State productivity and economic growth

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\textbf{ABSTRACT}
This study uses Bureau of Economic Analysis data on state-level productivity levels and growth rates over the period 1977–2019. We find that states with relatively high productivity tend to experience somewhat lower productivity growth over time, whereas states with relatively lower productivity experience somewhat higher productivity growth over time. We find compelling evidence for significant contributions from education (in the form of a college degree) as well as the role played by higher growth rates in the state-level Hispanic population as factors contributing to increased productivity. Worker/labour productivity constitutes a good indicator of changes to wages and living standards. Empirically examining interstate differences in state-level worker productivity growth across different time intervals helps to identify factors that influence geographical differentials in productivity as well as aids in the identification of the specific factors that determine rates of productivity growth and decline.

\textbf{ARTICLE HISTORY}
Received 21 May 2021; Accepted 10 March 2022

\textbf{KEYWORDS}
economic growth; labour productivity; real gross domestic product (GDP) per worker; per cent of population with a bachelor’s degree; wages and living standard

\textbf{JEL}
O3; R1; J0

\section*{INTRODUCTION}

Labour productivity is a good indicator of changes in wages and living standards; hence, it has been the subject of considerable research and scrutiny (Cebula & Coombs, 2008; Hotchkiss, 2006; Nourse, 1968, pp. 219–221). Annual changes in labour productivity are volatile and influenced by, among other things, both long-term trends and business cycles. Historically, economies experience large increases in productivity when they transition from agricultural societies to industrial economies. The transition from an industrial-based economy to an information economy driven by knowledge, technology, genomics and artificial intelligence raises concerns about continued prosperity because the changes occur during times of low overall productivity growth and increasing income inequality.
Growth in average productivity across the United States for each business cycle since the Second World War is presented in Figure 1. Productivity growth remained above 2% until 1975, but remained below 2% for three consecutive business cycles thereafter. Annual productivity growth averaged more than 2% from 1991 to 2009, but averaged 1.4% per year since 2009. It is this recent decline in productivity growth during the last 10 years that gained the attention of economists, policymakers and the public.

The data provided above define labour productivity as output per work-hour, the conventional measure reported by the Bureau of Labor Statistics (BLS). In order to examine state and regional changes in productivity growth, the present study uses a related measure of productivity. Real output per worker is calculated as the ratio of real gross state product (RGSP) to the total number of employees for all industries. Data were obtained from the Bureau of Economic Analysis (BEA).

Productivity calculations reflect the comingling of full- and part-time workers and the variation in average hours worked per year. The share of full-time workers in total employment is

![Figure 1. Average US productivity growth trough to trough of the business cycle.](image)

Sources: Bureau of Labor Statistics (BLS) (https://data.bls.gov/timeseries/PRS85006092); and National Bureau of Economic Research (NBER) (http://www.nber.org/cycles/cyclesmain.html).

### Table 1. Full-time workers as a share of total employment, 2010–19.

| Year | Full-time/all workers |
|------|-----------------------|
| 2010 | 80.3%                 |
| 2011 | 80.5%                 |
| 2012 | 80.6%                 |
| 2013 | 80.8%                 |
| 2014 | 81.1%                 |
| 2015 | 81.6%                 |
| 2016 | 81.7%                 |
| 2017 | 82.2%                 |
| 2018 | 82.5%                 |
| 2019 | 82.9%                 |

Source: Bureau of Labor Statistics (BLS) (https://data.bls.gov/timeseries/LNU02500000 and https://data.bls.gov/timeseries/LNU02600000).
fairly stable, as shown in Table 1. The mean of the data shown is 81.4%, with a standard deviation (SD) of only 0.9%.

Table 2 shows the average hours worked by employees since the Great Recession. For the 11 years shown, the average annual hours worked was 1758.2, with an SD of 12.65 hours. Hours worked increased between 2010 and 2019 by a total of 1.75% over the study period, yielding a compound annual growth rate of 0.19%.

Taken together, these two measures of labour input indicate that the output per worker productivity measure is lower than the output per work-hour measure. This difference is illustrated in Figure 2, but the two measures track almost identically over the cycle.

Real GDP (RGDP) growth effectively derives from two sources. Potential RGDP increases either from an increase in the labour force, or an increase in productivity, or some combination of the two. The \(\%\Delta RGDP = %\Delta LF + %\Delta LP\) (1)

Table 2. Hours worked per employee per year, 2010–19.

| Year | Average hours worked/year | % Change |
|------|--------------------------|----------|
| 2010 | 1735                     | 0.37%    |
| 2011 | 1745                     | 0.57%    |
| 2012 | 1747                     | 0.11%    |
| 2013 | 1753                     | 0.32%    |
| 2014 | 1758                     | 0.33%    |
| 2015 | 1770                     | 0.67%    |
| 2016 | 1767                     | −0.19%   |
| 2017 | 1764                     | −0.17%   |
| 2018 | 1775                     | 0.62%    |
| 2019 | 1765                     | −0.53%   |

Source: FRED (https://fred.stlouisfed.org/series/AVHWPEUSA065NRUG).

**Figure 2.** Growth rates of alternative productivity measures, 2010–19.

Sources: Bureau of Labor Statistics (BLS) (https://data.bls.gov/timeseries/PRS85006092); and Bureau of Economic Analysis (BEA) (https://www.bea.gov/itable/iTable.cfm?ReqID=70&step=1#reqid=70&step=1&isuri=1).
Annual labour force growth since 2000 averaged only 0.6%, as compared with 1.4% between 1977 and 2000. Figure 3 reveals the substantial decline in annual labour force growth during the last two decades of the 20th century and the first two decades of the 21st century.

There are two major causes for the observed decline. First, there is ongoing decline in the overall US labour force participation rate beginning in the year 2000. The US labour force participation rate peaked in May 2000 at 67.3%. Over the first two decades of the 21st century the labour force participation rate dropped to a low of 62.4% in September 2015. As the economy improved during the period 2016–19, the labour force participation rate increased, but only slightly, to 63.3% in December 2019. The decline in the total labour force participation rate can be attributed to ageing of the baby-boomers and to changes in certain government programmes, such as the Social Security Disability Insurance (SSDI) (Cebula & Coombs, 2008; Fullerton, 1997; Hipple, 2021; Hotchkiss, 2006; Perez-Arce et al., 2018; US Census Bureau, 2021). Overall ageing of the population is interesting because as workers retire, the age cohort entering the labour force is smaller than the exiting age cohort. This phenomenon may very well dominate labour market demographic changes for the foreseeable future.

As a result of the decline in labour force growth, labour productivity takes on additional importance in fostering economic growth. Broad-brush federal policies and national approaches will not effectively increase productivity if sources of the decline differ across regions and states. This paper considers productivity changes at state and regional levels to determine where patterns of productivity decline differ. Additional consideration is given to identifying whether there are unique factors leading to reduced productivity growth. Considerations of the quantity and quality of labour and capital and technical change offer only weak explanations for national productivity decline. We expand the analysis to consider other factors including: infrastructure decline; ‘institutional sclerosis’ (Olson, 1983); government policies (Porter et al., 2017); overwhelming regulation (Rothwell, 2016); unionization; the nature of recent innovation (Gordon, 2016); measurement problems; declining labour mobility; and the sectoral shifting of the economy from manufacturing to services. Ultimately, the empirical estimates reveal a pattern in
which states with relatively higher productivity tend to experience somewhat lower productivity growth whereas those with relatively lower productivity tend to experience somewhat higher productivity growth. Consistent with mainstream human capital theory, we find compelling evidence that education (in the form of a college degree) is a significant contributor to higher productivity. Estimated coefficients for Hispanic population growth are positive and statistically significant for every sample period, implying that greater growth amongst this demographic enhanced productivity.

**LITERATURE INSIGHTS**

There is little consensus on the pattern of declining productivity growth. Gordon (2016) argues a convergence of factors that limit growth in productivity. Innovations may not be as effective at increasing productivity as in the past. Business is largely being conducted the same way it was a decade ago. Total factor productivity (TFP) typically is an important driver of productivity growth, but it seems to be contributing less than in previous waves of innovation.

