American Economic Journal: Macroeconomics 2017, 9(4): 184–224
https://doi.org/10.1257/mac.20160255

Knowledge Capital and Aggregate Income Differences: Development Accounting for US States†

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Improvement in human capital is often presumed to be important for state economic development, but little research links better education to state incomes. We develop detailed measures of worker skills in each state that incorporate cognitive skills from state- and country-of-origin achievement tests. These new measures of knowledge capital permit development accounting analyses calibrated with standard production parameters. Differences in knowledge capital account for 20–30 percent of the state variation in per capita GDP, with roughly even contributions by school attainment and cognitive skills. Similar results emerge from growth accounting analyses. These estimates support school improvement as a strategy for state economic development. (*JEL* I25, I26, J24, R11, R23)

A key element of economic development policies has been the improvement of the human capital of workers through such policies as upgrading public schooling or enticing the migration of skilled workers. Most empirical research has, however, focused more narrowly on school attainment, both distorting the empirical assessments and removing much of the analysis from the actual policy debates. We have two objectives in this study. First, we develop new measures of worker skills, or knowledge capital, that are designed to incorporate both quantity and quality of skill investments. Second, we investigate the extent to which difference in knowledge capital can explain variations in income across US states. The more complete measurement of worker skills proves very important in understanding state growth and development.

Not much attention has been paid to the substantial income differences among US states and the role of differences in state human capital as a possible source. The magnitude of variation in gross domestic product (GDP) per capita across US states is actually quite significant. At $59,251, per capita GDP in Connecticut is twice as

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† Go to https://doi.org/10.1257/mac.20160255 to visit the article page for additional materials and author disclosure statement(s) or to comment in the online discussion forum.

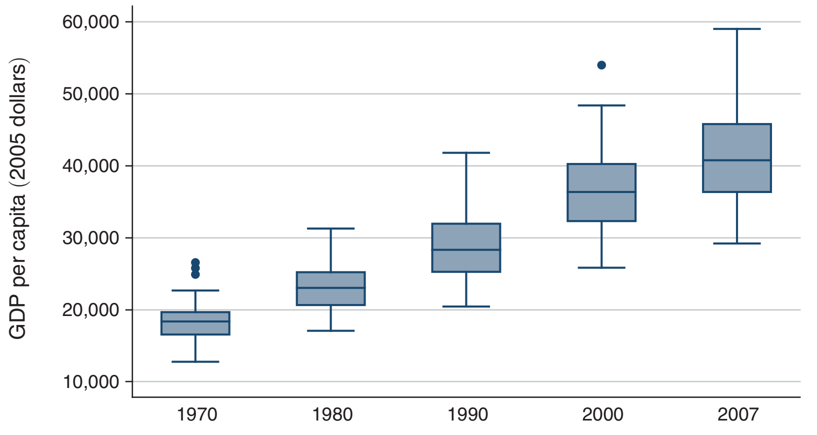

Figure 1. Distribution of GDP per Capita of US States, 1970–2007

Notes: GDP per capita denoted in 2005 US dollars. Boxplots of 47 US states (Alaska, Delaware, and Wyoming excluded). Boxplot description: the line in the middle of each box depicts the median state. The bottom and top of each box indicate the states at the twenty-fifth and seventy-fifth percentiles, respectively. Dots indicate large outliers outside of the normal data range.

Source: US Bureau of Economic Analysis (2013a, b, c)

high as that in West Virginia.[1] The standard deviation in state incomes of $6,388 is more than 15 percent of the national average, indicating that states have clearly reached very different levels of development. In addition, average annual growth rates between 1970 and 2007 range from 1.6 percent in Michigan to 2.9 percent in South Dakota. That is, while South Dakota's GDP per capita increased by 187 percent—lifting it from 43rd to 21st in the national state ranking—Michigan's GDP per capita increased by 77 percent, making it drop from ninth to 35th rank. As is evident from Figure 1, which shows the full distribution of state GDPs per capita from 1970 to 2007, the variation (in terms of standard deviations) in state incomes has more than doubled since 1970.

Past analyses of state income and growth have focused so consistently on school attainment as a measure of worker skills that years of schooling has become virtually synonymous with human capital.[2] A key component of our addressing the underlying causes of income variations is developing more complete estimates of the skills of workers in each US state. Importantly, we consider investments in both a quantity dimension and a quality dimension. We refer to the expanded aggregate measures as knowledge capital in order to distinguish sharply from the historical focus of human capital measurement exclusively on quantity measures of worker skills. For the quantity dimension, we simply employ the traditional attainment

[1] See Tables A3 and A4 in the online Appendix. Data refer to 2007 in 2005 US dollars. Throughout the paper, the analysis stops in 2007 to avoid any distortion of the long-run picture by the 2008 financial crisis, but results are very similar for 2010. Part of these differences reflect price differences across states. If adjusted for the regional price parities of the US Bureau of Economic Analysis, the ratio of high to low drops to 1.6. We consider the impact of price differences on our development accounting in the robustness analysis.

[2] This correspondence between years of schooling and human capital derives in part from the common acceptance of Mincer earnings functions that focus on years of schooling as a measure of human capital (see Mincer 1974, Card 2001, and Hanushek et al. 2015).

measure of years of schooling of each state, which can readily be derived from census micro data.

The more challenging task is to derive quality measures. For this, we focus on standardized assessments of cognitive skills of each state's working-age population. Cross-state and cross-country migration, however, lead to substantial differences between schooling location and current residency (Bound et al. 2004), so that test scores of current students do not accurately indicate the skills of current workers. We use the migration history of current workers—including international migrants—in order to construct a state-by-state-plus-country matrix that maps the current residence of the workforce of each state to the appropriate location of schooling. Combining measures of achievement test scores by schooling location from the National Assessment of Educational Progress (NAEP) and from international tests with this migration matrix allows us to construct measures of the cognitive skills of the working-age population of each state. Testing, however, was not done during the schooling years of some older workers, so we also project backward state NAEP test scores, which are available since 1990, in order to allow for variation in cognitive skills over age cohorts.

We pay particular attention to selective migration. As indicated in the discussions of the effects of state variation in school resources on individual returns to education (Card and Krueger 1992), selectivity of cross-state migration is an important issue (Heckman, Layne-Farrar, and Todd 1996).[3] We adjust for the selectivity of interstate migrants based on separate test scores by educational background of parents. In addition, we adjust for the selectivity of international immigrants based on where in their home country's schooling distribution immigrants are drawn from, thus recognizing the highly selective nature of international migration (e.g., Borjas 1987, Grogger and Hanson 2011). Altogether, our most refined test score measure is based on more than a thousand different subpopulation cells (of different age cohorts from different states and countries of origin with different educational backgrounds) for each state and year.

The two dimensions of workers' skills are integrated according to market prices in a Mincer-type specification of aggregate knowledge capital. The parameters of the economic value of school attainment and cognitive skills are derived from the micro literature. These new measures of state knowledge capital are central to our analysis of state income differences.

To avoid identification problems of estimating parameters in aggregate regression analyses, we employ a development accounting approach that uses an aggregate Cobb-Douglas production function to decompose output variation into contributions by factor inputs. Our choice of development accounting for analyzing state income differences reflects the conceptually appealing elements that have led to its popularity in investigations of international income differences. By applying externally estimated production parameters to variations in state economic inputs, the analysis avoids a central concern about endogeneity in such estimation.

[3] See Borjas, Bronars, and Trejo (1992) and Dahl (2002) for additional evidence of selective regional migration within the United States.

It is interesting to place this analysis into the context of international applications of development accounting. There are reasons to believe that the cross-state application of development accounting is more appropriate than the international application. A concern with cross-country analysis is the difficulty of applying consistent economic models across extremely diverse economies, where comparisons are made between economies that have incomes differing by a factor of 30 such as between the United States and Uganda. It is much more plausible that US states operate under a common aggregate production function. Further, the common cultural and institutional milieu across the United States eliminates major structural factors that are generally unmeasured and likely to distort cross-country analyses. Relatedly, issues of data quality across diverse countries add to these concerns. On the other hand, free movement of workers, capital, and technologies, among others, and the resulting smaller income differences within a country suggest difficulties in extracting the influence of underlying input differences from other factors entering into state income determination.

Depending on the specific test score measure and accounting method used, we find that state differences in knowledge capital account for about 20–30 percent of the current variation in GDP per capita across US states. Differences in school attainment and in cognitive skills contribute roughly evenly to this, implying that the evidence across US states is surprisingly similar to the existing cross-country evidence. Recent international investigations of differences in income and growth indicate that 20–40 percent of existing cross-country income differences can be accounted for by skill differences incorporating both quantity and quality of education (e.g., Schoellman 2012, Hanushek and Woessmann 2012b). Nevertheless, together with physical capital, the accumulated inputs account for less than half the total variation in state incomes, leaving an important role for state differences in total factor productivity.

We also introduce our knowledge capital measures into growth accounting analyses, where the separate components account for roughly similar shares of average US growth since 1970, with some variation across states.

We view our cross-state estimates as lower bounds on the impact of knowledge capital. They are derived from a neoclassical production function that describes growth as occurring through the added accumulation of skills.[4] This formulation ignores any elements of endogenous growth or complementarity of inputs and technology. Further, measurement error in knowledge capital likely acts to lessen its role in explaining income differences.

Our analysis contributes a within-country perspective to the substantial literature on human capital in cross-country development accounting analyses.[5] While much of that literature has focused on years of schooling, an extension to considering

[4] Growth theory has modeled human capital as an accumulated factor of production in augmented neoclassical growth models (e.g., Mankiw, Romer, and Weil 1992), as a source of technological change in endogenous growth models (e.g., Lucas 1988, Romer 1990, and Aghion and Howitt 1998), or as a factor crucial for technology adoption in models of knowledge diffusion (e.g., Nelson and Phelps 1966). While we do not attempt to distinguish among these alternatives here, it is clear that the neoclassical model incorporates a more limited role for human capital than the others.

[5] E.g., Klenow and Rodríquez-Clare (1997), Hall and Jones (1999), Bils and Klenow (2000), Caselli (2005, 2016), and Hsieh and Klenow (2010).

differences in the quality of education has proved important. Schoellman (2012) estimates quality differences from returns to schooling of immigrants on the US labor market (see also Hendricks 2002), while Hanushek and Woessmann (2012b) use direct measures of quality differences from test scores.[6]

The role of skill differences in explaining cross-state income variations has been much less studied, especially when measurement is expanded from just school attainment to include a quality dimension. Work on convergence across US states has usually not incorporated human capital (e.g., Barro and Sala-i-Martin 1992, Evans and Karras 1996). Aghion et al. (2009) uses cross-state variation to estimate the causal impact of different types of education spending on state growth. Turner et al. (2007) and Turner, Tamura, and Mulholland (2013) applies an extensive state-level dataset on years of schooling to growth regression and growth accounting analyses of US states over 1840–2000.[7] The extended analysis in Gennaioli et al. (2013) of regional development for more than 1,500 regions in 110 countries also focuses on years of schooling. In a more recent analysis, You (2014) investigates the roles of school spending (as a measure of school quality) and of school selection in the determination of aggregate US growth over time. Consistent with other evidence on the relationship of school resources with student outcomes (Hanushek 2003), You's results indicate a very low elasticity of spending on school quality. In this paper, we aim to understand to what extent differences in worker skills can account for the substantial differences in income levels that exist across US states, widening the focus from educational attainment to measures of cognitive skills.[8]

Section I describes our construction of state knowledge capital measures from years of schooling and cognitive skills in a Mincer-type specification of aggregate knowledge capital (with further detail provided in the online Appendix). Section II introduces the income data and development accounting framework. Section III applies our state knowledge capital measures in development accounting analyses. Section IV derives how they can be incorporated in growth accounting analyses. Section V concludes.

I. Constructing Measures of State Knowledge Capital

Measuring the human capital of workers has traditionally relied solely on observing the quantity of schooling. This near-universal approach follows partly from the seminal theoretical and empirical analyses of investment and wage determination by Jacob Mincer (1974) and partly from expediency based on data availability. But

[6] See also Gundlach, Rudman, and Wößmann (2002) and Kaarsen (2014). While issues of identification are larger in cross-country growth regressions, their results show a similar pattern on the quantity and quality dimension; see, e.g., Barro (1991) and Mankiw, Romer, and Weil (1992) on school attainment and Hanushek and Kimko (2000), Hanushek and Woessmann (2008, 2012a), and Ciccone and Papaioannou (2009) on cognitive skills.

[7] Tamura (2001) and Tamura, Simon, and Murphy (2016) provide additional analyses of schooling and state incomes. Examples of analyses of US regional growth and income at the substate (city, county, or commuting zone) level include Rappaport and Sachs (2003); Glaeser and Saiz (2004); Higgins, Levy, and Young (2006); Autor, Dorn, and Hanson (2013); and Glaeser, Ponzetto, and Tobio (2014).

