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ABSTRACT

How Do Latin American Migrants in the U.S. Stand on Schooling Premium? What Does It Reveal about Education Quality in Their Home Countries?*

Indicators for quality of schooling are not only relatively new in the world but also unavailable for a sizable share of the world's population. In their absence, some proxy measures have been devised. One simple but powerful idea has been to use the schooling premium for migrant workers in the U.S. (Bratsberg and Terrell, 2002). In this paper we extend this idea and compute measures for the schooling premium of immigrant workers in the U.S. over a span of five decades. Focusing on those who graduated from either secondary or tertiary education in Latin American countries, we present comparative estimates of the evolution of such premia for both schooling levels. The results show that the schooling premia in Latin America have been steadily low throughout the whole period of analysis. The results stand after controlling for selective migration in different ways. This contradicts the popular belief in policy circles that the education quality of the region has deteriorated in recent years. In contrast, schooling premium in India shows an impressive improvement in recent decades, especially at the tertiary level.

JEL Classification: I26, J31, J61

Keywords: schooling premium, returns to education, wage differentials, immigrant workers

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* We would like to thank seminar participants at LACEA 2015 and RIDGE 2015 for useful comments and suggestions.

1. Introduction

Education is critical for economic growth, poverty reduction, wellbeing, and a plethora of desirable social outcomes. The individual contribution of schooling has often been measured by labor market earnings. For almost five decades, researchers have examined the patterns of estimated schooling premia across economies.[1] The premia are typically shown as the estimated proportional increase in an individual's labor market earnings for each additional year of schooling completed.

However, there are two main reasons as to why researchers are limited in their comparisons of this expansive empirical literature: differences in data sample coverage and methodology. First, survey samples may not accurately reflect population distributions. For cost or convenience, surveys may concentrate on subpopulations that are easier or less expensive to reach, focus on firms rather than households, or concentrate on urban populations while excluding rural residents. Second, studies rarely use the same model to estimate returns. Variation in the control variables used in the models can affect estimated returns, as can variation in the used estimation strategy (Psacharopoulos and Patrinos, 2004).

In this paper, we overcome both sources of non-comparability by focusing on a single economy (the U.S.), a sequence of the same survey instrument (the population census), and the same regression analysis during a period that comprises five decades. Along the lines of Bratsberg and Terrell (2002), we explore labor earnings differentials for immigrant workers in the U.S. by presenting comparable estimates of the schooling premium at the secondary and tertiary levels of education for individuals who were educated in their home country.

The analysis of immigrant workers in the U.S. is not new. The resurgence of large-scale immigration sparked the development of an extensive literature that examines the performance of immigrant workers in the labor market, including their earnings upon entry and their subsequent assimilation toward the earnings of native-born workers (see Borjas, 1999; and LaLonde and Topel, 1997, for surveys). An important finding of this literature is that, over the period 1960-1990, there was a continuous decline in the relative entry wage of new immigrants. This is true in terms of both unadjusted earnings and earnings conditional upon characteristics such as education and experience. Borjas (1992) and Borjas and Friedberg (2009) show that there was a decline in cohort quality between 1960 and 1980, and this pattern was reversed during the 1990s. Most of these fluctuations can be explained by a shift in the origin-country

composition of immigration to the United States. Following the 1965 Amendments to the Immigration and Nationality Act, fewer immigrants originated in Europe. Instead, the majority came from developing countries, particularly Latin American and Asia. Immigrants from these countries tended to be less skilled and had worse outcomes in the U.S. labor market than immigrants from other regions. Hanushek and Kimko (2000) find that this can be explained by the immigrants' home-country education quality. For immigrants who are educated in their own country but not in the United States, the quality of education in their country of origin is directly related to U.S earnings.

Similar to the methodological approach of this paper, Bratsberg and Terrell (2002) focus on the U.S. labor markets and investigate the influence of the country of origin on the schooling premium of immigrants. In particular, they link the schooling premium to the school quality of the countries of origin. They show that immigrants from Japan and Northern Europe receive high returns and immigrants from Central America receive low returns. Similarly, Bratsberg and Ragan (2002) find significant earnings differentials between immigrants that acquired schooling in the U.S. and those that did not. Hanushek and Woessmann (2012a) provide new evidence about the potential causal interpretation of the cognitive skills-growth relationship. By using more recent U.S. data, they were able to make important refinements to the analysis of cognitive skills on immigrants' labor market earnings that were previously introduced in Hanushek and Kimko (2000). They also included the specification of full difference-in-differences models that we will use in this paper.

Hanushek and Woessmann (2012b) use a new metric for the distribution of educational achievement across countries, which was introduced in Hanushek and Woessmann (2012a), to try and solve the puzzle of Latin American economic development. The region has trailed most other world regions over the past half century despite relatively high initial development and school attainment levels. This puzzle, however, can be resolved by considering educational achievement, a direct measure of human capital. They found that in growth regressions, the positive growth effect of educational achievement fully accounts for the poor growth performance of Latin American countries. These results are confirmed in a number of instrumental-variable specifications that exploit plausible exogenous achievement variations, which stem from historical and institutional determinants of educational achievement. Finally, a development accounting analysis finds that, once educational achievement is included,

human capital can account for between half to two-thirds of the income differences between Latin America and the rest of the world.

In this paper we also focus on the schooling premia for the Latin American and the Caribbean region (LAC) and compare them to those of migrants from other regions, particularly from East Asia and Pacific (EAP), India, Northern Europe, and Southern Europe, all relative to immigrants from former Soviet Republics[2]. The available data allows us to measure such premia for workers who graduated from school, either at the secondary or tertiary levels, in their home countries between 1940 and 2010.

The rest of the paper proceeds as follows. The next section contains a description of the methodology. In section 3 we introduce the data sources and some descriptive statistics that compare immigrants educated in their country of origin versus immigrants educated in U.S. by census year and region of origin. Section 4 presents estimates of the schooling premium (secondary and tertiary) for male immigrants from 17 LAC countries and 4 other regions relative to male immigrants from the former Soviet Republics. Section 5 examines the robustness of results after controlling for non-random migration, and section 6 concludes.

2. Methodology

Mincer (1974) has provided a great service in estimating the schooling premium by means of the semi-log earnings function. The now standard method of estimating private benefits per year of schooling is by determining the log earnings equations with the form:

$$\ln(w_i) = \alpha + \beta_1 EDUC_i + \beta_2 Age_i + \beta_3 Age_i^2 + \beta_4 X_i + \mu_i \qquad (1)$$

where $ln(w_i)$ is the natural log of hourly earnings for the ith individual; $EDUC_i$ is years of schooling (as a continuous variable); $Age_i$is the age of the individual; X_i is a set of control variables, and μ_i is a random disturbance term reflecting unobserved characteristics. The set of control variables X_i is kept deliberately small to avoid overcorrecting for factors that are correlated with years of schooling. In this way β_1 can be interpreted as the average premium per year of schooling.

In this paper, we are also interested in the schooling premium received by immigrant workers in the U.S who graduated from school during the last five decades. For this purpose, we add a set of dummy variables D which account for the country of origin of all workers. Additionally,

we use a linear-spline specification where EDUC appears in two segments: years greater than 8 and less than or equal to 12 (secondary education) and years greater than 12 (tertiary education) to allow for a nonlinear fit. As a result, the main equation to estimate is:

$$\ln(w_{ijt}) = \alpha + \beta_1 D * EDUC_i + \beta_2 EDUC_i + \beta_3 Age_{it} + \beta_4 Age_{it}^2 + \beta_5 X_{ijt} + \mu_{jt} + \varepsilon_{it} \quad (2)$$

Now, $ln(w_{ijt})$ is the natural log of hourly earnings for the *i*th individual graduated in cohort year t. The vector of control variables X contains the following variables: a set of dummy variables for English proficiency (speaks English well, very well or native), a dummy for marital status (married with spouse present), eight census divisions, years in the United States as a control for assimilation, and the average growth in GDP per capita of the country of origin during the five years prior to immigration in the US to control for economic conditions. The error tem of the wage regression consists of a country-specific component (μ) and an individual component (ε).

First, we focus on workers who acquired all their education outside the U.S. The estimate of the country-of-birth's specific schooling premium is the coefficient of the interaction term between the country-specific dummy variable and years of (secondary or tertiary) schooling of the individual. The omitted level is immigrants from former soviet republics[3] (with secondary or tertiary schooling). In this way β_1, the premium per year of schooling, can be estimated for each country of origin for different levels of schooling.

Such set of coefficients β_1 can also be interpreted as the "first differences" in schooling premia between migrants from different countries/regions (vis-a-vis those of migrants that are in the base category) for different schooling levels. We closely follow this approach, which was introduced by Bratsberg and Terrell (2002), to make our estimations in section 4. Later in section 5, we will introduce different ways of controlling for non-random selection into migration.

3. Data and Descriptive Statistics

We use a pooled data set from the Public Use Microdata for the 1980-2000 U.S. Censuses 5% sample and the American Community Survey 2008-2012 5-Year sample[4].The analysis is restricted to men aged 25-64 currently working and not in school, with incomes more than $1,000 a year, who have worked 50 weeks or more during the last year[5], and have worked more than 30 hours during the last week. Hourly earnings are calculated from the annual wage and

salary income divided by weeks worked per year, which is then divided by hours worked per week. All earnings are in 1999 dollars. We complement this with additional data from the World Bank national accounts data and OECD National Accounts data files for information on GDP growth.

Following Jaeger's method (1997), we convert educational attainment to years of schooling using the following rule[6]: years of schooling equals zero if educational attainment is less than first grade; 2.5 if first through fourth grade; 5.5 if grade fifth or sixth grade; 7.5 if grade seventh or eighth grade; educational attainment if ninth through twelfth grade; 12 if GED earned; 13 if some college, but no degree; 14 if associate degree earned; 16 if bachelor's degree earned; 18 if master's degree earned; 19 if professional degree earned; and 20 if doctorate degree earned[7]. Finally, as mentioned in the methodology section, we split the years of schooling variable intro three categories—years of primary, secondary and tertiary schooling.

Non-citizens and naturalized citizens are labeled as "immigrants". All others are classified as "natives." "Immigrants educated in origin" are defined as those whose final year of graduation is before their year of immigration. "Immigrants educated in the U.S." are defined as those who arrived to the U.S. with six or fewer years of education in their origin country and continued their education within the U.S. We exclude persons from the regression sample if we cannot identify which group they belong to.

Table 1 shows descriptive statistics for relevant variables. We can observe some differences between regions and some general trends over time. Regarding education, the other regions clearly have a much larger proportion of immigrants with tertiary education than LAC. The fact that LAC immigrants are less educated is reflected by the fact that a much larger proportion of Latin American workers are in blue collar occupations. As expected, the main trend observed over time is the increase in the levels of education of all immigrants. On the other hand, the increase in the access to secondary education of LAC immigrants is particularly remarkable. Less than 27% of immigrants from LAC who graduated in the 40's or 50's had secondary education, and now more than 68% of recent Latin American graduated immigrants have reached that level.

