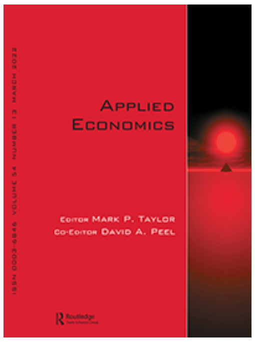

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Human capital and state income differences in Mexico

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ABSTRACT
We study the relationship between differences in human capital and differences in output per worker of the federal entities of Mexico. We consider both quantity and quality of education in human capital formation. Our measure of quality of education is constructed using the OECD's programme for International Student Assessment (PISA) maths achievement test scores. Our results are consistent with different methodologies and data sources. We find that variations in human capital explain upwards of 40% of the variations in state GDP per hour worked. Our results indicate that Mexican states should place more emphasis both in the quantity as well as quality of schooling to support economic development of the states.

KEYWORDS
Education; human capital; Mexico; development accounting

JEL CLASSIFICATION
I25; I26; J24; R11; O54; O15

1. Introduction

Traditional development accounting literature is focused on understanding differences in income by decomposing them into differences due to physical capital, labour, and to total factor productivity (TFP). Our focus is on how differences in labour, more broadly human capital, contribute to differences in income at the state level. In particular, we study differences in human capital, and how these impact economic development of the federal entities in Mexico.[1]

In Mexico, significant differences exist in terms of state GDP per worker and state GDP per hour worked. Important differences are also present in terms of human capital measured through the average years of schooling. We refer to human capital as the one derived from schooling, and not from work experience as in Bils and Klenow (2000), nor from externalities as in Lucas (1988). We estimate human capital using the human capital formation model of Hall and Jones (1999) to make our results as comparable as possible to those in Hanushek, Ruhose, and Woessmann (2017), following their methodology when possible. In the model, the effects of years of schooling are added to its quality. We follow Hanushek, Ruhose, and Woessmann (2017) who utilize test scores to measure the quality of education, we use the PISA Mathematics test. We then study whether differences in human capital across states can explain differences in GDP per worker and per hour worked.

International empirical studies suggest that differences in human capital (in terms of both quantity and quality of education) explain between 20 and 40% of the income differences of countries (Schoellman (2012), Hanushek and Woessmann (2012)). The cross-country studies aid in understanding why some countries are wealthier than others, and how human capital plays a role. However, there is scant evidence on whether income variability between the states in a country are due to human capital differences. The within-country estimates are necessary to fully understand income differences.

There are important distinctions between our cross-state study compared to cross-country studies. Parente and Prescott (2002) argue that to fully understand differences in development across countries one should study differences in relative income, and not differences in growth rates of income. They find that most differences in relative income are due to TFP, and more specifically, to the protection of concessions and monopoly rights across countries. These different protections at the country level are less likely to apply in the same manner across states

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[1]The federal entities include the 32 Mexican states.

within a country. Additionally, there are other reasons to believe that the study at the state level adds insights beyond those at the country level. The study of a single country allows to control for other factors affecting income, therefore estimating the effects of quality of schooling to income with greater certainty. In cross-country studies, the country where the individual works might be different to the country where the education was received. In a single country although the state where the education is received and the state where the individual works might be different, we are able to control for language and the culture of work, which one expects vary less within a country than internationally.

In a national context, Hanushek, Ruhose, and Woessmann (2017) find between 20% and 30% of the variation in a state's GDP per capita can be explained by human capital differences in the case of the United States. However, there is still a need to understand how this applies in developing economies. It is possible that in the case of Mexico, human capital differences among the states are even more important in explaining income differences. Bils and Klenow (2000) model the effects of education on growth of GDP per capita and find that schooling can explain less than one-third of the schooling/growth cross-country relationship. They use parameters that assume decreasing returns to education, based on estimates by Psacharopoulos (1994) for several countries. Even though decreasing returns to education arises from the comparison between countries, this does not imply that each country has decreasing returns. By assuming diminishing returns, the importance of human capital in their model falls as more human capital is acquired, but growth in human capital can be important in explaining the schooling/growth relationship if there are no diminishing returns to education. Harberger and Guillermo-Peón (2012) find in Mexico the returns to education are not decreasing,[2] implying a stronger importance of schooling in explaining income differences in such case.

Our paper contributes to the literature by studying how differences in human capital of the states, in particular schooling, contribute to differences in income in the case study of a developing economy known for having increasing returns to education.[3] The focus of our study is on human capital through schooling, measured in quantity (years) and quality. The adjustment for quality of skills is done using one of the most widely used tests for educational comparisons. In the case of Mexico, starting in 2003 and every three years since then, the PISA test is representative for each of the 32 Mexican states, which allows us to use PISA for national comparisons of education. Another advantage is the use of a single survey for the comparisons, as well as a common measurement of GDP and years of education, to understand the influence of human capital on income. We contribute to the understanding of how schooling differences contribute to income differences in a developing economy. The study is important for Mexico where the education system has not had major changes in decades and an educational reform has been hard to establish.

Our findings indicate that quality-adjusted human capital explains upwards of 40% of the variations in GDP per hour of the states. This suggests human capital is a significant component of income differences between the states in Mexico. As a comparison, Hanushek, Ruhose, and Woessmann (2017) find that between 20% and 30% of the variation in GDP per capita can be explained by human capital differences in the case of the United States. It is important to note that we do not include human capital that could have been acquired after schooling. Considering human capital acquired after schooling, Manuelli and Seshadri (2014) and Lucas (2015), find human capital to be the most important factor that explains variations in income per unit of labour, explaining upwards of 80% of variations in income. Even though some work has been done to study income convergence among the Mexican states (Rodríguez-Oreggia 2005), this study is important as there are no

[2]Patrinos, Ridao-Cano, and Sakellariou (2006) find increasing returns to education for other countries also used in Psacharopulos's (1994) sample.

[3]Psacharopoulos and Patrinos (2018) estimate returns to education around the world to be approximately 9%, and 11% for Latin America and the Caribbean. Their estimate for Mexico is 13.2%. It can be that in Mexico returns to private education, especially at the college level, are higher than those to public education, and higher than 50% (Binelli and Rubio-Codina 2013). Patrinos, Ridao-Cano, and Sakellariou (2006) find increasing returns for the 8 Latin American countries in their sample, including Mexico. The large informal sector in Mexico is important as it distorts the economy and generates lower rates of return than if there were no such distortions (Levy and Lopez-Calva, 2020).

attempts in the literature to study the role of human capital as a source of income differences among the Mexican states. Further, only one other work studies the role of human capital as a source of income differences among states in a country (Hanushek, Ruhose, and Woessmann 2017, for the United States). This study allows us to understand the role of human capital, specifically schooling, on the income of the people of the Mexican states, so that states can approve public policies effective in improving the income of their constituents. Our study emphasizes the importance of cultivating the quality of education in the country.