Before proceeding, it is useful to clarify the term ‘total factor productivity’. TFP is a measure of productivity calculated by dividing an economy-wide level of total production by the weighted average of inputs, that is, labour and capital. Alternatively stated, TFP measures the relationship between outputs (total production) and inputs used in the production process, that is, the so-called factors of production (primarily labour and capital). TFP equals total output divided by the inputs. There are two primary measures of productivity: (1) labour productivity, which equals total output divided by units of labour per se; and (2) total factor productivity, which equals total output divided by a suitably (realistic) weighted average of the inputs involved: TFP = total output/total input.

A 2016 study conducted by Gallup for the US Council on Competitiveness (Rothwell, 2016) found that regulations, notably in the housing, healthcare and education industries, are among the main causes of US productivity declines. These three sectors accounted for 25% of the economy in 1980, rising to 36% by 2015. Compliance adds to business costs and employment but not to measured output; thus, increased expenditures on compliance generate declines in measured productivity. As evidence, the Office of Management and Budget estimates that federal government regulations cost businesses US$250 billion per year. The cost of regulatory compliance is not only cumulative but also may increase exponentially.

Porter et al. (2017) identified a constellation of factors related to productivity and competitiveness and then rated these as either a strength or weakness for the United States. Strengths included management skills, entrepreneurial context, efficient capital markets, innovative infrastructure and research universities. These strengths are difficult to create and form the basis for an enduring competitive advantage for the United States for some time to come. The weaknesses generally relate to federal policy: the tax code, the political system, logistics infrastructure, healthcare and regulation. The US strengths would support sustained or even increased growth in productivity if the impact of the weaknesses could be mitigated. Porter et al. (2017) conclude that the United States should develop a national strategy to promote an increase in both productivity and shared prosperity as the optimal means to restoring competitiveness. This strategy should focus on modifications to federal policies that have the largest impact on productivity.

Hulten and Schwab (1984) conducted an analysis of the variation of regional productivity growth in manufacturing from 1951 to 1978. They considered the national decrease in productivity along with the causes of productivity differences across US regions and states. While national growth is attributable to increases in TFP, regional changes in productivity were mainly driven by changes in the capital-to-labour ratio in the region, a finding consistent with the modelling in Gallaway and Cebula (1972). In other words, there were/are non-trivial
interstate differentials in the ratio of capital (inclusive of human capital) to labour, which account in part for interstate growth differentials.

Caliendo et al. (2014) conducted another analysis of regional productivity differences and their impact on aggregate outcomes. Their model considers linkages across regions at a sectoral level, including the costs of interregional trade. This model can analyse the aggregate impact of productivity increases in a specific sector-location combination. The results demonstrate that changes in regional productivity result from a complex interaction amongst the change in sectoral productivities where the changes are introduced, and the costs of trade between the originating region and the other regions. This set of findings underlines the importance of focusing on productivity enhancements at a state or regional level rather than on national policies.

Rigby and Essletzbichler (2002) adopt plant-level data obtained from the Longitudinal Research Database of the US Census Bureau to estimate the impact of agglomeration economies on industry productivity across metropolitan areas in the United States. This empirical analysis is portrayed as rectifying the three shortcomings of previous empirical studies on the effects of agglomeration economies: (1) reliance on aggregate spatial or sectoral data; (2) lack of attention to spatial dependence in data; and (3) representation of agglomeration economies with vague proxies such as mere city-size. Rigby and Essletzbichler demonstrate how a number of establishment-, industry- and city-specific factors influence labour productivity across US cities, paying particular attention to separating the influence of different agglomeration economies on firm efficiency. Overall, they find that regardless of the specific agglomeration economies present, greater agglomeration economies elevate firm efficiency, labour productivity and total productivity.

Moreover, the issue of interregional productivity differentials entails other considerations. For example, Fallah et al. (2011) draw upon urban agglomeration theories to empirically investigate the relationships between the economic performance of metropolitan areas in the United States and their respective degrees of urban sprawl. To measure urban sprawl, the authors construct a distinctive measure that captures the distribution of population density and land-use within metropolitan areas. Both ordinary least squares (OLS) and instrumental variables estimations (IVs) yield the conclusion that greater levels of urban sprawl are negatively associated with average labour productivity. This pattern holds within given industries as well as within given occupational classifications.

Human capital differences between areas/regions are also important (Gallaway & Cebula, 1972). An empirical study by Shapiro (2006) finds that from 1940 to 1990, a 10% rise in a metropolitan area’s relative concentration of college-educated residents was associated with a 0.8% increase in subsequent employment growth. IVs provide support for a causal relationship between college graduate composition and the rate of employment growth, although these studies offer no evidence for an effect of high school graduates on employment growth rates. Using data on growth in wages, rents and house values, Shapiro calibrates a neoclassical city growth model, concluding that approximately 60% of the employment growth effect of college graduates is due to enhanced labour productivity growth with the balance attributable to improved quality of life. This finding contrasts with the common argument that human capital generates employment growth in urban areas solely through changes in productivity.

More recently yet, Gallardo et al. (2021) investigate the impact of multiple broadband indicators on job productivity. They adopt cross-section county-level data and spatial econometric modelling. Their findings indicate that more extensive adoption of broadband exercised a positive impact on job productivity. They further conclude, among other things, that the relationship between broadband metrics and economic productivity should be assessed from a broad and comprehensive socioeconomic perspective.
REGIONAL PRODUCTIVITY PATTERNS

This study investigates productivity patterns by region and state between 1977 and 2019. The principal focus will be comparing the end of the 20th-century productivity levels and growth rates to the 21st-century productivity levels and growth rates. The analysis begins with a consideration of the regional productivity. The productivity measure used is RGDP for all industries divided by total employment; all data are obtained from the BEA’s regional accounts. The US productivity profile by BEA regions is presented in Figure 4.

The pattern of regional productivity growth reveals at least two interesting trends. First, during the last two decades of the 20th century, with the exception of the Mideast region, there is a tight grouping of the other seven regions. This tight grouping begins to change at the end of the 20th century as productivity in the New England region and the Far West begins to accelerate. By 2015, productivity in the Far West region slides above the Mideast region for the first time. The New England region, which had been keeping pace with the productivity growth in the Far West region began to level off and remained level over the past four years.

Second, the other five BEA regions basically tracked productivity gains consistent with overall US productivity growth. There are, however, a couple of exceptions. The Southeast region, which had been experiencing significant gains in productivity during the 20th century, peaked in 2005. This dropped the region’s productivity level from sixth to eight in just 10 years. The other region which entered a flat productivity period beginning in 2005 was the Great Lakes region. However, the decline in productivity was not as sharp as in the Southeast, and the Great Lakes region was able to maintain fifth place level.

Examining Figure 4, it is apparent that variation in productivity across the individual regions generally mirrors the business cycle trends presented in Figure 1 during the last two decades of the 20th century. The effects of averaging explain the greater variation at the region level as compared with smaller national level variation. As previously noted, New England and the Far West experienced consistently larger productivity growth during the latter part of the

Figure 4. Real gross domestic product (RGDP)/worker, 1977–2019.
20th century as compared with national productivity trends, suggesting that these regions were less impacted by volatility in overall national growth over the period. While the early 21st century produced regional productivity trends that generally reflect business cycle data from Figure 1, examination of Figure 4 reveals important departures for individual regions. Major exceptions from national trends for the period 2000–19 are apparent for the Southeast region, which experienced consistently flat productivity growth from 2005 onward, and the Far West, which enjoyed surging productivity growth over the first two decades of the 21st century. The trends for the Southeast and Far West are somewhat anomalous as the remaining regions generally followed the national business cycle trends from Figure 1, which reveal strong national productivity growth from 2001 to 2009 and a flattening of productivity growth thereafter.

Prior literature offers insight into factors that likely played a role in the regional trends described above. Relative productivity increases in the Far West, New England and Southeast regions over the relevant time periods may be due to favourable combinations of factors such as wider broadband growth and usage (Gallardo et al., 2021), human capital advantages (Gallaway & Cebula, 1972), and greater prevalence and impact of strong research universities (Porter et al., 2017).