[Insert Here Table 1: Descriptive statistics (Men immigrants educated in country of origin by graduation year cohorts)]

	1940-59						1960-69						1970-79						1980-89						1990-2010					
	Educated in						Educated in						Educated in						Educated in						Educated in					
				N.	S.					N.	S.					N.	S.					N.	S.					N.	S.	
	EAP	India	LAC	Europe	Europe	Other	EAP	India	LAC	Europe	Europe	Other	EAP	India	LAC	Europe	Europe	Other	EAP	India	LAC	Europe	Europe	Other	EAP	India	LAC	Europe	Europe	Other
Age																														
25-34	0.83	0.48	5.1	0.13	3.1	0.26	12.01	7.62	19.72	11.77	25.06	9.86	12.03	11.5	20.77	14.04	19.67	6.98	15.49	14.8	40.95	21.57	27.05	14.01	36.69	51.82	67.61	46.05	47.27	47.88
35-44	19.43	18.17	24.77	16.42	24.57	14.35	26.07	27.85	24.83	27.78	24.74	18.32	29.37	26.75	39.42	31.05	35.52	25.22	38.97	39.45	40.01	41.52	41.52	44.01	58.96	46.7	32.01	50.84	49.36	48.92
45-64	79.74	81.35	70.13	83.45	72.33	85.39	61.92	64.53	55.45	60.45	50.2	71.82	58.6	61.75	39.8	54.91	44.81	67.8	45.54	45.75	19.05	36.91	31.44	41.98	4.34	1.48	0.38	3.11	3.37	3.21
Education																														
Primary or less	15.2	8.81	57.58	5.62	43.49	11.45	5.93	2.72	48.3	1.58	22.17	3.8	1.87	1.05	32.13	0.54	7.53	0.83	1	0.49	21.55	0.13	2.95	0.56	0.25	0.01	2.88	0.02	0.46	0.09
Secondary	28.23	20.32	26.69	42.47	39.98	43.86	26.21	15.07	35.03	25.91	53.39	42.87	23.74	15.76	45.4	19.94	52.51	32.07	16.77	11.92	54.76	16.56	41.89	26.18	11.15	3.21	68.77	7.22	16.26	23.16
Some tertiary or more	56.57	70.87	15.73	51.91	16.53	44.69	67.86	82.22	16.67	72.51	24.43	53.34	74.39	83.19	22.47	79.52	39.96	67.11	82.23	87.6	23.69	83.3	55.15	73.26	88.6	96.78	28.35	92.76	83.28	76.75
Ocupation																														
Managerial	15.66	20.32	6.41	24.22	11.83	13.77	17.71	18.74	5.43	32.34	14.46	10.64	18.49	20.57	5.34	32.51	19.21	11.22	17.28	22.34	5.36	34.08	23.01	12.52	15.61	19.55	6.01	34.39	29.37	12.77
Profesional specialty	15.14	30.08	3.45	16.13	4.87	15.5	18.24	40.02	3.32	20.9	5.3	15.1	17.56	30.09	3.83	23.9	9.67	18.1	26.33	29.89	3.77	24.81	16.97	21.32	40.96	31.08	5.04	32.63	38	23.87
Other white collar	43.01	29.92	26.94	24.13	25.08	20.72	41.19	26.24	26.49	25.09	28.46	23.79	42.46	31.91	27.62	24.58	27.9	25.58	40.21	35.85	27.74	25.6	28.59	27.86	34	45.59	29.44	24.71	21.56	30.38
Blue collar	26.18	19.68	63.2	35.52	58.22	50.01	22.85	14.99	64.76	21.67	51.78	50.46	21.49	17.43	63.21	19.02	43.22	45.09	16.18	11.93	63.13	15.51	31.42	38.3	9.43	3.79	59.52	8.26	11.07	32.98
Total observations	7962	1260	30759	11053	7673	4954	14750	4381	38857	6329	4289	3793	20556	6097	50428	7246	2272	6904	15303	5757	52927	7408	1320	5569	9299	10191	30859	5468	861	3463

4. Results

Table 2 shows results for the regressions that estimate Equation (2). In the table we combine results for four world regions (East Asia and Pacific, India, Northern Europe and Southern Europe) and seventeen countries from Latin America and the Caribbean. In each pair of columns, we report the results for a pooled set of immigrants by graduation cohorts (1940-59, 1960-69, 1970-79, 1980-89 or 1990-2010). We report only the coefficient of interest, β_1, the difference in schooling premia between each country/region and the base category. This schooling premia is for every year of education. As outlined in Equation (2), we allow such schooling premia to vary between levels (secondary and tertiary). In addition to tables with the estimated coefficients and with a visual purpose, we also compute the parameter estimates over a rolling window of a fixed size[8] through the sample, so we can get smooth time-varying parameters and plot them against the year of graduation[9] of immigrants as time variable.

Regarding migrants with only high school studies, the most salient fact is that most of the countries in Latin America show stagnancy or decline in the evolution of their schooling premium relative to those of other immigrants (Figure 3). For other regions of the world, the evolution has been somewhat different. The schooling premium of immigrants from southern Europe begun to grow in mid-70´s and started to fall in the early 90´s. Immigrants from both India and East Asian and the Pacific show a schooling premium that originally was lagging behind than those from LAC, but now the situation is reversing.

Within Latin America and the Caribbean, it is interesting to note that the southern cone countries have the highest premium but showing a negative tendency. From the mid-40´s until the early 70´s Central American countries showed a temporary improvement. The case of Cuba is interesting as it is the only country with constant improvements in their relative schooling premium since the early 60´s. However, most of the countries show a stagnation or even a decline in schooling premium, although some countries such as Brazil and to a lesser extent the Andean countries at least seem to show an improvement in their premia since the mid-80´s,

For migrants with tertiary studies in their home country the situation is somewhat different. All in all, the Latin American relative schooling premium is even worse than the one reported for secondary, falling behind from other regions relative to other immigrants premium (figure 4). Whereas all regions´ premia, except India, remain stagnated for the period, Latin America and the Caribbean premia show a clear decline, widening the gap with other regions. India's schooling premium in tertiary education has been consistently increasing since the late 70´s,

showing the highest increase. Within Latin America and the Caribbean, only the southern cone shows positive schooling premium, although the Andean region had positive premium for those graduated in the 50's. By country, in central America and in the Caribbean, there seem to be two clear groups of countries within those regions. In central America, Costa Rica and Panama clearly show higher premia than their peers in the region (figure 6) and in the Caribbean, Jamaica and Trinidad and Tobago over perform their Spanish speaking neighbors (Cuba and Dominican Republic) even though we are controlling for English proficiency. Overall, all countries in the region show either a stagnancy or a clear decline in their tertiary premia over the past decade, raising a flag and should be cause of concern on how Latin American immigrants education is rewarded in the US.

Table 2: Schooling premium by selected countries of birth by graduation year cohorts[10]

	1940-59		1960-69		1970-79		1980-89		1990-2010	
	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary
Argentina	-0.0226*	0.0456***	-0.0098	0.0491***	-0.0100	0.0277***	-0.0366***	0.0203**	-0.0453***	0.0045
	(0.0137)	(0.0147)	(0.0116)	(0.0108)	(0.0099)	(0.0091)	(0.0128)	(0.0085)	(0.0131)	(0.0083)
Brazil	0.0288	0.0626***	-0.0173	0.0384**	-0.0446***	0.0403***	-0.0213***	0.0252***	-0.0249***	0.0252***
	(0.0198)	(0.0207)	(0.0141)	(0.0170)	(0.0092)	(0.0082)	(0.0080)	(0.0080)	(0.0092)	(0.0068)
Chile	-0.0325**	0.0164	-0.0167*	0.0275*	-0.0416***	0.0249**	-0.0586***	0.0201*	-0.0749***	0.0015
	(0.0137)	(0.0159)	(0.0098)	(0.0142)	(0.0101)	(0.0109)	(0.0184)	(0.0114)	(0.0262)	(0.0111)
Colombia	-0.0383***	0.0100	-0.0249***	0.0107	-0.0460***	-0.0192***	-0.0314***	-0.0265***	-0.0454***	-0.0260***
	(0.0097)	(0.0169)	(0.0061)	(0.0110)	(0.0053)	(0.0069)	(0.0062)	(0.0055)	(0.0098)	(0.0059)
Costa Rica	-0.0299	-0.0158	-0.0113	-0.0008	-0.0159	0.0226	-0.0460***	-0.0144	-0.0573***	-0.0222
	(0.0256)	(0.0346)	(0.0120)	(0.0476)	(0.0160)	(0.0195)	(0.0124)	(0.0179)	(0.0181)	(0.0196)
Cuba	-0.0435***	-0.0551**	-0.0426***	-0.0518***	-0.0547***	-0.0375***	-0.0303***	-0.0605***	-0.0374***	-0.0825***
	(0.0119)	(0.0261)	(0.0064)	(0.0112)	(0.0057)	(0.0061)	(0.0055)	(0.0052)	(0.0074)	(0.0066)
Dominican Republic	-0.0612***	-0.0471**	-0.0478***	-0.0890***	-0.0641***	-0.0626***	-0.0517***	-0.0635***	-0.0460***	-0.0778***
	(0.0124)	(0.0223)	(0.0074)	(0.0255)	(0.0056)	(0.0085)	(0.0062)	(0.0073)	(0.0090)	(0.0103)
Ecuador	-0.0545***	-0.0337	-0.0276***	-0.0237	-0.0474***	-0.0456***	-0.0513***	-0.0579***	-0.0533***	-0.0686***
	(0.0138)	(0.0223)	(0.0077)	(0.0151)	(0.0069)	(0.0113)	(0.0076)	(0.0077)	(0.0091)	(0.0099)
El Salvador	-0.0708***	-0.1098***	-0.0462***	-0.0304*	-0.0555***	-0.0468***	-0.0374***	-0.0584***	-0.0434***	-0.0828***
	(0.0183)	(0.0244)	(0.0077)	(0.0183)	(0.0047)	(0.0087)	(0.0052)	(0.0099)	(0.0067)	(0.0099)
Guatemala	-0.0756***	-0.0372	-0.0385***	-0.0140	-0.0626***	-0.0496***	-0.0472***	-0.0661***	-0.0678***	-0.0760***
	(0.0192)	(0.0334)	(0.0077)	(0.0162)	(0.0057)	(0.0119)	(0.0057)	(0.0108)	(0.0071)	(0.0105)
Haiti			-0.2862**	0.0000	-0.0166		-0.0356*		-0.0657***	
			(0.1344)	(0.0000)	(0.0313)		(0.0194)		(0.0158)	
Honduras	-0.0787***	0.0031	-0.0586***	-0.0155	-0.0524***	-0.0680***	-0.0412***	-0.0582***	-0.0499***	-0.0929***
	(0.0213)	(0.0499)	(0.0111)	(0.0242)	(0.0075)	(0.0202)	(0.0070)	(0.0149)	(0.0080)	(0.0132)
Jamaica	-0.0569***	-0.0304	-0.0278***	-0.0047	-0.0297***	0.0144**	-0.0239***	-0.0084	-0.0323***	-0.0195
	(0.0112)	(0.0234)	(0.0060)	(0.0114)	(0.0048)	(0.0072)	(0.0060)	(0.0073)	(0.0115)	(0.0136)
Mexico	-0.0437***	-0.0176	-0.0490***	-0.0256***	-0.0640***	-0.0493***	-0.0582***	-0.0618***	-0.0661***	-0.0579***
	(0.0078)	(0.0139)	(0.0047)	(0.0089)	(0.0035)	(0.0045)	(0.0040)	(0.0037)	(0.0056)	(0.0041)
Panama	-0.0612***	0.0173	-0.0476***	0.0009	-0.0176	0.0026	-0.0116	-0.0048	-0.0499	-0.0078
	(0.0193)	(0.0212)	(0.0151)	(0.0147)	(0.0128)	(0.0150)	(0.0180)	(0.0160)	(0.0324)	(0.0210)
Peru	-0.0337***	0.0243	-0.0353***	-0.0193	-0.0462***	-0.0340***	-0.0323***	-0.0265***	-0.0492***	-0.0397***
	(0.0115)	(0.0236)	(0.0078)	(0.0125)	(0.0064)	(0.0064)	(0.0068)	(0.0065)	(0.0099)	(0.0088)
Trinidad and Tobago	-0.0264**	0.0189	-0.0164**	0.0122	-0.0385***	0.0220*	-0.0215***	0.0091	-0.0110	-0.0008
	(0.0121)	(0.0215)	(0.0077)	(0.0114)	(0.0079)	(0.0118)	(0.0079)	(0.0106)	(0.0141)	(0.0193)
Uruguay	-0.0018	0.0836***	-0.0011	0.0059	-0.0246	0.0549***	-0.0428***	-0.0145	-0.0415**	0.0100
	(0.0197)	(0.0249)	(0.0151)	(0.0237)	(0.0169)	(0.0208)	(0.0162)	(0.0233)	(0.0185)	(0.0253)
EAP	-0.0643***	0.0836***	-0.0466***	0.0075*	-0.0639***	0.0062**	-0.0515***	0.0063**	-0.0617***	-0.0054*
	(0.0077)	(0.0249)	(0.0049)	(0.0041)	(0.0040)	(0.0025)	(0.0051)	(0.0026)	(0.0074)	(0.0029)
India	-0.0617***	0.0107	-0.0502***	0.0194***	-0.0651***	0.0113***	-0.0606***	0.0300***	-0.0498***	0.0559***
	(0.0115)	(0.0084)	(0.0075)	(0.0042)	(0.0061)	(0.0028)	(0.0075)	(0.0029)	(0.0112)	(0.0029)
Northern Europe	0.0354***	0.0146	0.0574***	0.0745***	0.0468***	0.0713***	0.0606***	0.0734***	0.0358***	0.0468***
	(0.0072)	(0.0093)	(0.0060)	(0.0045)	(0.0054)	(0.0030)	(0.0061)	(0.0029)	(0.0105)	(0.0031)
Southern Europe	-0.0001	0.0761***	-0.0093*	0.0278***	-0.0017	0.0421***	0.0334***	0.0415***	-0.0046	0.0122**
	(0.0076)	(0.0087)	(0.0054)	(0.0072)	(0.0057)	(0.0062)	(0.0080)	(0.0061)	(0.0142)	(0.0052)
Observations	26,474		45,881		74,600		75,387		58,598	
R-squared	0.2311		0.2809		0.2941		0.3639		0.4568	

