Knowledge Capital and U.S. State-level Differences in Labor Productivity

Sabrina Wulff Pabilonia, Ph.D.
U.S. Bureau of Labor Statistics
2 Massachusetts Ave., NE, Rm. 2180
Washington, DC 20212
Email: Pabilonia.Sabrina@bls.gov

Susan Fleck, Ph.D.
U.S. Bureau of Labor Statistics
2 Massachusetts Ave., NE, Rm. 3955
Washington, DC 20212
Email: Fleck.Susan@bls.gov

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Abstract: Hanushek, Ruhose, and Woessmann used income measures to analyze the impact of knowledge capital on state-level economic development. Recently published experimental state-level labor productivity measures from the U.S. Bureau of Labor Statistics provide the opportunity to extend their analysis to labor productivity. We find that in 2018, 13 percent of the dispersion in labor productivity levels is attributable to variation in knowledge capital. We also find that over the post-Great Recession period (2009–2018), initial knowledge capital is positively correlated with productivity growth: increasing test scores by one standard deviation is associated with a 1.6-percentage-point-faster average annual productivity growth rate.

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I. Introduction

Human capital is an important input in economic growth. Most prior research on the contribution of human capital to cross-state or cross-country differences in growth has used years of schooling as a measure of workers' skills, yet skills clearly encompass more than schooling attainment. Recently, Hanushek, Ruhose, and Woesmann (2017b) (hereafter HRW) developed a detailed measure of state-level knowledge capital using a combination of years of schooling and achievement test scores to capture both the quantity and quality of skill investments. Their measure accounts for state-level skill differences resulting from differences in families, innate abilities, health, the quality of schools, etc. for state residents who remain in their state of birth as well as the skills for those who migrate from other states or countries.

HRW apply this knowledge capital measure in a development accounting framework to explain state-level GDP per capita differences. They present a model based on an aggregate Cobb-Douglas production function and use GDP per capita as their measure of labor productivity. Whereas GDP per capita better measures income, GDP per hour worked is by far a better measure of labor productivity. GDP per capita is influenced by fertility and mortality rates, the number of hours worked, labor force participation, and employment rates (Santacreu 2015). In a cross-country analysis, Santacreu (2015) shows that there are large differences in the relative position of countries to the United States when using GDP per capita instead of GDP per hour worked. The decomposition of GDP per capita for the total economy displayed below shows how labor productivity is related to GDP per capita:

$$\frac{GDP}{Population} = \frac{GDP}{Hours\ worked} * \frac{Hours\ worked}{Employed\ persons} * \frac{Employed\ persons}{Population} \quad (1)$$

Of the three terms on the right-hand side of the equation, the first term — labor productivity — captures technological change, capital deepening and labor composition; the second term —

hours worked per employed person — captures effort, and the final term — the employment-to-population ratio — reflects both labor force participation and employment rates. It is primarily through the effect of knowledge skills on the labor productivity term that we expect to see changes in knowledge skills impacting GDP per capita.

The current paper examines the contribution of knowledge capital to state-level labor productivity differences. We do so by replacing the outcome variable in HRW's model, GDP per capita, with an experimental state-level labor productivity measure by the U.S. Bureau of Labor Statistics (BLS) (2020).[1] While HRW's analyses are based on GDP per capita for the total economy, the new BLS output per hour worked data series cover the private nonfarm sector (PNF) and align with official U.S. national-level productivity measures.[2] The state-level output series is constructed using the U.S. Bureau of Economic Analysis's (BEA) (2020a) GDP by state and detailed industry measures. The state-level hours worked series is constructed following the methodology for BLS national-level productivity measures to the extent possible with the state-level hours data available.[3] The new BLS hours worked series begins in 2007, the year HRW's analysis ended. Thus, our analysis begins in 2007 for comparison purposes. We then provide

[1] This experimental data set can be found at: https://www.bls.gov/lpc/state-productivity.htm. BLS began producing this annual series that starts in 2007 in June 2019. The latest data was released in June 2020 and includes 2019 preliminary state-level labor productivity.

[2] The nonfarm business sector labor productivity measure is a principal federal economic indicator. The experimental state-level data series has slightly different sectoral coverage because it 1) excludes government enterprises and 2) includes nonprofits serving households. Nevertheless, the official U.S measures and sum-of-states measures trend closely (Pabilonia et al. 2019). National productivity measures exclude the general government sector and nonprofits because output measures for these sectors are measured using compensation. Thus, both output and hours for these sectors will trend similarly. The inclusion of these sectors in productivity measures may bias productivity estimates toward zero. Agricultural hours are also difficult to measure at the state level.

[3] The hours methodology for national estimates can be found at: https://www.bls.gov/lpc/lprswawhtech.pdf (U.S. Bureau of Labor Statistics 2004).

development accounting estimates for more recent years and examine the relationship between knowledge capital in 2009 and the growth in output per hour worked over the post-Great Recession period (2009–2018).[4] Given that our new measure is not a total economy measure, we slightly modify equation 1 and add two additional terms, a government/agriculture effect and a private nonfarm sector employment share, in order to show how GDP per capita is related to output per hour worked in the private nonfarm sector as shown below:

$$\frac{GDP}{Population} = \frac{GDP}{Output_{PNF}} * \frac{Output_{PNF}}{Hours\ worked_{PNF}} * \frac{Hours\ worked_{PNF}}{Employed\ persons_{PNF}} * \frac{Employed\ persons_{PNF}}{Employed\ persons} * \frac{Employed\ persons}{Population} \quad (2)$$

We find that 8–16 percent of the dispersion in the 2007 state productivity levels and 13 percent of the dispersion in the 2018 state productivity levels is attributable to state-level variation in knowledge capital. Over the period 2009–2018, we find a positive relationship between knowledge capital in 2009 and productivity growth, which can be explained by differences in state average test scores rather than years of schooling.

Section II describes the state-level labor productivity and knowledge capital measures used. Section III uses these measures in a developmental accounting framework. Section IV presents the results from growth regression models that incorporate knowledge capital. Section V concludes.

II. Data

A. State-level Labor Productivity

[4] Even though state-level labor productivity measures are available for 2019, IPUMS USA data used to construct knowledge capital is only available through 2018.

Most prior research on state-level labor productivity has used either total population or the number of employed persons as the labor input whereas this study uses hours worked as the labor input. Hours worked is the preferable labor input, because it measures time available for production. In 2007, the BLS began publishing state-level all-employee average weekly hours paid using data from its establishment survey, the Current Employment Statistics (CES); hours from a business survey in theory count the hours worked in the state where the production takes place rather than the place of residence. This new measure made it possible for BLS to construct the experimental state-level output per hour series where output and hours measures have the same geographic coverage. Hours paid are converted to hours worked using information on paid leave from the National Compensation Survey. Hours worked include those worked by wage and salary workers, unincorporated self-employed workers, and unpaid family workers.

The private nonfarm output measure is a real output series constructed from the all-private industries output measure in the BEA's GDP by state accounts and removing output for the farm sector, private households and owner-occupied housing. Although state prices differ, there are currently no state-level price deflators, so national-level industry price deflators are used. The base year for real output is 2012. Productivity measured in levels is constructed as real output divided by hours worked. Productivity growth is the percentage growth in output minus the percentage growth in hours worked. For more details on the methodology and construction of the new measure, see Pabilonia et al. (2019).

For comparison's sake in the developmental accounting analyses, we first calculate results using the same 47 states considered by HRW. HRW excluded Alaska and Wyoming, where over 27 percent of GDP resulted from extraction activities in 2007; they excluded Delaware because Delaware is a tax haven for many companies, and finance and insurance accounted for over 35 percent of that state's GDP in 2007. They also exclude the District of Columbia, because it is difficult to measure the District's knowledge and physical capital. All other estimates in the paper are based upon all 50 states.

Summary statistics for the data used in this paper are presented in Table 1. We compare our findings in 2007 with HRW's results using GDP per capita. We also estimate models using productivity data for 2009 and 2018. Figure 1 highlights the dispersion in productivity levels across states. Between 2007 and 2018, the mean output per hour worked rose from \$55.24 to \$61.56. Dispersion across states (as measured by the standard deviation) fell slightly from \$10.57 to \$10.35 over the same time period. Using the interquartile range as an alternative measure of dispersion, we find that the state at the 75th percentile of the productivity distribution was 1.2 times more productive than the state at the 25th percentile in both 2007 and 2018.