The paper is structured as follows. In Section 2, we discuss the sample selection and data. Section 3 presents an overview of the Mexican economy and its education system. Section 4 describes the analytical framework including our human capital measure. In section 5 we describe the measure of quality of education, the PISA test scores for mathematics, and in Section 6 shows the decomposition of variations in GDP that are accounted by differences in human capital. In section 7 we evaluate the robustness of the results. Section 8 discusses the results and Section 9 concludes.

2. Sample selection and data

To estimate the working population and the hours worked in the labour market we use the 2010 Census (Censo de Poblacion y Vivienda, INEGI (2012)), the available data includes more than 11.9 million observations. Following Hanushek, Ruhose, and Woessmann (2017) we select the working population between the ages of 20 and 65 who are not currently in school, leaving 3,304,715 observations, which, using expansion factors, represent 36.3 million workers. An alternative source of data is the National Employment Survey, ENOE (Encuesta Nacional de Ocupacion y Empleo). We corroborate the robustness of our results by using data from the 2016 ENOE in section 7 of this study. Taking the population between 20 and 65 years of age who are declared working and not currently in school leaves 136,197 ENOE observations representing 42.5 million workers.

To estimate state real GDP per worker we use INEGI (2018). GDP is measured in real terms, deflated using 2013 national price indexes. Real GDP per worker and real GDP per hour worked are found by taking the state's real GDP and dividing by the selected working population and by the annual hours worked of the selected population, respectively, using either the 2010 Census or data from the third trimester of the 2016 ENOE.[4] The Census data report the years of schooling of each individual, ranging from 0 years to 21+ years. We directly take the years of schooling data of individuals from the Census and if education is coded as more than 21 years, we re-code it as 21 years of schooling. To compute average years of schooling we take years of schooling for each individual in the sample and add them applying the Census sample expansion factors. We similarly compute the population applying the expansion factors. Finally, we divide the sum of years of education by the total population.

3. The Mexican economy and education system

Mexico is characterized by disparities in both social development and economic growth, and differences between the north and south have widened with crises and the liberalization process (Rodríguez-Oreggia 2005). Table 1 shows GDP for 2010 and 2016, measured in millions of 2013 Mexican Pesos. A comparison of 2010 and 2016 GDP gives a compound annual growth rate of 2.89% on average for these years. There are significant income differences among the 32 Mexican states. For instance, in 2016 the GDP per worker of Coahuila was 546,131 Mexican Pesos (MP), more than twice that of Michoacán, which was MP 261,831. Excluding the two states where the production of oil occurs in Mexico, Campeche and Tabasco, the second largest 2016 GDP per worker is Nuevo Leon at MP 642,637, which is more than three times higher than that of the second lowest which is Oaxaca at MP 195,321. The standard deviation in state incomes (excluding Campeche and Tabasco) is MP 146,715, which is higher than 39% of the national average. As a comparison, Hanushek, Ruhose, and Woessmann (2017) report

[4]In the rest of the paper, we refer to this real GDP per worker/per hour worked as GDP per worker/per hour worked for simplicity.

Table 1. GDP and years of schooling for the Mexican states.

		2010 GDP	2016 GDP	2010 GDP per worker	2016 GDP per worker	2010 GDP per hour worked	2016 GDP per hour worked	2010 Years of schooling	2016 Years of schooling
1	Aguascalientes	152,205	216,703	401,990	471,061	164	190	10.0	10.5
2	Baja California	428,163	524,405	376,012	403,685	156	173	9.7	10.1
3	Baja California Sur	110,656	133,147	441,152	450,063	186	193	10.3	10.6
4	Campeche	753,969	600,771	2,767,822	1,836,844	1,104	780	9.4	10.0
5	Coahuila	489,952	583,873	541,627	546,131	220	232	10.2	10.5
6	Colima	81,992	101,336	340,332	364,120	139	158	9.7	10.1
7	Chiapas	270,989	288,692	207,848	178,923	89	81	7.3	7.7
8	Chihuahua	417,796	539,144	378,700	390,336	160	166	9.4	10.0
9	Ciudad de Mexico	2,446,910	2,974,071	716,881	843,660	292	358	11.3	11.7
10	Durango	169,268	202,998	363,232	341,422	150	148	9.5	9.9
11	Guanajuato	517,169	691,613	313,169	356,276	127	145	8.6	9.2
12	Guerrero	211,891	238,468	226,295	210,202	94	92	8.3	8.5
13	Hidalgo	206,304	264,242	253,440	261,985	106	113	9.0	9.1
14	Jalisco	925,372	1,161,406	377,290	412,538	156	185	9.5	10.1
15	México	1,226,814	1,478,587	238,680	241,531	93	100	9.6	10.0
16	Michoacán	329,767	406,185	260,443	261,831	110	123	8.2	8.5
17	Morelos	174,984	191,797	286,990	278,932	117	119	9.8	9.9
18	Nayarit	97,786	119,106	281,850	277,000	119	125	9.5	9.9
19	Nuevo León	1,025,184	1,228,744	627,538	642,637	252	272	10.5	10.9
20	Oaxaca	228,089	257,146	218,661	195,321	92	86	7.9	8.1
21	Puebla	469,968	557,877	270,890	254,118	111	114	8.7	9.0
22	Querétaro	287,403	385,622	464,254	581,925	195	241	9.9	10.3
23	Quintana Roo	195,149	262,760	386,601	393,597	150	161	9.7	10.2
24	San Luis Potosí	269,397	346,378	355,697	379,290	151	168	9.4	9.8
25	Sinaloa	312,655	381,109	366,133	385,254	150	172	10.0	10.4
26	Sonora	431,502	570,174	489,434	547,739	202	234	10.1	10.7
27	Tabasco	525,012	523,613	764,475	692,312	305	291	9.7	9.9
28	Tamaulipas	448,215	489,100	414,387	388,932	168	172	10.0	10.2
29	Tlaxcala	88,810	97,665	234,560	218,018	97	93	9.5	9.9
30	Veracruz	718,149	811,543	307,670	319,747	124	140	8.6	8.8
31	Yucatán	196,150	242,005	295,846	294,169	121	131	9.0	9.3
32	Zacatecas	144,731	157,898	363,048	324,869	153	141	8.9	9.4
	All Mexico	14,352,401	17,028,177	395,809	400,283	162	172	9.4	9.8
	Mean			447,905	429,515	183	184	9.4	9.8
	Std. Dev.			437,608	294,048	174	124	0.8	0.8

* GDP is measured in millions of 2013 pesos. GDP per hour worked and per worker are in constant 2013 pesos.

the 2007 standard deviation in state incomes being around 15% of the national average in the case of the United States.

We focus on schooling as the source of income variations across states. We consider both quantity and quality of schooling in our analysis. The last two columns of Table 1 show the average years of schooling for the population in the work force in years 2010 and 2016. The difference in years of schooling between the top and bottom states is four years or five standard deviations. In comparison, the difference in years of schooling between the U.S. states with the maximum and minimum values is 3.6 standard deviations. Hence, in addition to significant income differences, we also observe significant differences in terms of years of schooling among the Mexican states. The study of development accounting across states provides insights beyond those found in an international context (Hanushek, Ruhose, and Woessmann 2017), and the study of a developing country with substantial income differences across states contributes to our understanding of what drives differences in incomes across states.

