These results show that the payoffs to over-education are not affected by the quality of the origin-country schooling, as measured by the PISA scores.[16] The insignificance of this relationship implies that years of surplus schooling among immigrants are relatively poorly rewarded in the US labor market, irrespective of the quality of the origin-country schooling system. Perhaps this arises because most of the years of surplus schooling were obtained at an age older than the age at which the PISA scores are measured. Years of surplus schooling among the native born are also poorly rewarded in the US labor market (see Chiswick and Miller, 2008).[17]

[16] As shown in Appendix B, the payoffs to years of over-education are also not related to the Hanushek and Kimko (2000) index, or to the PISA scores in an alternative sample considered in Appendix B.

[17] In Chiswick and Miller's (2008) aggregate-level analysis, the payoff to years of surplus schooling was 5.6 percent for the native born and 4.4 percent for the foreign born. For each birthplace group the payoff to years of schooling that were usual in the occupation of employment was around 15.5 percent.

Table 7

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses, Focus on Over-education

Variable	Reading Literacy (i)	Reading Literacy (ii)	Mathematics Literacy (i)	Mathematics Literacy (ii)	Science Literacy (i)	Science Literacy (ii)
Constant	-0.034	-0.003	-0.029	-0.012	-0.028	0.000
	(1.38)	(0.09)	(1.87)	(0.71)	(1.32)	(0.02)
PISA/100	0.004	-0.007	0.003	-0.005	0.003	-0.007
	(0.63)	(0.94)	(0.69)	(0.96)	(0.46)	(1.21)
1980 GDP per	0.023	0.031	0.023	0.031	0.024	0.031
capita/10000	(3.29)	(3.93)	(3.46)	(4.06)	(3.68)	(4.29)
Country fixed effects in first step	No	Yes	No	Yes	No	Yes
R^2	0.415	0.370	0.416	0.370	0.412	0.380
Sample Size	37	37	37	37	37	37

Note: For notes to the table, see Table 4.
Source: Authors' calculations.

Table 8 presents information on the links between the payoff to the reference levels of schooling and the quality of immigrants' origin-country schooling, as indexed by the PISA variables. In this instance the estimated partial effect of the PISA scores on the differentials in the payoffs to schooling is significant in the majority of the models.[18] Hence, a 200-point increase in a specific PISA score is associated with an increase in the payoff to the reference years of schooling of up to 2.6 percentage points. The partial effects in Table 8 are, however, smaller than the partial effects in Table 4 for actual years of schooling. Recall that the payoff to a year of reference schooling is a payoff to the acquisition of that year of schooling and to moving to an occupation where the extra year of schooling is the usual or reference level. The relatively smaller partial effects in Table

[18] The Hanushek and Kimko (2000) index is a statistically significant determinant of the variation across countries in the payoff to required years of education (see Appendix B). The PISA scores are also statistically significant in each of the models of the determination of the variation in the payoff to years of required education in the alternative sample considered in Appendix B.

8 suggest that the effect on earnings of the occupational mobility is hardly enhanced by the quality of schooling acquired abroad.

Table 8

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses. Focus on Required Education

	Reading Literacy		**Mathematics Literacy**		**Science Literacy**	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
Constant	-0.063	-0.137	-0.048	-0.127	-0.057	-0.129
	(4.88)	(3.62)	(6.24)	(5.48)	(4.93)	(3.88)
PISA/100	0.012	0.014	0.009	0.013	0.010	0.012
	(3.50)	(1.42)	(4.07)	(1.96)	(3.39)	(1.39)
1980 GDP per	0.013	0.033	0.013	0.031	0.014	0.034
capita/10000	(3.34)	(2.98)	(3.69)	(3.01)	(4.01)	(3.38)
Country fixed effects in first step	No	Yes	No	Yes	No	Yes
R^2	0.664	0.456	0.693	0.483	0.659	0.455
Sample Size	37	37	37	37	37	37

Note: For notes to the table, see Table 4.
Source: Authors' calculations.

