Economic Gains from Educational Reform by US States

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There is limited evidence justifying the economic case for state education policy. Using new measures of workers' cognitive skills that allow for selective internal migration and foreign immigration, we provide preliminary estimates of growth regressions that incorporate worker skills. Our descriptive models show that educational achievement predicts economic growth across US states over the past four decades. Projections from our growth models show the substantial potential scope for state economic development through improving school quality. While we consider the impact of a range of educational reforms, an improvement that moves each state to the best-state level would in the aggregate yield an estimated present value of long-run gains of 8 percent of discounted future GDP.

I. Introduction

Education is often seen as an important instrument of state and local economic development, and this presumed linkage motivates many of the policy discussions across US states. Yet evidence on the economic impact of school improvement for individuals and for states is largely lacking. This paper evaluates the economic implications of improved educational achievement and provides projections for individual states of how economic development might be altered by school improvement.

Virtually all existing research on how human capital affects economic development rests on measures of school attainment, even though the

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vast majority of policy discussions are about achievement and the quality of schooling. Measuring human capital with some variant of years of schooling reflects both the ready availability of data and its long-standing acceptance through a multitude of different analyses. But, as data become available about variations in achievement across schools, this choice appears increasingly problematic both from an analytical and from a policy viewpoint.

This paper makes three contributions to the literature on economic benefits of education. First, we develop and analyze more refined measures of skills for workers across US states, which in the aggregate we call "knowledge capital" to distinguish it from the standard years-of-schooling measures. Second, on the basis of these measures, we estimate how state growth and development are related to the quality of schools and of workers. Third, using these estimates, we develop state-by-state projections of the future economic benefits of various educational reforms.

Estimation of the impact of skill differences across states is complicated. Going beyond school attainment generally requires using specialized data sets that often do not suit the purposes of the analysis. For this analysis, we build upon international studies that show measures of cognitive skills to be a good index of important skill differences of workers, indicating that achievement scores across states may be an appropriate basis for estimating differences in worker skills. But, when focused on US states and the policies related to current schools, it is important to understand the high degree of mobility of the US population, which implies that the achievement scores for students in a state will differ noticeably from measures of the skills of the workers in a state.

We construct measures of the knowledge capital of the workers in each state by tracing back to the place of education for each adult worker. Armed with these measures, we can describe how worker skills relate to the economic growth of each state. In this, it is clearly not possible to verify the causality of the estimated growth relationships. However, these state-level descriptive estimates are virtually identical to the corresponding country-level parameters from international growth analysis. These latter estimates have been subjected to extensive scrutiny over causal interpretations, and they afford external support for using the state-level models to project potential future economic outcomes.

Importantly, our measures of the knowledge capital in each state provide a way to link potential changes in the quality of schools in a state to the productive skills of the future workforce. With this mapping, we can describe the economic value of improving schools in each state on the basis of our historical description of labor force quality and growth.

Our projections emphasize the dynamics of any policy improvements—allowing for the phasing-in of school quality changes, for migration of workers into and out of each state, and for the incremental nature of labor force improvement. Nonetheless, after discounting for these delayed impacts of school quality changes, the results suggest that relatively modest but feasible quality improvements (improvements by one-quarter of a standard deviation) begun in 2015 are associated with very large potential economic returns that could exceed the total spending on K–12 education by 2050. According to our growth estimates, such a reform would, on average, add 5 percent to state GDPs in 2054, 10 percent in 2069, and 20 percent in 2096. While the exact gains would differ across the states, all states, including those experiencing substantial out-migration, would benefit economically.

These estimates are of course subject to uncertainty arising from the estimation of state variations in worker skills, from the assumptions about the selectivity of interstate migration and immigration from abroad, and from the identification of the state growth model. Extensive specification tests, however, show consistently strong impacts of knowledge capital on aggregate economic outcomes. Any state improvement in knowledge capital would lead to increased output in the aggregate only if it came from genuine improvements in worker skills, rather than improvements just from attracting better-skilled workers that came at the expense of other states.

Section II reviews the existing research on the impact of human capital on economic growth that forms the foundation for this study. Section III describes how we develop cognitive-skills measures for each US state. Section IV presents results of growth regressions across US states. Section V introduces the projection model. Section VI presents results on the projected economic gains from a number of educational reforms for each US state. Section VII concludes.

II. Conceptual Framework

For state policy, two kinds of economic impacts of education are relevant. The first is simply the impact on individual citizens: How different are expected future wages and economic well-being if an individual obtains more human capital? The second involves the macroeconomic outcomes for the state: How is state economic development altered by changing the human capital of the state? This analysis focuses on the second topic of the aggregate effects of schooling on state economic development, a topic that has received relatively little analysis. The impact of education on individuals has been extensively studied but more importantly is largely subsumed in the consideration of aggregate outcomes.[1] The aggregate analysis has the advantage that it incorporates any externalities of schooling while also focusing on the local benefits that net out any movements of human capital across state lines.[2]

[1] See Mincer (1974), Card (2001), Heckman, Lochner, and Todd (2006), and Hanushek et al. (2015). We do provide some direct evidence in Section IV.

[2] This analysis essentially assumes that state decision makers are interested in only those citizens and economic activity remaining in the state. As others have discussed, from a larger societal view this would lead to underinvestment in human capital. We do not deal with this

A primary focus of state policy is invariably the nature and performance of the public schools. Unfortunately, virtually all existing economic analyses of state economic development suffer from poor and indirect measures of schooling outcomes. Instead of actually measuring the skills of individuals, these studies rely on a simple proxy—school attainment, or the average years of schooling of the population. This measure has prima facie support, because a primary purpose of schooling is increasing the skills of citizens. It also proves convenient, because of its ready availability in individual data and in aggregate state and national data. Nonetheless, measurement issues are severe and compromise investigations of the growth implications of educational improvements.[3]

The inappropriate measurement of skills based solely on school attainment introduces significant analytical problems. Perhaps more importantly, it also removes the analysis from the key policy issues surrounding school quality.

For understanding the aggregate impact of human capital, the most relevant prior research comes from cross-country analyses that focus on international growth. This cross-country analysis is far more extensive than analysis of within-country growth, and it is relevant to development across regions of the United States.[4]

Prior theoretical and empirical work in an international context has pursued a variety of specifications of the underlying growth process.[5] A simple characterization of this structure, however, is that growth rates can be considered as a function of workers' skills along with other systematic factors,

$$\text{growth} = \alpha_1 \text{ human capital} + \alpha_2 \text{ other factors} + \varepsilon. \tag{1}$$

This formulation suggests that nations or states with more human capital tend to continue to make greater productivity gains than nations or states with less human capital, although it is possible that any induced growth in productivity disappears over time.[6]

issue except for presenting impact data for the case of individual states making different investments.

[3] Similar measurement problems affect analyses of the individual returns to schooling; see Hanushek et al. (2015).

[4] Note that historically, empirical growth analysis focused on the time-series patterns for the United States as a whole; see Jorgenson and Griliches (1967), Denison (1985), and Turner, Tamura, and Mulholland (2013).

[5] See the reviews in Hanushek and Woessmann (2008, 2015*a*).

[6] A major difference of perspective in modeling economic growth rests on whether education should be thought of as an input to overall production, affecting the level of income but not the growth rate in the long run (augmented neoclassical models, as in Mankiw, Romer, and Weil 1992) or whether education directly affects the long-run growth rate (endogenous-growth models, as in Lucas 1988, Romer 1990, and Aghion and Howitt 1998). See Aghion and Howitt (2009) for a textbook introduction. Our projections are mostly based on an endogenous-growth framework, but, as we show, a neoclassical framework does not produce very different results within our time frame.

Within this framework, it is possible to see the analytical problems that arise from literature focusing on school attainment to test the human capital aspects of growth models. Even though empirical applications have tended to find a significant positive association between quantitative measures of years of schooling and economic growth, these formulations introduce substantial bias into the picture of economic growth.

Average years of schooling is a particularly incomplete and potentially misleading measure of education for comparing the impacts of human capital on the economies of different countries or states. It implicitly assumes that a year of schooling delivers the same increase in knowledge and skills regardless of the education system. For example, a year of schooling in Brazil is assumed to create the same increase in productive human capital as a year of schooling in Korea or a year of schooling in Mississippi the same increase as a year in Massachusetts.

Formulations relying on attainment as the measure of human capital also implicitly assume that formal schooling is the only source of education and that variations in nonschool factors have negligible effects on education outcomes and skills. This neglect of differences in the quality of schools and in the strength of family, health, and other influences is probably the major drawback of such a quantitative measure of schooling.

The role of other influences is in fact central to standard versions of education production functions as employed in a very extensive literature (see Hanushek 1986, 2002 for reviews). A stylized version of an education production function expresses skills as a function of a range of factors (expressed linearly for expositional purposes):

$$\begin{aligned}\text{human capital} = {} & \beta_1 \text{ schools} + \beta_2 \text{ families} + \beta_3 \text{ ability} \\ & + \beta_4 \text{ health} + \beta_5 \text{ other factors} + v.\end{aligned} \tag{2}$$

In general, human capital combines both school attainment and its quality with the other relevant factors, including education in the family, health, labor market experience, and so forth.

Thus, while school attainment has been a convenient measure of human capital to use in empirical work because the data are readily available across individuals, across time, and across countries, its use ignores differences in school quality as well as other important determinants of people's skills.

Following the educational production function literature, a more satisfying alternative is to consider variations in cognitive skills as a direct measure of the human capital input into empirical analyses of economic growth. A focus on cognitive skills has a number of potential advantages. First, it captures variations in the knowledge and ability that schools strive to produce and thus relates the putative outputs of schooling to subsequent economic success. Second, by emphasizing total outcomes of education, it incorporates skills from any source—including families and innate ability as well as schools. Third, by allowing for differences in performance among students whose schooling differs in quality (but possibly not in quantity), it acknowledges—and invites investigation of—the effect of different policies on school quality.

This approach has proved very successful in understanding cross-country differences in economic growth (see Hanushek and Woessmann 2015*a*). Cognitive-skill measures based on international achievement tests can explain three-quarters of the variation in country growth rates (while school attainment measures explain just one-quarter of the variation).[7] Moreover, in the international context, many of the difficult issues of causal structure underlying growth can be addressed when human capital is measured by knowledge capital (see Hanushek and Woessmann 2015*a*).

The approach that we pursue in this paper is to mimic the cross-country growth regressions for US states. We view this estimation as a natural extension of the international estimation, but one that amplifies the international work. Specifically, given the commonly held view that the operations of US labor and capital markets are superior to those found in most other countries, the US growth results potentially show what the growth frontier looks like.