B. State Knowledge Capital

We next briefly summarize the state knowledge capital measures, which were developed by HRW (2017b). Using a Mincer-type earnings function, HRW augment school attainment with test scores to create a measure of aggregate knowledge capital per worker. Specifically, knowledge capital h is represented as

$$h = e^{rS+wT} \tag{3}$$

where S is the average years of schooling in a state for the non-enrolled working-age population aged 20–65, T is the average test score for a state's working-age population aged 20–65 (in standard deviations), r is the earnings gradient for years of schooling (assumed to be equal to 0.08), and w is the earnings gradient for test scores (assumed to be equal to 0.17). These gradient values are based upon findings from the micro-economics literature. For example, Hanushek et al. (2015) and Hanushek and Zhang (2009) both find r = 0.08 using recent U.S. data and estimating returns across the lifecycle. Hanushek and Zhang (2009) find w = 0.193 using the

International Adult Literacy Survey (IALS), while Hanushek et al. (2015) find $w = 0.138$ using the 2012 Programme for the International Assessment of Adult Competencies (PIAAC). In both instances, they estimate the returns to skills across the lifecycle, although they use tests administered at the time earnings are observed rather than during earlier schooling. In an additional analysis to account for the effects of skill-biased technological change, HRW allow r to vary based upon the average years of schooling at the tertiary and non-tertiary levels, where the former is set to 0.157 and the latter is set to 0.057 based upon results from a standard Mincer wage regression using the 2007 American Community Survey (ACS).

HRW calculate average years of schooling in a state for the working-age population aged 20–65 not currently enrolled in school using the highest years of schooling completed reported in the ACS. We first follow HRW's data restrictions but then also calculate years of schooling for the entire working-age population aged 20–65, because we are interested in the relationship between knowledge capital available for production and productivity growth, which is important when we examine productivity growth over the post-recessionary period. In addition, many students work while enrolled in school. We follow HRW's methodology for constructing years of schooling by converting degree attainment reported in the ACS to years of schooling following Jaeger (1999) and assigning GED holders 10 years of schooling.[5] Figure 2 shows the distribution of mean years of schooling across states. The average of the state average years of schooling increases slightly from 13.17 in 2007 to 13.43 in 2018 (Table 1) and, for each state, the average years of schooling in 2018 are slightly greater than the average years of schooling in 2007 (see Appendix Table A1).

[5] We use data from IPUMS-USA (Ruggles et al. 2020). GED holders are assigned 10 years of schooling because they tend to have relatively weak labor market performance (Heckman, Humphries, and Mader 2011).

HRW's preferred test score measures, which we use here without modification, are based primarily upon eighth grade mathematics achievement test scores from the National Assessment of Educational Progress (NAEP) administered from 1978 to 1992 at the national level and from 1992 at the state level (but not every year). State test scores are initially normalized to have a U.S. mean of 500 and standard deviation of 100 in the year 2011. In addition, their measures account for both selective migration and heterogeneous fertility. They impute test scores for individual observations in the ACS based upon state identifiers and educational attainment (university degree or not). Furthermore, HRW combine data from international achievement tests with population shares of international migrants based upon their country of origin to adjust for selective migration. They then backcast state scores from 1978 to 1992 using national trends to obtain the skills of the current working-age population. HRW's 2012 test score measures, the latest available, are used as a proxy for the 2018 test scores in the developmental accounting analyses.[6] See HRW (2017b) for more details on the construction of the test score measures and Appendix Table A1 for the schooling data used in this paper.

III. Development Accounting Framework

One goal of this paper is to determine the extent to which productivity-level differences across U.S. states can be accounted for by state-level knowledge capital differences. Figures 3–8 show scatterplots of the association between log output per hour worked and the schooling measures in 2007, 2009, and 2018. In 2007, the cross-state correlations are 0.227 between log

[6] In an analysis of variance over two decades, HRW (2017b) find that 88 percent of NAEP test score variation is between states and only 12 percent of the variation is over time. Given time constraints and the complexity of replicating their measures, we make the assumption that the 2012 test score measures approximate the 2018 measures if they were to be constructed.

output per hour worked and mean years of schooling and 0.216 between log output per hour worked and test scores (Table 2). These correlations are significantly lower than the correlations of the knowledge capital components with log GDP per capita (0.464 and 0.470 respectively). We note that the correlation between log GDP per capita and log output per hour worked is 0.882 in 2007. In 2009, the cross-state correlations are 0.266 between log output per hour worked and mean years of schooling and 0.208 between log output per hour worked and test scores (Table 3). In 2018, the cross-state correlations are 0.322 between log output per hour worked and mean years of schooling and 0.365 between log output per hour worked and test scores (Table 3).

We apply HRW's development accounting framework in order to provide an indication of the causal contributions of knowledge capital to labor productivity. This framework is based upon the following aggregate Cobb-Douglas production function:

$$Y = (hL)^{1-\alpha} K^{\alpha} A^{\lambda} \tag{4}$$

where Y is output; L is labor input measured as hours worked; h is aggregate knowledge capital per worker; K is physical capital stock; and A^{λ} represents multi-factor productivity. Assuming $\lambda = 1 - \alpha$ (i.e. Harrod-neutral productivity), then labor productivity, y, can be written as:

$$\frac{Y}{L} \equiv y = h \left(\frac{k}{y}\right)^{\alpha/(1-\alpha)} A, \tag{5}$$

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

After taking logarithms, we can write the decomposition of the variations in labor productivity as

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

We then divide each term in equation 5 by the variance in state-level labor productivity in order to put each component in terms of its proportional contribution to the variance in state-level labor productivity:

$$\frac{cov(ln(y),ln(h))}{var(ln(y))} + \frac{cov\left(ln(y),ln\left(\left(\frac{k}{y}\right)^{\alpha/(1-\alpha)}\right)\right)}{var(ln(y))} + \frac{cov(ln(y),ln(A))}{var(ln(y))} = 1. \tag{7}$$

We estimate only the first covariance term of the decomposition, the contribution of knowledge capital to the variance in labor productivity, in equation 7.[7] Results using our state-level labor productivity measure, private nonfarm output per hour worked, compared to HRW's GDP per capita measure are presented in Table 4.

We find that in 2007 using HRW sample restrictions, 10 percent of the dispersion in state-level labor productivity results from differences in knowledge capital, with 6 percent coming from differences in test scores and 4 percent coming from differences in years of schooling (row 2). This is low compared to HRW (see row 1), who find that 23 percent of the variation in GDP per capita in the same year is explained by differences in knowledge capital. To explain the difference, we can write out an additional covariance decomposition of equation 2. For simplicity of exposition, we rename the terms in equation 2 as y_0-y_5:

$$\underbrace{\frac{GDP}{Population}}_{y_0} = \underbrace{\frac{GDP}{Output_{PNF}}}_{y_1} * \underbrace{\frac{Output_{PNF}}{Hours\ worked_{PNF}}}_{y_2} * \underbrace{\frac{Hours\ worked_{PNF}}{Employed\ persons_{PNF}}}_{y_3}$$
$$* \underbrace{\frac{Employed\ persons_{PNF}}{Employed\ persons}}_{y_4} * \underbrace{\frac{Employed\ persons}{Population}}_{y_5}$$

[7] Even though *A* can be endogenous, Klenow and Rodríquez-Clare (1997) conclude that it is still useful to examine this decomposition because education policies can affect *h* more than other factors. Therefore, finding that high levels of labor productivity are explained mostly by high levels of *h* would suggest that differences in education policies are important for explaining state-level differences in labor productivity.

The covariance decomposition is then:

$$\frac{cov(lny_0, lnh)}{var(lny_0)} = \frac{var(lny_1)}{var(lny_0)}\frac{cov(lny_1, lnh)}{var(lny_1)} + \frac{var(lny_2)}{var(lny_0)}\frac{cov(lny_2, lnh)}{var(lny_2)} + \frac{var(lny_3)}{var(lny_0)}\frac{cov(lny_3, lnh)}{var(lny_3)} + \frac{var(lny_4)}{var(lny_0)}\frac{cov(lny_4, lnh)}{var(lny_4)} + \frac{var(lny_5)}{var(lny_0)}\frac{cov(lny_5, lnh)}{var(lny_5)} \quad (8)$$

The first term on the left $\frac{cov(lny_0,lnh)}{var(lny_0)}$ is what HRW (2017b) estimate while we estimate $\frac{cov(lny_2,lnh)}{var(lny_2)}$. In Table 5, we present estimates for the terms in the decomposition for the year 2007 using the latest state GDP per capita measures from BEA, last revised in November 2019 (U.S. Bureau of Economic Analysis 2020). The first covariance (row 1) is very close to the estimate in HRW (2017b) (0.224 versus 0.228). We find that the contribution of knowledge capital to the variance in GDP per capita can also be explained to a great extent by the contribution of knowledge capital to the variance in the employment-to-population ratio (row 11). Interestingly, the contribution of knowledge capital to the variance in state hours per worker is negative (row 7), indicating they vary in opposite directions.

We next loosen the sample restrictions and extend the analysis to 2018. In row 3 of Table 4, we expand the sample to include all 50 states in 2007. In this sample, only 8 percent of the dispersion in state-level labor productivity results from differences in knowledge capital, with slightly more explained by test scores than years of schooling. In 2009 at the trough of the business cycle, we also find that knowledge capital explains 8 percent of the dispersion in labor productivity. In row 5, we show that including those enrolled in school has no measurable impact on the estimates. In 2018, 13 percent of the dispersion in state productivity results from differences in knowledge capital, with 8 percent coming from differences in test scores and 5 percent coming from differences in years of schooling.