[1] The coefficients are differences in schooling premia with respect to the base category: immigrants from the former soviet republics (Albania, Armenia, Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Macedonia, Moldova, Poland, Romania, Russian Federation and Slovak Republic). In all regressions we use controls for marital status, English fluency, census divisions, assimilation (years in the US) and economic situation in the country of origin (growth in gdp per capita during the five years previous to immigration).

Figure 1. Evolution of Secondary schooling premium relative to other[11] immigrants by global regions

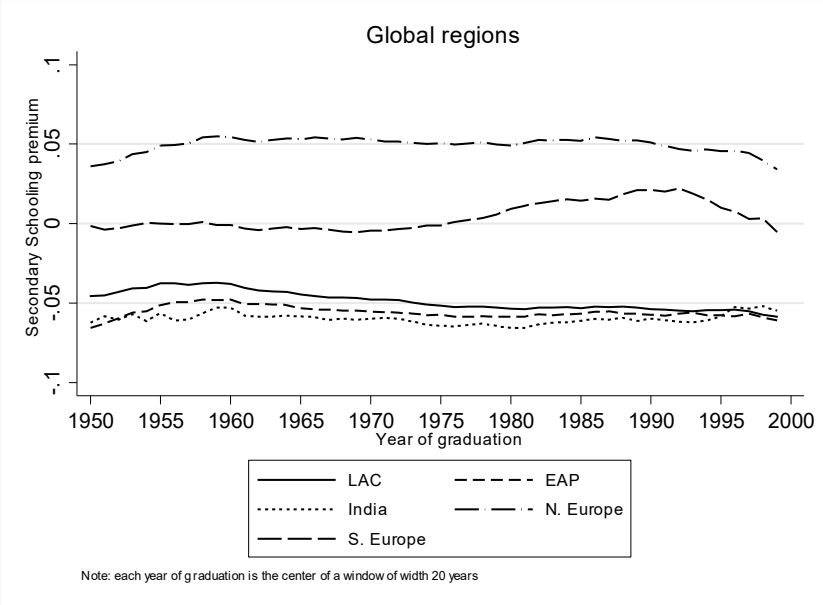


Figure 2. Evolution of Secondary schooling premium relative to other immigrants by LAC regions

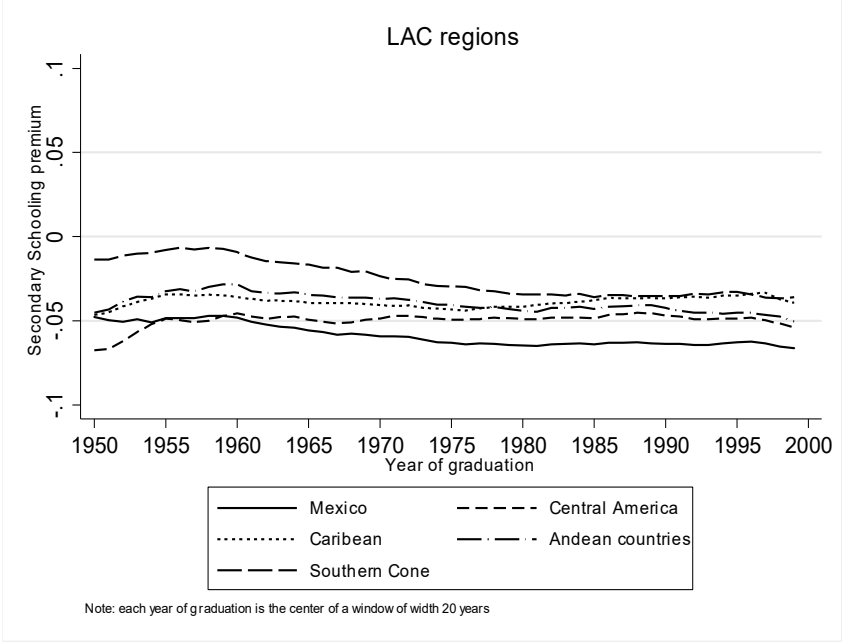
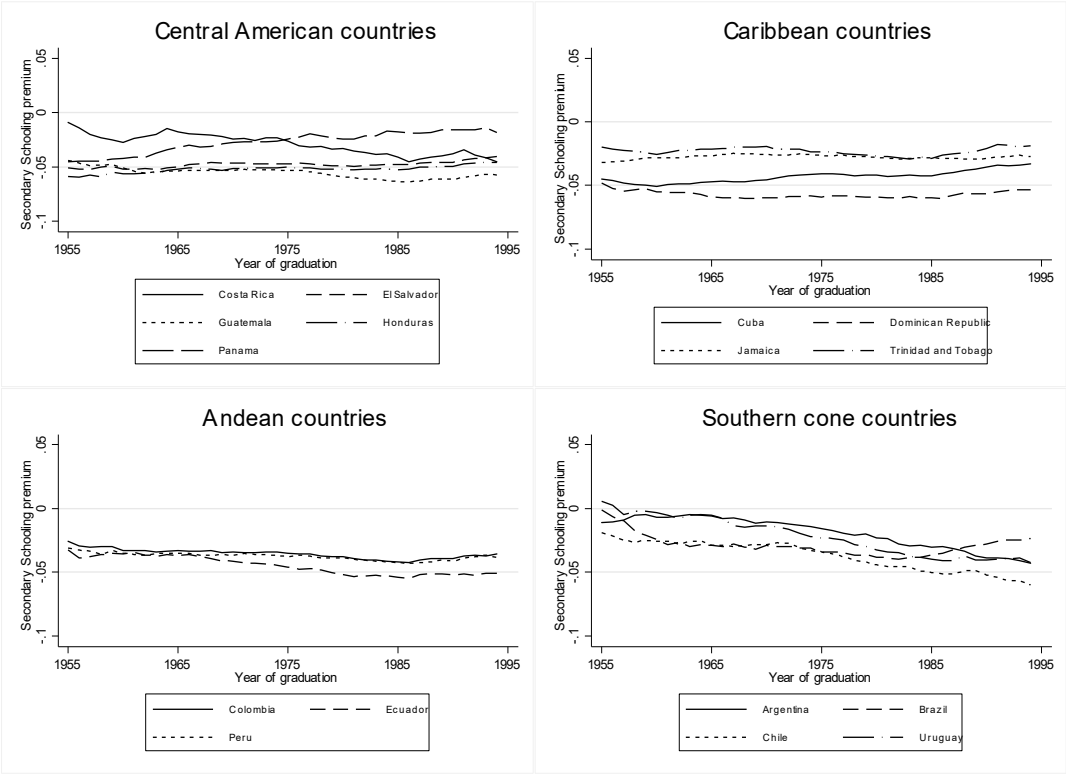
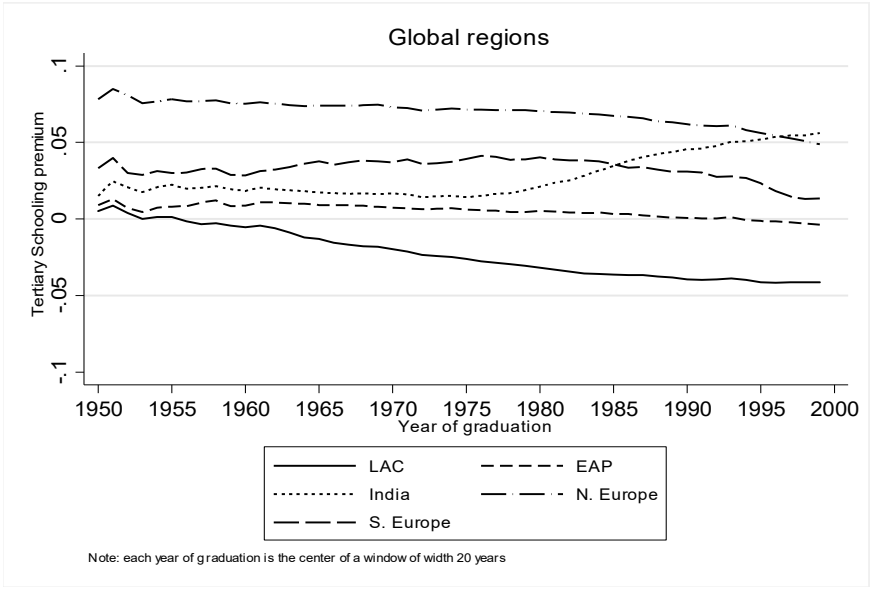