III. Constructing Measures of the Knowledge Capital of US States

Duplicating the international models requires developing measures of the knowledge capital for each state—something that has not previously been available.[8] The fundamental difficulty is that no direct measures of cognitive skills exist for the labor force in each state. We have measures of skills of the student body by state from the National Assessment of Educational Progress (NAEP), but the students are not the same as the adults in the workforce because of the significant mobility across states.

Our derivation of state knowledge capital measures proceeds in three steps. First, we construct mean test scores of the students of each state in order to provide an index of the cognitive skills of those students who remain in the state and become part of the relevant labor force (Sec. III.A). Second, we adjust state test scores for migration between states, assuming that migration is not selective (Sec. III.B). Third, we adjust these scores for selectivity of the interstate migration flows as well as for selective international migration (Sec. III.C).

[7] An alternative approach, development accounting, imposes a common production function on the data and uses variations in inputs to explain differences in the level of income across countries (see Klenow and Rodríguez-Clare 1997; Hall and Jones 1999). In the international context, knowledge capital can account for 40 percent of income differences across countries (Hanushek and Woessmann 2015*a*; across states, it can account for 20–30 percent of state income difference; Hanushek, Ruhose, and Woessmann 2017).

[8] Some prior analysis has considered growth and income differences across states, but the measures of human capital have focused on school attainment. See, in particular, the important contributions by Turner et al. (2007, 2013), and Tamura, Simon, and Murphy (2016). Tamura (2001) is an exception in looking at school inputs (instruction time, class size, and relative teacher salary) and income growth across states.

The discussion here provides an overall summary of the estimation of state knowledge capital. The details of the data development can be found in appendix E; appendixes B–E are available online.[9]

A. *In-State Cognitive Skills*

The starting point for estimating the knowledge capital of each state is consideration of the skills measured for students. Conceptually, we want the entire history of skills relevant for the youngest to the oldest worker in the economy, something that does not exist. As discussed below, however, test measures of the relevant skills prove to be relatively stable over time for each state, with the largest differences coming between states. Therefore, we use more contemporary differences in state achievement tests to proxy the skills of each worker ever born in the state.

The NAEP provides reliable US state-level test score data (see NCES 2014), and we start by combining all available state test score information into one average score for each state. We focus on the NAEP mathematics test scores in grade 8.[10] For a majority of states, NAEP started to collect eighth-grade math test scores on a representative sample at the state level in 1990 and repeated testing every 2–4 years.[11] From 2003 forward, these test scores are consistently available for all states. We use all available state NAEP data through 2011. Note that an eighth-grader in 1990 would be age 35 in 2011, implying that the majority of workers in the labor force would never have participated in the testing program.

The NAEP state-level test results, however, prove to be quite stable over time. An analysis of the variance of grade 8 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, due to changed performance or to test measurement error.[12] Thus, we begin by

[9] Additional construction details and descriptive data for state knowledge capital can be found in our analysis of development accounting for US states (Hanushek et al. 2017).

[10] If we use reading test scores in grade 8, which are available only from 1998 onward, the results are very similar. NAEP also tests students in grade 4, 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 each of the test scores provides similar information about the position of the state in terms of student achievement.

[11] The 1990 testing was the beginning of state-representative samples and was viewed as experimental; it covered 37 states in eighth-grade math. In 1992, 41 states participated in eighth-grade math and fourth-grade math and reading assessments. In 2003 and later, all states participated in fourth- and eighth-grade in both math and reading.

[12] Because we are interested in test scores across the full age range, reliance on just scores from 1990–2011 clearly weights more recently educated workers more heavily than if we had the full range. At the state level, there is a modest change in the ranks of states on the NAEP between 1990 and 2010. The Pearson correlation of ranks between 1990 and 2010 (for the 35 states observed) is 0.71; when all states are observed between 2003 and 2010, the correlation is 0.90. Of course, it is the test score levels that are important in calculating the knowledge capital of states, so that minor changes in ranks around the middle of the overall distribution do not affect our calculations by much. We return below to further analysis of possible changes in scores over time.

calculating an average state score using all available NAEP observations for each state. These are estimated as state fixed effects in a regression with year 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.[13]

Our primary analysis relies on these estimates of skills for students educated in each of the states. Ranked by their average test score, 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 over the two decades (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 equivalent to one-quarter to one-third of a standard deviation in test scores. That is, in eighth-grade math, the average achievement difference between the top- and the bottom-performing state amounts to some three grade-level equivalents, underscoring the importance of attention to the skill differences of workers as opposed to relying just on school attainment.[14]

B. *Adjustment for Nonselective Interstate Migration*

The second step of our derivation involves adjusting for migration between US states. We start by assuming that migration is not selective and turn to a consideration of selectivity in the migration process in the next section.

Obviously, not all current workers in a state were educated in that state. From the census data, we know the state of birth of all workers who were born in the United States. On average, just 54 percent of the working-age population in 2010 are living in their state of birth (see fig. A1), 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, in Nevada, only 17 percent of the state's residents in 2010 report having been born there. At the other extreme, 77 percent of the residents of Louisiana were born there. These numbers indicate that interstate migration is a major issue when assessing the cognitive skills of a state workforce and highlight the varying importance of migration for assessing the workforce of each state.

[13] To be clear, we do not believe that eighth-grade scores per se identify the skills that are relevant for the economy. Instead, we believe that they provide an index of general skill differences and that later achievement (and skills) will follow the pattern of these scores—which are the inputs to later schooling. This perspective represents the measurement analog to the idea of dynamic complementarity, developed by James Heckman and his coauthors, that is summarized by the argument that "skill begets skill" (see, e.g., Cunha et al. 2006; Cunha and Heckman 2007).

[14] Note also that these differences cannot be interpreted as a measure of school quality differences across states, because, as equation (2) emphasizes, they combine the impacts of the various inputs to achievement and go beyond school quality.

To adjust for interstate migration, we start by computing the birthplace composition of each state from the census data. We then divide the state working-age population into state locals (those born in their current state of residence), interstate migrants from other states (those born in the United States but outside their 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 working-age population born in each of the other states. For the purposes of the growth models, the adjustments are based on state population shares for the year 1970, which is the starting period of our main growth analysis below.

Assuming that interstate migrants have not left their state of birth before finishing grade 8, we can then combine test scores for all US-born workers of a state according to the separate birth-state scores.[15] 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 Washington, DC (34 percent), and Alaska (53 percent)—neither of which is used in our growth analysis—the share is well beyond 70 percent in each individual state.[16] This adjusted skill measure thus assigns all state locals and all interstate migrants the mean test score of their state of birth—which only for the state locals will be equivalent to the mean test score of students in their state of residence.

Note that we rely on residential location but that workplace location may actually be in another state. This issue is potentially most important in the areas of Washington, DC, New York City, Philadelphia, and Boston. For our main results that focus on knowledge capital of states in 1970, we lack sufficient census information on workplace location to do calculations by workplace and thus rely just on residential location. However, excluding states for which cross-state commuting is most important has only minor impact on our estimates.[17]

C. Adjustment for Selective Interstate and International Migration

The next step in our analysis is to take into consideration that interstate migration is, in fact, selective and to adjust for international migration.

1. Adjustment for Selective Interstate Migration

The previously derived 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, Ohio univer-

[15] This approach parallels that of Card and Krueger (1992), except that our focus is on achievement in birth states, as opposed to resources.

[16] Authors' calculations based on the 2010 US census data (Ruggles et al. 2010).

[17] Note also that Washington, DC, and Delaware are excluded from the growth estimation because of the special structure of their industries.

sity graduates might migrate to a very different set of states than Ohioans with less education might migrate to—and it would be inappropriate to treat both flows the same.[18]

The NAEP scores of population subgroups by educational background provide an overall suggestion of the potential importance of selective migration. Comparing the NAEP scores of students from families where at least one parent has some kind of university education with students from families where the parents do not have any university education, we find an average difference of over 0.6 standard deviations for the United States as a whole.

Against this background, to account for selective interstate migration we allow for different migration patterns across states by education levels. In particular, 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 the equivalent assumption for those without any university education.[19] That is, from the census data we first compute separate population shares of university graduates and non–university graduates by state of birth for the working-age population of each state. With these population shares, we then assign separate test scores by educational category. This adjustment is done for interstate migrants to deal with selectivity of in-migration but is also done for state locals to deal with the selective out-migration and differential fertility that generate differences in the cohort composition between those in the workforce and those taking the NAEP tests.

2. Adjustment for Selective International Migration

A remaining topic is how to treat immigrants—those educated in a foreign country. On average, international migration is less frequent than interstate migration, with more than 90 percent of US workers born in the United States. However, recent years show large state variation in this percentage: in 2010, 99 percent of the working-age population in West Virginia was born in the United States, compared to 70 percent of the working-age population in California.

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.[20] What we need is

[18] This selective migration was one of the fundamental critiques of Heckman, Layne-Farrar, and Todd (1996) about the analysis of Card and Krueger (1992).

[19] The NAEP sampling provides a representative sample of the population within each state and reports scores for various subgroups; see NCES (2014).

[20] 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).

where in the distribution of skills the immigrants from each country would fall.[21]

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 (Ortega and Peri 2013; Bertoli and Fernández-Huertas Moraga 2015). 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; Grogger and Hanson 2011).

To provide a starting point for where immigrants fall in the distribution of cognitive skills of their home country, our approach uses information about the selectivity of immigration into the United States in terms of school attainment.[22] This is motivated by the fact that the achievement of individual students is a strong, albeit imprecise, predictor of further school attendance. We do not believe that it is sufficient, however, because the data on the distribution of attainment are quite coarse and because school access policies have varied across countries and across time.

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, for each country of origin 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 (see Hanushek et al. 2017 for details).

[21] The test score distribution information uses the aggregate country information from all assessments that each country participated in between 1995 (the first TIMSS test) or 2000 (the first PISA test) and 2011. While there might be some concern that the historical test distributions at the time of immigration would be different and would thus affect the results, the most significant difference in test scores comes across countries, as opposed to across time. If we do a simple variance decomposition of all scores going back to the first such assessments in the mid-1960s, 73 percent is between countries and only 27 percent comes from the combination of changes in scores over time and of measurement error for individual countries (Hanushek and Woessmann 2015*a*). In the recent international samples, 93 percent of TIMSS variation since 1995 is between countries, and 91.5 percent of PISA variation since 2000 is between countries. Thus, we do not believe that aggregation of scores across time for countries has a material impact on our estimates. Nevertheless, we provide additional evidence on this below.

[22] An alternative approach, following the work of Heckman et al. (1996), would consider wage differences between migrants and nonmigrants in each state labor market. In the case of immigrants, however, this approach may have serious potential flaws because of worker downgrading on immigration and because of slow integration into the local labor market (e.g., Dustmann and Preston 2012; Dustmann, Frattini, and Preston 2013).