We then compute 2007 estimates where we allow the return per year of schooling to differ for tertiary and non-tertiary schooling (rows 7 and 8). Allowing for varying returns, HRW (2017b) found that knowledge capital explains 32 percent of the dispersion in GDP per capita. We find that knowledge capital explains only 16 percent of the dispersion in labor productivity, with the differences in years of schooling explaining almost double the differences in test scores (10 percent versus 6 percent).

Next we examine the contribution of knowledge capital to the average log difference in labor productivity between the top-five and bottom-five states in the productivity distribution. The five-state measure below shows the proportional contribution of the factors and total factor productivity to the average log difference in the top-five and bottom-five states:

$$\frac{\ln[(\prod_{i=1}^{5} h_i / \prod_{j=n-4}^{n} h_j)^{1/5}]}{\ln[(\prod_{i=1}^{5} y_i / \prod_{j=n-4}^{n} y_j)^{1/5}]} + \frac{\ln[(\prod_{i=1}^{5} k_i / \prod_{j=n-4}^{n} k_j)^{1/5}]}{\ln[(\prod_{i=1}^{5} y_i / \prod_{j=n-4}^{n} y_j)^{1/5}]} + \frac{\ln[(\prod_{i=1}^{5} A_i / \prod_{j=n-4}^{n} A_j)^{1/5}]}{\ln[(\prod_{i=1}^{5} y_i / \prod_{j=n-4}^{n} y_j)^{1/5}]} = 1, \tag{9}$$

where i and j are states ranked according to their output per hour worked, $i,\ldots,j,\ldots,n$, among the total of n states.[8] The five-state knowledge capital measure, which we estimate, is the first term in equation 9.

Comparing our results to HRW's with the same knowledge capital measure for 2007, we find that the five-state knowledge capital measure accounts for only 5 percent of the difference in

[8] In 2007, the top five most productive states (in levels) of the 47 states HRW examined are Connecticut, New York, New Jersey, Louisiana, and Massachusetts. The least productive states in 2007 are Mississippi, Montana, Maine, Vermont, and Idaho. This ranking differs from the GDP per capita ranking, especially for the least productive states. In 2018, the ranking changed so the top five most productive states are New York, Washington, Connecticut, California, and Massachusetts. The least productive states in 2018 are Arkansas, Vermont, Idaho, Mississippi, and Maine.

labor productivity in contrast to 31 percent of the difference in GDP per capita (Table 4). For the same year, test scores and years of schooling contribute equally to the difference; in the HRW specification, test scores contribute 55 percent more than years of schooling (19 percent and 12 percent respectively). In 2018, we find that the five-state knowledge capital measure accounts for 11 percent of the difference in labor productivity, with test scores almost twice as important as years of schooling (8 percent and 4 percent).

IV. Growth Regression Models

We next examine cross-state differences in private nonfarm labor productivity growth over the post-Great Recession expansionary period (2009–2018). Over this period, official nonfarm business sector labor productivity grew on an average annual basis by 1.3 percent while a sum-of-states measure indicates private nonfarm labor productivity grew on an average annual basis by 1.1 percent. However, we find considerable heterogeneity across states, with a standard deviation in the growth rate of 0.71 percent and range of 3.5 percentage points (Figure 9; Table 1).

Motivated by Hanushek, Ruhose, Woessmann (2017a) (hereafter HRW (2017a)), we estimate the following productivity growth model that incorporates test scores:

$$\%\Delta y_s = \alpha + \beta_1 T_s + \beta_2 S_s + X_s \delta + \varepsilon_s \tag{10}$$

where $\%\Delta y_s$ is the average annual growth rate in labor productivity in state *s* between 2009 and 2018, T_s is the average test score of the working-age population in state *s* divided by 100 (the standard deviation) in 2009, S_s is the average years of schooling of the working-age population in state *s* in 2009, X_s is a matrix of state-level control variables all measured in 2009 including the log of initial level of output per hour, the log of physical capital stock per worker, the log of population density, state industrial structure (measured as the percent of private nonfarm sector output in each NAICS supersector, with the percent in manufacturing being omitted), and Census region fixed effects, and ε_s is an error term.[9] This analysis is descriptive and not meant to establish causality. However, numerous cross-country analyses have established that greater knowledge capital leads to greater economic growth (Hanushek and Woessmann 2012, 2015) when accounting for endogeneity bias.[10]

Table 6 presents estimates for five specifications of our productivity growth model to examine the relationship between knowledge capital and labor productivity growth. The first three specifications follow HRW, including state-level controls for the log of the initial level of output per hour and the log of physical capital stock per worker. The first model uses years of schooling as the human capital measure. The second model adds test scores as a cognitive skills measure. The third model includes Census region fixed effects in order to account for differences that are geographically correlated. In the fourth model, we add the additional state-level controls — population density and state industrial structure. In the fifth model, the observations are weighted by the state population in 2009 so that small states do not overly affect the estimates.

[9] The inclusion of these additional controls is motivated in part by Panda (2017). The 2009 capital stock per worker measure is constructed for the private nonfarm sector using methodology outlined by Garofalo and Yamarik (2002) and data from the U.S. Bureau of Economic Analysis (2020b; 2020c). The methodology assumes that each industry has the same capital-output ratio across all states. Capital is the sum of the capital in each industry weighted by the state industry output share. Most recent work relates density and productivity at the city or MSA level, e.g. Combes et al. (2012). The state population data for 2009 was obtained from the U.S. Bureau of Economic Analysis (2020d). The state area is from the U.S. Census Bureau (2018). The percent of private nonfarm sector output in each NAICS supersector in 2009 is estimated using GDP by state data (U.S. Bureau of Economic Analysis 2020a).

[10] For example, faster growth could lead states to invest more in education, and higher-skilled migrants could move to high-growth states (HRW 2017a).

In the first specification, we find a statistically significant positive relationship between years of schooling and productivity growth. In specification two, we find that test scores and productivity growth have a statistically significant positive relationship, but years of schooling and productivity growth do not. The R-squared value increases from 0.39 to 0.47 with the addition of the test scores. In the third specification when we add Census region, the coefficient on test scores increases from 1.4 to 1.7. In specifications 1–3, we also find a negative relationship between the initial productivity level in 2009 and subsequent productivity growth, which is consistent with the early literature on state-level productivity convergence (Barro and Sala-i-Martin 1992; Mankiw, Romer and Weil 1992). In other words, states that are initially behind in levels grow faster. In the fourth specification, the R-squared value increases from 0.50 to 0.71, indicating that industrial structure is important to explaining productivity growth differences. We again find a statistically significant positive relationship between test scores and productivity growth (β_1 = 1.9). However, with the addition of controls for industrial structure, the coefficient on the initial productivity level is no longer statistically significant, though still negative, and the magnitude of the estimate falls.[11] In addition, we do not find a statistically significant relationship between population density and productivity growth, though the coefficient is positive. In the final specification (column 5), where the observations are population weighted, we again find a statistically significant positive relationship between test scores and productivity growth (β_1 = 1.6) — a one-standard-deviation increase in test scores is

[11] Prior research on the pre-2000 period shows unconditional convergence. Recently, convergence between states appears to be weakening. For example, Kinfemichael and Morshed (2019) found no unconditional convergence across U.S. states for the 1997–2015 period using GDP per capita; however, using an output-per-worker measure, they found convergence, though weaker, for some subsectors of the economy when they used disaggregated data.

associated with a 1.6-percentage-point-faster average annual productivity growth rate since the Great Recession.[12]

V. Conclusion

There is substantial variation in U.S state-level labor productivity levels and growth rates. In this paper, we examine the contribution that state-level knowledge capital, a measure based on not just schooling attainment but also cognitive skills, makes to these productivity differences. We replicate models examined in HRW (2017a; 2017b) but replace their outcome variable, GDP per capita, with a more refined measure of labor productivity, output per hour worked. Using a development accounting framework, we find that about 13 percent of the dispersion in state productivity in 2018 results from differences in knowledge capital, with 5 percent coming from differences in years of schooling and 8 percent coming from differences in test scores. Over the period 2009–2018, we also find a statistically significant positive relationship between initial test scores and productivity growth. These findings validate previous research on the importance of cognitive skills in explaining productivity.

[12] If the sample is restricted to the 47 states used in HRW (2017a; 2017b), β_1 equals 1.2.

