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

Sabrina Wulff Pabilonia
(U.S. Bureau of Labor Statistics)
Pabilonia.Sabrina@bls.gov

Susan Fleck
(U.S. Bureau of Labor Statistics)

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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: We investigate the contribution of knowledge capital as measured by school attainment and achievement test scores to state-level productivity differences for the private nonfarm business sector. Our analysis closely follows the methodology used by Hanushek, Ruhose, and Woessmann (2017a, 2017b); we update their work through 2016 and improve upon their methodology by using a measure of output per hour worked. Updating HRW's development accounting model, we find about 19 percent of the dispersion in state productivity in 2016 is attributable to state-level variation in knowledge capital. However, over the period 2007–2016, there is no association between knowledge capital and productivity growth.

JEL codes: I25, I26, J24, R11, R23

Keywords: state productivity, knowledge capital, human capital

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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 use 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 describe their outcome as labor productivity even though they estimate the model using GDP per capita. GDP per hour worked is by far a better measure of labor productivity than GDP per capita, which is affected 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 versus when using GDP per hour. The decomposition of GDP per capita displayed below clearly shows how labor productivity is related to GDP per capita:

$$\frac{GDP}{Population} = \frac{GDP}{Hours\ worked} * \frac{Hours\ worked}{Employed\ Persons} * \frac{Employed\ Persons}{Population} \qquad (1)$$

Of the three terms on the right-hand side of the equation, 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 worker-to-population ratio – reflects both labor force participation and employment rates.

The contribution of the current paper is to examine the contribution of knowledge capital to state-level labor productivity differences. We do so by replacing the outcome variable in HRW's model with state labor productivity measures constructed as GDP per hour worked. While HRW is based on GDP per capita for the total economy, we use output and input measures for the private nonfarm business (PNFB) sector. Hours measures for state PNFB are calculated following the methodology for BLS national-level productivity measures to the extent possible with the state-level data available. We also provide estimates for the most recent year of data, 2016, and examine the relationship between initial knowledge capital in 2007 and state productivity growth over the latest business cycle (2007–2016).

We find about 14 percent of the dispersion in the 2007 state productivity level is attributable to state-level variation in knowledge capital. In 2016, knowledge capital explained 19 percent of the dispersion. In each instance, test scores contribute slightly more than years of schooling in explaining level differences in state productivity. Over the period 2007-2016, we find a great degree of variation across states in the productivity growth rate; however, we do not find a relationship between knowledge capital and the growth rate.

Section II describes the state 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 Labor Productivity

Most prior research on state labor productivity has used either population or employed persons as the labor input whereas this study uses hours worked as the labor input.[1] In 2007, the U.S. Bureau of Labor Statistics (BLS) began publishing state-level all-employee average weekly hours (AWH) 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 approach makes it possible to construct an output per hour series where output and hours have the same geographic definitions. To the extent possible, we use methods for estimating hours following those used for BLS productivity measures, including hours worked of employees, self-employed workers, and unpaid family workers.[2] We find that the average state hours worked per employed person was 1,675 hours per year with a standard deviation of 51 hours in 2007. Summary statistics for the data used in this paper are presented in Table 1. We compare our results with HRW's results using GDP per capita in the same year. We also estimate models using productivity data for 2016, the latest available data. In 2016, the average state hours worked per employed person was 1,647 with a standard deviation of 35 hours per year.

The output measure in this paper adjusts the U.S. Bureau of Economic Analysis (BEA) measure of real private business GDP by state to exclude the farm sector. For goods-producing industries, BEA uses Census Bureau value-added data from the Census of Manufactures and the Annual Survey of Manufactures. For service-providing industries, BEA uses Census Bureau receipts and payroll data or company financial data to estimate gross operating surplus; BEA

[1] The U.S. Bureau of Labor Statistics is currently developing an annual experimental state labor productivity series for the PNFB sector using hours worked as the labor input.
[2] Details on the methodology used for estimating state hours will be forthcoming in a BLS publication. The hours methodology for national estimates can be found at https://www.bls.gov/lpc/lprswawhtech.pdf (U.S. Bureau of Labor Statistics 2004).

adjusts payroll data/labor earnings to account for interstate commuters at the state level using the percentage of workers who work outside their state of residence data from the American Community Survey (ACS) (U.S. Bureau of Economic Analysis 2018c). For example, a portion of the earnings of those living in New Jersey are allocated to New York where many are employed but do not reside. Furthermore, factor incomes are reconciled with GDP and state estimates are controlled to the U.S. national GDP.

In a sensitivity analysis, HRW found no significant difference in their results when they used BEA regional price parities (these price parities exist at the private business sector level only and are based upon the CPI and housing rents from the ACS) to deflate GDP. Although state prices differ, there are no state-level price indexes available and thus we make no adjustment for these differences. In this study, we create a real PNFB output measure by adjusting GDP by state using a chain-type quantity index formula that excludes the farm sector.

For comparison's sake, our analysis limits results to 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 it 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 Washington, D.C., because it is difficult to measure its knowledge capital.

Figure 1 highlights the dispersion in productivity levels across states in 2007 and 2016. Between 2007 and 2016, the mean output per hour worked rose from \$55.25 to \$60.34. Dispersion across states (as measured by the standard deviation) fell slightly from \$9.00 to \$8.50 over the same time period. Using another measure of dispersion, we find that the state at the 75th percentile of the log-level productivity distribution was 1.2 times more productive than the state at the 25th percentile in 2016.