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:

$$\begin{aligned} p = {} & s_{\mathrm{US}}^{\mathrm{pri}} \times \frac{1}{2} s_{\mathrm{home}}^{\mathrm{pri}} + s_{\mathrm{US}}^{\mathrm{sec}} \times \left(s_{\mathrm{home}}^{\mathrm{pri}} + \frac{1}{2} s_{\mathrm{home}}^{\mathrm{sec}} \right) \\ & + s_{\mathrm{US}}^{\mathrm{ter}} \times \left(s_{\mathrm{home}}^{\mathrm{pri}} + s_{\mathrm{home}}^{\mathrm{sec}} + \frac{1}{2} s_{\mathrm{home}}^{\mathrm{ter}} \right), \end{aligned} \tag{3}$$

where the respective educational degrees of the population are given by "pri" for primary, "sec" for secondary, and "ter" for tertiary, s refers to the shares of the population with the respective degrees (with $s^{\mathrm{pri}} + s^{\mathrm{sec}} + s^{\mathrm{ter}} = 1$), "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.

For intuition, consider the example of US immigrants from South Africa, 81.6 percent of whom had a tertiary education. By contrast, only 10 percent of those residing in South Africa itself had a tertiary education. In line with this, the 6 percent of South African immigrants with just a primary education are drawn from the 42 percent of South Africans with just a primary education. Seen from the perspective of the United States, 81.6 percent of immigrants thus fall in the 90th–100th percentile of the South African attainment distribution, and 6 percent fall in the 0th–42nd percentile. Using the selectivity estimate in equation (3), we can calculate that the average South African immigrant comes from the 87th percentile of the attainment distribution of South Africa. While immigrants from Niger and Kenya come almost entirely college educated—only 0.5 and 1.2 percent of the home country populations, respectively—the selectivity falls for US neighbors. Selectivity on attainment is just 0.46 for Mexico and 0.53 for Canada.

But there is ample evidence that selectivity can also be very strong within educational-degree categories (e.g., Parey et al. 2017), implying that the selectivity on school attainment may not itself be an appropriate estimate of selectivity in terms of cognitive skills. 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, which would 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 upward, using the country-specific measure of attainment selection; that is, we use the attainment selection parameter p to indicate where in the gap between p and perfect selectivity we find the percentile of the cognitive-skill distribution for the average immigrant. In the prior example, instead of assigning the average South African immigrant to the United States the 87th percentile, to recognize the further selectivity of skills, the selectivity parameter for the skill distribution is estimated at $0.87 + 0.87 \times (1 - 0.87)$, that is, the 98th percentile. The average immigrant from Mexico is estimated to be at the 71st percentile of the home-country skill distribution and that from Canada at the 77th percentile of the home-country distribution.

For calculating the knowledge capital of each state's workers, these estimates of average cognitive skills vary both with the skill distribution in each sending country and with 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, an immigrant from a generally poorly performing country may still be better performing than the typical native-born American, whereas Mexican immigrants are substantially behind native-born Americans as they are drawn from lower in a poor home-country skill distribution.[23] While we cannot make any adjustments for possible changes in the distribution of skills over time for immigrants of any country, we can incorporate the complete cross-sectional information.

D. Net Impact of Interstate and International Migration

When we calculate the knowledge capital of each state, we can see substantial differences in the overall impact on state labor forces compared to the skills just of state natives.[24] In 2010, the skills of workers educated locally and of those educated elsewhere vary considerably by state. 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.

[23] The full skill measure with the various adjustments for selectivity is reported in Hanushek et al. (2017).

[24] Detailed descriptions of the state differences in the components of the labor force can be found in Hanushek et al. (2017).

A total of 26 states see net gains in knowledge capital when compared to that available just from home-grown workers. 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 (see Hanushek et al. 2017).

IV. Growth Models across US States

The measures of knowledge capital are designed to index relative differences in skills for the workers of each state. They employ a consistent test-based method for equating the skills of the heterogeneous adult populations of workforce age found in the different states. Without attempting to decompose the causes for differences in skills, the knowledge capital measures are constructed to aggregate the various factors affecting individual skills—school quality, family background, health differences, or what-have-you. We rely on variants of the knowledge capital measures for estimation of growth models. This approach, in turn, is motivated by existing international growth models but applied to economic differences across US states. In this estimation, we show the importance of such more accurate estimates of the human capital stock of each state.

Looking across states is obviously different from the international comparisons that motivate this growth analysis. Cross-country analyses introduce assumptions that all countries are operating on the same production function—even though GDP per capita in Uganda is only one-thirtieth that in the United States. Because the US states can be more readily presumed to be operating on the same production function, it is more natural to look at how human capital and other input differences affect state incomes. At the same time, one might expect interstate movement of people and of capital to erode differences in economic advantages, making it more difficult to extract the impact of worker skills.

In this analysis, we focus on the state differences in average annual growth rate (g_s) in real per capita state GDP for the period 1970–2010.[25]

[25] Real state GDP per capita of each state is constructed by following the approach of Peri (2012), using nominal GDP data at the state level from the Bureau of Economic Analysis (2013*b*). Nominal GDP is deflated to the base year 2005 by the nationwide implicit GDP price deflator (Bureau of Economic Analysis 2013*c*). For real GDP per capita, we divide total real GDP by total population from the Bureau of Economic Analysis (2013*a*). We do consider the sensitivity of our estimates to alternative growth periods beginning in 1990 or in 2000. We believe that the long-run growth differences from starting in 1970 give a better starting point for our subsequent long-run projections, but shorter, more recent periods give higher estimates for the impact of knowledge capital, implying that we are providing conservative projections.

The basic growth model is

$$g_s = \gamma_0 + \gamma_1 \hat{T}_s + \gamma_2 S_s + \boldsymbol{X}_s \boldsymbol{\delta} + \varepsilon_s, \tag{4}$$

where $\hat{T}_s$ is the specific measure of the test scores of the adult population (estimated in varying ways) for state s in 1970, S_s the average school attainment in state s in 1970,[26] $\boldsymbol{X}_s$ is a matrix of various state controls for state s, and ε_s is an error term. In the basic estimation, $\boldsymbol{X}_s$ includes the log of the initial level of GDP per capita in 1970[27] and the log of physical capital per worker.[28] Our state sample for the growth analysis refers to 47 states. Alaska, Delaware, and Wyoming are excluded from the analysis because of their GDPs' dependence on natural resources or finance.[29] (In the later projections, we include all states.) Table A1 provides descriptive statistics.

Table 1 provides estimates of our state growth model that utilize progressively more refined measures of the knowledge capital of each state. By way of comparison, column 1 provides the simple growth model based just on school attainment as the measure of human capital. Without regard for quality, school attainment is significantly related to state growth rates. Nonetheless, these estimates are quite misleading, and any trace of the impact of pure school attainment disappears when the measures of knowledge capital are included.

The remaining columns investigate the alternative test measures of the knowledge capital in each state. Column 2 employs average test scores with no adjustment for interstate migration or immigration, a measure that we believe is quite imperfect. But even such an imperfect measure has a strong and statistically significant relationship with state growth, and the explained variance in growth rates increases from 0.23 with just school attainment to 0.39.

We then employ our crudest adjustment for the scores of interstate migrants between US states (col. 3). This adjustment brings us closer to our preferred adjustment, but it ignores the selectivity on internal migration, along with the character of international immigration to each state.

Column 4 introduces our preferred measure of a state's cognitive skills that adjusts the internal US migrants for selectivity based on education

[26] 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 20–65 not currently in school. The transformation of educational degrees into years of schooling follows Jaeger (1997). Because of their relatively weak labor market performance (Heckman, Humphries, and Mader 2011), GED (general education diploma) holders are assigned 10 years of schooling.

[27] Following standard growth estimation from international analyses, we include the initial level of GDP per capita to reflect the possibility of (conditional) catch-up; that is, states beginning behind in output can grow faster simply by copying what more advanced states do (see Hanushek and Woessmann 2015*a*). For the projections below, the inclusion of the log of initial income permits consideration of both endogenous growth and augmented neoclassical models.

[28] Data on physical capital per worker in 1970 are provided in Turner et al. (2013).

[29] See Hanushek et al. (2017) for details of the state industrial distribution. Washington, DC, is also excluded not only for the impossibility of estimating its knowledge capital but also because it is almost certainly operating on a different production function.

TABLE 1

State Growth Regressions with Knowledge Capital, 1970–2010

	(1)	(2)	(3)	(4)	(5)	Population weighted (6)
Knowledge capital measure (1970 adult population)						
Average state test score		1.010***				
		(.313)				
Adjusted for nonselective interstate migration			1.263***			
			(.450)			
Adjusted for selective interstate and international migration				1.427**	1.141**	1.314**
				(.556)	(.531)	(.558)
Initial years of schooling (1970)	.146*	−.129	−.140	−.179	.136	.073
	(.083)	(.110)	(.127)	(.146)	(.173)	(.234)
Log (initial physical capital per worker) (1970)	−.209	.369	.297	.133	.523	.275
	(.313)	(.397)	(.402)	(.365)	(.395)	(.380)
Log (initial GDP per capita) (1970)	−1.108**	−1.040**	−1.067***	−1.129***	−1.440***	−1.028**
	(.474)	(.391)	(.394)	(.398)	(.408)	(.482)
Census region fixed effects	No	No	No	No	Yes	Yes
Constant	13.715***	4.250	4.211	6.640*	3.149	1.855
	(3.314)	(3.562)	(3.999)	(3.418)	(3.108)	(3.055)
Number of states	47	47	47	47	47	47
R^2	.235	.392	.360	.348	.489	.491

Note.—Dependent variable: average annual growth rate in GDP per capita, 1970–2010. Average state test score: estimated average NAEP test score for the state over all available years (1992–2011) in eighth-grade math. Adjusted for nonselective interstate migration: average state test score adjusted by assigning interstate migrants the mean test score of their state of birth. Adjusted for selective interstate and international migration: test score assigns all US-born people the average test score of their state of birth by educational level (high school or less vs. at least some college education) and international migrants the selectivity-adjusted home-country test score. In all adjustments, state population shares for the year 1970 are used to weight the different test scores. Column 6: observations are weighted by state population in 1970. Robust standard errors are in parentheses.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