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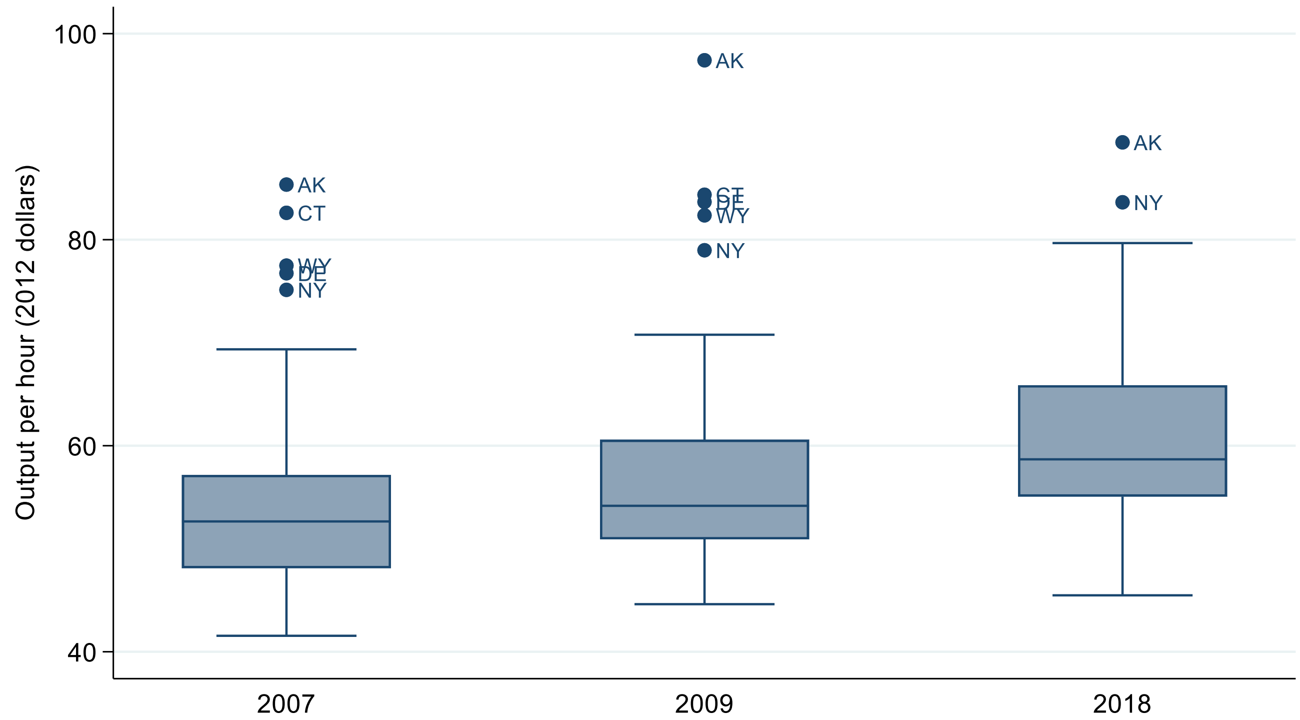

Figure 1. Distribution of Output per Hour Worked of U.S. States, 2007–2018

Notes: Output per hour worked for the private nonfarm sector denoted in 2012 U.S. dollars. Boxplots comprise all 50 U.S. states. The line in the middle reports the output per hour worked for the median state. The interquartile range (IQR) bounds the states that lie between the 25th and 75th percentiles, respectively. The upper and lower whiskers span the lowest and highest quartiles within 1.5 IQR of the nearest quartile. The dots represent outliers (>1.5 IQR).

Source: U.S. Bureau of Labor Statistics (2020)

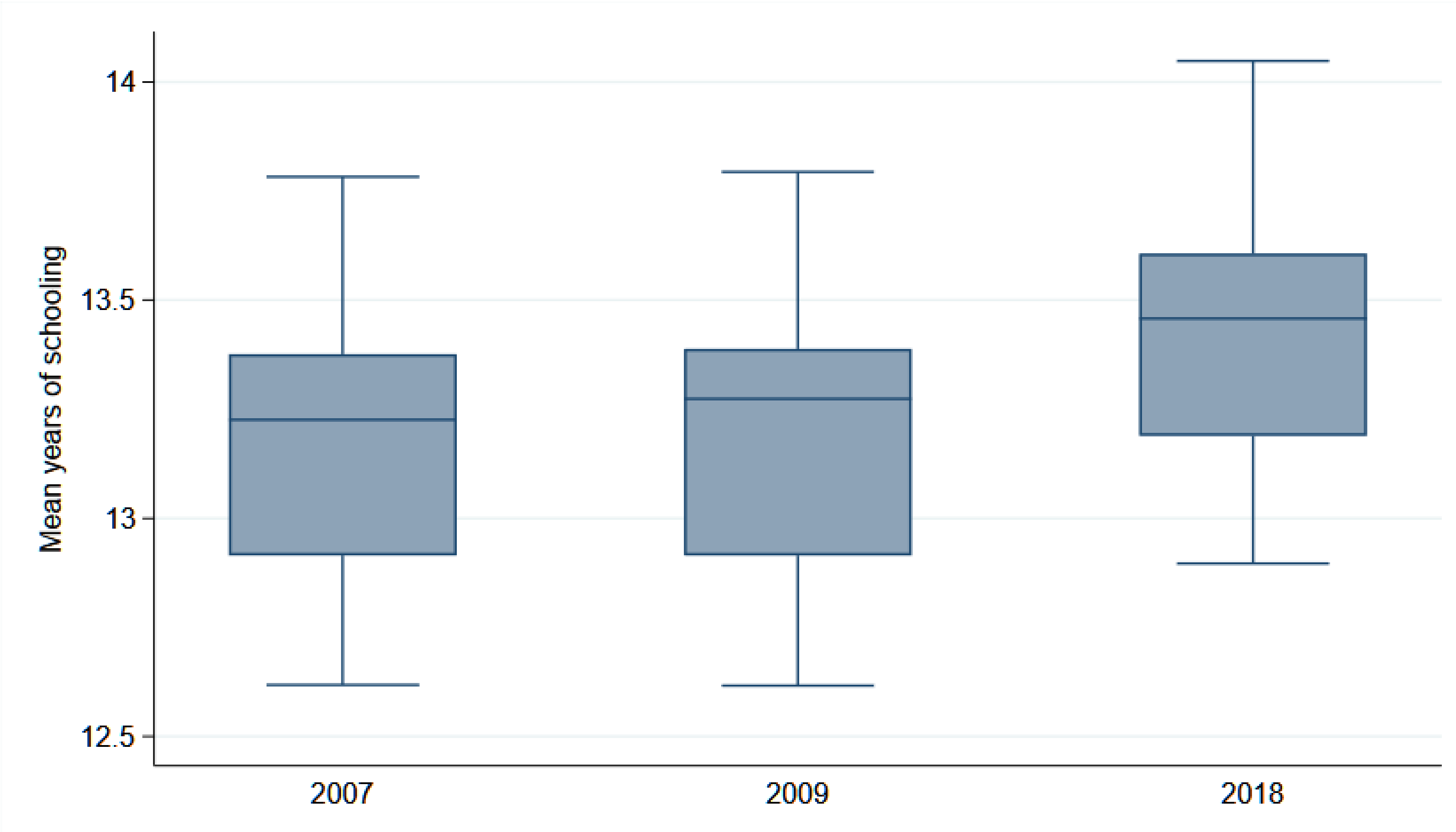

Figure 2. Distribution of Average Years of Schooling of U.S. States, 2007–2018

Source: Ruggles et al. (2020)

Figure 3. Years of Schooling and Output per Hour across U.S. States, 2007

Sources: Ruggles et al. (2020); U.S. Bureau of Labor Statistics (2020)