Table 9 presents the estimated relationships between the wage effects of years of under-education across birthplaces and the quality of the schooling acquired abroad. When interpreting these effects it is useful to bear in mind what the negative estimated coefficient on the under-education variable means. It indicates that a worker who obtains a job in an occupation that has a usual or reference level of education greater than the worker's actual level of schooling receives a lower wage than the workers in the same occupation who have the usual or reference level of education.

Table 9

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses, Focus on Under-education

Variable	Reading Literacy (i)	Reading Literacy (ii)	Mathematics Literacy (i)	Mathematics Literacy (ii)	Science Literacy (i)	Science Literacy (ii)
Constant	0.079	0.081	0.069	0.067	0.078	0.079
	(2.44)	(2.55)	(3.47)	(3.52)	(2.75)	(2.87)
PISA/100	-0.015	-0.016	-0.013	-0.014	-0.014	-0.016
	(1.77)	(1.99)	(2.45)	(2.68)	(2.00)	(2.24)
1980 GDP per capita/10000	-0.009	-0.008	-0.007	-0.006	-0.009	-0.009
	(0.92)	(0.89)	(0.77)	(0.76)	(1.09)	(1.07)
Country fixed effects in first step	No	Yes	No	Yes	No	Yes
R^2	0.238	0.265	0.292	0.323	0.255	0.285
Sample Size	37	37	37	37	37	37

Note: For notes to table, see Table 4.
Source: Authors' calculations.

The Table 9 results indicate that the wage disadvantage to these under-educated workers rises with the PISA score.[19] That is, a foreign-born worker who obtained his schooling abroad in a lower quality school system has a smaller earnings disadvantage than a foreign-born worker who obtained his schooling abroad in a higher quality school system. Under-educated native-born workers are shown by Chiswick and Miller (2008) to have a greater earnings disadvantage than the comparable foreign born.[20] Hence, the Table 9 results indicate that under-educated foreign-born workers educated abroad in a higher quality school system are more like under-educated native-born workers than are under-educated foreign-born workers educated abroad in a lower quality school system.

Chiswick and Miller (2008) link the differential between the native born and foreign born in the earnings effects of under-education to self-selection in immigration.

[19] Similar findings arise when the Hanushek and Kimko (2000) index is used, or the PISA scores are applied in alternative samples—see Appendix B.

[20] The estimated partial effects of the under-education variable in the aggregate-level analysis in Chiswick and Miller (2008) were -0.067 for the native born and -0.021 for the foreign born.

This argument drew upon Chiswick (1978, p.912), who suggested that “Suppose that among those with little schooling only the most able and most highly motivated migrate, while among those with high levels of schooling the immigrants are drawn more widely from the ability distribution”. The findings here in relation to the quality of schooling suggest a generalization of Chiswick’s (1978) argument, to “Suppose that among those from countries with a poorer quality of school system only the most able and most highly motivated migrate, while among those from countries with a higher quality of school system the immigrants are drawn more widely from the ability distribution”.

The variations in the earnings effects of each of the ORU variables are related to the PISA scores in ways that will lead to the payoff to actual years of schooling being positively related to the PISA scores. The relative importance of the relationships summarized in Tables 7-9 in this regard can be assessed using a method based on Chiswick and Miller (2008). This involves using the estimates from the ORU model to predict earnings for workers, and then relating the means of these predictions at each level of actual education to the years of actual education in a linear regression model, weighted by the number of workers at each level of education. The coefficient on the years of actual education variable in this later regression is an estimate of the conventional payoff to schooling.

The estimated earnings effects of the ORU variables in Tables 7-9 are first evaluated at values of the PISA scores that generate an implied payoff to schooling that is the same as the actual payoff for the foreign born who migrated at age 18 or over (4.9 percent).[21] The estimated effect of the ORU variables can then be evaluated at other

[21] The payoff to schooling for all the foreign born (*i.e.*, including those who immigrated before age 18) is 5.2 percent (see Chiswick and Miller, 2008).

values of the PISA scores (*e.g.*, benchmark ± 100 points, which will yield a 200-points range, similar to that in the PISA scores) and the simulation exercise described above repeated to assess how the PISA scores impact the payoff to schooling in the conventional earnings equation through each of the ORU variables. Table 10 presents findings from this analysis based on the PISA reading scores.

