

ECONOMETRIC ANALYSIS OF STATE HEALTH EXPENDITURES: METHODOLOGY AND MODEL SPECIFICATION

Introduction

Periodically, the Office of the Actuary (OACT) in the Centers for Medicare & Medicaid Services (CMS) estimates State Health Expenditure Accounts (SHEA) data. Detailed tables for the historical SHEA data and methods by State of Provider and State of Residence are available online.^{1,2}

Beginning with the 2011 release of these estimates (for data through 2009), OACT also prepared supplemental econometric analysis of the state health spending data. These findings were discussed in the detailed methods paper published in the journal *Medicare & Medicaid Research Review*.³ For a subsequent release of these expenditures in 2017, which used data through 2014, detailed econometric analysis was discussed in the methodology paper⁴ that accompanied the article published in the journal *Health Affairs*.⁵ For the current release, covering 1991-2020, this econometric analysis was updated. However, given the unique and substantial effects of the COVID-19 pandemic on health spending in 2020, this year was excluded for modeling purposes.

The main purpose of this econometric analysis and related research is to augment the descriptive analysis of the SHEA data with additional quantitative investigation based on multivariate regression analysis. The regression analysis focuses on the level of per capita total personal health care spending by state of residence and state-level factors associated with geographic variation in health spending between states. To assess the robustness of the results, several model variations and methodologies are employed.

This paper provides an overview of the data, sources, and methods used in OACT's econometric analysis. Furthermore, the paper also provides a discussion of the results and findings from this analysis.

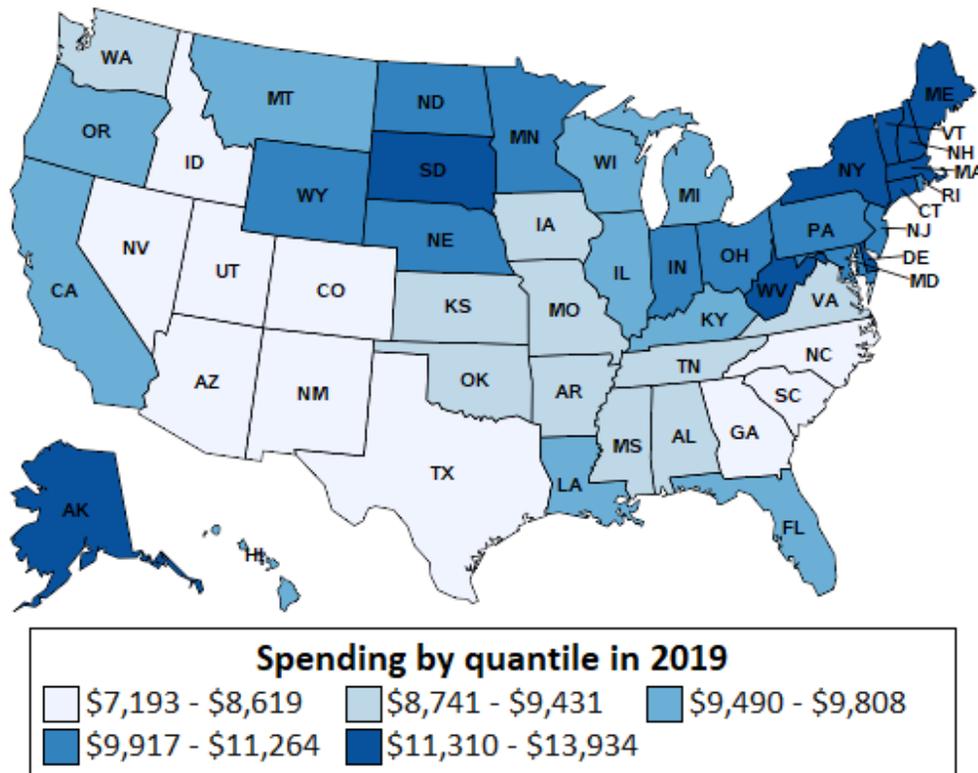
Table of Contents

- Background
- Data
 - State Health Expenditure Accounts
 - Exogenous Data
 - *Personal Income and Price Proxies*
 - *Insurance and Coverage-Related Factors*
 - *Health Care Capacity*
 - *Health Status*
- Methods
- Results
 - Pooled Model
 - Fixed Effects Model
 - Between Model
 - Annual Models
 - Specification Variants
 - *Adjusting for Price*
- Conclusion
- Appendix
 - *Major Coverage Expansions under the Affordable Care Act*
- Endnotes

Background

The map below (Exhibit 1) illustrates the extent of state-level variation in per capita personal health care expenditures in 2019. Some of the highest levels of per capita health spending were observed in the Northeast and Mid-Atlantic regions, whereas some of the lowest levels were observed in the Southwest region.

Exhibit 1: Personal Health Care Spending Per Capita by State Of Residence, Calendar Year 2019



SOURCES: U.S. Census Bureau; and Centers for Medicare and Medicaid Services, Office of the Actuary, National Health Statistics Group

While there is a large body of literature devoted to understanding the factors associated with geographic variation in health care spending, much of the focus is on individual-level Medicare spending (specifically, per beneficiary spending) and sub-state regional spending (such as hospital referral region). Only a small subset of this research focuses on state-level variation in health spending, and an even smaller number focus on personal health care spending per capita (for all payers) as in this econometric analysis of the SHEA data.

Among the research studies that focus on state-level spending, several common factors were found to be important in explaining variation in the level of health spending by state.³ These factors tended to fall into the following major categories: income, provider supply or health care capacity, population demographics, health status indicators, insurance coverage types, insured status, and a measure of time (such as a time trend or period fixed effects). A state-level price proxy is also included in some cases (although such a variable had previously not been available, so proxies were used to attempt to identify some of the variation associated with price). On the other hand, some studies use national inflation measures, given that a standard state level price index is not readily available.

In addition to identifying key factors associated with geographic variation in state-level health spending, there were also other technical challenges to consider in this econometric analysis. The first is related to the state-level unit of analysis. Specifically, modeling at the state level involves the use of average metrics versus individual level metrics, which results in higher levels of multicollinearity and endogeneity. For example, the number of physicians in a state may not be related to an individual's income, but it may be related to the attractiveness of a state's overall average per capita personal income to physicians or workers in general.

Another challenge is the time-series-cross-sectional structure of our dataset: 50 state units for each year. The nature of the data set, as well as a test for redundancy in fixed effects (versus a shared common effect across all states and time periods), favored the use of a fixed effects model, which accounts for cross-sectional units (such as states) that are consistently geographically fixed over time. However, state fixed effects are correlated with many state-level variables that do not change substantially over time, and thus the coefficients for these state-level variables cannot be estimated efficiently using fixed effects models, creating a trade-off between the advantages of fixed effects and capturing the effects of slow-moving variables. Finally, though state fixed effects models can reduce serial correlation, the method will not necessarily eliminate it. Researchers have used various other tools to address serial correlation (such as adding in autoregressive terms or lagged dependent variables), but those methods (dynamic models) inherently change the research question and modeling approach from a spending level focus to a growth focus.