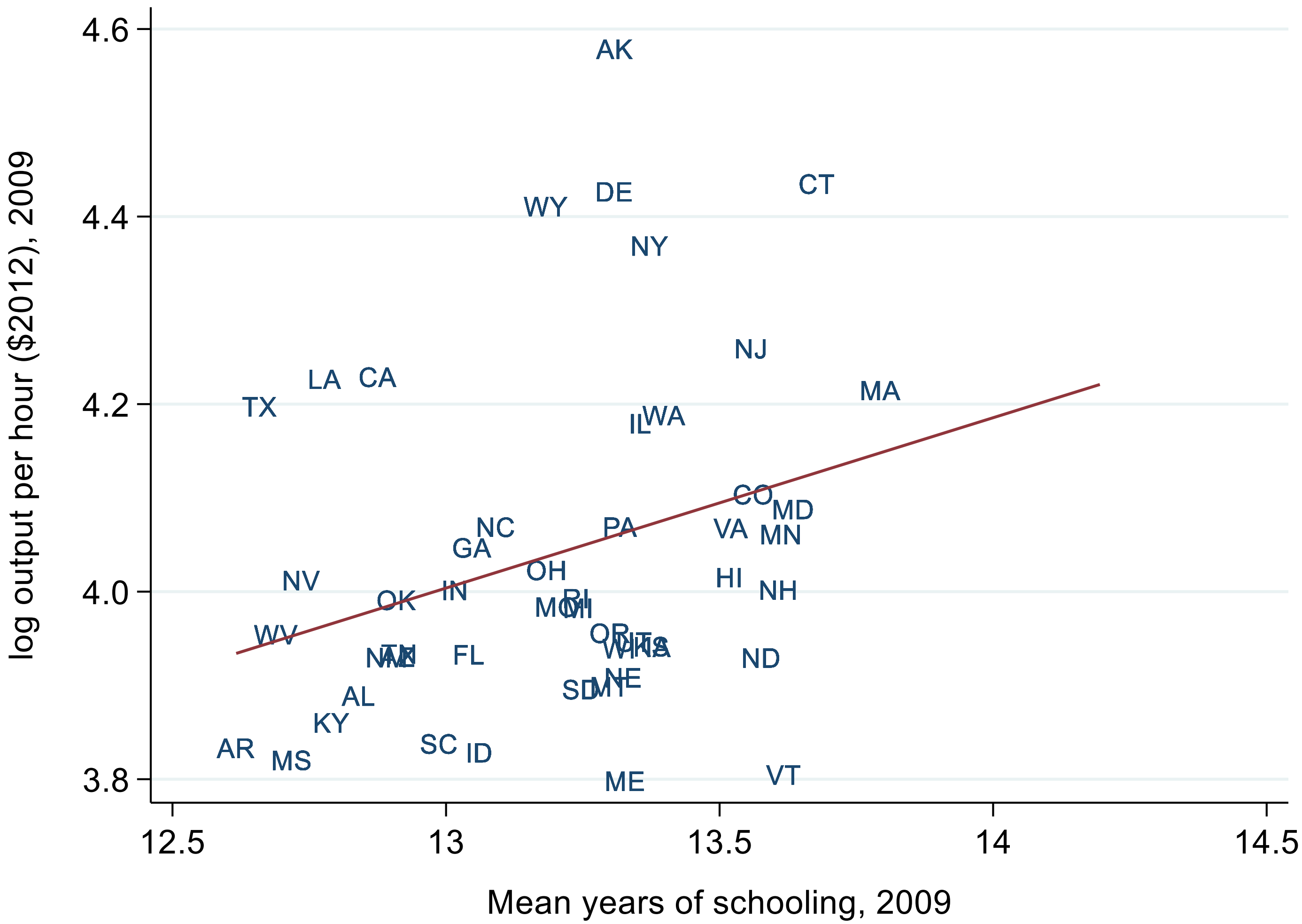

Figure 4. Years of Schooling and Output per Hour across U.S. States, 2009

Sources: Ruggles et al. (2020); U.S. Bureau of Labor Statistics (2020)

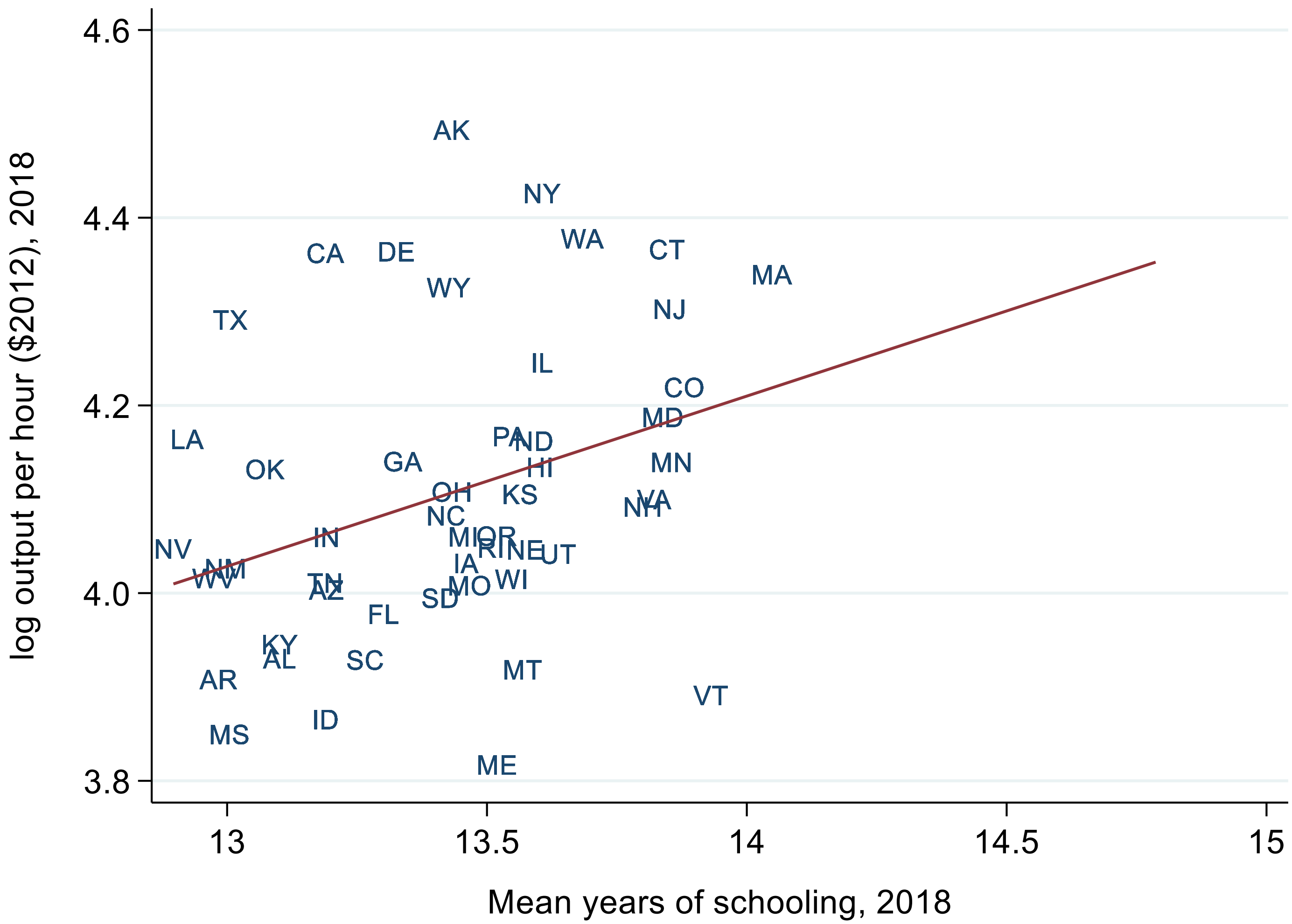

Figure 5. Years of Schooling and Output per Hour across U.S. States, 2018

Sources: Ruggles et al. (2020); U.S. Bureau of Labor Statistics (2020)

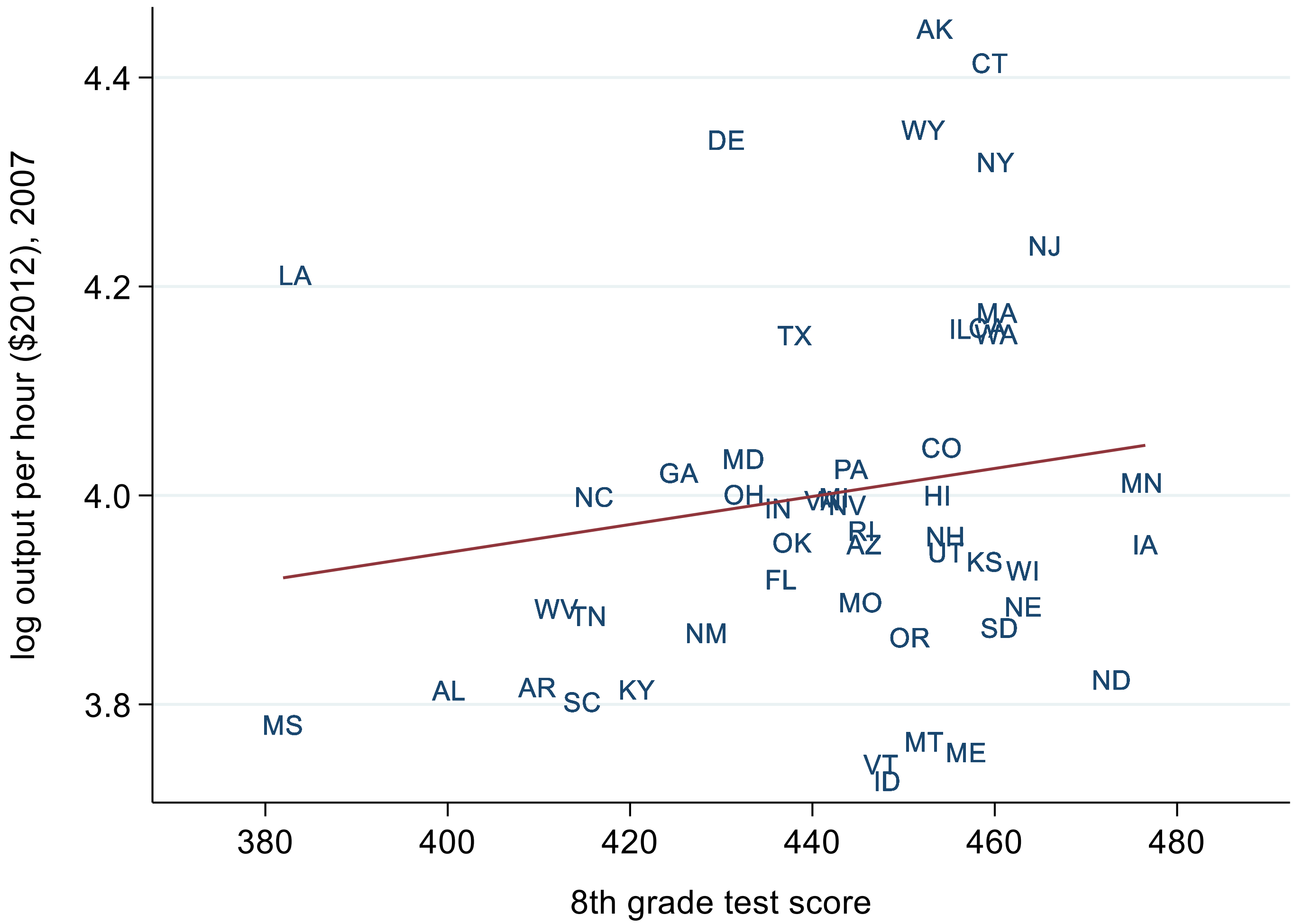

Figure 6. Cognitive Skills and Output per Hour across U.S. States, 2007

Sources: Hanushek, Ruhose, Woessmann (2017b); U.S. Bureau of Labor Statistics (2020)