Table 10

Implied Payoffs to Schooling, Adjusting for Effects of ORU Variables at Various PISA Reading Scores

	-100 PISA Points	Benchmark	+100 PISA Points
i. Native born	10.5	10.5	10.5
Foreign born:			
ii. no adjustment	-	4.9	-
iii. adjustment only to the earnings effects of reference education for the foreign born	4.6	4.9	5.2
iv. adjustment only to the earnings effects of over education for the foreign born	5.0	4.9	4.8
v. adjustment only to the earnings effects of under education for the foreign born	3.9	4.9	5.9
vi. adjustment to all three ORU variables	3.7	4.9	6.1

Source: Authors' calculations

The first row of Table 10 contains the implied payoff to schooling for the native born. This does not vary with the PISA score, and so is recorded at 10.5 percent in each column. The second row presents the implied payoff to schooling for the foreign born. This has been computed from the predictions of the ORU model, calibrated to produce the actual payoff to schooling for this birthplace group of 4.9 percent. The payoff to schooling for the foreign born who immigrated at age 18 or older is thus less than one-half that for the native born.

The third row of Table 10 explores the impact of variation in the PISA scores through the estimated effects of the reference years of education in the ORU model. A change up (down) in the PISA reading score of 100 points is associated with an increase (decrease) of around 0.3 percentage point in the payoff to schooling. As shown in the fourth row of the table, adjustment for the estimated effects of the over-education variable has minimal effect on the payoff to schooling (the effect is just 0.1 percentage point). However, with the adjustment for under-education, as seen from the fifth row of the table, a change up (down) in the PISA reading score of 100 points is associated with an increase (decrease) in the payoff to schooling of about one full percentage point. The far greater effect of the PISA scores via the under-education variables is consistent with Chiswick and Miller's (2008) inference that the earnings effects of under-education are the more important contributor to the lower payoff to schooling for immigrants in the US labor market. This effect is linked in their analysis to more intense selection in migration among those with lower levels of schooling.

In the final row of Table 10 the roles of changes in the PISA scores via all the ORU variables are considered simultaneously. These show that at 100 higher PISA scores the implied payoff to schooling is 6.1 percent compared to 4.9 percent at the immigrant benchmark, but still less than the 10.5 percent for the native born.

Thus, these findings show that the quality of schooling acquired abroad matters to the payoff to the schooling that immigrants receive in the US. However, while some of the effects appear to operate in the expected way—by increasing the payoff to correctly matched schooling, the most important effect appears to operate by altering the selectivity of immigrants at low levels of schooling where under-education is relatively more important. Hence, immigrants from countries with higher quality school systems, as proxied by the PISA scores, have a more negative earnings effect associated with under-education. This leads them to be more like the native born in terms of earnings determination. The interpretation of this offered above is that these relatively less-well educated immigrants from countries with high quality school systems are less intensely self-selected for migration to the US.

Analyses of the effects that the PISA mathematics and science scores have on immigrants' payoffs to schooling via the earnings effects in the ORU model were also undertaken. Similar findings emerge, which demonstrates the robustness of the results. Relevant findings are presented in Appendix C.

V. CONCLUSION

The payoff to schooling for immigrants in the US labor market is only around one-half of that for the native born. This paper examines whether this difference is linked to the quality of the schooling acquired abroad by immigrants, and if so, how the school quality effects are transmitted to earnings in the US. The analyses offer a comparative assessment of the relative strengths of two measures of the quality of immigrants' origin-country schooling, the PISA scores and the Hanushek and Kimko (2000) Human Capital Quality Index. As argued above, the Hanushek and Kimko data relate to a period when many of the immigrants in the US labor market in 2000 would have been enrolled in school in their country of origin, whereas the PISA scores relate to testing undertaken in the origin countries in 2000. However, the PISA data relate to single tests for a specific age group, whereas the Hanushek and Kimko (2000) data are averages for a number of age groups, test types and years of test assessment. Yet the two test scores are highly correlated across countries.