[8] Recent contributions to the cross-country literature have generalized the accounting framework to reevaluate the possible role of human capital (Erosa, Koreshkova, and Restuccia 2010; Manuelli and Seshadri 2014; and Jones 2014). In order to highlight the measurement issues of quality and skill differences, our analysis stays with a standard accounting framework to allow direct comparison with the existing literature in a simple model framework.

this approach ignores the extensive work showing the variation in school quality that exists and showing the importance of other factors such as families and peers that enter into individual skill differences. We thus expand on prior measures of state worker skills by bringing in a quality dimension in addition to the more usual quantity dimension. We rely on market prices derived from Mincer-type specifications of earnings determination to aggregate years of schooling and cognitive skills into a composite measure of knowledge capital (Section IA).[9] Calculating average years of schooling of US state working age populations from census micro data is relatively straightforward (Section IB). Obtaining reliable and valid measures of state cognitive skills, however, is a much more substantial task and constitutes a core part of our analysis (Section IC), which results in rich measurement of patterns of knowledge capital across US states (Section ID).

A. *Mincer-Type Measure of Aggregate Knowledge Capital*

Our starting point for measuring knowledge capital, or the aggregate worker skills in a state, is the quantitative dimension captured by school attainment, but we augment school attainment by test scores that are designed to measure variations in cognitive skills. Following the basic setup of Bils and Klenow (2000), we use the Mincer representation of an earnings function to create a measure of aggregate knowledge capital per worker h by combining average years of schooling S and test scores T according to prices in the labor market:[10]

$$h = e^{rS+wT}. \tag{1}$$

The respective parameters r and w are the earnings gradients for each component of knowledge capital and are used as weights to map years of schooling and test scores into a single knowledge capital indicator according to their respective impact on individual earnings and productivity.

We turn to the existing literature to calibrate the knowledge capital measure empirically. While no available estimate is perfect, we select estimates that we think best fit the required purpose but then provide a sensitivity analysis based on a realistic range of possibilities. By far the most common estimates involve standard Mincer values for r from estimation that excludes any measures of cognitive skills or of other inputs to the determination of skills. The gradient for years of schooling is typically estimated to be around $r = 0.10$ (e.g., Card 1999), but these estimates are not appropriate for our purpose because they implicitly include the impact of the portion of cognitive skills that is correlated with school attainment. We instead look

[9] See Jones (2014) for a general discussion of aggregating human capital in a development accounting context, although that work is more focused on aggregating school attainment in the more challenging cross-country setting.

[10] The standard Mincer equation also contains labor market experience. We investigated including experience in our knowledge capital measure by adding state averages of experience and experience squared using return parameters estimated from the 2007 IPUMS data. Estimated coefficients are 0.041 on experience and -0.0006 on experience squared. Experience did not contribute significantly to our development accounting analysis, presumably because of the limited variation in experience across US states, and we dropped this from the analysis. The existing literature from which we draw our estimates of r and w does, however, always condition on experience.

for joint estimates of earnings functions that avoid any double counting of schooling and cognitive skills.

The ideal estimates for our purposes would be how school-age skills and subsequent school attainment affect lifetime earnings, but such estimates do not exist in the literature. There are two canonical sets of estimates. The first group of studies provides estimates of returns to school-age skills early in a person's career, while the second group estimates lifetime earnings based on skills measured during the worker's career.[11] The measures of returns in early career miss systematic differences across lifetime earnings, while the late skill measures introduce the possibility that career outcomes affect measured skill differences.

Examples of the first group, based on different nationally representative panel datasets that follow students after they leave school and enter the labor force, indicate that a one standard deviation increase in mathematics performance at the end of high school translates into 9–15 percent higher annual earnings (e.g., Mulligan 1999, Murnane et al. 2000, and Lazear 2003).[12] A separate review of earlier studies of the impact of measured cognitive skills on early-career earnings by Bowles, Gintis, and Osborne (2001) finds that the mean estimate is 0.15.[13]

However, all of these estimates come early in the workers' career, and there are reasons to expect that these estimated returns are lower than later in the lifecycle and that they understate the impact on lifetime earnings. A rising pattern over the lifecycle could reflect better employer information with experience (Altonji and Pierret 2001), improved job matches over the career (Jovanovic 1979), steeper earnings trajectories of people with higher lifetime earnings (Haider and Solon 2006), or the effects of technological change over time.[14]

In addition, a number of these studies rely on the AFQT test and similar tests that are often taken as a measure of IQ. IQ has been shown to vary with schooling, but it generally is meant to signify a measure that is less malleable than achievement, and thus it would be less sensitive to variations in cognitive skills that develop over time from various sources. As a consequence, estimates from test measures that are closer to IQ than to overall achievement will suffer from attenuation bias when used as parameters for the effect of total skills on earnings.

The second set of estimates refers to the return to skills across the lifecycle but relies on tests of cognitive skills that are given at the individual's age at the time earnings are observed. Hanushek and Zhang (2009) estimate a gradient of 0.193 for the

[11] A third set of studies looks at how cognitive skills affect early career earnings but does not condition on school attainment. Chetty et al. (2011) look at how kindergarten test scores affect earnings at age 25–27 and find an increase of 18 percent per standard deviation. Neal and Johnson (1996) emphasize estimates of school-age AFQT scores on earnings of approximately 20 percent per standard deviation when unconditional but also provide estimates of 0.13–0.14 when school degree levels are included.

[12] More details on the individual studies shown here can be found in Hanushek (2011).

[13] Examples of earlier studies include Bishop (1989) and Murnane, Willett, and Levy (1995). Bowles, Gintis, and Osborne (2001) emphasize the returns to school attainment that are independent of cognitive skills as measuring the returns to noncognitive skills. While they report that the mean estimate of the regression coefficients of standardized cognitive skills on log earnings is 0.15 across their surveyed studies, the main focus of their analysis relates to a measure that is normalized for the distribution of earnings (which equals 0.07 on average).

[14] 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).

United States using the International Adult Literacy Survey (IALS), a 1995 dataset covering the entire working life; their returns to quantity are $r = 0.080$. Hanushek et al. (2015) provide estimates of w for the United States of 0.138, based on data from the 2012 Programme for the International Assessment of Adult Competencies (PIAAC) and similarly find $r = 0.081$.[15,16]

The latter estimates of w are actually very consistent with the early career estimates. Hanushek et al. (2015) explicitly looks at the age pattern of returns and finds that the impact of skills indeed rises during the early career. Returns to prime-age males (age 35–54), which are most likely to capture lifetime earnings (Haider and Solon 2006), are 25 percent above those for workers of lower age in the United States. Thus, for example, the average value of $w = 0.15$ from Bowles, Gintis, and Osborne (2001) would be equivalent to $w = 0.1875$ for prime-age workers, which is slightly above the average of the direct estimates from the two studies of career earnings.

We thus calibrate our baseline model with $r = 0.08$ and $w = 0.17$, and in robustness checks, we investigate the sensitivity of the estimates to these parameter choices.[17]

B. *Years of Schooling*

The most straightforward component of state knowledge capital is average completed years of schooling. The US census micro data permit a calculation of school attainment for the working-age population of each state (Ruggles et al. 2010). We focus on the population aged 20 to 65 not currently in school.

The transformation of educational degrees into years of schooling follows Jaeger (1997). Due to their relatively weak labor market performance (Heckman, Humphries, and Mader 2011), GED holders are assigned ten years of schooling.

Based on these data, we calculate the average years of schooling completed by the working-age individuals living in a state in the different census years.[18] Figure 2 shows the distribution of average years of schooling of US states over time. Mean

[15] Hanushek et al. (2015) emphasizes estimates of cognitive skills in the absence of school attainment, viewing schooling as just one input into skill production. This estimate for the United States of $w = 0.28$ is included in the sensitivity analysis below with $r = 0$.

[16] Using yet another method that relies on international test scores and immigrants into the United States, Hanushek and Woessmann (2012a) 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. 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 age range of the workforce, the slightly lower estimates are consistent with the lower gradients for immigrants found in Hanushek et al. (2015).

[17] In his baseline calibration for a Latin American analysis, Caselli (2016) assumes a return to cognitive skills of close to zero ($w = 0.014$) based on a coefficient estimate in one Mexican study on the score on a shortened-version Raven test, which is referred to by the author as a "noisy measure of cognitive skills" (Vogl 2014). Separate estimates kindly provided by the author show that the low coefficient on the Raven score is not related to the fact that the specification reported in the paper also controls for health as measured by height. More importantly, Raven tests are generally not regarded as a measure of general skills but rather of the abstract reasoning component of intelligence. In an alternative calibration, Caselli (2016) chooses parameters similar to the ones used here. We view the range of US-based studies employing measures of cognitive skills rather than an intelligence component as more appropriate for our analysis, but we also report sensitivity results with lower parameter choices below.

[18] Online Appendix A provides additional detail. Column 2 of Table A4 in the online Appendix reports the average years of completed schooling of the working-age population of each state in 2007.

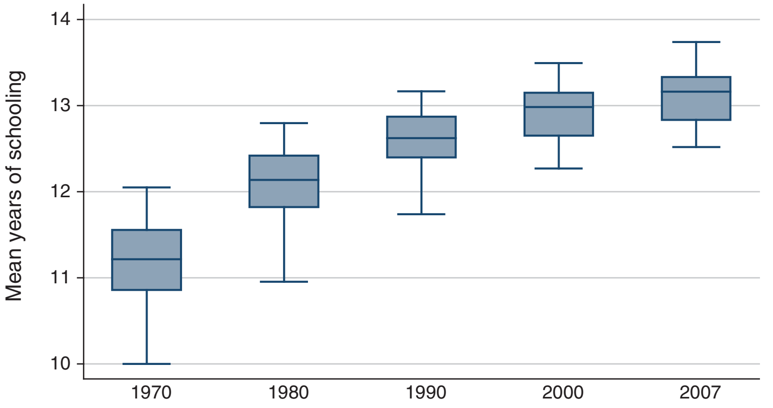

Figure 2. Distribution of Average Years of Schooling of US States, 1970–2007

Note: See Figure 1 for sample and boxplot description.
Source: Ruggles et al. (2010)

educational attainment of the working-age population of the median US state has steadily increased, albeit at a decreasing rate, from just over 11 years in 1970 to just over 13 years in 2007. The considerable variation in the average years of schooling across states has noticeably narrowed over time due to migration, school policies, and individual schooling decisions.

C. *Cognitive Skills*

The second task is developing a measure of the cognitive skills for each state's working-age population. No complete measure exists for the current working-age population, which is made up of people educated in the state at various times, of people educated in other US states at various times, and of people educated in other countries at various times. In recent periods, state-specific achievement test information is available for current students, and we develop a mapping from these test data to the skills of the current working-age population.

Going from the available information to an estimate of the skills of the state working-age population involves four steps. First, we construct mean test scores of the students of each state across the available test years. Second, we adjust state test scores for migration between states, with a special focus on selectivity of the interstate migration flows. Third, we adjust the score for international migration, again with a focus on selectivity. Fourth, we allow the state scores to vary over time by projecting available score information backward for older cohorts. Here, we just describe the main ideas of the derivations; online Appendix B provides additional details on each of the steps.[19]

[19] The aim here is to measure differences in the quality dimension of worker skills, irrespective of where they stem from—be it families, innate abilities, health, the quality of schools, or any other influence.

Construction of Mean State Test Scores.—We start by combining all available state test score information into a single average score for each state, using the reliable US state-level test score data from the National Assessment of Educational Progress (NAEP 2014). In our main analysis, we focus on the NAEP mathematics test scores in grade eight.[20] For 41 states, NAEP started to collect eighth-grade math test scores on a representative scale at the state level in 1990 and repeated testing every two to four years. After 2003, these test scores are consistently available for all states. An eighth-grader in 1990 would be aged 31 in 2007, implying that the majority of workers in the labor force would not have participated in the testing program.

Importantly, the distribution of NAEP results across states is relatively stable over time. An analysis of variance for grade eight math tests shows that 88 percent of test variation lies between states and just 12 percent represents variation in state-average scores over the two decades of observations. Thus, we begin by calculating an average state score using all the available NAEP observations for each state, but we subsequently also project age-varying test scores. As described in online Appendix B.1, the average state scores are estimated as state fixed effects in a regression with year (and, where applicable, grade-by-subject) fixed effects on scores that were normalized to a common scale that has a US mean of 500 and a US standard deviation of 100 in the year 2011. The average state score in eighth-grade math is provided in column 3 of Table A4 in the online Appendix.