As a result of these econometric challenges, a number of modeling approaches have been employed in this analysis. Both pooled and fixed effects models are estimated, in addition to a "between" model (a model based on the means by state over time), annual regressions, and other modeling variants that are constructed to provide sensitivity testing to changes in methodology.⁶ Based on the broad perspective that these models provide, the factors that are most robust across methods are identified and discussed in this analysis.

Data

In addition to the SHEA and enrollment data compiled by OACT, several other state-level characteristics are also incorporated into this econometric analysis. The various sources are discussed in more detail below.

State Health Expenditure Accounts

The SHEA data are a subset of the National Health Expenditure Accounts (NHEA) and represent a consistent set of estimates that utilize the same methodology for all states and all years.⁷ The SHEA are based on the Personal Health Care (PHC) component of the NHEA, which is defined as total spending on health care goods and services; however, it is important to note that PHC (and therefore the SHEA) exclude several NHEA categories: administration and the net cost of private health insurance, government public health activities, and investment in research, structures, and equipment.

Some SHEA data are excluded from the analysis due to outlier behavior or limited availability. The District of Columbia, for example, was excluded from the modeling dataset, as it was an outlier in interstate flows of health spending, health spending per capita, and multiple indicators related to health spending (consistent with the prior OACT analysis).⁴ Though OACT has developed estimates of private health insurance spending, the data are only available after 2000, and thus they are not incorporated separately into the modeling and analysis presented here.

In addition to SHEA data, OACT also prepares estimates of Medicare and Medicaid enrollment by state using the latest available source data at the time of estimation.⁸ The use of enrollment data as part of the model specification is discussed further in the next section.

Exogenous Data

Personal Income and Price Proxies

Personal income per capita was calculated using total personal income by state from the Bureau of Economic Analysis (BEA)⁹ divided by the U.S. Census Bureau's state population estimates.¹⁰ Both income and health expenditures were deflated using the chain-weighted US Personal Consumption Expenditures (PCE) price index from the BEA.¹¹

Data from the BEA on Regional Price Parities (RPPs) were also utilized in this analysis to study the effects of state variation in prices.¹² These data are not specific to industry and cover a limited period of time (2008 forward); thus, in order to have an index that covers the entire sample, the data were back cast to 1991 using a linear trend. Then, as was done in the previous OACT analysis, these RPPs were combined with the US Personal Consumption Expenditure Deflator to develop an implicit regional price deflator consistent with the BEA's calculations used to estimate real personal income by state.¹³ Ideally, the current analysis would have also included a health-specific price parity, but such data were not available.

Insurance and Coverage-Related Factors

The model specification also includes several categories of insurance coverage type and status. First, the share of the population enrolled in Medicare was included in the model specification to primarily capture the role of the elderly population on state level spending. Second, the share of the population enrolled in Medicaid was included in the model specification to capture the role of poverty and disability coverage in the state.

To quantify access to care, an adjusted measure of the uninsured percentage of the state population was included in the model specification based on an integrated public use databases that harmonizes data from the U.S. Census Bureau's Current Population Survey (CPS)¹⁴ and the American Community Survey (ACS).¹⁵ The use of ACS to estimate the uninsured share of state population is necessitated by a methodology change to the CPS in 2013 (2012 insured year) specifically related to health insurance questions that impacted the continuity and comparability of the series with past trends. While the ACS has a much larger sample and is much more robust for state level analysis, the data are only available from 2008 onward.

After studying differences between the CPS and ACS, a methodology was developed to incorporate the ACS data into the uninsured estimates. First, consistent with the prior analysis, the CPS was adjusted for observed underreporting of Medicaid coverage by state, based on research by Davern et al. for insured years 1991-2008.^{16, 17} Second, growth rates in the uninsured estimates from ACS were used to extrapolate the adjusted CPS data for insured years 2009 through 2019. The year 2009 was selected as the transition year between the two surveys because the distributions of the uninsured populations were calculated to have been closest between surveys for that year. By combining the surveys in this way, the changes observed in insured years 2013 and 2014 in these estimates are based on results from a consistent survey with a relatively more robust state-level sample. Third, the estimates were then controlled to the NHE uninsured levels published in the estimates released in 2021.¹⁸ Finally, an uninsured rate is calculated using population estimates consistent with NHE. Thus, these state uninsured rates are fully comparable with national level estimates published with the NHE.

Finally, given the passage of the ACA and the enactment of the major coverage expansions in 2014, data from the Kaiser Family Foundation state health facts were used to identify states that expanded eligibility for their Medicaid programs after 2013.¹⁹

Health Care Capacity

One measure of health care capacity is included in the current model specification. For the count of community hospital beds per 1,000 population, data were sourced from the American Hospital Association published in Health United States and the Kaiser Family Foundation State Health Facts.²⁰

Health Status

To capture a measure of population health, a “bad health” index was calculated by multiplying the reported proportion of the state population that smokes times the reported proportion of the state population that is obese (multiplied by 100), based on Behavioral Risk Factor Surveillance System survey data from the Centers for Disease Control and Prevention (CDC)²¹; this index ideally captures the intersection of residents that share these two unhealthy behaviors by state.²² To assess the reasonability of this conceptual metric, a comparison was made between the bad health index value and the value obtained from a 2006 study, which measured the co-occurrence of these two behaviors on a national basis.²³ The researchers from the 2006 study used data from the National Health Interview Survey and found overlap between the populations that are obese and smoke (4.7 percent of the U.S. population on average in 2002), a finding similar to the overlap indicated by the bad health index estimates (cross-state estimated average of 5.2 percent for the same year). In addition, the bad health index was also compared with the age-adjusted death rates from the CDC’s National Vital Statistics Reports.²⁴ On an annual basis, there was a relatively high correlation (for example, 0.89-0.93 per year in the last three years, 2017-19), suggesting that the bad health index is related to severe health conditions and is not an unreasonable metric to use to control for health status. However, when the correlation is calculated over the full sample period, 1991-2019, the correlation is lower (0.27) due to the disparate trends in the data over time with improvements in mortality in general leading to the death rate trending lower, despite a rising bad health index due to worsening obesity. In general, the bad health index tracked more closely with pattern of health spending and as such, continues to be preferred in the specification over the age-adjusted death rate as an indicator of health status.

See Exhibit 2 below for details on these variables and their associated descriptive statistics.