The results suggest that, from the perspective of predicting the payoff to pre-immigration schooling among adult male immigrants in the US, the PISA scores are relevant indicators of origin-country school quality.[22] There is a strong, positive relationship between the payoff to schooling for immigrants in the US labor market and the quality of the schooling they acquired prior to immigration, as measured by the PISA reading, mathematics and science literacy scores. Moreover, the results suggest that a higher quality of schooling acquired abroad is associated with a higher payoff to correctly matched schooling in the US, a slightly higher payoff to schooling that appears to be surplus of the usual standards in the jobs held by immigrants, and a greater (in absolute value) penalty associated with years of under-education. The predictions presented suggest that the latter phenomenon is of greater importance to understanding the lower payoff to schooling among the foreign born in the US. Chiswick and Miller (2008) associate the differential in the earnings penalty for under-education between the native born and the foreign born with positive selection in immigration among the foreign born. The results in this paper suggest that immigrants from countries with a poorer quality of school system are associated with more intense selection in immigration, and it is this selection process, rather than the quality of immigrants' schooling per se, that is the major driver of the lower payoff to schooling among immigrants in the US.

[22] Similar results emerge using the Hanushek and Kimko (2000) index.

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APPENDIX A
DEFINITIONS OF VARIABLES

The variables used in the statistical analyses are defined below.

Data Source: 2000 Census of Population, Public Use Microdata Sample, 5 percent sample of the foreign born, and 0.15 percent random sample of the native born. The foreign-born sample is restricted to those who were at least 18 years of age at the time of immigration.

Definition of Population: Native-born and foreign-born employed men aged twenty-five to sixty-four years who had non-zero earnings in 1999.

Dependent Variables	
Earnings in 1999	Natural logarithm of earnings in 1999 (where earnings are defined as gross earnings from all sources).
Explanatory Variables	
PISA	The mean score for the immigrant's country of origin from the OECD Programme for International Student Assessment. Separate scores for reading, mathematics and science literacy are used.
GDP per Capita in 1980	Data on real GDP per capita for 1980 were obtained from Version 6.2 of the Penn World Tables (Alan Heston, Robert Summers and Bettina Aten, Penn World Table, Version 6.2, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, September 2006). These data are denominated in a common currency so that real quantity comparisons can be made across countries.
Years of Education	This variable records the total years of full-time equivalent education. It has been constructed from the Census data on educational attainment by assigning the following values to the Census categories: completed less than fifth grade (2 years); completed fifth or sixth grade (5.5); completed seventh or eighth grade (7.5); completed ninth grade (9); completed tenth grade (10); completed 11th grade (11); completed 12th grade, no diploma (11.5); completed high school (12); attended college for less than one year (12.5); attended college for more than one year or completed college (14); Bachelor's degree (16); Master's degree (17.5); Professional degree (18.5); Doctorate (20). As with other Census data, the values for educational attainment are self-reported responses. While academic degrees may have required different

	years of schooling for immigrants educated in some countries of origin, US values are used in the analysis.
Usual Level of Education	This variable records the reference years of education. It is constructed using the modal level of education of the native-born workers in the respondent's occupation of employment based on the *Realized Matches* procedure.
Years of Over-education	The over-education variable equals the difference between the person's actual years of education and the years of education required for the person's job where this computation is positive. Otherwise, it is set equal to zero.
Years of Under--education	The over-education variable equals the difference between the reference years of education in the person's job and their actual years of education where this computation is positive. Otherwise, it is set equal to zero.
Weeks worked in 1999	This is a continuous variable for the numbers of weeks the individual worked in 1999.
Experience	Age – Years of Education – 6.
Location	The two location variables record residence in a metropolitan area or in the Southern States. The states included in the latter are: Alabama, Arkansas, Delaware, District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, Missouri, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, West Virginia.
Marital Status	This is a binary variable that distinguishes individuals who are married, spouse present (equal to 1) from all other marital states.
Veteran	This is a binary variable set equal to one for someone who had served in the US Armed Forces, and set equal to zero otherwise.
Race	This is a dichotomous variable that distinguishes between individuals who are Black (= 1) and all other races (= 0).
English Language Proficiency	Three dichotomous variables (speaks English very well; well; not well or not at all) are used to record the English language proficiency of the respondents who speak a language other than English at home. The benchmark group is those who speak only English at home.
Years Since Migration	This is computed from the year the foreign-born person came to the United States to stay.
Citizenship	This is a dichotomous variable set equal to one for foreign born who hold an US citizenship.