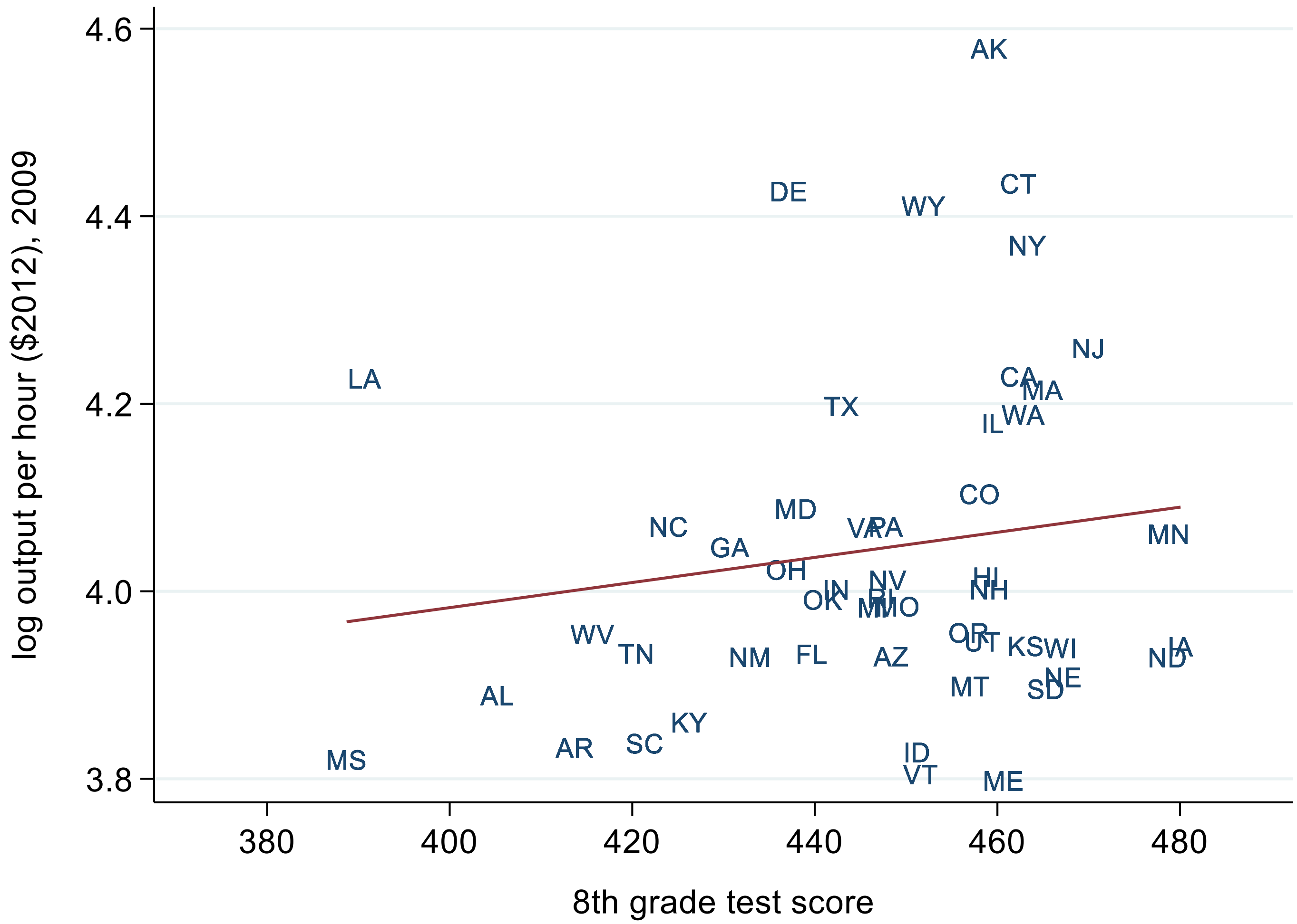

Figure 7. Cognitive Skills and Output per Hour across U.S. States, 2009

Sources: Hanushek, Ruhose, Woessmann (2017b); U.S. Bureau of Labor Statistics (2020)

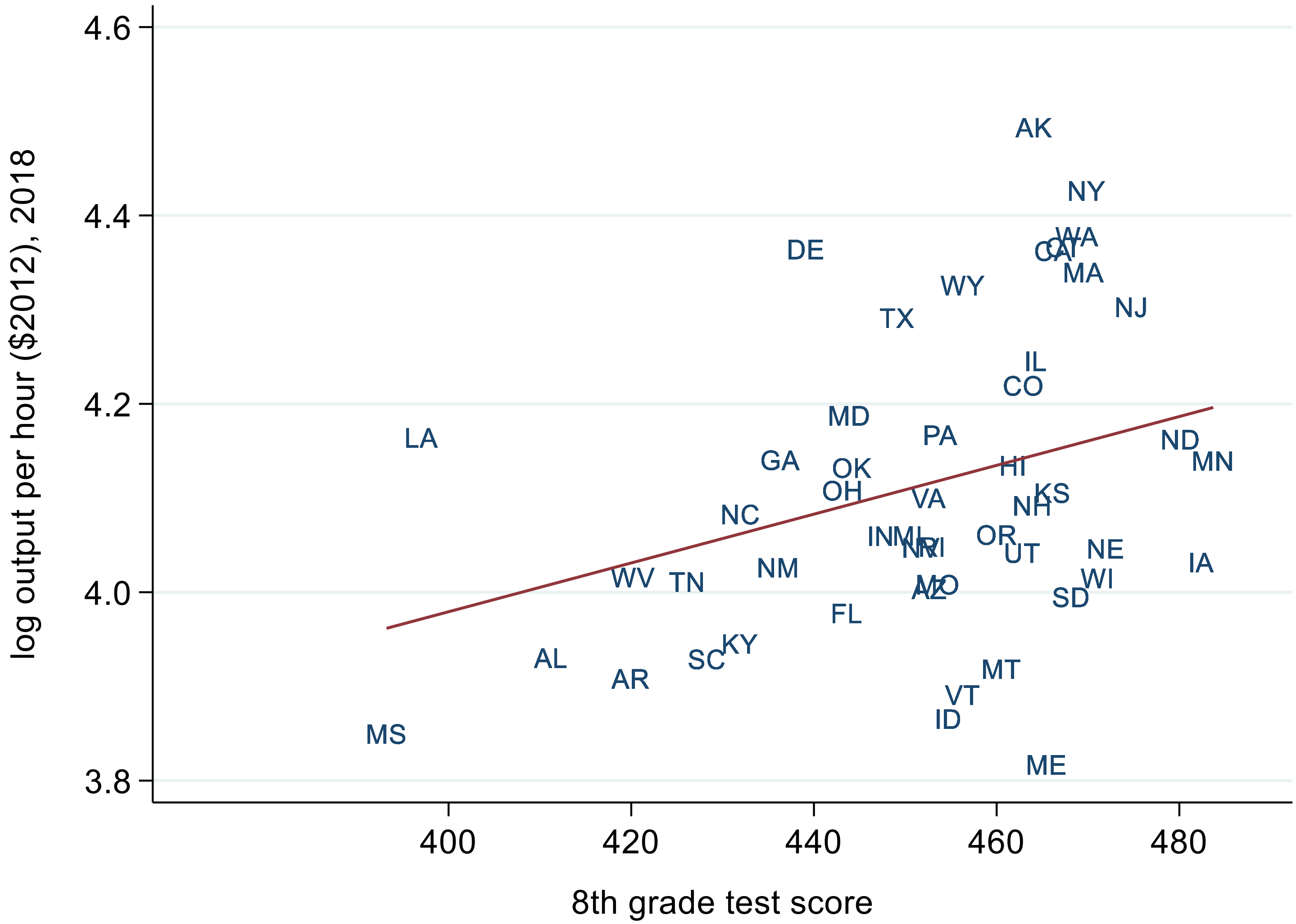

Figure 8. Cognitive Skills and Output per Hour across U.S. States, 2018

Sources: Hanushek, Ruhose, Woessmann (2017b); U.S. Bureau of Labor Statistics (2020)