Exhibit 2: Dependent and Independent Variables Selected for Per Capita Personal Health Care Model, Descriptive Statistics Calculated for 1991-2019

Dependent and Independent Variables	N	Mean	Std.	Min	Max
Personal health care spending per capita, adjusted by the PCE deflator to 2012 dollars	1450	\$6,412	\$1,815	\$3,009	\$12,032
Personal Income per capita, adjusted by the PCE deflator to 2012 dollars	1450	\$39,388	\$8,224	\$21,370	\$68,953
Percent of the population enrolled in Medicare	1450	15.3	2.8	4.7	25.2
Percent of the population enrolled in Medicaid	1450	14.7	6.1	3.2	45.3
Percent of the population that is uninsured	1450	11.6	4.0	3.4	25.8
Community hospital beds per 1,000 population	1450	3.0	1.0	1.6	7.0
Bad health index (smoking rate*obesity rate*100)	1450	4.8	1.5	1.5	10.0

Methods

Several variations of multivariate regression models were estimated to study the relationship between state level characteristics with geographic variation in health spending and also the robustness of these state characteristics across various estimation methods. The two base models are estimated via Ordinary Least Squares (OLS) with year fixed effects: with state fixed effects (fixed effects model) and without state fixed effects (pooled model). The structures of these models are as follows:

Fixed Effects Model

$$Y_{it} = \alpha + \beta X_{i,t} + \delta Year_t + \gamma State_i + v_{i,t}$$

Pooled OLS Model

$$Y_{i,t} = \alpha + \beta X_{i,t} + \delta Year_t + \mu_{i,t}$$

$Y_{i,t}$ is the natural log of per capita total health care expenditures deflated by the PCE price index by state i (excluding District of Columbia) and year t ($t = 1991$ to 2019). $X_{i,t}$ is a vector of the state-specific characteristics described in the previous section and Exhibit 2. $Year_t$ represents period fixed effects (binary indicator variables for the years 1991-2019). $State_i$ denotes binary indicator variables for each of the states ($i = 1$ to 50), and $v_{i,t}$ and $\mu_{i,t}$ represent the error terms for the fixed effects and pooled models, respectively. In addition, standard errors were clustered by state using White robust covariance computations to account for serial correlation and heteroskedasticity in the errors. Analysis discussed in this paper was conducted using EViews 12 software.

Additional sensitivity analysis specific to time-series-cross-sectional data was conducted to understand the robustness of various state factors effects across methods: 1) a “between” model, in which the mean of the dependent variable is regressed on the means of the independent variables, and 2) a set of incremental, annual regressions covering the full timeseries. In the “between” and annual models, the model specification is identical to the pooled model shown above and applied to 50 state observations. The standard errors calculated under both of these approaches were adjusted using the White correction for heteroskedasticity. The goal of estimating these variants related to the time dimension of the data is to understand the potential effects of serial correlation on variable significance when the time dimension is either removed from or transformed in the data set.

Finally, variants of the pooled and fixed effects models were studied to understand the implications of available data for regional prices, and the major coverage expansion under the ACA on variation in health spending. First, to estimate the regression incorporating the regional price data, personal health care spending per capita and personal income per capita were both divided by the product of the overall Regional Price Parity or RPP series (for all goods and services) and the US PCE deflator series. This adjustment ideally deflates these spending series into real dollars that account for regional price differences over time. Second, regressions were estimated to study the effects of the 2014 coverage expansions under the Affordable Care Act.

Results

Though this analysis largely builds from the prior published analysis on state health spending data by OACT,³ relationships between the state characteristics and state health spending can change over time. As such, the econometric work has been updated to reflect both revisions in the data and the extended sample period. Overall, the various regression methods conducted suggest that

several state characteristics are important for understanding geographic variation in health spending. The factors that are most robust across modeling methods are personal income per capita, the share of the population enrolled in Medicare, and the share of the population enrolled in Medicaid. The supply of community hospital beds, health status, and the share of the population that is uninsured are less robust to changes in methodology. Detailed results for the current pooled and fixed effects models are shown below in Exhibit 3. The results for the between and annual models are shown in Exhibits 4 and 5, respectively.

Exhibit 3: Comparison of Pooled and State Fixed Effects Models

	[A]	[B]
Dependent Variable: Log of Total PHC Spending Per Capita (2012\$)	Pooled Model	Fixed Effects Model
Independent variables	Coef.(Std.Err.)	Coef.(Std.Err.)
Constant	0.605 (0.719)	2.804*** (0.981)
Log of Personal Income per capita (2012\$)	0.718*** (0.071)	0.505*** (0.086)
% of Population enrolled in Medicare	0.022*** (0.009)	0.034*** (0.007)
% of Population enrolled in Medicaid	0.006*** (0.002)	0.001 (0.001)
% of Population Uninsured	-0.002* (0.002)	0.002 (0.002)
Community Hospital Beds per 1,000 population	0.027*** (0.008)	0.016 (0.018)
Bad Health Index (%Smoker*%Obese*100)	0.014* (0.010)	-0.006 (0.006)
Fixed Effects	Period Fixed Effects -	Period Fixed Effects State Fixed Effects
Sample	1991-2019	1991-2019
n	1450	1450
Adjusted R-squared	0.942	0.984

Notes:

Personal Consumption Expenditure (PCE) deflator was used to adjust spending to 2012 dollars.

Coefficients and standard errors (in parentheses). Standard errors are clustered by state and adjusted for arbitrary heteroskedasticity and within state serial correlation.

Numbers with ***, **, and * are significant at the 5%, 10%, and 20% levels, respectively.

Pooled Model

Consistent with research on national-level health spending patterns over time, measures of income (personal income per capita) and indicators of technology (captured by period or year fixed effects) are highly significant factors explaining variation in state-level health care spending.^{25,26} Although per capita income is intended to measure differences in state resources to pay for health care, due to the lack of a state or regional price measure, the cross-state income effect also includes a pricing effect (discussed in more detail below). As a result, the reasonableness of our income coefficient (0.718) was assessed based on comparisons with coefficients estimated in our prior econometric analysis published with the prior release of state health spending data for 1991-2014 (also 0.718⁴) and in similar studies on cross-state or subnational income elasticity (which tended to range from 0.5 to 0.7^{22, 27}).

The average yearly increases in year fixed effect coefficients (for 1991-2019) suggested roughly a 0.9-percent increase in health spending per year (implicitly associated with technological advances), which was lower than that observed among OACT's prior pooled model regression and some earlier studies that estimate separate income and time trend coefficients in health spending regressions (period fixed effects not shown).²² These average yearly effects also seem to have been influenced by the recession and the historically low health spending growth that occurred in the years that followed.

The share of the state population enrolled in either Medicare or Medicaid was associated with relatively higher state spending levels. A one-percentage point increase in the share of the state population enrolled in Medicare is associated with an estimated increase in real personal health care spending per capita of 2.2 percent, similar to the coefficient estimated in OACT's prior pooled

model regression for this variable (2.0 percent). Subsequent to the prior OACT analysis from 2014, the baby-boom generation has continued to enter into the program, which substantially contributed to the program's enrollment growth, but at the same time brought the average age of the beneficiary down (implying relatively less spending per beneficiary on average), which would tend to constrain the magnitude of the coefficient that measures the effect of coverage over this period.