The study is timely and important in the case of Mexico. The current public education system was implemented in 1959 and had not had any significant changes since then. A proposal of an educational reform that looked to improve the quantity and quality of education in Mexico was presented in late 2012 by then President Enrique Peña Nieto, and was subsequently signed into law. However, in 2019 the educational reform was repealed. The quality of education has restrictions and differences at the state level in part due to the presence of large unions in the Mexican education sector, and to its management by the Mexican state. For instance, Estrada (2019) compares the way in which teachers are hired in Mexico and finds that the students of teachers who were hired based on competency exams (which started in 2008 and were later generalized in 2014), achieve higher maths and Spanish test scores compared to students of teachers hired in discretionary form influenced by unions. These teacher unions, although present in all of Mexico, exert an influence which strength differs between the states. A more detailed discussion of the union power and its application to the case of education in Mexico can be found in Estrada (2019) and Elizondo Mayer-Serra (2009).

Implicit in the educational reform proposal is the key assumption that such improvements in education will lead to a reduction in inequality and to greater economic development of the country, which will lead to an improvement in the lives of the country's constituents. There is some empirical evidence that a higher quality of education is related to higher wages in the case of Mexico. For instance, De Hoyos, Estrada, and Vargas (2018) find a positive relationship between individual test scores and individual wages. Further, their findings indicate that higher test scores are associated with a higher probability of a student going to college. The study of human capital as a possible source of income differences among the Mexican states is thus significant for the country.

4. Analytical framework

Development accounting studies how much of the variation in output, in cross-sectional within or across country studies, can be attributed to human capital, physical capital, and to the residual known as total factor productivity (TFP) (Caselli 2005). It focuses on two aspects: the production function to be used and the measurement of inputs.

There are two basic models for the production function. First, the neutral technical progress of Harrod, Y = Y[K, A(t)L], where Y is output, K is physical capital, L is labour and A(t) is TPF. Here, the number of labour efficiency units increases with time, it is a technical progress where the relation between capital and labour increases and is neutral in the sense that with constant returns to scale the relative income distribution stays constant. The second model, the technical progress of Hicks, Y = A(t)f[K, L], is neutral in the sense that if factor prices do not change then K/L is not altered. In the case of the Cobb–Douglas production function, which is the most common in development accounting models, technical progress is neutral in both the sense of Harrod as well as in sense of Hicks; therefore, in both cases, the relative income distribution is constant.

We consider a Harrod-neutral Cobb–Douglas production function, $Y_i = K_i^{\alpha}(A_iH_i)^{1-\alpha}$, as in Hall and Jones (1999), Jones (2016), and Hanushek, Ruhose, and Woessmann (2017) among others. H is the amount of labour-augmented human capital used in production and α refers to the proportion of income assigned to capital. This function allows the decomposition of the variations in output per unit of labour into different factors including human capital per worker h. The production function can be re-written as:

$$\frac{Y}{L}\equiv y = hA\left(\frac{k}{y}\right)^{\alpha/(1-\alpha)} \tag{1}$$

where $k\equiv\frac{K}{L}$ is the relation of capital to labour, and y is income per unit of labour.[5] We can decompose the variance from log GDP per unit of labour as in Klenow and Rodríguez-Clare (1997), the decomposition is presented by Hanushek et al. (2015) and by Hanushek, Ruhose, and Woessmann (2017) as:

$$\frac{\mathrm{cov}(\ln(y),\ln(h))}{\mathrm{var}(\ln(y))}+\frac{\mathrm{cov}\left(\ln(y),\ln\left(\left(\frac{k}{y}\right)^{\alpha/(1-\alpha)}\right)\right)}{\mathrm{var}(\ln(y))}+\frac{\mathrm{cov}(\ln(y),\ln(A))}{\mathrm{var}(\ln(y))}=1 \tag{2}$$

The first term refers to the variation in GDP per unit of labour that can be attributed to human capital differences, which is the focus of this study. As units of labour we use the count of workers and, alternatively, the counts of hours worked in our main tables. Because the number of hours can vary by worker, we focus on the measure of GDP per hour worked for the later analysis as both measures give similar results.

As Caselli (2005) points out, the variance decomposition analysis is sensitive to outliers, so it is recommended to also look at a measure that is less sensitive to such outliers. We follow Hall and Jones (1999) and Hanushek, Ruhose, and Woessmann (2017) and compare the relative variations in human capital against output per unit of labour of the five states with most and least output per unit of labour. As in the prior decomposition, we express equation (1) in relative terms, for the five states with most and least output per unit of labour, where states are ordered from highest to lowest output per unit of labour. This is expressed in the equation below where i and j refer to states among n total states. We also report results for the highest and lowest three states in terms of output per unit of labour worked.

$$\frac{\ln\left[\left(\prod_{i=1}^{5}h_i\Big/\prod_{j=n-4}^{n}h_j\right)^{1/5}\right]}{\ln\left[\left(\prod_{i=1}^{5}y_i\Big/\prod_{j=n-4}^{n}y_j\right)^{1/5}\right]}+\frac{\ln\left[\left(\prod_{i=1}^{5}\left(\frac{k}{y}\right)_i^{\alpha/1-\alpha}\Big/\prod_{j=n-4}^{n}\left(\frac{k}{y}\right)_j^{\alpha/1-\alpha}\right)^{1/5}\right]}{\ln\left[\left(\prod_{i=1}^{5}y_i\Big/\prod_{j=n-4}^{n}y_j\right)^{1/5}\right]}+\frac{\ln\left[\left(\prod_{i=1}^{5}A_i\Big/\prod_{j=n-4}^{n}A_j\right)^{1/5}\right]}{\ln\left[\left(\prod_{i=1}^{5}y_i\Big/\prod_{j=n-4}^{n}y_j\right)^{1/5}\right]}=1 \tag{3}$$

4.1. Human Capital Measure

The estimates of the importance of human capital in explaining differences in GDP vary widely. For instance, Jones (2014) and Manuelli and Seshadri (2014) find human capital explains more than 75% of income differences, while other studies like Hall and Jones (1999) find it to be less than 25%. In the case of Mexico, Jones (2016) finds human capital explains 32% of the differences in GDP per worker between Mexico

[5]An alternative is to use a Hicks-neutral Cobb–Douglas production function, or $Y_i = A_iK_i^{\alpha}H_i^{1-\alpha}$, or $y_i = Ak^{\alpha}h^{1-\alpha}$ in per unit of labour terms, as in Caselli (2005), Hsieh and Klenow (2010) and Schoellman (2011). Note that in equation (1) h and A grow at the same rate and that their decomposition would not depend on parameter α, while in Hicks' model it would. The value of α is difficult to estimate for developing countries like Mexico where close to 60% of labour originates in the informal sector and where the proportion of self-employment is high, as this makes the separation between labour and capital difficult. This would make the estimation of α challenging even in the case of developed countries (Elsby, Hobijn, and Şahin (2013). For instance, Hsieh and Klenow (2010, ec. (3)) prefer to use a production function where H does not depend on α in their logarithmic decomposition of y.

and the United States, and 61% is attributed to differences in TFP. However, Jones (2016) only includes differences in years of schooling and not its quality. Other authors, like Restuccia (2019), while acknowledging the importance of quality of human capital to explain differences among countries, consider such differences to be generated through TFP.

