Human Capital and Income Differences across States: Development Accounting for the U.S.*

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Abstract

Although many U.S. state policies presuppose that human capital is important for state economic development, there is little research linking better education to state incomes. We develop detailed measures of state human capital based on school attainment from census microdata and cognitive skills from state- and country-of-origin achievement tests. Partitioning current state workforces into state locals, interstate migrants, and immigrants, we adjust achievement scores for selective migration. We use the new human capital measures in development accounting analyses calibrated with standard production parameters. We find that differences in human capital account for 20-35 percent of the current variation in per-capita GDP among states, with roughly even contributions by school attainment and cognitive skills. Similar results emerge from growth accounting analyses.

Keywords: economic growth, human capital, cognitive skills, schooling, U.S. states

JEL codes: I25, O47, J24

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1 Introduction

One of the key elements of state policies for economic development has been the development of the human capital of its workforce – either through schooling for its youth or through attracting skilled workers from other states and countries. While considerable attention has gone to the role of human capital in determining international differences in income and growth, much less attention has been given to differences among the U.S. states. As a result, the impact of state schooling and human capital policies on incomes remains imperfectly understood. This paper presents preliminary attempts to understand the importance of state human capital on income and development.

Of the many studies investigating cross-country economic differences, human capital has virtually always been included as a primary driving factor. Yet, the results have also tended to be inconsistent across studies. A variety of explanations have been advanced for the inconsistency of measured human capital on cross-country estimated models, including the possibility that human capital is simply not as important as generally presumed. The alternatives include simultaneity issues, omitted variables problems, and issues surrounding the specification of the underlying economic models.

Closely related to the work here, however, we emphasize fundamental measurement issues in these international models. Virtually all early analyses relied out of necessity on measures of the quantity of schooling (enrollment rates or school attainment). Among other concerns, questions were raised about how school quality could be introduced.

Importantly, aggregate economic fortunes appear to be much more closely related to the skills of the work force, and these skills in an international context are readily proxied by cognitive skills as measured by international assessments.[5] The importance of cognitive skills in the research literature mirrors the policy focus of many if not most developed countries and dovetails with the focus here on state human capital.

Analyses of differences in income across states have focused on a variety of factors including agriculture, capital stock, and natural resources. Invariably, however, human capital enters the picture. The most extensive studies by Robert Tamura and his colleagues identify a strong influence of human capital over a century and a half (see, for example, Tamura (2006),

[5] See, for example, Hanushek and Kimko (2000), Bosworth and Collins (2003), Hanushek and Woessmann (2012), Schoellman (2012), and the review in Hanushek and Woessmann (2011).

Turner et al. (2007), and Turner, Tamura, and Mulholland (2013)). But, as in the international literature, the emphasis remains on school attainment measures due to the lack of any qualitative information on human capital and skills.

Investigating state income differences is of course difficult. Given the free labor and capital markets and the presumed access to common technologies, most economic models would predict convergence of state incomes. Yet when investigated directly, it is clear that state income differences have existed over a long time, even if they also show signs of conditional convergence (Barro and Sala-i-Martin (1992)). These continuing differences could reflect historical development patterns of industries, investments in fixed capital, and the like. But uncertainty remains about the nature of the forces dictating the pattern of state development.

This paper is designed to do a variety of things simultaneously. First, it brings what is known from international development to the realm of state income differences. Second, it deals with the severe measurement problems that exist at the state level by developing a new series of state human capital stock. Third, it applies standard development accounting approaches to understand today’s income differences across states. Fourth, it investigates the stability of these explanations of income differences over time.

2 Income and Growth Variations across States

Before beginning, it is useful to consider how much variation can be seen across states. That is, is there anything substantial to explain?

Figure 1 shows the distribution of state GDP per capita of the 1970-2007 period. (Throughout this analysis we stop in 2007 in order to avoid distortions to the long run picture that come from the 2008 recession).

In 2007, state GDP per capita differed by $30,000 between lowest income state (West Virginia) and the highest income state (Connecticut). The U.S. average of $41,218 (excluding Alaska, Delaware, and Wyoming) with a standard deviation of $6,388 shows that states in fact have reached very different levels of development (see Table 1).

Perhaps as interesting, the U.S. average annual growth rate of 2.19 percent masks a range of growth rates for states that goes from 1.56 to 2.89 over the period 1970 to 2007. North Dakota grew by 2.86 percent, sufficient to move it from 46th in the nation to 26th. Similarly, with a growth rate of 1.8, Ohio saw its ranking across the states fall significantly over the period (from 15th to 36th).

While a variety of factors might contribute to these variations, we focus on the role of human capital. We decompose the variations in income across states in human capital and other factors. In this we are particularly interested in the role of cognitive skills as measured by standardized tests of mathematics and other subjects. This focus on cognitive skills reflects prior work showing that they are extraordinarily important in understanding international differences in income, suggesting this might also hold for differences within the U.S. In part, this focus also dovetails with the attention that these issues receive in state policy deliberations.

3 Development Accounting

Development accounting provides a means of decomposing variations in GDP per capita between states into the different components of input factors of a GDP production function.

The basic development accounting framework, previously set out in Klenow and Rodriquez-Clare (1997) Gundlach, Rudman, and Woessmann (2002), is based on an aggregate Cobb-Douglas production function:

$$Y = K^{\alpha}(hL)^{1-\alpha}A^{\lambda} \tag{1}$$

where *Y* is GDP, *K* is capital, *L* is labor, and h is a measure of labor quality or human capital per worker. A^{λ} describes productivity. With Harrod-neutral productivity ($\lambda = 1 - \alpha$), we can express the production function in per capita terms:

$$\frac{Y}{L} \equiv y = \left(\frac{k}{y}\right)^{\alpha/(1-\alpha)} hA \tag{2}$$

where $k \equiv \frac{K}{L}$ is equal to the capital-labor ratio and $h \equiv \frac{H}{L}$ is equal to the human capital-labor ratio.

The decomposition of variations in per capita production is then straightforward. Taking logarithms of Eq. (2), we see that the covariances of log GDP per capita with the fundamental inputs are additively separable.

$$var(\ln(y)) = cov(\ln(y), \ln(y)) \tag{3}$$

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

Dividing Eq. (3) through the variance of GDP per capita puts each component in terms of its proportional contribution to the variance of income.

$$\frac{cov\left(\ln(y), \ln\left(\left(\frac{k}{y}\right)^{\alpha/(1-\alpha)}\right)\right)}{var(\ln(y))} + \frac{cov(\ln(y), \ln(h))}{var(\ln(y))} + \frac{cov(\ln(y), \ln(A))}{var(\ln(y))} = 1 \tag{4}$$

Our interest is the importance of human capital for income differences. Thus, we focus on the second term of Eq. (4), the share of the variance due to human capital, $\frac{cov(\ln(y),\ln(h))}{var(\ln(y))}$.

To check the robustness of our results, we also look at how well we can explain the extremes of GDP per capita of the five states with the highest GDP per capita and the five states with the lowest GDP per capita. We will refer to this measure as the 5-state measure.

The formula is described in Eq. (5) (see Hall and Jones (1999) and Gundlach, Rudman, and Woessmann (2002).

$$\frac{ln\left[\left(\prod_{i=1}^{5} X_i / \prod_{j=n-4}^{n} X_j\right)^{1/5}\right]}{ln\left[\left(\prod_{i=1}^{5} y_i / \prod_{j=n-4}^{n} y_j\right)^{1/5}\right]} + \frac{ln\left[\left(\prod_{i=1}^{5} A_i / \prod_{j=n-4}^{n} A_j\right)^{1/5}\right]}{ln\left[\left(\prod_{i=1}^{5} y_i / \prod_{j=n-4}^{n} y_j\right)^{1/5}\right]} = 1 \tag{5}$$

Here, *i* and *j* are states which are ranked according to their GDP per capita, $i, \ldots, j, \ldots, n$. The total number of states is equal to *n*. GDP per capita is again *y* and *A* is factor productivity. The variable *X* is either the physical capital-labor ratio term of the production function (see above) or the human capital part. Using this decomposition method, we can explain the contribution of the difference in human capital for the difference in GDP per capita between the five richest and five poorest states. The five richest states in 2007 are: Connecticut, New York, Massachusetts, New Jersey, and California. The five poorest states in 2007 are: Alabama, Kentucky, Arkansas, Mississippi, and West Virginia.[6]

A key remaining task is measuring human capital, *h*. Our starting point, following the existing literature (see, for example, Klenow and Rodriquez-Clare (1997), Bils and Klenow (2000)), begins with a quantitative dimension captured by school attainment. Here, however, we go further by incorporating a qualitative dimension. Specifically, we augment school attainment by test scores that are designed to measure cognitive ability (see, for example, Hanushek and Kimko (2000); Hanushek and Woessmann (2012)).

Following the Mincer representation of an earnings function, we create a measure of human capital by combining test scores and mean years of schooling according to prices in the labor market:

$$h = e^{rS+wT} \tag{6}$$

In this formulation, *S* represents mean years of schooling and *T* denotes test scores. The parameters for *S* and *T* (i.e., r and w) are the earnings gradients for each component of human capital and are used as weights to map schooling and test scores into a single human capital indicator according to their impact on individual earnings and productivity. The human capital parameters can be obtained from previous micro-level estimates. The gradient for schooling is typically estimated in the U.S. to be around $r = 0.10$ (Card (1999)). Thus, an increase in years of schooling by one year is associated with an increase in earnings by 10 percent.

[6] The five richest states in 2010 are: Connecticut, New York, Massachusetts, New Jersey, and North Dakota. The five poorest states in 2010 are: Alabama, Arkansas, South Carolina, West Virginia, and Mississippi.

Estimates of the gradient for cognitive skills, *w*, are less commonly available and are not completely satisfactory for our purposes. Several recent U.S. studies, employing very different data and approaches, provide gradient estimates. The first group of these provides estimates of the early career returns to skills. Three base estimates on different nationally representative data sets that follow students after they leave school and enter the labor force (Mulligan (1999); Murnane et al. (2000); Lazear (2003)). When scores are standardized, they suggest that one standard deviation increase in mathematics performance at the end of high school translates into 10-15 percent higher annual earnings.[7] Chetty et al. (2010) look at how kindergarten test scores affect earnings at age 25-27 and find an increase of 18 percent per standard deviation.

But, importantly, all of these estimates come early in the worker's career, and there are reasons to believe that these are less than those for later in the life cycle. A rise could reflect either improved job matches and better employer information with experience (such as in Altonji and Pierret (2001)) or the effects of technological change over time.[8] Hanushek and Zhang (2009) estimate a gradient of *0.20* for the U.S. using the International Adult Literacy Survey (IALS), a dataset covering the entire working life. Hanushek et al. (2013) explicitly look at the age pattern of returns and find that the impact of skills actually rises with experience. Their estimates for the U.S., based on data from the Programme for the International Assessment of Adult Competencies (PIAAC), range between 0.14-0.28 depending on the precise specification.[9]

From this range of estimates, we rely in the main analysis on a median estimate of returns to prime age workers of 0.20, or 20 percent higher earnings for one standard deviation of tests. Thus, we calibrate our baseline model with $r = 0.1$ and $w = 0.2$. Subsequent

[7] It is convenient to convert test scores into measures of the distribution of achievement across the population. A separate review of earlier studies of the normalized impact of measured cognitive skills on earnings by Bowles, Gintis, and Osborne (2001) finds that the mean estimate is only 0.07, or slightly over half of the specific studies here. More details on the individual studies shown here can be found in Hanushek (2011).