B. State Knowledge Capital

We next briefly summarize the state knowledge capital measures, which were developed by HRW (2017b) and which we update to include 2016. Using a Mincer-type earnings function, HRW augments school attainment (measured as highest years of schooling completed using the ACS) by test scores to create a measure of aggregate knowledge capital per worker. Thus, knowledge capital h can be represented by:

$$h = e^{rS+wT} \tag{2}$$

where S is the mean years of schooling, T is mean test scores, 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). The gradient values are based upon the micro-economic literature (Hanushek et al. 2015; Hanushek and Zhang 2009).

Years of schooling are calculated from the ACS for the working-age population aged 20–65 not currently enrolled in school. For 2007, we use HRW's data directly. For 2016 data, we convert degrees attained from ACS to years of schooling following Jaeger (1999) and assign GED holders 10 years of schooling following HRW.[3] Figure 2 shows the distribution of mean years of schooling across states in 2007 and 2016. The average years of schooling increases slightly from 13.11 in 2007 to 13.28 in 2016.

Test scores are taken from HRW's preferred test score measures for each state's working-age population; 2007 and 2012 data are used for the 2007 and 2016 analyses, respectively.[4] HRW's measures are based primarily upon eighth grade mathematics achievement test scores from the

[3] GED holders tend to have relatively weak labor market performance (Heckman, Humphries, and Mader 2011).

[4] HRW's 2012 measures incorporate two additional years of data beyond 2007 for the working-age population. Given time constraints and the complexity of replicating their measures, we make the assumption that the 2012 test score measure approximates a 2016 measure if it were to be constructed.

National Assessment of Educational Progress (NAEP) from 1978 to 1992 at the national level and 1992 through 2011 at the state level. HRW's 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 combines data from international achievement tests with population shares of international migrants based upon their country of origin to adjust for selective migration. They backcast state scores from 1978 to 1992 using national trends to obtain the skills of the current working-age population. Test scores are normalized to have a U.S. mean of 500 and standard deviation of 100 in the year 2011. See HRW (2017b) for more details on the construction of the test score measures. The schooling data are available in Appendix Table A1.

III. Development Accounting Framework

One goal of the 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 3-6 show scatterplots of the association across states of log output per hour with mean years of schooling and with test scores, respectively, for 2007 and 2016. In 2007, the cross-state correlations are 0.346 between log output per hour and mean years of schooling and 0.336 between log output per hour and test scores (Table 2). In 2016, the cross-state correlations are 0.402 between log output per hour and mean years of schooling and 0.423 between log output per hour and test scores (Table 3). These correlations are lower than the correlations of the knowledge capital components with log GDP per capita in 2007. We note that the correlation between log GDP per capita and log GDP per hour is 0.876 in 2007.

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

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

where Y is GDP; L is hours worked; h is aggregate knowledge capital per worker; K is capital; and A^{λ} represents multi-factor productivity. Assuming $\lambda = 1 - \alpha$ (i.e. Harrod-neutral productivity), then labor productivity is

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

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

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

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

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

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

We estimate the first term of the decomposition, the share of the productivity variance due to knowledge capital.[5] Results with our state productivity measure, PNFB output per hour, compared to HRW's GDP per capita are presented in Table 4.

[5] Even though A can be endogenous, Klenow and Rodríquez-Clare (1999) 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 y would suggest that differences in education policies are important for explaining state-level differences in labor productivity.

We find that in 2007, 14 percent of the dispersion in state productivity results from differences in knowledge capital, with 8 percent coming from differences in test scores and 6 percent coming from differences in years of schooling. This is low compared to HRW, who find that 23 percent of the variation in GDP per capita in the same year is explained by differences in knowledge capital. In 2016, 19 percent of the dispersion in state productivity results from differences in knowledge capital, with 11 percent coming from differences in test scores and 8 percent coming from differences in years of schooling and.

We also examine the contribution of knowledge capital to the difference in output per hour worked between the top five and bottom five states in the productivity distribution, extending HRW's five-state measure. 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 11 percent of the difference in output per hour in contrast to 31 percent of the difference in GDP per capita (Table 4). For the same year, the contribution of test scores relative to years of schooling is more than twice the contribution of years of schooling to the difference (7.7 percent and 3.3 percent respectively); in the HRW specification, test scores contribute only 55 percent more than years of schooling (18.6 percent and 12 percent respectively). Our result validates HRW's augmentation of the human capital model to include test scores/cognitive skills. Furthermore, our result shows that using the more precise measure of productivity raises the importance of cognitive skills' role in explaining differences in productivity. The results for 2007 hold for 2016.

IV. Growth Regression Models

We next examine cross-state differences in productivity growth for the period 2007–2016. Over the period, the unweighted average growth was 1.02 percent. We also find considerable heterogeneity across states, with a standard deviation in the growth rate of 0.69 percent.

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

$$\%\Delta y_s = \alpha + \beta_1 T_s + \beta_2 S_s + X_s\delta + \varepsilon_s \qquad (7)$$

where $\%\Delta y_s$ is the average annual growth rate in labor productivity in state *s* between 2007 and 2016, T_s is the mean test scores of the working-age population in state *s* in 2007, S_s is the mean years of schooling of the working-age population in state *s* in 2007, X_s is a matrix of state controls including the log of initial level of output per hour in 2007, the log of physical capital stock per worker as measured in 2000, total area in square miles in state *s*, and Census region fixed effects, and ε_s is an error term.[6] This analysis is descriptive and not meant to establish causality. Numerous cross-country analyses have established that greater knowledge capital leads to greater economic growth (Hanushek and Woessmann 2012, 2015) even when accounting the potential for endogeneity bias.[7]

Table 5 presents three specifications of our productivity growth model to examine relationship between knowledge capital and growth. 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 other institutional differences that are geographically correlated.