Table 3 provides the actual levels of RGDP per worker for the eight BEA regions in 1977, 2000 and 2019. It also presents the percentage growth in RGDP/worker for each region between 1977 and 2000 and between 2000 and 2019. Despite the slight differences in total years included in the two periods, it is clear that RGDP/worker growth declined in the 21st century as compared with the last two decades of the 20th century. Only the Southwest and the Far West show RGDP/worker growth close to the 1977–2000 period. Extrapolating from the study by Glaeser and Tobio (2007), who focus on the significance and contribution of rising productivity, the latter outcome involving the Southwest and Far West is not surprising. Indeed, in view of the findings in Table 7, where productivity growth is found to be an increasing function of the percentage of the adult population with a college degree and the percentage of the population that is Hispanic, it would appear that the Far West and Southwest benefitted more than other regions from the productivity growth attributable to both of these sources.
Over time, the regional output per worker has been volatile. Regions have changed ranking and the spread (range) in RGDP/worker increased over time. In 1977, the regional SD of RGDP/worker was 10.5% of the average. By 2019 that measure had increased to 12.1%, indicating that over time there has actually been divergence in RGDP/worker amongst the eight BEA regions in the United States.

**STATE PRODUCTIVITY PATTERNS**

Table 4 presents the state RGDP/worker summary statistics for 1977, 2000 and 2019. The most striking change over the 42-year period is that the state RGDP/worker SD as a percentage of the state of the state unweighted mean rose from 28.3% in 1977 to 51.6% by 2019. This near doubling indicates that RGDP/worker has been diverging over the last two decades.

Table 5 provides summary statistics for changes in state RGDP/worker growth rates during the 1977-2019 period. Comparing the RGDP/worker growth rate between 1977 and 2000 with the RGDP/worker growth rate between 2000 and 2019, it is clear that the last two decades of the 20th century produced almost double the growth rate compared with the first two decades of the 21st century. In addition, while over the 42-year period nine states saw their ranking increase by at least 10 positions and 10 states saw their ranking decline by at least 10 positions remain very consistent.

Figures 5 and 6 presents state productivity trends over the 1977-2019 period. Figure 5 traces the RGDP/worker levels with states grouped into five quintiles based on the 1977 levels of state RGDP/worker. The 10 states with the highest RGDP/worker are grouped into the top quintile and the 10 states with the lowest RGDP/worker are grouped into the bottom quintile. Looking at the trend over time shows a possible RGDP/worker convergence based on the 1977 quintile groupings. However, when using the 2019 quintile groupings, a completely different picture emerges. Figure 6, which traces the 1977-2019 RGDP/worker levels, displays a divergent trend in productivity amongst the top quintile states and the remaining four quintile groups, which contain 40 states. Indeed, it appears that over this 42-year period there were a small number of ‘winner’ states and a large number of ‘loser’ states.

**Table 4.** State real gross domestic product (RGDP)/worker Summary Statistic: 1977, 2000 and 2019.

|          | 1977 GDP/worker | 2000 GDP/worker | 2019 GDP/worker |
|----------|-----------------|-----------------|-----------------|
| United States | US$59,900   | US$79,403   | US$93,674   |
| State unweighted average | US$58,744 | US$76,047 | US$87,688 |
| State SD | US$16,654 | US$15,560 | US$45,256 |
| State SD as a % of the average | 28.3% | 20.5% | 51.6% |
| State range | US$70,151 | US$59,903 | US$70,798 |

Note: SD, standard deviation.

**Table 5.** State real gross domestic product (RGDP)/worker summary statistic: 1977, 2000 and 2019.

|          | 1977–2000 | 2000–19 | 1977–2019 |
|----------|-----------|---------|-----------|
| US RGDP/worker growth rate | 32.6% | 18.0% | 56.4% |
| State unweighted average | 31.6% | 16.3% | 52.8% |
| State SD | 16.0% | 25.5% | 22.4% |
| State range | 77.8% | 69.4% | 99.1% |
| State rank order correlation | 0.970 | 0.967 | 0.945 |

Note: SD, standard deviation.
A least squares regression model relating state-level percentage growth in productivity to regional dummy variables, state productivity relative to US GDP per worker, state-level education variables and the percentage of the state’s population identified as Hispanic is presented in equation (2):

\[
\text{PRODGROWTH}_{it} = B_1 \text{USPRODUCTIVITY}_{it} + B_2 \text{COLLEGE}_{it} + B_3 \text{PCHISPANIC}_{it} + B_4 \text{NEW ENGLAND}_j \\
+ B_5 \text{MIDEAST}_j + B_6 \text{SOUTHEAST}_j + B_7 \text{GREATLAKES}_j + B_8 \text{PLAINS}_j + B_9 \text{SOUTHWEST}_j \\
+ B_{10} \text{ROCKYMOUNTAIN}_j + B_{11} \text{FARWEST}_j + \mu_{it}
\]  

(2)

**Figure 5.** Real gross domestic product (RGDP)/worker by 1977 quintiles, 1977–2019.

**Figure 6.** Real gross domestic product (RGDP)/worker by 2019 quintiles, 1977–2019.
where $PRODGROWTH_{it}$ is the percentage growth in GDP/worker for state $i$ during period $t$ – time periods cover the intervals 1977–2019, 1977–2000 and 2000–19; $US\ PRODUCTIVITY_{it=0}$ is the state GDP/worker for state $i$ as a percentage of US GDP/worker at the beginning of the time period $t=0$, where 0 is the base period for each regression (1977–2000, 2000–19, 1977–2019); $COLLEGE_{it=0}$ is the percentage of the adult population age 25 years and older for state $i$ with at least a four-year degree at the beginning of period $t=0$, where 0 is the base period for each regression (1977–2000, 2000–19, 1977–2019); $PCHISPANIC_{it}$ is the percentage change in state $i$ Hispanic population over period $t$ where time periods are 1977–2019, 1977–2000 and 2000–19; $NEW\ ENGLAND_j$ is a regional dummy with a value of 1 if the state is in the New England BEA Region, and 0 otherwise; $MIDEAST_j$ is a regional dummy with a value of 1 if the state is in the Mideast BEA Region, and 0 otherwise; $SOUTHEAST_j$ is a regional dummy with a value of 1 if the state is in the Southeast BEA Region, and 0 otherwise; $GREATLAKES_j$ is a regional dummy with a value of 1 if the state is in the Great Lakes BEA Region, and 0 otherwise; $PLAINS_j$ is a regional dummy with a value of 1 if the state is in the Plains BEA Region, and 0 otherwise; $SOUTHWEST_j$ is a regional dummy with a value of 1 if the state is in the Southwest BEA Region, and 0 otherwise; $ROCKYMOUNTAIN_j$ is a regional dummy with a value of 1 if the state is in the Rocky Mountain BEA Region, and 0 otherwise; $FARWEST_j$ is a regional dummy with a value of 1 if the state is in the Far West BEA Region, and 0 otherwise; and $\mu_{it}$ is a stochastic error term.

The dependent variable for equation (2) is percentage change in labour productivity. Prior literature provides the theoretical justification for each of the variables included on the right-hand side of the model. $US\ PRODUCTIVITY$ is included as a benchmark for state productivity levels relative to corresponding national values. Controlling for GDP per worker for the state relative to US productivity levels focuses the analysis on the central issue for this study which addresses the convergence or divergence of state-level labour productivity. The purpose of our model is identifying specific factors that determine whether individual state productivity levels are converging to or diverging from the nation. Research regarding the productivity enhancing role of education dates to the work of Mincer (1974) and finds additional support using increasingly sophisticated empirical methods (Baldwin et al., 2011; Card, 2001). Recent work by Hanushek et al. (2017) confirms the important role that human capital plays for present day productivity growth.