Our primary analysis relies on these estimates of skills for students educated in each of the states. Minnesota, North Dakota, Massachusetts, Montana, and Vermont make up the top five states, whereas Hawaii, New Mexico, Louisiana, Alabama, and Mississippi constitute the bottom five states. The top-performing state (Minnesota) surpasses the bottom-performing state (Mississippi) by 0.87 standard deviations. Various analyses suggest that the average learning gain from one grade to the next is roughly between one-quarter and one-third of a standard deviation in test scores (Hanushek, Peterson, and Woessmann 2013, 72). Thus, the average eighth-grade math achievement difference between the top-performing and the bottom-performing state amounts to about three grade-level equivalents—highlighting the problem of relying exclusively on school attainment without regard to quality.

Adjustment for Interstate Migration.—The second step of our derivation involves adjusting for migration between US states, first without and then with consideration of selectivity in the migration process.

Adjusting for State of Birth: Obviously, not all current workers in a state were educated in their state of current residence. From the census data, we know the state of birth of all persons in each state who were born in the United States. On average,

[20] In robustness analyses, we also consider results using reading test scores in grade eight, even though those are available only from 1998 onward. Results are very similar. NAEP also tests students in grade four, but these are not available by parental education, which is vital information for our adjustment for selective migration. We did construct mean state test scores for the different grades and subjects, however, and they turn out to be very highly correlated. The correlations range from 0.87 between eighth-grade math and fourth-grade reading to 0.96 between eighth-grade reading and fourth-grade reading, indicating that the test scores provide similar information about the position of the state in terms of student achievement.

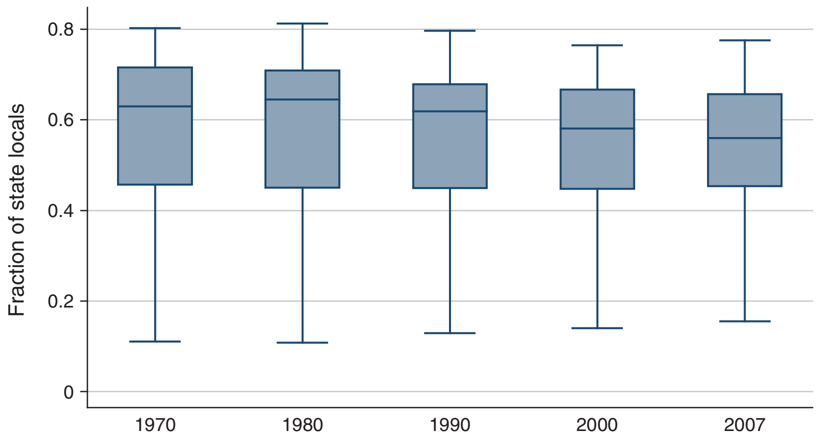

FIGURE 3. SHARE OF STATE LOCALS IN THE POPULATION OF US STATES, 1970–2007

Notes: Fraction of people with state of birth equal to current state. See Figure 1 for sample and boxplot description.
Source: Ruggles et al. (2010)

somewhat less than 60 percent of the working-age population in 2007 is living in their state of birth (see Figure 3), indicating that many were unlikely to have been educated in their current state of residence. But there is also substantial variation across states. For example, only 16 percent of Nevada's residents in 2007 report having been born there, while 78 percent of the population in Louisiana was born there. These numbers indicate that interstate migration is a major issue when assessing the cognitive skills of the working-age population of a state.

To adjust for interstate migration, we start by computing the birthplace composition of each state from the census data. That is, for each state, we break the state working-age population into state locals (those born in their current state of residence), interstate migrants from all other states (those born in the United States but outside current state of residence), and international immigrants (those born outside the United States). For the US-born population, we construct a state-by-state matrix of the share of each state's current population born in each of the other states.

Assuming that interstate migrants have not left their state of birth before finishing grade eight,[21] we can then combine test scores for the US-born population of a state according to the separate birth-state scores. Our baseline skill measure thus assigns all state locals and all interstate migrants the mean test score of students in their state of birth—which only for the state locals will be equivalent to the mean test score of their state of residence. This baseline skill measure is reported in column 4 of Table A4 in the online Appendix for each state.

[21] Across the United States as a whole, 86 percent of children aged 0–14 years still live in their state of birth, so that any measurement error introduced by this assumption should be limited. With the exception of Alaska (34 percent) and Washington, DC (54 percent)—neither of which is used in our analysis—the share is well beyond 70 percent in each individual state (own calculations based on the 2007 US census data Ruggles et al. 2010).

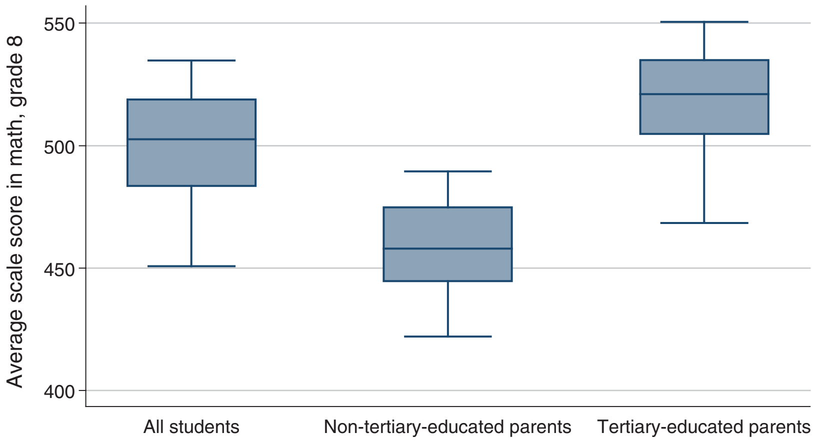

Figure 4. Average Math Test Scores of US States by Educational Background

Notes: NAEP test score in eighth-grade math, 1990–2011. See Figure 1 for boxplot description.
Source: NAEP (2014)

Adjusting for Selective Interstate Migration Based on Educational Background: The baseline skill measure implicitly assumes that the internal migrants from one state to another are a random sample of the residents of their state of origin. This obviously need not be the case, as the interstate migration pattern may be (very) selective. For example, graduates of Ohio universities might migrate to a very different set of states than Ohioans with less education—and it would be inappropriate to treat both flows the same.

The potential importance of selective migration can be seen from NAEP scores by educational background. Figure 4 displays the overall distribution of state scores for students from families where at least one parent has some kind of university education and for students from families where the parents do not have any university education. Children of parents with high educational backgrounds record much higher test scores than children of parents with lower educational backgrounds, with an average difference of over 0.6 standard deviations.

To account for selective interstate migration, we consider the migration patterns by education levels and adjust test scores accordingly. We make the assumption that we can assign to the working-age population with a university education the test score of children with parents who have a university degree in each state of birth, and equivalently for those without a university education. From the census data, we first compute separate population shares of university graduates and nonuniversity graduates by state of birth for the current working-age population of each state. With these population shares, we then assign separate test scores by educational category (including those born and still living in the state as well as migrants). Note that this adjustment also deals with another aspect of selection that is often ignored: it allows for selectivity of outmigration and for any differential fertility that generate differences in the cohort composition between the working-age population and those taking the NAEP tests.

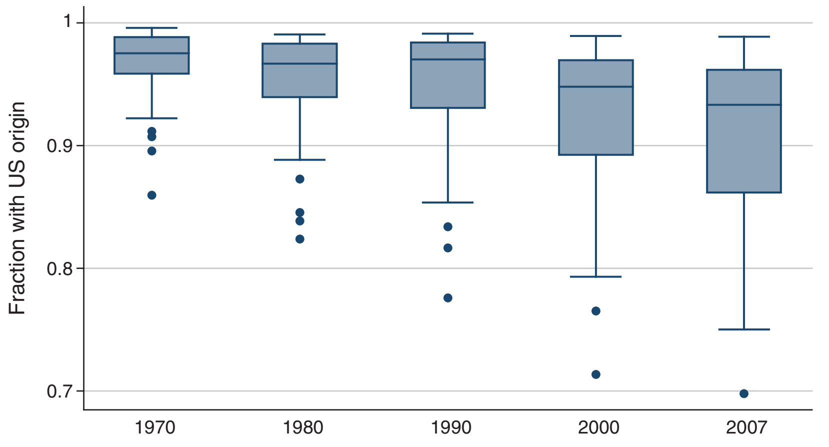

Figure 5. Share of US-Born People in the Population of US States, 1970–2007

Note: See Figure 1 for sample and boxplot description.
Source: Ruggles et al. (2010)

The refined average scores for each state that adjust both locals and interstate migrants by education category provide cohort-adjusted and selectivity-adjusted estimates of state test scores for the working-age populations of state locals and interstate migrants.

Adjustment for International Migration.[22]—A remaining topic is how to assess the skills of immigrants who were educated in a foreign country. On average, international migration is less frequent than interstate migration, but, more importantly for our purposes, there is wide variation in both the country patterns and the level of immigration across states. Figure 5 shows that more than 90 percent of the US working-age population was born in the United States, but the variation across states is large (and has been increasing): in 2007, 99 percent of the working-age population in West Virginia was born in the United States compared to only 70 percent of the working-age population in California.

Since we already know the school attainment of immigrants in each state, the challenge is estimating their cognitive skills. The census data provide the country of origin of each immigrant, and we can assess whether the immigrants were educated in the United States or in their home country by age of entry to the United States. Also, the major international tests—PISA, TIMSS, and PIRLS—provide information about the cognitive skill levels of students in the home countries that is directly comparable to US student performance.[23] What we lack is information about where in the distribution of skills the immigrants from each country would fall.

[22] The approach for adjusting for selectivity in international migration was suggested in helpful referee comments.

[23] PISA stands for Programme for International Student Assessment, TIMSS for Trends in International Mathematics and Science Study, and PIRLS for Progress in International Reading Literacy Study. We rescale these test scores to the NAEP scale as in Hanushek, Peterson, and Woessmann (2013).

Even more than for interstate migration, selectivity is a major concern when considering international immigrants. The United States has rather strict immigration laws, and skill-selective immigration policies represent a substantial hurdle for many potential immigrants (Bertoli and Fernández-Huertas Moraga 2015, Ortega and Peri 2013). The research on selective immigration has mainly focused on school attainment measures, but from this we know that international migration is a highly selective process: the existing research mostly indicates that migrants who go to developed countries are better educated, on average, than those they leave behind (Borjas 1987, Chiswick 1999, and Grogger and Hanson 2011).

While it is easy to conclude that the mean test score of the country of birth is unlikely to represent the cognitive skills of the migrant group accurately because of selection, it is more difficult to pinpoint immigrant location in the home-country skill distribution. Moreover, because the pattern of immigrant home countries varies considerably across states, it is important to consider the possibility of differential selectivity across the various countries of origin.

Our approach is based on using information about the selectivity of immigration into the United States in terms of school attainment to provide an initial benchmark for where immigrants fall in the distribution of cognitive skills of their home country. This approach is motivated by the fact that the achievement of individual students is a strong, albeit imprecise, predictor of further school attendance. Unfortunately, the available data on the distribution of attainment are quite coarse and school access policies have varied across countries and across time, leading us to adjust the benchmark selectivity.

We know the proportion of US immigrants from each country of origin whose school completion is primary school or less, secondary school, or tertiary school, and this matches information on the distribution of attainment by these same categories in each country of origin (using data available for 2000 from Docquier, Lowell, and Marfouk 2009). From this, we can estimate the average percentile of the distribution of attainment for the typical immigrant by using the relevant percentiles of the home-country distribution to weight the distribution of immigrant school categories in the United States.

For each country of origin (country subscripts omitted), we calculate the selectivity parameter for school attainment as the percentile p of the home country distribution from which the average immigrant to the United States is drawn:

$$(2)\quad p = s_{US}^{pri} \times \frac{1}{2} s_{home}^{pri} + s_{US}^{sec} \times \left(s_{home}^{pri} + \frac{1}{2} s_{home}^{sec} \right) + s_{US}^{ter} \times \left(s_{home}^{pri} + s_{home}^{sec} + \frac{1}{2} s_{home}^{ter} \right),$$

where the respective educational degrees of the population are given by pri = primary, sec = secondary, and ter = tertiary, s refers to the shares of the population with the respective degrees (with $s^{pri} + s^{sec} + s^{ter} = 1$), home refers to the population in the respective home country, and US refers to the immigrants from the specific home country living in the United States.