Figure 3. Evolution of Secondary schooling premium relative to other immigrants by LAC countries



Note: each year of graduation is the center of a window of width 30 years

Figure 4. Evolution of Tertiary schooling premium relative to other immigrants by global regions



Note: each year of graduation is the center of a window of width 20 years

Figure 5. Evolution of Tertiary schooling premium relative to other immigrants by LAC regions

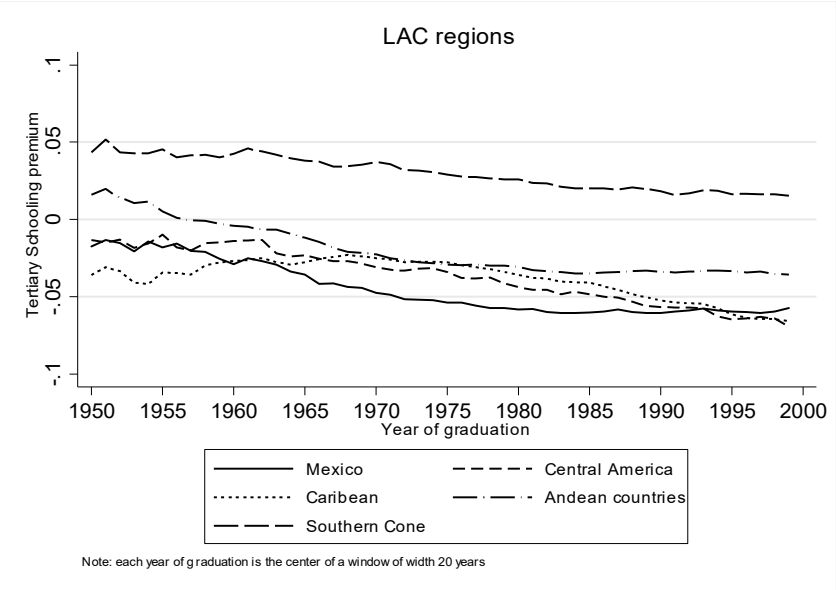
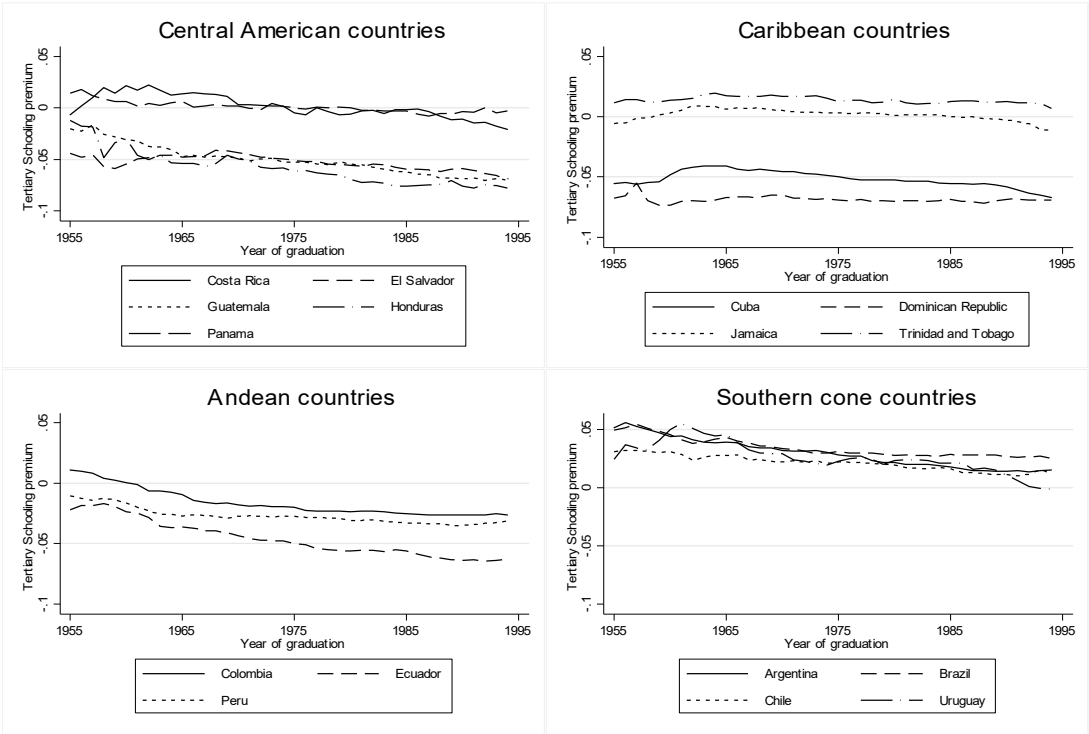


Figure 6. Evolution of Tertiary schooling premium relative to other immigrants by LAC countries



Note: each year of graduation is the center of a window of width 30 years

5. Controlling for non-random selection into migration

Migrants in the U.S. are not a random sample of the populations of their corresponding countries of origin. Self-selection into emigration as well as into a subsequent non-return to their home countries occurs both in observable and unobservable characteristics (Borjas, 1987; Borjas & Bratsbert, 1996). Figure A1 in the appendix shows that this is the case for years of schooling when comparing the data for migrants (from the U.S. Census) and that of populations in the home countries (from the Barro & Lee data sets). Immigrants are selected on various characteristics in addition to education, such as occupations, skills, age, gender, ambitions, and other hard-to-observe traits. The selection process occurs on several complex and interrelated ways and such selectivity could bias our estimators of schooling premia.

Furthermore, the literature suggests that the degree to which immigrants differ in education from nonimmigrants in their homelands varies by source country. Even if immigrants are all positively selective (in the sense that their characteristics are linked to higher labor earnings), there may be substantial variability in the level of selectivity by origin country. There are various factors for these variations. First, migrants from more-educated populations may be less positively selective, since the possibility that they have more schooling than the average person in their home country is not high. Additionally, migrants from countries which are further from the United States should be more highly selective because there are greater costs associated with migrating long distances. And according to Lee (1966), migrants who respond to push factors will be less selective. Economists have also assumed that selectivity applies only to economic migrants (Chiswick 2000).

Figure A1 in the appendix shows that all immigrants in our sample are positively selective and there is substantial variability in the level of selectivity by origin country. In general, immigrants from LAC countries seem to be less positively selective than immigrants from other regions. Immigrants from Mexico and other countries from Central America are less educationally selective, whereas those from the Southern cone and Asia are more. In particular, selection for immigrants from India seems to be high, supporting the idea that migrants from countries that are farther from the United States should be more highly selective.

Another source of selection might stem from the occupations that immigrants ending up working in the United States. As Figure A2 show, the proportion of immigrants working in

white and blue collar occupations varies considerably across cohorts within the same country, reflecting the changes in the mix of occupations in the U.S labor force. Although the shift from a labor force composed of mostly manual laborers to mostly white collar and service workers could be observed from the beginning of the 20th century, a notable acceleration of this trend occurred in the 1980s and is still growing. Even though this trend can be observed for most countries, there are some countries, particularly immigrants from Mexico, Central America and to a lesser extent from the Caribbean that are still employed mainly in blue collar occupations probably reflecting that immigrants from those countries are less educational selective as we mentioned previously.

Finally, it's worth mentioning that as expected, the number of immigrants vary by country, but also by cohort from a same country. Figure A3 shows the waves of immigrants by selected regions. As expected, Mexico is by large the main country of origin of immigrants, and there is a clear decline in the number of immigrants for recent cohorts, being in general the most populous cohorts those graduated between 1970 and 1990.

In this section we address the selection issue with three different approaches: a diff-in-diff setup, occupation-restricted regressions, and a non-parametric matching tool[12].

5.1. A diff-in-diff approach

Table 3 shows the same descriptive statistics but for immigrants educated in the US and US natives. The first obvious difference with respect to the sample of immigrants educated in their country of origin is the limited number of observations, especially for the first few censuses. Additionally, we have a much younger sample for the first few censuses. Most of immigrants who migrated with less than six years of education in their countries of origin were less than 34 years-old at the time of the census. In the following censuses, this particular sample becomes more evenly distributed in regards to age but still younger than the immigrant sample educated in their countries of origin. Finally, this sample is more educated than their counterparts who were educated in their countries of origin.

Table 3: Descriptive statistics by graduation year cohorts (Men immigrants educated in the US and US natives)

	1940-59							1960-69							1970-79							1980-89							1990-2010						
	Educated in US from						US	Educated in US from						US	Educated in US from						US	Educated in US from						US	Educated in US from						US
				N.	S.						N.	S.						N.	S.						N.	S.						N.					
	EAP	India	LAC	Europe	Europe	Other	Native	EAP	India	LAC	Europe	Europe	Other	Native	EAP	India	LAC	Europe	Europe	Other	Native	EAP	India	LAC	Europe	Europe	Other	Native	EAP	India	LAC	Europe	S. Europe	Other	Native
Age																																			
25-34	0	0	11.04	4.76	0	0	0.38	9.23	5.26	12.41	15.36	11.14	6.81	22.1	19.16	12.2	19.85	20.35	17.43	13.7	24.82	32.67	28.14	36.6	31.74	34.44	27.76	36.46	63.02	59.86	72.65	61.46	57.34	74.52	67.5
35-44	16.67	50	18.83	7.14	3.7	0	21.15	13.65	10.53	18.07	20.11	17.39	20	28.29	26.92	34.15	31.44	27.2	28.04	30.75	31.31	38.57	40.12	38.83	36.63	36.16	41.64	37.8	36.18	38.06	27.03	37.29	41.16	25.29	31.83
45-64	83.33	50	70.13	88.1	96.3	100	78.48	77.12	84.21	69.51	64.53	71.47	73.19	49.61	53.92	53.66	48.71	52.44	54.53	55.56	43.87	28.75	31.74	24.57	31.62	29.4	30.6	25.74	0.8	2.08	0.32	1.25	1.5	0.19	0.67
Education																																			
Primary or less	16.67	50	68.83	21.43	29.63	28.57	7.24	2.58	0	17.08	1.21	4.35	1.28	1.64	0.26	7.32	5.84	0.21	0.77	0	0.37	0.37	1.2	3.79	0.1	0.83	0.36	0.34	0.02	0	0.31	0	0.1	0	0.03
Secondary	41.67	50	23.38	26.19	33.33	28.57	54.39	29.15	15.79	39.62	35.55	50	21.28	43.65	23.39	9.76	38.55	31.24	37.72	33.07	38.93	19.98	7.19	40.49	23.23	34	23.49	35.34	11.23	3.33	45.25	18.08	20.18	17.49	26.26
Some tertiary or more	41.67	0	7.79	52.38	37.04	42.86	38.37	68.27	84.21	43.3	63.25	45.65	77.45	54.71	76.36	82.93	55.61	68.55	61.5	66.93	60.7	79.66	91.62	55.72	76.68	65.17	76.16	64.32	88.75	96.67	54.44	81.92	79.72	82.51	73.71
Ocupation																																			
Managerial	8.33	0	5.26	26.19	3.7	28.57	17.58	16.79	42.11	13.31	19.77	18.26	24.68	17.57	18.93	24.39	16.88	19.34	20.63	18.13	17.37	21.65	30.54	15.37	21	21.84	23.02	17.76	22.39	31.42	12.23	21.09	19.48	22.26	17.7
Profesional specialty	0	0	3.95	7.14	7.41	14.29	9.3	13.81	26.32	6.71	10.8	9.26	23.4	11.03	18.66	19.51	10.45	16.02	14.53	18.13	13.37	22.71	32.34	12.61	19.76	14.41	20.5	14.8	29.16	43.16	12.29	24.76	22.81	23.61	19.23
Other white collar	33.33	0	17.11	35.71	33.33	28.57	28.19	38.81	21.05	28.73	32.94	31.34	28.51	28.73	33.73	34.15	33.7	30.75	32.11	25.65	28.73	34.25	31.74	34.3	32.19	32.05	28.42	30.38	35.57	21.79	37	33.12	35	38	33.01
Blue collar	58.33	100	73.68	30.95	55.56	28.57	44.93	30.6	10.53	51.25	36.49	41.14	23.4	42.66	28.68	21.95	38.97	33.89	32.73	38.08	40.54	21.39	5.39	37.73	27.04	31.71	28.06	37.06	12.88	3.63	38.48	21.02	22.71	16.12	30.07
Total observations	12	2	154	42	27	7	1005631	271	19	1007	2650	368	235	1272455	2322	41	4192	8966	1291	387	1834942	3544	167	7634	8241	1806	281	1299708	5127	720	8134	4492	1001	526	872571