[8] These estimates are derived from observations at a point in time. Over the past few decades, the returns to skill have risen. If these trends continue, the estimates may understate the lifetime value of skills to individuals. On the other hand, the trends themselves could change in the opposite direction. For an indication of the competing forces over a long period, see Goldin and Katz (2008).

[9] Using yet another methodology that relies upon international test scores and immigrants into the U.S., Hanushek and Woessmann (2012) obtain an estimate of 14 percent per standard deviation. These estimates come from a difference-in-differences formulation based on whether the immigrant was educated in the home country or in the United States. They find that skills measured by international math and science tests from each immigrant's home country are significant in explaining earnings within the United States. While covering the full work force age range, the lower estimates are consistent with the lower gradients for immigrants found in Hanushek et al. (2013).

robustness checks, however, investigate the sensitivity of the estimates to these choices – and particularly to the gradient for test scores. In this paper, we are interested in the contribution of human capital to economic development. Thus, we will concentrate on these aspects and will not discuss the contribution of physical capital or technological progress in detail.

4 U.S. State Data

4.1 Basic Sample

Following Mankiw, Romer, and Weil (1992), we exclude states that are natural resource abundant, since their income will depend more on sales of raw material and less on the production of Eq. 1. As measure of abundance of natural resources, we look at the industry share in mining. Alaska and Wyoming have more than 20 percent of GDP that comes from mining activities. This industry is also the largest industry of all industries in both states.[10] Furthermore, we also exclude Delaware from the analysis because with a GDP share of 39 percent, this state has a dominant industry sector in finance and insurance. Delaware is also known as a tax haven for companies. For example, Delaware hosts more companies (ca. 945,000) than people (ca. 917,000) (Economist (2013)).

4.2 GDP per capita

Nominal GDP data at the state level come from the website of the U.S. Bureau of Economic Analysis[11] As introduced previously, Figure 1 shows real GDP per capita over time, starting in 1970. While it is well known that mean real GDP per capita has more than doubled from 1970 to 2007, the dispersion across states is less well known. As noted, the $30,000 mean difference between the richest and poorest states in 2007 motivates the analysis of underlying causes of these differences. Figure 1 reveals that the dispersion across states has increased substantially. The standard deviation across states increases from $2,894 in 1970 to $6,388 in 2007.

4.3 School Attainment

As indicated, to construct our measures of U.S. state human capital, we focus on two proxy variables, years of completed schooling and test scores. The most straightforward component of state human capital is average completed years of schooling. The census microdata permit calculation of school attainment for the working age population (Ruggles et al. (2010)).

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[10] See Appendix Table A1. Note also that the rapid income growth of North Dakota also reflects the very recent rise in income from natural gas extraction.

[11] A detailed description of all data sources and data manipulations is available in the data appendix. The state level nominal GDP can be found at: http://www.bea.gov/regional/. For intertemporal comparisons, we deflate nominal GDP by the nation-wide implicit GDP price deflator (http://www.bea.gov/iTable/iTable.cfm?reqid=9&step=3&isuri=1&903=13#reqid=9&step=3&isuri=1&903=13) and divide real GDP by total population (http://www.bea.gov/iTable/iTableHtml.cfm?reqid=70&step=1&isuri=1) to arrive at GDP per capita in 2005 U.S. dollars (see Peri (2010)).

Figure 2 shows the distribution of average years of schooling over time. First, educational attainment of the U.S. workforce has steadily increased from slightly more than 11 years in 1970 to more than 13 years in 2007, but the rate of increase has slowed in recent periods.[12] Second, the average years of schooling show considerable variation across states. And, third, the dispersion in completed schooling across states has narrowed over time.

4.4 Test Scores and Cognitive Skills

Unlike the direct measurement of school attainment, obtaining state estimates of cognitive skills is complicated and leads us to present alternative approaches. The challenge is easily seen. We want data on the skills of the state workforce – but our only state level test information are for students in the state over relatively recent periods. The current state workforce of any given state is made up of mixture of people educated in the state at various times, of people educated in other U.S. states at various times, and of people educated in other countries at various times. We can estimate the average test scores of the current workforce based on distributional information about the educational origins of the workforce along with location specific test information. But, because there is uncertainty in this, we will actually develop a series of alternative estimates of the skills of each state's workforce.

On average 60 percent of the population is living in their state of birth (see Figure 3) – leading us to be confident that they were likely educated in their current state of residence.[13] But we also see a huge variation across states. For example, in Nevada only 16 percent of the people living in Nevada in 2007 report having been born in Nevada. On the other extreme, 78 percent of the population in Louisiana is also born there. These numbers indicate that internal migration is a major issue when we would like to assess the cognitive ability of a state.

International migration is less frequent on average. Figure 4 shows that more than 90 percent is born in the U.S. However, recent years show a large variation also in these shares: In 2007, 98.9 percent of the population in West Virginia is born in the U.S. while only 70 percent in California was born in the U.S.

There are reliable U.S. state level test score data from the National Assessment of Educational Progress (NAEP). NAEP tests students in grade 4 and 8 in many different subject

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[12] Refer to the data appendix for a detailed description of the construction of the years of schooling.

[13] Throughout, when we refer to the population, we really mean the working age population of 20-65.

areas, although our main analysis focuses on mathematics test scores in grade 8.[14] NAEP collected its first test scores at the state level in 1990. However, they are only consistently available for all states from 2003 in two-year intervals.[15] An eighth grader in 1990 will just be 32 in 2008, implying that the majority of workers in the labor force would never have participated in the testing program.

At the same time, the NAEP state level tests are quite stable over time. An analysis of variance of the grade 8 math tests shows that 88 percent of test variation lies between states and just 12 percent represents within state variation for the two decades of observations.[16] Thus, we begin by calculating a fixed state score using all available NAEP observations for each state.

In part to compare with international data that we will use for immigrants, the NAEP data is rescaled to the US mean and US SD of the year 2011 which in turn is rescaled to have a mean of 500 and a within-state standard deviation of 100.[17] We then compute the state mean from running regressions of the test score on state fixed effects and time fixed effects. The coefficients on the state fixed effects serve as our average test score for the state.

Figure 5 shows the distribution of these test scores across states for all students, where the top state (Minnesota) surpasses the bottom state (Mississippi) by 0.87 standard deviations. Because we will subsequently employ variations across parental groups, we also display state scores for students from families where the parents have some kind of university education versus parents who do not have university education (see Figure 6). As expected, children from high educational backgrounds receive much higher test scores than children from lower educational backgrounds, with an average difference of over 0.6 standard deviations.

Ranking states by their average test score in math in grade 8, we find that Minnesota, North Dakota, Massachusetts, Montana, and Vermont make up the top five, whereas Hawaii, New Mexico, Louisiana, Alabama, and Mississippi constitute the bottom five of the ranking

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[14] For a description of NAEP and access to data, see http://nces.ed.gov/nationsreportcard/. Expanding the analysis to test scores in other subjects and grades, which are highly correlated at the state level, leads to qualitatively similar results.

[15] Before 2003, state participation in NAEP was voluntary. A total of 41 states participated before 2003.

[16] For grade 8 reading, the between state variance rises to 92 percent. For grade 4, the between state variance is 87 and 86 percent for math and reading respectively.

[17] Detailed description of the rescaling process and summary statistics of the raw test score data can be found in the data appendix.

(see Figure 5). Our primary analysis relies on these estimates of skills for students educated in each of the states.[18]

For all workers in each state who were born in the U.S., we know their state of birth, and we assume that their state of birth is that same as their state of education. Thus, we combine test scores for all U.S. born workers according to the separate birth state scores.

We deal with immigrants (born in a foreign country) in a similar manner. For people born abroad, we know the country of origin. We combine information from the major international tests (PISA, TIMSS, and PIRLS (IDE 2013) for each country of origin for immigrants.[19] The international test scores are rescaled to the NAEP test scores (Hanushek, Peterson, and Woessmann (2012)). We again use national averages which are obtained from simple regressions with country, survey, and time fixed effects.[20] We determine whether the worker was educated in the home country by information on age of immigration into the U.S.[21] These data allow us to add in scores for the foreign born population of working age for each state.

This approach parallels that used in the classic study of expenditure variations by Card and Krueger (1992) that also attributed the schooling characteristics of workers according to state of birth. That study was criticized by Heckman, Layne-Farrar, and Todd (1996) in part because it did not consider selectivity of migration. The Heckman et al. critique developed tests that indicated differential migration across states.

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[18] We do attempt to project test scores back in time, and the results of this are reported below. The idea of our backward projection is to use an average of the linear trend in the state test score and the observed national trend, which dates back to 1978, to predict the test score of the state in a given year. The resulting test score is adjusted such that the weighted average meets the national average where weights are based on average daily attendance in public elementary and secondary schools (U.S. Department of Education (2013)).The result of the extrapolation can be found in the data appendix. Because we needed to project scores even earlier than the initial national scores, we were concerned that the projections would not be superior to the assumed constancy in the main analysis. In fact, as seen in Section 6, the variance decompositions are similar but the role of human is somewhat elevated.

[19] PISA relates to the *Programme for International Student Assessment*, TIMSS to *Trends in International Mathematics and Science Study*, and PIRLS to *Progress in International Reading Literacy Study*. We draw the data International Data Explorer (IDE), National Center of Education Statistics, Institute of Education Sciences, http://nces.ed.gov/surveys/international/ide/.

[20] To match the international test data with the population shares from the Census, we sometimes have to impute test scores because not all countries or regions in the Census are covered by the international test data. We do that by imputing regional averages of countries which are close. Se the data appendix for a detailed description.

[21] Immigrants who were seen to be in the U.S. when of school age are assigned their current state of living as the state of their schooling.

To deal not only with the selectivity of migration but also changes in cohort composition between those in the workforce and current test takers, we go to data about NAEP scores of children of university graduates versus nongraduates. As shown in Figure 6, these scores differ noticeably. For the current working age population, we find the distribution of those with university or less than university by state of birth and then calculate new average scores for each state. This provides state tests for the working age populations who are locals (born in current state) or internal migrants (born in U.S. but in different state).

Table 1, Panel B provides summary statistics for all composite test scores which are used in the main analysis of our 47 states in 2007. The baseline composite test score assigns all locals the mean test score of the state where they are living (which is also their state of birth). All internal migrants receive the mean test score of their state of birth. (Here we implicitly assume that internal migrants have not left their state of birth before finishing grade 8). The international migrants receive, in this variant, the mean score of their current state of living.

The next test score adjusts the locals by education category. Thus, we replace the average test score of the state of living with the average test score of the state of living by education category (university / no university). As a next refinement, we also adjust the average test scores of the internal migrants by education category. The assumption is that we can assign to the work age population with a university education the test score children with parents who have an university degree in each state. This is designed to account partly for selective migration because it allows for different migration patterns across states by education levels. For example, university graduate out-migrants from Ohio might go to a very different set of states than Ohio out-migrants with less education – and it would be inappropriate to treat both flows the same.