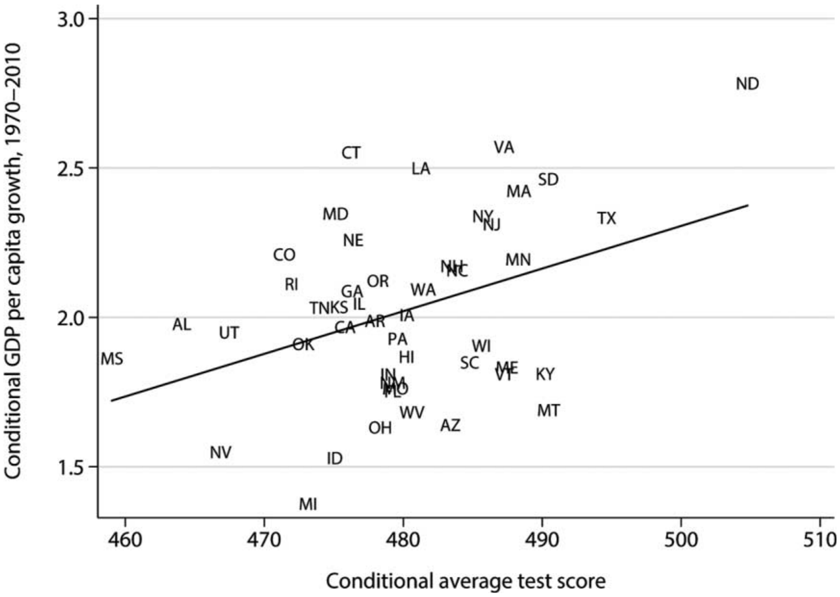

Figure 1.—Test scores and economic growth across US states. Added-variable plot of a regression of the average annual rate of growth (in percent) of real GDP per capita in 1970–2010 on the initial level of (log) real GDP per capita in 1970, average test scores adjusted for interstate migrants by education and for international migrants by the selectivity-adjusted home-country test score (weighted by the adult population in 1970), average years of schooling in 1970, and (log) real physical capital per worker in 1970 (mean of the unconditional variables added to each axis).

levels and introduces the quality of the immigrants into each state on the basis of our estimated selectivity from the cognitive-skill distribution for their home country.[30] The results of this basic specification indicate a clear and significant relationship between growth and knowledge capital, after initial (1970) state GDP, the 1970 capital stock, and school attainment in the state in 1970 are controlled for. Importantly, once there is a measure of the quality of workforce skills, years of schooling—the simple but standard measure of human capital—is statistically insignificant and even has a negative point estimate. The results indicate that a one-standard-deviation increase in scores, from whatever source, is associated with a 1.43-percentage-point-faster annual growth of state GDP per capita over the past four decades. Figure 1 shows the relationship between this test score measure and the growth in GDP per capita (net of initial levels of GDP per capita in 1970, average years of schooling in 1970, and real physical capital per worker in 1970) graphically.

These estimates are descriptive of how the patterns of growth rates follow the knowledge capital of the states. It is difficult to develop any con-

[30] Note that the R^2 falls slightly between columns 2 and 4, which might reflect increased error in the measurement of knowledge capital. We do not believe that these changes can be easily interpreted. Similarly, the pattern of estimates across columns, with insignificant changes in magnitudes, is difficult to ascribe to any particular underlying cause.

vincing approach to establish the causality of these estimates. The states are thoroughly interconnected in terms of school policies, movement of capital and labor, spending patterns, and the like. Likewise, states with higher growth potential may attract higher-skilled migrants, raising issues of endogenous movements. It is difficult to identify clearly independent variation in knowledge capital across states on which to base the estimation of the growth models. These issues of potential bias from omitted variables lead us to investigate some alternative specifications and estimation approaches.

As an overall attempt to incorporate general development patterns, such as cultural and institutional differences, that might be spatially correlated, we include census-region fixed effects in column 5. This reduces the magnitude of the estimated coefficient on knowledge capital to 1.14, but it remains highly significant. Further, in order to ensure that small states do not unduly affect the estimates, we weight the estimates by the 1970 state population in column 6. This estimation produces our primary estimate of 1.314 that is used in the subsequent growth projections; that is, the results indicate that a one-standard-deviation increase in scores, from whatever source, is associated with a 1.31-percentage-point-faster annual growth of state GDP per capita over the past four decades.

These extensions, of course, do not take care of all concerns about potential contaminants of the estimates. One specific concern comes from simple reverse causation—faster growth from whatever source provides the state with added resources that can be used to improve the schools.[31] A straightforward investigation of this issue in the context of the estimated growth models, however, does not suggest that this is driving our estimates. Table 2 shows the basic growth model estimated for growth between 1990 and 2010. The first column uses all 47 states and relates growth to our adjusted test score measure, using the baseline specification in column 6 of table 1. For this more recent and shorter period, the impact of adjusted test scores is estimated to be even larger: 1.53, as compared to 1.31. The second column uses just the state test score for 1992 (in the sample of 39 states for which 1992 scores are available). The estimate of 1.33 is virtually identical to the estimated test impact over the full growth period (which uses the contemporaneous test measures of concern).

A second potential bias comes from that lack of early NAEP data for the states, implying that there might be systematic measurement error for older workers. To provide some evidence on this, we estimated individual-level earnings functions that explain differences in gross hourly wages for 2010 on the basis of schooling, sex, potential experience and experience

[31] There is a large and contentious debate about the impact of added funding on student outcomes that goes beyond the scope of this paper. If, however, changes in NAEP scores of states from 1992–2011 are compared to increases in real spending per pupil over the period, there is no significant relationship (Hanushek, Peterson, and Woessmann 2012*a*, 2012*b*).

TABLE 2
STATE GROWTH REGRESSIONS WITH KNOWLEDGE CAPITAL, 1990–2010

	(1)	(2)
Knowledge capital measure adjusted for selective interstate and international migration (1990 adult population)	1.526**	
	(.639)	
State test score (1992)		1.331***
		(.425)
Initial years of schooling (1990)	.271	−.045
	(.177)	(.177)
Log (initial physical capital per worker) (1990)	1.242***	1.320**
	(.455)	(.582)
Log (initial GDP per capita) (1990)	−2.402***	−1.629**
	(.482)	(.669)
Census region fixed effects	Yes	Yes
Constant	.746	−2.651
	(3.020)	(3.191)
Number of states	47	39
R^2	.387	.498

Note.—Dependent variable: average annual growth rate in GDP per capita, 1990–2010. Knowledge capital measure adjusted for selective interstate and international migration: test score assigns all US-born people the average test score of their state of birth by educational level (high school or less vs. at least some college education) and international migrants the average selectivity-adjusted home-country test score. State population shares for the year 1990 are used to weight the different test scores. State test score: NAEP test score for the state in eighth-grade math. Observations are weighted by state population in 1990. Robust standard errors are in parentheses.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

squared, state-of-residence fixed effects, and our state-level test score measure for individuals based on state or country of birth.[32] First, test scores are highly significant in this augmented Mincer equation. Second, while there are small differences between test score effects for those workers less than 40 years old (for which state NAEP data exist) and those for workers over 40 (for which state NAEP data do not exist), the estimates are quantitatively very similar.[33] These estimates provide suggestive evidence that the assumed stability of state test scores over time is not a major issue.

We have done further explorations of other potential influences on growth, including incorporating information about labor force participation differences across states and measures of family structure, but they have modest impact on our estimated impact of knowledge capital. In addition, in the growth projections below, we analyze the sensitivity to alternative estimates of the impact of knowledge capital, including the range of estimates in table 1.

Two aspects of the work on international growth patterns that motivated this state-level analysis are also relevant. First, the international

[32] We thank an anonymous referee for this suggested test.
[33] The estimated test coefficient for the pooled sample is 0.075, that for the less-than-40 sample is 0.081, and that for the over-40 sample is 0.064. All are statistically significant at above the 1 percent level in a sample of 892,112 observations. The age-specific coefficients are different from each other at the 5 percent level.

growth estimates of the impact of knowledge capital have been proved to be very stable and consistent across a wide variety of specification and robustness checks (Hanushek and Woessmann 2015*a*). Moreover, while not conclusive, the investigations of the identification of causal impacts have excluded most major threats to identification, including omitted measures of economic and political institutions, cultural influences, and simple reverse causation, and thus have established a prima facie case that greater knowledge capital leads to more rapid economic growth (Hanushek and Woessmann 2012, 2015*a*).[34]

Second, the preferred state growth estimate in column 6 is very close to the causally validated international estimates. The estimate of the growth parameter of 1.31 compares directly to the relevant international coefficient of 1.43.[35] Thus, the projections we provide in the next section can be interpreted alternatively as representing the best descriptive parameter estimates from the cross-state analysis or as representing what it would mean if US states followed the best international estimates (which themselves incorporate the aggregate US experiences).

V. A Basic Framework for Growth Projections

The focus of this paper is understanding what school improvement would mean for state incomes. Note that we describe changes in terms of school improvement, but—just as with the existing differentials across states—this does not imply that we think schools are the only possible source of skills. Indeed, as highlighted in equation (2), many other factors, including parents and peers, enter into achievement. We emphasize schools because they are the institution charged with developing skills and they are the input that is more readily altered by government. Nevertheless, for the projections, the precise source of the given improvement is not important.

For the projections, we assume that our baseline model of growth (col. 6 of table 1) holds into the future. By this, a one-standard-deviation improvement in skills would imply a 1.31-percentage-point-faster growth in state income in the long run.[36] Of course, a one-standard-deviation improve-

[34] The causal investigations include a series of instrumental variable estimates, of difference-in-difference estimates of US labor markets, and of analysis of how changes in knowledge capital relate to changes in growth rates. Each is subject to some specific (and different) concerns, but each reinforces the basic estimates of the impact of knowledge capital.

[35] The preferred comparison of coefficients relies on the estimates adjusted for economic institutions, since the United States already has high-quality institutions and the institutions are mostly constant across states. See the international estimates in Hanushek and Woessmann (2015*a*).

[36] One point of disagreement among macroeconomists is whether expanding knowledge capital will affect long-run growth rates or simply move the economy to higher levels of income while eventually returning to the prior long-run growth rate. Because any observed differences between the two models appear in the distant future, there has been no clear testing of the competing models. We return below to the effects of the alternative approaches on our projections.

ment in state average scores is a huge change—somewhat more than today's range across states. Therefore, we consider a range of alternative achievement goals that appear quite feasible.

An important aspect of education policy is how it affects dynamic changes over time. Education policy is not instantaneous, and it takes some time before the effects of any education policy are fully felt. We consider a series of state changes that are assumed to begin in 2015 and to occur over 10 years; that is, student achievement moves fully to higher levels only after 10 years of reform.[37] We further assume that the pace of student improvement is linear, so that 10 percent of the ultimate gain accrues each year.

Of course, improvement of students is also not the same as improvement in the labor force. The labor force improves only as new, more skilled students replace retiring, less skilled workers. We calculate how the average quality of the labor force changes by assuming that 2.5 percent of the labor force retires each year and is replaced by better-educated workers. This implies that the labor force does not fully reach its ultimate quality for 50 years (10 years of reform followed by 40 years of retirements).