To estimate human capital, most work focuses on Mincer (1974), assuming that one extra year of education is equal to the rate of mincerian return. This method is inadequate to measure differences in quality of human capital, so Manuelli and Seshadri (2014) propose a mincerian-style equation that incorporates differences in quality of human capital, which we express as follows:

$$\hat{h} = e^{h\left(X_{jt}\right)} e^{f(s)+g(a-s)+k(0)} \tag{4}$$

Here, a refers to age, s to the years of schooling, t to time, and j to country. X refers to the factors that determine the quality of schooling, *a-s-6* indicates the years of work experience, and *0* are other factors affecting human capital, for instance health (Caselli 2016; Hidalgo-Cabrillana, Kuehn, and Lopez-Mayan 2017), or investments in early childhood (Manuelli and Seshadri 2014). In general, f'(s) is the rate of return to education θ, but this can vary, for instance in Bils and Klenow (2000) $f'(s) = \theta/s^{\Psi}$, where $\psi > 0$ assumes decreasing returns to education.[6] Other studies, referring to differences across countries, consider different rates of return (θ_j) depending on the level of development of the country to measure human capital (Hall and Jones 1999; Caselli 2005).

In measuring the quality of education, the first term in equation (4), Klenow and Rodríguez-Clare (1997) use the capital stock per student in the education sector, as well as the human capital of workers. Bils and Klenow (2000) use human capital of the teacher. Hanushek, Ruhose, and Woessmann (2017) use test scores of the National Assessment of Educational Progress. Caselli (2016) uses PISA 2009 for a comparison across countries and notes little variation through time and across PISA sections (i.e. mathematics vs. science). Manuelli and Seshadri (2014) consider training after schooling as a measure of quality. Quantity of schooling is measured using years of schooling (Schoellman 2012). For instance, Hanushek, Ruhose, and Woessmann (2017) use the average years of schooling for population aged 20 to 65 who are not in school.

To measure human capital, we consider a model that explains human capital formation as a function of the years of schooling, s, and the quality of schooling, Q. In this model, used by Bils and Klenow (2000) and Hanushek, Ruhose, and Woessmann (2017) among others; years of schooling are added to quality of schooling in the human capital formation function. Human capital formation is formulated as a variation of equation (4) above, in particular:

$$h = e^{\theta s + \pi Q} \tag{5}$$

The earning gradients to years of schooling θ, and quality of schooling π, establish the relationship of quantity and quality of schooling with human capital, h. There are two issues when determining the earnings gradients for years of schooling (θ) and quality of schooling (π). The first is that the obtained values are useful in determining human capital and wages through the working life of individuals, and that they include individuals already in the workforce. The second is that the values of θ and π have to be estimated simultaneously, otherwise θ could contain information about the quality of schooling and the cognitive abilities of the individual.

Our approach is to take the parameters of the earnings gradients from the current literature. The most common way of measuring the schooling gradient, θ, is using Mincer regressions as in Card and Krueger (1992) and Schoellman (2012). However, the exclusion of cognitive skills measures confounds the estimation and hence the estimation is not appropriate in our context. We look for joint estimates of the earnings gradients for years of schooling and quality of schooling. Hanushek and Zhang (2009) estimate the value for individual literacy scores to school attainment and provide joint estimates for the parameters for 13 countries.

[6]As mentioned earlier, it is possible in Mexico returns to education are increasing, so we assume instead that Ψ = 0.

Once Hanushek and Zhang (2009) adjust for cognitive skills their estimation of θ is 8.0% for the United States and 8.9% for Chile, while their estimations of π are 19.3% and 13.1%, respectively. Facing the problem of no available joint estimates for Mexico and to make our study comparable to that of Hanushek, Ruhose, and Woessmann (2017) who study the United States, we follow them and use values of 8.1% for θ and 17% for π. As a robustness check, in Section 6 we vary the values of θ and π and find similar results.

The value of *s* for each state is determined by the average years of schooling for the working population. We use the average adjusted PISA Maths test scores as a measure of quality of schooling.

5. Measure of education quality: PISA mathematics test achievement scores

We use the OECD's Program for International Student Assessment (PISA) maths achievement test scores as a measure of cognitive skills. Starting in 2003 the PISA test is representative for each of the Mexican states. PISA measures student performance in mathematics, reading and science literacy, and each cycle it assesses one of the three areas in depth, which is considered the major subject that cycle. Mathematics was the major subject of PISA in 2003 and 2012. The correlation between the 2003 and 2012 test results, when mathematics was the focus of the PISA exam, is 0.91.

Mexico scored well below the OECD average of 494 in the Mathematics portion of the 2012 PISA test (OECD 2014), with a score of 413, close to that of other Latin American countries and well below the score for the United States (481). According to the OECD, Mexico placed the equivalent of 2 years of schooling below the average OECD countries for same-grade students, and about 1.6 years of schooling lower than the United States.

We take the mathematics score on the PISA test for each state for the years 2003, 2006, 2009 and 2012[7] We then calculate the average score across states by year and normalize it with mean 500 and standard deviation of 100, to make it comparable to the data in Hanushek, Ruhose, and Woessmann (2017). We use the 2003–2012 state average as a measure of cognitive abilities of the working population. We assume that test scores (and therefore quality) are stable over time, even though test scores can vary across successive tests.[8] Hence, we assume that skill level does not differ across age cohorts, which is different

Table 2. PISA mathematics test scores for the Mexican states.

	PISA test scores 2003	PISA test scores average 2003–2006–2009–2012
Aguascalientes	639	634
Baja California	482	487
Baja California Sur	518	447
Campeche	364	370
Coahuila	541	544
Colima	555	544
Chiapas	242	279
Chihuahua	544	580
Ciudad de Mexico	577	653
Durango	586	527
Guanajuato	550	546
Guerrero	286	263
Hidalgo	556	537
Jalisco	637	618
México	499	564
Michoacán	538	506
Morelos	608	575
Nayarit	514	491
Nuevo León	703	704
Oaxaca	486	432
Puebla	518	526
Querétaro	538	605
Quintana Roo	451	458
San Luis Potosí	498	480
Sinaloa	491	513
Sonora	492	492
Tabasco	284	288
Tamaulipas	511	488
Tlaxcala	444	440
Veracruz	398	448
Yucatán	429	444
Zacatecas	520	519
Mean	**500**	**500**
Std. Dev.	**100**	**100**
Max-Min	**461**	**425**

[7]The exam was not administered in Michoacán (in 2003, 2012), Oaxaca (in 2012) and Sonora (in 2012). We replace 2006 for 2003 and 2009 for 2012 missing values..