APPENDIX B

ANALYSES USING THE HANUSHEK AND KIMKO DATA

(a) Analyses of Hanushek and Kimko Using Full Sample of 73 Countries

There are 73 countries for which there is information on the Hanushek and Kimko (2000) Human Capital Quality Index and data on workers in paid employment in the 2000 US Census. Table B.1 lists results obtained from the second-step regression of the across-country variation in the payoff to schooling against the Hanushek and Kimko (2000) index. Tables B.2, B.3 and B.4 report findings from the second-step regression based on the ORU specification of the earnings equation. While the imputed values of the Hanushek and Kimko (2000) index are based, among other variables, on GDP per capita (in 1960), the GDP per capita variable is retained in the estimating equation for comparison with the models based on the PISA scores.

Table B.1

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses, Based on the Hanushek and Kimko (2000) Index

Variable	(i)	(ii)
Constant	-0.019	-0.033
	(3.69)	(2.33)
HCAP/100	0.034	0.068
	(2.50)	(1.85)
1980 GDP per capita/10000	0.008	0.007
	(2.32)	(0.72)
Country fixed effects in first step	No	Yes
R^2	0.224	0.081
Sample Size	73	73

Note: Model (i) has a single intercept, β_0, in the first-step regression. Model (ii) is based on the flexible specification in the first-step regression, where the intercepts are given by $\sum_{j=1}^{J}\left[\beta_{0j} I_j\right]$. Absolute values of 't' statistics in parentheses.
Source: Authors' calculations.

Table B.2

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses, Focus on Over-education, Based on the Hanushek and Kimko (2000) Index

Variable	**(i)**	**(ii)**
Constant	-0.025	-0.018
	(3.53)	(2.20)
HCAP/100	0.084	0.065
	(4.65)	(3.08)
1980 GDP per capita/10000	-0.001	-0.002
	(0.10)	(0.44)
Country fixed effects in first step	No	Yes
R^2	0.270	0.130
Sample Size	73	73

Note: For note to table, see Table B.1.
Source: Authors' calculations.

Table B.3

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses. Focus on Required Education, Based on the Hanushek and Kimko (2000) Index

Variable	**(i)**	**(ii)**
Constant	-0.008	-0.037
	(2.20)	(2.59)
HCAP/100	0.006	0.031
	(0.65)	(0.87)
1980 GDP per capita/10000	0.010	0.001
	(3.74)	(0.15)
Country fixed effects in first step	No	Yes
R^2	0.223	0.015
Sample Size	73	73

Note: For note to table, see Table B.1.
Source: Authors' calculations.

Table B.4

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses, Focus on Under-education, Based on the Hanushek and Kimko (2000) Index

Variable	**(i)**	**(ii)**
Constant	0.005	0.007
	(0.57)	(0.61)
HCAP/100	-0.010	-0.012
	(0.46)	(0.40)
1980 GDP per capita/10000	-0.003	-0.005
	(0.58)	(0.60)
Country fixed effects in first step	No	Yes
R^2	0.013	0.012
Sample Size	73	73

Note: For note to table, see Table B.1.
Source: Authors' calculations.

(b) Analyses of Hanushek and Kimko Indices Using Sub-set of Countries with both PISA and Hanushek and Kimko Measures

There are 32 countries for which there is information on the Hanushek and Kimko (2000) Human Capital Quality Index, PISA scores, and data on workers in paid employment in the 2000 US Census. Table B.5 lists results obtained from the second-step regression of the across-country variation in the payoff to schooling against the Hanushek and Kimko (2000) index for this sub-set of countries. Tables B.6, B.7 and B.8 report findings from the second-step regression based on the ORU specification of the earnings equation for the same set of countries.