We project the annual growth of each state in each year on the basis of the average quality of the labor force in each given year.[38] The projections assume that the mobility patterns across states will hold in the future but that the size of the state populations will remain constant. In other words, the mix of the workforce by state of education remains constant into the future. We look at the implications for state GDP growth over an 80-year period, reflecting the expected lifetime of somebody born today. Given the extended period of labor force reform, the largest impacts clearly appear in the more distant future. In recognition of this, we weight early gains more heavily than later gains. Specifically, we calculate present values by discounting future years at 3 percent per year (implying that gains in 2095, after 80 years, are weighted only 9 percent as heavily as initial-year gains).[39]

[37] Details of the projections are described in appendix B.

[38] As indicated above, economists have used different models to characterize long-run growth. In Section VI, instead of having growth rates directly dependent on the level of cognitive skills (endogenous growth), we also consider the possibility that growth rates depend just on the amount of change in cognitive skills (augmented neoclassical growth).

[39] A standard value of the social discount rate used in long-term projections on the sustainability of pension systems and public finance is 3 percent (e.g., Börsch-Supan 2000), a precedent that is followed here. As a practical value for the social discount rate in cost-benefit analysis (derived from an optimal-growth-rate model), Moore et al. (2004) suggest using a time-declining scale of discount rates for intergenerational projects that do not crowd out private investment, starting with 3.5 percent for years 0–50, followed by 2.5 percent for years 50–100. By contrast, the influential Stern Review report that estimates the cost of climate change uses a discount rate of only 1.4 percent, thereby giving a much higher value to future costs and benefits (Stern 2007).

With these parameter choices, we project how the GDP of each state would develop with and without the modeled reform.[40] The economic gain of each reform is then calculated as the difference in discounted future GDP between situations with and without reform. While we take into account the ability of Silicon Valley and other high-knowledge areas to attract skilled workers, we do not consider any cross-state externalities in productivity and growth (except that some states lose high achievers to other states in greater numbers). Thus, we assume that all states can grow faster if all states improve their skills. We do not, however, have any tests of this general equilibrium assumption.

Below we also show the sensitivity of the projections to different parameter choices. Appendix B describes the different steps of this projection model in detail; see also Hanushek and Woessmann (2011).

VI. Projected Economic Gains of Alternative School Improvement Programs

We provide economic calculations for various plausible state improvement scenarios. The scenarios differ in the magnitude of the improvement from reform and in the actions that other states take toward reform. In particular, the interrelationships among states through migration imply that individual state actions have a muted impact on economic growth when not accompanied by complementary actions by other states.

For perspective, between 1992 and 2011 Maryland, Florida, Delaware, and Massachusetts each were able to gain over 60 percent of a standard deviation on NAEP.[41] Our baseline reform scenario below considers an improvement of one-quarter of a standard deviation over a 10-year period. Each of the 14 most improved states was able to obtain average gains at a rate sufficient to bring scores up by this amount. (State variations in achievement growth are found in fig. A3.)

A. *Scenario I: Improvement by a Quarter of a Standard Deviation*

Our baseline economic projections consider the impact on each state of having its workers improve by one-quarter of a standard deviation. This is consistent with a variety of underlying changes: a state improves its own students by one-quarter of a standard deviation and keeps all of them in the state, a state improves its own students sufficiently to make up for the fact that some will leave, or the workers migrating into the state show the same improvement. In all three cases, the aggregate effect is

[40] The growth of the economy with the current level of skills is projected to be 1.5 percent, consistent with the projected growth in labor productivity from the Congressional Budget Office or the rough average of OECD (Organization for Economic Cooperation and Development) growth in GDP per capita over the past two decades.

[41] For a discussion of these calculations, see Hanushek et al. (2013). Note that data are available for only 41 states because not all states participated in the state-representative samples before 2003.

simply a one-quarter of a standard deviation improved score of future workers in the state. (Subsequently, we also consider the isolated improvement by each state that is not compensated for by improved immigrants.) Note that in each of these cases, the gain in GDP would constitute a true gain in GDP for the United States. If, by contrast, a state would improve its knowledge capital just by attracting better-educated workers from other states, the GDP gains would come at the expense of the losing states, and aggregate US GDP would not improve.

One-quarter of a standard deviation does not have much natural appeal, but it can be interpreted readily from the current state distribution of NAEP scores (eighth-grade math in 2015). A gain of one-quarter of a standard deviation implies that the lowest-ranked state (Alabama) would move up to being forty-first in the ranking (currently California). Or, alternatively, one-quarter of a standard deviations would move the eighth-ranked state (Virginia) to the top.

This improvement translates into a uniform gain across states of a 0.33-percentage-point-faster growth rate in the long run (i.e., $1.31 \times 0.25 = 0.33$). This improvement, while seemingly modest, yields future increases in state GDP that have a present value of 2.4 times the current state GDP. There are a variety of ways to understand this, but it effectively amounts to a level increase of (discounted) GDP of 5.2 percent on average—considerably above the current total spending on education across the states. By the end of our projection period (2095), state GDP would be 20 percent above that expected with the current level of achievement in each state.

The absolute magnitude of the increase of course depends on the size of the state. (Individual state projections are found in table B1; tables B1–B5, E1, and E2 are available online.) Because California's economy is the largest, it would see a present value of reform of some $5.6 trillion. New York would see gains of almost $3.4 trillion.

It is important, however, to understand the time path of these gains. Figure 2 displays the time path of increases in aggregate GDP compared to the GDP expected without improvements in knowledge capital. Gains are initially small, reflecting the time required to improve the schools and the absorption of higher-skilled people into the labor force. The quality of the labor force is actually continually increasing until 2065 after a reform program begun in 2015. By 2050, this reform program would lead to GDP gains that exceeded the 4 percent currently devoted to total US expenditure on K–12 schools. Nevertheless, this figure illustrates the underlying fact that education reform, while ultimately very powerful, according to past economic impacts, requires patience as the economy adjusts to higher-skilled workers.

B. *Scenario II: Improvement to Top-Performing State*

An alternative reform would be bringing each state up to the level of the best state over the past two decades: Minnesota. This improvement clearly

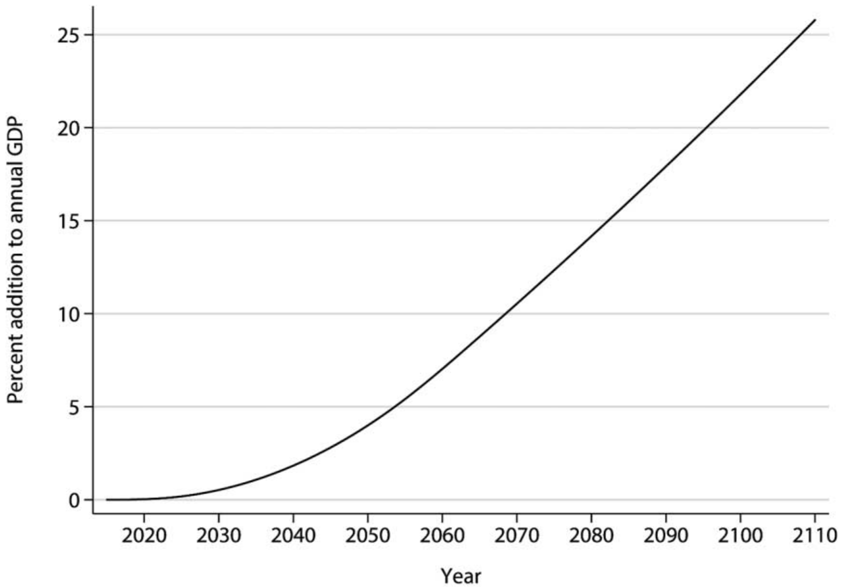

Figure 2.—Time path of percentage increases in aggregate GDP due to educational reform. The figure displays the predicted time path of increases in aggregate GDP as percentage gains in annual GDP due to an educational reform that increases test scores of all states by a quarter of a standard deviation.

has varying impacts, depending on how far each state is from Minnesota. Minnesota, by this scenario, stays the same, and another 20 states have gains of less than the baseline scenario of 0.25 standard deviations. (See table B2 and fig. 4.) Nonetheless, the overall improvement for the nation is larger than that for the baseline scenario by 50 percent.

Again, this scenario is meant to match a feasible scenario where the schools across the nation are sufficient to bring up all students to high standards. Of course, since the schools are not the only factor in achievement, this requires that the schools in states with more disadvantaged populations to improve even more than those with less disadvantaged populations.

The average growth improvement in the long run for the United States would be one-half of a percentage point higher with this improvement than with current skill levels. The overall present value of gain is almost four times current US GDP—or the equivalent of an average increase of 8.3 percent over the next 80 years.

But there is considerable heterogeneity of the effects of such a reform across US states. States that perform close to the level of Minnesota, such as North Dakota, Massachusetts, and Montana, would see relatively modest economic gains of 1.3 percent of discounted future GDP, on average. By contrast, states whose performance is rather distant from that of the top-performing state, such as Mississippi, Alabama, Louisiana, New Mexico, Hawaii, and California (as well as the District of Columbia), would all see gains that exceed 14 percent of discounted future GDP on average—or more than six times their current GDP. Obviously, however, having the lowest-performing states move to equal the best-performing within 10 years is a very ambitious, and perhaps unrealistic, scenario.

C. Scenario III: Improvement to Best State in the Region

The ambitiousness of the prior scenario is documented by the fact that the seven enumerated states would have to improve by more than 0.6 standard deviations. This is the rate of improvement seen by Maryland, the fastest-improving state over the past two decades—feasible but difficult in 20 years and likely unattainable in 10 years.

Therefore, we next consider a more modest scenario where each state improves to the level of the best state in its division.[42] The largest required improvements (except for Washington, DC) are now New Mexico (0.6 standard deviations) and Nevada (0.5 standard deviations), to rise to the level of the State of Washington. The overall average improvement in worker skills is now 0.18 standard deviations for the nation.

This more modest improvement in worker skills still implies a present value of improved GDP that averages almost twice current GDP over 80 years (table B3). This gain is 4 percent of discounted future GDP, but, as pointed out, the gains are back-loaded.

Again, the projected reform gains vary greatly across states. States such as New Mexico, Nevada, Hawaii, California, Rhode Island, and Arizona (and Washington, DC) would gain more than four times their current GDP, whereas by construction all nine division leaders would see no improvement in achievement and thus no economic gain.

D. Scenario IV: Getting Every Student at Least to the Basic Level

The prior scenarios imagine improvements across the full range of schooling. An alternative, which is essentially a more limited variant of No Child Left Behind (NCLB), is to bring all students (and subsequent workers) at least up to the "basic skill level" as defined by NAEP (for calculations, see app. C). According to NAEP, the basic level implies "partial mastery of prerequisite knowledge and skills that are fundamental for proficient work at each grade."[43] In 2011, 27 percent of students in the United States fell

[42] The division leaders in achievement are Wisconsin (East North Central), Kentucky (East South Central), New Jersey (Mid-Atlantic), Montana (Mountain), Massachusetts (New England), Washington (Pacific), Virginia (South Atlantic), Minnesota (West North Central), and Texas (West South Central).