[8]We do not have test results at the state level prior to 2003, and it is difficult to infer any trends from the PISA test results we do have. As an example, the overall PISA mathematics score for Mexico was 387 in 2000, 385 in 2003, 405 in 2006, 418 in 2009, 413 in 2012 and 408 in 2015. One could erroneously infer an improving trend by looking at the 2000–2009 scores, which clearly is not the case once we see 2012–2015 scores.

Table 3. Adjustment of PISA test scores for interstate migration, self-selection of interstate migration, and international migration.

Variable	Obs	Mean	Std. Dev	Min	Max
Average 2003–2012 standardized	32	500	100	263	704
Average + interstate migrants	32	500	88	286	647
Average + interstate migrants + adjustment by educational category	32	496	78	296	602
Average + interstate migrants + adjustment by educational category + international migrants	32	497	78	298	602

from Hanushek, Ruhose, and Woessmann (2017).[9] However, we examine the robustness of our results by using the PISA test score for 2003 in Section 7. We also assume that the average PISA test scores apply to the working population in 2010 and 2016.

Table 2 shows the standardized PISA mathematics test scores for 2003 and for the average 2003, 2006, 2009 and 2012. The state with the highest average standardized score is Nuevo Leon, with 704, the lowest scoring state is Chiapas with 279. These two test scores are four standard deviations away from each other. As a comparison, Hanushek, Ruhose, and Woessmann (2017, online appendix Table 2) report the biggest difference in average standardized NAEP scores is between Minnesota and Missouri, 534.8 and 450.8, respectively, a difference of less than one standard deviation. These significant differences in quality of schooling across Mexico mirror the significant variations in GDP and in years of schooling discussed in Section 3.

We next adjust mean test scores for each state for interstate migration, the self-selection of interstate migration, and for international migration also considering its possible self-selection, following the methodology in Hanushek, Ruhose, and Woessmann (2017). A brief description follows with more details of these adjustments available in the appendix.

We start with the adjustment for interstate migration. This considers that individuals who were born in a state different from where they reside might have been educated in their state of birth. We construct a matrix where we identify the proportion of individuals residing in each state that were born in the different states. We also categorize those individuals residing in Mexico but born outside Mexico (international migrants). We use this matrix to assign individuals residing in a state the average test score of their state of birth. The adjustments are summarized in Table 3. Adjusting for interstate migration, the mean PISA test score is unchanged while the standard deviation falls to 88. Next, we adjust test scores for self-selection of interstate migration as it is possible that migrants into a state are not a random sample of the individuals in the state of origin. For instance, it is possible that highly educated individuals from one state select a different emigration state compared to individuals that are less educated. To adjust for this self-selection of interstate migration we make the assumption that we can assign individuals with higher education the test score of children whose parents have higher education, and vice versa for individuals without higher education. Using Census data, we calculate the proportion of working age population in each state that have up to 12 years of schooling and the proportion with 13 or more. We use these proportions to assign different test scores by educational category. After adjusting the test scores of state residents for their educational background, the mean test score falls. We finally adjust for international migration, less than 0.3% of our sample are international immigrants. We obtain PISA test scores for their countries of origin to gauge the cognitive skill level of students in their country. We also consider the selectivity of international immigrants. Once we adjust for international migration the difference between the maximum and minimum state scores is at its lowest, with a difference in scores of 304 points, representing more than 3 standard deviations.[10] We finally standardize the values with mean zero and variance of one, then further adjust so that our relative measure of quality (standardized difference in the PISA test score)

[9]This is one difference between Hanushek, Ruhose, and Woessmann (2017) and our paper. They make use of NAEP 1992–2011, and extrapolate tests scores back using the NAEP trend available since 1978. Further, they also estimate test scores before 1978 by assuming a linear trend before 1978.

[10]The appendix (available from the authors) details the methodology used and shows the adjustments of test scores and the human capital estimates by state.

Table 4. Percentage of variability of income attributed to human capital, using 2010 Census data.

	Share Q quality		Years of schooling	Total sum of quality and quantity Q and S		Top and bottom 5 statesQ and S		Top and bottom 3 statesQ and S	
	ln GDP per worker	*ln GDP per hour*		*ln GDP per worker*	*ln GDP per hour*	*ln GDPper worker*	*ln GDP per hour*	*ln GDP per worker*	*ln GDP per hour*
Average 2003–2012 standardized	0.35	0.34	0.18	0.53	0.52	0.57	0.58	0.75	0.77
Average + interstate migrants	0.33	0.33	0.18	0.51	0.51	0.56	0.56	0.74	0.77
Average + interstate migrants + adjustment by educational category	0.31	0.31	0.18	0.49	0.49	0.54	0.55	0.72	0.75
Average + interstate migrants + adjustment by educational category + international migrants	0.31	0.31	0.18	0.49	0.49	0.54	0.55	0.73	0.75

Table 5. Percentage of variability of GDP per hour worked attributed to human capital using 2016 ENOE.

	Share Q quality	Years of schooling	Total sum of quality and quantity Q and S
Average 2003–2012 standardized	0.32	0.17	0.49
Average + interstate migrants	0.31	0.17	0.48
Average + interstate migrants + adjustment by educational category	0.29	0.17	0.46
Average + interstate migrants + adjustment by educational category + international migrants	n/a	0.17	n/a

Table 6. Sensitivity Analysis.

	Return parameters		Share Q quality	Years of schooling	Total sum of quality and quantity Q and S
	θ	π			
Mathematics	0.081	0.17	0.31	0.18	0.49
Reading	0.081	0.17	0.20	0.18	0.38
Science	0.081	0.17	0.31	0.18	0.49
PISA 2003 Mathematics	0.081	0.17	0.28	0.18	0.46
PISA 2003 Reading	0.081	0.17	0.24	0.18	0.42
PISA 2003 Science	0.081	0.17	0.30	0.18	0.48
Vary returns to test scores π Mathematics	.081	0.131	0.24	0.18	0.42
Reading	0.081	0.131	0.16	0.18	0.34
Science	0.081	0.131	0.24	0.18	0.42
Vary returns to schooling θ	0.04	0.17	0.31	0.09	0.40
Uniform returns estimate	0.104	0.17	0.31	0.23	0.54
Schooling level specific	Primary 0.054 Secondary 0.066 Tertiary 0.189	0.17	0.31	0.21	0.52

has the minimum value of zero. Results of human capital estimates by state appear in Table 2A in the Appendix.