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[6] The 2000 physical capital stock per worker measure is for the total economy and taken from Turner, Tamura, and Mulholland (2013). The state total area in square miles is from the U.S. Census Bureau (2018).

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

In all three specifications of productivity growth, the human capital measures are statistically insignificant. These results differ from HRW (2017a) who find that knowledge capital explains greater economic growth as measured by GDP per capita over the period 1970-2010. The different results are either related to the length of the time period covered or the dependent variable.[8] We find the traditional negative relationship between the initial productivity level and productivity growth, which is consistent with the literature on state-level convergence (Barro and Sala-i-Martin 1992; Mankiw, Romer and Weil 1992). In other words, states that are behind in levels grow faster. In addition, total area is positively correlated with growth, possibly reflecting resource- rich economic activity.

V. Conclusion and Future Work

There is substantial variation in U.S state productivity levels and growth rates. In this paper, we examine the contribution that knowledge capital, a measure based upon not just schooling attainment but also skills, makes to these productivity differences. We replicate models examined in HRW (2017a; 2017b) but replace their outcome, GDP per capita, with the better measure of labor productivity, output per hour. Using a development accounting framework, we find that about 19 percent of the dispersion in state productivity in 2016 results from differences in knowledge capital, with 8 percent coming from differences in years of schooling and 11 percent coming from differences in test scores. This validates the importance of cognitive skills in explaining productivity. Over the period 2007–2016, we do not find that initial knowledge capital contributes to productivity growth.

[8] Future work will consider using a GDP per capita specification for 2007-2016 to determine whether the output measure impacts the results.

In future work, we intend to investigate alternative human capital measures that address cognitive skill, such as applying BLS-consistent state-level labor composition measures and replacing years of schooling with college-degree attainment in a knowledge capital measure. We will also update HRW's GDP per capita specification for 2007-2016 to probe the relationship of various human capital measures interaction with different 'productivity' measures.

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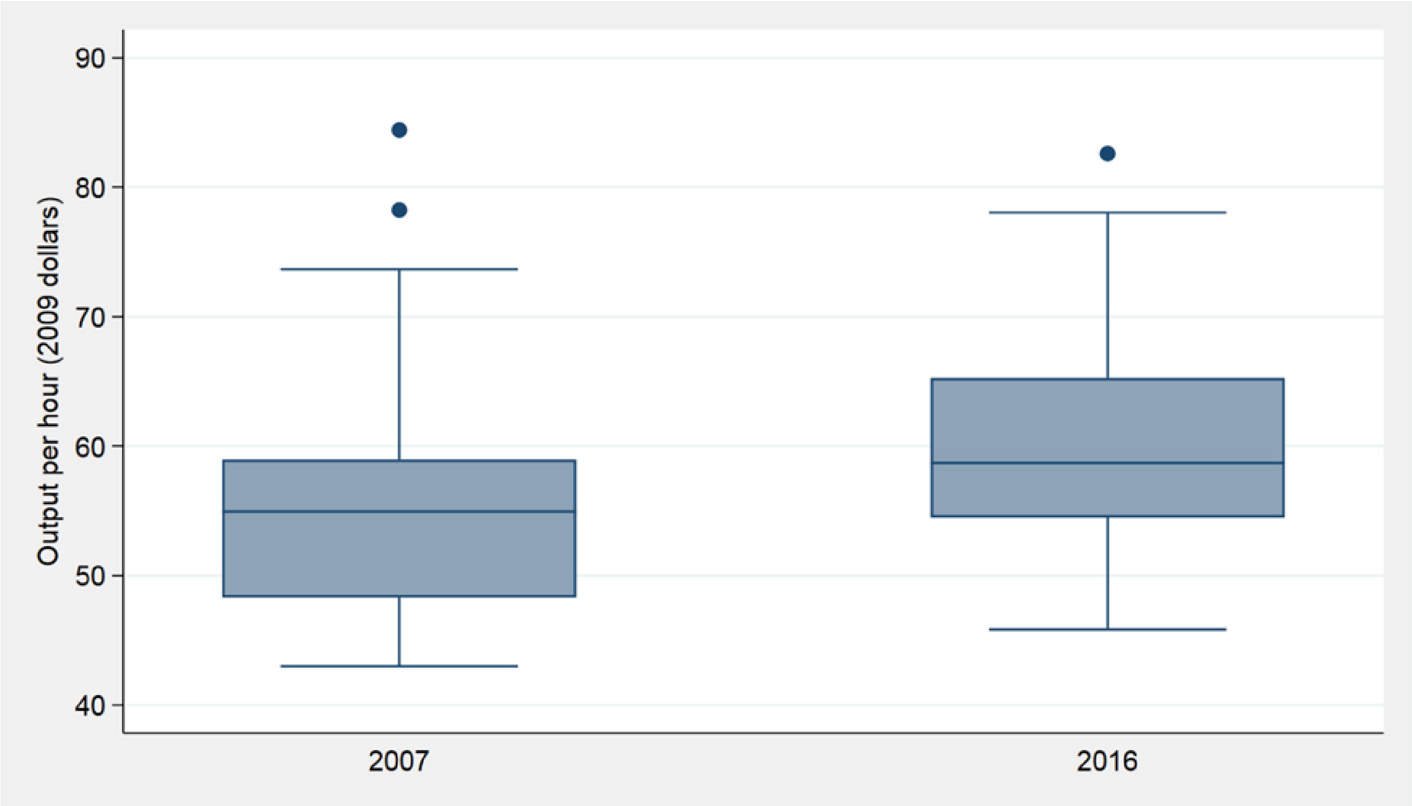

Figure 1. Boxplot of Output per Hour Worked of U.S. States

Notes: Output per hour worked for the private nonfarm business sector denoted in 2009 US dollars. Boxplots comprise 47 US states (Alaska, Delaware, and Wyoming excluded). 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 nearer quartile. The dots represent outliers (>1.5 IQR).