The variable percentage change in the Hispanic population is included based upon recent empirical research which points to the importance of the Hispanic population as an important driver of economic growth, particularly in rural areas. Lichter and Johnson (2020) describe Hispanic population growth as changing the trajectory of population and economic growth in many areas. Moreover, much of the changing population trajectory is due to factors other than migration. Johnson and Lichter (2016) point to the importance of natural increase related to birth rates among both Hispanic and white populations to explain trends in local area ethnic composition. A number of studies point to socio-demographic, climate and culture as factors explaining location choices including: Ketterer and Rodriguez-Pose (2015) who focus on the importance of local amenities including those provided by the public sector and DaVanzo (1983) who provides evidence that immigrants follow migration paths established by relatives. While prior literature points to factors other than local economic conditions as driving location decisions, the impact of Hispanic populations for reversing population decline and driving economic growth once settled in an area is undeniable (Coates & Gindling, 2013; Johnson & Lichter, 2019). We include percentage change in the Hispanic population to capture the role that changing Hispanic population exerts on percentage change in state-level labour productivity.

Regional fixed effects are included based upon previous literature regarding the importance of region in cross sectional studies, which is methodologically consistent with Hausman (1978)
Region fixed effects appear in studies regarding a variety of economic variables including: analysis of employment growth and migration (Partridge & Rickman, 2003); labour market models (Partridge & Rickman, 2003); family income equality (Levernier et al., 1998); state-level economic growth (Akai & Sakata, 2002) and state-level cost of living (Berry et al., 2000). Our models were estimated with the intercept term suppressed and all regions included in the model. This allows the reader to directly compare intercepts across regions.

A list of states included for each of the eight BEA regions is given in Appendix A. Washington, DC, is included in the analysis, although not a state, because of its size and autonomy as well as its immediate proximity to other contiguous states. All data were obtained from the BEA’s Regional Economic Accounts. Samples for each period include 50 states across the eight regions listed above. Models were estimated with the intercept \( (B_0) \) excluded in order to facilitate interpretation of the regional dummy variable coefficients. With the intercept suppressed, individual intercepts for each of the eight BEA regions are obtained directly from the coefficient for the specific regional dummy.

Estimated OLS coefficients with White’s robust errors are found in Tables 6 and 7. Separate columns contain estimated coefficients for the three separate time periods: 1977–2019, 1977–

| Table 6. Regression results, PCHISPANIC excluded. |
|---------------------------------------------------|
| **Dependent variable: PRODGROWTH_{it}**            |
| **Robust standard errors and covariance^a**        |
| Variable                                          | 1977–2019 Coefficient (SE) | 1977–2000 Coefficient (SE) | 2000–19 Coefficient (SE) |
| US PRODUCTIVITY_{it} = 0                          | −0.8767** (0.0965)          | −0.5358** (0.0784)          | −0.4280** (0.0868)        |
| COLLEGE_{it} = 0                                  | 3.3450** (0.8264)           | 1.8620* (0.7206)           | 1.0214* (0.3646)          |
| NEW ENGLAND_{j}                                   | 0.8556** (0.1352)           | 0.6407** (0.1341)           | 0.2493* (0.0950)          |
| MIDEAST_{j}                                       | 0.0963** (0.1238)           | 0.6391** (0.1372)           | 0.3337** (0.1065)         |
| GREAT LAKES_{j}                                   | 0.8500** (0.0903)           | 0.5450** (0.0985)           | 0.3194** (0.0833)         |
| PLAINS_{j}                                        | 0.9272** (0.1149)           | 0.4697** (0.1015)           | 0.4187** (0.1107)         |
| SOUTHEAST_{j}                                     | 0.8245** (0.0847)           | 0.5720** (0.0916)           | 0.2803** (0.0773)         |
| SOUTHWEST_{j}                                     | 0.7936** (0.1045)           | 0.4598** (0.1216)           | 0.3692** (0.0990)         |
| ROCKYMOUNTAIN_{j}                                 | 0.6403** (0.1377)           | 0.3988* (0.1500)            | 0.2754** (0.0844)         |
| FARWEST_{j}                                       | 0.8868** (0.1411)           | 0.5040** (0.1289)           | 0.3995** (0.1049)         |
| R²                                                | 0.7186                       | 0.6184                       | 0.5445                   |
| Adjusted R²                                       | 0.6482                       | 0.5346                       | 0.4445                   |
| Durbin–Watson statistic                           | 1.9402                       | 1.8080                       | 1.8173                   |
| Mean dependent variance                           | 0.5272                       | 0.3158                       | 0.1623                   |
| SD dependent variance                             | 0.2239                       | 0.1620                       | 0.1166                   |
| F-statistic                                       | 10.2130**                    | 7.4545**                    | 8.0882**                 |

Note: ^aWhite heteroskedasticity-consistent standard errors and covariance.
*Statistically significant at the 0.05 level; **statistically significant at the 0.01 level.
Because the data are cross-sectional, there is very little risk of autocorrelation. Nevertheless, reported values for the Durbin Watson statistic provide no evidence of autocorrelation. Models presented in Table 6 were estimated with the percentage change in the Hispanic population excluded, whereas results for the estimates including the percentage change in the Hispanic population are contained in Table 7. State-level productivity growth relative to US productivity at the beginning of the time period is included to control for differences in the relative starting position for each state.

An examination of Table 6 reveals that the coefficients US PRODUCTIVITY\textsubscript{it} are negative and statistically significant in all three estimates. Negative and significant coefficients for US PRODUCTIVITY\textsubscript{it} indicate a pattern in which states with relatively higher productivity experience somewhat lower productivity growth, whereas higher productivity growth rates are experienced for relatively lower productivity states. These results are thus consistent with the tight grouping of productivity growth among seven of the eight regions as presented in the descriptive analysis. It is important to emphasize that the inclusion of dummy variables for BEA regions implies that the influence of US PRODUCTIVITY\textsubscript{it} is observed after controlling for regional

| Variable                      | 1977–1999 Coefficient (SE) | 1977–2000 Coefficient (SE) | 2000–2019 Coefficient (SE) |
|-------------------------------|----------------------------|-----------------------------|----------------------------|
| US PRODUCTIVITY\textsubscript{it} \textsuperscript{1} | -0.8083** (0.1029) | -0.4922** (0.0819) | -0.2318** (0.0778) |
| COLLEGE\textsubscript{it} \textsuperscript{1} | 3.3341** (0.8671) | 1.6852* (0.7255) | 1.3538** (0.4317) |
| PCHISPANIC\textsubscript{it} | 0.0002* (0.0001) | 0.0004* (0.0002) | 0.0017* (0.0007) |
| NEW ENGLAND\textsubscript{j} | 0.6926** (0.1606) | 0.5439** (0.1516) | -0.3763 (0.2423) |
| MIDEAST\textsubscript{j} | 0.7235** (0.1601) | 0.5297** (0.1559) | -0.3165 (0.2529) |
| GREATLAKES\textsubscript{j} | 0.7002** (0.1188) | 0.4491** (0.1203) | -0.2459 (0.2097) |
| PLAINS\textsubscript{j} | 0.7955** (0.1496) | 0.3645** (0.1249) | -0.1914 (0.2204) |
| SOUTHEAST\textsubscript{j} | 0.6444** (0.1287) | 0.462** (0.1145) | -0.3256 (0.2282) |
| SOUTHWEST\textsubscript{j} | 0.6694** (0.1237) | 0.3835* (0.1399) | -0.1322 (0.1909) |
| ROCKY MOUNTAIN\textsubscript{j} | 0.5186** (0.1538) | 0.3288* (0.1619) | -0.2514 (0.2034) |
| FAR WEST\textsubscript{j} | 0.7328** (0.1762) | 0.406* (0.1537) | -0.1545 (0.2170) |
| R\textsuperscript{2} | 0.7186 | 0.6508 | 0.6691 |
| Adjusted R\textsuperscript{2} | 0.6482 | 0.5635 | 0.5864 |
| Durbin–Watson statistic | 1.9402 | 1.7135 | 1.8153 |
| Mean dependent variance | 0.5272 | 0.3158 | 0.1623 |
| SD dependent variance | 0.2239 | 0.1620 | 0.1166 |
| F-statistic | 10.2130** | 7.4545** | 8.0882** |

Note: *White heteroskedasticity-consistent standard errors and covariance.  
**Statically significant at the 0.05 level; ***statistically significant at the 0.01 level.
effects. It is entirely reasonable to observe diverging productivity across regions, while individual states within the regions exhibit growth patterns consistent with the observed negative coefficient for $US\ \text{PRODUCTIVITY}_{it}$. For example, identical absolute changes in productivity across all states in a region would result in the observed coefficients for $US\ \text{PRODUCTIVITY}_{it}$ due to differences in states’ beginning productivity level relative to the national average.