Selectivity of international immigrants is also a major concern. Using just country average scores is unlikely to deal with international migrants satisfactorily. We know that especially international migration is a highly selective process (Borjas (1987)), implying that the mean of the country of birth is likely not to be a good approximation of the skills of the migrant group. While we do not have direct information on the selectivity of migration from specific countries, we consider two specific variants: assigning the 75th or the 90th percentile of the source country skill distribution to the population shares. For these test score variants, we assume that the migrants are positively selected from the source country population, i.e.

that they are much more skilled than those left behind – although immigrants from a low-performing country will still be below immigrants from a high performing country.

Table 2, Panel A shows a correlation matrix of these composite test scores. We see that the correlation between the test scores is 90 percent or higher in most cases. However, especially the correlation between the test scores which adjust for international migration by imputing the 90^{th} percentile of their home country shows a lower correlation with all other test scores. Thus, we can expect that the outcomes of the development accounting differ regarding the test score which is used to describe cognitive skills.

5 The Contribution of Human Capital

We are now in a position to decompose state variations in GDP per capita. Table 3 shows the results of the development accounting for different test score specifications. At this point, we focus on GDP per capita in 2007.[22] Subsequently, we consider earlier periods. Throughout, we use math test scores in grade 8, and Alaska, Wyoming, and Delaware are dropped due to their incompatibility with a human capital growth model.[23]

We begin with the raw test score data for states and then proceed to refine the estimates of worker skills. The baseline specification adjusts the local average test score for the portion of the workforce that is made up of internal migrants. Locals and international migrants receive the test score of their state of living and internal migrants receive the test score of their state of birth. With this measure of human capital for the working age population, we can explain 18.4 percent of the variation in GDP per capita. The composite average test score accounts for 6.7 percent, and years of schooling accounts for 11.7 percent. As comparison, we use data on physical capital from 2000 (Turner et al., 2013). We see that it can explain roughly 28 percent in GDP per capita differences.

With the covariance measure for the development accounting, we can also test for whether the impact of human capital is significant using bootstrapped standard errors. As a general rule throughout our different variants, both the overall variance estimate for human capital and the separate estimates for the components are highly significant statistically.

The 5-state measure provides a slightly different perspective on income variations. From this, we see that total human capital can account for 25.9 percent in the variation of GDP per capita among the five richest and poorest states. Across these extremes, 10.9 percent is explained by differences in test scores and 14.9 percent by differences in years of schooling.

The remainder of the table provides results for the more refined composite test scores for the working age population in each state. Since the measure of school attainment is held constant, it explains a constant portion of the variance in income, and we focus on how income variations are related to alternate test score measures. The most straightforward step is adjustment of the test scores of the locals for educational background, i.e., whether the

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[22] Results by using GDP per capita in 2010 are very similar.

[23] Note also that North Dakota was previously identified as the fastest growing state for the 1970-2007 period. This growth largely reflects its emergence as an energy producer. Dropping North Dakota, similar to that for Alaska and Wyoming, however, has virtually no impact on our findings.

workers have a university degree or not.[24] With this refinement, composite test score account for 7.8 percent of the variation in GDP per capita, and similarly adjusting scores of the internal migrants by educational background raises the explanation of tests to 8.9 percent. Thus, after adjusting scores of U.S. born workers, we explain 20.6 percent of the total income variation in GDP per capita with human capital differences across states. Of the human capital portion, 43.2 percent derives from variation in test scores and 56.8 percent from variation in years of schooling.

In terms of the variation in income between the richest and poorest five states, adjusting locals and internal migrants by education category raises the explained income variation to 13 percent, or close to equal to the impact of variations in years of schooling.

We now turn to the skills of immigrants from abroad. The prior estimates simply assigned international migrants the composite average test score of their state of living. The most direct approach is to adjust the test score of the international migrants to the average test score of their country of birth by education category. But, somewhat surprisingly, we see a large drop in the covariance measure for the test score to 3.8 percent, and the estimate is not statistically different from zero at the 10 percent level.

What can explain the poor performance of our human capital measure once we try to account for international migration? The most obvious explanation is that the quality measure for immigrants is very error prone. While we have adjusted for the educational distribution of immigrants, this adjustment is likely to be insufficient. The US has a rather strict immigration law with a skill-selective immigration policy that makes immigration policies a substantial hurdle for migrants (Bertoli and Moraga (2012); Ortega and Peri (2013). In addition, individuals self-select in migration (McKenzie, Gibson, and Stillman (2010)). Thus, for example, only the most skilled are able to gather information on possible destination countries or possess skills that are rewarded in the foreign country. While generally framed in terms just of school attainment, the existing research on international migration is mostly that migrants who go to developed countries are on average better educated than their native counterparts left behind (Borjas (1987); Chiswick (1999); Grogger and Hanson (2011)). If this is true, then it is not surprising that average test scores of the source country, either simple averages or averages by parental background, also do a poor job in describing migrant skill levels. The true skill level should exceed the home country mean test score and even the mean test score

[24] Implicitly, since international migrants are assumed to line up with the scores for the native population of each state, this also adjusts immigrant scores.

within each educational category. To account for this selection, we assign international migrants the 75th in one specification and the 90th percentile of their home country test score distribution.

By basing our estimates of immigrant skills on an assumption of highly selective international flows we provide a much stronger picture of the importance of human capital for variations in state income. According to the 90th percentile estimate of selection, test score variation explains 11.1 percent of the variation in GDP per capita – almost precisely the same as school attainment. The 5-State measure shows total human capital explaining one-third of the variation in state incomes and the test score component being slightly larger than that of years of schooling.[25]

[25] The basic estimates in Table 3 are, however, conditional on the received parameters for the human capital aggregation. While the schooling parameter (r=0.10) has been widely and consistently estimated with earnings data, the cognitive skills parameter (w=0.20) is more uncertain. Table A2, Panel A investigates the sensitivity of the prior estimates to the skill parameter. The first column for both the covariance and for the 5-state measure matches that in Table 3; the next two columns investigate both less impact (w=0.15) and greater impact (w=0.25) of skills. (Since the estimated impact of school attainment is unaffected, the table focuses just on the test score component). The estimates match intuition. If the cognitive skills measured by test scores have a stronger impact than the baseline, human capital can explain a larger portion of the overall variance in income. If the skill gradient is 0.25 – a value that is plausible by the estimates in Hanushek et al. (2013) – the total variation in incomes explained by human capital would rise to over 25 percent with the covariance decomposition and 34 percent with the 5-state decomposition. But, even if the gradient is really lower than the baseline, one-fifth of the variance state income is still explained by human capital.

6 Age Projections of Historical Achievement Patterns

We have already discussed that the average state test score (over the period 1990-2011) might not be a good proxy for the cognitive skills of the working age population. An extension of the previous analysis involves backward projections of test scores to estimate the quality of skills of older workers.[26] In order to do this, we make use of the patterns of scores within each state along with the overall U.S. test performance. We then develop new test score composites and re-do the development accounting presented previously.

6.1 Backward Projections of State NAEP Scores

We have two pieces of information that help us to estimate the scores of older workers educated in each state. First, we know the time pattern of NAEP score changes over the period 1990-2011. Moreover, we know the aggregate NAEP performance for the nation from 1978-2012. We use both to extrapolate scores for older age cohorts.[27]

First, we can linearly extrapolate individual state scores based upon the observed test information. (For states that just began testing in 2003, we rely on just the more recent patterns). Second, for the period 1978-1990, we force the state values to aggregate (on a pupil weighted basis) to the national trend.

This part of the extrapolation is perhaps easiest seen in Figure 7 that shows both the observed data and the extrapolated state trends for two states: Massachusetts and Mississippi. Massachusetts in above the national average in 2011 but also has a steeper trend than the national average. As such, we shrink the extrapolated trend toward the national trend. Mississippi is different in having a steeper trend that is below the national average, but we again shrink the extrapolation to the nationally observed trend. As a robustness check, we also perform development accounting by assuming the linear state trend or the national trend between 1978 and 1992.

[26] We provide an overview of the approach here and the details in the data appendix.

[27] Note that the international test scores are not adjusted by age category.

We do these projections for the entire population and for the separate education categories. Because the projections include obvious estimation error, we consider the development accounting exercise with both alternatives.

For period before 1978, we have no other information on performance from NAEP. This leads us to assume two possible test score developments. The first variant holds all state scores at their estimated 1978 values. Thus, for all workers older than 43 – the age in 2007 of an 8th grader who took the test in 1978 – have the constant test score value of the average estimated state value in 1978. The second variant estimates linear state trends on the state time series between 1978 and 2011 and assumes this linear development prior to 1978. Figure 8 best describes the four test score series for Mississippi. From 1992 to 2011, we use the actual NAEP test score data for each state and test score series. The yellow solid line represents our most preferred test score series with the combined weighted national and linear state trend between 1978 and 1992 and the linear state trend on the (predicted) series between 1978 and 2011 for years prior to 1978. This series is complemented by the green dash-dotted line that assumes constant 1978 values instead of the linear time trend. The blue dashed line represents the national trend with constant values prior to 1978 and the red dotted line represents the linear state trend on the data between 1992 and 2011 and constant values prior to 1978 as well. Table 2 previously shows in Panel A a correlation matrix of composite average test scores. In Panel B and C of the same table, we can find the correlation between the composite average test scores from before and (selected) composite average projected test scores by age (Panel B) and by age-education (Panel C). The test scores in row 7 and 9 adjust for internal migration and the test scores in row 8 and 10 adjust additionally for international migration. We see that the correlation is still very high, indicating that all test scores describe a similar distribution of cognitive skills. However, the correlation sometimes decreases to around 80 percent which signals that there are notable changes for some states.

We stated earlier that we do not have other information on performance from NAEP, but there is time series information at the state level coming from SAT scores which dates back to 1972 (College Board, 2013). In subsection 6.3, we use this information to estimate alternative test score developments which on the one hand check on the robustness of our baseline projections and on the other hand extend the series back to 1968.

6.2 *Development Accounting with Test Score Projections by Age*

Table 4 shows the results of the 2007 development accounting for the composite average projected test scores by age category. In this table, we only present the results for test scores adjusting for internal migration and for additionally adjusting for international migration by imputing the 90th percentile of the home country test score distribution. The first column of this table reports the results by using the composite average test scores again. The next four columns change the assumption about the test score development prior to 1992. In the second column, we assume the national trend for each state between 1978 and 1992. Before 1978, the test score is constant at the 1978 value. We see the development accounting results increase by almost 2 percentage-points by assuming this trend in test scores instead of assuming the same average test scores for each cohort of the working age population. This does not change very much when we use the linear state trend only in the third column. The results are almost identical. However, standard errors are slightly increasing. Using the combined national and state trend has also no significant effect on the outcome. The best results, however, are obtained by using the combined national and linear state trends for the period between 1978 and 1992 and a linear state trend on the whole series for years before 1978. There, we are finally able to explain 16 percent of GDP per capita across states with differences in cognitive skills. Running the development accounting on the five poorest and richest states in the last column, confirms that cognitive skills, measured by these test scores, play a major role in explaining income differences across states.[28]

For 2007, the projected test scores are more able to explain the variation in GDP per capita than the average test scores. In fact, Table 5 shows that this is not only true for 2007, but for other years as well. Column 2 of this table shows the development accounting results for the different years by using the simple averages. We see that they are able to explain the more recent years relatively well. However, the average test score struggles to explain earlier variation in GDP per capita. The explained variation decreases from around 9 to 11 percent for 2000 and 2011 to 5 to 8 percent for other years. There are two possible reasons: First, cognitive skills are not so important in earlier years. This would also best suggested by an increasing explanatory power for years of schooling for earlier years. Second, measurement

[28] Table A2, Panel B and C, in the appendix check the robustness of our results by using different returns to skills.

error biases the estimates downward because for these earlier years, we do not observe an actual test score anymore.