Source: Authors' calculations from U.S. Bureau of Economic Analysis (2018 a, b), U.S. Bureau of Labor Statistics

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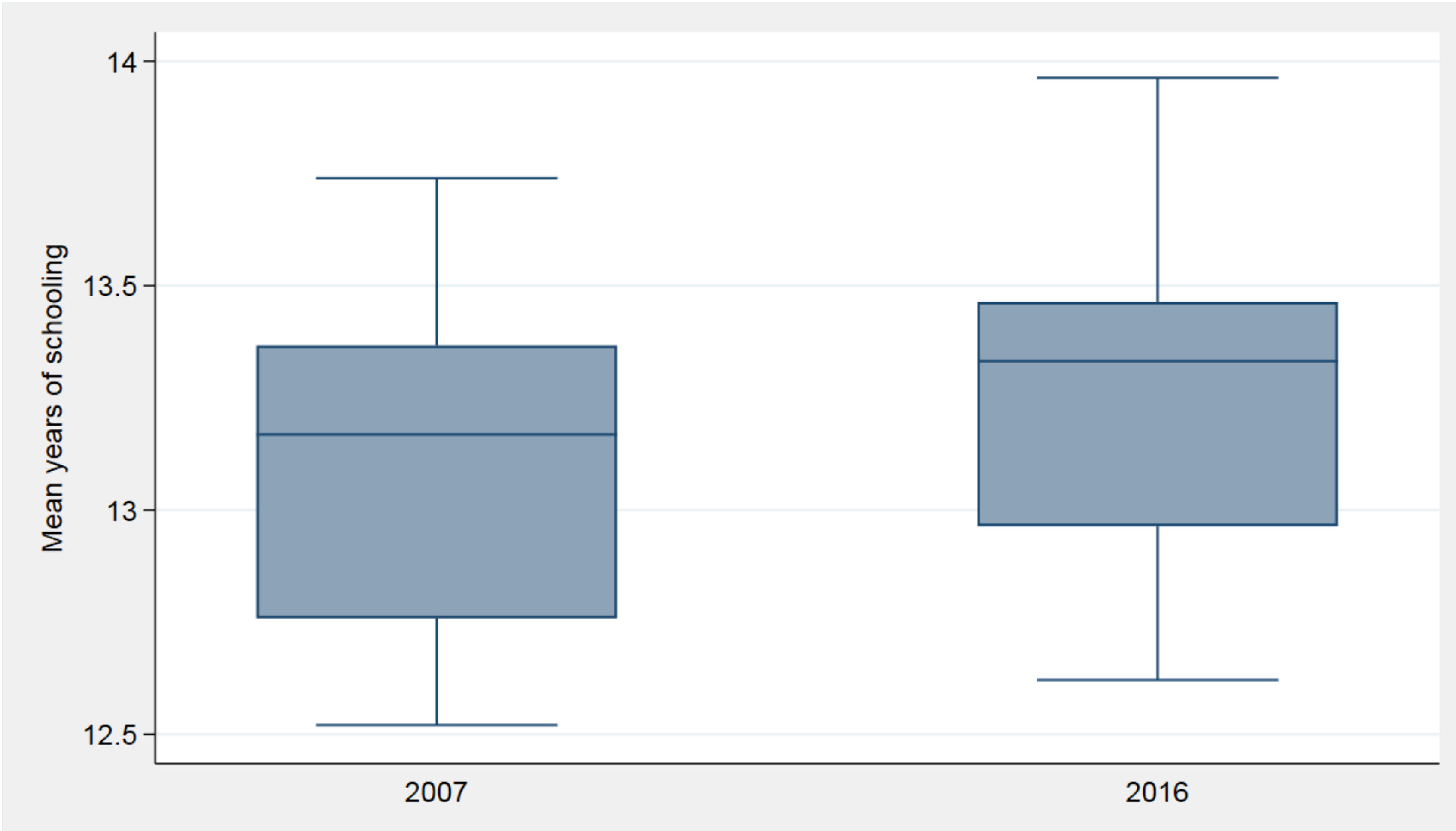

Figure 2. Boxplot of Average Years of Schooling of U.S. States

Source: 2007 data from Hanushek, Ruhose, Woessman (2017b); 2016 data from Ruggles et al. (2017)