The positive and significant coefficients from Table 6 for COLLEGE for each of our sample periods provide supporting evidence regarding the importance of education in determining productivity. The 45% decline in the coefficient for per cent college (1.86–1.02) from the period 1977–2000 to 2000–19 is consistent with the diminished explanatory power of simple education level measures, as reported by Hanushek et al. (2017), and potentially signals the need for using broader knowledge-based measures of educational achievement.

The coefficients in Table 6 for each of the eight regional dummy variables are positive and statistically significant in every sample period. There is considerable variability in relative magnitudes of the dummy variable coefficients across sample periods with the largest dummy coefficients corresponding to the full sample period 1977–2019, smaller dummy variable coefficients for 1977–2000 and the smallest coefficients for 2000–19. Examining the coefficients within each sample period, coefficient magnitudes line up according to the descriptive data provided previously in the paper.

For the 1977–2019 period, coefficients for four of the regional dummy variables are notably larger than the coefficients for the four remaining groups. In order from largest to smallest the categories with the largest coefficients for the 1977–2019 period are: Plains Region (0.9272), Mideast Region (0.9063), Far West Region (0.8868) and New England Region (0.8556). Larger dummy variable coefficients for these regional groupings are consistent with the descriptive analysis presented previously. The descriptive analysis indicates that RGDP per worker for the Mideast region is at or near the top of the regional rankings for the entire sample period, with New England and Far West consistently ranked in the upper half among the eight regions.

Although RGDP per worker for the Plains Region remained near the bottom of the eight BEA regions for the entire sample period, the large coefficient for the Plains Region could result from greater productivity increases in three states that feature prominently in terms of positive ranking changes: North Dakota (45–15), Nebraska (40–20) and Iowa (39–29). All three states benefited from state-level energy sector changes. North Dakota’s economy reaped important economic benefits due to the introduction of hydraulic fracturing (fracking). A recent Yale study cites fracking as the main factor propelling North Dakota into second position among US oil-producing states and oil undoubtedly receives most of the credit for lowering North Dakota’s unemployment rate to a second best in the nation 2.9%. A different set of energy market changes played important roles for productivity growth in Iowa and Nebraska.

Table 7 contains estimated coefficients for models which include the percentage change in the Hispanic population over each time period. Recent literature documents the potential importance of Hispanic population growth for economic development. Demographic data indicate that beginning in the early 1990s, Hispanic population growth began to reverse declining population in many rural counties (Zuniga & Hernandez-Leon, 2005). Moreover, Johnson and Lichter (2008) note that much of the rural Hispanic population growth resulted principally from births rather than migration. That the population growth resulted significantly from births is important for two
reasons: (1) growth through births changes/reduces the age structure of these rural counties; and (2) population growth based on births tends to be self-sustaining. Evidence for the economic impact of rural Hispanic population growth is found in Coates and Gindling (2013), who offer convincing evidence that faster growth in the Hispanic populations was a major source of rural economic development. We include percentage growth in the Hispanic population in our regressions recognizing that state-level effects likely occur as a result of changes at the rural county level.

Examining Table 7, the estimated coefficients for the Hispanic population growth variable are positive and statistically significant for all three study periods.

In comparing coefficients for US PRODUCTIVITY and COLLEGE across Tables 6 and 7, there are generally few meaningful changes. Coefficients for US PRODUCTIVITY are negative and statistically significant for every sample period in both tables. Moreover, coefficient absolute values for US PRODUCTIVITY from Table 7 are comparable with those reported in Table 6 for periods 1977–2019 and 1977–2000, although they are of lower magnitude for the 2000–19 period. Similarly, Table 7 coefficients for the population percentage with a four-year college degree are positive and statistically significant for all sample periods. Once again, coefficients for per cent college provide comparable magnitudes for the 1977–2019 and 1977–2000 sample periods but the coefficient is somewhat larger for 2000–19. Clearly, there are few changes in the results for US PRODUCTIVITY or COLLEGE regardless of whether percentage change in the Hispanic population is included or excluded in the model. Differences in US PRODUCTIVITY and COLLEGE that do exist tend to be differences in coefficient magnitudes for 2000–19.

For the model with variable PCHISPANIC included, coefficients for the regional dummy variables are all positive and statistically significant for the 1977–2019 and 1977–2000 periods, although most dummy variable coefficients are somewhat smaller in magnitude when compared with their corresponding values in Table 6 Comparing R² values across Tables 6 and 7 for the 1977–2019 and 1977–2000 sample periods, values are very comparable regardless of whether the specification includes change in percentage Hispanic population In summary, there are few substantive changes in overall findings between Tables 6 and 7 for sample periods 1977–2019 or 1977–2000. However, substantial differences related to the regional dummy variables and R² values are evident for the 2000–19 models, with results varying with the inclusion or exclusion of PCHISPANIC.

The first notable difference for the period 2000–19 from adding percentage growth in the Hispanic population is that none of the coefficients for regional dummy variables is statistically different from zero. By contrast, adding PCHISPANIC had no such impact on dummy variable coefficients for the 1977–2019 or 1977–2000 periods. Moreover, adding PCHISPANIC results in a rather substantial difference in adjusted R² with increasing adjusted R² for the 2000–19 sample period from 0.44 to 0.59. By way of contrast, adjusted R² values for the other two time periods are very comparable regardless of whether HISPANIC is included or excluded (0.65 for both specifications for 1977–2019 and 0.53 versus 0.56 for 1977–2000). Taken together, differences in dummy variable significance levels and adjusted R² values clearly point to potential structural changes in the model resulting from the growth in the Hispanic population during the 2000–19 sample period. Given the finding in Johnson and Lichter (2008) that rural Hispanic population growth is achieved primarily through births, it seems reasonable to expect that economic effects would increase with the passage of time due to increasing numbers of working-age Hispanic residents.

One possible critique of the model is that the PCHISPANIC variable may be endogenous with respect to the dependent variable PRODGROWTH. Studies by Greenwood (1997), Rodriguez-Pose and von Berlepsch (2020) and Cebula et al. (2021) suggest that Hispanic migration is influenced by wage levels; hence, there is the implication that productivity levels influence Hispanic migration. On the surface, this possibility appears reasonable. However, the dependent variable for this study is percentage change in state productivity over time, not productivity
levels. There are at least two relevant factors regarding differences between productivity levels and the percentage change in productivity: (1) differences in productivity levels distort comparisons of percentage changes in productivity; and (2) wages are tied much more closely to productivity levels than to percentage change in productivity. Due to state differences in productivity levels, it is just as likely for states with low productivity levels to demonstrate high percentage changes in productivity as it is for states with high productivity levels, and vice versa. As a result, there is no sound foundation to suspect that productivity levels are correlated with percentage changes in productivity over time. If productivity levels and percentage changes in productivity were positively correlated, we expect to observe productivity divergence. While it might be reasonable to expect individual demographic groups to be aware of regional wage levels, it is extremely unlikely that any demographic group would be aware of local percentage changes in productivity. So far as other sources of endogeneity such as omitted variable bias are concerned, the $R^2$ values for our models (in the range of 0.6–0.7) indicate high levels of explanatory power for cross-sectional data and thus at least should mitigate potential concerns over specification bias. Nevertheless, our empirical results could well be influenced by endogeneity/simultaneity bias as well as omitted variable bias; consequently, the results in principle should not necessarily be interpreted as strictly causal. This is a limitation of our exploratory study, one that future research may delve into and resolve.