Similarly, a one-percentage point increase in the share of the state population enrolled in Medicaid is associated with a relative increase in real personal health care spending per capita (of 0.6 percent), essentially the same as the prior OACT estimate. The relatively lower coefficient magnitude compared to that of Medicare seems reasonable given the differences in spending for each program on a per capita basis (which would implicitly include effects from Medicaid's lower relative provider payment rates compared to Medicare). Medicaid spending on personal health care per capita is 26 percent lower than Medicare (in 2019), which implies that the coefficient should also be lower for Medicaid (since the coefficient is measuring an impact on overall spending per capita). The coefficient magnitude is actually estimated to be lower by 74 percent, however. This additional difference in coefficient magnitudes is likely somewhat explainable by the effect of dual enrollees (people who are enrolled in both Medicare and Medicaid, who tend to spend more on health care than younger, non-disabled Medicaid enrollees), which suggests that some of the effect of Medicaid coverage might also be captured in the estimated Medicare enrollment coefficient. This is further supported by the 1991-2019 correlation between the two variables (sample correlation is significant at 0.557 percent). While the correlation is statistically significant, it was not high enough to suggest removal from the model specification given the variance inflation factors for each variable were below five indicating only moderate severity in multicollinearity.

On the other hand, the lack of insurance, as measured by the share of the population that is uninsured, was associated with a relative decrease in personal health care spending per capita. A one-percentage point increase in the share of the uninsured of the state population was associated with a 0.2-percent decline in real personal health care spending per capita. In the pooled model, this factor was only marginally significant. The negative coefficient likely reflects limited access to, and resources to pay for, medical care due to lack of insurance coverage.²²

Community hospital beds per 1,000 population, which is a measure of health care capacity, was estimated to have a positive estimated coefficient. An increase of one hospital bed per 1000 population was associated with an estimated 2.8-percent increase in real personal health care spending per capita by state. The magnitude of this effect is in line with the previous OACT pooled regression (previously, the effect was slightly lower at 2.5 percent). In addition, other researchers identified comparatively higher health spending for certain insured populations where there were higher concentrations of hospital beds.²⁸

Finally, consistent with prior analysis, the bad health index also had an estimated positive sign, indicating higher medical costs in states with higher shares of residents with relatively lower health status. Thus, a 1-percentage point increase in the bad health index (smoking rate * obesity rate * 100) was associated with an estimated 1.4-percent increase in real personal health care spending per capita by state. However, the effect was only marginally significant in the pooled model.

Fixed Effects Model

Consistent with our prior analysis, a test for the redundancy of state fixed effects indicated that the fixed effects coefficients are statistically significant versus the assumption that the constant is shared across the states. This was expected given the limited number of state-level variables available. However, as stated previously, state fixed effects are likely to be correlated with slow

moving state characteristics of interest. As such, it is expected that not all of the variables in the specification will be robust to both the pooled and fixed effects models. In line with this, four factors became insignificant with the addition of state fixed effects.

As was the case in previous analysis, the cross-state income elasticity estimated in the fixed effects model remained highly significant. The coefficient for the variable declined from 0.718 to 0.505 (0.213 difference from the pooled model). The reduction in the income elasticity between the pooled and fixed effects models is likely related to state fixed effects potentially picking up price variation across states. Additional analysis conducted with the limited data available on the regional price parities by state is discussed in more detail below. In general, the ability of the cross-state income variable to explain most of the variation in health spending between states (in and of itself) and its statistical significance between models supports the robustness of this factor to both methods.

In addition to income, the percent of the state population enrolled in Medicare retained significance and its coefficient was higher in magnitude in this regression. This suggests that this factor is more robust to the inclusion of fixed effects.

Conversely, the rest of the independent variables from the pooled model specification became insignificant in the fixed effects model. In the fixed effects model, the percent of the population enrolled in Medicaid, the percent of the population that is uninsured, the count of community hospital beds per 1,000 population, and the bad health index, all exhibited substantial losses in significance, indicating that these factors are not robust to this method. In addition, the bad health index not only declined in significance, but also its coefficient changed signs, which is counter to the theory for inclusion into the specification.

As discussed earlier, since fixed effects ideally represent regional characteristics that do not change over time, they interact with exogenous state-level characteristics that also do not change substantially over time. The current set of independent variables varies little over time, particularly when compared to the variation across states. An analysis of the coefficients of variation (COV), measured by the ratio of the standard deviation to the mean, was used to demonstrate the difference in period-specific and cross-sectional specific variation. For four out of the six state-specific variables that were included in the model specification, the cross-sectional variation exceeded period-specific variation (Medicare enrollment share of the population, the uninsured share of the population the count of community hospital beds per 1,000 population and the bad health index). As such, the addition of state fixed effects to the model would be expected to greatly increase the multicollinearity in the model and thus make these coefficients more difficult to estimate efficiently. Consequently, the addition of fixed effects resulted in a loss of significance for several variables in the specification.

Between Model

The “between” model was estimated using the means of all the variables over time (see results in Exhibit 4 below). This model is conceptually similar to the pooled model, but attempts to remove the element of time from the regression and thus theoretically addresses two key issues: 1) it removes the need for fixed effects and associated multicollinearity between state fixed effects and the independent variables and 2) it also removes relationships with prior period variables and consequently, serial correlation arising from slow-moving variables. However, this technique is not as useful for examining periodic effects, such as economic cycles, and the use of the mean for each variable can make it more challenging to identify statistically significant relationships. Therefore, while the “between” model results were somewhat similar to those of the pooled model, some variable coefficients may have shifts in magnitude or significance.

Despite the challenges, this alternative modeling approach helps to identify which independent variables have relatively more robust relationships with variation in health spending across states. Using this approach, several variables remained highly significant with similar estimated coefficient magnitudes: real personal income per capita, the share of the population enrolled in Medicaid, and the count of community hospital beds per 1,000 population. Given that income has previously shown robustness across various methods, it's not surprising to find that it remains robust in this method. In addition, the percent of the population enrolled in Medicaid would be expected to have a strong and consistent relationship with health spending variation since this variable is directly related to health spending. The count of community hospital beds remained highly significant in this method with a nearly identical estimated coefficient. Further, the bad health index remained marginally significant at the 20 percent level for both the pooled and between models, albeit with a higher estimated magnitude for the between model.

However, two key variables change notably in significance, which are: the percent of the population that is uninsured and the percent of the population enrolled in Medicare. First, the uninsured variable is more cyclical in nature. Thus, in one sense, it is somewhat surprising to see this variable increase in significance in this method; although, this factor's importance in this setting may be an indication of the severity of the 2008-09 recession and modest recovery that followed, which coincided with substantial losses of coverage during and just after the recession. Second, the percent of the population enrolled in Medicare loses some significance with the between model, which may be attributable to this method dampening the impact of the baby-boom generation increasingly entering the Medicare program beginning in 2011. While some of these factors are not as robust as other factors, the increase in significance or maintenance of at least marginal significance across all factors in the between model does suggest that these factors are still important to consider in explaining geographic variation in health spending.