The projections, here again our preferred test score specification with combined national and linear state trends between 1978 and 1992 and linear state trend on the series between 1978 and 2011, performs much better in most years. The magnitude is almost comparable to the most recent years. This indicates that there is measurement error in the average test scores and that the projections provide useful information which can explain variation in GDP per capita.

6.3 Development Accounting with Test Score Projections based on SAT scores

How reliable are our projections? To test the robustness of our whole approach to project test scores back in time, we use information on SAT scores by state. College Board (2013) provides data on mean test scores and participation by state for the period 1972 to 2013. We use this information to predict NAEP scores on the basis of the development of SAT scores.

We cannot relate the SAT scores directly to the NAEP scores because mean SAT scores are not representative for the pupil population in a state[29]. The mean SAT score depends strongly on the participation rate.[30] A higher participation rate signals a less selected student body and therefore lower mean SAT scores. By regressing mean SAT scores on the participation rate and including state and year fixed effects, we predict mean SAT scores as if all states would have shown a participation rate that is equal to the mean US participation rate (47 percent). Then, we relate the predicted SAT score to the NAEP scores and predict NAEP scores depending on the relationship between predicted SAT scores and NAEP scores for

[29] Include references: Graham, Amy E. & Husted, Thomas A., 1993. Understanding state variations in SAT scores. Economics of Education Review, 12(3), pp.197–202.

Coulson, Andrew J. (2014). Drawing meanigful trends from the SAT. CATO Working Paper.

[30] College Board (2013) provides only total numbers of participation. We construct participation rates, by dividing SAT participation through public high school graduates of the respective year. This data comes from various years of the Digest of Education Statistics.

each state. The result is a projected NAEP test score series based on the SAT score from 1968 to 1991.[31]

Table 6 shows development accounting results by assuming the predicted NAEP scores between 1968 and 1992 for each state. As with the combined test scores from before, we assume either a constant 1968 value for years prior to 1968 or a linear state trend on the series between 1968 and 2011. Columns 1 and 3 show the previous results from Table 4 for comparison. Using this very different projection approach to construct test scores before 1992, we can resemble our baseline results very closely. However, the estimates are slightly less precise, indicated by a higher standard error.

[31] The SAT is normally taken at the end of high school. Therefore, we lag the SAT scores by four years to align them with the NAEP score which is from grade eight. See the data appendix for extensive documentation and details on the construction of the predicted NAEP score series based on the SAT data.

7 Growth Accounting

7.1 Introducing Mincer-style human capital into growth accounting analysis

Consider a standard Cobb-Douglas production function:

$$Y = AK^{\alpha}(hL)^{1-\alpha} \tag{1}$$

which, in per-capita terms, is:

$$y \equiv \frac{Y}{L} = A\frac{K^{\alpha}(hL)^{1-\alpha}}{L^{\alpha}\mathrm{L}^{1-\alpha}} = Ak^{\alpha}\mathrm{h}^{1-\alpha} \tag{2}$$

That is, average annual growth in output per capita can be decomposed into three parts – the contributions of physical capital, human capital, and total factor productivity, respectively – as follows:

$$g \equiv \frac{1}{t}\Delta \ln y = \frac{1}{t}\alpha\Delta \ln k + \frac{1}{t}(1-\alpha)\Delta \ln h + \frac{1}{t}\Delta \ln A \tag{3}$$

Human capital per capita is given by the Mincer-type specification, augmented by test scores:

$$h = e^{(rS+wT)} \tag{4}$$

Then, the contribution of human capital to the average annual rate of economic growth has a straightforward expression:

$$\begin{aligned}
&\frac{1}{t}(1-\alpha)\Delta \ln h \\
&= \frac{1}{t}(1-\alpha)[\ln h_t - \ln h_0] \\
&= \frac{1}{t}(1-\alpha)[(rS_t + wT_t) - (rS_0 + wT_0)] \\
&= \frac{1}{t}(1-\alpha)r\Delta S + \frac{1}{t}(1-\alpha)w\Delta T
\end{aligned} \tag{5}$$

Thus, the *absolute change* in years of schooling, as well as the absolute change in test scores, have a direct linear mapping into economic growth rates. The mapping is given by the standard parameterization of the share of capital in income α = ⅓, the earnings rate of return to years of schooling r = 0.1, and the earnings rate of educational achievement w = 0.2 per standard deviation in test scores.

For example, if average years of schooling S were to increase by 1 over a 10-year period, the contribution to average annual growth in GDP per capita g would be:

$$\frac{1}{t}(1-\alpha)r\Delta S = \frac{1}{10} * \frac{2}{3} * .1 * 1 = 0.67\%$$

I.e., by assuming the production function with the standard parameterization, we can incur that an increase in the population's schooling by 1 year, obtained over one decade, can account for ⅔ of a percentage point average annual growth over the decade.

Similarly, if the average educational achievement level T of the population were to increase by 10 percent of a standard deviation over a 10-year period (1 percent SD per annum), the contribution to average annual growth in GDP per capita g would be:

$$\frac{1}{t}(1-\alpha)w\Delta T = \frac{1}{10} * \frac{2}{3} * .2 * .1 = 0.13\%$$

I.e., again assuming the production function with the standard parameterization, we can incur that an increase in the population's educational achievement by .1 SD, obtained over one decade, can account for 0.13 percent average annual growth over the decade.

7.2 Growth accounting for the United States

Table 7 provides some basic growth accounting analysis for the United States over recent decades. Average annual growth in GDP per capita was 2.17 percent over the 1970s, 2.39 percent over the 1980s, 2.47 percent over the 1990s, and 1.52 percent over the 2000s (excluding the crisis years).

Average years of schooling in the working-age population (source: Ruggles *et al.* 2010, own calculations) increased from 11.1 in 1970 to 12.0 in 1980, 12.5 in 1990, 12.8 in 2000, and 13.04 in 2007. Based on the analysis above, this can account for 0.59% average annual growth in GDP per capita over the 1970s, 0.37% over the 1980s, 0.19% over the 1990s, and 0.20% over the 2000s.

Consider the average annual growth rate in NAEP test scores in column 3 (see Hanushek *et al.* 2012). For the U.S. as a whole, this was 2.6 percent of a SD average annual growth over the period 1992-2011. This is the coefficient estimate on years in a regression that has standardized test scores as the dependent variable, so 10 years means 0.26 SD increase, 20 years means 0.52 SD increase. Now, assume that the average achievement of the working population increased by the same amount. Based on the analysis above, this would account for 0.35 percent of average annual growth in GDP per capita.

So, e.g., of the total average annual growth in GDP per capita in 1970-2007 of 2.19 percent, 0.35 percentage points (16.1 percent) could be accounted for by increases in years of schooling and 0.35 percentage points (15.8 percent) by increases in educational achievement, bringing the total contribution of human capital to 0.7 percentage points or 31.9 percent of the total economic growth. Figure 9 shows growth accounting results for each state separately. The figure reveals that growth in years of schooling and test scores can explain a substantial part in the overall economic growth between 1970 and 2007. However, there is some heterogeneity regarding effect sizes. For example, test score growth in Iowa or Nebraska is not able to explain a larger part of overall economic growth. The opposite is true for states like North and South Dakota, Kentucky, or Massachusetts.[32]

[32] Table A3 in the appendix provide the results of the growth accounting by state in table form.

8 Conclusions

While differences may be narrowing over time, variations in income across the United States are large and important. More importantly, the sources of these variations are imperfectly understood.

This paper focuses on the contribution of human capital differences to the variations in state income per capita. Almost all states in their effort to foster economic development emphasize the human capital of their labor force and introduce policies both to improve the skills of their youth (the future labor force) and to attract skilled people from other states or from abroad. Yet the impact of human capital policies on state development is far from completely understood, particularly in light of population shifts across the states.

We pursue development accounting to decompose variations in state GDP per capita over the past half century. The decomposition relies on external estimates of the key parameters of a neoclassical production function, so we do not attempt to simultaneously identify the importance of human capital in production.

The central challenge is developing a human capital series for the individual states. Following research on international differences in income and growth, we are particularly interested in the role of cognitive skills. While it is easy to measure the school attainment of each state's workforce, it is much more challenging to incorporate differences in cognitive skills of the workforce.

We base our cognitive skills measure on test scores of the school age population in each state (from the National Assessment of Educational Progress) and in each country internationally (from international assessments of achievement). However, we must translate scores of students at different times into the skills of the current workforce of each state. We do this by building on the most likely location of schooling for workers, which provides the skill mapping for the current workforce. But, as is apparent from prior analyses of migration, it is also necessary to consider the selectivity of migration.

Our analysis confirms the importance of detailed identification of cognitive skills for the workforce. In our preferred model, we allow for differences in the cognitive skills of the workforce according to schooling levels, incorporating selective migration from other states and other countries for immigrants to the U.S. who were educated in a different country. Because the test score information by state of birth (the main indicator of likely schooling location) is unavailable for older workers in each state, we use the time pattern of state achievement scores to project cognitive skills developed when the oldest workers were in school.

Our estimates of human capital combine cognitive skills with school attainment of the workforce. We use market prices for each as estimated by other studies to aggregate the two components of human capital.

Our estimates indicate that 20-30 percent of the overall variation in state GDP per capita is attributable to variations in human capital across states. The lower end of the range reflects decompositions based on the crudest estimates of the cognitive skills of the workforce, and the importance of cognitive skills rises with more precision in the estimation. The variation attributed to human capital is roughly evenly split to that arising from differences in cognitive skills and that arising from differences in school attainment.

These estimates appear remarkably large for a variety of reasons. First, the U.S. is known for the openness of its labor and capital markets, allowing free movement of workers across states and presumably evening out the relevant distribution of human capital. Second, the estimation of state human capital stocks is subject to error, which most likely drives down the variations in income that can be attributed to it. As noted, the contribution of human capital is consistently larger when the most refined estimates of skills are used, but even the most refined undoubtedly contain error.

These estimates reinforce the instincts of state policy makers to be concerned about school quality as a way to improve the human capital of the state. They also support the efforts of states to attract higher skilled workers, although this would be zero-sum for the nation to the extent that the policies just redistribute the existing human capital stock.