An example provides the intuition. 81.6 percent of immigrants to the United States from South Africa had a tertiary education, while only 10 percent of those residing in South Africa itself had a tertiary education. The South African immigrants with a

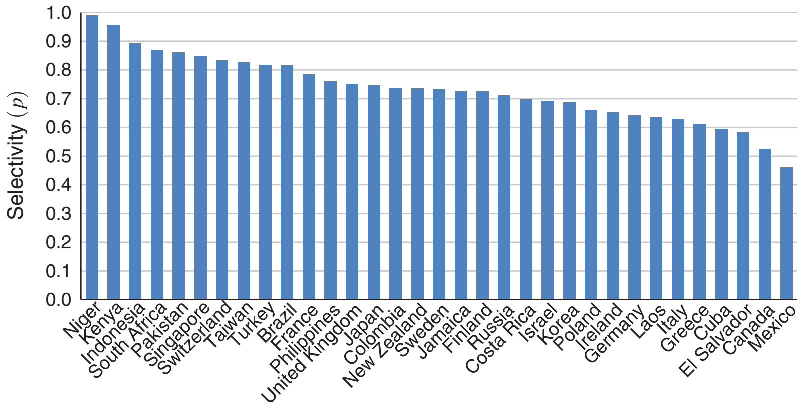

Figure 6. Attainment Selectivity of Immigrants into United States (*sample countries*)

Notes: Selectivity of US immigrants based on their home-country distribution of school attainment. See Section IC for details.

Source: Ruggles et al. (2010)

secondary education (13 percent) come from the 47 percent still residing in South Africa, while the 6 percent of immigrants with just a primary education are drawn from the 42 percent of South Africans with just a primary education. But, seen from the perspective of the United States, 81.6 percent of immigrants fall in the ninetieth to one-hundredth percentile of the South African attainment distribution, 13 percent fall in the forty-second to ninetieth percentile, and 6 percent fall in the zero to forty-second percentile. From this we can estimate that the average South African immigrant comes from the eighty-seventh percentile of the attainment distribution of South Africa ($0.06 \times 21 + 0.13 \times 66 + 0.816 \times 95 = 87$).

The pattern of selectivity on school attainment is shown in Figure 6 for a sample of countries (see Table A2 in the online Appendix for details). While immigrants from Niger and Kenya come almost entirely from the college educated part of the distribution (which is only 0.5 and 1.2 percent of the home country populations, respectively), the selectivity falls to the level of Canada and Mexico, which have the least selective immigrants based on school attainment.

But the selectivity parameter for the aggregate attainment distribution of immigrants is not itself an appropriate estimate for the selectivity parameter for the cognitive skill distribution. The assumption that immigrants are drawn uniformly from within the range of the coarse distributional information of educational degrees is inconsistent with the spirit of this estimation. There is ample evidence that selectivity can be very strong also within educational degree categories (e.g., Parey et al. forthcoming). Moreover, access to schooling in many countries has historically involved political and economic forces that make school attendance an error-prone indicator of underlying skills, and again likely yield an underestimate of the skills of immigrants.

We lack country-specific information on cognitive-skill selectivity of immigrants, but a straightforward approach is to adjust the estimate of selectivity from the school attainment distribution upwards using the country-specific attainment selection parameter p. Thus, our baseline estimate calculates the percentile of the cognitive skill distribution for the average immigrant as $p^* = p + p(1 - p)$.

Returning to the prior example, instead of assigning the average South African immigrant to the United States the eighty-seventh percentile, to recognize the further selectivity of skills, the selectivity parameter for the skill distribution is estimated at the ninety-eighth percentile. In terms of cognitive skills, the two neighboring countries remain the least selective. The average immigrant from Mexico is estimated to be at the seventy-first percentile of the home-country skill distribution; for Canada at the seveny-seventh percentile of the home-country distribution.

Importantly, we now have a way for assigning scores for cognitive skills by using these country-specific selectivity parameters for immigrants with the country-specific score distribution from the international math tests. These estimates of average cognitive skills vary by country—reflecting both the skill distribution in each sending country and the place in this distribution where the average immigrant is estimated to fall. Thus, for example, while the score of the average native born American is 500, the average immigrant from South Africa is estimated to have a score of 514, the average Mexican of 458, and the average Canadian of 614. In other words, coming high up in the distribution of a generally poorly performing country may mean that immigrants are still better performing than the typical native-born American, whereas Mexican immigrants are substantially behind native-born Americans as they are drawn from lower down in a poor home-country skill distribution.

The skill measure with adjustment of international immigrants by selectivity is reported in column 5 of Table A4 in the online Appendix. In our sensitivity analysis below, we also report lower bound results using the estimate of international skills using just the unadjusted school-attainment selectivity factor.

Backward Projection of Time-Varying Scores.—The measures so far are based on the assumption that the achievement levels produced in each state are constant over time. As a final step, we develop two methods to project the available test scores backward in time so as to allow for skill levels to differ across age cohorts of graduates from each state, one based on an extrapolation of NAEP trends and one based on a projection from available SAT scores. With the latter, we have observed state scores as far back as for those aged 53 in 2007, having to rely on trend extrapolations only for those older than that.

Extrapolation of NAEP Trends: We can potentially obtain a better estimate of older workers' skills (than obtained from relying just on the observed average state test scores) by projecting the available test scores backward in time. This makes use of the time patterns of scores within each state observed for the period 1992–2011, as well as the long-term national NAEP trend data available since 1978.

First, we linearly extrapolate state scores based upon the time pattern of NAEP score changes for each state over the period 1992–2011.[24] Second, because we worry about the validity of the linear extrapolation over long periods, we force the state values for the period 1978–1992 to aggregate on a student-weighted basis to the national trend in NAEP performance.

[24] For the nine states that just began testing in 2003, we rely only on the pattern since then.

We lack NAEP information on performance for the period before 1978, so we use two simple variants for prior test score developments. The first holds all state scores at their estimated values for 1978. Thus, people older than 43—the age in 2007 of an eighth-grader who took the test in 1978—have the same test score as a 42-year-old with the same birth state. The second estimates linear state trends on the state time series between 1978 and 2011 and assumes this linear development prior to 1978, starting from the projected 1978 value of each state. (For further details, see online Appendix B.4).

We combine the projected test score series with information on the age pattern of the working-age population from the census. For each census year and state of residence, we compute population shares by state of origin and education category in five-year age intervals. We then similarly construct five-year averages of the projected test score series which we match to the population shares of the appropriate age. For example, people aged 20–24 in 2007 were aged 13, the age at which the test was taken, in 1996–2000. Thus, we average the projected test scores between 1996 and 2000 and assign these test scores to the age group of 20–24 in 2007. Proceeding in the same way for the other age groups yields a new measure of cognitive skills for each state based on test scores that vary with age (see column 6 of Table A4 in the online Appendix).

Note that in this final measure, state scores are adjusted for differences in scores between large numbers of subpopulations. In particular, for each state, we assign more than a thousand different scores for different subgroups of the resident population: residents from 51 states of origin times two education categories times nine age groups (918 scores) plus residents from 96 countries of origin times two education categories. We thus create more than 50,000 separate test score cells (for each year for which we create the skill measure).

Projection from State SAT Scores: There is one other test score series at the state level, albeit not representative for the state population, that goes back further in time: the SAT college admission test. We obtained data on mean SAT test scores and participation by state for the period 1972 to 2013 from the College Board. We use this information to predict NAEP scores backwards 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 student population in a state (Graham and Husted 1993, Coulson 2014). In particular, the mean SAT score depends strongly on the participation rate.[25] A higher participation rate signals a less selective 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).

[25] The College Board provided the total number of participants. We construct participation rates by dividing SAT participation by the number of public high school graduates in the respective year, obtained from various years of the Digest of Education Statistics.

Table 1—Correlations among Test Score Measures, 2007

	Test score specification	1	2	3	4	5	6
1	Baseline: local average adjusted for interstate migrants	1					
2	+ adjustment of locals by education category	0.990	1				
3	+ adjustment of interstate migrants by education category	0.984	0.996	1			
4	+ adjustment of international migrants' scores by selectivity	0.914	0.945	0.959	1		
5	Age adjustment with extrapolation of NAEP trends by education category	0.803	0.848	0.862	0.922	1	
6	Age adjustment with projection from SAT scores	0.668	0.704	0.707	0.746	0.911	1

Notes: Test scores refer to eighth-grade math. Locals are all persons who report a state of birth equal to the current state of residence. Interstate migrants report another state of birth than state of residence. International migrants report another country of birth than the United States. "By education category" indicates that individuals with/without university education are assigned the test scores of children of parents with/without university education.

Source: Ruggles et al. (2010) and College Board, NAEP (2014)

We use these state-specific participation-adjusted SAT scores to predict state NAEP scores before 1992. First, for each state we regress NAEP scores on participation-adjusted SAT scores in the years since 1992 when both data series are available. As the SAT is normally taken at the end of high school, we lag the SAT scores by four years to align them with the eighth-grade NAEP score. Using the coefficients from these state-specific regressions, we then predict NAEP scores from the available SAT score for the period 1968 to 1991.

The projected NAEP test score series is then used to construct alternative aggregate test scores for each state and year by applying the same algorithm for the projection of test scores by age as before. This skill measure with SAT-based adjustment is reported in column 7 of Table A4 in the online Appendix for each state.

D. *Patterns of Gains and Losses in Knowledge Capital from Migration*

The United States is well known for the volume of internal migration, but the implications of this migration for the knowledge capital of the workforce across states have not previously been available. Table 1 provides a correlation matrix of the different skill measures. The correlations are usually very high and many exceed 0.9, indicating that all test scores describe a similar distribution of cognitive skills. However, there are also notable differences for some states. The adjustment of international immigrants, even though a relatively small group overall, leads to somewhat lower correlations with the other measures. The correlation is least strong between measures based on backward projections of time-varying scores and measures based on constant scores. Still, the relevance of the different adjustments for understanding cross-state income differences remains to be explored.

At the level of individual states, we can see substantial differences in the overall impact on state labor forces when we trace through the previously described estimates that take us to the estimates of the knowledge capital of each state. The skills of workers educated locally and of those educated elsewhere vary considerably by state. (See Appendix Table A1A for state data on quality of the workforce by origin location). Moreover, the distribution of the workforce by place of origin and education differs dramatically. (See Appendix Table A1B for state data on location of origin).

In 18 states, locally educated students make up less than half of the overall workforce. Over a fifth of the total workforce in five states were international immigrants (California, 30 percent; New York, 25; New Jersey, 24; Nevada, 22; and Florida, 22).

In almost all states, the emigrants—those born in the state but subsequently leaving—have higher school attainment than those staying in the state, with Maine being the one exception. This pattern also implies that test scores of emigrants exceed those of students continuing to live in the state, with Arkansas and Mississippi being the exceptions.

While international immigrants almost always have lower school attainment than those born in each state and those who have emigrated to a different state, the selectivity of immigrants implies that the test scores of immigrants on average exceed those of locals. Surprisingly, international immigrants do not align closely with the locals in each state; the correlation of school attainment is just 0.08, while the correlation of test scores is 0.4.

Internal and international migration have varying effects on states. As shown on the map of Figure 7, a total of 26 states see net gains in knowledge capital when compared to that available just from home-grown workers. (See Appendix Table A1B for state data on net gains in knowledge capital). The remaining states lose, largely from out-migration to other states. The states that gain the most are Hawaii, Georgia, Virginia, Maryland, and North Carolina. The states that lose the most are Iowa, South Dakota, Montana, Wisconsin, and North Dakota. In general, the states losing knowledge capital are clustered in the center of the country with the gaining states found along the coasts and the southern border. While we use these data to perform development accounting analyses here, they also intersect with the larger research on the character of cross-state migration patterns within the United States (e.g., Kennan 2015).

II. Development Accounting Framework

We aim to evaluate the extent to which income differences across US states can be accounted for by cross-state differences in knowledge capital. This section introduces the state sample, GDP data, and the analytical framework. The next section then presents the results.

A. *State Sample and GDP Data*

From the 50 US states, we employ 47 in our analysis. Three states are excluded from the analysis sample because of a very particular industry structure that makes their GDP unlikely to be well described by a standard macroeconomic production function based on physical and human capital. In particular, following the convention in the cross-country literature (Mankiw, Romer, and Weil 1992), we exclude states that are abundant in natural resources, since their income will depend more on sales of raw material and less on production. Hence, we leave out Alaska and Wyoming, where 27.3 percent and 30.6 percent, respectively, of GDP comes from extraction activities in 2007. All other states have extraction shares of less than 12 percent.