Finally, based upon findings summarized in Krogstad (2016), the effort was made to provide insights into the issue at hand by investigating the possibility of a linkage between the Hispanic population variable and the education variable (earned four-year bachelor’s degree). To do this, we introduced a multiplicative interaction term, \textit{INTERHISPCOLL}, into the model. For all three time periods, the empirical results produced a coefficient for \textit{INTERHISPCOLL} that failed to be statistically significant the 5% level. Hence, this possibility was dismissed. Interestingly, Krogstad provides reasons for this statistical insignificance. In particular, finding that although the high-school dropout rate among Hispanics dropped over the period 2000–15, nearly half of those who proceeded to a higher level of education only went to a two-year college. Among those who enrolled in a four-year college, only 15% completed bachelor’s degrees, lowest among any major racial category (22% of blacks, 41% of whites and 63% of Asians).

CONCLUSIONS

This study uses BEA regional account data to analyse regional and state-level productivity growth as measured by change in state-level RGDP/employment. The data cover the period 1977–2019. Our empirical methods employ both descriptive analysis and multivariate OLS regression. Descriptive data offer insights at both the regional and state levels. Examining productivity growth at the BEA region level reveals that there was a tight grouping of productivity for seven of the eight BEA regions until late in the 20th century, a period during which the Mideast region separated from the pack by enjoying significantly higher productivity growth. Toward the end of the 20th century, the tight clustering began to change due to the emergence of the Far West and New England regions. The pre-eminence of the Mideast region persisted until 2015, when Mideast productivity growth was overtaken by productivity growth in the Far West. New England, which appeared to track similarly to the Far West in the early part of the 21st century, experienced a flattening of productivity growth beginning in 2015. A graph of 2019 regional growth rates demonstrates the Far West region at the top in terms of both GDP per worker and productivity growth, followed by the Mideast region and New England. The remaining five BEA regions appear to be roughly tracking in a fashion that parallels national productivity growth, although interesting patterns began to emerge around 2009 for the Plains region, most likely the consequence of energy market considerations. The most interesting state-level results relate to patterns of convergence/divergence in productivity growth. When quintiles are defined
based upon 1977 productivity growth, state-level productivity appears to be converging, whereas 2019 quintiles reveal clear signs of divergence in productivity growth.

The regression estimates relate state-level productivity growth to percentage of the state population with at least a four-year degree, a set of dummy variables denoting the states’ respective census region, and percentage growth in the states’ Hispanic population. Separate models were estimated for each of three time periods (1977–2019, 1977–2000 and 2000–19), with percentage growth in the Hispanic population both included and excluded. Specifying the dependent variable as percentage change in labour productivity positions the model as an examination of state-level convergence or divergence of labour productivity. Analysis of the coefficients for variables included in the model offer insight into factors that contribute whether a state’s productivity is converging to or diverging from average productivity. We believe these results regarding factors that contribute to convergence/divergence are among the first of their kind.

Arguably, the most interesting findings from the regression model relate to the Hispanic population growth variable. Positive and statistically significant coefficients for the state’s percentage growth rate of the Hispanic population were observed for every time period. Moreover, adding percentage growth in the Hispanic population to the 2000–19 model brings about a substantial increase in adjusted $R^2$ as compared with models for the remaining sample periods. BEA region dummy variables, statistically significant for every other estimation, are all statistically insignificant for the 2000–19 model when Hispanic population growth is included. Finding a positive and statistically significant coefficient robust across three time periods when Hispanic population growth is included, together with the substantial overall changes observed for the 2000–19 model, offer support for the previous findings of Coates and Gindling (2013) regarding Hispanic population and economic development. Consistently positive and statistically significant coefficients for the state’s percentage of population with at least a four-year college degree provide evidence for the important role that human capital plays in determining productivity growth. The smaller coefficient magnitude for the 2000–19 sample period complements previous findings of Hanushek et al. (2017) regarding the growing importance of broader knowledge capital as compared with the prior focus on simple measures of educational attainment. The interested reader is referred to Table A1 in Appendix A and Tables B1–B4 in Appendix B for further insights.

The evidence regarding divergence in productivity growth at the regional level, when analysed in the context of previous literature, offers important policy insights. The relative separation of the Far West, Mideast and New England from the other regions provides evidence for the importance of efforts to promote greater productivity growth and to do so across wider geographical areas. Infrastructure investment, especially broadband in more rural environments (Gallardo et al., 2021), as well as creating incentives at research universities for promoting majors in areas fitting into the science, technology, engineering and mathematics (STEM) classification could be very beneficial (Koch & Cebula, 2020). As Koch and Cebula (2020) observe: ‘Many of the prime opportunities for social and economic mobility [in the U.S.] are to be found in productivity-dense jobs related to science, technology, engineering, and math’ (p. 208).

**DISCLOSURE STATEMENT**

No potential conflict of interest was reported by the authors.

**NOTE**

1 Although our data include both time-series and cross-sectional elements, our model specifications do not constitute a panel, which would include pooling observations across both time and cross-sectional units. Our regression models relate growth rates in state-level GDP per worker (one observation per state) over three distinct time periods: 1977–2019, 1977–
2000 and 2000–19. Accordingly, panel data techniques, including tests for random versus fixed effects, are not appropriate for these data.

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**APPENDIX A**

**Table A1.** State and Bureau of Economic Analysis (BEA) regions, including Washington, DC.

| State           | BEA region  | State          | BEA region  |
|-----------------|-------------|----------------|-------------|
| Alabama         | Southeast   | Montana        | Rocky Mountain |
| Alaska          | Far West    | Nebraska       | Plains      |
| Arizona         | Southwest   | Nevada         | Far West    |
| Arkansas        | Southeast   | New Hampshire  | New England |
| California      | Far West    | New Jersey     | Mideast     |
| Colorado        | Rocky Mountain | New Mexico  | Southwest |
| Connecticut     | New England | New York       | Mideast     |
| Delaware        | Mideast     | North Carolina | Southeast   |
| DC              | Mideast     | North Dakota   | Plains      |
| Florida         | Southeast   | Ohio           | Great Lakes |
| Georgia         | Southeast   | Oklahoma       | Southwest   |
| Hawaii          | Far West    | Oregon         | Far West    |
| Idaho           | Rocky Mountain | Pennsylvania | Mideast    |
| Illinois        | Great Lakes | Rhode Island   | New England |
| Indiana         | Great Lakes | South Carolina | Southeast   |
| Iowa            | Plains      | South Dakota   | Plains      |
| Kansas          | Plains      | Tennessee      | Southeast   |
| Kentucky        | Southeast   | Texas          | Southwest   |
| Louisiana       | Southeast   | Utah           | Rocky Mountain |
| Maine           | New England | Vermont        | New England |
| Maryland        | Mideast     | Virginia       | Southeast   |
| Massachusetts   | New England | Washington     | Far West    |
| Michigan        | Great Lakes | West Virginia  | Southeast   |
| Minnesota       | Plains      | Wisconsin      | Great Lakes |
| Mississippi     | Southeast   | Wyoming        | Rocky Mountain |
| Missouri        | Plains      |                |             |