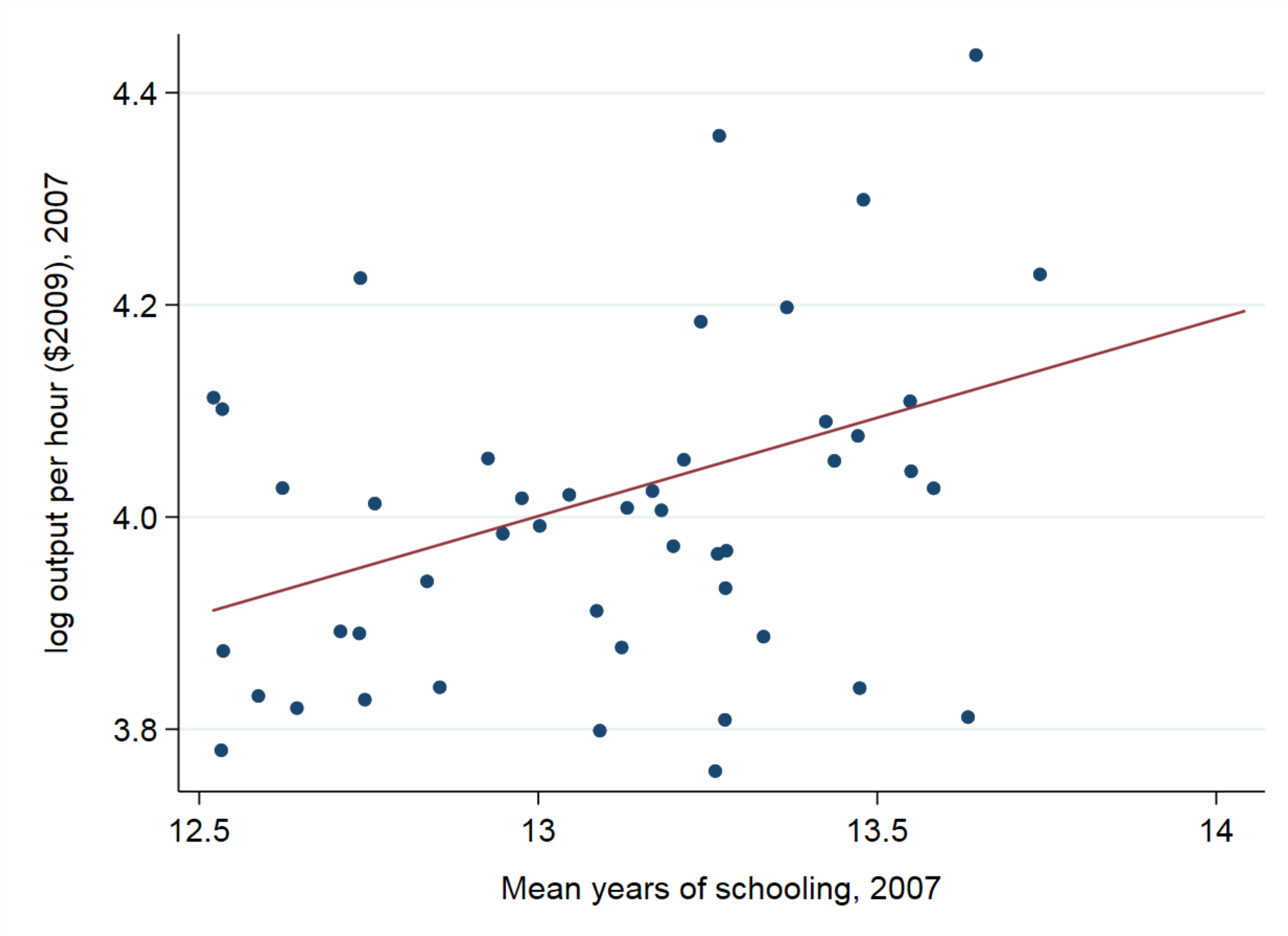

Figure 3. Years of Schooling and Output per Hour across U.S. States, 2007

Source: Authors' calculations from U.S. Bureau of Economic Analysis (2018 a, b), U.S. Bureau of Labor Statistics; Hanushek, Ruhose, Woessman (2017b)