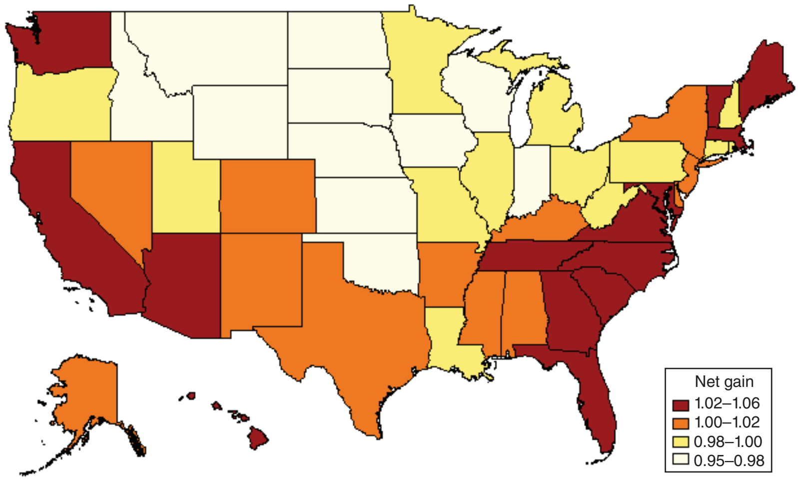

Figure 7. Net Gain in Knowledge Capital from Migration

Notes: Net gain in knowledge capital from migration: ratio of the actual returns-weighted knowledge capital measure (calculated from equation (1)) over a knowledge capital without any migration. See Appendix Table A1 for details.

Source: Ruggles et al. (2010) and NAEP (2014)

We also exclude Delaware from the analysis. Finance and insurance in the state account for more than 35 percent of Delaware's GDP in 2007, more than twice that in any other state. Delaware is also known as a tax haven for companies; for example, Delaware hosts more companies (about 945,000) than people (about 917,000) (*Economist* 2013). Such factors reduce the dependence of the state's income on production.[26]

For each of the 47 states in our sample, we calculate the real state GDP per capita. This measure is constructed by using nominal GDP data at the state level from the US Bureau of Economic Analysis (2013b). We deflate nominal GDP by the nationwide implicit GDP price deflator (US Bureau of Economic Analysis 2013c), following the approach of Peri (2012).[27] We set the base year for real GDP to 2005. For real GDP per capita, we divide total real GDP by total state population. The population data also comes from the US Bureau of Economic Analysis (2013a). Column 1 of Table A4 in the online Appendix reports the real GDP per capita of each state in 2007.

While it is well known that mean real GDP per capita more than doubled from 1970 to 2007, the dispersion across states is less well known. As noted earlier, there was a $30,000 mean difference between the richest and poorest states in 2007. Figure 1 also reveals that the dispersion across states has increased substantially. In real dollar terms, the standard deviation across states increased from $2,895 in 1970 to $6,388 in 2007. This dispersion motivates the analysis of the underlying causes of the differences.

[26] Consequently, including these three states would reduce our baseline estimate from 0.228 to 0.163.

[27] In sensitivity analyses in Section IIID, we show that results are very similar when additionally adjusting for state-specific price deflators.

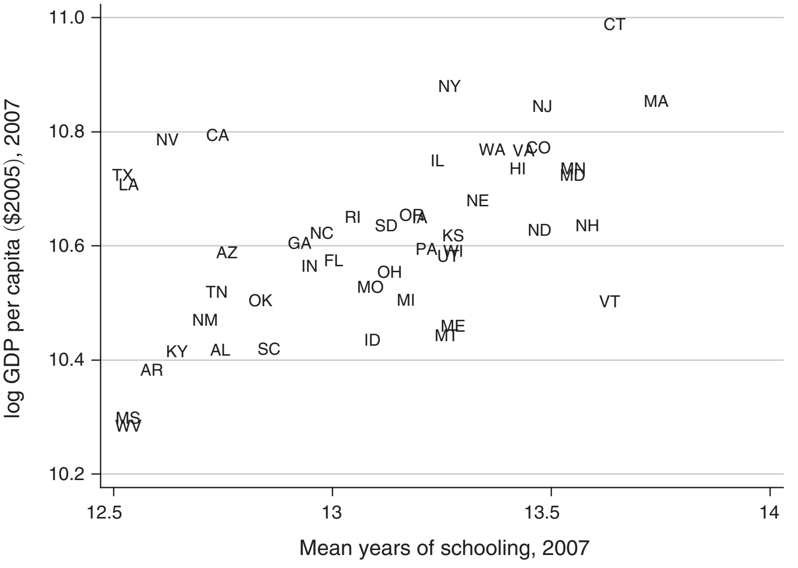

Figure 8. Years of Schooling and GDP per Capita across US States, 2007

Source: US Bureau of Economic Analysis (2013a, b, c) and Ruggles et al. (2010)

State incomes are strongly correlated with both measures of knowledge capital. Figures 8 and 9 show scatterplots of the association across states of log GDP per capita in 2007 with average years of schooling and with the skill measure adjusted for selective interstate and international migration, respectively. The cross-state correlations are 0.521 between log GDP per capita and average years of schooling and 0.555 between log GDP per capita and the cognitive skill measure. Similarly, average years of schooling and the skill measure are strongly correlated at 0.718 (see Figure A1 in the online Appendix). To go beyond these correlations and provide an indication of the causal contributions of the different knowledge capital components to income differences across states, we next turn to an augmented development accounting framework.

B. *Analytical Framework*

Development accounting provides a means of decomposing variations in the level of GDP per capita between states into the different components of input factors of a macroeconomic production function.[28] Our basic development accounting framework begins with an aggregate Cobb-Douglas production function:

$$Y = (hL)^{1-\alpha} K^{\alpha} A^{\lambda}, \tag{3}$$

[28] Caselli (2005) and Hsieh and Klenow (2010) provide additional detail on the approach of development accounting.

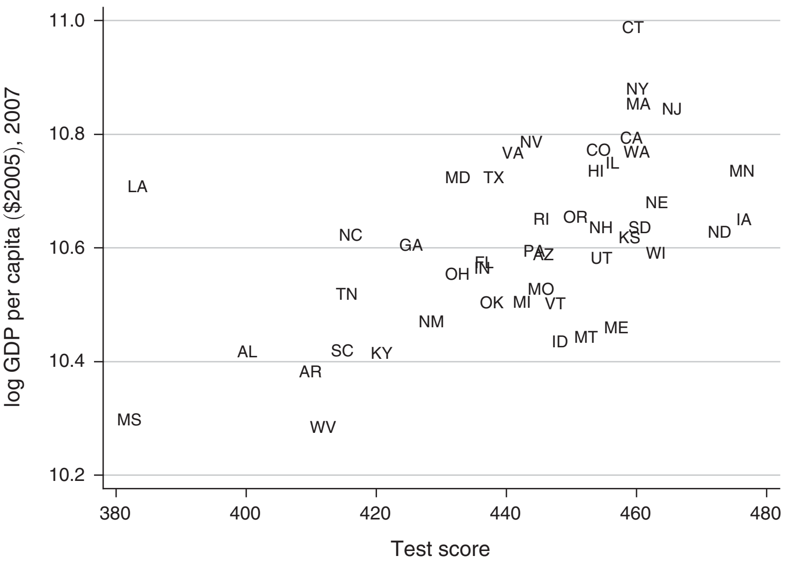

FIGURE 9. COGNITIVE SKILLS AND GDP PER CAPITA ACROSS US STATES, 2007

Source: US Bureau of Economic Analysis (2013a, b, c), Ruggles et al. (2010), and NAEP (2014)

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

$$\text{(4)} \qquad \frac{Y}{L} \equiv y = h\left(\frac{k}{y}\right)^{\alpha/(1-\alpha)} A,$$

where $k \equiv \frac{K}{L}$ is the capital-labor ratio.

The decomposition of variations in per capita production is then straightforward. Taking logarithms, the covariances of log GDP per capita with the input factors are additively separable (Klenow and Rodríquez-Clare 1997):

$$\text{(5)} \qquad \mathrm{var}(\ln(y)) = \mathrm{cov}(\ln(y), \ln(h)) + \mathrm{cov}\left(\ln(y), \ln\left(\left(\frac{k}{y}\right)^{\alpha/(1-\alpha)}\right)\right) + \mathrm{cov}(\ln(y), \ln(A)).$$

Dividing by the variance of GDP per capita puts each component in terms of its proportional contribution to the variance of income:

$$\text{(6)} \qquad \frac{\mathrm{cov}(\ln(y), \ln(h))}{\mathrm{var}(\ln(y))} + \frac{\mathrm{cov}\left(\ln(y), \ln\left(\left(\frac{k}{y}\right)^{\alpha/(1-\alpha)}\right)\right)}{\mathrm{var}(\ln(y))} + \frac{\mathrm{cov}(\ln(y), \ln(A))}{\mathrm{var}(\ln(y))} = 1.$$

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

To check the robustness of our results, we also look at how well we can account for 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 (Hall and Jones 1999). We will refer to this measure as the five-state measure:

$$(7) \qquad \frac{\ln\left[\left(\prod_{i=1}^{5} X_i \,/\, \prod_{j=n-4}^{n} X_j\right)^{1/5}\right]}{\ln\left[\left(\prod_{i=1}^{5} y_i \,/\, \prod_{j=n-4}^{n} y_j\right)^{1/5}\right]} + \frac{\ln\left[\left(\prod_{i=1}^{5} A_i \,/\, \prod_{j=n-4}^{n} A_j\right)^{1/5}\right]}{\ln\left[\left(\prod_{i=1}^{5} y_i \,/\, \prod_{j=n-4}^{n} y_j\right)^{1/5}\right]} = 1,$$

where i and j are states which are ranked according to their GDP per capita, $i, \ldots, j, \ldots, n$, among the total of n states and X refers to the two factor input components (human and physical capital) as above. Using this decomposition method, we can account for the contribution of human capital to the difference in GDP per capita between the five richest and five poorest states.[29]

III. The Contribution of Knowledge Capital to State Income

We are now in a position to decompose state variations in GDP per capita into contributions that can be accounted for by differences in the two components of knowledge capital, years of schooling, and cognitive skills. For that, we introduce the different test score specifications developed in Section IC into the aggregate knowledge capital measure derived in Section IA and apply it in the development accounting framework of Section IIB.[30]

A. *Basic Results*

Table 2 shows the results of the development accounting exercise for different basic test score specifications. At this point, we focus on GDP per capita in 2007 (although results for 2010 are very similar). Subsequently, we consider earlier periods.

[29] The five richest states in 2007 are Connecticut, New York, Massachusetts, New Jersey, and California. The five poorest states in 2007 are West Virginia, Mississippi, Arkansas, Kentucky, and Alabama.

[30] For completeness, we can report information about the full decomposition of income differences even though we concentrate completely on the knowledge capital component. Using the 2000 value of state physical capital from Turner, Tamura, and Mulholland (2013) in our development accounting analysis and assuming a production elasticity of physical capital of $\alpha = 1/3$, differences in physical capital can account for 14.1 percent of the cross-state income variation with the covariance measure and 18.1 percent with the five-state measure. With 22.8 and 30.6 percent, respectively, attributed to differences in our preferred knowledge capital measure with the two decomposition methods (see below), the unexplained part of the income variation that could be attributed to differences in total factor productivity would be 63.1 percent with the covariance measure and 51.3 percent with the five-state measure. In these calculations, our measure of knowledge capital is correlated with the total factor productivity term calculated from the neoclassical production framework at 0.12.

TABLE 2—DEVELOPMENT ACCOUNTING RESULTS WITH DIFFERENT TEST SCORE SPECIFICATIONS, 2007

	Covariance measure			Five-state measure		
Test score specification	Total knowledge capital	Test scores	Years of schooling	Total knowledge capital	Test scores	Years of schooling
Baseline: local average adjusted for interstate migrants	0.150 (0.045)	0.057 (0.025)	0.093 (0.023)	0.213	0.093	0.120
+ adjustment of locals by education category	0.159 (0.043)	0.066 (0.024)	0.093 (0.023)	0.221	0.101	0.120
+ adjustment of interstate migrants by education category	0.169 (0.043)	0.076 0.024)	0.093 (0.023)	0.231	0.111	0.120
+ adjustment of international migrants by selectivity-adjusted home country scores	0.190 (0.041)	0.097 (0.022)	0.093 (0.023)	0.255	0.135	0.120
+ backward projection of NAEP scores by age	0.215 (0.045)	0.122 (0.029)	0.093 (0.023)	0.295	0.175	0.120
+ backward projection of NAEP scores by age and parental education	0.228 (0.044)	0.135 (0.028)	0.093 (0.023)	0.306	0.186	0.120

Notes: Development accounting results for 47 US states with different test score specifications. Test scores refer to eighth-grade math. Locals are all persons who report a state of birth equal to the current state of residence. Interstate migrants report another state of birth than state of residence. International migrants report another country of birth than the United States. "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 a return of $w = 0.17$ per standard deviation in test scores and a return of $r = 0.08$ per year of schooling. Bootstrapped standard errors are in parentheses with 1,000 replications.