[43] See https://nces.ed.gov/nationsreportcard/achievement.aspx, accessed April 18, 2015. Note that there is confusion about various achievement levels. The NAEP basic level corresponds roughly to the achievement level that the average state chose to define as proficient under the federal NCLB Act (Hanushek and Lindseth 2009). The PISA achievement level 1 used in international projections is quite close to the NAEP basic level (Hanushek and Woessmann 2015*b*).

below the basic level. Implemented across the United States, this reform would raise average achievement by 17 percent of a standard deviation.

Note, however, that this projection is a rather artificial policy change, because it assumes no spillovers in quality to anybody starting with basic or above achievement. Not only is it difficult to understand what kind of policies might produce such a pattern of gains, but it also does not match historical evidence across the NCLB era (Hanushek et al. 2013).

One thing that this policy does promise is more inclusive growth. Specifically, it is designed to bring up those with the lowest skill levels—just the group that has found it increasingly difficult to participate effectively in the labor market. Given the strong relationship between skills and individual earnings in the US economy (Hanushek et al. 2015), enhancing the skills at the bottom would have a noticeable impact on the distribution of earnings, and ultimately income, in the United States.

In terms of aggregate income, this reform would raise the level of future GDP by 3.5 percent on average (table B4). In 2095, GDP would be 15 percent higher than without the reform. Some states with few current students falling below the basic level, such as North Dakota, Massachusetts, Minnesota, South Dakota, Montana, Texas, and New Hampshire, would see reform gains that are somewhat less than their current GDP (fig. 3). But some other states with large numbers of students below the basic level, such as California, Alabama, and Mississippi (as well as the District of Columbia), would see gains of almost three times their current GDP.

E. *Scenario with Single-State Improvement and Out-Migration*

The prior estimates provided a picture of the results of simultaneous improvement of schools across the states. As a result, any locally educated student who subsequently moves to another state is replaced by a student who has been on a similar path of skill improvement. What would it mean for each state to be the only improving state?

The implications of this alternative scenario are easiest to see in terms of the baseline projections of scenario II—all states improve up to the level of the best state. But now on a state-by-state basis, we assume that educational improvement applies just to the students who are both educated in the state and remain in the state. In other words, the quality of education for in-migrants does not improve. We also assume that the historical proportion of students educated within each state that migrated out continues to be the same in the future. At the extremes, only 23.1 percent of the people born in Texas migrated out and are no longer living in the state, but as many as 64.5 percent of the people born in Alaska migrated out (see fig. A2).[44] Other states where more than half of the peo-

[44] Note that because of changes in the size of the state population, the share of the state-born population that still lives in the state can differ markedly from the share of the current state population that was born in the state (as depicted in fig. A2). For example, Texas has

ple born in the state migrated out are Wyoming, North and South Dakota, Montana, and Nevada.

Given these historical rates of interstate mobility, the skill increase of the workforce that is ultimately seen in each state is 0.24 standard deviations on average, instead of 0.38 standard deviations when all states are moving to the level of the best state. As a result, the gains for each state fall, on average, from four times current GDP to, on average, 2.4 times.

But the specific difference for each individual state is very important, because it shows how the incentives change when states operate in their own local interest (table B5). This difference varies greatly across states (fig. 4). In states such as Texas, North Carolina, Georgia, Wisconsin, Minnesota, South Carolina, and Tennessee, with relatively little out-migration, results are not much affected. By contrast, in states with substantial out-migration, such as Alaska and Wyoming, results decline dramatically.

To be sure, the more skilled workers that migrate out of state will help the economy in other states to which they move. It is just that the state making the investment sees a noticeably smaller economic improvement if the state is the only reformer. And this presumably lessens the interest in school investment for each state.

F. Alternative Parameter Choices

The projections obviously depend on the specific model and parameter assumptions. The rows of table 3 present summaries of how varying parameter choices affect the estimates of the aggregate economic gains as variants of scenario I. Given that the growth coefficient is estimated with some statistical uncertainty, including potential issues of identification of the precise causal impact, the first two rows use the alternative growth estimates from columns 4 and 5 of table 1 that do not include region fixed effects and do not weight by state populations, respectively (point estimates of 1.4 and 1.1, respectively, rather than 1.3). This leads to somewhat larger and smaller projection values, respectively. Alternatively, the next two rows report results when using a growth coefficient that is greater or smaller by 1 standard error of the baseline coefficient estimate in column 6 of table 1. That is, the growth coefficient is taken at 1.87 and 0.76, respectively, as opposed to the best estimate of 1.31. While this obviously affects the projection results, the lower estimate still produces an increase in the level of GDP of 2.9 percent.

In figure 2, we showed the time path of GDP growth. We calculated the present value of gains over an 80-year period, the life expectancy of somebody born at the beginning of the reform period. Shortening the time

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the lowest rate of out-migration as a share of the state-born population but is a middling state in terms of the share of the current population born in the state. By contrast, Nevada has the lowest fraction of the current population born in the state but not the highest share of out-migration.

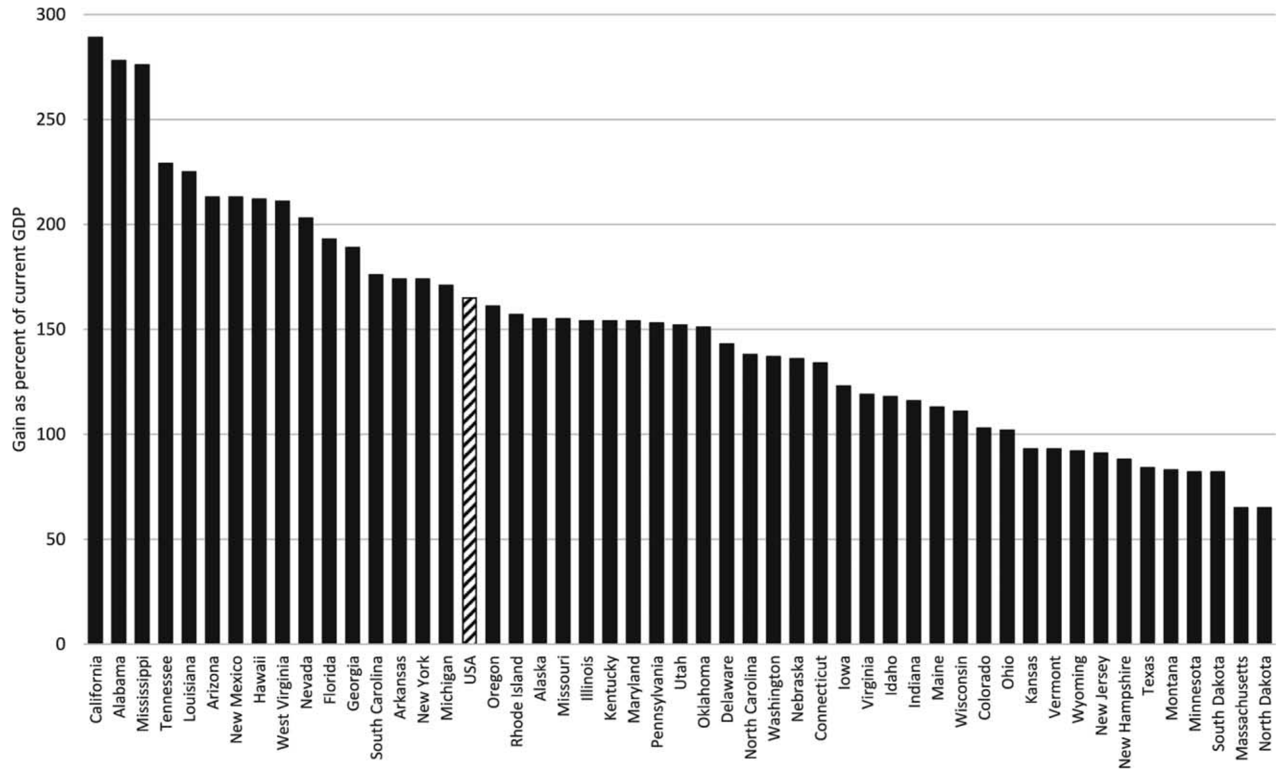

Figure 3.—Effect on GDP of scenario IV: getting every student at least to the basic level. Present value of future increases in GDP until 2095 due to a reform that brings each student at least to the basic level, expressed as a percentage of current GDP. See table B4, available online, for details. Washington, DC (469 percent), is missing for expositional purposes.

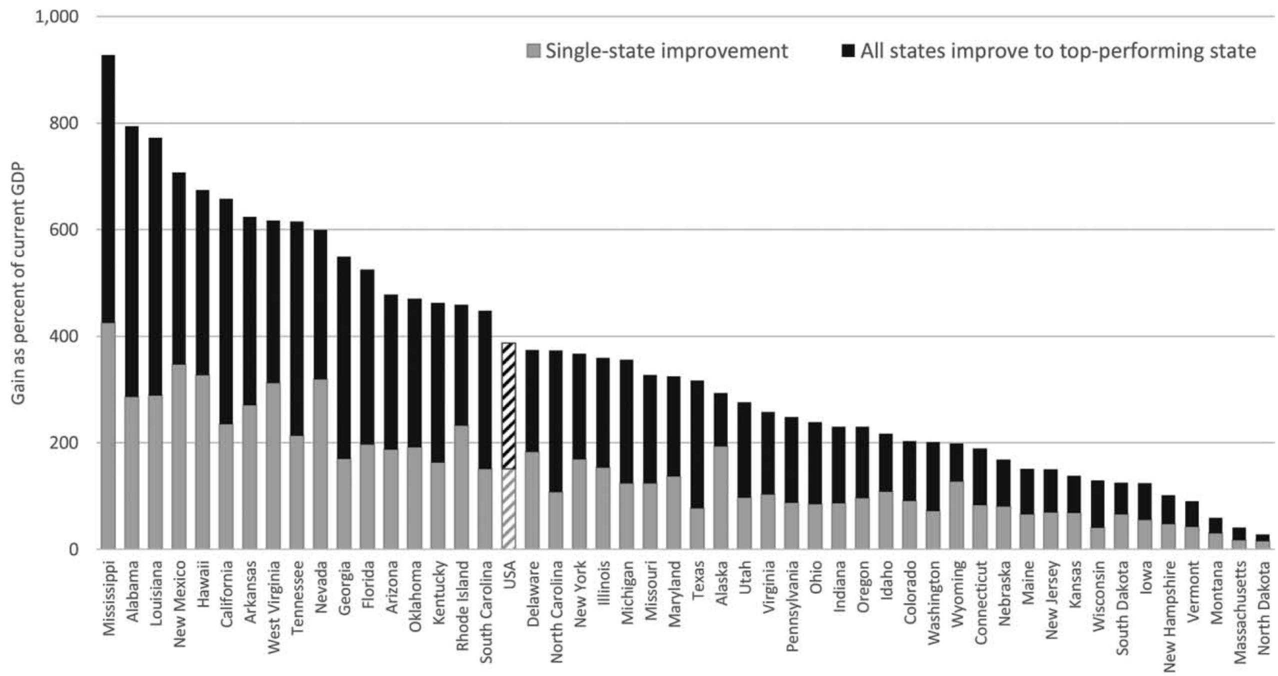

Figure 4.—Difference in the effect on GDP between individual and joint state reform (scenario II). The figure shows the present value of the reform in percent of current GDP when all states improve to the level of the top-performing state (Minnesota) and when each state improves individually (light parts of the bars). Washington, DC (167 percent for single-state improvement, 1,537 percent for all-states improvement), is missing for expositional purposes.