Exhibit 4: Comparison of Pooled and Between Models

	[A]	[B]
Dependent Variable: Log of Total PHC Spending Per Capita (2012\$)	Pooled Model	Between Model
Independent variables	Coef.(Std.Err.)	Coef.(Std.Err.)
Constant	0.605 (0.719)	0.235 (0.989)
Log of Personal Income per capita (2012\$)	0.718*** (0.071)	0.761*** (0.096)
% of Population enrolled in Medicare	0.022*** (0.009)	0.016* (0.012)
% of Population enrolled in Medicaid	0.006*** (0.002)	0.009*** (0.003)
% of Population Uninsured	-0.002* (0.002)	-0.007*** (0.003)
Community Hospital Beds per 1,000 population	0.027*** (0.008)	0.027*** (0.010)
Bad Health Index (%Smoker*%Obese*100)	0.014* (0.010)	0.026* (0.017)
Fixed Effects	Period Fixed Effects	-
Sample	1991-2019	Average over 1991-2019
n	1450	50
Adjusted R-squared	0.942	0.726

Notes:

Personal Consumption Expenditure (PCE) deflator was used to adjust spending to 2012 dollars. Coefficients and standard errors (in parentheses). Numbers with ***, **, and * are significant at the 5%, 10%, and 20% levels, respectively.

¹Coefficients and standard errors (in parentheses). Standard errors are clustered by state and adjusted for arbitrary heteroskedasticity and within state serial correlation.

²Standard errors are adjusted for heteroskedasticity using the White correction.

³For the "Between" model, all variables were averaged over 1991-2019 to obtain a sample of 50 average values by state for the dependent and independent variables.

Annual Models

Another method to test the robustness of these state characteristics is an approach in which 29 year-specific regressions are estimated individually (Exhibit 5). Since the time dimension is estimated separately, state fixed effects are not needed and serial correlation is removed. Like the between model, this approach is meant to remove some of the inefficiencies created by slow-

moving variables combined with the inclusion of fixed effects. On the other hand, unlike the between model, this approach allows for the tracking of time-related effects by looking at the change in coefficient estimates and their significance incrementally over time. Hence, this method allows for the possibility that various factors will be more or less important during different periods within the overall sample. Consistent with prior analysis, the resulting coefficient magnitudes were more comparable to the pooled model (versus the fixed effects model), suggesting that the pooled model explains mostly cross-sectional variation.

Accordingly, there was fluctuation in the magnitudes and/or significance of the estimated coefficients over time for all of the variables in the model. As seen previously, the income coefficient was highly significant over time and the coefficient ranged from 0.6 to 0.9 (increasing noticeably after 2008), which was close to the pooled model estimate of 0.718. The slightly increasing trend, particularly after 2008, suggests that this changing effect is tied to the 2008-2009 recession. The data set contains two recessions including the Great Recession over 2008-2009, as well as the 2001 recession. The data do not technically include a third recessionary period, as the start of this sample begins in 1991 and thus it excludes the first year of the 1990-1991 contraction. After the 2001 recession, the income coefficient showed a marked uptick in 2002. For the 2008-09 recession, there was another substantial uptick in the magnitude of the income coefficient during the recessionary period, which is not surprising given the substantial decline in income and loss of employment that occurred. Thus, the timing of the responsiveness of health spending to income changes was more immediate with the 2008-09 recession compared to the prior recession, which is not surprising given the relative severity of 2008-09 recession.

In addition to income, the variables that maintained at least marginal significance (at the 20 percent level) or higher for at least half of these regressions include: percent of the state population enrolled in Medicare, percent of the state population enrolled in Medicaid, and community hospital beds per 1,000 population. The coefficient for the share of the population enrolled in Medicare is somewhat stable overtime, rounding to 0.02 for the majority of the annual regressions (mirroring the magnitude of the pooled coefficient of 0.02). The coefficient for the share of the population enrolled in Medicaid oscillates fairly closely around its average of 0.006 over the 29 periods (essentially identical to the pooled coefficient of 0.006). Interestingly, the magnitude for the coefficient for Medicaid was lower from 2014 through 2018. This may be capturing the effect of the lower per enrollee spending trend when an increasing share of non-aged, non-disabled enrollees (who are comparatively less expensive than the program's more traditional aged and disabled beneficiaries) entered the Medicaid program due to expansions of coverage under the Affordable Care Act in 2014 and beyond.²⁹ In the 2000s, the uninsured share of the population tended to be more significant with a higher magnitude compared to the coefficient estimated in the pooled regression. This is likely due to the share of the uninsured population reflecting cyclical effects of recent recessions and, in 2014, expanded insurance coverage under the Affordable Care Act; hence, it is inherently capturing two key factors that have substantially impacted health spending in recent years.

The coefficients for the count of community hospital beds per capita was most significant in the 1990s, early 2000s, as well as the most recent four years, rounding to about 0.03-0.04 during those years compared to 0.027 for the pooled model. The trend in this coefficient is capturing a period of a relative decline in community hospital beds as the population grew, particularly in the 1990s. Given the trend of hospital inpatient services shifting to outpatient services during this time, encouraged by the rapid growth of Health Maintenance Organization plans in the 1990s, the decline in capacity and the decline in its ability to explain variation across states through the mid-2010s, seems reasonable. However, the importance of the count of hospital beds in recent years coincides with a growing share of the population enrolled in Medicare (as aging baby-boomers increasingly

became eligible for the program). Notably, the increase in the significance and magnitude of the Medicare coefficient precedes, but then overlaps with, the significance and increase in magnitude of the coefficient for the count of hospital beds. Finally, the bad health index was only occasionally significant, suggesting that this variable is less robust to this change in methodology.

In this method, lower adjusted R-squared estimates were observed (averaging just under 0.7) compared to the pooled model regression (0.9), which suggests that serial correlation causes some bias in the adjusted R-squared for the pooled models. There also seems to be a cyclical pattern in the annual regression adjusted R-squared with relatively higher values occurring during or just after a period of recession, indicating that state-level economic factors become more dominant in explaining health spending variation during periods of economic contraction.