We introduce a refinement to Equation (2) along the lines of Hanushek and Woessmann (2012a). This takes into consideration that the unobserved component may contain information about certain traits that are shared by all migrants originating from certain areas, such as work ethics, perseverance, attitudes, etc. If it were the case that these characteristics are ingrained in the populations from certain areas, it is not necessarily the case that these are the "results" of their educational systems.

Fortunately, there is a nice way to clean the results for these unobservable characteristics. To do this, we introduce a new group of workers, also migrants, but with differences in their place of education. These migrant workers are second generation immigrants who received their education in the U.S. By using their information with a "differences-in-differences" setup, we are able to clean the results from the unobservable factors/values that are nurtured in the original local societies and stay fixed after migration. Thus, we first follow a difference-in-differences strategy, comparing the returns of schooling for immigrants educated in their country of origin to those of immigrants from the same country educated within the United States. The equation of estimation (based on 2) is:

$$\ln(w_{ijt}) = \alpha + \beta_1 D * EDUC_i * O + \beta_2 D * EDUC_i + \beta_3 EDUC_i * O + \beta_4 Age_{it} + \beta_5 Age_{it}^2 + \beta_6 X_{ijt} + \mu_{jt} + \varepsilon_{it} \qquad (3)$$

The parameter β_1 captures the relevant contrast in skills between home-country schooling and U.S. schooling[13]. We interpret β_1 as a difference-in-differences estimate of the effect of home-country schooling on earnings, where the first difference is between home-country educated immigrants (the "treatment group") and U.S.-educated immigrants (the "control group") from the same country, and the second difference is in the average years of schooling of the home country. The parameter β_2 captures the bias that would emerge in standard cross-sectional estimates from omitted variables like cultural traits that are correlated with home-country years of schooling in the same way for all immigrants from the same country of origin (independent of where they were educated).

The results previously reported remain after using the diff in diff methodology. The schooling premium for Latin America and the Caribbean is stagnated. In tertiary, again, Latin America and the Caribbean shows the lowest premium but now the decline trend seems to be reversed since the late 80's, catching up with East Asian and the Pacific although still far from the other regions. In fact, the gap is widening with respect to India, since its impressive positive trend stands.

Table 4: Schooling premium by selected regions by graduation year cohorts

(Diff in Diff specification)

	<=1969		1970-79		1980-89		1990-2010	
	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary
EAP	-0.0509***	-0.0105	-0.0537***	-0.0352***	-0.0545	0.0029	-0.0208	-0.0068
	(0.0168)	(0.0232)	(0.0119)	(0.0097)	(0.0352)	(0.0334)	(0.0171)	(0.0087)
India	0.0131	0.0417	-0.0299	0.0083	-0.1263**	0.0075	-0.0615*	0.0406***
	(0.0518)	(0.0319)	(0.0647)	(0.0489)	(0.0639)	(0.0355)	(0.0328)	(0.0098)
LAC	-0.0018	0.0177	-0.0202*	-0.0478***	-0.0384	-0.0234	-0.0024	-0.0067
	(0.0124)	(0.0215)	(0.0106)	(0.0101)	(0.0347)	(0.0335)	(0.0156)	(0.0089)
Northern Europe	0.0552***	0.0802***	0.0615***	0.0340***	0.0475	0.0786**	0.0787***	0.0621***
	(0.0104)	(0.0181)	(0.0107)	(0.0092)	(0.0351)	(0.0333)	(0.0184)	(0.0089)
Southern Europe					-0.0060	0.0342	0.0123	0.0267**
					(0.0357)	(0.0341)	(0.0222)	(0.0108)
Observations	76,472		87,231		87,398		78,239	
R-squared	0.2559		0.2901		0.3567		0.4301	

Figure 7. Evolution of Secondary schooling premium relative to other immigrants by global regions (Diff in Diff specification)

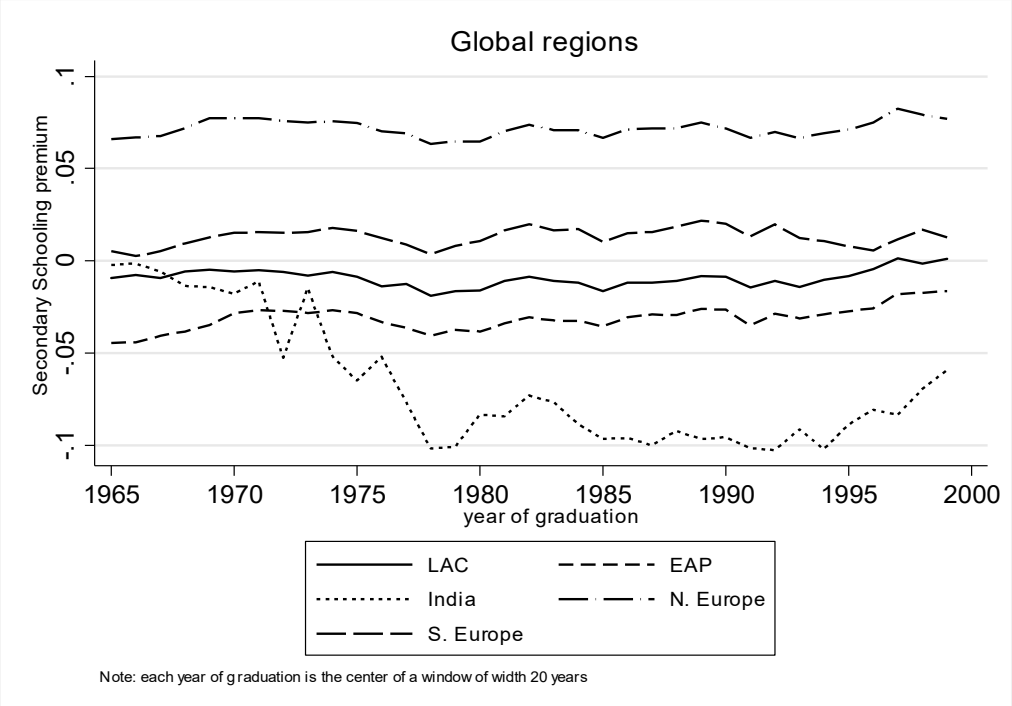
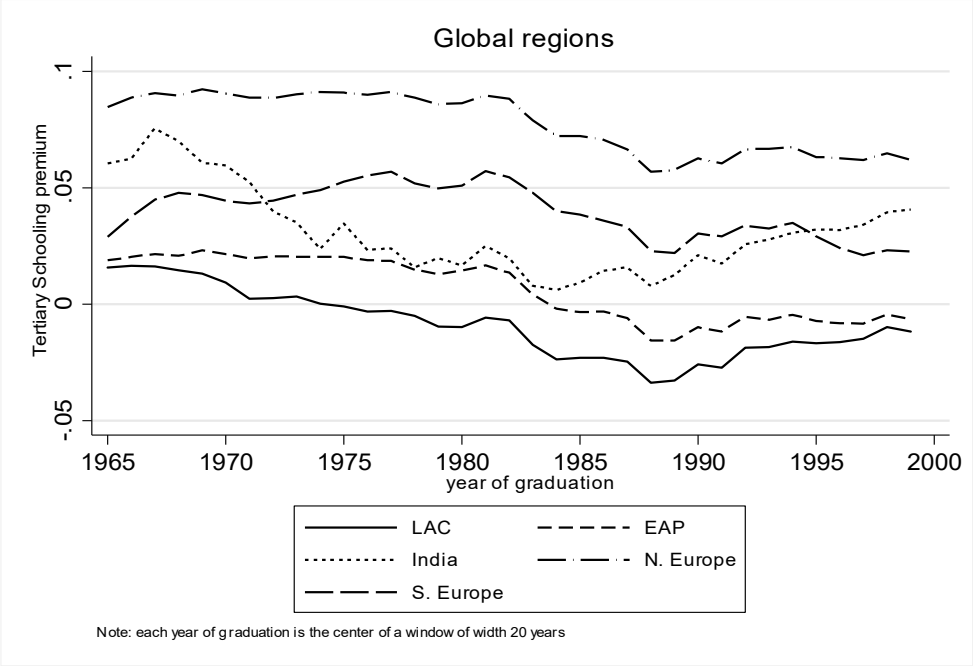


Figure 8. Evolution of Tertiary schooling premium relative to other immigrants by global regions (Diff in Diff specification)



5.2. By occupation

What can explain the remarkable performance of India and the poor one in Latin America and the Caribbean? In this section we explore a possible additional way of selective migration: by occupations. We divide the sample of immigrant workers in four occupational groups: managerial, professional specialties, other white collars and blue collars[14]. In all four occupational groups in tertiary, Latin America and the Caribbean shows the lowest schooling premia. The impressive performance of India, in contrast, is still present in all but one occupational group: among blue collars the improvement of the schooling premium is not so marked, even there is also a positive trend for recent cohorts. However, it's for specialized professionals (doctors, engineers, architects, etc) and for other white collars, most of the jobs related to new technologies (telecommunications, computers, etc) are included in this category, where the increase in premia compared to other immigrants has been even more remarkable. This goes in line with the idea that the selective migration of Indian workers to the US emphasized on highly-trained technologically-oriented individuals. On the other hand, Latin America and the Caribbean gap premia in those two groups of occupations are widening from other immigrants and regions, showing that immigrants from LAC are no taking advantage of the shift in America's Labor Market towards a more Technology-Driven market.