Source: US Bureau of Economic Analysis (2013a, b, c), Ruggles et al. (2010), and NAEP (2014)

Baseline Test Score Specification.—The contribution of knowledge capital to state differences in the level of income can be separated into quantitative (attainment) and qualitative (cognitive skills) dimensions. Based on a rate of return per year of schooling of 8 percent, state differences in average years of schooling of the working-age population account for 9.3 percent of the cross-state variance in GDP per capita in 2007.[31] This component of our knowledge capital measure does not change in most of our subsequent analysis, so its contribution stays the same.

For the baseline measure of the cognitive skill component of knowledge capital, we begin with the raw math test score data for states and proceed to refine the skill estimates of the working-age population. The baseline specification adjusts the local average test score for the portion of the working-age population that is made up of interstate migrants. Locals and international migrants receive the test score of their state of residence, and interstate migrants receive the test score of their state of birth.

State differences in this baseline cognitive skill measure account for 5.7 percent of the variance in GDP per capita across states, based on a return per standard deviation in test scores of 17 percent. Differences in aggregate knowledge capital of the working-age population thus account for 15.0 percent of the variation in GDP per capita in this specification.

The five-state measure provides a slightly different perspective on income variations. From this, we see that knowledge capital can account for 21.3 percent of the

[31] Reported standard errors are bootstrapped with 1,000 replications throughout.

variation of GDP per capita between the five richest and the poorest states. Across these state extremes, 9.3 percent of the variation is accounted for by differences in test scores, and 12.0 percent is accounted for by differences in years of schooling.

Adjustment of Test Scores for Selective Interstate Migration.—The remainder of Table 2 provides results for the more refined test score measures of the knowledge capital of the working-age population in each state. Since the measure of school attainment is held constant, it accounts for a constant portion of the variance in income (9.3 percent), and we focus on how income variations are related to alternative test score measures.

The distribution of skills in the labor force differs from that of students because of both selective migration and heterogeneous fertility. The most straightforward step is adjusting the test scores of locals for their educational background, i.e., whether the working-age locals have a university degree or not. With this refinement, differences in cognitive skills account for 6.6 percent of the state variation in GDP per capita.

Similarly adjusting the scores of interstate migrants by educational background raises the explanatory value of test scores to 7.6 percent. Thus, after adjusting scores of the US-born population for education levels, we account for 16.9 percent of the total variation in GDP per capita with knowledge capital differences across states with 45 percent derived from variations in test scores and 55 percent from variations in years of schooling.

In terms of the variation in income between the richest and poorest five states, adjusting the test scores of locals and interstate migrants by education category raises the explained income variation to 11.1 percent, or close to equal the impact of variations in years of schooling.

Adjustment of Test Scores for International Migration.—The uneven distribution of international immigrants across states also has significant impacts on the knowledge capital in each state and on differences in GDP per capita. The prior estimates simply assigned international migrants the average test score of their state of residence. We now use our estimates of the scores for immigrants based on their country-specific selectivity.

As Table 2 shows, refinement of measurement of worker skills leads to an increase in the share of GDP per capita that is accounted for by cognitive skills. Knowledge capital now accounts for 19.0 percent of the variation in GDP per capita with cognitive skill differences contributing slightly more than half of the total. The five-state measure shows total knowledge capital accounting for one-quarter of the variation in state incomes, with the test score component being slightly larger than the years of schooling component.

Our measure of selectivity-adjusted scores for immigrants of course has error because the observed selectivity for school attainment by itself is likely not perfectly correlated with the selectivity based on cognitive skills. We have looked at a series of alternatives (not shown), but none appeared to be superior in explaining state differences in income. The alternative of using just the school-attainment selection parameter performs noticeably worse than our preferred adjustment for selectivity in the cognitive skill distribution (see also the sensitivity analysis below). An alternative to using the country-specific selectivity is simply to use a constant value across countries. If we assume that immigrants uniformly come from the ninetieth percentile of their home country skill distribution, we explain slightly less of the variation than in our base case. Those results are unaffected by assuming that Mexico is the exception and that Mexican immigrants come from the mean of their country.

B. *An Historical Picture of the Contribution of Knowledge Capital*

While our next refinement involves improving the age-matching of test scores to workers, it is useful first to consider some parallel evidence on the historical pattern of state incomes. It is possible to conduct development accounting analysis for earlier decades, building on the picture of the state working-age population available in prior decennial censuses. Table A6 in the online Appendix reports the covariance measure results of development accounting analyses going back to 1970. In constructing the skill measure for the earlier years, the population shares of state locals, interstate migrants, and international immigrants by education categories of each state are taken from the respective year. The test scores that are assigned to the different groups, though, still come from the assumption of a constant test score level being produced for each education category in the school system of each state.

Three broad patterns of results emerge in the historical picture. First, while there is some variation over time, the importance of knowledge capital in accounting for state income variations remains quite similar over the four decades of the analysis. The total variation due to knowledge capital remains between 17 percent and 20 percent.

Second, the proportion attributed to years of schooling, or school attainment, is consistently higher in earlier decades than in 2007. In 1970, 15.1 percent of state income variations were related to years of schooling; this fell to 9.3 percent in 2007.

Third, independent of the precise approach to estimating test scores for locals, interstate migrants, and international migrants, the proportion of variations in state GDP per capita accounted for by test scores falls as we move back from 2007. This changing pattern is particularly important for guiding further improvements on the measurement of knowledge capital. While this result might arise if there was less demand for skilled workers in the past, we suspect that it more likely reflects the measurement errors in cognitive skills becoming more important for earlier generations of workers. Indeed, in the earliest two years analyzed—i.e., 1970 and 1980—none of a state's workers actually participated in any of the NAEP testing.

The weakened explanatory power of test scores as we look at income patterns further in the past reinforces the potential gains from improving on the historical measurement of worker skills. Therefore, we now turn to our backward extrapolations of test scores by age.

C. *Backward Projection of Historical Achievement Patterns*

The alternative to assuming a constant achievement level for each state is to project achievement levels backward, either based on observed state trends in NAEP achievement or additionally using earlier information on SAT scores as explained previously.

Extrapolation of NAEP Trends.—We begin with the extrapolation of trends based on the state-level time patterns of NAEP scores observed from 1992 to 2011 and on the long-term national NAEP trend data going back to 1978 (see Section IC above). In the results reported here, we assume linear state trends before 1978. We perform the projections for each of the 47 states in our analysis and for the separate education categories. Because the projections include obvious estimation error, we consider the development accounting exercise first without and then with division by education category.

The second row from the bottom of Table 2 shows the results of the 2007 development accounting for the test scores projected by five-year age cohorts. Once we adjust the test scores of locals and interstate migrants for the projections by age category, the variation in GDP per capita accounted for by the test scores rises to 12.2 percent—greater than the 9.3 percent that years of schooling account for—yielding a total due to knowledge capital of 21.5 percent.

Our preferred specification is found in the last row of Table 2. There, we push the projections one step further and use projected test scores adjusted for both age and education category to allow for selectivity of locals and interstate migrants. It increases the portion of income variation attributed to test scores to 13.5 percent. Total knowledge capital accounts for 22.8 percent of the variation in GDP per capita across states.

While not emphasized, the role of knowledge capital in explaining differences in the extremes of the state income distribution as seen in the five-state analysis is uniformly larger. With the full projections of skills, the five-state measure accounts for 30.6 percent of the variation, with 18.6 percentage points attributed to cognitive skills and 12.0 percentage points attributed to years of schooling.

Projection from State SAT Scores.—A check on the reliability of the age projections based on NAEP trends comes from the test score projections based on participation-adjusted SAT scores, which are observed at the state level back to 1968. Unfortunately, SAT scores are not available by educational background, so we cannot perform the selectivity adjustment by educational categories here.

The first cell of Table 3 reproduces the respective development accounting results based on the extrapolated NAEP trends by age (but not educational categories) for comparison. The second column reports the respective development accounting results based on the SAT projections. The results from this very different projection approach to constructing test scores before 1992 closely resemble our main results, providing added confidence in the results based on time-varying test scores.[32] However, the estimates based on SAT projections are slightly less precise, as indicated by a larger standard error.

We do not have information on test score trends before the first observed scores for either case: 1978 in the case of national NAEP and 1968 in the case of SAT. While the specifications reported so far assume backward projections of observed linear state trends before the first observed test score, an alternative is to simply

[32] Note that test scores between 1992 and 2011 are the same for the two projections.

Table 3—Development Accounting Results with Alternative Projections of Cognitive Skills from SAT Scores by Age, 2007

	Extrapolation of NAEP trends	Projection from state SAT scores
Linear state trend before first observed score	0.122	0.124
	(0.029)	(0.042)
Constant before first observed score	0.114	0.115
	(0.026)	(0.038)

Notes: Development accounting results for 47 US states with different test score specifications based on projections by age. First scores are observed in 1978 in the case of national NAEP and in 1968 in the case of SAT. Test scores refer to eighth-grade math. Calculations assume a return of $w = 0.17$ per standard deviation in test scores and a return of $r = 0.08$ per year of schooling. Bootstrapped standard errors are in parentheses with 1,000 replications.

Source: US Bureau of Economic Analysis (2013a, b, c); College Board, Docquier, Lowell, and Marfouk (2009); NAEP (2014); and Ruggles et al. (2010)

assume that state scores remained constant before the first observed score. As seen in the final row of Table 3, development accounting estimates are somewhat lower, but do not differ markedly in this specification.

D. *Sensitivity Analysis*

We close the development accounting analysis with evidence on the sensitivity of the accounting results across different subjects, alternative return parameters, to regional price adjustment, for different modeling of the selectivity of international migrants, and for different numbers of states included in the top-bottom comparison of states. In general, results provide the same qualitative picture for reasonable variations of chosen parameters.

While our analysis has focused on achievement in math throughout, we can perform the same analysis for reading, where state-specific scores are available just from 1998 onwards. Results are quite similar: The 13.5 percent of the cross-state income variation attributed to math scores in our preferred specification corresponds to 12.2 percent based on the reading scores. When math and reading test scores are combined into one measure, the value is 13.2 percent.

As discussed in Section IA, we chose a return of $w = 0.17$ per standard deviation in test scores and a return of $r = 0.08$ per year of schooling as parameters in our main calibration. Table 4 reports results for alternatives for each for the two parameters that are 20 percent higher/lower than the baseline values. For test scores, these estimates effectively also reflect the range given by the two studies of Hanushek and Zhang (2009) and Hanushek et al. (2015). With the different parameter values, the contribution attributed to test scores ranges from 11.1 to 15.9 percent and the contribution attributed to years of schooling ranges from 7.0 to 11.7 percent.

One specific alternative, consistent with the estimation of skill returns in Hanushek et al. (2015), is to treat years of schooling as just one input to human capital (along with families, peers, and other inputs). As such, r is set to zero and $w = 0.28$. Interestingly, this formulation of knowledge capital explains virtually the same proportion of the variations in GDP per capita across states as our baseline case.

Table 4—Sensitivity to Alternative Return Parameters

	Return parameters r	Return parameters w	Total knowledge capital	Test scores	Years of schooling
Baseline	0.08	0.17	0.228	0.135	0.093
			(0.044)	(0.028)	(0.023)
Alternative returns to test scores	0.08	0.14	0.204	0.111	0.093
			(0.040)	(0.023)	(0.023)
	0.08	0.20	0.252	0.159	0.093
			(0.049)	(0.033)	(0.023)
Alternative returns to years of schooling	0.06	0.17	0.205	0.135	0.070
			(0.040)	(0.028)	(0.017)
	0.10	0.17	0.252	0.135	0.117
			(0.049)	(0.028)	(0.028)
Pure skills	0.0	0.28	0.222	0.222	0.000
			(0.046)	(0.046)	
Price-adjusted GDP per capita	0.08	0.17	0.229	0.147	0.082
			(0.088)	(0.054)	(0.040)
Unadjusted school-attainment selectivity	0.08	0.17	0.181	0.088	0.093
			(0.047)	(0.029)	(0.023)
International migrants at 90th percentile	0.08	0.17	0.226	0.133	0.093
			(0.044)	(0.029)	(0.023)
Returns to years of schooling estimated from IPUMS 2007:					
Uniform returns estimate	0.124	0.17	0.280	0.135	0.145
			(0.055)	(0.028)	(0.035)
Schooling level-specific returns estimates	$r_{non\text{-}tertiary} = 0.057$	0.17	0.315	0.135	0.180
	$r_{tertiary} = 0.157$		(0.052)	(0.028)	(0.032)

Notes: Development accounting results (covariance measure) for 47 US states with different assumptions on the return w per standard deviation in test scores and the return r per year of schooling. Test score specification adjusts locals and interstate migrants by age-education category based on extrapolation of NAEP trends by education category and international migrants with selectivity-adjusted home country scores of birth. Test scores refer to eighth-grade math. Bootstrapped standard errors are in parentheses with 1,000 replications.