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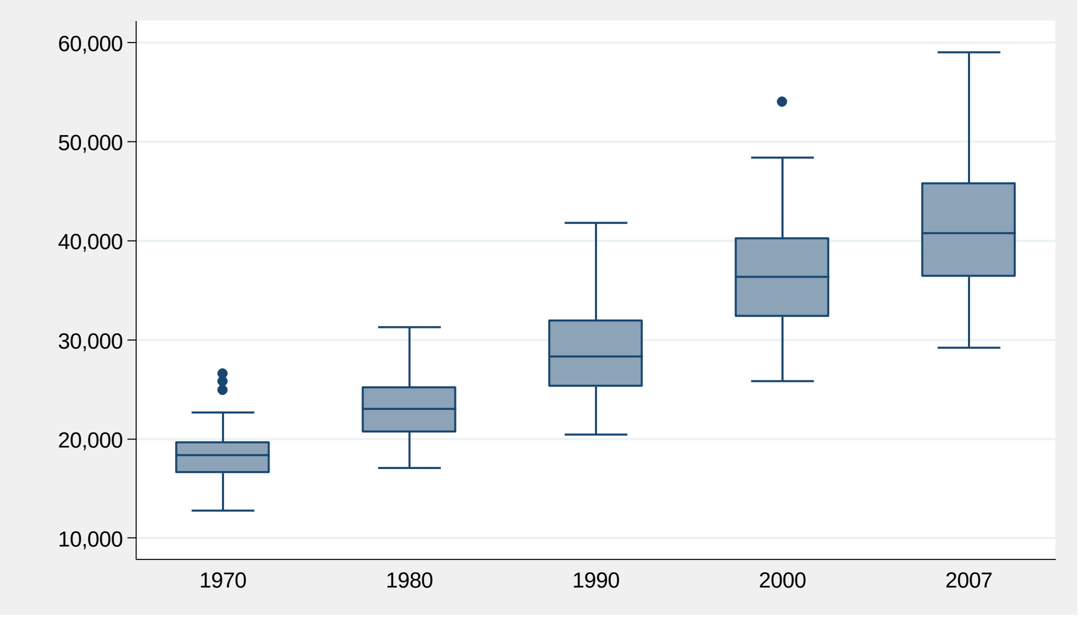
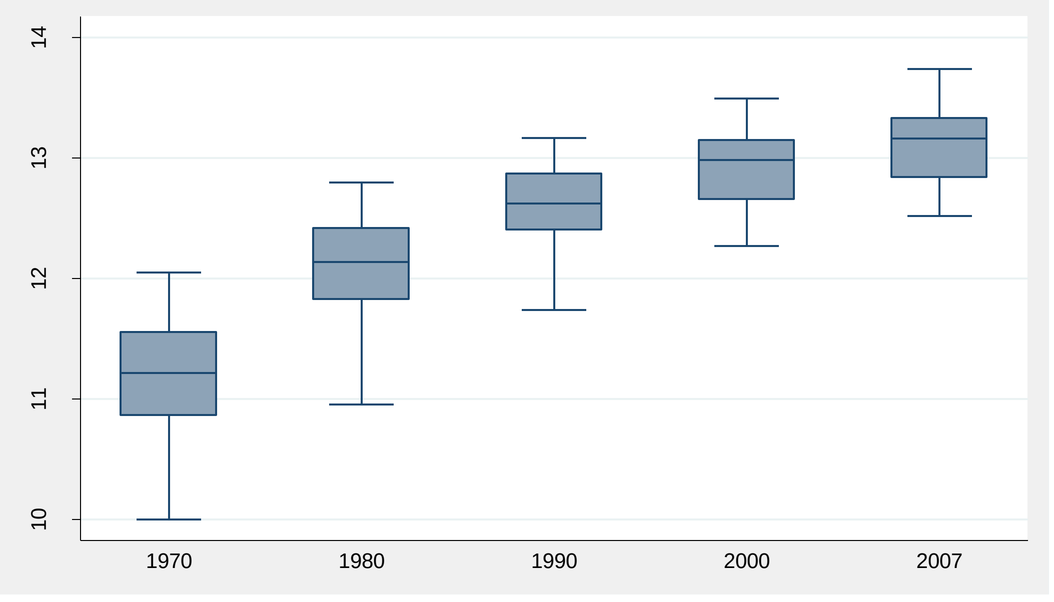
A Figures

Figure 1. Distribution of state GDP per capita over time



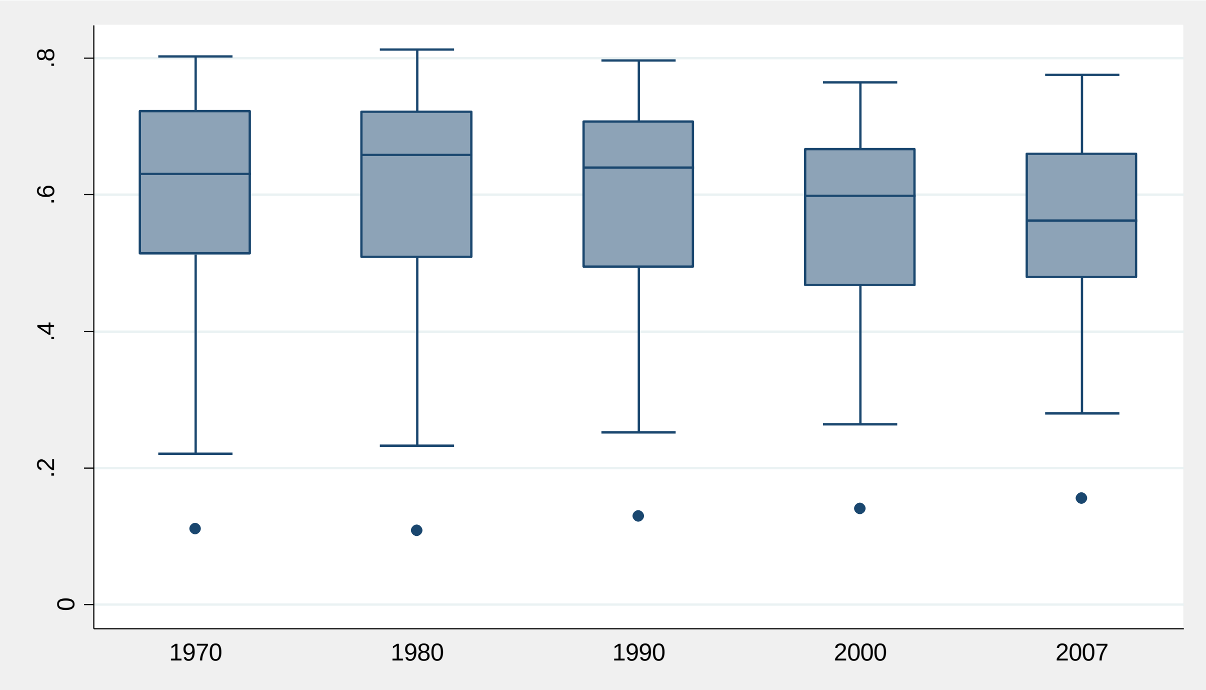
Notes: GDP per capita is denoted in 2005 U.S. dollars. Alaska, Delaware, and Wyoming are excluded. Source: Own calculations based on electronic data from the U.S. Bureau of Economic Analysis (http://www.bea.gov/); see data appendix for details.

Figure 2. Distribution of average years of schooling by year and state



Notes: Alaska, Delaware, and Wyoming are excluded. Source: Own calculations based on Ruggles et al. (2010).

Figure 3. Distribution of fraction of people with state of birth equal to current state by year and state

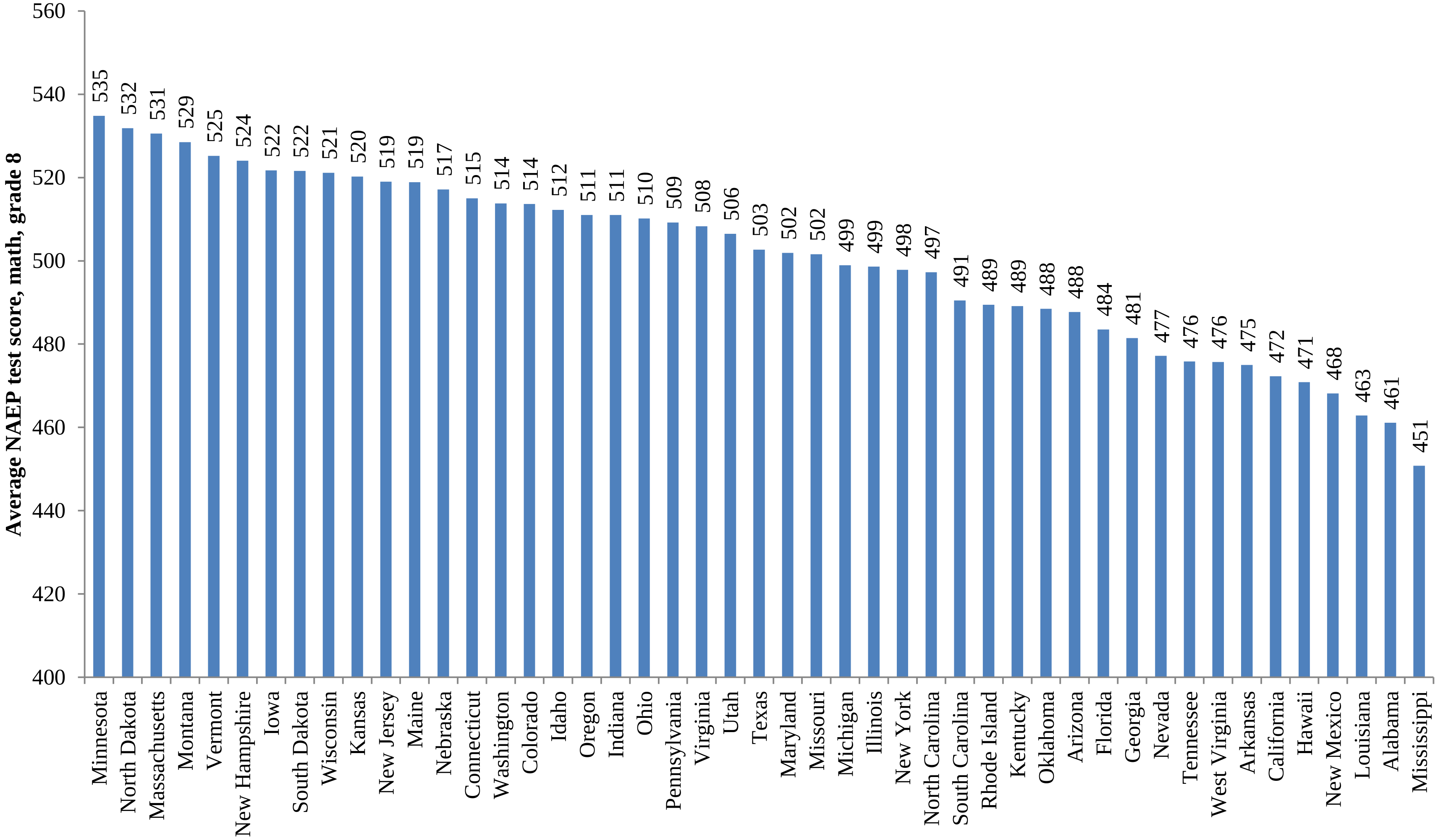


Notes: Alaska, Delaware, and Wyoming are excluded. Source: Own calculations based on Ruggles et al. (2010).