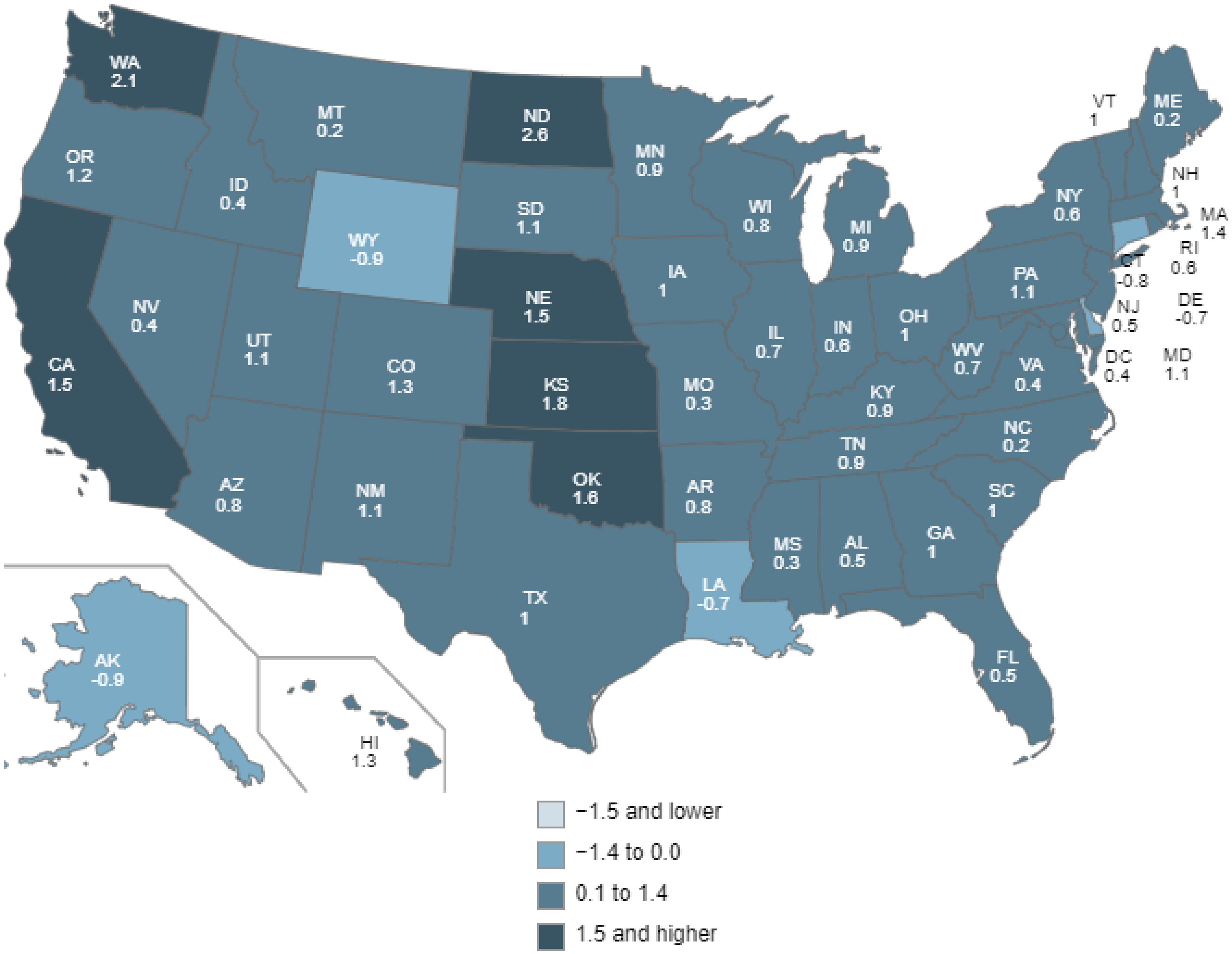

Figure 9. State-level Labor Productivity Average Annual Growth, 2009–2018

Source: U.S. Bureau of Labor Statistics (2020)

Table 1. Summary Statistics (N = 50)

	Mean	Std. dev.	25th percentile	75th percentile	Min.	Max.
Output per Hour Worked 2007 ($2012)	55.24	10.57	48.11	57.16	41.55	85.35
Output per Hour Worked 2009 ($2012)	57.74	11.55	50.91	60.58	44.62	97.42
Output per Hour Worked 2018 ($2012)	61.56	10.35	55.06	65.87	45.48	89.45
Years of schooling 2007 (excluding enrolled in school)	13.11	0.334	12.84	13.33	12.52	13.74
Years of schooling 2007	13.17	0.318	12.92	13.38	12.62	13.78
Years of schooling 2009	13.21	0.306	12.92	13.39	12.62	13.79
Years of schooling 2018	13.43	0.298	13.19	13.61	12.90	14.05
Test scores 2007	442.6	21.52	432.48	458.94	381.9	476.5
Test scores 2009	447.0	20.82	437.15	462.32	388.7	480.1
Test scores 2018 (2018 = 2012)[1]	451.7	20.27	443.15	466.12	393.2	483.7
Ratio of GDP/private nonfarm output 2007 ($2012)	1.28	0.07	1.24	1.31	1.17	1.47
Hours worked per worker 2007	1,675.63	50.14	1,640.00	1,710.30	1,587.99	1,815.30
Private nonfarm sector employment share 2007	0.70	0.03	0.68	0.72	0.62	0.75
Employment-to-population ratio 2007	0.61	0.05	0.58	0.65	0.50	0.74
Average annual labor productivity growth, 2009–2018 (%)	0.76	0.71	0.4	1.1	-0.9	2.6
Log (capital per worker) 2009 ($2012)	9.91	1.03	9.16	10.75	7.71	11.91
% Forestry and Fishing 2009	0.30	0.27	0.12	0.35	0.03	1.02
% Mining 2009	4.06	8.26	0.22	4.05	0.00	40.22
% Construction 2009	5.60	1.33	4.56	6.29	3.62	9.66
% Manufacturing 2009	14.90	5.98	11.05	18.82	3.06	32.00
% Trade, Transportation, and Utilities 2009	21.81	3.12	20.13	24.03	13.05	28.79
% Information 2009	5.19	2.18	3.73	6.15	1.96	13.01
% Financial Activities 2009	15.47	5.84	12.54	16.49	7.44	44.11
% Professional and Business Services 2009	13.17	3.63	11.04	15.07	5.19	25.34
% Education and Health Services 2009	11.72	2.55	9.84	13.04	5.15	17.98
% Leisure and Hospitality 2009	5.01	2.69	3.82	5.22	3.10	20.47
% Other Services 2009	2.76	0.40	2.51	2.94	1.77	3.58
Log (population density) 2009	4.49	1.41	3.76	5.35	0.20	7.08

Notes: Summary statistics are created weighting each state equally. Test scores refer to eighth-grade math scores.
[1] Test scores for the working-age population in 2012 are used as a proxy for 2018.

Table 2. Correlations, 2007 (N = 50)

Measure	Log GDP per capita	Log output per hour worked	Mean years of schooling	Test score
Log GDP per capita	1			
Log output per hour worked	0.882	1		
Mean years of schooling	0.464	0.227	1	
Test score	0.470	0.216	0.718	1

Table 3. Correlations (N = 50)

Measure	Log output per hour worked	Mean years of schooling	Test score
Year = 2009			
Log output per hour worked	1		
Mean years of schooling	0.266	1	
Test score	0.208	0.712	1
Year = 2018			
Log output per hour worked	1		
Mean years of schooling	0.322	1	
Test score	0.365	0.681	1

Table 4. Development Accounting Results with Alternative Productivity Measures

				Covariance measure			Five-state measure		
Row	Productivity measures	N	Year	Total knowledge capital	Test scores	Years of Schooling	Total knowledge capital	Test scores	Years of Schooling
Sample excludes those enrolled in school									
1	GDP per capita (HRW 2017b)	47	2007	0.228	0.135	0.093	0.306	0.186	0.120
				(0.044)	(0.028)	(0.023)			
2	Output per hour	47	2007	0.099	0.057	0.042	0.054	0.027	0.027
				(0.063)	(0.040)	(0.028)			
3	Output per hour	50	2007	0.077	0.044	0.033	0.054	0.038	0.016
				(0.047)	(0.029)	(0.021)			
4	Output per hour	50	2009	0.079	0.043	0.036	0.098	0.058	0.039
				(0.041)	(0.026)	(0.018)			
Sample includes those enrolled in school									
5	Output per hour	50	2009	0.079	0.043	0.036	0.097	0.058	0.039
				(0.041)	(0.026)	(0.018)			
6	Output per hour	50	2018	0.125	0.078	0.048	0.113	0.075	0.038
				(0.043)	(0.027)	(0.021)			
Schooling-level specific returns									
7	GDP per capita (HRW 2017b)	47	2007	0.315	0.135	0.180			
				(0.052)	(0.028)	(0.032)			
8	Output per hour	47	2007	0.158	0.057	0.100			
				(0.078)	(0.040)	(0.042)			

Note: Results in the first two rows and last two rows exclude Alaska, Delaware, and Wyoming. Test scores refer to eighth-grade math scores from NAEP with backward projections by age and parental education. Calculations in rows 1–6 assume a return of w = 0.17 per standard deviation in test scores and a return of r = 0.08 per year of schooling while calculations in rows 7–8 assume a return of w = 0.17 per standard deviation in test scores and a return of r = 0.057 per year of non-tertiary schooling and a return of r = 0.157 per year of tertiary schooling. Bootstrapped standard errors are in parentheses with 1,000 replications.