Source: US Bureau of Economic Analysis (2013a, b, c); Docquier, Lowell, and Marfouk (2009); NAEP (2014); and Ruggles et al. (2010)

So far, we use common return parameters for different levels of the knowledge capital measures. It has been argued, however, that technological change over recent decades has raised the returns to human capital at the higher end compared to at the lower end. While we do not have access to micro estimates of returns to cognitive skills that vary across skill levels, we can use the IPUMS data to estimate returns to years of schooling that differ for different levels of education. Estimating the average return to years of schooling in the standard Mincer way on the 2007 IPUMS data yields a return estimate of $r = 0.124$, or more than half higher than the $r = 0.08$ we assume in our calibration. But when returns are allowed to differ between years of schooling at the tertiary and non-tertiary levels, the return to non-tertiary years of schooling is estimated at 0.057 and the return to tertiary years of schooling at 0.157. That is, returns to years of schooling appear to be substantially larger at higher rather than lower levels of education.

Results using these level-specific returns to years of schooling in our development accounting analysis are reported in the last row of Table 4. Interestingly, the share of state income variation attributed to state differences in years of schooling rises from 14.5 percent with the average return estimate (when estimated from the current IPUMS data) to 18.0 percent with the level-specific return estimates. Together with the cognitive skill component, this raises the total contribution of knowledge capital to 31.5 percent. This suggests that high-end human capital may play a particular role in state development and that our main analysis based on average human capital potentially represents a lower bound of the true contribution of knowledge capital to income differences across states.

While estimates so far are based on national prices, price levels tend to be higher in high-income states. We can use estimates of regional price parities to adjust the GDP data for differences in price levels across states (available for 2008 from the US Bureau of Economic Analysis).[33] As is evident from the results shown in Table 4, our development accounting results are quite insensitive to these local price adjustments. Interestingly, though, the share attributed to test scores increases from 0.135 to 0.147, whereas the share attributed to years of schooling declines from 0.093 to 0.082.

We also return to alternative approaches for considering the selectivity of immigrants. On the one hand, if we simply use the unadjusted selectivity parameter based just on school attainment for each country, the estimated impact of knowledge capital falls noticeably. On the other hand, if we place all immigrants at the ninetieth percentile of their home skill distribution, we obtain results that are very similar to our country-specific selectivity estimates.

Finally, the choice of five—rather than some other number of—states at the top and bottom of the state income distribution to estimate the five-state measure is somewhat arbitrary. Table A7 in the online Appendix shows, however, that the qualitative results of this measure are quite similar when using three or seven states at the top and bottom of the distribution.

IV. Growth Accounting

The analysis so far has considered income levels across the US states. We close with a brief corresponding growth accounting exercise that analyzes the extent to which changes in knowledge capital can consistently account for differences in observed growth rates across US states over the past decades.

A. *Introducing Mincer-Type Knowledge Capital into Growth Accounting Analysis*

We begin with the derivation of a growth accounting decomposition in our model framework. We show that both years of schooling and test scores have a straightforward mapping into growth rates once a Mincer-type specification of aggregate knowledge capital is applied.

Consider again a standard Cobb-Douglas production function:

$$Y = (hL)^{1-\alpha} K^{\alpha} A, \tag{8}$$

[33] See http://www.bea.gov/newsreleases/regional/rpp/rpp_newsrelease.htm.

which in growth accounting analyses is usually taken to exhibit Hicks-neutral productivity.[34] This can be written in per capita terms as

$$y = \frac{(hL)^{1-\alpha} K^{\alpha}}{L^{\alpha} L^{1-\alpha}} A = h^{1-\alpha} k^{\alpha} A. \tag{9}$$

Accordingly, average annual growth in GDP per capita can be decomposed into three components—the contributions of human capital, physical capital, and total factor productivity, respectively—as follows:

$$g \equiv \frac{1}{t}\Delta \ln y = \frac{1}{t}(1-\alpha)\Delta \ln h + \frac{1}{t}\alpha \Delta \ln k + \frac{1}{t}\Delta \ln A. \tag{10}$$

As before, human capital per capita is given by the Mincer-type specification augmented by cognitive skills in equation (1), $h = e^{rS+wT}$. Then, the contribution of human capital to the average annual rate of growth has a straightforward expression:

$$\begin{aligned} \frac{1}{t}(1-\alpha)\Delta \ln h &= \frac{1}{t}(1-\alpha)\left[\ln h_t - \ln h_0\right] \\ &= \frac{1}{t}(1-\alpha)\left[\left(rS_t + wT_t\right) - \left(rS_0 + wT_0\right)\right] \\ &= \frac{1}{t}(1-\alpha) r\Delta S + \frac{1}{t}(1-\alpha) w\Delta T. \end{aligned} \tag{11}$$

That is, 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, which is usually assumed at $\alpha = 1/3$, the earnings rate of return to years of schooling $r = 0.08$, and the earnings returns to cognitive skills $w = 0.17$ per standard deviation in test scores.

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

$$\frac{1}{t}(1-\alpha) r\Delta S = \frac{1}{10} \times \frac{2}{3} \times 0.08 \times 0.5 = 0.27\%.$$

That is, by assuming the production function with the standard parameterization, we can infer that an increase in a population's average schooling by half a year, obtained over one decade, would account for slightly more than one-fourth of a percentage point average annual growth over the decade.

Similarly, if the average educational achievement level T of a population were to increase by 25 percent of a standard deviation over a ten-year period, the contribution to average annual growth in GDP per capita g would be given as

$$\frac{1}{t}(1-\alpha) w\Delta T = \frac{1}{10} \times \frac{2}{3} \times 0.17 \times 0.25 = 0.28\%.$$

[34] See Gundlach, Rudman, and Wößmann (2002) on the relevance of the differences in the different neutrality concepts.

Table 5—Growth Accounting Results

	Average annual growth rate of real GDP per capita (percent)	Absolute change in years of schooling	Average annual growth rate accounted for by			Percent of total growth		
			Total knowledge capital	Test scores	Years of schooling	Total knowledge capital	Test scores	Years of schooling
1970–1980	2.17	0.89	0.83	0.36	0.47	38.2	16.5	21.7
1980–1990	2.39	0.56	0.66	0.36	0.30	27.5	15.0	12.5
1990–2000	2.47	0.29	0.51	0.36	0.15	20.7	14.5	6.3
2000–2007	1.52	0.22	0.52	0.36	0.16	34.4	23.6	10.8
1970–2007	2.19	1.95	0.64	0.36	0.28	29.2	16.4	12.9
1970–2000	2.35	1.74	0.67	0.36	0.31	28.4	15.3	13.2
1970–1990	2.28	1.45	0.74	0.36	0.39	32.6	15.7	16.9
1990–2007	2.08	0.50	0.52	0.36	0.16	24.9	17.2	7.6

Notes: Estimated annual change in test scores is 3.16 percent of a standard deviation, obtained from a regression of test scores (NAEP scores projected based on participation-corrected SAT scores as derived in Section IC) on years for each state, 1968–2011; see text.

Source: US Bureau of Economic Analysis (2013a, b, c); College Board, NAEP (2014); and Ruggles et al. (2010)

That is, again assuming the production function with the standard parameterization, we can infer that an increase in educational achievement by 0.25 standard deviations over one decade would also account for somewhat more than one-fourth of a percentage point average annual growth over the decade.

B. *Growth Accounting for the United States*

Table 5 provides some basic results of growth accounting analyses for the United States over recent decades. Average annual growth in GDP per capita amounted to 2.2 percent over the 1970s, 2.4 percent over the 1980s, 2.5 percent over the 1990s, and 1.5 percent over the 2000s (excluding the crisis years).

Average years of schooling in the working-age population increased from 11.1 in 1970 to 12.0 in 1980, 12.5 in 1990, 12.8 in 2000, and 13.04 in 2007.[35] Based on the derivation above, these increases can account for 0.5 percent average annual growth in GDP per capita over the 1970s, 0.3 percent over the 1980s, and 0.15–0.16 percent over the 1990s and the 2000s.

Quantifying changes in the cognitive skills of the working-age population over time is much harder. But to pin down magnitudes, consider the change in the projected test scores based on SAT scores derived above, which provide us with test-score trends since 1968 (see Section IC for details). For the United States as a whole, test scores increased by 3.16 percent of a standard deviation per year over the observed period. If we were to assume that the average achievement of the working-age population increased by the same amount, this would account for 0.36 percent of average annual growth in GDP per capita based on the derivation above.

Over the entire period 1970–2007 when growth was 2.2 percent, the total change in knowledge capital accounts for 0.64 percent average annual growth, or 29 percent

[35] Own calculations based on Ruggles et al. (2010).

of the total observed growth in the United States. Changes in test scores contribute somewhat more to this number than changes in years of schooling.

C. *Growth Accounting for Individual States*

The prior growth accounting for the nation can be extended to look at growth within each of the states. There is considerable heterogeneity across states in growth rates since 1970: seven states have real growth of GDP per capita that exceeds 2.5 percent annually, while another seven states have growth less than 2 percent per year.

If we decompose these different growth experiences in the same way as the national experience, we see even further heterogeneity in the role of knowledge capital and other factors. Figure 10 shows growth accounting results separately for each state.[36] It is obvious that growth in years of schooling and in test scores can account for a substantial part of the overall economic growth between 1970 and 2007 in all states, but there appears to be no simple pattern. For example, in Iowa, Nebraska, and North Dakota, three states with above average growth, test score growth explains little. In contrast, Washington, North Carolina, Massachusetts, and South Carolina are driven significantly more by knowledge capital growth and especially test score growth.

These estimates are surely quite error prone, in particular because of the lack of data on longer term test score trends for the working-age population. Nonetheless, they provide data for further investigations of growth dynamics.

V. Conclusions

Variations in state income across the United States remain large and important. Indeed, the variation of state GDP per capita expanded in recent decades even in the face of substantial migration of the population. But, the sources of these variations are imperfectly understood.

This paper focuses on the contribution of knowledge capital to the variations in state GDP per capita. Almost all states, in their efforts to foster economic development, introduce policies to improve the skills of their youth (the future labor force), to attract skilled people from other states or countries, and to otherwise improve the knowledge capital of their labor force. One might expect population shifts across the states to equalize incomes across states and to blunt the impact of skill policies on state development, but the net result remains uncertain.

We pursue development accounting analyses to decompose variations in state GDP per capita. The decomposition relies on external estimates of the key parameters of a neoclassical aggregate production function. By its nature, this accounting is conservative, relying on just the accumulation of human capital and not allowing for skills to directly affect growth as in endogenous growth models.

[36] Detailed results of the growth accounting by state are provided in Table A8 in the online Appendix.

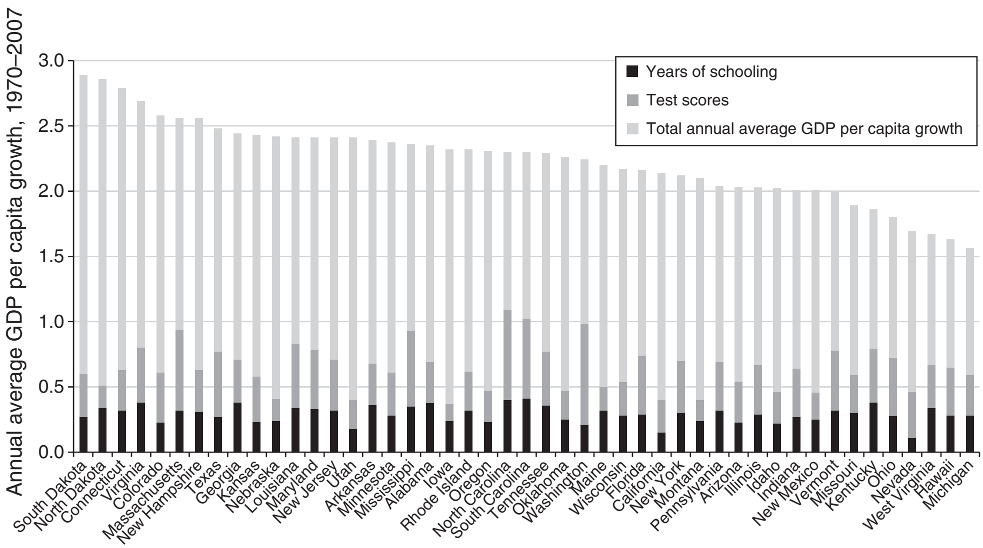

FIGURE 10. GROWTH ACCOUNTING BY STATE, 1970–2007

Notes: Growth accounting results by US states. Contribution of changes in years of schooling and in estimated test scores to the average annual rate of growth in GDP per capita in 1970–2007. See Table A8 in the online Appendix for details.