Figure 4. Distribution of fraction of workers with US origin/state of birth by year and state

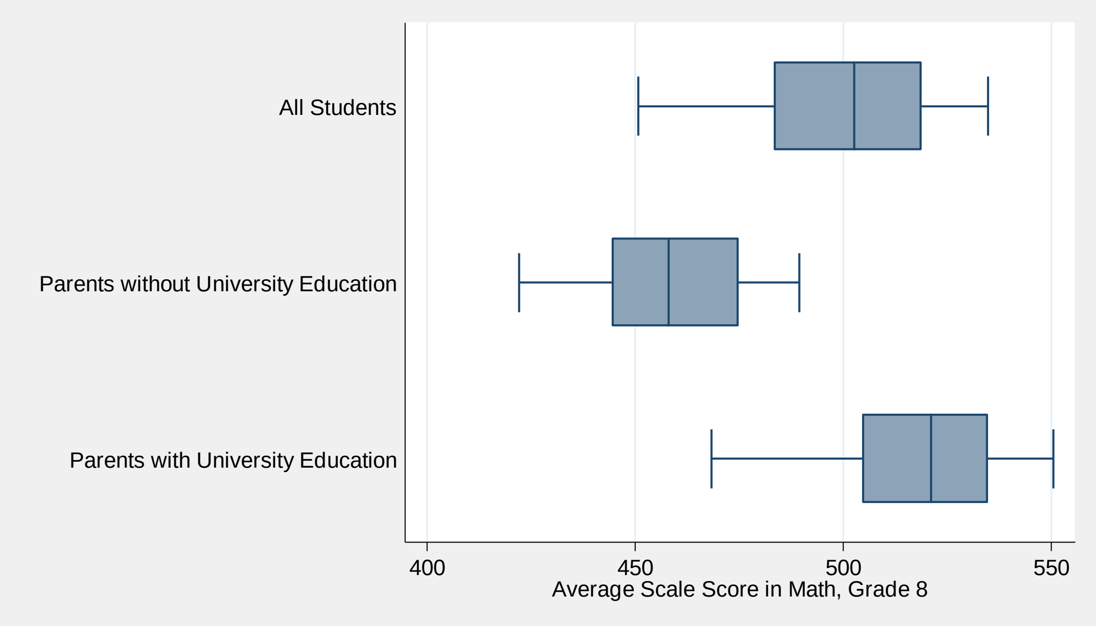
Notes: Alaska, Delaware, and Wyoming are excluded. Source: Own calculations based on Ruggles et al. (2010).

Figure 5. Ranking of states by estimated average NAEP score in math, grade 8



Notes. Alaska, Delaware, and Wyoming are excluded.
Source: Own calculations based on data from NAEP data from http://nces.ed.gov/nationsreportcard/.

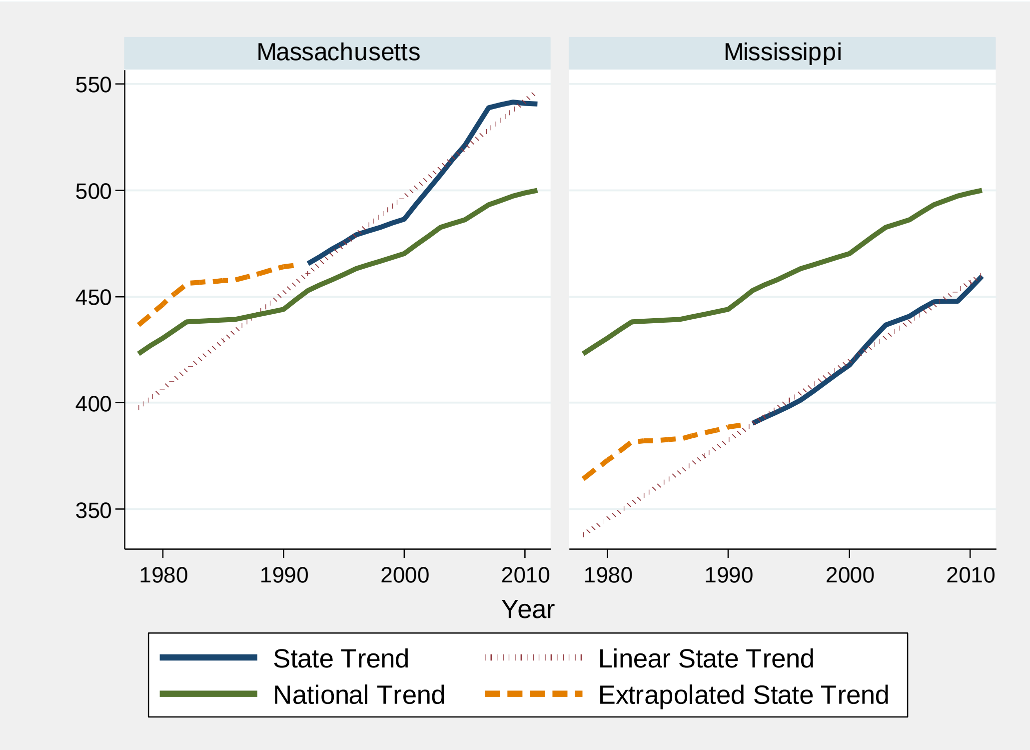
Figure 6. Distribution of estimates for the scale score by state and by sample



Notes: Alaska, Delaware, and Wyoming are excluded.

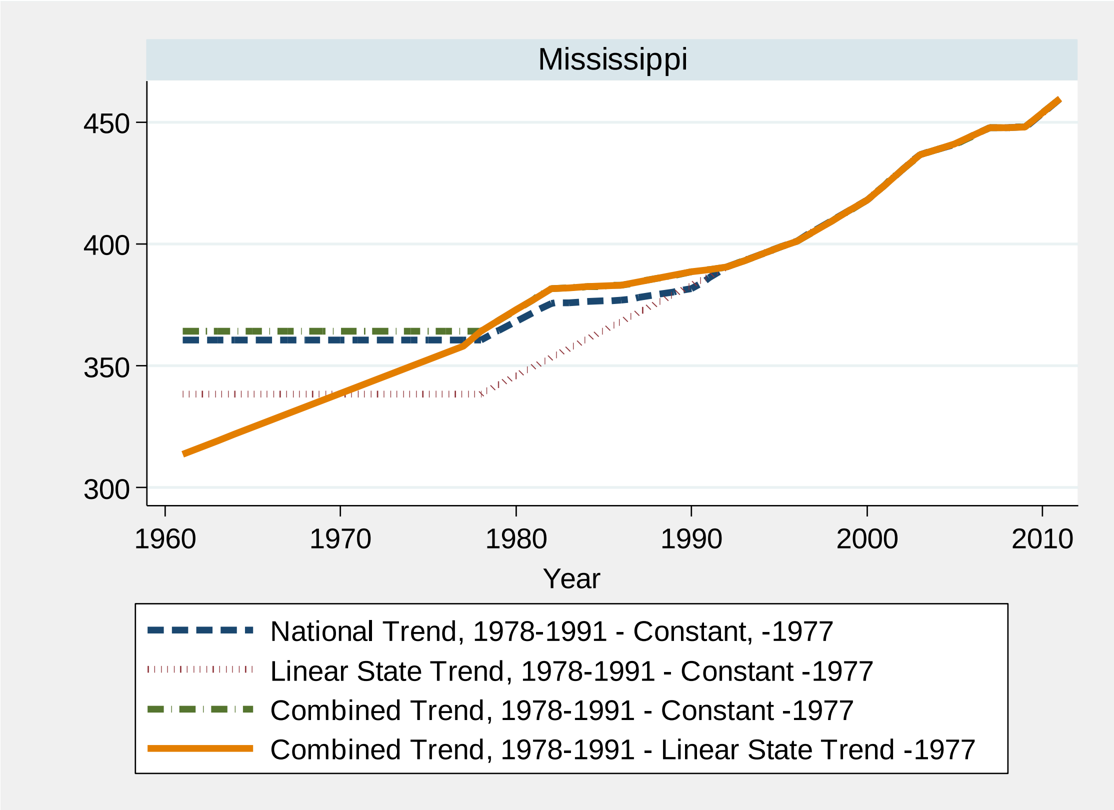
Source: Own calculations based on data from NAEP data from http://nces.ed.gov/nationsreportcard/

Figure 7. Extrapolated math grade 8 test scores for Massachusetts and Mississippi



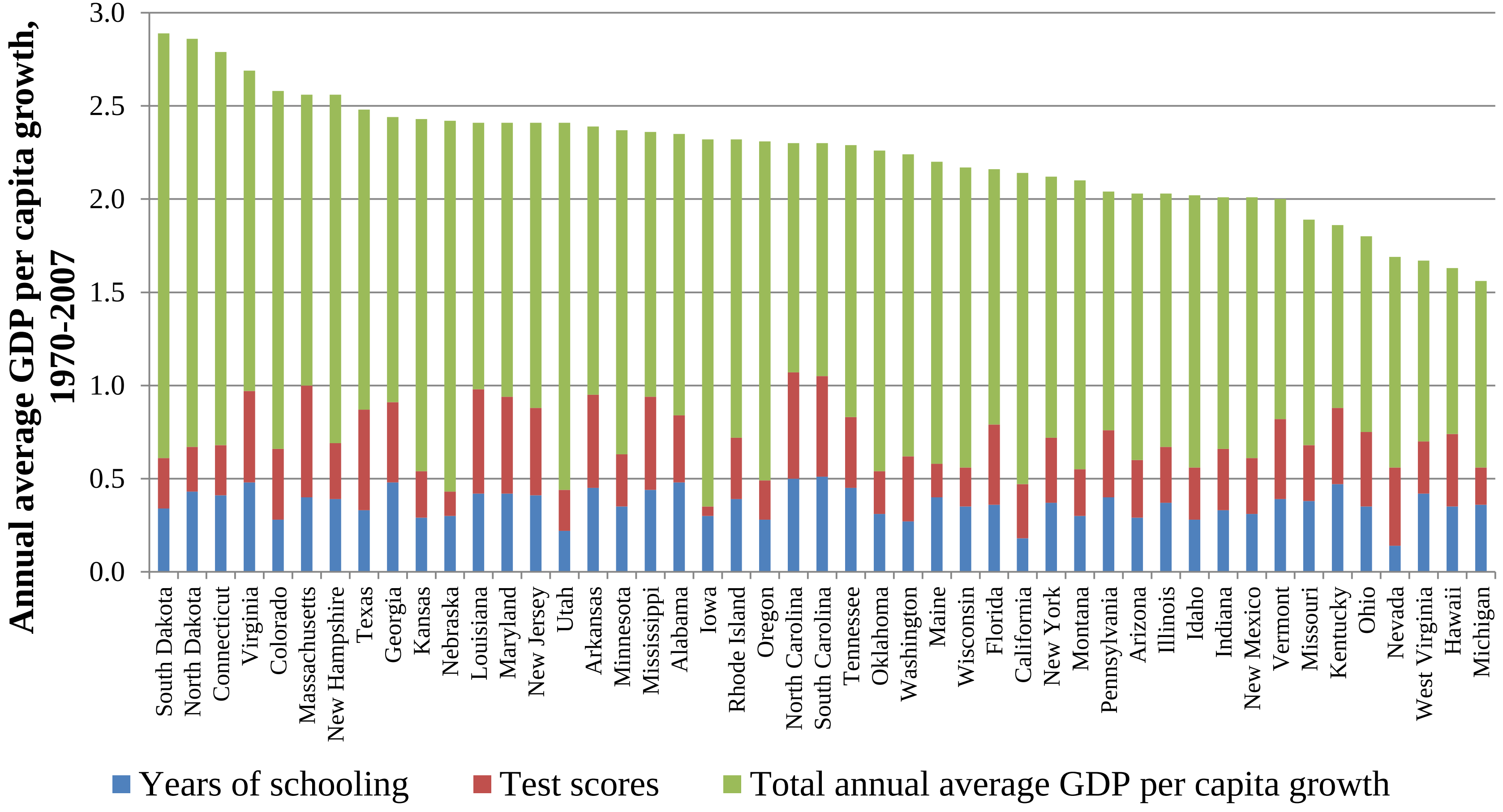
Source: Own calculations based on data from NAEP data from http://nces.ed.gov/nationsreportcard/.