Exhibit 5: Individual Year Regressions

Dependent Variable: Log of Total PHC Spending Per Capita (2012\$)
Independent variables:

Year	Constant	Log of Personal Income per capita (2012\$)	% of Population enrolled in Medicare	% of Population enrolled in Medicaid	% of Population Uninsured	Community Hospital Beds per 1,000 population	Bad Health Index (%Smoker *%Obese* 100)	Adjusted R ²
1991	0.245	<i>0.734</i>	<i>0.016</i>	<i>0.011</i>	0.002	<i>0.026</i>	0.009	0.788
1992	0.004	<i>0.754</i>	<i>0.020</i>	<i>0.010</i>	0.002	<i>0.019</i>	<i>0.017</i>	0.772
1993	-0.299	<i>0.782</i>	<i>0.021</i>	<i>0.013</i>	<i>0.003</i>	<i>0.024</i>	0.004	0.756
1994	-0.782	<i>0.827</i>	<i>0.022</i>	<i>0.011</i>	0.003	<i>0.029</i>	0.009	0.743
1995	-0.100	<i>0.765</i>	<i>0.023</i>	<i>0.007</i>	0.001	<i>0.033</i>	0.012	0.718
1996	0.341	<i>0.726</i>	<i>0.021</i>	<i>0.006</i>	0.001	<i>0.027</i>	0.015	0.661
1997	1.104	<i>0.653</i>	<i>0.022</i>	<i>0.005</i>	0.000	<i>0.032</i>	0.017	0.638
1998	<i>1.123</i>	<i>0.655</i>	<i>0.022</i>	<i>0.007</i>	-0.002	<i>0.030</i>	0.014	0.677
1999	<i>1.134</i>	<i>0.649</i>	<i>0.025</i>	<i>0.007</i>	0.000	<i>0.030</i>	0.012	0.650
2000	<i>1.387</i>	<i>0.631</i>	<i>0.022</i>	<i>0.006</i>	-0.001	<i>0.039</i>	0.013	0.666
2001	<i>1.553</i>	<i>0.626</i>	0.017	<i>0.005</i>	<i>-0.005</i>	<i>0.037</i>	<i>0.021</i>	0.673
2002	1.058	<i>0.678</i>	<i>0.018</i>	0.004	-0.003	<i>0.036</i>	<i>0.018</i>	0.664
2003	1.030	<i>0.685</i>	<i>0.020</i>	0.004	<i>-0.004</i>	<i>0.030</i>	0.016	0.642
2004	1.607	<i>0.640</i>	<i>0.018</i>	<i>0.004</i>	<i>-0.007</i>	<i>0.019</i>	<i>0.022</i>	0.629
2005	<i>2.185</i>	<i>0.594</i>	0.018	<i>0.005</i>	<i>-0.010</i>	0.011	0.018	0.601
2006	<i>2.177</i>	<i>0.595</i>	0.016	<i>0.006</i>	<i>-0.010</i>	<i>0.025</i>	0.014	0.617
2007	<i>1.889</i>	<i>0.623</i>	0.016	<i>0.006</i>	<i>-0.010</i>	0.014	0.017	0.648
2008	1.423	<i>0.658</i>	<i>0.022</i>	<i>0.007</i>	<i>-0.006</i>	0.011	0.009	0.668
2009	0.591	<i>0.735</i>	<i>0.025</i>	<i>0.006</i>	-0.003	<i>0.015</i>	0.006	0.736
2010	0.723	<i>0.728</i>	<i>0.021</i>	<i>0.007</i>	<i>-0.006</i>	<i>0.016</i>	0.013	0.757
2011	0.162	<i>0.773</i>	<i>0.022</i>	<i>0.006</i>	<i>-0.005</i>	0.004	<i>0.020</i>	0.759
2012	0.595	<i>0.731</i>	<i>0.023</i>	<i>0.007</i>	<i>-0.004</i>	0.009	0.013	0.693
2013	0.002	<i>0.785</i>	<i>0.024</i>	<i>0.006</i>	<i>-0.005</i>	-0.001	0.020	0.695
2014	0.188	<i>0.766</i>	<i>0.025</i>	<i>0.004</i>	-0.005	0.007	0.021	0.656
2015	-0.657	<i>0.839</i>	<i>0.025</i>	<i>0.004</i>	-0.001	0.025	0.017	0.654
2016	-0.992	<i>0.870</i>	<i>0.021</i>	<i>0.004</i>	0.000	<i>0.039</i>	<i>0.023</i>	0.682
2017	-1.191	<i>0.885</i>	<i>0.022</i>	<i>0.004</i>	-0.002	<i>0.036</i>	<i>0.030</i>	0.709
2018	-0.586	<i>0.831</i>	<i>0.021</i>	<i>0.005</i>	-0.004	<i>0.049</i>	0.019	0.703
2019	-0.735	<i>0.843</i>	<i>0.020</i>	<i>0.006</i>	<i>-0.005</i>	<i>0.058</i>	<i>0.020</i>	0.714

Notes: Personal Consumption Expenditure (PCE) deflator was used to adjust spending to 2012 dollars. Numbers in bold-italic are significant at the 5% level. Numbers in bold are significant at the 10% level. Numbers in italics are significant at the 20% level. Standard errors are corrected for heteroskedasticity using the White correction. Shaded rows indicate recession periods as indicated by the National Bureau of Economic Research.

Specification Variants

Adjusting for Price

To assess the impact of using a state-level price indicator and to differentiate the impact of regional price trends, additional pooled regressions were estimated using a relatively newer state price indicator (Regional Price Parity or RPP) from the BEA (available for 2008 forward). As mentioned earlier, these RPPs were only available over a limited period of time, and were thus back cast to

cover the full sample period. The RPPs were then combined with the US PCE deflator to obtain an implicit regional price deflator in these regressions. Despite the limited availability, the variable is useful in giving a potential indication of the portion of the cross-state income elasticity that is related to price effects. Results are shown in Exhibit 6.

As expected, the inclusion of a state price adjustment (to the income and health spending variables) in the pooled model reduced the income elasticity from 0.718 to 0.642. Similarly, there is a reduction of the magnitude of the income elasticity between the pooled and fixed effects model in the current analysis (0.718 in the pooled model to 0.505 in the fixed effects model). Though the differential in magnitude is larger when state fixed effects are included versus the state price adjustment, the inclusion of the state price adjustment explains more than a third of the difference. Thus, the income elasticity in the regressions where this price adjustment is not included is likely capturing some price effects.

Generally, with the exception of the income coefficient, these estimated coefficients and magnitudes for the other variables were similar to those of the pooled model without the state price adjustment. In a couple of cases (community hospital beds per 1,000 population and the bad health index), the magnitude of the coefficient increased somewhat, likely indicating some state price interaction with those variables. The bad health index also increased in significance in the pooled model with the state price adjustment.

For the fixed effects model, the addition of the state price adjustment resulted in fairly similar coefficients and variables that were highly significant remained highly significant. Interestingly, several variables increased in significance in the fixed effects model with the price adjustment, including the percent of the population enrolled in Medicaid, the percent of the population that is uninsured, count of community hospital beds per 1,000 population, and the bad health index (although as with the fixed effects model without the price adjustment, the bad health has a negative sign, which is contrary to the expected impact of this variable). This may be an indication that some of the variables that are insignificant in the fixed effects model without the state price adjustment, are capturing price effects and thus become more important when the personal income per capita is adjusted to account for state price differences.