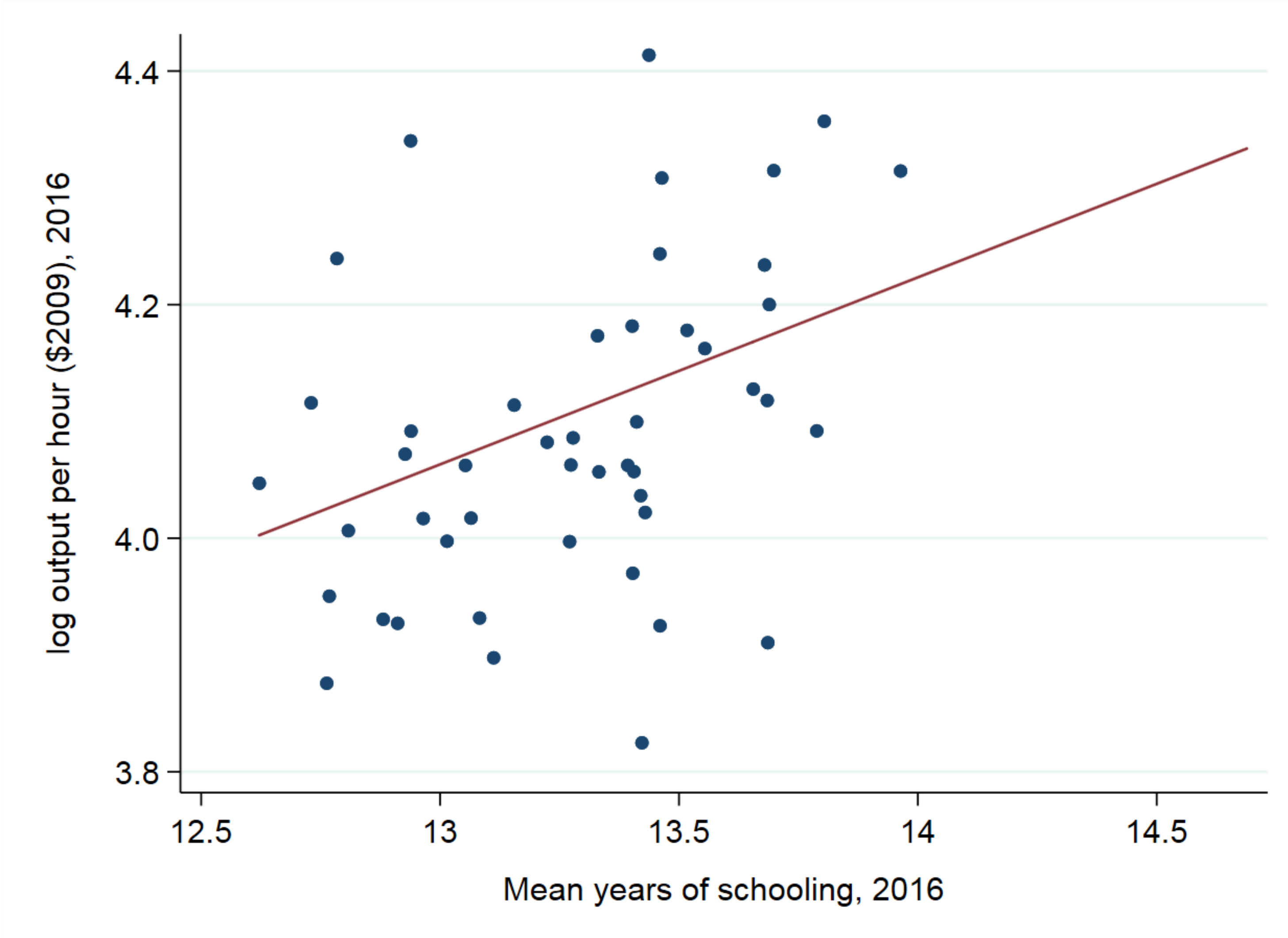

Figure 4. Years of Schooling and Output per Hour across U.S. States, 2016

Source: Authors' calculations from U.S. Bureau of Economic Analysis (2018 a, b), U.S. Bureau of Labor Statistics; Ruggles et al. (2017)

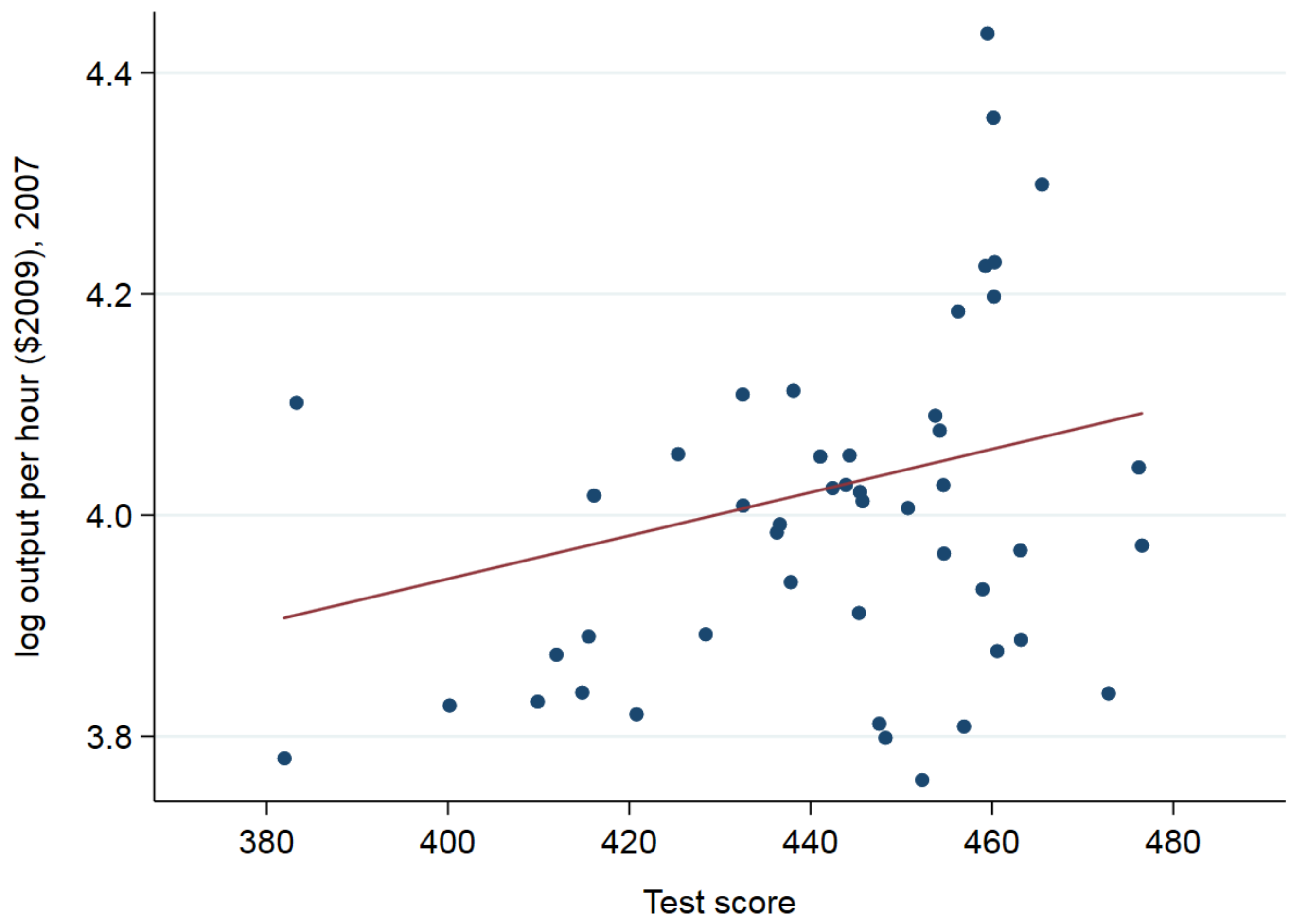

Figure 5. Cognitive Skills and Output per Hour across US States, 2007

Source: Authors' calculations from U.S. Bureau of Economic Analysis (2018 a, b), U.S. Bureau of Labor Statistics; Hanushek, Ruhose, Woessman (2017b)