6. Decomposing State Variations in GDP per Hour Worked into contributions Accounted by Differences in Quality and Quantity of Schooling

We next decompose the variation in output that can be attributed to differences in human capital. We exclude states whose industry structure makes GDP unlikely to be described well by a capital and labour production function, hence, we exclude those with abundant natural resources following Hall and Jones (1999) and Hanushek, Ruhose, and Woessmann (2017). There are two states where we cannot expect a direct relationship between human capital and output per worker, these are the states where the production of oil occurs in Mexico: Campeche and Tabasco. According to the Economic Census of 2008 (INEGI 2015), 96% of the value added in Campeche and 82% in Tabasco corresponds to the extraction of oil, thus one would expect a very weak relationship between GDP per worker and human capital in these two states, they are excluded from our sample at this point.

Table 4 shows the percentage of the variability in income attributed to human capital, estimated as in equation (2). Years of schooling explain 18% of the variation in GDP per worker, while cognitive abilities explain 31% using the adjusted PISA test scores. Therefore, human capital differences explain 49% of the differences in GDP. Note that results are robust to using GDP per worker or GDP per hour as a measure of output per unit of labour. We use GDP per hour for the rest of our analysis. Contrary to the findings in Hanushek, Ruhose, and Woessmann (2017) for the U.S., once test scores are adjusted for migration and self-selection human capital is less important in explaining income differences. The last four columns show the model preserves its strong predictive power even in the case of largest and smallest states in terms of GDP per unit of labour, where human capital differences explain between 55% and 77% of the differences between GDP per hour of the states. From these estimates, the variation in income attributed to human capital does not fall once we use the five-state or three-state measure. A potential explanation is that we excluded the two outliers: Campeche and Tabasco. The results when we include Campeche and Tabasco will be discussed in Section 8.

7. Robustness checks

We start by examining if the estimates are robust to the test period and data source. Instead of using the 2010 Census, we could use the 2016 ENOE (Encuesta Nacional de Ocupacion y Empleo-National Survey of Occupation and Employment) which provides quarterly data on the working characteristics of the population. We use the third quarter from ENOE for 2016. Imposing the same data restrictions as before our sample is 82,845 observations (compared to 2,244,341 with the Census). The Census indicates place of birth, and in the case of international migration country of birth, allowing the adjustment of PISA test scores for international migration. This information is not available when using the ENOE.

The results using GDP per hour worked[11] are shown in Table 5. The percentage explained by human capital, which was 49% or more using the 2010 Census (Table 4), falls to 46%. Overall, our findings indicate that using ENOE 2016 the variations in the log of human capital still explain upwards of 46% of the variations in log GDP.

We also gauge whether the results are sensitive to using PISA 2003 test scores instead of the 2003–2012 averages, using a different test subject, and varying the parameters of the calibration. All the sensitivity analysis is done using PISA scores adjusted interstate migrants, educational category and international migrants. These estimates represent a lower bound compared to the unadjusted estimates as shown in Table 4.

We consider using the reading and science sections of the PISA test in lieu of the mathematics test scores.[12] At the national level, mathematics is the subject with the lowest scores for all years considered. Table 6 shows the estimates are similar for mathematics (our baseline from Table 4) and science, where schooling explains 47% and 49% of the variation in income, while using reading test scores schooling accounts for 38% of the variation.

We then re-estimate the results using the 2003 PISA test scores in lieu of the 2003–2012. A 15-year -old student who took the test in 2003 would be 22 years old in 2010. In this case, we assume that the 2003 score is the appropriate one that applies to the working population in 2010. Our results are robust to this correction. Table 6 shows that under such scenario differences in the quality and quantity of education explain between 42% (using the reading test scores) and 48% (using the science test scores) of the differences in the incomes (GDP per hour) of the states.

Finally, we consider different parameter values. If we vary the returns to test scores from 0.17 to 0.131 (the value for Chile estimated by Hanushek and Zhang 2009), then cognitive abilities explain 16%–24% of the variation in income, and human capital explains between 34% and 42% of the variations in states' incomes. Alternatively, we can vary the parameter for returns to schooling. If we consider a lower the value of the parameter, for instance half the original value, 0.04, differences in years of schooling would explain 9% of differences in income, for a total of 40% of variations in income attributed to human capital. Following Hanushek, Ruhose, and Woessmann (2017), we consider different return parameters for different levels of education, namely across primary, secondary and tertiary education. We estimate returns to schooling using the standard Mincer equation and the 2010 Census data, this yields a return of 10.4%, and returns across different schooling levels of 5.4%, 6.6%, and 18.9% for primary, secondary, and tertiary education. Such estimates in the development accounting exercise result in a larger proportion of variation in states' income being explained by years of schooling, from 18% to 23% and 21%, respectively, for the uniform returns estimate and schooling level-specific estimate. Therefore, quantity and quality of schooling account for

[11]The results using GDP per worker are qualitatively and quantitatively similar.

[12]We use data from Vidal and Díaz (2004) for year 2003, INEE (2007) for 2006, INEE (2010) for 2009, and INEE (2013) for 2012. There is no data for 2006 for the state of Morelos, we use the average of 2003 and 2009.

Table 7. Variability of GDP per hour worked attributed to schooling when including campeche and tabasco.

	Baseline (30 states)		Baseline+ Tabasco		Baseline+ Tabasco+ Campeche	
	2010	2016	2010	2016	2010	2016
Number of states	30	30	31	31	32	32
Var ln GDP per hour	0.09	0.12	0.10	0.13	0.23	0.21
Quantity of schooling	0.18	0.17	0.15	0.10	0.07	0.07
Quality of schooling	0.31	0.29	0.16	0.19	0.00	0.05
Total (quality + quantity)	0.49	0.46	0.31	0.29	0.07	0.12

54% and 52% of variations in state's incomes. The schooling-level specific return estimates lower the total estimate compared to the uniform estimate, as in Mexico there is a large proportion of the population with low levels of schooling.

8. Discussion of results

Hanushek, Ruhose, and Woessmann (2017) find human capital explains 15% to 22.8% of the variations in GDP between the U.S states, after the sensitivity analysis these estimates are 18.1% to 31.5%. In Schoellman (2012), human capital explains between 19% and 36% of the variations in income in a cross-country study. Our main results, however, show that in the case of the Mexican states the variability in GDP that can be explained by human capital is much larger, upwards of 40%.

Oil Producing States

One possible explanation for the larger estimates for Mexico is that we excluded the two Mexican states characterized by their oil extraction activity: Campeche and Tabasco. The value of production in these states depends in large part on the price of oil and on the existence of oil reserves, and not on the amount of labour and capital, so empirically this would affect the value of total factor productivity. Table 7 shows results of our analysis with and without the inclusion of these two states. The variance in ln GDP per hour in 2010 is 0.9 when we exclude Campeche and Tabasco, 0.10 including Tabasco and 0.23 including both states. The variance in GDP increases more than 10-fold by including the two states, so variations in human capital are less able to explain this variance in GDP. By excluding them, we exclude a source of the variations in total factor productivity and the variance is better explained directly by the inputs. In particular, human capital explains 49% of the variations in income in 2010 excluding the two states but only 7% if they are included.