**APPENDIX B**

In 1977, the mean annual value of US productivity was US$59,900. State annual productivity ranged between a high of US$109,712 (Alaska) to a low of US$39,561 (South Dakota). By 2019, US productivity was US$93,674 and state productivity ranged from a high of US$134,267 (DC) to a low of US$63,469 (Mississippi). Table B1 presents the real gross domestic product (RGDP)/worker levels for each state and DC for 1977, 2000 and 2019. By 2019, the US RGDP/worker increased to US$93,674 and state productivity ranged from a high of US$134,267 (DC) to a low of US$63,469 (Mississippi). Only two ‘states’, Alaska and DC, had RGDP/worker in excess of US$100,000 in 1977. By 2019, eight states had exceeded US $100,000 in RGDP/worker.
| State            | 1977 RGDP/worker | 2000 RGDP/worker | 2019 RGDP/worker | State            | 1977 RGDP/worker | 2000 RGDP/worker | 2019 RGDP/worker |
|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| United States    | US$59,900        | US$79,403        | US$93,674        | Missouri         | US$54,981        | US$70,663        | US$75,266        |
| Alabama          | US$49,655        | US$65,921        | US$73,410        | Montana          | US$57,905        | US$56,758        | US$68,920        |
| Alaska           | US$109,712       | US$101,523       | US$115,826       | Nebraska         | US$49,022        | US$65,314        | US$87,447        |
| Arizona          | US$55,439        | US$74,165        | US$81,524        | Nevada           | US$72,036        | US$84,071        | US$80,821        |
| Arkansas         | US$45,619        | US$60,862        | US$70,170        | New Hampshire    | US$42,488        | US$72,387        | US$85,354        |
| California       | US$62,670        | US$88,902        | US$113,832       | New Jersey       | US$66,716        | US$99,563        | US$98,782        |
| Colorado         | US$58,192        | US$79,792        | US$90,203        | New Mexico       | US$57,491        | US$74,576        | US$87,355        |
| Connecticut      | US$61,846        | US$102,113       | US$107,787       | New York         | US$77,562        | US$104,067       | US$115,794       |
| Delaware         | US$76,840        | US$111,758       | US$106,016       | North Carolina   | US$50,343        | US$73,145        | US$82,658        |
| DC               | US$104,903       | US$115,852       | US$134,267       | North Dakota     | US$45,401        | US$55,948        | US$91,889        |
| Florida          | US$56,134        | US$72,202        | US$74,920        | Ohio             | US$59,215        | US$75,060        | US$86,173        |
| Georgia          | US$51,198        | US$80,483        | US$85,285        | Oklahoma         | US$56,496        | US$62,293        | US$84,689        |
| Hawaii           | US$66,349        | US$75,310        | US$88,467        | Oregon           | US$57,459        | US$68,857        | US$86,019        |
| Idaho            | US$41,746        | US$61,133        | US$69,926        | Pennsylvania     | US$59,906        | US$77,913        | US$92,226        |
| Illinois         | US$64,112        | US$87,106        | US$97,092        | Rhode Island     | US$52,188        | US$77,674        | US$81,745        |
| Indiana          | US$55,201        | US$72,380        | US$84,264        | South Carolina   | US$52,972        | US$65,972        | US$74,076        |
| Iowa             | US$49,278        | US$63,887        | US$82,878        | South Dakota     | US$39,964        | US$57,378        | US$77,053        |
| Kansas           | US$53,942        | US$64,726        | US$82,259        | Tennessee        | US$47,924        | US$67,556        | US$78,085        |
| Kentucky         | US$54,809        | US$65,829        | US$74,175        | Texas            | US$66,375        | US$82,228        | US$97,887        |
| Louisiana        | US$84,619        | US$86,434        | US$87,414        | Utah             | US$56,067        | US$67,095        | US$79,357        |
| Maine            | US$48,755        | US$61,891        | US$68,660        | Vermont          | US$39,561        | US$57,419        | US$67,569        |
| Maryland         | US$64,523        | US$81,126        | US$98,330        | Virginia         | US$57,960        | US$78,878        | US$90,464        |
| Massachusetts    | US$54,992        | US$88,270        | US$105,325       | Washington       | US$72,802        | US$88,649        | US$118,067       |
| Michigan         | US$70,161        | US$77,977        | US$81,701        | West Virginia    | US$58,342        | US$70,813        | US$80,810        |
| Minnesota        | US$53,143        | US$74,242        | US$89,290        | Wisconsin        | US$51,815        | US$68,319        | US$82,070        |
| Mississippi      | US$44,630        | US$59,669        | US$63,469        | Wyoming          | US$74,894        | US$85,250        | US$95,003        |

Note: Real GDP, real gross domestic product.
Table B2 presents the RGDP/worker state rankings for 1977, 2000 and 2019. For the most part, state rankings did not change very much over the 42-year period. Nine states (shown in bold) had a positive change in their state ranking of at least 10 positions over the 1977–2019 period. North Dakota had the largest change in state rank between 1977 and 2019, moving up 30 spots from 45th to 15th. The change in North Dakota occurred mainly during the last 20 years and is a direct result of the fracking industry development within the state. Oregon also saw large improvement in RGDP/worker ranking moving from 43rd in 1977 to 24th by 2019.

Table B2. State real gross domestic product (RGDP)/worker ranking: 1977, 2000 and 2019.

| State            | 1977 Rank | 1990 Rank | 2019 Rank | State            | 1977 Rank | 1990 Rank | 2019 Rank |
|------------------|-----------|-----------|-----------|------------------|-----------|-----------|-----------|
| United States    | Missouri  | 30        | 32        | 41               |           |           |           |
| Alabama          | 38        | 37        | 45        | Montana          | 22        | 50        | 48        |
| Alaska           | 1         | 5         | 3         | Nebraska         | 40        | 40        | 20        |
| Arizona          | 27        | 26        | 35        | Nevada           | 8         | 13        | 36        |
| Arkansas         | 44        | 46        | 46        | New York         | 48        | 28        | 25        |
| California       | 15        | 7         | 5         | New Jersey       | 10        | 6         | 9         |
| Colorado         | 20        | 17        | 17        | New Mexico       | 23        | 24        | 22        |
| Connecticut      | 16        | 4         | 6         | New York         | 4         | 3         | 4         |
| Delaware         | 5         | 2         | 7         | North Carolina   | 37        | 27        | 30        |
| DC               | 2         | 1         | 1         | North Dakota     | 45        | 51        | 15        |
| Florida          | 25        | 30        | 42        | Ohio             | 18        | 23        | 23        |
| Georgia          | 36        | 16        | 26        | Oklahoma         | 24        | 43        | 27        |
| Hawaii           | 12        | 22        | 19        | Oregon           | 43        | 38        | 24        |
| Idaho            | 49        | 45        | 47        | Pennsylvania     | 17        | 20        | 14        |
| Illinois         | 14        | 10        | 12        | Rhode Island     | 34        | 21        | 33        |
| Indiana          | 28        | 29        | 28        | South Carolina   | 47        | 36        | 44        |
| Iowa             | 39        | 42        | 29        | South Dakota     | 50        | 49        | 40        |
| Kansas           | 32        | 41        | 31        | Tennessee        | 42        | 34        | 39        |
| Kentucky         | 31        | 39        | 43        | Texas            | 11        | 14        | 11        |
| Louisiana        | 3         | 11        | 21        | Utah             | 26        | 35        | 38        |
| Maine            | 41        | 44        | 49        | Vermont          | 51        | 48        | 50        |
| Maryland         | 13        | 15        | 10        | Virginia         | 21        | 18        | 16        |
| Massachusetts    | 29        | 9         | 8         | Washington       | 7         | 8         | 2         |
| Michigan         | 9         | 19        | 34        | West Virginia    | 19        | 31        | 37        |
| Minnesota        | 33        | 25        | 18        | Wisconsin        | 35        | 33        | 32        |

Tables B3 and B4 present state RGDP/worker as a percentage of the United States in 1977, 2000 and 2019, and the state RGDP/worker growth rates over the periods 1977–2000, 2000–19, and 1977–2019. From 1977 to 2019 state RGDP/worker growth rates ranged from only 3.3% in Louisiana to 102.4% in North Dakota. Both these states were either harmed or benefitted from significant changes in the pattern of energy development within the country. Eliminating the energy wild card between 1997 and 2019, state RGDP/worker ranged from 12.2% in Nevada to 100.9% in New Hampshire.
Table B3. State real gross domestic product (RGDP)/worker as a percentage of the United States and percentage growth rates, 1977–2019.