Figure 8. Different projections for test scores before 1991



Source: Own calculations based on data from NAEP data from http://nces.ed.gov/nationsreportcard/.

Figure 9. Growth accounting by state



Notes: Alaska, Delaware, and Wyoming are excluded. Test scores refer to the composite average projected test scores with combined national and linear state trend between 1978 and 1992 and linear state trend before 1978 based on the series between 1978 and 2011.

B Tables

Table 1. Summary statistics, 2007

Variable	Obs	Mean	Std.Dev.	Min	Max
Panel A: State characteristics					
Real GDP per capita	47	41,218	6,388	29,302	59,251
Physical capital/GDP per capita ratio	47	2.51	0.22	2.12	3.32
Mean years of schooling	47	13.11	0.35	12.52	13.74
Panel B: Composite average test scores					
Local average adjusted for internal migrants	47	499.9	15.98	460.4	527.7
+ Adjustment of locals by education category	47	494.4	15.46	454.9	521.3
+ Adjustment of internal migrants by education category	47	493.9	15.80	453.1	522.0
+ Adjustment of international migrants					
By education category in country of birth	47	487.4	15.69	452.5	518.0
By 75th percentile in country of birth	47	492.3	14.86	453.8	519.0
By 90th percentile in country of birth	47	498.4	15.21	455.2	522.9
Panel C: Composite average projected test scores by age category					
Local average adjusted for internal migrants by age category	47	437.4	20.05	387.9	475.0
+ Adjustment of international migrants by 90th percentile in country of birth	47	447.9	19.52	391.7	478.2
Panel D: Composite average projected test scores by age-education category					
Local average adjusted for internal migrants by age-education category	47	445.8	19.55	397.1	480.8
+ Adjustment of international migrants by 90th percentile in country of birth	47	456.5	19.76	400.7	485.7

Notes: Test scores refer to 8th-grade math. Locals are all persons who report a state of birth equal to the current state of living. Internal migrants report another state of birth than state of living. International migrants report another country of birth than the U.S. “By education category” indicates that individuals with/without university education are assigned the test scores of children of parents with/without university education. Panel A describes results by using test score projections by five-year age cohorts. Panel B splits the age cohorts by education category. Alaska, Wyoming, and Delaware are dropped.

Table 2. Correlation matrix of test scores, 2007

No.	Test score specification	1	2	3	4	5	6	7	8	9	10
	Panel A: Composite average test scores										
1	Local average adjusted for internal migrants	1									
2	+ Adjustment of locals by education category	0.990	1								
3	+ Adjustment of internal migrants by education category	0.984	0.996	1							
	+ Adjustment of international migrants										
4	By education category in country of birth	0.958	0.942	0.934	1						
5	By 75th percentile in country of birth	0.968	0.979	0.980	0.971	1					
6	By 90th percentile in country of birth	0.904	0.945	0.959	0.851	0.952	1				
	Panel B: Composite average projected test scores by age category										
7	Local average adjusted for internal migrants by age category	0.931	0.930	0.920	0.929	0.939	0.870	1			
8	+ Adjustment of international migrants by 90th percentile in country of birth	0.831	0.875	0.884	0.780	0.888	0.947	0.907	1		
	Panel C: Composite average projected test scores by age-education category										
9	Local average adjusted for internal migrants by age-education category	0.948	0.954	0.950	0.940	0.965	0.912	0.992	0.924	1	
10	+ Adjustment of international migrants by 90th percentile in country of birth	0.818	0.870	0.886	0.763	0.885	0.962	0.873	0.993	0.904	1

Notes: Test scores refer to 8^{th}-grade math. Locals are all persons who report a state of birth equal to the current state of living. Internal migrants report another state of birth than state of living. International migrants report another country of birth than the U.S. Panel A describes results by using test score projections by five-year age cohorts. Panel B splits the age cohorts by education category. Alaska, Delaware, and Wyoming are excluded.

Table 3. Development accounting results, 2007

	Covariance Measure		5-State Measure	
	Years of schooling	Physical capital	Years of schooling	Physical capital
	0.117***	0.283***	0.149	0.362
	(0.028)	(0.081)		
Test score specification	Test scores	Total human capital	Test scores	Total human capital
Local average adjusted for internal migrants	0.067**	0.184***	0.109	0.259
	(0.030)	*(0.054)*		
+ Adjustment of locals by education category	0.078***	0.195***	0.119	0.268
	(0.028)	*(0.052)*		
+ Adjustment of internal migrants by education category	0.089***	0.206***	0.131	0.280
	(0.028)	*(0.053)*		
+ Adjustment of international migrants				
By education category in country of birth	0.038	0.154***	0.070	0.219
	(0.030)	*(0.054)*		
By 75th percentile in country of birth	0.070**	0.187***	0.108	0.257
	(0.027)	*(0.051)*		
By 90th percentile in country of birth	0.112***	0.229***	0.156	0.306
	(0.025)	*(0.048)*		

Notes: Development accounting results for different test score specifications. Test scores refer to 8th-grade math. Locals are all persons who report a state of birth equal to the current state of living. Internal migrants report another state of birth than state of living. International migrants report another country of birth than the U.S. "By education category" indicates that individuals with/without university education are assigned the test scores of children of parents with/without university education. Calculations assume 0.2 return per std. dev. of test scores and 0.1 return per year of schooling. Alaska, Wyoming, and Delaware are dropped. The five richest states in 2007 are: Connecticut, New York, Massachusetts, New Jersey, and California. The five poorest states in 2007 are: Alabama, Kentucky, Arkansas, Mississippi, and West Virginia. Bootstrapped standard errors in parentheses with 1,000 replications. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Development accounting results with projected test scores, 2007

	Averages	1978-1992	National Trend	Linear State Trend	Combined State and National Trend	Combined State and National Trend	Combined State and National Trend
		-1977	Constant	Constant	Constant	Linear State Trend	Linear State Trend
	Covariance Measure						5-State Measure
Panel A: Development accounting results with projections by age							
Local average adjusted for internal migrants by age category	0.089*** (0.028)		0.113*** (0.032)	0.113*** (0.038)	0.109*** (0.033)	0.119*** (0.036)	0.177
+ Adjustment of international migrants by 90th percentile in country of birth	0.112*** (0.025)		0.135*** (0.030)	0.135*** (0.038)	0.131*** (0.032)	0.141*** (0.035)	0.203
Panel B: Development accounting results with projections by age and education							
Local average adjusted for internal migrants by age-education category	0.089*** (0.028)		0.125*** (0.031)	0.128*** (0.037)	0.125*** (0.032)	0.134*** (0.034)	0.190
+ Adjustment of international migrants by 90th percentile in country of birth	0.112*** (0.025)		0.148*** (0.030)	0.151*** (0.036)	0.147*** (0.031)	0.156*** (0.034)	0.216

Notes: Development accounting results for different test score specifications. Test scores refer to 8th-grade math. Locals are all persons who report a state of birth equal to the current state of living. Internal migrants report another state of birth than state of living. International migrants report another country of birth than the U.S. Panel A describes results by using test score projections by five-year age cohorts. Panel B splits the age cohorts by education category. Calculations assume 0.2 return per std. dev. of test scores and 0.1 return per year of schooling. Alaska, Wyoming, and Delaware are dropped. The five richest states in 2007 are: Connecticut, New York, Massachusetts, New Jersey, and California. The five poorest states in 2007 are: Alabama, Kentucky, Arkansas, Mississippi, and West Virginia. Bootstrapped standard errors in parentheses with 1,000 replications. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Development accounting results with projections by year (covariance measure)

Year	Averages	Projections	Years of Schooling
Panel A: Development accounting results with projections by age			
Local average adjusted for internal migrants by age category			
2007	0.089	0.119	0.117
2000	0.090	0.108	0.110
1990	0.057	0.060	0.120
1980	0.055	0.112	0.163
1970	0.041	0.080	0.189
+ Adjustment of international migrants by 90th percentile in country of birth			
2007	0.112	0.141	0.117
2000	0.109	0.127	0.110
1990	0.084	0.087	0.120
1980	0.078	0.135	0.163
1970	0.064	0.103	0.189
Panel B: Development accounting results with projections by age and education			
Local average adjusted for internal migrants by age category			
2007	0.089	0.134	0.117
2000	0.090	0.127	0.110
1990	0.057	0.078	0.120
1980	0.055	0.110	0.163
1970	0.041	0.070	0.189
+ Adjustment of international migrants by 90th percentile in country of birth			
2007	0.112	0.156	0.117
2000	0.109	0.146	0.110
1990	0.084	0.104	0.120
1980	0.078	0.133	0.163
1970	0.064	0.092	0.189

Notes: Development accounting results for different test score specifications. “Averages” uses the composite average test score. “Projections” shows the results for combined test score of national and linear state trend between 1978 and 1992 and a linear state trend prior to 1978 based on the series between 1978 and 2011. Test scores refer to 8^{th}-grade math. Locals are all persons who report a state of birth equal to the current state of living. Internal migrants report another state of birth than state of living. International migrants report another country of birth than the U.S. Panel A describes results by using test score projections by five-year age cohorts. Panel B splits the age cohorts by education category. Calculations assume 0.2 return per std. dev. of test scores and 0.1 return per year of schooling. Alaska, Wyoming, and Delaware are dropped.

Table 6: Sensitivity of development accounting to projection method, 2007

	Combined State and National Trend, 1978-1992	Predicted NAEP Scores based on SAT, 1968-1992	Combined State and National Trend, 1978-1992	Predicted NAEP Scores based on SAT, 1968-1992
	Constant	Constant	Linear State Trend	Linear State Trend
	-1977	-1967	- 1977	- 1967
Development accounting results with projections by age				
Local average adjusted for internal migrants by age category	0.109***	0.110**	0.119***	0.121**
	(0.033)	*(0.046)*	*(0.036)*	*(0.051)*
+ Adjustment of international migrants by 90th percentile in country of birth	0.131***	0.133***	0.141***	0.143***
	(0.032)	*(0.046)*	*(0.035)*	*(0.051)*

Notes: Development accounting results for different test score specifications. Columns 1 and 3 show the baseline composite test scores for comparison. Columns 2 and 4 show the development accounting results based on the predicted NAEP test score series which use the (predicted) SAT scores. Test scores between 1992 and 2011 are the same for all projections. Test scores refer to 8th-grade math. Locals are all persons who report a state of birth equal to the current state of living. Internal migrants report another state of birth than state of living. International migrants report another country of birth than the U.S. Panel A describes results by using test score projections by five-year age cohorts. Panel B splits the age cohorts by education category. Calculations assume 0.2 return per std. dev. of test scores and 0.1 return per year of schooling. Alaska, Wyoming, and Delaware are dropped.