Table 5. Covariance Decomposition of the Contribution of Knowledge Capital to the Variance in GDP per Capita (2007) (N = 47)

Row	Term	Total knowledge capital	Test scores	Years of schooling
1	$\frac{cov(\ln y_0, \ln h)}{var(\ln y_0)}$	0.224 (0.044)	0.131 (0.030)	0.093 (0.020)
2	$\frac{var(\ln y_1)}{var(\ln y_0)}$	0.102 (0.035)	-	-
3	$\frac{cov(\ln y_1, \ln h)}{var(\ln y_1)}$	0.189 (0.179)	0.087 (0.114)	0.102 (0.084)
4	$\frac{var(\ln y_2)}{var(\ln y_0)}$	0.932 (0.146)	-	-
5	$\frac{cov(\ln y_2, \ln h)}{var(\ln y_2)}$	0.099 (0.063)	0.057 (0.040)	0.042 (0.028)
6	$\frac{var(\ln y_3)}{var(\ln y_0)}$	0.036 (0.012)	-	-
7	$\frac{cov(\ln y_3, \ln h)}{var(\ln y_3)}$	-1.422 (0.242)	-0.780 (0.189)	-0.642 (0.083)
8	$\frac{var(\ln y_4)}{var(\ln y_0)}$	0.069 (0.022)	-	-
9	$\frac{cov(\ln y_4, \ln h)}{var(\ln y_4)}$	0.225 (0.221)	0.155 (0.138)	0.070 (0.097)
10	$\frac{var(\ln y_5)}{var(\ln y_0)}$	0.256 (0.071)	-	-
11	$\frac{cov(\ln y_5, \ln h)}{var(\ln y_5)}$	0.574 (0.071)	0.032 (0.050)	0.241 (0.033)

Notes: Results exclude Alaska, Delaware, and Wyoming. Test scores refer to eighth-grade math scores from NAEP with backward projections by age and parental education. Calculations assume a return of *w* = 0.17 per standard deviation in test scores and a return of *r* = 0.08 per year of schooling. Bootstrapped standard errors are in parentheses with 1,000 replications.

Table 6. State Labor Productivity Growth Regressions (2009–2018) (N = 50)

VARIABLES	(1)	(2)	(3)	(4)	Population weighted (5)
Average state test score		1.387***	1.681**	1.878**	1.591**
		(0.441)	(0.677)	(0.805)	(0.610)
Average years of schooling	0.788***	0.117	0.321	-0.413	-0.519
	(0.277)	(0.309)	(0.352)	(0.545)	(0.517)
Log (output per hour)	-2.311***	-2.334***	-2.411***	-1.494	-1.628
	(0.451)	(0.412)	(0.409)	(1.263)	(1.311)
Log (capital per worker)	-0.227***	-0.219***	-0.226**	0.130	0.061
	(0.081)	(0.073)	(0.089)	(0.160)	(0.147)
Log (population density)				0.099	0.157
				(0.131)	(0.131)
%Forestry and Fishing				-0.449	-0.292
				(0.402)	(0.374)
%Mining				-0.007	0.013
				(0.036)	(0.036)
%Construction				0.024	0.027
				(0.120)	(0.109)
%Trade, Transportation, and Utilities				0.001	-0.027
				(0.036)	(0.033)
%Information				0.195***	0.160***
				(0.042)	(0.037)
%Financial Activities				-0.034	-0.045**
				(0.026)	(0.022)
%Professional and Business Services				-0.020	-0.014
				(0.032)	(0.032)
%Education and Health Services				0.044	0.041
				(0.050)	(0.051)
%Leisure and Hospitality				-0.011	-0.043
				(0.044)	(0.038)
%Other Services				0.027	-0.105
				(0.269)	(0.236)
Census region fixed effects	NO	NO	YES	YES	YES
R-squared	0.388	0.469	0.498	0.714	0.692

Notes: The dependent variable is the average annual growth rate in output per hour worked, 2009–2018. The independent variables are measured in 2009. All specifications also include a constant term. Robust standard errors are in parentheses.
* Significant at the 10 percent level
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Appendix

Table A1. Mean Years of Completed Schooling and Eighth Grade Math NAEP Test Scores (by State)

	Years of schooling 2007 (1)	Years of schooling 2009 (2)	Years of schooling 2018 (3)	Test scores 2007 (4)	Test scores 2009 (5)	Test scores 2018 (6)
Alabama	12.8	12.8	13.1	400.2	405.2	411.2
Alaska	13.2	13.3	13.4	453.5	459.1	464.1
Arizona	12.9	12.9	13.2	445.7	448.4	452.6
Arkansas	12.7	12.6	13.0	409.9	413.7	420.0
California	12.8	12.9	13.2	459.2	462.4	466.2
Colorado	13.5	13.6	13.9	454.2	458.1	462.9
Connecticut	13.7	13.7	13.8	459.5	462.3	467.3
Delaware	13.2	13.3	13.3	430.6	437.2	439.1
Florida	13.1	13.0	13.3	436.6	439.7	443.6
Georgia	13.0	13.0	13.3	425.4	430.7	436.3
Hawaii	13.5	13.5	13.6	453.7	458.8	461.8
Idaho	13.1	13.1	13.2	448.2	451.2	454.7
Illinois	13.3	13.4	13.6	456.2	459.5	464.3
Indiana	13.0	13.0	13.2	436.2	442.4	447.3
Iowa	13.3	13.4	13.5	476.5	480.1	482.4
Kansas	13.4	13.4	13.6	458.9	463.2	466.1
Kentucky	12.7	12.8	13.1	420.8	426.3	431.9
Louisiana	12.6	12.8	12.9	383.3	390.7	397.0
Maine	13.3	13.3	13.5	456.9	460.7	465.5
Maryland	13.6	13.6	13.8	432.5	438.0	443.9
Massachusetts	13.8	13.8	14.0	460.3	465.0	469.5
Michigan	13.2	13.2	13.5	442.4	446.3	450.3
Minnesota	13.6	13.6	13.9	476.2	478.8	483.7
Mississippi	12.6	12.7	13.0	381.9	388.7	393.2

Notes: Years of schooling are for the working-age population. Test scores for 2012 are used as proxy for 2018.
Sources: Ruggles et al. (2020); Hanushek, Ruhose, Woessmann (2017b)

Table A1 Continued. Mean Years of Completed Schooling and Eighth Grade Math NAEP Test Scores (by State)

	Years of schooling 2007 (1)	Years of schooling 2009 (2)	Years of schooling 2018 (3)	Test scores 2007 (4)	Test scores 2009 (5)	Test scores 2018 (6)
Missouri	13.2	13.2	13.5	445.3	449.1	453.5
Montana	13.3	13.3	13.6	452.3	457.0	460.5
Nebraska	13.4	13.3	13.6	463.2	467.2	472.0
Nevada	12.7	12.7	12.9	443.9	448.0	451.7
New Hampshire	13.6	13.6	13.8	454.6	459.1	463.9
New Jersey	13.5	13.6	13.9	465.5	470.0	474.7
New Mexico	12.8	12.9	13.0	428.4	432.9	436.1
New York	13.3	13.4	13.6	460.1	463.3	469.8
North Carolina	13.0	13.1	13.4	416.1	424.0	432.0
North Dakota	13.5	13.6	13.6	472.8	478.6	480.1
Ohio	13.2	13.2	13.4	432.5	436.9	443.1
Oklahoma	12.9	12.9	13.1	437.8	440.9	444.1
Oregon	13.2	13.3	13.5	450.7	456.9	460.0
Pennsylvania	13.3	13.3	13.5	444.3	447.8	453.8
Rhode Island	13.1	13.2	13.5	445.4	447.3	452.9
South Carolina	12.9	13.0	13.3	414.8	421.4	428.3
South Dakota	13.2	13.2	13.4	460.5	465.3	468.2
Tennessee	12.8	12.9	13.2	415.5	420.5	426.1
Texas	12.6	12.7	13.0	438.1	442.9	449.1
Utah	13.3	13.3	13.6	454.7	458.4	462.8
Vermont	13.7	13.6	13.9	447.5	451.6	456.3
Virginia	13.5	13.5	13.8	441.0	445.5	452.6
Washington	13.4	13.4	13.7	460.2	462.9	468.8
West Virginia	12.6	12.7	13.0	411.9	415.7	420.2
Wisconsin	13.3	13.3	13.5	463.1	466.9	471.0
Wyoming	13.3	13.2	13.4	452.2	451.9	456.3

Notes: Years of schooling are for the working-age population. Test scores for 2012 are used as proxy for 2018.

Sources: Ruggles et al. (2020); Hanushek, Ruhose, Woessmann (2017b)