Table 5: Schooling premium by selected regions and occupation (men immigrants)

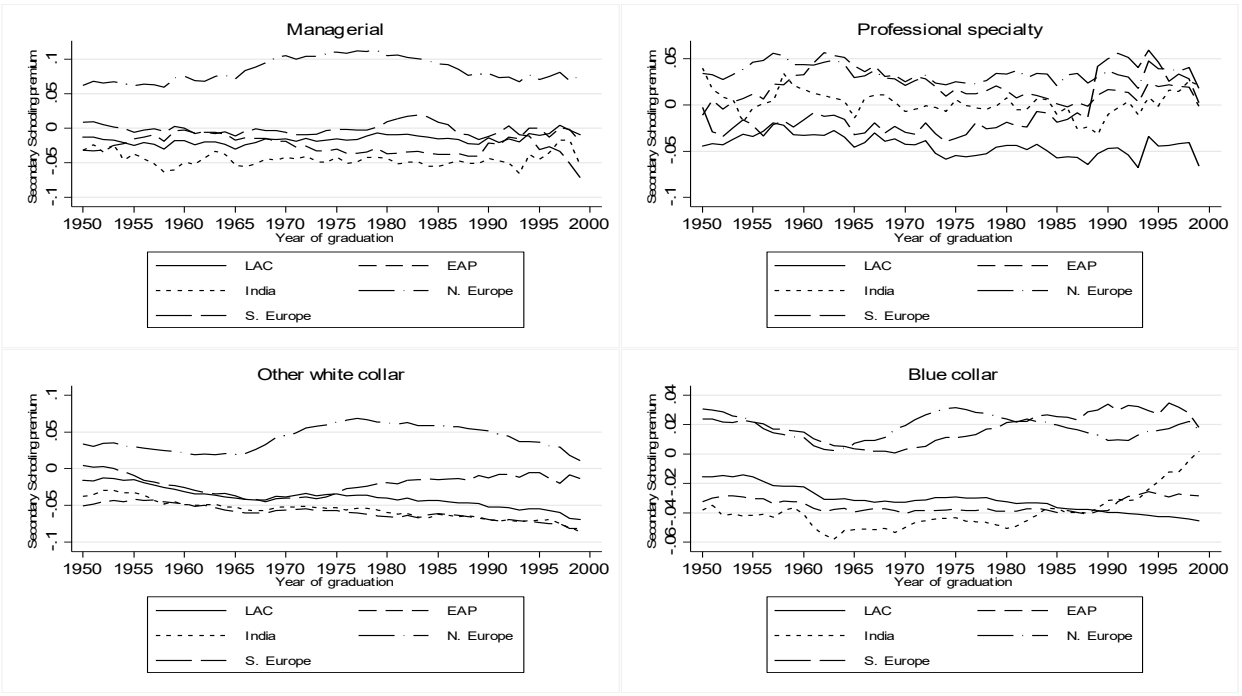
Managerial	<=1969		1970-79		1980-89		1990-2010	
	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary
EAP	-0.0184	-0.0049	-0.0444**	0.0138**	-0.0032	0.0098	-0.0403	0.0017
	(0.0204)	(0.0105)	(0.0210)	(0.0070)	(0.0229)	(0.0071)	(0.0360)	(0.0077)
India	-0.0586**	-0.0069	-0.0619**	0.0100	-0.0252	0.0246***	-0.0386	0.0369***
	(0.0280)	(0.0110)	(0.0304)	(0.0072)	(0.0301)	(0.0072)	(0.0437)	(0.0074)
LAC	-0.0227	-0.0110	-0.0169	-0.0004	-0.0033	-0.0044	-0.0164	0.0001
	(0.0193)	(0.0117)	(0.0194)	(0.0075)	(0.0189)	(0.0069)	(0.0273)	(0.0074)
Northern Europe	0.0950***	0.0806***	0.1081***	0.0844***	0.0986***	0.0909***	0.0733*	0.0601***
	(0.0192)	(0.0103)	(0.0218)	(0.0069)	(0.0226)	(0.0066)	(0.0420)	(0.0068)
Southern Europe	0.0039	0.0308**	0.0129	0.0443***	0.0202	0.0656***	-0.0827*	0.0291***
	(0.0201)	(0.0137)	(0.0249)	(0.0118)	(0.0294)	(0.0120)	(0.0423)	(0.0103)
Observations	11,779		10,781		9,987		7,777	
R-squared	0.1640		0.1909		0.2386		0.2670	

Professional specialty	<=1969		1970-79		1980-89		1990-2010	
	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary
EAP	-0.0423	0.0087	0.0170	0.0061	0.0695	-0.0024	-0.0321	-0.0031
	(0.0399)	(0.0055)	(0.0348)	(0.0040)	(0.0478)	(0.0043)	(0.0559)	(0.0042)
India	-0.0356	0.0181***	0.0146	0.0267***	0.0322	0.0267***	-0.0213	0.0351***
	(0.0504)	(0.0057)	(0.0520)	(0.0039)	(0.0553)	(0.0044)	(0.0800)	(0.0046)
LAC	-0.1063***	0.0062	-0.0948***	-0.0086*	-0.0082	-0.0129***	-0.1101**	-0.0177***
	(0.0360)	(0.0068)	(0.0316)	(0.0048)	(0.0399)	(0.0044)	(0.0482)	(0.0049)
Northern Europe	0.0024	0.0150***	-0.0069	0.0261***	0.1074**	0.0231***	0.0097	0.0229***
	(0.0361)	(0.0058)	(0.0361)	(0.0042)	(0.0446)	(0.0044)	(0.0582)	(0.0043)
Southern Europe	-0.0497	-0.0071	-0.0549	0.0257***	0.1257**	0.0196**	0.0025	0.0078
	(0.0435)	(0.0094)	(0.0478)	(0.0093)	(0.0614)	(0.0080)	(0.0566)	(0.0062)
Observations	10,256		10,253		10,761		11,350	
R-squared	0.1453		0.1706		0.1484		0.1824	

Other white collar	<=1969		1970-79		1980-89		1990-2010	
	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary
EAP	-0.0481***	-0.0118	-0.0618***	-0.0209***	-0.0583***	-0.0225***	-0.0778***	-0.0199***
	(0.0075)	(0.0075)	(0.0081)	(0.0048)	(0.0094)	(0.0049)	(0.0119)	(0.0051)
India	-0.0476***	-0.0073	-0.0571***	-0.0446***	-0.0621***	-0.0016	-0.0778***	0.0479***
	(0.0101)	(0.0085)	(0.0107)	(0.0057)	(0.0125)	(0.0056)	(0.0157)	(0.0047)
LAC	-0.0323***	-0.0270***	-0.0524***	-0.0578***	-0.0499***	-0.0806***	-0.0750***	-0.0869***
	(0.0070)	(0.0084)	(0.0076)	(0.0053)	(0.0084)	(0.0050)	(0.0101)	(0.0055)
Northern Europe	0.0502***	0.0855***	0.0580***	0.0559***	0.0802***	0.0522***	0.0195	0.0321***
	(0.0080)	(0.0088)	(0.0108)	(0.0070)	(0.0117)	(0.0063)	(0.0187)	(0.0059)
Southern Europe	-0.0172**	0.0429***	-0.0221*	0.0135	0.0043	-0.0001	-0.0061	-0.0028
	(0.0083)	(0.0119)	(0.0117)	(0.0130)	(0.0162)	(0.0146)	(0.0224)	(0.0155)
Observations	22,802		24,067		23,497		18,897	
R-squared	0.2074		0.2234		0.3177		0.4912	

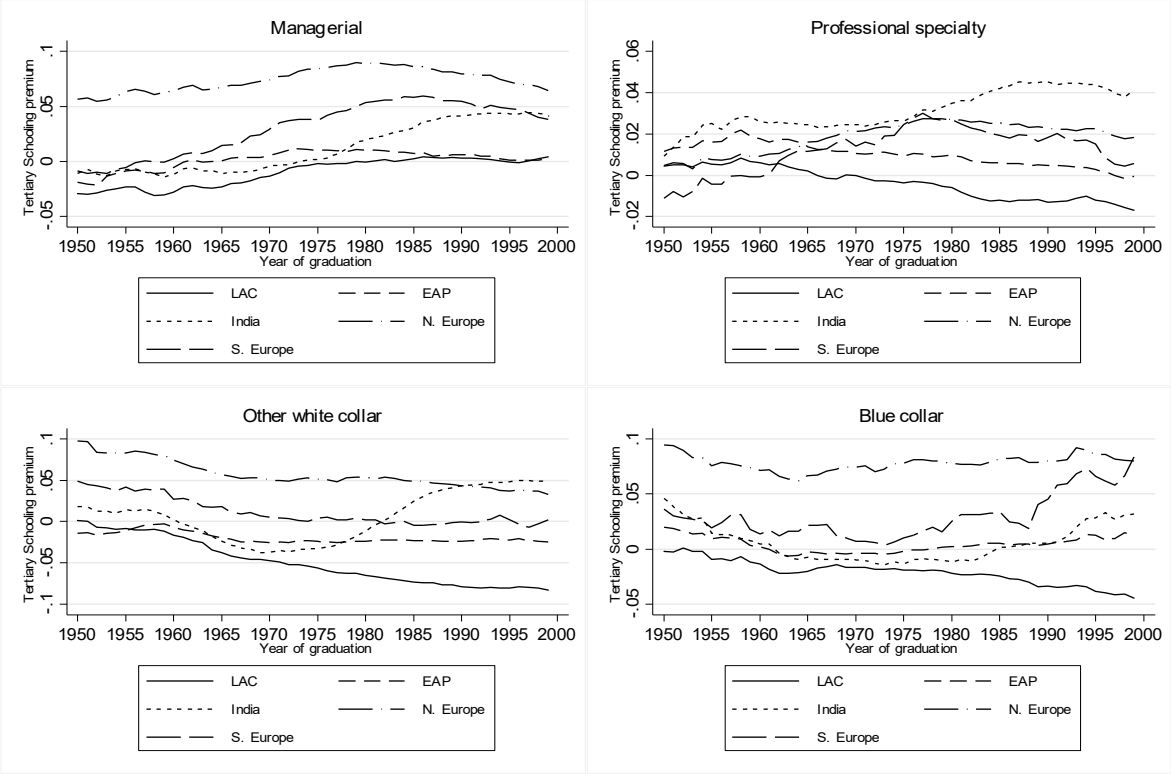
Blue collar	<=1969		1970-79		1980-89		1990-2010	
	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary
EAP	-0.0341***	-0.0000	-0.0428***	-0.0010	-0.0302***	0.0171***	-0.0318***	0.0128
	(0.0052)	(0.0069)	(0.0050)	(0.0053)	(0.0069)	(0.0065)	(0.0107)	(0.0096)
India	-0.0405***	0.0012	-0.0592***	-0.0126*	-0.0453***	0.0004	0.0028	0.0316***
	(0.0082)	(0.0097)	(0.0078)	(0.0071)	(0.0105)	(0.0093)	(0.0181)	(0.0113)
LAC	-0.0343***	-0.0192**	-0.0514***	-0.0237***	-0.0471***	-0.0261***	-0.0549***	-0.0541***
	(0.0041)	(0.0077)	(0.0036)	(0.0050)	(0.0044)	(0.0053)	(0.0067)	(0.0074)
Northern Europe	0.0434***	0.0993***	0.0207***	0.0802***	0.0231***	0.0930***	0.0273**	0.0772***
	(0.0047)	(0.0095)	(0.0066)	(0.0098)	(0.0074)	(0.0098)	(0.0127)	(0.0128)
Southern Europe	0.0181***	0.0302**	0.0080	0.0384*	0.0474***	0.0200	0.0111	0.0771***
	(0.0048)	(0.0148)	(0.0066)	(0.0217)	(0.0091)	(0.0218)	(0.0230)	(0.0279)
Observations	26,941		28,935		30,811		20,396	
R-squared	0.1906		0.1498		0.1485		0.1364	