| State         | 1977 GDP/worker as a % of the United States | 2000 GDP/worker as a % of the United States | 2019 GDP/worker as a % of the United States | 1977–2000 GDP/worker % growth | 2000–19 GDP/worker % growth | 1977–2019 GDP/worker % growth |
|---------------|--------------------------------------------|--------------------------------------------|--------------------------------------------|-------------------------------|-------------------------------|-------------------------------|
| United States | 32.6%                                      | 18.0%                                      | 56.4%                                      |                               |                               |                               |
| Alabama       | 82.9%                                      | 83.0%                                      | 78.4%                                      | 32.8%                         | 11.4%                         | 47.8%                         |
| Alaska        | 183.2%                                     | 127.9%                                     | 123.6%                                     | −7.5%                         | 14.1%                         | 5.6%                          |
| Arizona       | 92.6%                                      | 93.4%                                      | 87.0%                                      | 33.8%                         | 9.9%                          | 47.1%                         |
| Arkansas      | 76.2%                                      | 76.6%                                      | 74.9%                                      | 33.4%                         | 15.3%                         | 53.8%                         |
| California    | 104.6%                                     | 112.0%                                     | 121.5%                                     | 41.9%                         | 28.0%                         | 81.6%                         |
| Colorado      | 97.1%                                      | 100.5%                                     | 96.3%                                      | 37.1%                         | 13.0%                         | 55.0%                         |
| Connecticut   | 103.2%                                     | 128.6%                                     | 115.1%                                     | 65.1%                         | 5.6%                          | 74.3%                         |
| Delaware      | 128.3%                                     | 140.7%                                     | 113.2%                                     | 45.4%                         | −5.1%                         | 38.0%                         |
| DC            | 175.1%                                     | 145.9%                                     | 143.3%                                     | 10.4%                         | 15.9%                         | 28.0%                         |
| Florida       | 93.7%                                      | 90.9%                                      | 80.0%                                      | 28.6%                         | 3.8%                          | 33.5%                         |
| Georgia       | 85.5%                                      | 101.4%                                     | 91.0%                                      | 57.2%                         | 6.0%                          | 66.6%                         |
| Hawaii        | 110.8%                                     | 94.8%                                      | 94.4%                                      | 13.5%                         | 17.5%                         | 33.3%                         |
| Idaho         | 69.7%                                      | 77.0%                                      | 74.6%                                      | 46.4%                         | 14.4%                         | 67.5%                         |
| Illinois      | 107.0%                                     | 109.7%                                     | 103.6%                                     | 35.9%                         | 11.5%                         | 51.4%                         |
| Indiana       | 92.2%                                      | 91.2%                                      | 90.0%                                      | 31.1%                         | 16.4%                         | 52.6%                         |
| Iowa          | 82.3%                                      | 80.5%                                      | 88.5%                                      | 29.6%                         | 29.7%                         | 68.2%                         |
| Kansas        | 90.1%                                      | 81.5%                                      | 87.8%                                      | 20.0%                         | 27.1%                         | 52.5%                         |
| Kentucky      | 91.5%                                      | 82.9%                                      | 79.2%                                      | 20.1%                         | 12.7%                         | 35.3%                         |
| Louisiana     | 141.3%                                     | 108.9%                                     | 93.3%                                      | 2.1%                          | 1.1%                          | 3.3%                          |
| Maine         | 81.4%                                      | 77.9%                                      | 73.3%                                      | 26.9%                         | 10.9%                         | 40.8%                         |
| Maryland      | 107.7%                                     | 102.2%                                     | 105.0%                                     | 25.7%                         | 21.2%                         | 52.4%                         |
| Massachusetts | 91.8%                                      | 111.2%                                     | 112.4%                                     | 60.5%                         | 19.3%                         | 91.5%                         |
| Michigan      | 117.1%                                     | 98.2%                                      | 87.2%                                      | 11.1%                         | 4.8%                          | 16.4%                         |
| Minnesota     | 88.7%                                      | 93.5%                                      | 95.3%                                      | 39.7%                         | 20.3%                         | 68.0%                         |
| Mississippi   | 74.5%                                      | 75.1%                                      | 67.8%                                      | 33.7%                         | 6.4%                          | 42.2%                         |
### Table B4. State real gross domestic product (RGDP)/worker as a percentage of the United States and percentage growth rates, 1977–2019.

| State          | 1977 GDP/worker as a % of the United States | 2000 GDP/worker as a % of the United States | 2019 GDP/worker as a % of the United States | 1977–2000 GDP/worker % growth | 2000–19 GDP/worker % growth | 1977–2019 GDP/worker % growth |
|----------------|---------------------------------------------|---------------------------------------------|---------------------------------------------|--------------------------------|-------------------------------|-------------------------------|
| United States  | 32.6%                                       | 18.0%                                       | 56.4%                                       |                                |                               |                               |
| Missouri       | 91.8%                                       | 89.0%                                       | 80.3%                                       | 28.5%                          | 6.5%                          | 36.9%                         |
| Montana        | 96.7%                                       | 71.5%                                       | 73.6%                                       | −2.0%                          | 21.4%                         | 19.0%                         |
| Nebraska       | 81.8%                                       | 82.3%                                       | 93.4%                                       | 33.2%                          | 33.9%                         | 78.4%                         |
| Nevada         | 120.3%                                      | 105.9%                                      | 86.3%                                       | 16.7%                          | −3.9%                         | 12.2%                         |
| New Hampshire  | 70.9%                                       | 91.2%                                       | 91.1%                                       | 70.4%                          | 17.9%                         | 100.9%                        |
| New Jersey     | 111.4%                                      | 125.4%                                      | 105.5%                                      | 49.2%                          | −0.8%                         | 48.1%                         |
| New Mexico     | 96.0%                                       | 93.9%                                       | 93.3%                                       | 29.7%                          | 17.1%                         | 51.9%                         |
| New York       | 129.5%                                      | 131.1%                                      | 123.6%                                      | 34.2%                          | 11.3%                         | 49.3%                         |
| North Carolina | 84.0%                                       | 92.1%                                       | 88.2%                                       | 45.3%                          | 13.0%                         | 64.2%                         |
| North Dakota   | 75.8%                                       | 70.5%                                       | 98.1%                                       | 23.2%                          | 64.2%                         | 102.4%                        |
| Ohio           | 98.9%                                       | 94.5%                                       | 92.0%                                       | 26.8%                          | 14.8%                         | 45.5%                         |
| Oklahoma       | 94.3%                                       | 78.5%                                       | 90.4%                                       | 10.3%                          | 36.0%                         | 49.9%                         |
| Oregon         | 78.6%                                       | 83.0%                                       | 91.8%                                       | 40.0%                          | 30.6%                         | 82.8%                         |
| Pennsylvania   | 100.0%                                      | 98.1%                                       | 98.5%                                       | 30.1%                          | 18.4%                         | 54.0%                         |
| Rhode Island   | 87.1%                                       | 97.8%                                       | 87.3%                                       | 48.8%                          | 5.2%                          | 56.6%                         |
| South Carolina | 71.7%                                       | 83.1%                                       | 79.1%                                       | 53.5%                          | 12.3%                         | 72.4%                         |
| South Dakota   | 66.7%                                       | 72.3%                                       | 82.3%                                       | 43.6%                          | 34.3%                         | 92.8%                         |
| Tennessee      | 80.0%                                       | 85.1%                                       | 83.4%                                       | 41.0%                          | 15.6%                         | 62.9%                         |
| Texas          | 110.8%                                      | 103.6%                                      | 104.5%                                      | 23.9%                          | 19.0%                         | 47.5%                         |
| Utah           | 93.6%                                       | 84.5%                                       | 84.7%                                       | 19.7%                          | 18.3%                         | 41.5%                         |
| Vermont        | 66.0%                                       | 72.3%                                       | 72.1%                                       | 45.1%                          | 17.7%                         | 70.8%                         |
| Virginia       | 96.8%                                       | 99.3%                                       | 96.6%                                       | 36.1%                          | 14.7%                         | 56.1%                         |
| Washington     | 121.5%                                      | 111.6%                                      | 126.0%                                      | 21.8%                          | 33.2%                         | 62.2%                         |
| West Virginia  | 97.4%                                       | 89.2%                                       | 86.3%                                       | 21.4%                          | 14.1%                         | 38.5%                         |
| Wisconsin      | 86.5%                                       | 86.0%                                       | 87.6%                                       | 31.9%                          | 20.1%                         | 58.4%                         |
| Wyoming        | 125.0%                                      | 107.4%                                      | 101.4%                                      | 13.8%                          | 11.4%                         | 26.9%                         |

Looking at RGDP/worker growth during the 2000–19 period, we observe a very different pattern. Overall RGDP/worker growth during 2000–19 is roughly half that of the 1977–2000 period. The state range of RGDP/worker growth during the 2000–19 period shows that both Nevada and New Jersey saw a decline in RGDP/worker, while Nebraska showed the largest gain in RGDP/worker amongst the non-energy-producing states. In fact, the region with the strongest RGDP/worker appears to be the BEA Plains region.