TABLE 3
Alternative Models and Parameter Choices

	Value of Reform (bn $)	% of Current GDP	% of Discounted Future GDP	% GDP Increase in Year 2095	Long-Run Growth Increase
Baseline model	43,561	242	5.2	19.8	.33
Baseline model: table 1, col. 4	47,552	264	5.6	21.7	.36
Baseline model: table 1, col. 5	37,575	209	4.5	17.0	.29
Growth coefficient + 1 standard error	63,582	353	7.6	29.4	.47
Growth coefficient − 1 standard error	24,429	136	2.9	10.9	.19
Time horizon: until 2055	7,763	43	1.4		.33
Time horizon: until 2075	22,931	127	3.2		.33
Reform duration: 20 years	35,894	199	4.3	17.9	.33
Discount rate: 2 percent	76,762	426	6.5	19.8	.33
Discount rate: 4 percent	25,478	141	4.1	19.8	.33
Neoclassical growth model	39,485	219	4.4	14.7	.00

Note.—Effect on GDP of scenario I (improvement by one-quarter of a standard deviation). Present value of future increases in GDP until 2095 due to reform is expressed in billions of 2015 dollars, as a percentage of current GDP, and as a percentage of discounted future GDP. “GDP Increase in year 2095” indicates by how much the GDP in 2095 is higher as a result of the reform. “Long-Run Growth Increase” refers to increase in annual growth rate (in percentage points) once the whole labor force has reached higher level of educational achievement. “Increase in NAEP Score” refers to the ultimate increase in educational achievement due to the reform. See text for parameters of the projection model.

horizon from 2095 to 2075 reduces the overall gain by nearly half, indicating that the strongest gains accrue once the reform has reached the whole labor force. With a time horizon of 2055, the gain in the level of GDP is just 1.4 percent, underscoring the fact that education is a long-run investment and cannot be expected to alter economies immediately.

Assuming that the educational reform takes 20 years rather than 10 years reduces the overall gains by 18 percent. The next two rows use discount rates of 2 and 4 percent, respectively, rather than the 3 percent of the baseline model. This parameter variation obviously has a substantial effect on the projected economic value of improvement, reflecting the long period of payback to educational investments. With these alternatives, the average increase in the level of GDP ranges from 4.1 to 6.5 percent.

Finally, as noted, economists have debated the correct way to specify the growth model. The leading alternative describes human capital as affecting the level of income instead of its growth rate, as assumed here (see app. D). In this neoclassical projection, where GDP is described as a standard production function in terms of capital and labor but augmented by human capital, increasing human capital lifts the level of GDP while moving from one steady state to another. But growth eventually returns to its prior level. It is possible to provide projections of this neoclassical alternative by incorporating the estimated convergence in growth implied by the coefficient on initial income found in table 1. This alternative reduces the present value of gains by just 9 percent, reflecting the slow convergence that mirrors what has been found in international estimates (Mankiw et al. 1992).

G. *Overall Summary and Extension*

We have presented a wide range of improvement scenarios. Table 4 provides an overall summary of the aggregate effects. The overall effects of the various scenarios for the United States as a whole range in present value from $30 trillion for bringing just the lowest-performing students up to a basic level to $70 trillion for bringing all states up to the level of the best-performing state. Compared to the level of expected GDP without skill improvement, this would be an average improvement of 3.5–10 percent.

TABLE 4
Summary of Results for the Different Scenarios of School Improvement

	Value of Reform (bn $)	% of Current GDP	% of Discounted Future GDP	% GDP Increase in Year 2095	Long-Run Growth Increase	Increase in NAEP Score
Scenario I: .25 standard deviation improvement	43,561	242	5.2	19.8	.33	.25
Scenario II: top-performing state	69.697	387	8.3	32.9	.50	.38
		(278)	(6.0)	(25.8)	(.32)	(.24)
Scenario III: best state in region	32,810	182	3.9	15.2	.24	.18
		(191)	(4.1)	(16.0)	(.25)	(.19)
Scenario IV: basic skill level	29,738	165	3.5	13.4	.23	.17
		(71)	(1.5)	(6.0)	(.09)	(.07)
Scenario II with single-state improvement	42,469	236	5.0	19.5	.32	.24
		(134)	(2.9)	(11.3)	(.17)	(.13)
Improvement to Canadian level	70,952	394	8.4	33.6	.51	.39
		(279)	(6.0)	(25.9)	(.32)	(.24)
Improvement to Finnish level	81,405	452	9.7	38.7	.58	.44
		(285)	(6.1)	(26.9)	(.32)	(.24)

Note.—Values for the United States as a whole and unweighted standard deviation across all US states. Present value of future increases in GDP until 2095 due to reform are expressed in billions of 2015 dollars, as a percentage of current GDP, and as a percentage of discounted future GDP. “GDP Increase in Year 2095” indicates by how much GDP in 2095 is higher as a result of the reform. “Long-Run Growth Increase” refers to increase in annual growth rate (in percentage points) once the whole labor force has reached higher level of educational achievement. “Increase in NAEP Score” refers to the ultimate increase in educational achievement due to the reform. See text for parameters of the projection model. Standard deviation across states is in parentheses.

But it is also clear that the different results vary greatly across the different US states. As indicated by the large standard deviations of the reform results across the US states (reported in parentheses), some states stand to gain even more from the specific reforms, whereas other states (that are already at a higher achievement level) gain less than the modal state.

Our projections so far have stayed within the limits of feasible reform scenarios based on achievement levels and growth that have been observed inside the United States. In a final set of projections, we can recognize the possibilities for improvement that can be seen in international data (Hanushek and Woessmann 2015*b*). Two straightforward comparison groups of students are Canadian and Finnish students. Canada is an obvious comparison because of its proximity to the United States, not only geographically and culturally but also economically. Finland is included because of its demonstrated improvement in international tests, making it a top-performing country and one that the United States might try to emulate.[45]

As indicated by the bottom two entries in table 4, projections of economic growth for reaching the Canadian level are very similar to those in scenario II, because the top-performing US state over the past 20 years (Minnesota) is roughly at the level of the average Canadian student. Finnish students, however, on average achieve 6 percent of a standard deviation above Minnesota, or 44 percent of a standard deviation above the US average. The aggregate economic impact of bringing all students up to Finnish levels would be $81 trillion in present value, or roughly 10 percent of the discounted future GDP, again with substantial variation across the US states.

VII. Conclusions

Improving the quality of a state's schools is frequently justified on the basis of presumed economic impact. Prior economic research, however, provides just narrow and imprecise evidence about what impacts might be expected from any quality-enhancing policy actions, particularly in terms of state economic development.

The lack of analysis is of course easily explained, because few data have been available on the skills of a state's labor force that go beyond crude measures of school attainment levels. Moreover, given the high levels of labor mobility in the United States and the growing importance of foreign-educated workers, it is very difficult to relate quality dimensions of school outcomes to any effects on a state's labor force or economic development.

[45] The Canadian and Finnish achievement levels are taken as averages from the available international tests, rescaled to the NAEP scale in the same way as used to adjust the immigrants in our analysis in Section III.C.

This paper provides a preliminary attempt to estimate the human capital stock for each US state in a way that is consistent with current policy discussions about school quality. In particular, we have estimated the cognitive skills of the workforce in each state, on the basis of estimates of the backgrounds and schooling of workers. Assumptions about the selectivity both of within-US migration and of immigration into the United States are a crucial element that we highlight in our estimation.

To consider the linkages between schools and state economies, we estimate state growth models that are related to the knowledge capital of states. While confirming any causal interpretation of these estimates is challenging, it is interesting that they align well with estimates for cross-country growth models that have a stronger claim on causal identification.

These growth models permit explicit consideration of how policies to improve school quality might be expected to affect the future income of each state. This consideration is based on the dynamics of improving the labor force, including the time to improve the schools and the deferred impact of school improvement on the quality of the future labor force.

All of these projections must be viewed as preliminary, relying both on estimates of the knowledge capital of each state over time and on parsing the impact of knowledge capital on state growth. We subject each set of estimates to a variety of sensitivity tests, and we provide alternative estimates of the long-run impact of policy improvements.

Interestingly, even with consideration of the underlying uncertainty, the growth projections have a simple interpretation. According to past systematic patterns of growth in state GDP, there is a large economic incentive for each state to improve its schools. These incentives are substantial, even for states with large outflows of educated youth. Thus, even for states interested just in the population remaining after out-migration, the results suggest a clear economic benefit from investing in their current schools. Improved schools lead naturally to higher-skilled workforces, and the impact of skills of the workforce is clear and strong. For the nation as a whole, improvement in knowledge capital by one-quarter of a standard deviation would, according to our estimates, lead to future gains in present-value terms that lift the level of GDP by 5.2 percent over the GDP expected with no schooling improvements. Even accounting for uncertainty, such improvement exceeds the roughly 4 percent of GDP annually spent on K–12 education in the United States.

The projections of economic impact take into account the dynamics of educational investment, as the impacts of educational improvements clearly take a considerable time to be realized. Improving the performance of today's students does not lead to an improved labor force until these students have left school and entered into employment and until more-skilled workers become a significant portion of the labor force. As a result, the economic gains come in the future—beyond the normal election cycles for current politicians. But, there are clear examples where politicians take long-run actions that far exceed election cycles: actions on climate change or actions on procurement of new weapon systems for defense, for example. Long-run investments simply take time before the benefits become apparent.

Appendix A

TABLE A1
Summary State Statistics

	Mean	Standard Deviation	Minimum	Maximum
GDP per capita annual growth rate, 1970–2010 (%)	2.022	.346	1.199	3.011
Real GDP per capita, 1970 ($)	18,166	2,895	12,531	26,057
Real physical capital per worker, 1970 ($)	129,815	24,700	88,945	212,186
Years of schooling, 1970	11.08	.578	9.999	12.05
Knowledge capital measure (1970 adult population)				
Average state test score	5.005	.213	4.508	5.348
Adjusted for nonselective interstate migration	5.007	.163	4.579	5.288
Adjusted for selective interstate and international migration	4.801	.152	4.393	5.038

Note.—Data refer to 47 US states (Alaska, Delaware, and Wyoming excluded).