Figure 9. Evolution of Secondary schooling premium relative to other immigrants by occupation



Note: each year of graduation is the center of a window of width 20 years

Figure 10. Evolution of Tertiary schooling premium relative to other immigrants by occupation



Note: each year of graduation is the center of a window of width 20 years

5.3. Non-parametric matching

During the half century of our analysis many workers' characteristics may have changed. This section reports the results of an exercise that attempts to control for those changes. For that purpose, we use the matching-on-characteristics approach developed in Ñopo (2008) to maintain fixed the distribution of observable characteristics of migrant workers into the US. In this way, for each country of birth, the distribution of characteristics in terms of gender, age and educational level attained is kept fixed and equal to the distribution of characteristics observed for the cohort of migrants who arrived into the US between 1950 and 1959. In this way we generate a counterfactual situation of the type: "how our results would change if the joint distribution of observable characteristics of the immigrants for each country (gender, age and educational level) is kept constant at how it was for migrants who arrived between 1950 and 1959?"

By matching on observables we obtain a new distribution of characteristics for immigrants from recent cohorts that mimic the one for immigrants from the 1950-1959 cohort. (See Ñopo, 2008, for further methodological details.) Therefore, we proceed to estimate:

$$\ln(w_{ijt})w_{matching} = [\alpha + \beta_1 D * EDUC_i + \beta_2 EDUC_i + \beta_3 Age_{it} + \beta_4 Age_{it}^2 + \beta_5 X_{ijt} + \mu_{jt} + \varepsilon_{it}]_{W_{matching}} \quad (4)$$

where $w_{matching}$ denotes the weights after matching (that is, after the differences in the distribution of observable characteristics have vanished).

Table 6: Schooling premium by selected regions (men immigrants)
(With weights after matching)

	<=1969		1970-79		1980-89		1990-2010	
	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary	Secondary	Tertiary
EAP	-0.0544***	0.0211***	-0.0630***	0.0075**	-0.0510***	0.0061**	-0.0452**	0.0040
	(0.0097)	(0.0055)	(0.0061)	(0.0036)	(0.0062)	(0.0029)	(0.0177)	(0.0052)
India	-0.0502**	0.0343***	-0.0424**	0.0130**	-0.0672***	0.0340***		0.0484***
	(0.0214)	(0.0081)	(0.0174)	(0.0051)	(0.0225)	(0.0033)		(0.0056)
LAC	-0.0225***	0.0146*	-0.0534***	-0.0230***	-0.0446***	-0.0348***	-0.0499***	-0.0346***
	(0.0060)	(0.0080)	(0.0042)	(0.0039)	(0.0047)	(0.0031)	(0.0109)	(0.0056)
Northern Europe	0.0406***	0.0660***	0.0466***	0.0712***	0.0733***	0.0845***	0.0557**	0.0681***
	(0.0066)	(0.0052)	(0.0065)	(0.0037)	(0.0082)	(0.0034)	(0.0269)	(0.0053)
Southern Europe	-0.0039	0.0296***	0.0004	0.0453***	0.0422***	0.0603***	-0.0092	0.0429***
	(0.0067)	(0.0084)	(0.0069)	(0.0079)	(0.0105)	(0.0070)	(0.0334)	(0.0094)
Observations	62,101		57,182		48,095		12,274	
R-squared	0.2626		0.2805		0.3660		0.4435	

Figure 11. Evolution of Secondary schooling premium relative to other immigrants (With weights after matching)

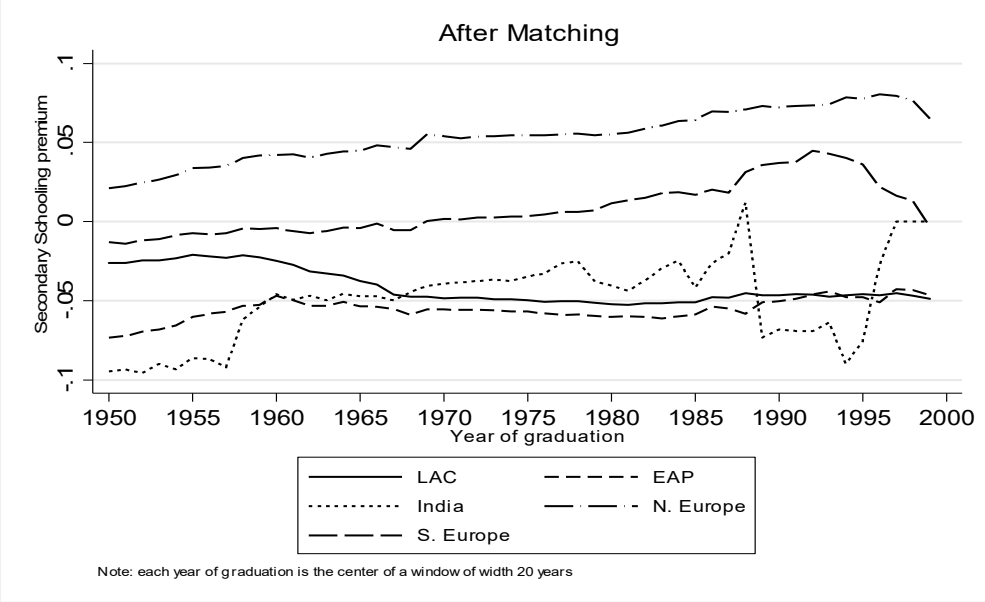
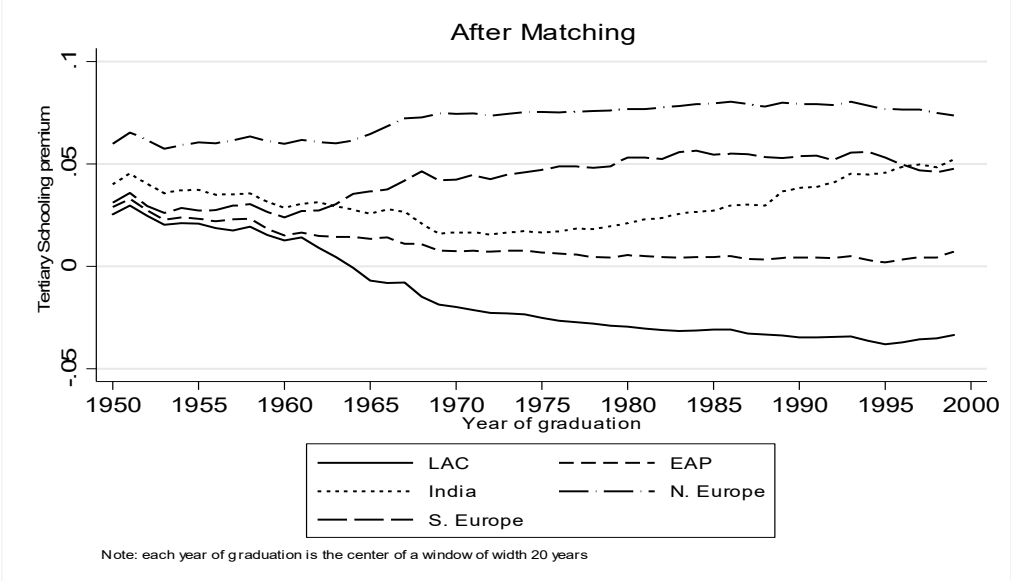


Figure 12. Evolution of Tertiary schooling premium relative to other immigrants (With weights after matching)



As table 6 and figures 11 and 12 show, the main results stand. Immigrants from Latin America and the Caribbean show the lowest premia both for secondary and tertiary, but particularly for tertiary where the premia for immigrants from LAC is clearly lagging behind. Besides, the remarkable improvement in premia for immigrants from India still stand.

6. Conclusions

In this paper we show proxy evidence that the schooling premia in Latin America have been steadily low for the last 50 years. Besides, these results stand after controlling for selective migration in different ways. This contradicts the popular belief in policy circles that the education quality of the region has deteriorated in recent years. However, Latin America and the Caribbean is a very heterogeneous region and there are certainly some differences among countries. Southern cone countries have better premia, particularly at the tertiary level. In Central America, Costa Rica and Panama stand out over their neighbors and Cuba show a significant improvement particularly at secondary during the period of analysis. All in all, the overall picture for the region shows little room for optimism and should be caused of concern.

The shift from a labor force composed of mostly manual laborers to mostly white collar and service workers occurred in the US a few decades ago. In this context, it seems that immigrants from LAC are not prepared enough and hence not taking advantage of the technology-driven shift. As a result, there is the concern that education systems in the region are failing to prepare students for the workforce and to compete in this context of rapid changes and global economy.

In contrast, schooling premium in India shows an impressive improvement in recent decades, especially at the tertiary level. This goes in line with the idea that the selective migration of Indian workers to the US emphasized on highly-trained technologically-oriented individuals, showing that least for a selected group, the education system in India is providing some skills that have been highly rewarded in the US for the last two decades.