Table B.5

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses, Based on the Hanushek and Kimko (2000) Index, 32 Countries Analyses

Variable	**(i)**	**(ii)**
Constant	-0.056	-0.128
	(13.95)	(10.66)
HCAP/100	0.082	0.165
	(7.41)	(4.99)
1980 GDP per capita/10000	0.017	0.040
	(6.25)	(5.00)
Country fixed effects in first step	No	Yes
R^2	0.887	0.808
Sample Size	32	32

Note: For note to table, see Table B.1.
Source: Authors' calculations.

Table B.6

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses, Focus on Over-education, Based on the Hanushek and Kimko (2000) Index, 32 Countries Analyses

Variable	**(i)**	**(ii)**
Constant	-0.008	-0.015
	(0.84)	(1.45)
HCAP/100	0.016	-0.038
	(0.62)	(1.36)
1980 GDP per capita/10000	0.021	0.030
	(3.28)	(4.38)
Country fixed effects in first step	No	Yes
R^2	0.317	0.425
Sample Size	32	32

Note: For note to table, see Table B.1.
Source: Authors' calculations.

Table B.7

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses. Focus on Required Education, Based on the Hanushek and Kimko (2000) Index, 32 Countries Analyses

Variable	**(i)**	**(ii)**
Constant	-0.036	-0.126
	(4.38)	(10.89)
HCAP/100	0.056	0.110
	(2.47)	(3.45)
1980 GDP per capita/10000	0.012	0.038
	(2.19)	(4.85)
Country fixed effects in first step	No	Yes
R^2	0.477	0.745
Sample Size	32	32

Note: For note to table, see Table B.1.
Source: Authors' calculations.

Table B.8

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses, Focus on Under-education, Based on the Hanushek and Kimko (2000) Index, 32 Countries Analyses

Variable	(i)	(ii)
Constant	0.054	0.048
	(4.81)	(4.44)
HCAP/100	-0.078	-0.074
	(2.50)	(2.50)
1980 GDP per capita/10000	-0.015	-0.014
	(2.01)	(1.97)
Country fixed effects in first step	No	Yes
R^2	0.463	0.458
Sample Size	32	32

Note: For note to table, see Table B.1.
Source: Authors' calculations.

(c) Analyses of PISA Scores Using Sub-set of Countries with both PISA and Hanushek and Kimko Measures

There are 32 countries for which there is information on the Hanushek and Kimko (2000) Human Capital Quality Index, PISA scores, and data on workers in paid employment in the 2000 US Census. Table B.9 lists results obtained from the second-step regression of the across-country variation in the payoff to schooling against the three PISA scores for this sub-set of countries. Tables B.10, B.11 and B.12 report findings from the second-step regression based on the ORU specification of the earnings equation for the same set of countries.

Table B.9

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses, Based on PISA Scores, 32 Countries Analyses

	Reading Literacy		Mathematics Literacy		Science Literacy	
Variable	(i)	(ii)	(i)	(ii)	(i)	(ii)
Constant	-0.131	-0.245	-0.096	-0.188	-0.121	-0.229
	(5.86)	(6.15)	(7.03)	(7.91)	(5.90)	(6.40)
PISA/100	0.027	0.047	0.020	0.036	0.024	0.042
	(4.97)	(4.85)	(5.71)	(5.86)	(4.94)	(4.96)
1980 GDP per capita/10000	0.008	0.002	0.008	0.019	0.011	0.025
	(1.39)	(1.94)	(1.44)	(2.01)	(1.95)	(2.51)
Country fixed effects in first step	No	Yes	No	Yes	No	Yes
R^2	0.597	0.618	0.649	0.683	0.595	0.625
Sample Size	32	32	32	32	32	32

Note: For note to table, see Table 4.
Source: Authors' calculations.