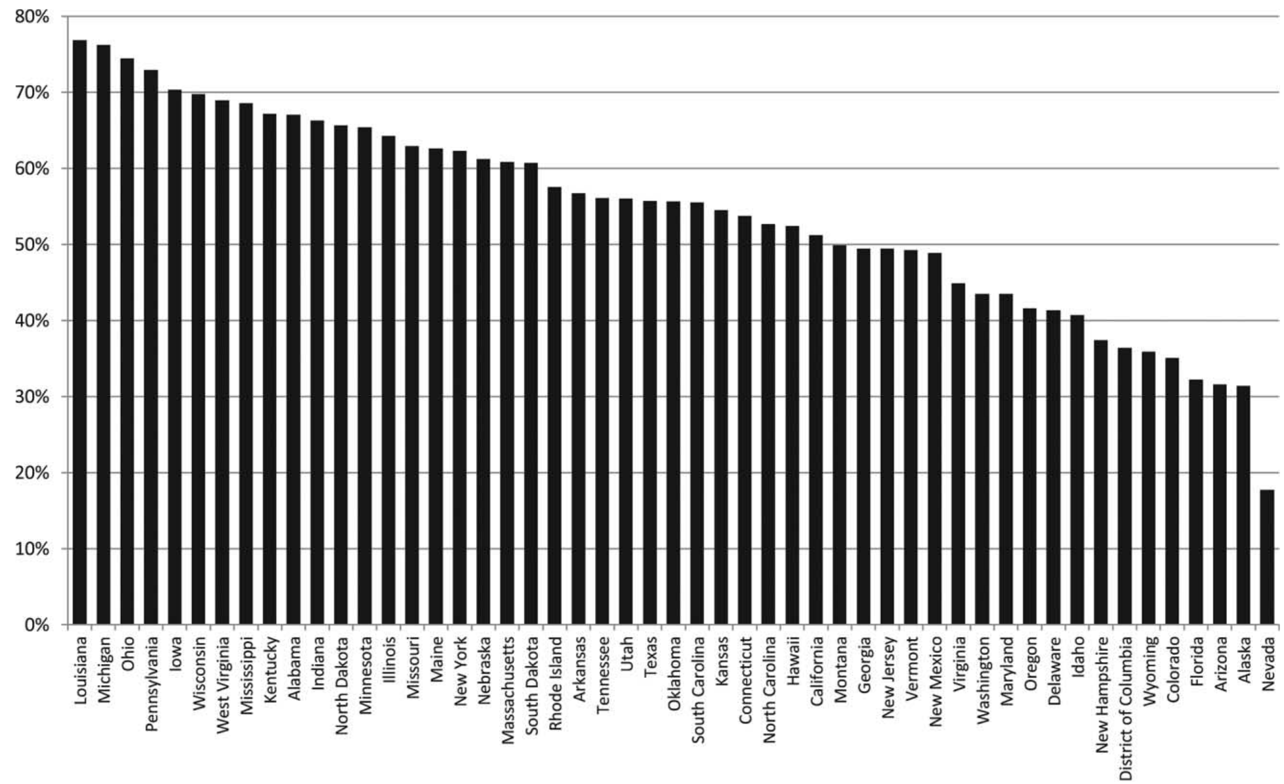

Figure A1.—Share of the current working-age population (20–65 years old) who were born in the state; three-year averages from 2010 to 2012. Source: authors' calculations based on data from the American Community Survey, taken from the IPUMS (Integrated Public Use Microdata Series; Ruggles et al. 2010).

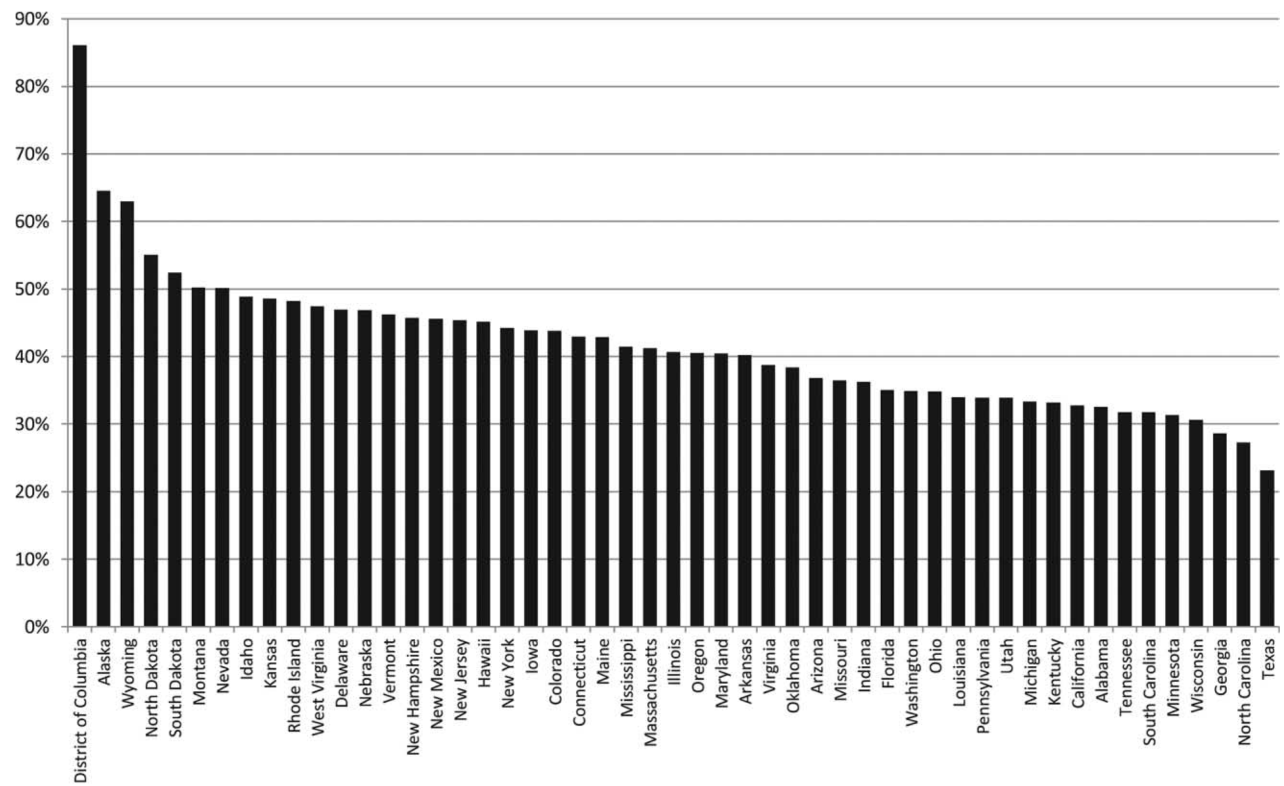

Figure A2.—Population loss rates: share of the current working-age population (20–65 years old) who were born in the state but are living in another state; three-year averages from 2010 to 2012. Source: authors' calculations based on data from the American Community Survey, taken from the IPUMS (Integrated Public Use Microdata Series; Ruggles et al. 2010).

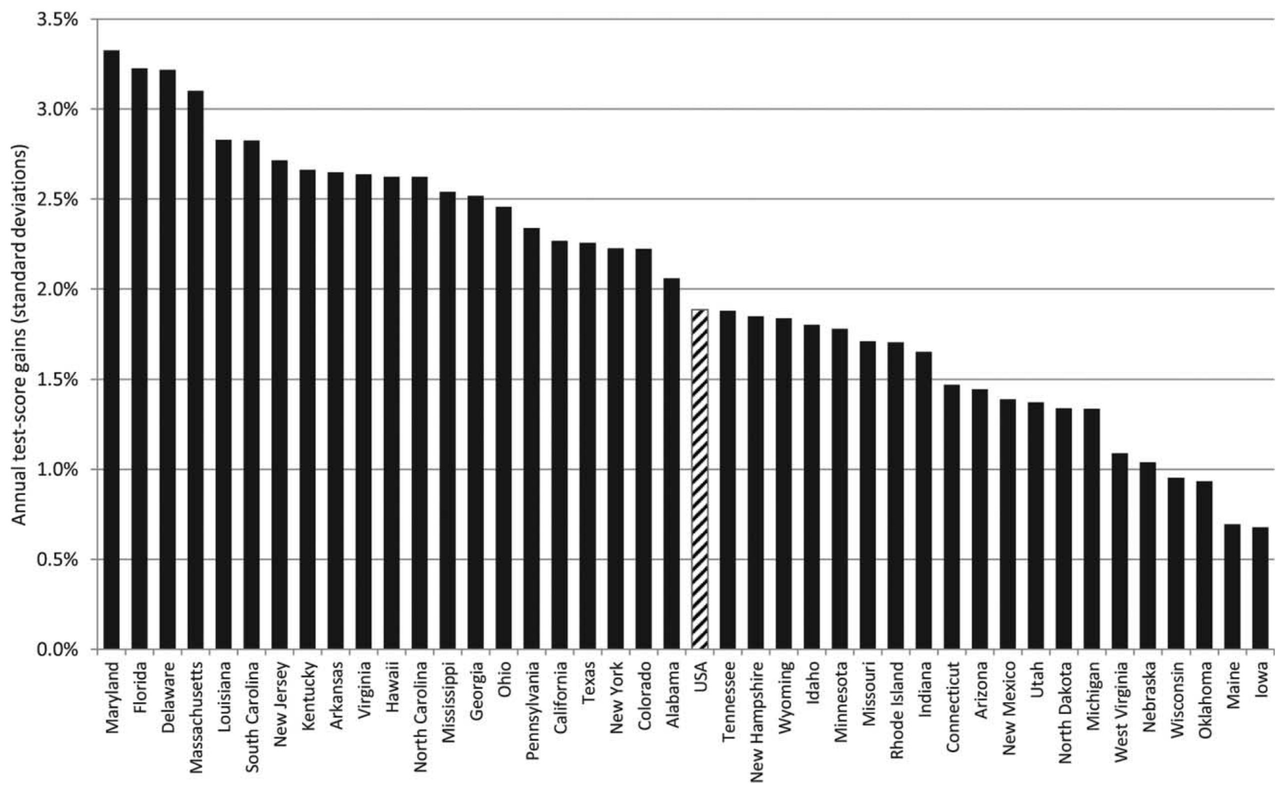

Figure A3.—Historical achievement growth, 1992–2011. Estimated average annual test score gains in percent of a standard deviation, based on NAEP achievement tests in math, reading, and science. Source: Hanushek et al. (2013).

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