Table 7: Growth accounting results

	Average annual growth rate of real GDP per capita (in percent)	Absolute change in years of schooling	Assumed annual change in test scores (percent of a std. dev.)	Average annual growth rate accounted for by			Percent of total growth		
				Total human capital	Test scores	Years of schooling	Total human capital	Test scores	Years of schooling
1970-1980	2.17	0.89	2.6	0.94	0.35	0.59	43.1	15.9	27.2
1980-1990	2.39	0.56	2.6	0.72	0.35	0.37	30.1	14.5	15.6
1990-2000	2.47	0.29	2.6	0.54	0.35	0.19	21.8	14.0	7.8
2000-2007	1.52	0.22	2.6	0.55	0.35	0.2	36.3	22.8	13.5
1970-2007	2.19	1.95	2.6	0.7	0.35	0.35	31.9	15.8	16.1
1970-2000	2.35	1.74	2.6	0.73	0.35	0.39	31.2	14.8	16.5
1970-1990	2.28	1.45	2.6	0.83	0.35	0.48	36.3	15.2	21.1
1990-2007	2.08	0.5	2.6	0.54	0.35	0.2	26.2	16.7	9.5

Notes: The assumed annual change in test scores is obtained by a regression of the NAEP test score on a linear year variable between 1992 and 2011.

C Appendix

Table A1. Industry shares by US states

State	Largest industry	Largest industry share	Mining share	State	Largest industry	Largest industry share	Mining share
Alabama	Government	0.17	0.014	Montana	Government	0.17	0.043
Alaska	Mining	0.21	0.214	Nebraska	Government	0.13	0.001
Arizona	Real estate and rental and leasing	0.15	0.017	Nevada	Accommodation and food services	0.13	0.036
Arkansas	Government	0.15	0.02	New Hampshire	Real estate and rental and leasing	0.14	0
California	Real estate and rental and leasing	0.16	0.009	New Jersey	Real estate and rental and leasing	0.17	0
Colorado	Government	0.13	0.037	New Mexico	Government	0.2	0.073
Connecticut	Finance and insurance	0.19	0	New York	Finance and insurance	0.17	0.001
Delaware	Finance and insurance	0.39	0	North Carolina	Manufacturing	0.19	0.001
Florida	Real estate and rental and leasing	0.16	0.001	North Dakota	Government	0.14	0.052
Georgia	Government	0.14	0.001	Ohio	Manufacturing	0.16	0.004
Hawaii	Government	0.24	0	Oklahoma	Government	0.18	0.093
Idaho	Government	0.14	0.014	Oregon	Manufacturing	0.27	0.001
Illinois	Real estate and rental and leasing	0.13	0.003	Pennsylvania	Manufacturing	0.12	0.012
Indiana	Manufacturing	0.26	0.004	Rhode Island	Real estate and rental and leasing	0.14	0
Iowa	Manufacturing	0.18	0.001	South Carolina	Government	0.18	0.001
Kansas	Government	0.15	0.012	South Dakota	Finance and insurance	0.17	0.003
Kentucky	Government	0.17	0.028	Tennessee	Manufacturing	0.15	0.001
Louisiana	Manufacturing	0.25	0.099	Texas	Manufacturing	0.14	0.079
Maine	Government	0.14	0	Utah	Manufacturing	0.14	0.02
Maryland	Government	0.18	0.001	Vermont	Government	0.14	0.002
Massachusetts	Real estate and rental and leasing	0.13	0	Virginia	Government	0.19	0.006
Michigan	Manufacturing	0.15	0.003	Washington	Government	0.15	0.002
Minnesota	Manufacturing	0.14	0.003	West Virginia	Government	0.19	0.098
Mississippi	Government	0.19	0.012	Wisconsin	Manufacturing	0.19	0.002
Missouri	Government	0.13	0.001	Wyoming	Mining	0.29	0.29

Source: Own calculations based on electronic data from the U.S. Bureau of Economic Analysis (http://www.bea.gov/).

TableA2. Sensitivity of development accounting to the returns to cognitive skills, 2007

Test score specification	Covariance Measure			5-State Measure		
	Test scores	Test scores	Test scores	Test scores	Test scores	Test scores
	w = 0.20	*w = 0.15*	*w = 0.25*	*w = 0.20*	*w = 0.15*	*w = 0.25*
Panel A: Development accounting results with average test scores						
Local average adjusted for internal migrants by education category	0.089^{***} *(0.028)*	0.067^{***} *(0.067)*	0.112^{***} *(0.035)*	0.131	0.098	0.163
+ Adjustment of international migrants by 90th percentile in country of birth	0.111^{***} *(0.025)*	0.084^{***} *(0.019)*	0.140^{***} *(0.032)*	0.156	0.117	0.195
Panel B: Development accounting with projections by age						
Local average adjusted for internal migrants by age category	0.109^{***} *(0.033)*	0.082^{***} *(0.025)*	*0.136**** *(0.041)*	0.164	0.123	0.205
+ Adjustment of international migrants by 90th percentile in country of birth	0.131^{***} *(0.032)*	0.098^{***} *(0.024)*	*0.164**** *(0.039)*	0.190	0.142	0.237
Panel C: Development accounting with projections by age and education						
Local average adjusted for internal migrants by age-education category	0.125^{***} *(0.032)*	0.093^{***} *(0.024)*	0.156^{***} *(0.040)*	0.178	0.133	0.222
+ Adjustment of international migrants by 90th percentile in country of birth	0.147^{***} *(0.033)*	0.110^{***} *(0.023)*	0.184^{***} *(0.038)*	0.203	0.153	0.254

Notes: Development accounting results for different test score specifications. Test scores refer to 8th-grade math. Locals are all persons who report a state of birth equal to the current state of living. Internal migrants report another state of birth than state of living. International migrants report another country of birth than the U.S. "By education category" indicates that individuals with/without university education are assigned the test scores of children of parents with/without university education. Alaska, Wyoming, and Delaware are dropped. The five richest states in 2007 are: Connecticut, New York, Massachusetts, New Jersey, and California. The five poorest states in 2007 are: Alabama, Kentucky, Arkansas, Mississippi, and West Virginia. Bootstrapped standard errors in parentheses with 1,000 replications. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TableA3. Growth accounting by state, 1970-2007

State	Average annual growth rate of real GDP per capita (in percent)	Absolute change in years of schooling	Assumed annual change in test scores (percent of a std.dev.)	Average annual growth rate accounted for by			Percent of total growth		
				Total human capital	Test scores	Years of schooling	Total human capital	Test scores	Years of schooling
Alabama	2.35	2.65	2.68	0.83	0.36	0.48	35.5	15.2	20.3
Arizona	2.03	1.6	2.3	0.6	0.31	0.29	29.3	15.1	14.2
Arkansas	2.39	2.5	3.75	0.95	0.5	0.45	39.7	20.9	18.8
California	2.14	1.01	2.16	0.47	0.29	0.18	21.9	13.4	8.5
Colorado	2.58	1.57	2.87	0.67	0.38	0.28	25.8	14.8	10.9
Connecticut	2.79	2.25	1.99	0.67	0.27	0.41	24.1	9.5	14.5
Florida	2.16	1.98	3.26	0.79	0.43	0.36	36.6	20.1	16.5
Georgia	2.44	2.66	3.26	0.91	0.43	0.48	37.5	17.8	19.7
Hawaii	1.63	1.96	2.94	0.75	0.39	0.35	45.8	24.1	21.7
Idaho	2.02	1.53	2.07	0.55	0.28	0.28	27.3	13.6	13.7
Illinois	2.03	2.03	2.28	0.67	0.3	0.37	32.9	15	18
Indiana	2.01	1.85	2.48	0.66	0.33	0.33	33	16.4	16.6
Iowa	2.32	1.64	0.39	0.35	0.05	0.3	15	2.3	12.8
Kansas	2.43	1.63	1.91	0.55	0.25	0.29	22.5	10.5	12.1
Kentucky	1.86	2.62	3.1	0.88	0.41	0.47	47.7	22.2	25.4
Louisiana	2.41	2.33	4.17	0.98	0.56	0.42	40.6	23.1	17.5
Maine	2.2	2.2	1.33	0.57	0.18	0.4	26	8.1	18
Maryland	2.41	2.32	3.91	0.94	0.52	0.42	39.1	21.7	17.4
Massachusetts	2.56	2.21	4.52	1	0.6	0.4	39.1	23.5	15.6
Michigan	1.56	1.97	1.53	0.56	0.2	0.36	35.8	13.1	22.8
Minnesota	2.37	1.96	2.11	0.63	0.28	0.35	26.7	11.9	14.9
Mississippi	2.36	2.46	3.71	0.94	0.5	0.44	39.7	21	18.7
Missouri	1.89	2.1	2.23	0.68	0.3	0.38	35.7	15.7	20
Montana	2.1	1.68	1.9	0.55	0.25	0.3	26.4	12	14.4
Nebraska	2.42	1.67	0.97	0.43	0.13	0.3	17.8	5.3	12.4
Nevada	1.69	0.78	3.11	0.56	0.42	0.14	32.9	24.6	8.3
New Hampshire	2.56	2.16	2.25	0.69	0.3	0.39	26.9	11.7	15.2
New Jersey	2.41	2.25	3.52	0.88	0.47	0.41	36.3	19.5	16.8
New Mexico	2.01	1.71	2.22	0.6	0.3	0.31	30.1	14.8	15.3
New York	2.12	2.05	2.66	0.72	0.35	0.37	34.1	16.7	17.4
North Carolina	2.3	2.76	4.24	1.06	0.57	0.5	46.2	24.6	21.7
North Dakota	2.86	2.38	1.76	0.66	0.24	0.43	23.2	8.2	15
Ohio	1.8	1.92	2.99	0.74	0.4	0.35	41.4	22.2	19.2
Oklahoma	2.26	1.71	1.71	0.54	0.23	0.31	23.7	10.1	13.7
Oregon	2.31	1.58	1.54	0.49	0.21	0.28	21.2	8.9	12.3

Pennsylvania	2.04	2.2	2.69	0.76	0.36	0.4	37	17.6	19.4
Rhode Island	2.32	2.19	2.45	0.72	0.33	0.39	31.1	14.1	17
South Carolina	2.3	2.86	4.04	1.05	0.54	0.51	45.8	23.4	22.4
South Dakota	2.89	1.89	2.04	0.61	0.27	0.34	21.2	9.4	11.8
Tennessee	2.29	2.52	2.82	0.83	0.38	0.45	36.3	16.4	19.9
Texas	2.48	1.85	4.01	0.87	0.54	0.33	34.9	21.6	13.4
Utah	2.41	1.22	1.68	0.44	0.22	0.22	18.4	9.3	9.1
Vermont	2	2.19	3.2	0.82	0.43	0.39	41	21.3	19.7
Virginia	2.69	2.66	3.69	0.97	0.49	0.48	36.1	18.3	17.9
Washington	2.24	1.48	2.64	0.62	0.35	0.27	27.6	15.7	11.9
West Virginia	1.67	2.33	2.07	0.7	0.28	0.42	41.6	16.5	25.1
Wisconsin	2.17	1.94	1.6	0.56	0.21	0.35	26	9.8	16.2

Notes: The assumed annual change in test scores is obtained by a regression of the NAEP test score on a linear year variable between 1992 and 2011.