8.1. The contribution of the relation of capital to output

The variance in GDP per hour worked can be attributed to three components as indicated in equation (2), the portions due to variations in human capital, to variations in capital/output, and to variations in total factor productivity. We estimate how the variation in GDP per unit of labour relates to physical capital differences (the second term in equation (2)) using capital stocks from INEGI (2021) and finds a value of almost zero for the covariance term when using $\alpha = 1/3$, and lower values as we increase α.[13] Given that our results show state variations in human capital explain about 40–50% of the variation GDP per hour, then the other 50% would be explained by TFP.

There are two possible reasons for this finding. Assuming the available data on physical capital is accurate; in the steady state the rate of return to capital is proportional to k/y, that is, the interest rate or marginal product of capital $\alpha k/y$. Given the existence of a capital market in Mexico,[14] the rate of return should be the same across states because of arbitrage, if α is the same across states then the k/y relation is equal for all states, which could not explain the variations in GDP per hour. Low values for k/y are also found for the United States, Jones

[13]The estimate for the covariance is −0.02 when $\alpha = 1/3$.

[14]We use the method of perpetual inventories, taking the methodology in Harberger (1988) and implement using the program in Amadou (2011), use a depreciation rate of 5% to find the estimators for the values of capital (K).

(2016) reports a small negative covariance between 1948 and 1973, the low values for the contribution of k/y are attributed to it being constant through time. Another possibility is that the measurement of physical capital by state has errors in its measurement in the case of Mexico. As an alternative, we take data on gross-fixed capital formation by state between 2003 and 2017 from INEGI (2019). We find a small negative covariance term in the second term of equation 2. Similar results are found if we use the Economic Census, accumulating the available results of gross capital formation for years 1994, 2004, 2008 and 2014. These results could be due to the presence of large governmental firms in the poorest states (producers of oil and electricity) whose investment measures are different from the ones of private enterprises as discussed in Pritchett (2000).[15] The lack of explanation of k/y could also be a result of having close to 60% of workers in Mexico in the informal sector. Levy Algazi (2018) poses that informality distorts the Mexican economy and absorbs a great amount of capital. In these cases, the explanation of variations in output per hour goes to the TFP.

9. Conclusions

Our study shows that differences in quantity and quality of schooling explain upwards of 40% of the changes in GDP per hour worked. This result is robust to taking the five states with higher and lower GDP per hour worked, and also to taking the top and bottom three states. Quantity and quality of schooling are added in the human capital production function, where quality of schooling is measured using the achievement scores of the PISA mathematics test. Using the science or reading sections of the PISA test schooling variations account for 34–48% of income variations. The result is robust to using a different survey and year for data, the 2016 ENOE in lieu of the 2010 census, and to the 2003 PISA test results instead of the 2003–2006-2009-2012 average, and to varying the parameters of the calibration. Our estimates do not include human capital that can be acquired outside schooling, including it would increase the estimates of the contribution of human capital to income even more.

Of particular importance is which states are included in our analysis. We exclude Campeche and Tabasco as they are oil producing states where GDP is not reflective of the amount of labour and capital of the state. When including these states variations in human capital explain only 7% of the variations in GDP per hour in the model. These oil-rich states lack in quality of schooling and have a large proportion of population in poverty.

A variation of the model in Bils and Klenow (2000) would show that the effects of education on growth of GDP per hour could be important in cases where countries do not exhibit diminishing returns to education, such as the case of Mexico. Our results support this, we show that schooling differences among the states are important in explaining income differences in Mexico. Accounting for the quality of schooling is important as our estimates show a great fraction of the variation in schooling that can account for income differences is due to quality, with quality contributing in a greater proportion to income differences than quantity of schooling. The focus on improving both quantity and especially quality of education in Mexico can contribute significantly to the economic development of the states. Further, in Mexico union strikes in the educational system are more prevalent in poor states, these strikes damage the quality of education and will affect the development of such states, leading to more income differences over time if they are not resolved.

Disclosure statement

No potential conflict of interest was reported by the authors.

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[15]Among the issues observed we find that the estimated capital per worker is higher in the poorest states, Chiapas and Oaxaca, with values of $58,462 and $48,921, respectively, while the richer states, Mexico City and Nuevo Leon, have values of $37,412 and $34,706 respectively.

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Appendix A: Methodology for adjusting test scores for migration between states, self-selection of migrants, and international migration

We adjust the PISA test scores of each state following Hanushek, Ruhose, and Woessmann (2017). First, we adjust test scores for interstate migration and for the self-selection of interstate migration, and then we adjust test scores for international migration and its self-selection.

Interstate Migration

In our base model, we assign each individual the PISA test score of their state of residence. To correct test scores by interstate migration, we distinguish between an individual’s state of birth and their state of residence. If an individual resides in a state other than their birth state, we assume the individual went to school in their birth state and therefore assign the birth-state PISA test scores to the individual. First, for each state, we group residents according to their birth state. For instance, in Aguascalientes 70.8% of the were born there, while 7% were born in Mexico City, 6% in Zacatecas, 5% in Jalisco and so on for each of the 32 states. We also form a category of state residents who were born outside Mexico (international migrants). To adjust the state average test score for interstate migrants in the case of Aguascalientes, we would then multiply the PISA test score of Aguascalientes by 70.8%, and to this add 7% of the score of Mexico City, and so on. In the case of international migrants, we assign them the average score of their state of residence initially. We correct for international migration as the last step of these adjustments.

Table 1A shows the 2003–2012 average Mathematics PISA test scores by state, standardized with mean 500 and standard deviation 100. After correcting for interstate migration (columns 3 and 4) the average score is still 500 while the standard deviation falls to 88.

Correction for migrant self-selection bias

To correct for migrant interstate self-selection, we separate workers into two groups, those with up to 12 years of schooling and those with 13 years or more, with the objective of