Source: US Bureau of Economic Analysis (2013a, b, c), Ruggles et al. (2010), and NAEP (2014)

The central empirical challenge is developing knowledge capital measures for the different 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 the working-age population of each state, it is much more challenging to measure the cognitive skills of each state's working-age population.

We base our cognitive skill measure on test scores of the school-age population in each state and in each country internationally. The challenge is to reconcile the different locations of schooling due to migration and the changing scores of different generations of students in our assessment of the skills of the current working-age population in each state. We do this by working with each person's state of birth as the main indicator of likely schooling location. This, in turn, provides the skill mapping for the current working-age population. But prior analyses of migration have made clear that we must also account for the selectivity of migration.

Our analysis confirms the importance of a detailed identification of cognitive skills for the working-age population. In our preferred model, we allow for differences in the cognitive skills of the working-age population according to education levels, incorporating selective migration from other states and other countries. Because the test score information by state of birth is unavailable for older workers in each state, we use time patterns of state and national achievement scores to extrapolate back in time and, thereby, to estimate the cognitive skills accrued by older workers when they were in school.

Our estimates of knowledge capital combine cognitive skills with school attainment of the working-age population. We use market prices estimated in micro studies for each of the two in order to aggregate the two components of knowledge capital.

Our results indicate that in the preferred specifications, roughly 20 to 30 percent of the overall variation in state GDP per capita is attributable to variations in knowledge capital across states. With cruder estimates of the cognitive skills of the state population, results are somewhat lower at around 15 percent. The importance of cognitive skills to economic performance rises with the precision of the measurement. Variations in cognitive skills and variations in school attainment contribute in approximately equal measure to the variations attributable to knowledge capital. Growth accounting exercises indicate similar results for the role of knowledge capital in accounting for observed US growth rates over the past several decades.

These estimates appear remarkably large for a variety of reasons. First, the estimation of state knowledge capital stocks is subject to error, even in our more refined estimates. There is measurement error in the student test scores themselves, and the adjustments for selective migration are imperfect. This inaccuracy most likely drives down the variations in income that can be attributed to knowledge capital. As noted, the contribution of knowledge capital is consistently larger when the most refined estimates of skills are used. Second, the United States is known for the openness of its labor and capital markets, which allow free movement of workers across state lines. This dynamic would presumably tend to equalize the marginal productivity of human capital and lead to convergence of and thus limited variation in state incomes.

Furthermore, the chosen simple neoclassical modeling framework likely underestimates the contribution of human capital. Allowing for complementarities of human capital with physical capital and with unskilled labor may lead to a significant increase in the income differences attributed to human capital (Jones 2014). Furthermore, human capital may have indirect effects on output by facilitating access to the best technologies and by driving technological change, making total factor productivity a function of human capital. For example, the availability of talented managers in the population may play a particular role in the organization of firms that has a bearing on the adoption of technologies and efficient use of resources not captured in our development accounting framework (e.g., Bloom et al. 2014). Thus, while our results highlight the importance of improved measurement of human capital, for a variety of reasons our estimates likely constitute a lower bound of the true contribution of knowledge capital to income differences across US states.

The importance of knowledge capital, and particularly cognitive skills, provides support for policies of various states that are aimed at improving the quality of schools, or indeed any other policies that raise the knowledge capital of the state population. Of course, the effect of school improvement on a state's own economic development depends on the extent of outmigration, as projection models in Hanushek, Ruhose, and Woessmann (forthcoming) indicate. While any details of policy considerations are beyond the scope of this analysis, the value of improving skills has clear implications for state incomes.

Appendix

Table A1A—Skills of Locals, Interstate Migrants, and International Immigrants by State

	Test scores				Years of schooling			
	Locals (1)	Interstate migrants (2)	International immigrants (3)	Emigrants (4)	Locals (5)	Interstate migrants (6)	International immigrants (7)	Emigrants (8)
Alabama	385.3	419.1	547.2	387.5	12.6	13.3	11.9	13.3
Alaska	455.5	438.6	561.9	461.1	12.4	13.6	12.5	13.1
Arizona	426.4	438.3	497.9	432.2	12.6	13.6	10.9	13.4
Arkansas	393.8	421.7	499.9	391.9	12.6	12.9	10.8	13.1
California	422.5	439.7	532.0	423.5	13.3	14.2	11.4	13.5
Colorado	445.2	446.1	521.9	449.3	13.2	14.1	11.6	13.7
Connecticut	448.8	439.4	535.8	461.2	13.5	14.5	12.6	14.4
Delaware	408.6	431.4	543.4	423.2	12.7	13.7	12.2	13.8
Florida	408.4	427.8	494.6	414.5	12.8	13.5	12.4	13.5
Georgia	400.5	427.3	529.3	407.9	12.5	13.8	11.9	13.3
Hawaii	408.9	443.1	602.2	418.4	13.4	14.0	12.8	13.8
Idaho	451.7	438.9	511.8	456.4	13.0	13.5	11.1	13.6
Illinois	441.3	438.7	538.2	444.6	13.4	14.1	11.9	13.9
Indiana	433.9	427.5	530.0	444.9	12.9	13.3	12.1	13.8
Iowa	482.7	446.7	550.9	491.5	13.1	13.7	12.2	14.2
Kansas	461.7	442.5	524.0	464.3	13.3	13.7	11.2	13.8
Kentucky	411.6	428.8	556.9	417.3	12.4	13.2	12.5	13.2
Louisiana	368.5	415.0	532.4	379.3	12.4	13.2	12.3	13.5
Maine	461.2	438.6	601.2	465.1	12.9	13.9	12.8	12.6
Maryland	410.3	415.5	554.6	421.3	12.9	14.3	13.2	13.8
Massachusetts	438.6	449.9	557.2	442.9	13.7	15.0	12.5	14.2
Michigan	434.3	426.0	581.3	440.7	13.1	13.6	12.9	14.0
Minnesota	474.0	458.3	568.7	477.8	13.5	14.2	11.9	14.1
Mississippi	365.0	410.9	526.2	362.6	12.4	12.9	11.5	13.0
Missouri	443.2	435.1	574.0	450.0	12.9	13.4	12.7	13.9
Montana	459.4	441.0	634.8	469.1	13.0	13.5	13.0	13.8
Nebraska	463.0	452.3	516.7	467.5	13.4	13.7	11.3	14.0
Nevada	414.6	427.5	510.7	422.0	12.8	13.2	11.3	13.3
New Hampshire	460.1	441.1	586.9	468.1	13.0	13.9	13.6	13.8
New Jersey	442.0	434.8	548.7	449.5	13.4	14.2	12.9	14.2
New Mexico	408.8	433.6	496.7	416.4	12.6	13.6	10.3	13.3
New York	428.3	439.7	549.9	435.5	13.5	14.4	12.3	14.3
North Carolina	389.1	432.4	517.6	394.1	12.7	13.7	11.5	13.5
North Dakota	475.5	459.6	592.8	479.7	13.4	13.7	13.1	14.1
Ohio	426.7	426.0	582.9	435.1	13.0	13.5	13.4	13.9
Oklahoma	435.7	426.3	526.5	441.9	12.9	13.1	11.2	13.7
Oregon	446.4	435.3	541.6	452.0	13.1	13.8	11.2	13.6
Pennsylvania	438.4	430.1	558.1	448.5	13.1	13.8	12.9	14.2
Rhode Island	425.5	445.1	522.6	436.3	13.1	14.1	11.2	14.1
South Carolina	397.3	423.8	537.4	406.2	12.5	13.5	12.0	13.4
South Dakota	461.5	454.6	535.4	465.8	13.0	13.5	11.4	14.0
Tennessee	401.4	421.1	541.0	407.7	12.4	13.3	11.9	13.4
Texas	420.9	431.6	498.0	426.6	12.8	13.8	10.6	13.3
Utah	450.5	442.1	520.6	457.4	13.2	13.9	11.7	14.0
Vermont	438.2	445.5	619.1	449.1	12.8	14.4	13.5	13.7
Virginia	420.2	431.8	555.5	432.4	12.7	14.3	13.0	13.7
Washington	442.7	442.6	577.1	444.5	13.3	13.9	12.2	13.8
West Virginia	405.2	421.7	589.9	410.5	12.3	12.9	13.6	13.1
Wisconsin	466.1	441.8	537.9	476.4	13.2	13.7	12.1	14.4
Wyoming	456.0	445.0	532.9	458.0	13.0	13.4	12.0	13.7

Note: Emigrants: share of the population born in this state that currently lives in another state.

Source: Author calculations based on Docquier, Lowell, and Marfouk (2009); NAEP (2014); and Ruggles et al. (2010).

Table A1B—Population Shares of Locals, Interstate Migrants, and International Immigrants and Net Gain in Knowledge Capital by State

	Population shares				Net gain in knowledge capital
	Locals (1)	Interstate migrants (2)	International Immigrants (3)	Emigrants (4)	(5)
Alabama	0.68	0.29	0.03	0.35	1.019
Alaska	0.28	0.63	0.08	0.70	1.008
Arizona	0.28	0.54	0.18	0.37	1.025
Arkansas	0.56	0.39	0.05	0.42	1.015
California	0.48	0.21	0.30	0.33	1.025
Colorado	0.35	0.54	0.11	0.44	1.020
Connecticut	0.52	0.32	0.16	0.44	0.994
Delaware	0.42	0.50	0.08	0.47	1.018
Florida	0.30	0.49	0.22	0.35	1.045
Georgia	0.49	0.40	0.11	0.29	1.057
Hawaii	0.52	0.30	0.18	0.45	1.060
Idaho	0.40	0.54	0.06	0.50	0.975
Illinois	0.63	0.21	0.16	0.41	0.998
Indiana	0.66	0.30	0.04	0.37	0.978
Iowa	0.71	0.25	0.04	0.45	0.954
Kansas	0.54	0.39	0.07	0.50	0.974
Kentucky	0.68	0.29	0.03	0.35	1.010
Louisiana	0.78	0.19	0.04	0.36	0.999
Maine	0.60	0.37	0.03	0.45	1.033
Maryland	0.43	0.43	0.14	0.41	1.052
Massachusetts	0.61	0.23	0.16	0.41	1.025
Michigan	0.75	0.19	0.07	0.33	0.993
Minnesota	0.66	0.27	0.07	0.31	0.992
Mississippi	0.69	0.29	0.02	0.44	1.019
Missouri	0.64	0.33	0.04	0.36	0.983
Montana	0.49	0.50	0.01	0.52	0.967
Nebraska	0.62	0.31	0.07	0.48	0.972
Nevada	0.16	0.62	0.22	0.52	1.013
New Hampshire	0.36	0.59	0.05	0.45	0.999
New Jersey	0.49	0.27	0.24	0.45	1.013
New Mexico	0.47	0.43	0.10	0.48	1.018
New York	0.62	0.13	0.25	0.45	1.008
North Carolina	0.54	0.38	0.08	0.28	1.052
North Dakota	0.68	0.30	0.02	0.58	0.968
Ohio	0.74	0.22	0.04	0.35	0.989
Oklahoma	0.56	0.38	0.06	0.41	0.973
Oregon	0.41	0.49	0.10	0.41	0.997
Pennsylvania	0.74	0.19	0.06	0.35	0.984
Rhode Island	0.58	0.27	0.15	0.48	0.987
South Carolina	0.56	0.39	0.05	0.33	1.032
South Dakota	0.63	0.35	0.02	0.53	0.965
Tennessee	0.57	0.38	0.05	0.32	1.020
Texas	0.55	0.26	0.19	0.24	1.004
Utah	0.57	0.33	0.10	0.34	0.988
Vermont	0.48	0.49	0.03	0.46	1.041
Virginia	0.45	0.43	0.12	0.39	1.057
Washington	0.42	0.45	0.13	0.35	1.026
West Virginia	0.70	0.28	0.01	0.50	0.990
Wisconsin	0.70	0.26	0.05	0.31	0.968
Wyoming	0.38	0.58	0.03	0.62	0.974

Notes: Population shares in columns 1–3 add up to 1 for each state. Column 4: share of the population born in this state that currently lives in another state. Column 5: net gain in knowledge capital: ratio of the actual returns-weighted knowledge capital measure (calculated from equation (1)) over a knowledge capital without any migration. Knowledge capital of each group is found in Appendix Table A1A.

Source: Author calculations based on Docquier, Lowell, and Marfouk (2009); NAEP (2014); and Ruggles et al. (2010)

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