Table B.10

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses, Focus on Over-education, Based on PISA Scores, 32 Countries Analyses

	Reading Literacy		Mathematics Literacy		Science Literacy	
Variable	(i)	(ii)	(i)	(ii)	(i)	(ii)
Constant	-0.035	-0.035	-0.024	-0.030	-0.029	-0.030
	(1.60)	(1.38)	(1.69)	(1.79)	(1.45)	(1.30)
PISA/100	0.006	0.003	0.004	0.002	0.005	0.002
	(1.14)	(0.52)	(1.01)	(0.49)	(0.95)	(0.36)
1980 GDP per capita/10000	0.014	0.019	0.014	0.019	0.015	0.020
	(2.38)	(2.85)	(2.47)	(2.90)	(2.65)	(3.08)
Country fixed effects in first step	No	Yes	No	Yes	No	Yes
R^2	0.298	0.304	0.292	0.303	0.289	0.301
Sample Size	32	32	32	32	32	32

Note: For note to table, see Table 4.
Source: Authors' calculations.

Table B.11

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses. Focus on Required Education, Based on PISA Scores, 32 Countries Analyses

	Reading Literacy		Mathematics Literacy		Science Literacy	
Variable	(i)	(ii)	(i)	(ii)	(i)	(ii)
Constant	-0.072	-0.207	-0.050	-0.169	-0.063	-0.196
	(5.97)	(5.50)	(6.32)	(7.25)	(5.50)	(5.74)
PISA/100	0.015	0.033	0.011	0.026	0.013	0.030
	(5.16)	(3.60)	(5.19)	(4.28)	(4.66)	(3.65)
1980 GDP per capita/10000	0.004	0.020	0.005	0.018	0.006	0.023
	(1.35)	(1.97)	(1.47)	(1.99)	(1.95)	(2.42)
Country fixed effects in first step	No	Yes	No	Yes	No	Yes
R^2	0.611	0.513	0.613	0.568	0.573	0.518
Sample Size	32	32	32	32	32	32

Note: For note to table, see Table 4.
Source: Authors' calculations.

Table B.12

Estimates from Second Step of Two-Step Model, Aggregate-Level Analyses, Focus on Under-education, Based on PISA Scores, 32 Countries Analyses

	Reading Literacy		**Mathematics Literacy**		**Science Literacy**	
Variable	**(i)**	**(ii)**	**(i)**	**(ii)**	**(i)**	**(ii)**
Constant	0.102	0.097	0.082	0.076	0.101	0.095
	(3.31)	(3.31)	(4.29)	(4.19)	(3.66)	(3.65)
PISA/100	-0.020	-0.020	-0.017	-0.017	-0.020	-0.020
	(2.72)	(2.86)	(3.44)	(3.56)	(3.02)	(3.15)
1980 GDP per	-0.006	-0.005	-0.005	-0.004	-0.008	-0.007
capita/10000	(0.79)	(0.70)	(0.65)	(0.57)	(1.03)	(0.95)
Country fixed effects in first step	No	Yes	No	Yes	No	Yes
R^2	0.311	0.321	0.385	0.394	0.341	0.352
Sample Size	32	32	32	32	32	32

Note: For note to table, see Table 4.
Source: Authors' calculations.

APPENDIX C

SUPPLEMENTARY RESULTS

Table C.1

Implied Payoffs to Schooling, Adjusting for Effects of ORU Variables at Various PISA Mathematics Scores

	-100 PISA Points	Benchmark	+100 PISA Points
i. Native born	10.5	10.5	10.5
Foreign born			
ii. no adjustment	-	4.9	-
iii. adjustment only to the earnings effects of reference education for the foreign born	4.7	4.9	5.2
iv. adjustment only to the earnings effects of over education for the foreign born	5.0	4.9	4.8
v. adjustment only to the earnings effects of under education for the foreign born	4.0	4.9	5.8
vi. adjustment to all three ORU variables	3.8	4.9	6.0

Source: Authors' calculations.

Table C.2

Implied Payoffs to Schooling, Adjusting for Effects of ORU Variables at Various PISA Science Scores

	-100 PISA Points	Benchmark	+100 PISA Points
i. Native born	10.5	10.5	10.5
Foreign born			
ii. no adjustment	-	4.9	-
iii. adjustment only to the earnings effects of reference education for the foreign born	4.7	4.9	5.1
iv. adjustment only to the earnings effects of over education for the foreign born	5.0	4.9	4.8
v. adjustment only to the earnings effects of under education for the foreign born	3.8	4.9	5.9
vi. adjustment to all three ORU variables	3.7	4.9	6.0

Source: Authors' calculations.