Table 1A. PISA test scores by state, adjustment of test scores for migration between states, self-selection of migrants and international migration.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
State	PISA Average 2003–2012	+ With interstate migration.		+ Adjusted for selective migration		+ Adjusted for international migrants	
		2010	2016	2010	2016	2010	2016
Aguascalientes	634	615	618	600	604	600	604
Baja California	487	500	494	487	481	489	482
Baja California Sur	447	473	456	480	456	484	457
Campeche	370	380	380	384	384	386	385
Coahuila	544	546	543	544	539	544	539
Colima	544	543	542	536	534	536	534
Chiapas	279	288	286	296	293	298	295
Chihuahua	580	564	565	545	546	545	546
Cd. de México	653	617	620	589	593	589	593
Durango	527	530	529	531	528	531	528
Guanajuato	546	549	548	551	550	551	550
Guerrero	263	286	279	305	294	306	295
Hidalgo	537	543	541	544	541	544	541
Jalisco	618	601	605	585	592	585	592
México	564	573	575	564	567	564	567
Michoacán	506	509	508	511	507	511	508
Morelos	575	538	544	513	523	513	523
Nayarit	491	500	499	502	501	502	501
Nuevo León	704	647	654	602	613	602	613
Oaxaca	432	436	434	439	437	440	437
Puebla	526	524	524	522	524	523	524
Querétaro	605	595	592	593	590	594	591
Quintana Roo	458	440	442	421	417	422	417
San Luis Potosí	480	491	487	499	495	501	496
Sinaloa	513	513	512	512	510	512	510
Sonora	492	497	497	497	497	497	497
Tabasco	288	312	304	335	322	336	322
Tamaulipas	488	492	490	487	483	487	484
Tlaxcala	440	462	457	476	470	476	470
Veracruz	448	453	453	456	456	457	457
Yucatán	444	447	445	451	446	452	447
Zacatecas	519	525	524	530	528	530	528
Mean	500	500	498	496	494	497	495
Standard deviation	100	88	90	78	82	78	81

identifying individuals with access to higher education. For instance, 70.8% of the residents of Aguascalientes were born in the state, this group can be split into 55.8% which have up to 12 years of schooling and 15% with 13 years or more. Then, for each state we subdivide the individual PISA test scores according to whether at least one of the test taker's parents has some higher education. We then make the assumption, as in Hanushek, Ruhose, and Woessmann (2017) that we can assign individuals with higher education the PISA test score of children whose parents have higher education, and vice versa for individuals without higher education. We then adjust PISA test scores by weighing them according to interstate migration, but adjusting separately for residents with higher education and those without. As a result of this adjustment, the average 2010 PISA score falls to 496 and the standard deviation falls to 78 (column 5 in Table 1A).

Correction for international migration.

Our sample (10% of the Population Census) contains 9613 working foreigners from 92 countries, out of 3,304,715 total workers; hence, less than 0.3% of the working population are international immigrants. To obtain test scores for these migrants, we use OECD (2004, Table 2.3 c) PISA mathematics test scores, where we take the mean, standard deviation, and 75 and 90 percentiles approximating the methodology of Hanushek, Ruhose, and Woessmann (2017). For the countries for which we do not have PISA scores, we approximate the scores using countries that are similar or geographically close.

To adjust for the selectivity of international migration in Mexico we follow Hanushek, Ruhose, and Woessmann (2017) who show that in the case of the U.S. such selectivity is significant. We start by computing the selectivity parameter p for each country, which indicates the percentile of the home country distribution from which the average immigrant comes, from educational degrees primary (pri), secondary (sec) or tertiary (ter). The equation that Hanushek, Ruhose, and Woessmann (2017) use to calculate the selectivity parameter is the following

$$p = s^{pri}_{MX} * \frac{1}{2} s^{pri}_{\mathrm{hom}\,e} + s^{\sec}_{MX} * \left(s^{pri}_{\mathrm{hom}\,e} + \frac{1}{2} s^{\sec}_{\mathrm{hom}\,e} \right) + s^{ter}_{MX} * \left(s^{pri}_{\mathrm{hom}\,e} + s^{\sec}_{\mathrm{hom}\,e} + \frac{1}{2} s^{ter}_{\mathrm{hom}\,e} \right)$$

Table 2A. Estimates of human capital by state.

	Standardized difference in PISA test (Quality Measure)	Human Capital (h)
Aguascalientes	3.81	1.46
Baja California	2.41	1.20
Baja California Sur	2.35	1.23
Campeche	1.10	0.95
Coahuila	3.11	1.35
Colima	3.00	1.29
Chiapas	0.00	0.59
Chihuahua	3.12	1.30
Cd. de México	3.67	1.54
Durango	2.94	1.27
Guanajuato	3.20	1.24
Guerrero	0.09	0.69
Hidalgo	3.10	1.25
Jalisco	3.62	1.38
México	3.35	1.35
Michoacán	2.68	1.12
Morelos	2.71	1.25
Nayarit	2.58	1.21
Nuevo León	3.84	1.50
Oaxaca	1.78	0.94
Puebla	2.83	1.18
Querétaro	3.73	1.43
Quintana Roo	1.59	1.05
San Luis Potosí	2.54	1.19
Sinaloa	2.70	1.27
Sonora	2.51	1.24
Tabasco	0.47	0.87
Tamaulipas	2.39	1.22
Tlaxcala	2.24	1.15
Veracruz	2.00	1.04
Yucatán	1.94	1.06
Zacatecas	2.92	1.22
Mean	2.51	1.19
Variance	1.00	0.04

Where s^{pri}_{MX} would indicate the proportion of the migrants from a particular home country working in Mexico who only have primary education, and s^{pri}_{home} would indicate the proportion of the population of the home country with only primary education. For instance, if from a country where schooling is (0.1, 0.1, 0.8) indicating 10% have primary education, 10% have secondary education and 80% tertiary education,[16] we have that immigrants into Mexico only have primary education, then p = 0.05. If from a country with low education (0.8, 0.1, 0.1) all of those who reside in Mexico have tertiary education, p = 0.95. If from a country with equal proportions of educational degrees (0.33, 0.33, 0.33) the workers in Mexico have the same proportions then we would have p = 0.5. The proportions of immigrants in Mexico with different educational degrees we obtain directly from the data, and the proportions with the respective degrees in the home countries we obtain from the database in Docquier, Lowell and Marfouk (2009, http://www.rnim.org/uploads/1/6/3/4/16347570/dm_dataset.xls). We find countries that are geographically close, such as USA and Guatemala have p of 0.4 and 0.52 while countries that are farther away have higher values, such as Japan and Ecuador with values of 0.8. As in Hanushek, Ruhose, and Woessmann (2017) we then adjust PISA test scores given the value of p as follows:

$$\text{scoreselp}_j = \text{invnormal}(p_j)*\text{pisa\_sd}_j + \text{pisa\_av}_j$$

where the invnormal function is the inverse of the normal, pisa_sd_j is the standard deviation of the mathematics PISA scores for country j, and pisa_av_j is the average score for country j.[17] The last two columns of Table 1A show the test scores corrected for international migration.

[16]For North Korea we use South Korea, and for Macao and Taiwan we use China. For other African and Asian countries we use the scores from Tunisia which is the only country available. For Center and South America we group the data according to the three countries for which we have PISA scores: Brazil, Mexico and Uruguay. For the rest of Europe we use Greece. According to the 2015 PISA test, which was administered in more countries, we use Germany for the case of England and we use Greece for the case of Israel.

[17]We also compute the values for the 75 and 90 percentiles, $\text{scoresel75}_j = \text{invnormal}(.75)*\text{pisasd}_j + \text{pisaav}_j$; and $\text{scoresel90}_j = \text{invnormal}(.90)*\text{pisasd}_j + \text{pisaav}$; and the correlation coefficients between the estimated values of scoresel75, scoresel90, and the real is of 0.98 for the 75th percentile and 0.97 for the 90th percentile.