Exhibit 6: Comparison of Current Models with Regional Price Adjusted Models

	[A]	[B]	[C]	[D]
Dependent Variable: Log of Total PHC Spending Per Capita (2012\$)	Pooled Model	Fixed Effects Model	Pooled Model Adjusted for State Price	Fixed Effects Model Adjusted for State Price
Independent variables	Coef.(Std.Err.)	Coef.(Std.Err.)	Coef.(Std.Err.)	Coef.(Std.Err.)
Constant	0.605 (0.719)	2.804*** (0.981)	1.370* (0.903)	2.368*** (0.926)
Log of Personal Income per capita (2012\$)	0.718*** (0.071)	0.505*** (0.086)	0.642*** (0.088)	0.541*** (0.083)
% of Population enrolled in Medicare	0.022*** (0.009)	0.034*** (0.007)	0.022*** (0.009)	0.037*** (0.007)
% of Population enrolled in Medicaid	0.006*** (0.002)	0.001 (0.001)	0.005*** (0.002)	0.002* (0.001)
% of Population Uninsured	-0.002* (0.002)	0.002 (0.002)	-0.003** (0.002)	0.002* (0.002)
Community Hospital Beds per 1,000 population	0.027*** (0.008)	0.016 (0.018)	0.041*** (0.008)	0.030** (0.018)
Bad Health Index (%Smoker*%Obese*100)	0.014* (0.010)	-0.006 (0.006)	0.019*** (0.009)	-0.011** (0.006)
Fixed Effects	Period Fixed Effects -	Period Fixed Effects State Fixed Effects	Period Fixed Effects -	Period Fixed Effects State Fixed Effects
Sample	1991-2019	1991-2019	1991-2019	1991-2019
n	1450	1450	1450	1450
Adjusted R-squared	0.942	0.984	0.942	0.984

Notes:

Personal Consumption Expenditure (PCE) deflator was used to adjust spending to 2012 dollars. Coefficients and standard errors (in parentheses). Standard errors are clustered by state and adjusted for arbitrary heteroskedasticity and within state serial correlation. Numbers with ***, **, and * are significant at the 5%, 10%, and 20% levels, respectively.

Conclusion

The analysis presented in this paper updates and builds upon prior work by OACT to better understand and quantify the effect of relevant state-level factors on per capita personal health care spending. Throughout this analysis, several state-level factors remained highly statistically significant across the majority of methodologies tested. First and foremost, personal income per capita (and period fixed effects, where applicable) remained highly significant, demonstrating a positive association with health spending throughout all methods and time periods tested, in addition to explaining the majority of the variation in health spending. The shares of the population that are enrolled in Medicare or Medicaid were also positively associated with health spending and robust across most methodologies. The share of the uninsured was negatively associated with health spending and was significant across several methods and has increased noticeably in importance during the years following the recession. Finally, though the number of community hospital beds per 1,000 population was estimated to be positively associated with health spending and robust across methods, it was shown to be more critical to explaining variation during limited periods (in the 1990s, early 2000s, and 2016-19).

In addition, the incremental or annual regressions demonstrate that the economic variables (personal income per capita and the uninsured rate) increase in magnitude and significance and become more critical to explaining variation in health spending across states during or just after recessionary periods. This is consistent with findings at the national level regarding the significant relationship between income and health spending. This is also indicative of the cyclical underpinnings of slow growth in personal health care spending per capita that followed the 2008-09 recession.

Consequently, the variables that are most important for explaining the variation in state health spending over time and across methodologies are personal income per capita, percent of the population enrolled in Medicare, and percent of the population enrolled in Medicaid.

Appendix

Major Coverage Expansions under the Affordable Care Act

The major health insurance coverage expansions through Medicaid and Health Insurance Marketplaces under the Affordable Care Act substantially contributed to an overall acceleration in personal health care spending growth at the national level in 2014, though effects were most evident at the payer level.³⁰ At the state level, however, accelerations in personal health care spending per capita growth on average were present, regardless of whether or not a state chose to expand their Medicaid program. Additionally, growth in per capita spending for expansion states were similar but slightly faster relative to non-expansion states in 2014.

Overall, several indicator variables were studied to assess the effect of the major coverage expansions on the variation in health spending across states. First, an indicator of state Medicaid expansion was tested. This binary indicator took a value of 1 when a state elected to expand their Medicaid program (as well as for the years following the expansion decision) and 0 otherwise. For the pooled model, this factor was not significant. While the indicator itself was significant in the fixed effects model, the percent of the population enrolled in Medicaid was insignificant with the addition of this variable (data not shown).

Further, year indicator variables for the years 2014-2016 were tested to assess the impact in the years during and after the implementation of the major coverage expansions. In order to test specific year indicator variables (2014, 2015, 2016), period fixed effects were replaced with a trend in addition to the 2014, 2015, and 2016 year indicator variables. In tandem with the trend, the 2014-2016 indicator variables were not consistently significant across the pooled and fixed effects models (data not shown). Another issue with using the year indicator variables is that, they could also be capturing other effects beyond the Affordable Care Act coverage expansions, such as lingering effects of the 2008-09 recession, medical specific price trends not captured in the national PCE deflator, or trends otherwise excluded from the model specification.

The lack of statistical significance for these indicator variables may be due to the aggregated nature of the dependent variable of the model (total personal health care per capita across all payers). Because the dependent variable is an all payer model, it is more difficult to identify a consistently significant effect from payer specific impacts under the Affordable Care Act.

Endnotes

- ¹ Centers for Medicare and Medicaid Services. Health expenditures by state of provider, 1980-2020 [Internet]. Baltimore (MD): CMS; 2022 Aug 12 [cited 2022 Aug 1]. Available from: <https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsStateHealthAccountsProvider.html>
- ² Centers for Medicare and Medicaid Services. Health expenditures by state of residence, 1991-2020 [Internet]. Baltimore (MD): CMS; 2022 Aug 12 [cited 2022 Aug 1]. Available from: <https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsStateHealthAccountsResidence.html>
- ³ Cuckler G, Sisko A. Modeling per capita state health expenditure variation: state-level characteristics matter. *Medicare & Medicaid Research Review* 2013; 3(4): E1-E21.
- ⁴ Centers for Medicare and Medicaid Services. Econometric analysis of state health expenditures: methodology and model specification [Internet]. Baltimore (MD). CMS; 2017 [cited 2022 Aug 1]. Available from: <https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/Downloads/State-Model-14.pdf>
- ⁵ Lassman D, Sisko AM, Catlin A, Barron, MC, Benson J, Cuckler GA, et al. Health spending by state of residence, 1991-2014. *Health Aff (Millwood)*. 2017; 36(8).
- ⁶ Suggested in Wilson S, Butler D. A lot more to do: the sensitivity of time-series-cross-section analysis to simple alternative specifications. *Political Analysis* 2007; 15(2): 101–123.
- ⁷ Centers for Medicare and Medicaid Services. State Health Expenditure Accounts: Methodology Paper, Definitions, Sources and Methods (ZIP) [Internet]. Baltimore (MD): CMS; 2022 Aug 12 [cited 2022 Aug 1]. Available from: <https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/NationalHealthAccountsStateHealthAccountsResidence>
- ⁸ Medicaid enrollment is based on unpublished analysis by the CMS Office of the Actuary of data from Medicaid Statistical Reports (HCFA-2082), the Medicaid Statistical Information System (MSIS), the Medicaid Analytical eXtract (MAX), and CMS-64 Quarterly Expense Reports. Medicare enrollment is based on Centers for Medicare & Medicaid Services, Office of Enterprise Data and Analytics. Chronic Conditions Data Warehouse. Baltimore (MD): CMS.
- ⁹ U.S. Bureau of Economic Analysis. Regional Economic Accounts (“Tools - Interactive Data: Regional Data GDP & Personal Income” with title “Annual Personal Income and Employment by State”) [Internet]. Washington (DC): BEA; [last revised 2022 Mar; cited 2022 Aug 1]. Available from: <https://www.bea.gov/data/economic-accounts/regional>
- ¹⁰ U.S. Census Bureau, Population Division. State Population Totals Tables: 2010-2020 (“Table 1. Annual Estimates of the Resident Population for the United States, Regions, States, and Puerto Rico: April 1, 2010 to July 1, 2020 (NST-EST2020)”) [Internet]. Washington (DC): Census; [cited 2022 Aug 1]. Available from: <https://www2.census.gov/programs-surveys/popest/tables/2010-2020/state/totals/nst-est2020.xlsx>
- ¹¹ U.S. Bureau of Economic Analysis. Regional Economic Accounts (“Tools - Interactive Data: GDP & Personal Income” with title “Table 1.1.9. Implicit Price Deflators for Gross Domestic Product”) [Internet]. Washington (DC): BEA; [last revised 2022 Mar; cited 2022 Aug 1]. Available from:

<https://apps.bea.gov/iTable/iTable.cfm?reqid=19&step=2#reqid=19&step=2&isuri=1&1921=survey>

¹² U.S. Bureau of Economic Analysis. Regional Economic Accounts (“Tools - Interactive Data: Regional Data GDP & Personal Income” with title “Real Personal Income (RPI), Regional Price Parities (RPPS), and Real Personal Consumption Expenditures (RPCE)”) [Internet]. Washington (DC): BEA; [cited 2017 Jun 2]. Available from: <https://www.bea.gov/data/economic-accounts/regional>

¹³ U.S. Bureau of Economic Analysis, Real Personal Consumption Expenditures and Personal Income by State, 2020 [Internet]:BEA; 2022 Dec 21 [cited 2022 May 5]. Available from: <https://www.bea.gov/news/2021/real-personal-consumption-expenditures-and-personal-income-state-2020>

¹⁴ Sarah Flood, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren and Michael Westberry. Integrated Public Use Microdata Series, Current Population Survey: Version 9.0 [dataset]. Minneapolis, MN: IPUMS, 2021 [cited 2022 May 31]. <https://doi.org/10.18128/D030.V9.0>

¹⁵ Steven Ruggles, Sarah Flood, Ronald Goeken, Megan Schouweiler and Matthew Sobek. Integrated Public Use Microdata Series, American Community Survey (IPUMS USA): Version 12.0 [dataset]. Minneapolis, MN: IPUMS, 2022 [cited 2022 May 31]. <https://doi.org/10.18128/D010.V12.0>

¹⁶ Davern M, Klerman JA, Ziegenfuss J, Lynch V, Greenberg C. A partially corrected estimate of Medicaid enrollment, uninsurance: results from an imputational model developed off linked survey, administrative data. *Journal of Economic and Social Measurement* 2009; 34(4): 219-240.

¹⁷ Updated adjustment estimates were provided to OACT by J. Ziegenfuss by email on September 6, 2011.

¹⁸ Centers for Medicare & Medicaid Services. Table 22 Health Insurance Enrollment and Uninsured [Internet]. Baltimore (MD): CMS; 2022 Dec 15 [cited 2022 May 31]. Available from: <https://www.cms.gov/files/zip/nhe-tables.zip>

¹⁹ Kaiser Family Foundation. Status of State Action on the Medicaid Expansion Decision [Internet]. Washington (DC): Kaiser Family Foundation [cited 2022 Jun 2] Available from <http://kff.org/health-reform/state-indicator/state-activity-around-expanding-medicaid-under-the-affordable-care-act>

²⁰ American Hospital Association, Community hospital beds per 1,000 resident population, by state 1991, 1999–2020 [Internet]. Chicago (IL): AHA [cited 2022 May 27]. Available from: <http://www.ahaonlinestore.com>.

²¹ Centers for Disease Control and Prevention. Behavioral Risk Factor Surveillance System [Internet]. Atlanta (GA): CDC, 2021 [cited 2021 Jul 1]. Available from <http://www.cdc.gov/brfss/>

²² Rettenmaier AJ, Saving TR. Perspectives on the geographic variation in health care spending [Internet]. Dallas (TX): National Center for Policy Analysis; 2009 Jul 29. Available from <http://www.ncpa.org/pub/perspectives-on-the-geographic-variation-in-health-care-spending>

-
- ²³ Healtton, CG, Vallone, D, McCausland KL, Xiao H, Green M. Smoking, obesity, and their co-occurrence in the United States: cross-sectional analysis. *BMJ (Clinical Research Ed)*. 2006; 333:25-26.
- ²⁴ Centers for Disease Control and Prevention, National Center for Health Statistics. Multiple Cause of Death 1999-2020. 1999-2019 [dataset]. 2021[cited 2022 May 4]. In CDC WONDER Online Database [Internet]. Atlanta (GA): CDC. 2021 Available at: <http://wonder.cdc.gov/mcd-icd10.html>
- ²⁵ Smith S, Newhouse J, Freeland, M. Income, insurance, and technology: why does health spending outpace economic growth? *Health Aff (Millwood)*. 2009; 28(5): 1276-1284.
- ²⁶ Di Matteo L. The macro determinants of health expenditure in the United States and Canada: assessing the impact of income, age distribution, and time. *Health Policy (Amsterdam)*. 2005; 71: 23-42.
- ²⁷ Getzen TE. Health care is an individual necessity and a national luxury: applying multilevel decision models to the analysis of health care expenditures. *Journal of Health Economics*. 2000; 19:259-270.
- ²⁸ Although this study was conducted based on Medicare enrollees, a similar positive association was identified. See Rettenmaier AJ, Wang Z. Regional variations in medical spending and utilization: a longitudinal analysis of US Medicare population. *Health Economics* 2012; 21(2): 67-82.
- ²⁹ Truffer C, Rennie K, Wilson L, Eckstein E. 2018 actuarial report on the financial outlook for Medicaid [Internet]. Baltimore (MD): Centers for Medicare and Medicaid Services; [cited 2022 Aug 1]. Available from: <https://www.cms.gov/files/document/2018-report.pdf>
- ³⁰ Martin AB, Hartman M, Washington B, Catlin A, National Health Expenditure Accounts Team. National health spending: faster growth in 2015 as coverage expands and utilization increases. *Health Aff (Millwood)*. 2017; 36(1):166-176.