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Appendix

Figure A1 Years of education, US immigrants (US census) vs Population of origin (Barro & Lee)

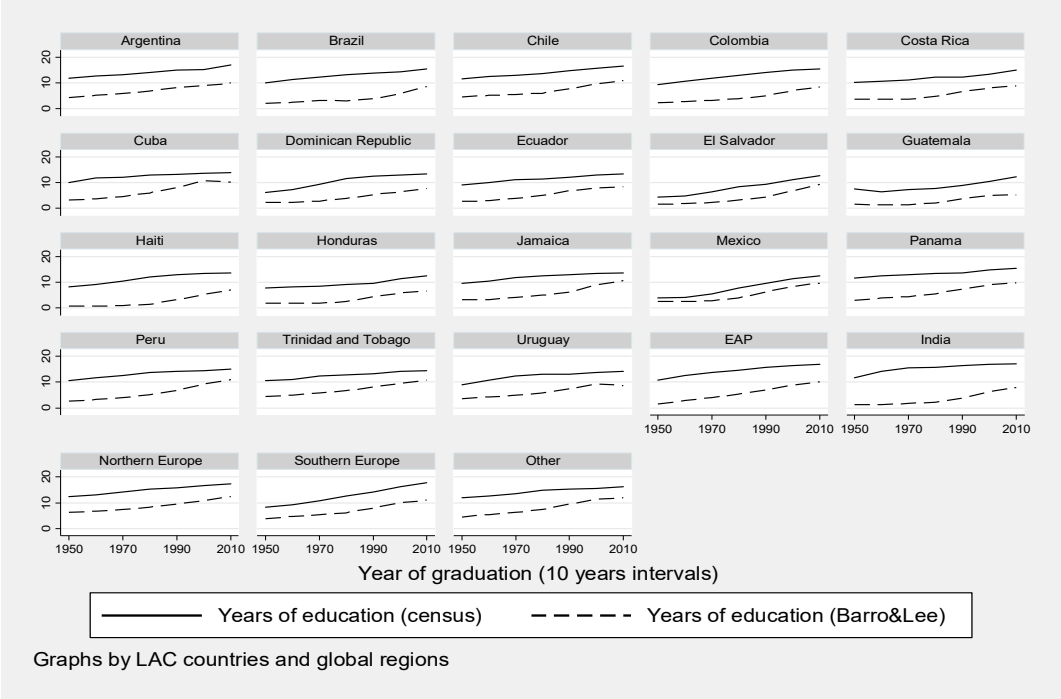

Figure A2. % of immigrants by occupation (Professional Specialty vs Blue collar)

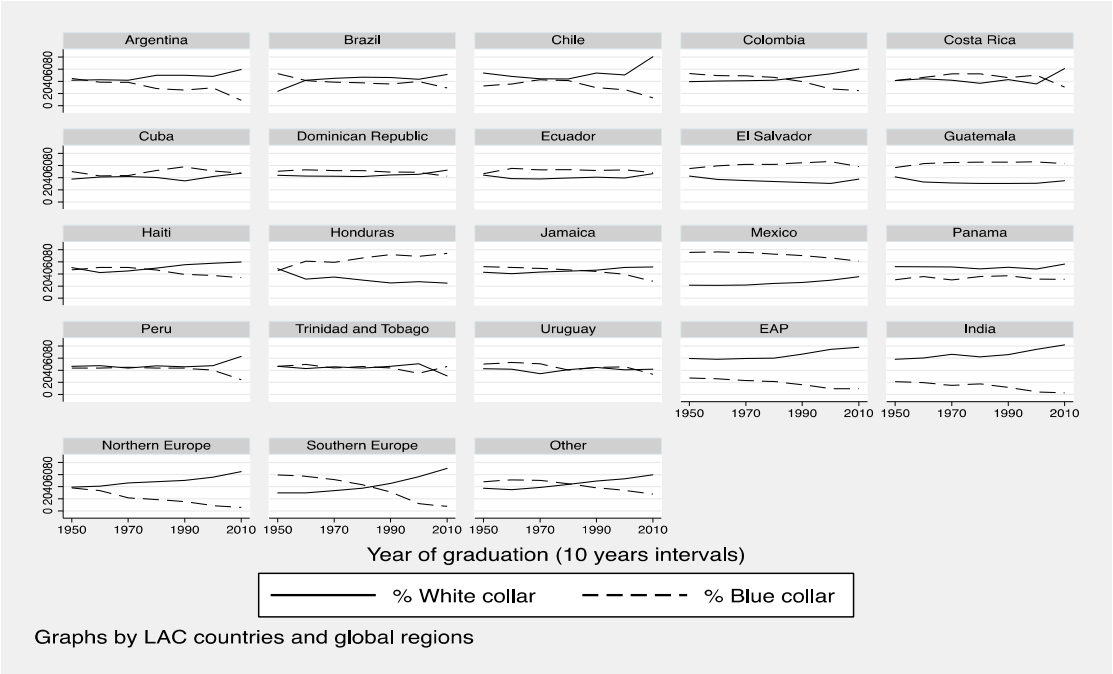

Figure A3. Waves of immigrants by country (5 years intervals)

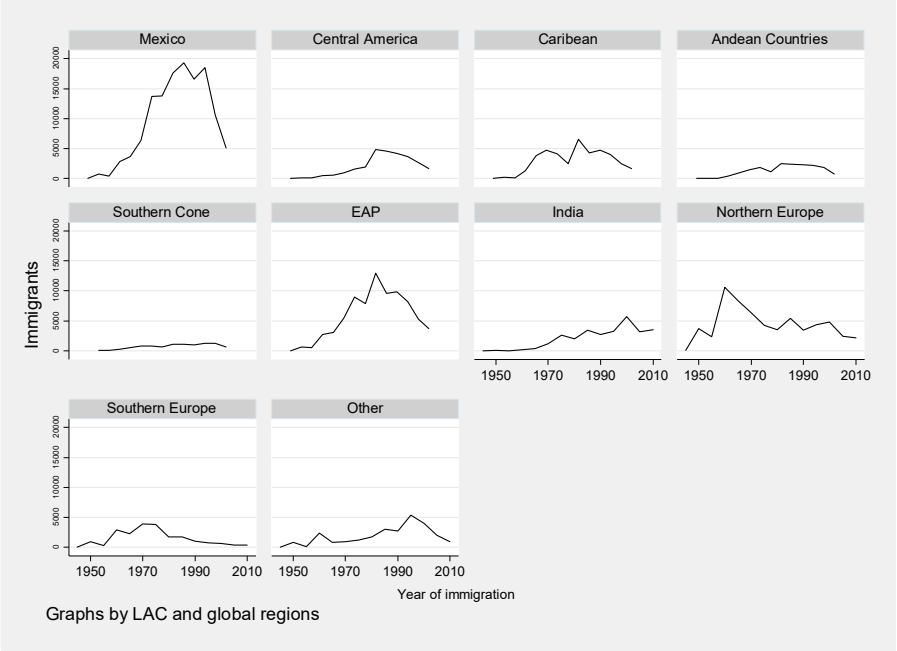

Table A1. List of countries by region

List of countries by region			
EAP	**N. Europe**	**S. Europe**	**Former Soviet republics**
China	Austria	Greece	Albania
Hong Kong	Belgium	Italy	Armenia
Indonesia	Denmark	Portugal	Bulgaria
Japan	Finland	Spain	Czech Rep.
Korea, Rep.	France		Estonia
Macao-China	Germany		Hungary
Malaysia	Iceland		Latvia
Philippines	Ireland		Lithuania
Singapore	Liechtenstein		Macedonia
Taiwan	Luxembourg		Moldova
Thailand	Netherlands		Poland
	Norway		Romania
	Sweden		Russian Fed.
	Switzerland		Slovak Rep.
	UK		

Table A2. List of occupations by categories

Ocupations by categories			
Managerial	**Professional specialty**	**Other white collar**	**Blue collar**
Executive, Administrative, and Managerial Occupations	Architects	Adjusters and Investigators	Construction Trades
Management Related Occupations	Engineers	Communications Equipment Operators	Extractive Occupations
	Health Assessment and Treating Occupations	Computer Equipment Operators	Farm Operators and Managers
	Health Diagnosing Occupations	Duplicating, Mail, and Other Office Machine Operators	Machine Operators, Assemblers, and Inspectors Machine Operators and Tenders, Except Precision
	Lawyers and Judges	Engineering and Related Technologists and Technicians	Mechanics and Repairers
	Librarians, Archivists, and Curators	Financial Records Processing Occupations	Other Agricultural and Related Occupations
	Mathematical and Computer Scientists	Health Technologists and Technicians	Precision Production Occupations
	Natural Scientists	Information Clerks	
	Social Scientists and Urban Planners	Mail and Message Distributing Occupations	
	Social, Recreation, and Religious Workers	Material Recording, Scheduling, and Distributing Clerks	
	Teachers	Miscellaneous Administrative Support Occupations	
	Therapists	Other service occupation	
	Writers, Artists, Entertainers, and Athletes	Other technicians	
		Private Household Occupations	
		Protective Service Occupations	
		Records Processing Occupations, Except Financial	
		Sales Related Occupations	
		Sales Representatives, Commodities Except Retail	
		Sales Representatives, Finance and Business Services	
		Sales Workers, Retail and Personal Services	
		Science Technicians	
		Secretaries, Stenographers, and Typists	
		Supervisors, Administrative Support Occupations	

[1] Mincer (1974), Psacharopoulos (1972, 1973, 1985, 1989, 1994), Harmon et al.(2003), Heckman et al. (2003), Psacharopoulos and Patrinos (2004), Banerjee and Duflo (2005), Colclough et al. (2010), Psacharopoulos and Layard (2012), Montenegro and Patrinos (2014).

[2] Table A1 in the appendix lists the countries included in each region.

[3] Pooled of immigrants from: Albania, Armenia, Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Macedonia, Moldova, Poland, Romania, Russian Federation and Slovak Republic.

[4] The ACS 2008-2012 is a 5% random sample of the population and contains all households and persons from the 1% ACS samples for 2008, 2009, 2010, 2011 and 2012, identifiable by year.

[5] In the ACS (2008-2012) the number of weeks is reported in intervals so to keep comparability throughout the different sources we impose this restriction. More than 80% of the sample meets this requirement.

[6] See Jaeger (1997) for a discussion of alternate conversion rules

[7] Due to differences in the educational attainment variable, in the 1980 census data we convert educational attainment to years of schooling using the following rule: years of schooling equals zero if educational attainment is less than first grade; 1 year per grade (grades 1 through 12), i.e. 1 year if finished 1st grade, 2 if finished 2nd grade and so on and so forth; and finally years of schooling equals 14 if 4 years of college and adds 1 year per additional year of college up to 17 if has 8 years of college.

[8] 21 years (leaving 10 years behind and 10 years ahead) when using global regions and 31 (15 and 15) when estimating the parameters for LAC countries.

[9] Because the questionnaire does not ask the year of graduation of the individual, we infer year of graduation as year of birth plus six plus years of schooling.

[10] The coefficients are differences in schooling premia with respect to the base category: immigrants from the former soviet republics (Albania, Armenia, Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Macedonia, Moldova, Poland, Romania, Russian Federation and Slovak Republic). In all regressions we use controls for marital status, English fluency, census divisions, assimilation (years in the US) and economic situation in the country of origin (growth in gdp per capita during the five years previous to immigration).

[11] Pooled of immigrants from: Albania, Armenia, Bulgaria, Czech Rep., Estonia, Hungary, Latvia, Lithuania, Macedonia, Moldova, Poland, Romania, Russian Fed. and Slovak Rep.

[12] In this section due to limitations in the number of observations, we perform the analysis using only region level aggregated data and 4 pooled sets of immigrants by graduation year (<=1969, 1970-1979, 1980-89 and 1990-2010).

[13] The assignment of individuals to U.S. schooling is based on census data indicating immigration before age 6. The assignment of individuals to schooling all in country of origin is based on age of immigration greater than years of schooling plus six. A person who moves back and forth during the schooling years could be erroneously classified as all U.S. or no U.S. schooling, even though they are really in the partial treatment category (which is excluded from the difference-in-differences estimation).

[14] See Table A2 for a list of occupations by category.