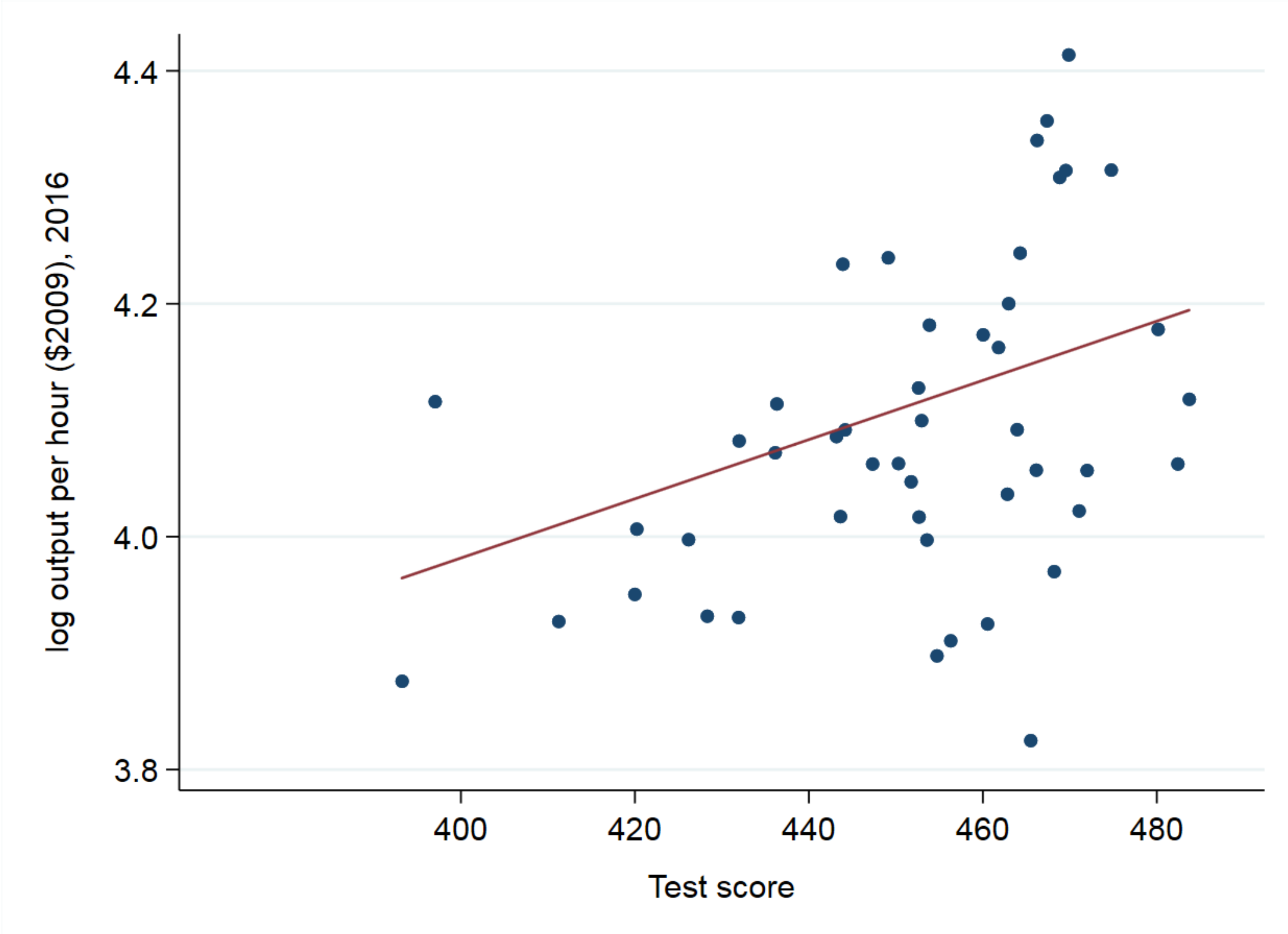

Figure 6. Cognitive Skills and Output per Hour across US States, 2016

Source: Authors' calculations from U.S. Bureau of Economic Analysis (2018 a, b), U.S. Bureau of Labor Statistics; Hanushek, Ruhose, Woessman (2017b)

Table 1. Summary State Statistics (N = 47)

	Mean	Std. dev.	25th percentile	75th percentile	Min.	Max.
Hours worked per worker 2007	1674.84	50.50	1640.54	1703.60	1589.37	1816.78
Hours worked per worker 2016	1646.51	34.85	1619.91	1672.03	1576.85	1727.58
Output per Hour Worked 2007 ($2009)	55.25	9.049	48.29	58.95	42.98	84.42
Output per Hour Worked 2016 ($2009)	60.34	8.547	54.47	65.25	45.84	82.59
Years of schooling 2007	13.11	0.345	12.76	13.37	12.52	13.74
Years of schooling 2016	13.28	0.333	12.96	13.46	12.62	13.96
Test scores 2007	442.40	22.04	432.48	459.25	381.90	476.50
Test scores (2016 = 2012)[1]	451.57	20.75	443.15	466.21	393.21	483.71
Average labor productivity growth rate, 2007–2016 (%)	1.02	0.69	0.66	1.38	-0.87	3.84
Log initial physical capital per worker 2000	0.92	0.08	0.85	0.97	0.75	1.20
Log total area (in square miles)	10.74	0.98	10.50	11.33	7.34	12.50

Notes: Summary statistics are created weighting each state equally. Test scores refer to eighth-grade math scores. Alaska, Delaware, the District of Columbia, and Wyoming are excluded.

[1] Scores for 2012 are used as proxy for 2016.

Table 2. Correlations, 2007

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	0.876	1		
Mean years of schooling	0.521	0.346	1	
Test score	0.555	0.336	0.718	1

Notes: 47 states

Table 3. Correlations, 2016

Measure	Log output per hour worked	Mean years of schooling	Test score
Log output per hour worked	1		
Mean years of schooling	0.402	1	
Test score	0.423	0.701	1

Notes: 47 states

Table 4. Development Accounting Results with Alternative Productivity Measures

	Covariance measure			Five-state measure		
Productivity measures:	Total knowledge capital	Test scores	Years of Schooling	Total knowledge capital	Test scores	Years of Schooling
2007 GDP per capita (Hanushek, Ruhose, Woessman 2017b)	0.228	0.135	0.093	0.306	0.186	0.120
	(0.044)	(0.028)	(0.023)			
2007 Output per hour	0.144	0.082	0.062	0.111	0.077	0.033
	(0.052)	(0.033)	(0.025)			
2016 Output per hour	0.186	0.108	0.078	0.135	0.087	0.049
	(0.054)	(0.033)	(0.027)			

Note: Development accounting results for 47 US states with different productivity specifications. Test scores refer to eighth-grade math scores from NAEP with backward projections by age and parental education. Calculations assume a return of w = 0.7 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 5. State Productivity Growth Regressions for the Private Nonfarm Business Sector (2007–2016)

VARIABLES	(1)	(2)	(3)
Mean test score (2007)		0.003	0.008
		(0.006)	(0.007)
Initial years of schooling (2007)	0.404	0.248	0.247
	(0.330)	(0.398)	(0.393)
Log (initial output per hour) (2007)	-2.420***	-2.471**	-2.442***
	(0.894)	(0.936)	(0.908)
Log (initial physical capital per worker) (2000)	1.559	1.502	1.526
	(1.155)	(1.126)	(1.370)
Log (total area in square miles)	0.205**	0.181**	0.104
	(0.095)	(0.088)	(0.124)
Census region fixed effects	NO	NO	YES
Constant	1.774	8.579**	2.962
	(3.731)	(3.824)	(4.759)
Observations	47	47	47
R-squared	0.315	0.319	0.345

Notes: The dependent variable is the average annual growth rate in output per hour, 2007–2016. Robust standard errors in parentheses.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

Appendix

Table A1. Years of Schooling and Test Scores (by State)

	Years of schooling 2007 (1)	Years of schooling 2016 (2)	Test scores 2007 (3)	Test scores 2016 (4)
Alabama	12.7	12.9	400.2	411.2
Arizona	12.8	13.0	445.7	452.6
Arkansas	12.6	12.8	409.9	420.0
California	12.7	12.9	459.2	466.2
Colorado	13.5	13.7	454.2	462.9
Connecticut	13.6	13.8	459.5	467.3
Florida	13.0	13.1	436.6	443.6
Georgia	12.9	13.2	425.4	436.3
Hawaii	13.4	13.6	453.7	461.8
Idaho	13.1	13.1	448.2	454.7
Illinois	13.2	13.5	456.2	464.3
Indiana	12.9	13.1	436.2	447.3
Iowa	13.2	13.4	476.5	482.4
Kansas	13.3	13.4	458.9	466.1
Kentucky	12.6	12.9	420.8	431.9
Louisiana	12.5	12.7	383.3	397.0
Maine	13.3	13.4	456.9	465.5
Maryland	13.5	13.7	432.5	443.9
Massachusetts	13.7	14.0	460.3	469.5
Michigan	13.2	13.3	442.4	450.3
Minnesota	13.5	13.7	476.2	483.7
Mississippi	12.5	12.8	381.9	393.2
Missouri	13.1	13.3	445.3	453.5
Montana	13.3	13.5	452.3	460.5
Nebraska	13.3	13.3	463.2	472.0
Nevada	12.6	12.6	443.9	451.7
New Hampshire	13.6	13.8	454.6	463.9
New Jersey	13.5	13.7	465.5	474.7
New Mexico	12.7	12.9	428.4	436.1
New York	13.3	13.4	460.1	469.8
North Carolina	13.0	13.2	416.1	432.0
North Dakota	13.5	13.5	472.8	480.1
Ohio	13.1	13.3	432.5	443.1

Notes: (1) and (2) Mean years of completed schooling. (3) and (4) Average eighth-grade math NAEP scores. Scores for 2012 are used as proxy for 2016.
Sources: Hanushek, Ruhose, Woessman (2017b); Author's calculations based on American Community Survey

Table A1. Years of Schooling and Test Scores (by State) (Continued)

	Years of schooling 2007 (1)	Years of schooling 2016 (2)	Test scores 2007 (3)	Test scores 2016 (4)
Oklahoma	12.8	12.9	437.8	444.1
Oregon	13.2	13.3	450.7	460.0
Pennsylvania	13.2	13.4	444.3	453.8
Rhode Island	13.0	13.4	445.4	452.9
South Carolina	12.9	13.1	414.8	428.3
South Dakota	13.1	13.4	460.5	468.2
Tennessee	12.7	13.0	415.5	426.1
Texas	12.5	12.8	438.1	449.1
Utah	13.3	13.4	454.7	462.8
Vermont	13.6	13.7	447.5	456.3
Virginia	13.4	13.7	441.0	452.6
Washington	13.4	13.5	460.2	468.8
West Virginia	12.5	12.8	411.9	420.2
Wisconsin	13.3	13.4	463.1	471.0